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THREE ESSAYS ON EMPIRICAL MACROECONOMICS

presented by

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Ph. D. degree in Economics


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THREE ESSAYS ON EMPIRICAL MACROECONOMICS

By

Christopher C. Douglas

A DISSERTATION

**Submitted to
Michigan State University
in partial fulfillment of the requirements
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ABSTRACT

THREE ESSAYS ON EMPIRICAL MACROECONOMICS

By

Christopher C. Douglas

Chapter 1, "What is the Best Way to Control for the Clustering in Central Bank Intervention Data?", investigates the "clustering" property of this data. That is, successive days of intervention are followed by successive days of no intervention. Clearly, this clustering contains information as to when an intervention will occur and must be dealt with in the time-series econometric specification. I apply two time series econometric specifications that are designed to control for this property, the Autoregressive Conditional Hazard (ACH) of Hamilton and Jordá and a modified version of the Autoregressive Conditional Multinomial (ACM) of Engle and Russell, both to test for traditional motivations for intervention and to find which model performs better. I find that the performance of the ACH is tied to the significance of the duration in a standard static model (such as a probit or logit). I show that the ACM outperforms the ACH in terms of goodness-of-fit, the significance of the duration in a logit model disappears with the inclusion of dynamics in the ACM model (a static ACM model reduces to a probit or logit), and find that the significance of explanatory variables is tied to the econometric specification. I argue that these results are relevant to applications using similarly clustered data.

Chapter 2, "Why are Gasoline Prices Sticky? A Test of Alternative Models of Price Adjustment", applies the modified ACM to a unique data set consisting of daily price and cost observations for nine Philadelphia gasoline wholesalers to examine why gasoline wholesalers change their price less frequently than their costs change. Unlike Davis and

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Hamilton (who apply the ACH), I find statistically significant time dependence for all wholesalers. I use the results from Chapter 1 to illustrate why this is the case; the lagged duration is insignificant for all wholesalers but one. Comparing this finding of time dependence to competing theoretical models of price adjustment suggests that a menu cost model is not broadly consistent with the data. However, the time dependence is consistent with strategic considerations related to the idea of "fair pricing" as well as somewhat supportive of bounded rationality explanations related to the costs of obtaining and processing information.

Chapter 3, "Dynamic Pricing and Asymmetries in Retail Gasoline Markets: What Can We Learn About Price Stickiness?" uses a data set consisting of daily observations of fifteen Philadelphia retail gasoline stations to examine the issues in Chapter 2 on the retail level. The retail price of gasoline changes less frequently than the wholesale price of gasoline. I find that a variable threshold model fits the data well, and the dynamics in a station's pricing decision are almost exclusively in the lower threshold. Prices are more flexible in the upward direction compared to the downward direction, as the distance between the upper and lower thresholds narrows as prices rise and widens as prices fall, and stations are more likely to make price increases rather than price decreases. I argue that this evidence is consistent with "search costs". Additionally, the dynamics and asymmetry differs for that of wholesalers as found in Chapter 2. I argue that differences in market structure can likely explain the difference.

Dedicated to the memory of Carl Winter

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dissertation committee, so I hope that I built solid relationships, or she will suffer a negative externality!

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Introduction

Many issues in empirical macroeconomics imply a binary choice. Will a central bank engage in monetary policy this week? Will a central bank intervene in the foreign exchange market today? Will a firm change its price today? And, not surprisingly, the binary choice we observe today often depends on the choice and data we observed in the past.

In Chapter 1, entitled “What is the Best Way to Control for the Clustering in Central Bank Intervention Data?”, I investigate the central bank’s choice on whether or not to intervene in the foreign exchange market on a given day. As Neely (2001, 2005) points out, there are three common reasons that are believed to explain why a central bank chooses to intervene. A central bank may intervene in order to resist short-term movements of the exchange rate (leaning against the wind), to move the exchange rate into line with long-run fundamentals, or to eliminate excess volatility from the market (calming disorderly markets). The Foreign Currency Directive of the Federal Reserve succinctly states the intervention policy of the United States is to “counter disorderly market conditions”, which could be any combination of these three motivations.

Yet, testing these motivations is complicated by a unique property of the data. That is, even a cursory look at intervention data reveals that successive days of intervention are followed by successive days with no intervention. Clearly, this “clustering” contains information as to when an intervention will occur and as a result, must be dealt with in the time-series econometric specification.

Using intervention data from January 5th, 1987 to January 23rd, 1993 for the Federal Reserve and the German Bundesbank, and intervention data from April 1st, 1991 to February 28, 2001 for the Bank of Japan, I investigate how best to control for this clustering. Then,

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employing the favored methodology, I investigate whether or not central banks intervene for the reasons described above.

I begin this examination by estimating the Autoregressive Conditional Hazard (ACH) model of Hamilton and Jordá (2002) for all the intervention data sets. The ACH model modifies Engle and Russell's (1998) autoregressive conditional duration (ACD) model by estimating a $\{0,1\}$ Bernoulli process in calendar time and allowing for the inclusion of exogenous variables in a linear manner. The ACH model controls for the clustering by including a lag of the duration, or time between successive interventions, in the central bank's reaction function and uses the lagged duration to impose a specific functional form assumption on the conditional probability. It assumes that the conditional probability of an intervention is equal to the reciprocal of the lagged duration. For example, if the lagged expected duration is 3 days, then the conditional probability of observing an intervention is $1/3$. The appeal of this model is that it outperformed a vector-autoregression in terms of mean squared error in predicting Federal funds target changes by the Federal Reserve in Hamilton and Jordá (2002). This is a noteworthy result because unlike the vector autoregression, the ACH minimized a likelihood function rather than minimizing a sum of squared errors.

Despite the promise of the ACH for predicting central bank interventions, I find it problematic in that the lagged expected duration is not always a significant predictor of an event occurring (in terms of statistical significance in a standard probit or logit model). When this happens, the ACH imposes a strict functional form assumption on an insignificant variable. Additionally, as in the case of the Federal Reserve, this functional form problem may give misleading significance in the other exogenous variables. In the case of the other

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central banks (where the lagged expected duration is significant, or nearly so, in a probit model), the ACH only offers slight improvement in terms of goodness-of-fit and offers little additional insight in terms motivations for central bank intervention over and above the insight offered by a standard probit.

To avoid the issues raised by the ACH, I estimate a version of Engle and Russell's (2005) autoregressive multinomial model modified as a binary choice model. This autoregressive conditional binomial model (ACB, Herrera 2004), controls for the clustering by lagging the indicator variable and lagging the response probability. Additionally, the ACB allows for the easy inclusion of exogenous variables, including the lagged duration. I show that the ACB represents a substantial improvement in terms of goodness-of-fit and when dynamics are included in the ACB (a static ACB reduces to a probit or logit depending on the functional form chosen), the significance of the lagged expected duration disappears. This suggests that lagging the expected duration is not the best way to control for the clustering, a useful result that can be applied to similar applications.

Using the ACB results, I find no statistically significant evidence that the Federal Reserve intervened in response to exchange rates being out-of-line with fundamentals and found statistically significant evidence that it preferred to intervene when markets were calmer. Additionally, I find a novel result that the spread between the Federal funds rate and the 6-month Treasury Bill rate contains statistically significant predictive power for an intervention, suggesting a link between intervention policy and monetary policy. For the Bundesbank, I find evidence that it was intervening in response to exchange rates being out-of-line with fundamentals, and like the Federal Reserve, preferred to intervene when markets were calmer.

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For the Bank of Japan, I find strong evidence that it has intervened in response to changes in the exchange rate. However, the response is different depending on the subsample examined. Prior to Eisuke Sakakibara becoming the Director General of the International Finance Bureau of the Ministry of Finance in Japan on June 1st, 1995, Japanese intervention can be described as “leaning against the wind”. That is, intervening to resist short-term undesirable changes in the exchange rate. However, after he became director, Japanese intervention can be described as “leaning with the wind”. That is, intervening in the same direction as the change in the exchange rate, if the change was favorable.

In Chapter 2, entitled “Why are Gasoline Prices Sticky? A Test of Alternative Models of Price Adjustment”, I examine why a firm chooses to leave its price unchanged on a given day, even if its costs changed on that same day. This “price stickiness” has to be modeled in theoretical macroeconomic models in order to generate short-run non-neutrality of money as documented in the literature on monetary policy transmission. However, different motivations for this price stickiness offered in these theoretical models offer different implications for inflation dynamics. Thus, understanding the motivation behind price stickiness on the micro level will help us to understand how to model price stickiness on the macro level. In fact, I find evidence that the price stickiness in wholesale gasoline prices is motivated by strategic concerns with regards to a “fair price” and well as some evidence of information processing delays on the part of consumers.

I use a data set consisting of daily observations of price and cost for nine Philadelphia gasoline wholesalers spanning January 1st, 1989 to December 31st, 1991 to investigate the motivations for price stickiness present on the firm level. Wholesale gasoline has several characteristics that facilitates investigation. It is a physically homogenous good, which

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controls for product heterogeneity in firm pricing decisions. Focusing on a single city (Philadelphia) minimizes the impact of changes in transportation costs and taxes. And, since gasoline is sold in standardized lots of one gallon, a wholesaler cannot simply reduce quantity in lieu of increasing price. Price stickiness is evident in this market in that the cost of wholesale gasoline (as quoted in the New York Mercantile Exchange) changes nearly every day, whereas the posted price of wholesale gasoline changes on 60% or less of the observations.

The motivations offered for price stickiness can be broken up into three general categories: menu costs, information processing delays, and strategic interactions. Menu costs posit that there is a fixed cost a firm must pay in order to change 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 of this is that if the additional profit resulting from a price change is less than the menu cost, the firm will elect to leave the price unchanged.

Information processing delays posit that it is difficult for a firm or consumer to continually collect and process information. Thus, sticky information models suggest there is a delayed response to market signals by firms when deciding whether or not to change their prices. Reis (2006) shows that if it is costly to obtain and process information, then firms will choose a price for their output and then derive an optimal time at which to be inattentive. While they are inattentive, firms receive no news about the state of the economy, until it is time to plan again. This suggests that the probability of successive days of price changes is very low. On the other hand, Levy, Chen, Ray, and Bergen (2006) suggest that if consumers are inattentive to small price increases, then firms will have incentive to price

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asymmetrically “in the small”. That is, firms will make small price increases, since such an increase will not result in a loss of business for the firm. But, firms will not make small price decreases, since consumers will be inattentive to this decrease and hence it will not generate an increase in business for the firm. That is, prices will be sticky on the downward direction in terms of small price decreases. There is no asymmetry “in the large”, since consumers are not inattentive to large price changes. Contrast this with inattention by producers. That model predicts no asymmetry “in the small” or “in the large”, as producers are not aware of information as it arrives, and hence cannot respond asymmetrically to it.

Strategic considerations suggest that firms are hesitant to raise prices if customers will retaliate. In this vein, Rotemberg (1982) posits that firms deliberately stretch out long price changes to avoid upsetting consumers. On the other hand, “fair pricing” theories such as Okun (1981) and Kahneman, Knetsch, and Thaler (1986) suggest that customers punish firms who raise prices unfairly. In fact, Rotemberg’s (2002, 2006) models of inflation can be traced to Kahneman et al.’s study. They find that consumers believe that they are entitled to their reference (past) price while firms are entitled to their reference (past) profit. When this reference profit is threatened, consumers believe it is fair for a firm to raise its price in order to protect this reference profit, even passing the complete loss onto them. However, consumers do not believe it to be fair for a firm to take advantage of excess demand, or to ration a shortage, by raising its price, as this generated an unfair “windfall” profit for the firm (profit over and above the reference profit). In short, absent a cost shock, consumers believe that maintaining the status quo is fair.

Each of these three categories implies different time dynamics in the pattern of price adjustment. And, competing explanations within a category can be differentiated by the

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different explanatory variables and asymmetry each implies. For example, menu costs imply no autocorrelation or asymmetry in price adjustment. All that matters is if the difference between the actual and optimal price is greater or less than the menu cost. Information processing delays imply negative serial correlation between price changes. For example, if the probability of the firm changing its price yesterday was high, and the firm changed its price, it is less likely to do so again today. Noting that inattention on the part of producers predicts no asymmetry, while inattention on the part of consumers predicts asymmetry “in the small” can further narrow this down. Partial adjustment and fair pricing imply positive autocorrelation in the pattern of price adjustment. However, partial adjustment implies that the size of the gap between the firm’s actual and optimal price remaining after the most recent price change contains information for a subsequent price change. Fair pricing does not, since consumers believe it to be fair for cost shocks to be passed through in a one-shot increase. And, fair pricing implies that there is asymmetry “in the large” in that firms are hesitant to make large price increases in order to ration a shortage, but would not be so hesitant to make a correspondingly large price decrease.

Using the ACB model described in Chapter 1, I find consistent evidence for fair pricing motivating the price stickiness. For 7 of the 9 firms, there is positive autocorrelation in the price change probabilities. If the probability of a price increase was high yesterday, and the firm changed its price, it is more likely to change its price again today. In response to a cost shock, the probability of a price change instantly increases and then returns to steady state, suggesting that these firms instantly pass the cost onto consumers. And, these firms exhibit “asymmetry in the large” in that they are more likely to make large price decrease over a large price increase.

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However, I also find firms are more likely to make a small price increase over a small price decrease. As described above, this is consistent with rational inattention by consumers. To explain this, I note that the average magnitude of a wholesale gasoline price change is less than one cent. However, when a gasoline retail station increases its price, it has to do so by increments of one cent or greater. Thus, retail gasoline stations (consumers) are inattentive to these small cost increases because this “menu cost” forces them to be.

Chapter 2 is related to the work done by Davis and Hamilton (2004). Using the same data set, Davis and Hamilton find that the menu cost model makes predictions “broadly consistent” with the data. They find that the only significant predictor of a price change is the gap between the firm’s actual and optimal price. There are no significant time dynamics in the pattern of price adjustment, just as a menu cost model would predict. I use the results from Chapter 1 to illustrate why this is the case. Davis and Hamilton use the ACH to test to time dependence. I show that the lagged duration is rarely a significant predictor of a price change. Only one firm has the lagged duration estimated to be statistically significant in a static logit model, and this is the only firm where the ACH finds significant time dependence. Thus, by estimating a more general time series model, I am able to uncover some significant dynamics in the pattern of price adjustments, and as a result, obtain a more precise explanation for the price stickiness observed in the data.

Chapter 3, entitled “Dynamic Pricing and Asymmetries in Retail Gasoline Markets: What Can We Learn About Price Stickiness” uses a data set consisting of daily observations of price and cost for fifteen Philadelphia retail gasoline stations to examine the issues of Chapter 2 on the retail level. That is, the retail price of gasoline changes on approximately 10% of the observations, whereas the wholesale price of gasoline changes on 30% - 60% of

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the observations (as illustrated in Chapter 2 and confirmed in the data set of Chapter 3).

In addition to the motivations for price stickiness previously described, two additional ones are often offered for retail gasoline prices. Focal point collusion (Borenstein, Cameron, and Gilbert, 1997) suggests that firms use past prices as “focal points” at which to collude. This also allows firms to price asymmetrically, offering large price increases but colluding to keep prices from falling. Since collusion is easiest to sustain when the number of competitors is the smallest, the asymmetry should be most pronounced in stations are the least competitive.

On the other hand, search costs suggest that customers search for the lowest price only if the gains from search offset the costs of searching. For example, if a customer sees a big price increase, he may believe that a competing station has yet to increase its price (since prices are sticky) and search. Clearly, stations would like to hold off on making large price increases to avoid search. But, if a station has to, it would prefer to make one price increase and tolerate one period of search, rather than successive price increases and successive periods of search. If a customer sees a small price decrease, he may believe the probability of finding an even lower price is low and hence not search. Stations know this and hence have incentive to make prices sticky in the downward direction.

Using the ACB methodology, I find evidence in favor of the search cost argument. If a station made a price change yesterday, it is less likely to make a successive one today. And, I find asymmetry in that stations are more likely to make large price increases over large price decreases. Comparing the ACB with a variable threshold model, I find that stations are averse only to successive price increases, but not successive price decreases. Thus, prices being more flexible in the upward compared with the downward direction coupled with

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aversion to successive price increases is consistent with search costs explaining price stickiness on the retail level.

It is an interesting result that the motivations for price stickiness in the market for gasoline differs on the wholesale level compared to the retail level. However, differences in market structure likely explain the difference. The idea of price fairness in Kahneman, Knetsch, and Thaler (1986) applied to long-term relationships bound by long-term contract. Kahneman et al. examined the relationship between landlord and tenant, and employer and employee. The relationship between gasoline wholesaler and retailer is such a relationship. However, the relationship between gasoline retailer and individual consumer is not. There is no long term relationship binding a consumer to a specific gasoline station, and few consumers purchase gasoline every day. In Kahneman et al., people believed it was fair if others did not receive as favorable of a transaction as they did. That is, new consumers were not entitled to the former consumer's reference transaction. Thus, people who purchased gasoline at the lower price yesterday may not believe that others are entitled to purchase gasoline at that low price today. If this is the case, it is not surprising that fairness is less of a concern in the retail gasoline market, compared to the wholesale market.

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Chapter 1: What is the Best Way to Control for the Clustering in Central Bank Intervention Data?

1 Introduction

Periods of sterilized central bank interventions are intriguing episodes in the monetary history of countries. An intervention is sterilized if it is offset by a corresponding change in the domestic monetary base, so that the intervention will have no net effect on the domestic money supply. Unlike the consensus amongst macroeconomists that monetary policy exhibits a real effect on output at least in the short run, there is little consensus that intervention has an effect on exchange rates or market volatility in the short or long run.¹ Looking at volume effects alone, it would be hard to make a case that intervention could influence exchange rates by shifting the supply or demand curves for foreign currency. For example, the largest magnitude of intervention in the \$/DM market in the 1980s was \$1.3 billion, compared with total activity in the \$/DM market of \$1,300 billion. Also, the Federal Reserve has intervened at times in amounts as little as \$50 million. Such interventions are only a tiny fraction of total market activity. Yet, all central bankers surveyed by Neely (2001) believe that intervention is effective in altering the exchange rate.

A characteristic of intervention data is that it is highly clustered, with successive days of intervention followed by successive days without intervention. This clustering has been dealt with in many ways in the intervention literature. For example, Herrera and Ozbay (2005) estimate a dynamic Tobit model that includes lags of purchase and sale interventions (which are the dependent variables) on the right-hand side for intervention by the Turkish Central Bank in support of the Lira. Lagging the intervention variable has been pursued by Kim and

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Sheen (2002) and Frenkel, Pierdzioch and Stadtmann (2003) by the Australian and Japanese central banks respectively. Ito (2002) includes lags of the dependent intervention variable in a standard OLS regression for the Bank of Japan reaction function.

The first-step of this paper is to control for this clustering by estimating the autoregressive conditional hazard (*ACH*) model of Hamilton and Jordà (2002). The *ACH* model modifies Engle and Russell's (1998) autoregressive conditional duration (*ACD*) model by estimating a $\{0,1\}$ Bernoulli process in calendar time and allowing for the inclusion of exogenous variables. The *ACH* model controls for the clustering by including a lag of the duration, or time between successive interventions, in the central bank's reaction function and uses the lagged duration to impose a functional form assumption on the conditional probability. Hamilton and Jordà, using an *ACH* model, are able to outperform a standard vector autoregression in terms of mean-squared error in predicting Federal funds rate target changes for the time period 1984-1989 and 1989-2001, with the break allowing for the change in Federal Reserve policy from targeting borrowed reserves to targeting the Federal funds rate that occurred in 1989. This is a noteworthy result because, unlike a vector autoregression, the *ACH* maximizes a likelihood function rather than minimizing the sum of squared errors. Since open market operations exhibit similar clustering, it seems natural to apply the *ACH* model to Federal Reserve intervention.

We estimate the *ACH* model for two intervention data sets for three central banks. As far as we know, this approach has not been attempted in the intervention literature. The first data set consists of interventions by the United States Federal Reserve and German Bundesbank between January 5th, 1987 and January 22nd, 1993 which coincide with the Plaza Agreement and Louvre Accord. The second data set contains unilateral interventions

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by the Bank of Japan between April 1st, 1991 and February 28, 2001.

Two problems are immediately apparent with the *ACH* model. First, since *ACH* is based on the *ACD* model, which is analogous to *GARCH*, stationarity requires that estimates of α and β are such that $\alpha + \beta < 1$. We show that this condition is violated for the Bundesbank and Bank of Japan. Second, nothing about the *ACH* process guarantees that the estimated probabilities fall within the range $(0,1)$. To guarantee this, we have to make use of a "smoothing function". We find that for the Federal Reserve and the Bank of Japan, the *ACH* estimated probabilities do fall outside of $(0,1)$. However, we offer evidence that the results do not hinge on these two issues. The estimates in models where these two issues are present are not markedly different from estimates in models where these two issues are not.

Yet, we do find that the *ACH* is not the best way to control for the clustering. In the case of the Federal Reserve, the *ACH* does worse, according to the Schwarz Bayesian Criterion (SBC) proposed by Schwarz (1978), than a simple probit model that does not control for the clustering. We show that this is likely due to the functional form imposed by the *ACH* for the estimated probability. The *ACH* assumes that the probability of intervention is equal to the reciprocal of the expected duration. That is, if the expected duration is 3, the probability of intervention is $1/3$. However, for the Federal Reserve, the lagged duration is highly insignificant in a probit model. Thus, the *ACH* imposes a severe functional form assumption on an insignificant variable. Besides worsening the goodness-of-fit, we find that in this case, the *ACH* may give misleading results as to the significance of other exogenous variables included in the model. For the other two central banks, the duration is significant, or nearly significant in a probit model. Yet, the *ACH* only slightly improves the goodness-of-fit compared to a probit model and offers little additional insight as to why the central bank

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intervenes that is not already offered in a standard probit model.

To avoid the issues associated with the *ACH* model that are described above, we estimate the autoregressive conditional binomial model (*ACB*) of Herrera (2004). The *ACB* is a calendar time modification of the autoregressive conditional multinomial model of Engle and Russell (2005). Thus, the *ACH* and *ACB* are similar in that they are calendar time modifications of Engle and Russell models that attempt to control for a common characteristic of time series data, making the comparison done in this paper a natural one.

An advantage of the *ACB* is that it is more general functional form than the *ACH*. In fact, the *ACB* with no dynamics is just a standard probit model. Exogenous variables can easily be included in the *ACB* specification, just as they can be included in the *ACH* model. Thus, it is straightforward to include lags of the duration as an exogenous variable in the *ACB* model. And, in addition to lags of the duration, the *ACB* model allows additional means of controlling for the clustering by lagging an indicator variable and lagging the response probability of intervention. We show that these two methods better account for the clustering than lagging the duration in that the *ACB* substantially outperforms the *ACH*, in terms of likelihood improvement and the SBC, and Rivers and Vuong (2002) test of non-nested likelihoods rejects the *ACH* in favor of the *ACB*. Additional evidence in favor of the *ACB* is that when the lagged duration is significant in a probit model, and dynamics are introduced in the *ACB* model, the significance of the lagged duration disappears. Finally, the *ACB* model guarantees that the estimated probabilities of intervention fall within the range of $(0, 1)$, so we do not have to use a "smoothing function" as with the *ACH*. For these reasons, we argue that the *ACB* model should be the first model considered when estimating a binary model with clustered data.

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There are three motivations commonly believed to explain why a central bank chooses to intervene in the foreign exchange market (see Neely 2001, 2005). The central bank may intervene in order to resist short-term movements of the exchange rate (leaning against the wind), to move the exchange rate into line with long-run fundamentals, or to eliminate excess volatility from the market (calming disorderly markets). The Foreign Currency Directive of the Federal Reserve succinctly states the intervention policy of the United States is to "counter disorderly market conditions", which could be any combination of these three motivations. We test these motivations for all three central banks. We find some evidence of the Bundesbank intervening to move the exchange rate into line with long-run fundamentals. We also show that the spread between the six month Treasury Bill rate and the Federal Funds rate contains predictive power as to when the Federal Reserve will intervene. As far as we know, this result has not been shown before elsewhere and suggests a link between Federal Reserve monetary policy and intervention. We also find strong evidence that the Bank of Japan has intervened in response to day-by-day changes in the nominal ¥/\$ exchange rate. Finally, we find statistically significant evidence that this response is different following Eisuke Sakakibara becoming the Director General of the International Finance Bureau of the Ministry of Finance in Japan on June 1st, 1995.² Intervention by the Bank of Japan can be described as "leaning against the wind" prior to Sakakibara's appointment and can be described as "leaning with the wind" following his appointment.³

The remainder of this paper is organized as follows. Section II gives a more thorough institutional background of U.S., German, and Japanese intervention. Section III describes the data. Section IV describes the models. Section V presents the results and a comparison

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2 Institutional Background

2.1 The Plaza and the Louvre

The practice of intervention by the United States represented a reversal of previous Reagan Administration policy. In April of 1981, then U.S. Secretary of the Treasury Donald Regan announced that the United States would not intervene in the foreign exchange markets except for "extraordinary circumstances". However, by the beginning of President Reagan's second term, this position was becoming untenable. As a Bundesbank official commented in an interview with *Business Week* magazine: "The Administration has conceded that its stance of 'benign neglect' was wrong....[and] has joined the rest of the world in saying that intervention can be helpful."⁴

The U.S. current account deficit was widening amongst its trading partners, especially with Japan and Germany, and this was spurring protectionist pressures in the U.S. Congress. For example, Senator Lloyd Bentsen (D-TX) and Representatives Dan Rostenkowski (D-IL) and Richard Gephardt (D-MO) introduced a bill that would have levied import surcharges on U.S. trading partners who were running a large surplus (coinciding with the U.S. trade deficit). These protectionist measures were not limited to the Democratic side of the aisle. Senator John Danforth (R-MO), Chairman of the Subcommittee on International Trade and Finance was enraged following the Reagan Administration refusal in the summer of 1985 not to protect the U.S. footwear industry using a protective tariff (Funabashi p16). Newly appointed Secretary of the Treasury, James Baker, observed the growing protectionist threat in an interview with *Business Week* magazine saying "There's a prairie fire burning out there.

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It's going to take considerable energy on our part to fight this."⁵

The remainder of the G-5 and G-7 countries agreed with Baker's sentiment. The prospect of closed world markets would be devastating for all countries. However, countries such as Japan and Germany that rely heavily on foreign trade would be particularly hit hard. Thus, to starve off the protectionist forces brewing in Congress and the American people, the G-5 issued an Announcement on January 17, 1985 to "undertake coordinated intervention in the markets as necessary." However, this statement left unclear whether or not this coordinated intervention would lead to a dollar depreciation, which would cause the prices of American goods to fall relative to foreign goods and thereby reduce the U.S. trade deficit. Therefore, this G-5 announcement did little to quell domestic protectionist pressures.

In direct response to the U.S. current account deficit and protectionist pressures⁶, the G-5 signed the "Plaza Agreement" in the Plaza Hotel in New York City. The goal of the Plaza agreement was threefold. First, the G-5 wanted to combat protectionist measures in Congress that threatened to close world markets. Second, the G-5 wanted to maintain world economic growth by stimulating the domestic economies of Germany and Japan. The Reagan Administration blamed the lack of domestic demand in these two countries for their trade surpluses that were leading to the U.S. deficits. The Administration believed that if demand in Germany and Japan was stimulated, then they could consume more of their output rather than exporting it to the U.S. The Germans and Japanese, however, argued that the U.S. current account deficit was a result of the record U.S. budget deficit following the "twin deficits" argument. In the Plaza Agreement, each country agreed to make fiscal policy changes to placate the other. The U.S. agreed to reduce the budget deficit by 1% of GDP in 1986 and to make continued reductions in subsequent years. West Germany agreed to reduce

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public sector involvement in the economy and to stimulate domestic demand through tax cuts in 1986 and 1988. The Japanese agreed to stimulate domestic demand by increasing private consumption and investment by enlarging consumer and credit markets. The third goal of the Plaza was to ease the burden of debt service to the U.S. Following these goals, the G-5 agreed to use coordinated intervention to depreciate the dollar against its main trading currencies.⁷ The implicit goal according to the secret "nonpaper" was to depreciate the dollar 10%-12% against the Deutsche mark and yen. Thus, the belief was that the dollar was overvalued, and by depreciating it, would reduce the prices of American goods relative to the prices of foreign goods, which would reduce the U.S. current account deficit.

By the time of the Louvre Accord in February 1987, the Deutsche mark had fallen to 1.8250 against the dollar from a pre-Plaza level of 2.85 and the Yen had fallen to 153.50 against the dollar from a pre-Plaza level of 240. Thus the Plaza was viewed amongst the G-5 as a remarkable success.⁸ In the official statement following the Louvre, the G-6 stated that "the substantial exchange rate changes since the Plaza Agreement will increasingly contribute to reducing external imbalances and have now brought their currencies within ranges broadly consistent with underlying economic fundamentals."⁹ The G-6 also stated that "further substantial exchange rate shifts among their currencies could damage growth and adjustment prospects in their countries." So rather than further depreciating the dollar, the G-6 at the Louvre desired to stabilize the dollar around the current exchange rate levels. Nigel Lawson, British Chancellor of the Exchequer, called the meeting "Plaza Two....I see this meeting as the lineal descendent of the Plaza meeting...Then we all agreed that the dollar should fall, now we all agree we need stability."¹⁰ Thus, if the goal of the Plaza was to intervene in order to depreciate the dollar, the goal of the Louvre Accord was to intervene in

order for the dollar not to depreciate further and to remove excess volatility from the foreign exchange market. West Germany and Japan agreed to stimulate domestic demand through tax cuts (Germany) and increased government spending (Japan). The U.S. agreed to further deficit reduction in line with the Gramm-Rudman-Hollings Amendment.

Intervention by the Federal Reserve and the Bundesbank was sterilized, though the issue was never explicitly discussed at the Plaza and the Louvre. All of the G-5 central banks believed that the sterilization issue was "largely academic" (Funabashi p34). A Bundesbank official claimed that the sterilization issue was avoided because the "argument was too academic" (Funabashi p34) and according to a Federal Reserve official, "as Federal Reserve intervention is sterilized. I think it's easier to think of it that way. And that certainly was true at the time of the Plaza Agreement. We did not nonsterilize" (Funabashi p35). Additionally, sterilization avoided the problem of coordinating monetary policy between the central banks. Such coordination would be required if coordinated nonsterilized intervention were to take place, and the central banks refused during the 1980s to relinquish their independence at setting monetary policy in favor of coordination. For these reasons, we assume that all Federal Reserve and Bundesbank interventions are sterilized.

2.2 Japan

Although the Japanese data set used in the paper spans the 1990s, the Japanese were heavily involved in the negotiations for the Plaza and Louvre Agreements. In fact, the Plaza Agreement originated from talks between the U.S. and Japan to address the huge trade imbalance between them (Funabashi p10). The U.S. position towards Japan was similar to the one towards Germany, namely that the overvalued dollar was giving Japanese imports a

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competitive advantage against American produced goods. Certainly this was the case and gave the Japanese little incentive to strengthen the yen. However, the Japanese believed that a strong yen was preferable to U.S. protectionism resulting in a trade war, which would devastate the small open economy. As described in section 2.1, following the Louvre Accord, the Japanese yen appreciated substantially against the American dollar. Three months after the Louvre, the yen/dollar exchange rate was at 146, down from a high of 240.

However, the yen did not stabilize at this new exchange rate, it continued to appreciate throughout the 1990s, reaching a 80.25 ¥/\$ at the close of trading in Tokyo on April 19, 1995. Ito (2002) contains detailed accounts of many of the intervention episodes throughout the decade. In general, during this decade, the Japanese wanted to keep the yen within a range of 128¥/\$ to 115¥/\$, buying yen when the nominal exchange rate crossed the upper limit and selling yen when it crossed the lower limit. Note that this is a slightly higher range than the range agreed to at the Louvre.

In 1993, the yen fell out of this range and did not return until early 1997 (Ito 2002). Thus, a motivation for Japanese intervention cannot be to defend this range, since the yen was not in this range, or even close to this range, for a large part of this sample. A more likely motivation is to lean against the wind, or resist short term movements in the nominal exchange rate. Ito (2002) is ripe with instances of this. For example, the intervention of February 15, 1994 was prompted by an overnight appreciation of the yen from 104¥/\$ to 102¥/\$.

Both Ito (2002) and Kearns and Rigobon (2004) note that the behavior of Japanese intervention changed with Eisuke Sakakibara becoming Director General of the International Finance Bureau of the Ministry of Finance in Japan on June 1st, 1995. Whereas intervention

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prior to Sakakibara was to lean against the wind, intervention during Sakakibara's tenure was to actively move the yen back to the desired range by "leaning with the wind". That is, if the yen started to depreciate in the market, the Bank of Japan would intervene by selling dollars to cause the yen to further depreciate. This behavior is exactly what we find in our sample.

3 Data

3.1 U.S. and Germany

We use daily weekday intervention and exchange rate data for the Federal Reserve and Bundesbank interventions in the \$/DM market spanning January 5th, 1987 through January 22nd, 1993, which corresponds to 1387 observations.¹¹

Table 1.1 presents summary statistics on the Federal Reserve and German intervention data sets. Note that the Federal Reserve only intervened 173 times during the sample period, or in 12.5% of the observations. The Bundesbank intervened more, 210 times, or 14.3% of the observations. Dollar buys were observed 65 times, accounting for 37.6% of Federal Reserve interventions, compared to 108 times, or 62.4% of Federal Reserve interventions for dollar sales. The fact that both the Federal Reserve and Bundesbank intervened the vast majority of times by selling dollars is consistent with the goal of the Plaza Agreement to depreciate the dollar against the Deutsche mark.

Table 1.1 gives evidence to the clustering present in the intervention data for both the Federal Reserve and the Bundesbank. For the Federal Reserve, only 13.3% of interventions took place in weeks with only one intervention. 29.5% of interventions took place in weeks with two interventions. 25.7% of interventions took place in weeks with three interventions. 17.1% of interventions took place in weeks with four interventions and 14.3% of

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interventions took place in weeks with five interventions. Thus, not only do interventions take place for only a small percentage of observations, but the vast majority of interventions take place in weeks with multiple interventions. The clustering is similar for the Bundesbank. Only 22% of interventions take place in weeks with one intervention. 18% take place in weeks with two interventions. 22.5% of interventions take place in weeks with three interventions. 20% of interventions take place in weeks with four interventions, and 17.5% of interventions take place in weeks with five interventions. Figures 1.1 and 1.2 give a graphical representation of the clustering for the Federal Reserve and Bundesbank respectively. This clustering is what we are seeking to control for using the *ACH* and *ACB*.

Daily data on all interest rates in the paper were downloaded from the Federal Reserve Bank of St. Louis FRED database.¹² Not all dates in the intervention and exchange rate data have a corresponding entry in the 6-month Treasury Bill data. The explanation is that the bond market was closed for trading on that particular day. When this was the case, we used the most recently observed Treasury Bill rate as the Treasury Bill rate for that corresponding day.

3.2 Japan

We use daily weekday intervention data for the Bank of Japan interventions in the Tokyo ¥/\$ market spanning April 1st, 1991 through February 28, 2001, which corresponds to 2538 observations.¹³

Table 1.2 presents summary statistics on the Japanese intervention data set. The Bank of Japan intervened 200 times throughout the time span covered by the data, which corresponds to 7.8% of the observations. Yen buys were observed 32 times or 16% of the interventions,

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while yen sales were observed 168 times or 84% of the interventions. This is consistent with the overall goal of depreciating the yen through intervention. Note that the smallest yen buys and sells were ¥3.2 billion and ¥5.1 billion respectively. This corresponds to a buy of \$25.1 million and a sale of \$45.1 million, using the spot ¥/\$ exchange rate for those days. Thus, Japanese intervention data is similar to the data for the Federal Reserve and Bundesbank in that interventions represent a small fraction of daily market activity.

Table 1.2 also breaks down the summary statistics into two subsamples, corresponding to intervention before and after Sakakibara. Two things are noteworthy about the subsamples. First, intervention was much more frequent in the first subsample than in the second. Second, intervention was much smaller in magnitude in the first subsample than in the second. Notice that for the entire sample, the smallest yen buys and sells took place during the first subsample while the largest buys and sells took place during the second subsample. Also, note that the magnitude of the largest buy in the first subsample (¥76.9 billion) is nearly the same as the smallest buy in the second subsample (¥76.4 billion). The reason for these two differences between the two subsamples is that Sakakibara believed that the market was becoming too accustomed to the smaller, more frequent interventions of the preceding regime. Sakakibara believed that by reducing the frequency and increasing the magnitude of intervention, he could more successfully depreciate the yen against the dollar.¹⁴

Table 1.2 presents evidence of the clustering of interventions both in the full sample and in the two subsamples. For the full sample, only 22% of interventions took place in weeks with only one intervention; 18% of interventions took place in weeks with two interventions; 22.5% of interventions took place in weeks with three interventions; 20% of interventions

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took place in weeks with four interventions and 17.5% of interventions took place in weeks with five interventions. Similar to the Federal Reserve and the Bundesbank, observations with interventions represent a small fraction of the observations and the vast majority of the interventions occur in weeks with multiple interventions. Figure 1.3 presents a graphical representation of the clustering for the full sample of the Bank of Japan. The clustering found in the first subsample is similar to what is found for the entire sample, and the clustering found in the second subsample is considerably less, consistent with the idea that Sakakibara preferred to intervene less frequently than his predecessor.

Dollar/yen exchange rate data is taken from the FRED data base. This exchange rate data is the spot rate at 12:00P.M. in the New York market. This is advantageous because when it is 12:00P.M. in New York City, it is 2:00A.M. on the next day in Japan. Assuming that the Japanese are not intervening at 2:00A.M. we can believe that the ¥/\$ are not being affected by Japanese intervention for that particular day.

4 Reaction Function

We model the reaction function of the Federal Reserve, the Bundesbank, and the Bank of Japan as a two step process. First, we model the probability of the central bank intervening on a particular day. Engle and Russell (1998) and Hamilton and Jordà (2002) call this the "point". Then, conditional on this probability, we estimate the magnitude of the intervention, called the "mark". Thus, we pose the central bank's decision process as a two step process. First, the central bank decides whether or not to intervene on a particular day. Then, after the central bank decides to intervene, it decides how much of the currency to buy or sell. This fits with Neely's (2001) survey results which show that 95.5% of central bankers

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"sometimes" or "always" first decide to whether or not to intervene, and then decide how much to buy or sell based on the "market reaction to initial trades".

We define the binary variable x_t taking the value of unity if there is an intervention at date t and zero otherwise. We define the variable y_t to be the magnitude of intervention. The joint probability distribution of x_t and y_t conditional on information known at time $t - 1$, denoted Y_{t-1} , can be modeled as:

$$f(x_t, y_t \mid Y_{t-1}, \theta_1, \theta_2) = g(x_t \mid Y_{t-1}; \theta_1) q(y_t \mid x_t, Y_{t-1}; \theta_2) \quad (1)$$

where θ_1 and θ_2 are chosen to maximize the log-likelihood:

$$\sum_{t=1}^T \log f(x_t, y_t \mid Y_{t-1}; \theta_1, \theta_2) = L_1(\theta_1) + L_2(\theta_2) \quad (2)$$

where $L_1(\theta_1) = \sum_{t=1}^T \log g(x_t \mid Y_{t-1}; \theta_1)$ and $L_2(\theta_2) = \sum_{t=1}^T \log q(y_t \mid x_t, Y_{t-1}; \theta_2)$. If θ_1

and θ_2 have no parameters in common, then maximization of the log-likelihood in equation (2) is equivalent to maximizing each of the two functions separately. Thus, the central bank's two-step decision process can be estimated in two separate steps. Thus, we can compare the *ACH* to the *ACB* in the point estimation.

4.1 Estimating the Point

4.1.1 ACH

Following the notation of Engle and Russell (1998) and Hamilton and Jordà (2002), we define the variable u_i as the length of time between the i^{th} and $(i + 1)^{th}$ intervention. Then we define ψ_i to be the expectation of u_i given past durations $u_{i-1}, u_{i-2}, \dots$. Then, the *ACD*(r, m) model of Engle and Russell is:

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$$\psi_i = \omega + \sum_{j=1}^m \alpha_j u_{i-j} + \sum_{j=1}^r \beta_j \psi_{i-j} \quad (3)$$

which is analogous to a $GARCH(m, r)$ process. Thus, the $ACD(1, 1)$ model posits that the expected duration is a weighted average of past durations:

$$\psi_n = \alpha u_{n-1} + \beta \alpha u_{n-2} + \beta^2 \alpha u_{n-3} + \dots + \beta^{n-2} \alpha u_1 + \beta^{n-1} \bar{u} \quad (4)$$

where $\bar{u}$ is the average duration. The parameter β controls how fast the past durations decay in predicting the n^{th} expected duration. Engle and Russell (1998) show that for the

$$ACD(r, m) \text{ process to be stationary, } \sum_{j=1}^m \alpha_j + \sum_{j=1}^r \beta_j < 1.$$

Following Hamilton and Jordà (2002), we transform the timing of the ACD model to calendar time. We define the function $N(t)$ as the cumulative number of interventions observed at time t . Thus, if we do not observe an intervention at time t , $N(t) = N(t-1)$. If we observe an intervention at time t , then $N(t) = N(t-1) + 1$. Using this notation, we can rewrite equation (3) as:¹⁵

$$\psi_{N(t)} = \sum_{j=1}^m \alpha_j u_{N(t)-j} + \sum_{j=1}^r \beta_j \psi_{N(t)-j} \quad (5)$$

The hazard rate, h_t , is defined as the conditional probability of an intervention taking place at time $t-1$ given information observed as of time $t-1$. Thus, the hazard can be written as:

$$h_t = \Pr[N(t) \neq N(t-1) \mid Y_{t-1}] \quad (6)$$

We follow Hamilton and Jordà (2002) and assume that the conditional distribution of the hazard is exponential. Under the exponential distribution, we can write the hazard for the ACH process as:¹⁶

$$h_t = \frac{1}{\psi_{N(t-1)} + \omega + \gamma' \mathbf{z}_{t-1}} \quad (7)$$

where ω is a constant and $\mathbf{z}_{t-1}$ is a vector of explanatory variables observed on the previous day. Thus, the *ACH* imposes the functional form that the probability of intervention is equal to the reciprocal of the expected duration, plus or minus some exogenous variables.

We appeal to the institutional background in deciding what variables to include in the $\mathbf{z}$ vector for each data set. For the U.S. and Germany, following the Plaza Agreement's declared goal that "exchange rates should better reflect fundamental economic conditions than has been the case",¹⁷ we include a measure of the deviation of the log of the exchange rate, s_t , from the log of the exchange rate based on purchasing power parity, s_t^* , which is the exchange rate that would prevail based on economic fundamentals (Neely 2005). Absolute purchasing power parity is defined as:

$$S_t = \frac{P_t}{P_t^f} \quad (8)$$

where S_t is the level of the exchange rate, P_t is the price level in the U.S. and P_t^f is the price level in the foreign country. Taking the natural logarithm of both sides of equation (8),

$$s_t^* = p_t - p_t^f \quad (9)$$

Thus, the exchange rate based on economic fundamentals can be calculated by simply taking the difference of the log of the price level between the U.S. and Germany.¹⁸

Following the Louvre Accord's goal to calm disorderly markets, we include a measure of daily excess volatility as in Baillie and Osterberg (1997). We define excess volatility as the difference between the conditional and unconditional variance of exchange rate returns, or $(\sigma_t^2 - \sigma^2)$. The conditional variance is generated through a *GARCH*(1,1) process for the

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log-difference of exchange rate returns:

$$\sigma_t^2 = \omega + \zeta \varepsilon_{t-1}^2 + \xi \sigma_{t-1}^2 \quad (10)$$

The unconditional variance can then be computed from equation (10):

$$\sigma = \frac{\omega}{1 - \zeta - \xi}$$

Fischer (2000) points out that a central bank's domestic monetary policy objective might be in conflict with current foreign exchange market conditions. For example, recall that the goal of the Plaza Agreement was to depreciate the dollar, which could be achieved by expansionary monetary policy.¹⁹ However, if the Federal Reserve's domestic monetary policy objective at the time was restrictive rather than expansionary, restrictive monetary policy would appreciate the dollar. As a result, the Federal Reserve may postpone a change in monetary policy so that the exchange rate is not further undermined and confusing signals are not sent to the foreign exchange market (monetary policy in support of the dollar alongside intervention to depreciate the dollar). To examine the link between the Federal Reserve's monetary policy and intervention objectives we include in the $\mathbf{z}$ vector the absolute value of the spread between the 6-month Treasury Bill and the Federal funds rate.

For Japan, rather than including the difference of the nominal logged exchange rate from fundamentals, we include the change in the natural log of nominal exchange rate from date t to date $t - 1$. This captures the idea that the Japanese intervened in response to changes in the ¥/\$ foreign exchange market as detailed in Section 2.2. Additionally, neither Ito (2002) nor Kearns and Rigobon (2004) explicitly model whether or not the Japanese intervened to calm disorderly markets. Ito implies that the Japanese may have intervened in response to excess market volatility in order to smooth the appreciation of the yen against the dollar. To test whether or not the Japanese intervened to calm disorderly markets, we include the

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measure of conditional volatility given by equation (10). In order to avoid an endogeneity problem, all variables (except the ¥/\$ exchange rate) are lagged by one period in the z vector as shown in equation (7).

Since the variable x_t is a binary variable, we can represent the $g(\cdot)$ distribution as Bernoulli:

$$P(x_t = 1 \mid Y_{t-1}) = g(x_t \mid Y_{t-1}; \theta_1) = (h_t)^{x_t} (1 - h_t)^{1-x_t} \quad (11)$$

where h_t is defined in equation (7) and $\theta_1 = (\gamma', \alpha', \beta')'$. Then, the log-likelihood becomes:

$$L_1(\theta_1) = \sum_{t=1}^T \{x_t \log(h_t) + (1 - x_t) \log(1 - h_t)\} \quad (12)$$

and we maximize equation (12) with respect to θ_1 , restricting $\alpha_j \geq 0$, $\beta_j \geq 0$, and $0 \leq \beta_1 + \dots + \beta_r \leq 1$. For the recursive estimation, we follow Hamilton and Jordà (2002) in using $\bar{u}$ and $\bar{\psi}$ as the starting values, where $\bar{u}$ is the average duration over the sample, and $\bar{\psi}$ can be computed for the $ACH(1, 1)$ model as $\bar{\psi} = \frac{\alpha \bar{u}}{1 - \beta}$.

4.1.2 ACB

The autoregressive conditional binomial (*ACB*) model of Herrera (2004) is a calendar time modification of the autoregressive conditional multinomial model of Engle and Russell (2005). Thus, the *ACH* and *ACB* are similar in that they are calendar time modifications of Engle and Russell models that attempt to control for a common characteristic of time series data, making the comparison done in this paper a natural one.

The *ACB* model is a flexible specification that captures the intervention clustering by lagging the link function and binary dependent variable. First, define the probability of an

intervention as,

$$h_t \equiv P(x_t = 1 \mid x_{t-1}, \dots, x_1, z_{t-1}, \dots, z_1) \quad (13)$$

where, as before, h_t is the probability of intervention, x_t is the binary dependent variable taking the value of unity if we observe an intervention, and z_{t-1} is a $1 \times n$ vector of exogenous variables that contain information about the latent variable x_t^* . In this case, z_{t-1} contains the same exogenous variables as z_{t-1} of the previous section. Additionally, we include the lag of the duration, $u_{N(t-1)}$ in the z_t vector. However, to avoid the stationarity issue, we do not model the expected duration as a distributed lag of past durations and expected durations as in equation (3).

The $ACB(q, r, s)$ model is then given by,

$$G^{-1}(h_t) = \omega + \sum_{j=1}^q \eta_j (x_{t-j} - h_{t-j}) + \sum_{j=1}^r \rho_j G^{-1}(h_{t-j}) + \sum_{j=1}^s \delta_j x_{t-j} + \gamma z_{t-1} \quad (14)$$

where $G(\cdot)$ is a strictly increasing, continuous cumulative distribution function, such as the standard normal or the logistic. Thus, $G^{-1}(h_{t-1}) = z_t \Leftrightarrow G(z_t) = h_t$, meaning that $G^{-1}(\cdot)$ is a 1-1 mapping from h_t to $\mathcal{R}$. Thus, the ACB controls for the clustering by allowing the current intervention decision to depend on the lagged response probability and the lagged indicator variable. Since $G(\cdot)$ is strictly increasing, we can obtain x_t by taking the inverse of equation (14),

$$h_t = G \left[\omega + \sum_{j=1}^q \eta_j (x_{t-j} - h_{t-j}) + \sum_{j=1}^r \rho_j G^{-1}(h_{t-j}) + \sum_{j=1}^s \delta_j x_{t-j} + \gamma z_{t-1} \right] \quad (15)$$

It is easy to see from equation (15) that the $ACB(0, 0, 0)$ is the standard probit or logit model, depending on whether the standard normal or logistic model is chosen for $G(\cdot)$.²⁰ Thus, including the same exogenous variables in the z_{t-1} vector in the ACH plus the lagged

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duration serves two purposes. First, comparing the *ACH* with the *ACB*(0,0,0) allows us to test the functional form of the *ACH* versus the functional form of the probit.²¹ Second, introducing lags into the *ACB*(0,0,0) allows us to compare the lagged duration in controlling for the clustering versus lags of $G^{-1}(h_t)$ and x_t . That is, does the significance of the lagged duration disappear when lags of $G^{-1}(h_t)$ and x_t are introduced or does the lagged duration remain significant while $G^{-1}(h_t)$ and x_t are insignificant? We offer evidence that the former is the case, and that when the lagged duration is highly insignificant in the probit, the *ACH* functional form does worse than the probit.

Given initial conditions for x_t and h_t , the path of intervention probabilities can be constructed and estimates for the parameters $\theta = \{w, \eta_1, \dots, \eta_q, \rho_1, \dots, \rho_r, \delta_1, \dots, \delta_s\}$ obtained. Estimation is straightforward through maximizing the likelihood function,

$$L(\theta) = \sum_{t=\max\{q,r,s\}+1}^T [x_t \log(h_t) + (1 - x_t) \log(1 - h_t)] \quad (16)$$

Immediately, there is a major advantage of the *ACB* specification over the *ACH* specification. Since $G(\cdot)$ is either the standard normal or logistic c.d.f., equation (15) is guaranteed to fall within the range (0,1). Note that for the *ACH* specification, the probability of intervention given by equation (7) can fall outside of (0,1), making use of the smoothing function given in footnote 16 necessary. Additionally, if the time dynamics are insignificant in the *ACB*, the model becomes a standard probit. Whereas, if the time dynamics in the *ACH* are insignificant, the model becomes the reciprocal of the linear probability model. We believe that the former is advantageous over the latter as well. The potential disadvantage, of course, is the possibility that the *ACB* does a worse job controlling for the clustering than the *ACH*. However, as we show in Section 5, the *ACB* specification

performs better than the *ACH*, in terms of likelihood improvement, goodness-of-fit as proposed by Schwarz (1978), and the Rivers and Vuong (2002) test rejects the *ACH* in favor of the *ACB*.

4.2 Estimating the Mark

Following Hamilton and Jordà (2002), we make use of an ordered probit model in order to estimate the mark, or magnitude of the intervention. Assume that the latent variable, y_t^* depends on w_{t-1} , a vector of variables observed on day $t - 1$, according to:

$$y_t^* = w_{t-1}' \pi + \varepsilon_t \quad (17)$$

where $\varepsilon_t \sim \text{Normal}(0, 1)$.

Assume that there are k possible discrete values for intervention from which the central bank can choose, denoted $s_1, s_2, \dots, s_k$, such that $s_1 < s_2 < \dots < s_k$. Conditional on $x_t = 1$, that is, there is an intervention, the observed value of the intervention is related to the latent variable by:

$$y_t = \left\{ \begin{array}{ll} s_1 & \text{if } y_t^* \in (-\infty, c_1] \\ s_2 & \text{if } y_t^* \in (c_1, c_2] \\ \vdots & \\ s_k & \text{if } y_t^* \in (c_{k-1}, \infty) \end{array} \right\}$$

where $c_1 < c_2 < \dots < c_{k-1}$.

The log of the probability of observing y_t conditional on w_{t-1} and x_t is:

$$\log q_t(y_t \mid w_{t-1}; \theta_2) =$$

$$\left\{ \begin{array}{ll} \log \left[\Phi \left(c_1 - w'_{t-1} \pi \right) \right] & \text{if } y_t = s_1 \\ \log \left[\Phi \left(c_j - w'_{t-1} \pi \right) - \Phi \left(c_{j-1} - w'_{t-1} \pi \right) \right] & \text{if } y_t = s_2, s_3, \dots, s_{k-1} \\ \log \left[1 - \Phi \left(c_{k-1} - w'_{t-1} \pi \right) \right] & \text{if } y_t = s_k \end{array} \right\}$$

where $\theta_2 = (\pi', c_1)'$. The conditional log-likelihood for the mark can then be written as:

$$L_2(\theta_2) = \sum_{t=1}^T x_t \log q(y_t \mid w_{t-1}; \theta_2) \quad (18)$$

and can be maximized via MLE.

5 Results

5.1 Point Estimation

In the first two subsections, we present the estimation result for the U.S., German, and Japan. In the third subsection, we present a discussion of why the *ACB* is preferred to the *ACH*.

5.1.1 U.S. and Germany

The results for estimating the probability of intervention by the Federal Reserve using the *ACH*(1,1) model are reported in Table 1.3. The estimated values for α and β are both significant at the 1% level, giving evidence that the *ACH* model fits the data well. We obtain an average expected duration of 4.701, meaning that on average, approximately 5 days are expected to pass between two interventions. The average hazard is 0.0984, which means that on average, the probability of intervention occurring on a given day is 9.84%. This is broadly consistent with the summary statistics in Table 1.1 where interventions happened for

12.47% of the observations

As seen from the table, there is mixed evidence on the predictive power of the two variables based on the G-5 agreements as to when the Federal Reserve will intervene. The estimated coefficient on $(\sigma_{t-1}^2 - \sigma^2)$, the variable implied by the Louvre Accord, is insignificant and the estimated coefficient on the first difference of $(s_{t-1} - s_{t-1}^*)$ as implied by the Plaza agreement is significant at the 10% level. However, upon dropping $(\sigma_{t-1}^2 - \sigma^2)$ and re-estimating the *ACH* model, which we do in specification (2), the first difference of $(s_{t-1} - s_{t-1}^*)$ becomes significant at the 5% level (p-value 0.0358). This is an interesting result because it suggests that the Federal Reserve is intervening as a result of the nominal \$/DM exchange rate moving away from the exchange rate based on fundamentals.

To see this, note that if the dollar is overvalued as the U.S. claimed, then $(s_{t-1} - s_{t-1}^*) > 0$ and the estimated coefficient on this term in the *ACH* model is negative. Thus, $\gamma_3 \Delta(s_{t-1} - s_{t-1}^*) < 0$. Notice from equation (7) that this term appears in the denominator of the hazard, which is the probability of intervention. Thus, this term being negative makes the denominator of the hazard smaller, which increases the probability of intervention.

The spread is significant, with the coefficient estimated to be -1.09 with a standard error of 0.296. This suggests that during a period of high $abs(spread)$, the probability of intervention by the Federal Reserve is greater than during a period of low spread. To see this, consider the following hypothetical example: Compare the hazard using $\bar{\psi}$ calculated from a value of $\overline{abs(spread)} = 0.615$ with the hazard using $\bar{\psi}$ calculated from a value of $\overline{abs(spread)} = 0.715$. This calculation results in the two hazards equaling 0.183 and 0.187 respectively, implying that a 0.1 percentage point increase in the spread increases the

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probability of Federal Reserve intervention by 0.4% in this sample.

These results are interesting because no study has established a statistical link between the value of the spread and the probability of intervention. Also, studies do not find the Federal Reserve responding to changes in the exchange rate (see, for example, Baillie and Osterberg 1997). Column 3 of Table 1.4 presents the results of a probit, or $ACB(0,0,0)$ model containing the same explanatory variables, including the lagged duration. Note that when we do not account for the clustering through the ACH , we do not find that the estimated coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$ to be significant, though the spread is positive and significant, giving the same interpretation as above. Thus, it would appear that the ACH is offering a new result.

The problem with this claim appears in Table 1.4 when we estimate the ACB model.²² Note that in this case, the estimated coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$ fails to be significant at the 10% level, even though the sign is consistent with the result for the $ACH(1,1)$ since it also suggests that a more overvalued dollar increases the probability of intervention. Also, notice the difference in the estimated coefficient on $(\sigma_{t-1}^2 - \sigma^2)$. Whereas this was insignificant in the ACH and probit models, it is significant in the $ACB(0,1,2)$ model. However, the sign is the opposite of what we would expect from the Louvre Accord. The negative sign indicates that a low volatility increases the probability of intervention. That is, the Federal Reserve prefers to intervene when the market is calmer. A possible explanation for this behavior is that intervention can increase market volatility (see, for example, Beine and Laurent 2003 and 2005, and Fatum 2002). Thus, the negative estimated sign on $(\sigma_{t-1}^2 - \sigma^2)$ may suggest that the Federal Reserve would prefer not to make an already volatile market even more volatile through intervention, although this is the opposite of

stated policy by the Federal Reserve.

Notice that the spread is still positive and significant, indicating that periods when the spread is higher are periods where the Federal Reserve is more likely to intervene. Suppose that the spread is large and positive, indicating that the market is expecting an increase in the Federal funds rate. As previously described, this would appreciate the dollar, which is in the opposite direction of the goal of the Plaza Agreement. Thus the sign and significance of the spread is consistent with the idea that the Federal Reserve may have to postpone a change in monetary policy and use sterilized intervention instead to achieve its exchange rate objective.

Another explanation is consistent with the idea that the Federal Reserve's monetary policy objective was expansionary, rather than restrictive. Consider a situation when the Federal funds rate is above the 6-month Treasury Bill rate, as it is for the majority of our sample. The high value of the Federal funds rate relative to the Treasury Bill rate suggests that the market expected the Federal Reserve to engage in an expansionary monetary policy, producing a subsequent fall in the Federal funds rate, which would also depreciate the dollar against the Deutsche mark. However, as Funabashi (1989) points out, the Federal Reserve wanted to conduct expansionary monetary policy jointly with the Bundesbank. The Bundesbank was reluctant to do so, given its strong anti-inflationary bias and its reluctance to relinquish its independence in setting monetary policy. Thus, rather than engaging in expansionary monetary policy to depreciate the dollar, the Federal Reserve chose to engage in sterilized intervention instead. This is consistent with Funabashi (1989) who found that "The Fed used monetary policy to stimulate the U.S. economy or at least to keep it buoyant, but it did not burden domestic monetary policy with exchange rate management" (p57).

We compute two measures to compare the *ACH* with the *ACB*. The Schwarz Bayesian

Criterion (SBC) adjusts the log-likelihood by subtracting $(r/2)$ times the log of the number of observations, where r is the number of parameters estimated by the model. The Rivers and Vuong z-statistic (RV) proposed by Rivers and Vuong (2002) is a time-series modification of the Vuong (1989) test of non-nested likelihoods. This tests whether the (absolute value) of the *ACH* log-likelihood is greater than, less than, or equal to the *ACB* log-likelihood. Rivers and Vuong (2002) show that the test statistic is distributed *Normal*(0, 1). The null hypothesis of the test is that the two models are equally close to the true specification, whereas the alternate hypothesis is that one model is closer than the other. Thus, if test statistic is statistically greater than zero at some critical value, the *ACH* is rejected in favor of the *ACB*, and vice versa if the test statistic is statistically less than zero. If the test statistic is not statistically different than zero, the test cannot distinguish between the two models, given the data. The SBC and RV for the Federal Reserve are reported in the bottom of Table 1.4. The SBC strongly prefers the *ACB*(0, 1, 2) over the *ACH*, and RV strongly rejects the *ACH* in favor of the *ACB* at for all *ACB* specifications. This suggests that the *ACB* is preferred to the *ACH*. Additional evidence for this is discussed in section 5.1.3.

The results of the *ACH*(1, 1) for Bundesbank intervention are reported in the last column of Table 1.3. The results are similar to those obtained in the case of the Federal Reserve in that α and β are both significant, albeit α is now significant at 5%, and the estimated coefficient on $(\sigma_{t-1}^2 - \sigma^2)$ is insignificant. One major difference between the two central banks is that the coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$ is insignificant for the Bundesbank, although with the expected sign. However, notice that $\alpha + \beta > 1$, which violates the stationarity condition given in section 4.1.2. This is obviously a disadvantage of the *ACH* model.²³

Column 3 of Table 1.5 presents the results of the probit model. The estimates of the

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coefficients on $(\sigma_{t-1}^2 - \sigma^2)$ and $\Delta(s_{t-1} - s_{t-1}^*)$ are both insignificant as in the *ACH*. The SBC suggests that the *ACH* fits the data better, and RV rejects the probit in favor of the *ACH* at the 5% level of significance.²⁴ We include $u_{N(t-1)}$ in the probit model and find that it is significant at the 5% level as in the case of the *ACH*, and in the same direction, also as in the *ACH* case.²⁵ In the *ACH* case, α , which is the coefficient of the lagged duration, is estimated to be positive. Since it appears in the denominator of the hazard, this means that as the duration becomes larger, the probability of intervention is reduced. In the probit case, the coefficient on the lagged duration is negative, giving the same interpretation.

The results are different, however, if we control for the clustering by including dynamics in the *ACB* model. The last three columns of Table 1.5 presents these results. Four interesting results are important to note. First, the goodness-of-fit is much better in this dynamic model than either in the *ACH* or probit models. The SBC strongly prefers the *ACB* to the *ACH* and RV rejects the *ACH* in favor of the *ACB* at the 1% level of significance for all specifications. Second, in this specification, γ_3 which is the estimated coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$, becomes positive and significant at the 1% level. Remember that if the dollar is overvalued and becomes more overvalued, then $\Delta(s_{t-1} - s_{t-1}^*) > 0$. Thus, a positive estimate of γ_3 means that the probability of intervention by the Bundesbank increases when the dollar becomes more overvalued. Recall that we do not get this result in either the *ACH* or probit models. The third interesting result of the *ACB* model is that when we control for clustering by introducing lags of the binary indicator x_{t-1} and the link function $G^{-1}(h_{t-1})$, the estimated coefficient on the lagged duration becomes insignificant. This suggests that including lags of the duration is not the best way to control for clustering

in the data. Fourth, the estimated coefficient on $(\sigma_{t-1}^2 - \sigma^2)$ is negative and significant, like it is for the Federal Reserve, suggesting that like the Federal Reserve, the Bundesbank may prefer to intervene in times of low market volatility so that intervention does not make an already volatile market more volatile.

5.1.2 Japan

Table 1.6 presents the results of the $ACH(1,1)$ for entire sample of Japanese intervention. Notice that γ_2 , which is the estimated coefficient on $(s_{t-1} - s_{t-2})$, is positive and significant, meaning that the Japanese were "leaning against the wind" for the sample. To see why this is the case, remember from Section 2.2 that the goal of Japan was to depreciate the yen against the dollar and that the exchange rate is in terms of yen per dollar. Thus, if $(s_{t-1} - s_{t-2}) < 0$, that means that yen appreciated ($s_{t-1} < s_{t-2}$). The positive estimated value of γ_2 thus makes $\gamma_2(s_{t-1} - s_{t-2}) < 0$ and thus the denominator of equation (7) smaller. However, like the Bundesbank, the stationarity condition is violated for the Bank of Japan.²⁶

Like with the Federal Reserve and Bundesbank, we compare the results of the ACH with those of the probit and dynamic ACB models. Column 3 of Table 1.7 presents the results of the probit for the entire sample. Here, we find a negative and significant estimate of γ_2 , the coefficient on $(s_{t-1} - s_{t-2})$. Thus, the leaning against the wind behavior is robust to the probit specification, since $\gamma_2(s_{t-1} - s_{t-2}) > 0$ following a yen appreciation, which increases the probability of intervention. As in the case of the Federal Reserve, the lagged duration is insignificant in the probit specification. Note that like the Bundesbank, the SBC favors the ACH over the probit model, and RV rejects the probit in favor of the ACH at the

5% level of significance. Also note that the coefficient on $(\sigma_{t-1}^2 - \sigma^2)$, insignificant in the *ACH* specification is also insignificant in both the probit and *ACB*(0,1,3) models.

Columns 4-6 of Table 1.7 presents the results of the *ACB*(0,1,3) model for Japan. Notice that the SBC strongly favors this model over the *ACH* model, and RV rejects the *ACH* in favor of the *ACB* for all specifications. Like the two previous models, we get the result that the Japanese are leaning against the wind, with the estimated coefficient on $(s_{t-1} - s_{t-2})$ negative, significant, and larger than that found with the probit. The fact that the *ACB*(0,1,3) is preferred over the *ACH* is again advantageous, since we do not have to worry about restricting the coefficients in order to achieve stationarity nor worry about the estimated probabilities falling outside of (0,1). As seen in Section 5.1.3, this is a problem for Japan.

To see how Japanese intervention differed before and after Sakakibara, we reestimate the *ACH*, probit, and *ACB* models before and after June 1, 1995. Columns 4 and 5 of Table 1.6 present the *ACH* results and Table 1.8 presents the *ACB*(0,1,2) results for the 1st subsample. This subsample corresponds to intervention prior to Sakakibara. These results are very similar to the results for the entire sample. The SBC favors the *ACH* over the probit, but the *ACB*(0,1,2) over both of the other models. And, RV fails to reject the *ACH* in favor of the probit and rejects the *ACH* in favor of the *ACB*(0,1,2) for all specifications. In each model, we find evidence for leaning against the wind, while we get a significant coefficient on the volatility variable only in the probit model, however this time with a positive coefficient providing some evidence for the "calming disorderly markets" motivation of intervention. Also, unlike in the full sample, the lagged duration is negative and significant in the probit model, giving the same interpretation as with the Bundesbank. However, the significance of

both variables disappears when dynamics are included in the *ACB* model.

Column 6 of Table 1.6 and Table 1.9 present the results of the second subsample. Note that these results are strikingly different than the results for the entire sample and the first subsample. Again, the SBC favors the *ACH* over the probit and the *ACB*(0,1,2) over both.. Although RV fails to reject one model in favor of the other, the estimated parameters are robust between the *ACH*, probit, and *ACB*. Here, the coefficient on $(\sigma_{t-1}^2 - \sigma^2)$ is insignificant even in the probit model. However, more importantly, notice the sign change in the coefficient on $(s_{t-1} - s_{t-2})$ in all three models for this subsample. This suggests that after Sakakibara, the Japanese were leaning *with* the wind. To see this, note that if the yen depreciates, $(s_{t-1} - s_{t-2}) > 0$. Thus, the negative estimated coefficient in the *ACH* model means $\gamma_2(s_{t-1} - s_{t-2}) < 0$, which makes the denominator of equation (7) smaller and thus the hazard larger. The positive estimated coefficient in the probit and *ACB*(0,1,2) means that $\gamma_2(s_{t-1} - s_{t-2}) > 0$, which makes the probability of intervention larger. This evidence suggests that Sakakibara preferred to influence the exchange rate by intervening when market conditions were already moving in the direction he favored. That is, if the yen was depreciating, Sakakibara intervened to further depreciate it.

These results of the two Japanese subsamples are strikingly different than what is found by Ito (2002). With our methodology, we find a result of the Japanese leaning against the wind prior to Sakakibara and leaning with the wind during Sakakibara's tenure. Ito, however, finds the lean against the wind hypothesis to be statistically insignificant during the first subsample. Also, whereas we find a significant lean with the wind effect in the second subsample, Ito finds a significant lean against the wind effect for the second subsample. Additionally, Ito finds that interventions in the second subsample were less predictable than

in the first subsample given the lower R^2 in his second subsample regression than his first. Our result is the opposite. We find that interventions in the second subsample are much more predictable than interventions in the first subsample. Both the log likelihood and SBC of each model is much lower in the second subsample than in the first.

5.1.3 Comparison of Econometric Methods

In the previous two subsections, we presented evidence that the stationarity condition was not causing the *ACB* to outperform the *ACH*. Below, we present evidence that the smoothing function is not responsible for this either. Rather, it is likely that the functional form assumption of the *ACH* and the significance of the lagged duration versus the significance of $G^{-1}(h_{t-1})$ and x_{t-1} are what is driving this result.

Figure 1.4 reports the *ACH* estimated probability of intervention for the Federal Reserve and Bank of Japan with all explanatory variables included in the $\mathbf{z}$ -vector. Notice how the probability of intervention falls below zero on numerous occasions. It is easy to see why this is happening. Notice in Table 1.3 that all parameters *except* γ_2 , the coefficient on $abs(spread)_{t-1}$ and γ_3 , the coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$ are estimated to be positive. Thus, if the magnitudes of $\gamma_2 abs(spread)_{t-1}$ and $\gamma_3 \Delta(s_{t-1} - s_{t-1}^*)$ sum to be larger than the sum of the other parameters, it will cause the denominator of equation (7) to be negative, causing the hazard to be negative. The same is true with the Bank of Japan. However, notice in Table 1.6 that all estimated coefficients are positive. However, $(s_{t-1} - s_{t-2})$ can be negative. This happens whenever the yen appreciates overnight ($s_1 < s_2$). Thus, we have to make use of the smoothing function whenever there is a positive variable in the $\mathbf{z}$ vector in equation (7) that increases the probability of the event happening, since the

estimated coefficient on that variable will be negative (assuming a positive constant). And, we will have to make use of the smoothing function whenever we have exogenous variables that can take on negative values, even if the estimated coefficients on these variables are positive.

However, looking at Figure 1.5, the transformation of the values of the hazard by the smoothing function seems rather arbitrary. The times that the hazard falls below zero are transformed into rather small positive probabilities that are greater than zero. Fortunately for the *ACH*, the results do not appear to hinge on this conversion. Specification (3) in Table 1.3 is able to converge without the smoothing function and the estimated coefficients are similar to those in specification (2), which cannot converge without the smoothing function.²⁷ Thus, the problem for the Federal Reserve is the volatility variable, which is causing the hazard to fall below zero. For the Bank of Japan, the results in Table 1.6 are similar to those found by the probit and *ACB*, in terms of sign and significance. However, if specification (3) for the Federal Reserve failed to converge without the smoothing function, and we did not compare the *ACH* to other models for the Bank of Japan, we would have to rely on the accuracy of the smoothing function in order to have confidence in our results. Also in the case of the Federal Reserve, the variable that was causing the problem was insignificant. Obviously this will not always be the case.

Why is it that the *ACB* does a better job than the *ACH* in controlling for the clustering for all central banks? Why is it that for the Federal Reserve, the basic probit model actually does a better job than the *ACH*? After all, time dependence is clearly present in the data and in the *ACB* model. The answer is the functional form implied by the *ACH* and the significance of the lagged duration. Notice from equation (7) that the *ACH* places a severe functional

form assumption on the lagged duration. For example, if the lagged expected duration is 3, then the hazard says that the probability intervention today is equal to 1/3. Recall from equation (3) that the expected duration is a decaying lag of past durations. Recall from Table 1.4 that the lagged duration is highly insignificant for the Federal Reserve (p-value 0.7973) in the probit. Thus for the Federal Reserve, the *ACH* is taking a highly insignificant variable and assuming that the probability of intervention for a particular day is equal to its reciprocal, plus or minus some exogenous variables. Thus, it is no surprise that the probit, which does not make such an assumption, does better than the *ACH* for the Federal Reserve. Also in this case, the *ACH* in this case may give misleading results as to the significance of the exogenous variables. Recall that the *ACH* finds $\Delta(s_{t-1} - s_{t-1}^*)$ significant for the Federal Reserve but neither the *ACB* nor the probit do. A likely explanation is that $\Delta(s_{t-1} - s_{t-1}^*)$ is "more" significant (p-value 0.4679) than the lagged duration in the probit. The *ACH*, given the functional form assumption made, finds the lagged duration to be significant. Thus, it is not surprising that the *ACH* finds $\Delta(s_{t-1} - s_{t-1}^*)$ significant also even though the other two models do not.

For the Bundesbank and 1st and 2nd subsamples of the Bank of Japan, the lagged duration enters into the probit model significantly at least at the 10% level (for the full Japanese sample, p-value on the lagged duration is 0.1645). Thus, the functional form assumption made by the *ACH* for these central banks is not as severe and hence the *ACH* can outperform the probit.

However, recall that when we include the lagged duration in a dynamic *ACB* specification, this significance disappears. For the Bundesbank, the p-value on the lagged duration goes from 0.0264 in the probit to 0.2077 in the *ACB*(0,1,3). For the 1st subsample

for Japan, the p-value of the lagged duration goes from 0.0105 in the probit to 0.7354 in the $ACB(0,1,2)$ and for the 2nd subsample, the lagged duration goes from having a p-value of 0.101 in the probit to 0.5073 in the $ACB(0,1,2)$. Finally, for the full Japanese sample, the p-value of the lagged duration goes from 0.1645 in the probit to 0.9815 in the $ACB(0,1,3)$. This explains why the ACB is so strongly favored over the ACH . Simply put, $G^{-1}(h_{t-1})$ and x_{t-1} control for the clustering present in the data better than the lagged duration. This is a very favorable result in that we do not have to worry about stationarity nor defend our results against the use of the smoothing function, as we would in with the ACH .

This insignificance of the lag of the duration in the ACB is why we choose not to model the ACB and ACD jointly as in Engle and Russell (2005). However, this approach may be desirable if the lagged duration is estimated significantly in a dynamic ACB specification, as it would not necessitate the use of a smoothing function, impose the functional form of the ACH , and may result in efficiency improvements over estimating the two models separately.

The following figures graphically illustrate why the ACB is preferred to the ACH . Figure 1.6 plots the probability of intervention for the ACH with the smoothing function and probit for the Federal Reserve with a constant and $\Delta(s_t - s_t^*)$ included as explanatory variables, since that was the most favored ACH specification. The figure shows that the probit model is picking up dynamics that the ACH is missing from October 1990 to the end of the sample. This would be a surprising result if we did not know that the lagged duration is insignificant as explained above. Figure 1.7 prints out the $ACB(0,1,3)$ probability of intervention for the Federal Reserve. Notice how the ACB picks up dynamics that both of the other two models miss throughout the entire sample. Thus, it is no surprise that the ACB is strongly favored by the SBC over the other two models

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Figures 1.8 and 1.9 present the probability of intervention for the *ACH* with the smoothing function, and the *ACB*(0,1,3) models for the Bundesbank with only a constant as an explanatory variable, since that was the most favored *ACH* model, according to the SBC and none of the exogenous variables are significant. For the probit, we plot the probability with a constant and lagged duration included as explanatory variables, since the latter was estimated to be significant. Clearly, the *ACH* captures more dynamics than the probit model, which can explain why the SBC favors the *ACH* over the probit. Recall from the above discussion that the lagged duration is significant at the 1% in the probit model. Thus, it is not surprising that the *ACH* does better than the probit. However, the *ACH* model never assigns a high probability to intervention occurring, with the probability never getting above 0.50. The *ACB*(0,1,3), on the other hand, does assign relatively high probabilities of intervention on several occasions, with the probability rising over 0.90. Also, note that the *ACB* picks up dynamics towards the end of the sample that the *ACH* misses. This gives additional evidence to the claim that $G^{-1}(h_{t-1})$ and x_{t-1} do a better job controlling for the clustering than the lagged duration.

Figures 1.10 and 1.11 plot the probability of intervention for the *ACH* with the smoothing function, probit, and *ACB*(0,1,3) models with a constant and $(s_{t-1} - s_{t-2})$ as explanatory variables for the entire Japanese sample. These figures shed further light on why the *ACH* performs better than the probit, and why the *ACB*(0,1,3) performs better than both. Notice that the probit model never assigns a very high probability to intervention, despite the significance of $(s_{t-1} - s_{t-2})$. The probability of intervention only moves slightly above and slightly below 0.10 for the entire sample. The *ACH*, however, assigns higher probabilities at several different instances. However, once you move past 8/4/1995, the probit and *ACH*

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models are nearly the identical. Contrast this with the $ACB(0,1,3)$. Again, like the Bundesbank, the ACB picks up dynamics that the ACH misses, particularly at the beginning and the end of the sample.

5.2 Ordered Probit Results

We allow the $\mathbf{w}_{t-1}$ vector to contain the same explanatory variables as the $\mathbf{z}$ vector plus a lag of the value of the last intervention by the central bank to account for central banks intervening in the same direction on consecutive days. As seen from the summary statistics in Tables 1.1 and 1.2, this is a property of the clustered data.

5.2.1 U.S. and Germany

We combined the many different discrete values of intervention into five indicator numbers for a dollar buy and five indicator numbers for a dollar sale according to the degree of the intervention magnitude. We defined the degrees of magnitude in the following fashion for Federal Reserve interventions:²⁸

$$y_t = \left\{ \begin{array}{ll} -5 \text{ (very high dollar sale)} & \text{if intervention} \in (-\infty, -375] \\ -4 \text{ (high dollar sale)} & \text{if intervention} \in (-375, -250] \\ -3 \text{ (moderate dollar sale)} & \text{if intervention} \in (-250, -125] \\ -2 \text{ (low dollar sale)} & \text{if intervention} \in (-125, -75] \\ -1 \text{ (very low dollar sale)} & \text{if intervention} \in (-75, 0) \\ 1 \text{ (very low dollar buy)} & \text{if intervention} \in (0, 35] \\ 2 \text{ (low dollar buy)} & \text{if intervention} \in [35, 70] \\ 3 \text{ (moderate dollar buy)} & \text{if intervention} \in [70, 140] \\ 4 \text{ (high dollar buy)} & \text{if intervention} \in [140, 280] \\ 5 \text{ (very high dollar buy)} & \text{if intervention} \in [280, \infty) \end{array} \right\} \quad (19)$$

For Bundesbank interventions, we defined the size of an intervention in a similar way:²⁸

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$$y_t = \left\{ \begin{array}{ll} -5 \text{ (very high dollar sale)} & \text{if intervention} \in (-\infty, -320] \\ -4 \text{ (high dollar sale)} & \text{if intervention} \in (-320, -160] \\ -3 \text{ (moderate dollar sale)} & \text{if intervention} \in (-160, -80] \\ -2 \text{ (low dollar sale)} & \text{if intervention} \in (-80, -20] \\ -1 \text{ (very low dollar sale)} & \text{if intervention} \in (-20, 0) \\ 1 \text{ (very low dollar buy)} & \text{if intervention} \in (0, 30) \\ 2 \text{ (low dollar buy)} & \text{if intervention} \in [30, 75) \\ 3 \text{ (moderate dollar buy)} & \text{if intervention} \in [75, 150) \\ 4 \text{ (high dollar buy)} & \text{if intervention} \in [150, 300) \\ 5 \text{ (very high dollar buy)} & \text{if intervention} \in [300, \infty) \end{array} \right\} \quad (20)$$

The results for intervention by the Federal Reserve are described in column 3 Table 1.10. As one would expect, the coefficient on $(\sigma_{t-1}^2 - \sigma^2)$ is insignificant, suggesting that the degree of market volatility does not affect the magnitude or direction of intervention.²⁹ Instead, the ordered probit results support the scenario of Federal Reserve setting the value of intervention according to the other two variables, $\Delta(s_{t-1} - s_{t-1}^*)$ and $spread_{t-1}$.³⁰ That is, the negative sign of the coefficient on $\Delta(s_{t-1} - s_{t-1}^*)$ implies that when the dollar is overvalued the Federal Reserve tends to react by a dollar sale. At the same time, the positive coefficient on $spread_{t-1}$ implies that when the Treasury Bill interest rate rises higher above the Federal Funds Rate the Federal Reserve tends to conduct a dollar buy. This appears to confirm our suggestion from section 5.1.1 that a higher value of the spread means that the domestic financial markets expect the Federal Reserve to contract money supply in the near future and that the Federal Reserve tends to fulfill this expectation by buying dollars. Not surprisingly, upon recognizing the clustering of interventions and their spread over consecutive days, the coefficient on the value of the last intervention is positive and highly significant.

Column 4 of Table 1.10 presents results for the Bundesbank intervention. Again, the

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value of the last intervention is an important determinant of the current intervention value and the coefficient on volatility is insignificant. However, unlike in the case of the Federal Reserve, the Bundesbank does not appear to consider the deviation from Purchasing Power Parity when deciding on the value of intervention. This result is somewhat puzzling in light of the significance of the deviation for the probability of the Bundesbank intervention suggested by the $ACB(0,1,3)$ specification, even though the sign, negative as expected, implies a sale of dollar when dollar becomes more overvalued.

5.2.2 Japan

Again, we consolidate the intervention values according to the degree of the intervention magnitude:³¹

$$y_t = \left\{ \begin{array}{ll} -5 \text{ (very high yen sale)} & \text{if intervention} \in (-\infty, -500] \\ -4 \text{ (high yen sale)} & \text{if intervention} \in (-500, -100] \\ -3 \text{ (moderate yen sale)} & \text{if intervention} \in (-100, -50] \\ -2 \text{ (low yen sale)} & \text{if intervention} \in (-50, -25] \\ -1 \text{ (very low yen sale)} & \text{if intervention} \in (-25, 0) \\ 1 \text{ (very low yen buy)} & \text{if intervention} \in (0, 15) \\ 2 \text{ (low yen buy)} & \text{if intervention} \in [15, 30) \\ 3 \text{ (moderate yen buy)} & \text{if intervention} \in [30, 45) \\ 4 \text{ (high yen buy)} & \text{if intervention} \in [45, 100) \\ 5 \text{ (very high yen buy)} & \text{if intervention} \in [100, \infty) \end{array} \right\} \quad (21)$$

Our results for the ordered probit model, presented in Table 1.11, corroborate the evidence provided in section 5.1.2 on the issue of whether the Bank of Japan was leaning against or with the wind during the sample period. The evidence on the full sample period is inconclusive, even though the negative coefficient on $(s_{t-1} - s_{t-2})$, significant at 10%, provides some evidence of leaning with the wind for the overall sample period. As implied

by the point estimation in section 5.1., the results on the two subsamples, before and after Sakakibara's appointment, are far more revealing. The coefficient on $(s_{t-1} - s_{t-2})$ obtained for the second subsample is negative and highly significant (p-value 0.011), providing strong support for the leaning *with* the wind claim raised in section 5.1. for the 1995-2001 Japanese intervention. Similarly, the ordered probit results for the first subsample provide evidence for leaning *against* the wind during 1991-1995, even though the evidence for the first subsample is far less conclusive with the p-value of the coefficient on $(s_{t-1} - s_{t-2})$ being 0.071.

Interestingly, we find a significant negative coefficient on the volatility variable for the full sample, with the sign being negative for both of the two subsamples as well. Despite its insignificance in both of the subsamples, the consistently negative sign suggests that Bank of Japan may have been more likely to sell Yen during the periods of higher volatility.

6 Conclusion

In this paper, we have argued that when presented with clustered data, the *ACB* model should be the first choice. Not only did this model fit the data better, but it also avoided the problems we faced for each central bank. With the Federal Reserve and Bank of Japan, the hazard fell below zero. This necessitated the use of the smoothing function described in Footnote 13. Fortunately, the results did not hinge on the smoothing function's transformation and for the Federal Reserve, we were able to isolate the problematic variable. But in practice, this will not always be the case.

With the Bundesbank and Bank of Japan, we found that α and β summed to more than one, which violated stationarity, forcing us to impose a boundary condition on β , although

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this still allowed the *ACH* to have a better fit than the probit model. Again, the *ACB* model gave us a better fit according to both the SBC and RV without worrying about this problem. The consistent result of the *ACB* performing better than the *ACH* suggests that lagging $G^{-1}(h_t)$ and x_t controls for the clustering better than lagging $u_{N(t)}$ and $\psi_{N(t)}$. Whenever the lagged duration was significant in the probit model and $G^{-1}(h_{t-1})$ and x_{t-1} were introduced, the significance of the lagged duration disappeared.

When using the *ACH* model, one should remove the smoothing function and reestimate the model to guarantee that one does not run into the problem illustrated by the Federal Reserve and Bank of Japan, where the explanatory variables caused the denominator of the *ACH* hazard to be negative. If one does face this issue, one should estimate a separate model to ensure that the results do not hinge on this conversion. Although we presented evidence that the results do not hinge on this conversion, this is by no means conclusive. More importantly, one should check and make sure that the lagged duration really is significant in predicting whether or not the event will occur, since the functional form implied by the *ACH* is equal to the reciprocal of a decaying sum of these lagged durations. As we showed for the Federal Reserve, when the lagged duration is insignificant, this functional form assumption can be too restrictive and may give misleading results in terms of the significance of exogenous variables.

In investigating why central banks intervene, we found that the Federal Reserve did not intervene in response to a deviation of the exchange rate from fundamentals.³² We also found some evidence that the Federal Reserve preferred to intervene when the market was calmer, and found that the spread between the 6-month Treasury Bill and Federal Funds rate contains predictive power for Federal Reserve intervention, suggesting a link between

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intervention and monetary policy decisions. We found that the Bundesbank intervened in response to the exchange rate deviating from the one implied by fundamentals and some evidence, like the Federal Reserve, that the Bundesbank intervened when the market was calmer. We found that the Bank of Japan was leaning against the wind during the time period before Sakakibara, whereas it leaned *with* the wind during Sakakibara. We also found little evidence for the Bank of Japan intervening in response to excess market volatility, a previously unexamined motivation.

Finally, we presented evidence that when facing clustered data such as intervention data, it is important to account for this clustering properly. Failure to control for the clustering (as in the probit case) would have lead us to believe that the Bundesbank did *not* intervene in response to a deviation of the exchange rate from the one implied by fundamentals. Had we controlled for the clustering through the *ACH* rather than the *ACB*, we would have believed that the Federal Reserve intervened in response to a deviation in the nominal exchange rate from the one implied by fundamentals, but not the Bundesbank. This reason, along with the issues encountered with the *ACH*, causes us to favor the *ACB* over the *ACH* when dealing with clustered data. We believe these results are relevant to other applications using data with similar properties.

Notes

1. See Sarno and Taylor (2001) for a thorough overview of the diverse opinions on this subject.
2. In Japan, intervention is under the jurisdiction of the Ministry of Finance. Once intervention orders are given, they are carried out by the Bank of Japan. See Ito (2002).
3. A separate question is whether or not intervention is successful in altering the exchange rate. Although an interesting question, given the first paragraph of the introduction, it is outside of the scope of this paper. Rather, we focus on why central banks intervene and how to control for the clustering present in the data.
4. *Business Week* of October 17, 1985 quoted in Funabashi (1989).
5. *Business Week* of October 7, 1985 quoted on page 16 of Funabashi (1989).
6. See point 14 in the G-5 announcement included in Funabashi (1989).
7. See point 18 of the official G-5 Plaza announcement included in Funabashi (1989). Note that rather than using the term "depreciate", the G-5 uses the phrase "appreciate the main non-dollar currencies against the dollar".
8. However, as Sarno and Taylor (2001) point out, the dollar was depreciating prior to the Plaza agreement.
9. See point 10 of the official G-6 Louvre announcement contained in Funabashi (1989).
10. See Lawson's interview with the New York Times quoted in Funabashi (1989).
11. The authors are grateful to Richard Baillie for providing the data.
12. Available at <http://research.stlouisfed.org/fred2/>
13. This data is publicly available on the Japanese Ministry of Finance web site at <http://www.mof.go.jp/english/e1c021.htm>
14. Sakakibara (2000) quoted on page 13 of Ito (2002).
15. We also follow Hamilton and Jorda (2002) in dropping the constant ω from equation (3) and instead include a constant in the denominator of the hazard.

- 16.** Following Hamilton and Jorda (2002), we ensure that equation (7) is continually differentiable by replacing the denominator with a smoothing function defined as:

$$\lambda(v) = \left\{ \begin{array}{ll} 1.0001 & \text{if } v \leq 1 \\ 1.001 + \frac{2*0.1(v-1)^2}{0.1^2+(v-1)^2} & \text{if } 1 < v \leq 1 + 0.1 \\ 0.0001 + v & \text{if } v \geq 1 + 0.1 \end{array} \right\}$$

where v is the denominator in equation (7) and $\lambda(v)$ is the denominator actually used.

- 17.** See point 18 of the official G-5 Plaza Agreement announcement.
- 18.** We cannot reject the null hypothesis that $(s_{t-1} - s_{t-1}^*)$ has a unit root (t-statistic: -2.02). This result is robust to the inclusion of a time trend and to the inclusion of ten lags of the difference of the series in an augmented Dickey-Fuller test. Thus, we replace $(s_{t-1} - s_{t-1}^*)$ with the first difference of it in the z vector of equation (7) for the Federal Reserve and Bundesbank. This is consistent with Meese and Singleton (1982) and Meese and Rogoff (1983) that exchange rates appear to be $I(1)$.
- 19.** That is, monetary policy is equivalent to unsterilized intervention.
- 20.** Note we choose standard normal for G .
- 21.** It might be argued that including the lagged duration, rather than the *ACD* modeled duration, in the *ACB*, is an unfair comparison. We argue against this. By including the lagged duration, we are simply assuming the expected duration is equal to its lag, rather than its sum of decaying lags. And, as we show, this lag enters the *ACB* insignificantly.
- 22.** In all cases, the order of the *ACB* model was selected by comparing the selected model with a higher order model via a likelihood ratio test.
- 23.** We constrain β to ensure stationarity and reestimate the *ACH* model and obtain nearly identical results (available from the authors upon request).
- 24.** Even in the case where β is constrained to ensure stationarity.
- 25.** We call this "lagged duration" in the table to emphasize that it is not modeled in the fashion of equation (3).
- 26.** Like the Bundesbank, the estimates are not dramatically different when β is constrained to ensure stationarity. Results available from the authors upon request.

- 27.** For all central banks, when the *ACH* could converge without the smoothing function, the results were nearly identical to when the smoothing function was removed. Results available from the authors upon request.
- 28.** The intervention values are in \$ million. None of the observed intervention values falls on an interval boundary.
- 29.** Nevertheless, we would expect the degree of market volatility to affect the magnitude of intervention.
- 30.** Note that the spread between the 6-month Treasury Bill and the Federal Funds Rate is used without taking absolute value when estimating the ordered probit.
- 31.** The intervention values are in ¥ billion. None of the observed intervention values falls on an interval boundary.
- 32.** These claims are based on the *ACB* results.

Table 1.1: Summary Statistics for Federal Reserve and Bundesbank Intervention

	Federal Reserve	Bundesbank
number of observations	1387	1461
number of interventions	173	210
number of dollar buys	65	55
number of dollar sells	108	155
largest dollar buy	\$395 million	\$567 million
largest dollar sell	\$740 million	\$887.7 million
smallest dollar buy	\$15 million	\$11.7 million
smallest dollar sell	\$25 million	\$2 million
weeks with 1 intervention	23	28
weeks with 2 interventions	27	31
weeks with 3 interventions	18	18
weeks with 4 interventions	8	9
weeks with 5 interventions	2	6
weeks with 0 interventions	222	225
number of dollar buys followed by dollar buys	60	50
number of dollar buys followed by dollar sells	4	4
number of dollar sells followed by dollar buys	4	4
number of dollar sells followed by dollar sells	104	151

Table 1.2: Summary Statistics for Bank of Japan Intervention

	full sample	1st subsample	2nd subsample
number of observations	2538	1038	1500
number of interventions	200	165	35
number of yen buys	32	26	6
number of yen sells	168	139	29
largest yen buy	¥2620.1 billion	¥76.9 billion	¥2620.1 billion
largest yen sell	¥1405.9 billion	¥338.8 billion	¥1405.9 billion
smallest yen buy	¥3.2 billion	¥3.2 billion	¥76.4 billion
smallest yen sell	¥5.1 billion	¥5.1 billion	¥43 billion
weeks with 1 intervention	44	23	16
weeks with 2 interventions	18	14	8
weeks with 3 interventions	15	14	1
weeks with 4 interventions	10	9	0
weeks with 5 interventions	7	7	0
weeks with 0 interventions	414	141	275
number of yen buys followed by yen buys	30	25	5
number of yen buys followed by yen sells	1	1	1
number of yen sells followed by yen buys	2	1	1
number of yen sells followed by yen sells	166	137	27

Table 1.3: $ACH(1,1)$ Estimation Results for Federal Reserve and Bundesbank Intervention

parameter	variable	Federal (1)	Reserve (2)	Bundesbank
α	$u_{N(t)-1}$	0.171 (0.0617)	0.173 (0.0615)	0.259 (0.115)
β	$\psi_{N(t)-1}$	0.511 (0.0949)	0.563 (0.0898)	0.800 (0.0745)
ω	constant	6.351 (0.831)	6.11 (0.741)	0.540 (0.438)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.0167 (0.0199)	—	-0.00326 (0.00643)
γ_2	$abs(spread)_{t-1}$	-1.18 (0.321)	-1.09 (0.296)	—
γ_3	$\Delta(s_{t-1} - s_{t-1}^*)$	-140.15 (72.06)	-99.48 (47.48)	-10.83 (28.16)
$\bar{\psi}$	(see note)	4.452	4.701	13.192
$\bar{h}$	(see note)	0.0990	0.0984	0.0728
log lik		-501.97	-502.31	-544.10
SBC		-523.67	-520.40	-562.32

Notes:

Standard errors are in parentheses

$\bar{\psi}$ is the typical expected length of time between the most recent intervention and the next intervention over the sample period conditional on the past values of ψ and past durations

Typical hazard over the sample computed as

$$h = \frac{1}{\bar{\psi} + \omega + \gamma_1 \overline{volat} + \gamma_2 \overline{abs(spread)} + \gamma_3 \overline{(s_{t-1} - s_{t-1}^*)}}$$

$\overline{volat}$ = is the average *volatility* over the sample period (0.1850 for Fed, 1.0430 for Bundesbank)

$\overline{abs(spread)}$ = 0.6149 is the average *abs(spread)* over the sample period

$\overline{(s_{t-1} - s_{t-1}^*)}$ = -0.00018 is the average of the first difference of $(s_{t-1} - s_{t-1}^*)$ over the sample period

Only one specification reported for each sample unless significance of explanatory variables changed when insignificant variables are dropped and the model reestimated.

Table 1.4: ACB Estimation Results for Federal Reserve Intervention

parameter	variable	probit	ACB(0,1,2)		
			(1)	(2)	(3)
ω	constant	-1.55 (0.0918)	-0.318 (0.0727)	-0.357 (0.0877)	-0.381 (0.0910)
ρ	$G^{-1}(h_{t-1})$	—	0.0820 (0.0421)	0.0832 (0.0408)	0.0811 (0.0441)
δ_1	x_{t-1}	—	1.20 (0.123)	1.16 (0.124)	1.17 (0.124)
δ_2	x_{t-2}	—	-0.664 (0.165)	-0.691 (0.159)	-0.659 (0.162)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	-0.00195 (0.00152)	—	-0.000878 (0.000382)	-0.000815 (0.000411)
γ_2	$abs(spread)_{t-1}$	0.593 (0.100)	—	0.0852 (0.0342)	0.0839 (0.0351)
γ_3	$\Delta(s_{t-1} - s_{t-1}^*)$	4.21 (5.80)	—	5.52 (3.59)	—
γ_4	lagged duration	-0.000511 (0.00199)	—	0.000628 (0.000395)	—
log lik		-500.84	-377.29	-368.81	-370.87
SBC		-518.92	-391.75	-397.75	-392.57
RV		0.1650	6.63	7.16	6.93
p-value		0.4345	0.0000	0.0000	0.0000

Note: Standard errors are in parentheses

Table 1.5: ACB Estimation Results for Bundesbank Intervention

parameter	variable	probit	ACB(0,1,3)		
			(1)	(2)	(3)
ω	constant	-1.06 (0.0405)	-0.163 (0.0770)	-0.0575 (0.0350)	-0.0423 (0.0275)
ρ	$G^{-1}(h_{t-1})$	—	0.907 (0.0445)	0.968 (0.0187)	0.975 (0.0150)
δ_1	x_{t-1}	—	1.11 (0.121)	1.09 (0.121)	1.11 (0.121)
δ_2	x_{t-2}	—	-0.466 (0.194)	-0.541 (0.197)	-0.550 (0.198)
δ_3	x_{t-3}	—	-0.345 (0.163)	-0.453 (0.130)	-0.486 (0.125)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	-0.00154 (0.00131)	—	-0.000313 (0.000122)	-0.000288 (9.23e-005)
γ_2	$\Delta(s_{t-1} - s_{t-1}^*)$	0.504 (3.20)	—	3.99 (1.51)	3.84 (1.37)
γ_3	lagged duration	-0.00463 (0.00209)	—	0.000177 (0.000141)	—
log lik		-597.77	-411.80	-405.09	-406.11
SBC		-608.70	-430.02	-434.23	-431.61
RV		-2.32	5.94	6.10	6.14
p-value		0.0102	0.0000	0.0000	0.0000

Note: Standard errors are in parentheses

Table 1.6: ACH(1,1) Estimation Results for Bank of Japan Intervention

parameter	variable	full sample	1st subsample (1) (2)		2nd subsample
α	$u_{N(t)-1}$	0.376 (0.132)	0.458 (0.255)	0.486 (0.212)	1.02e-010 (0.0994)
β	$\psi_{N(t)-1}$	0.707 (0.0532)	3.98e-012 (0.137)	0.170 (0.192)	0.00 ⁺
ω	constant	2.44 (0.884)	4.38 (0.654)	4.06 (0.870)	49.12 (12.96)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	-0.00515 (0.0255)	-0.0285 (0.0227)	—	0.362 (0.0405)
γ_2	$(s_{t-1} - s_{t-2})$	86.54 (27.80)	81.97 (42.77)	112.32 (25.27)	-2093.03 (711.57)
$\bar{\psi}$		21.428	4.812	6.145	2.15e-009
$\bar{h}$		0.0419	0.0107	0.0912	0.0191
log lik		-647.63	-437.07	-437.91	-155.26
SBC		-667.23	-454.43	-451.80	-173.54

Notes:

Standard errors are in parentheses

$\bar{\psi}$ is the typical expected length of time between the most recent intervention and the next intervention over the sample period conditional on the past values of ψ and past durations

Typical hazard over the sample computed as $h = \frac{1}{\bar{\psi} + \omega + \gamma_1 \overline{volat} + \gamma_2 (s_{t-1} - s_{t-2})}$

$\overline{volat}$ is the average *volatility* over the sample period (3.65 for full sample, -6.10 for 1st subsample, 10.41 for second subsample)

$(s_{t-1} - s_{t-2})$ is the average of $(s_{t-1} - s_{t-2})$ over the sample period (-0.0000706422 for full sample, -0.000486 for 1st subsample, 0.000217 for 2nd subsample)

+: β constrained to 0.00 to ensure convergence

Only one specification reported for each sample unless significance of explanatory variables changed when insignificant variables are dropped and the model reestimated. Omitted specifications available from authors upon request.

Table 1.7: ACB Estimation Results for Bank of Japan (full sample)

parameter	variable	probit	ACB(0, 1, 3)		
			(1)	(2)	(3)
ω	constant	-1.38 (0.0399)	-0.217 (0.0910)	-0.304 (0.0696)	-0.312 (0.0728)
ρ	$G^{-1}(h_{t-1})$	—	0.890 (0.0466)	0.846 (0.0352)	0.843 (0.0366)
δ_1	x_{t-1}	—	1.24 (0.121)	1.12 (0.125)	1.14 (0.124)
δ_2	x_{t-2}	—	-0.414 (0.195)	-0.323 (0.196)	-0.327 (0.195)
δ_3	x_{t-3}	—	-0.438 (0.171)	-0.320 (0.146)	-0.318 (0.147)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	-0.00293 (0.00192)	—	-0.000801 (0.000443)	—
γ_2	$(s_{t-1} - s_{t-2})$	-9.39 (4.76)	—	-16.32 (3.60)	-15.21 (3.46)
γ_3	lagged duration	-0.00168 (0.00121)	—	6.89e-005 (0.00297)	—
log lik		-694.61	-463.05	-448.80	-451.04
SBC		-710.29	-483.64	-480.15	-474.56
RV		-2.00	6.73	6.49	6.51
p-value		0.0228	0.0000	0.0000	0.0000

Note: Standard errors are in parentheses

Table 1.8: ACB Estimation Results for Bank of Japan Intervention (1st subsample)

parameter	variable	probit	ACB(0,1,2)		
			(1)	(2)	(3)
ω	constant	-0.872 (0.0554)	-0.411 (0.104)	-0.398 (0.0895)	-0.399 (0.0876)
ρ	$G^{-1}(h_{t-1})$	—	0.757 (0.0636)	0.770 (0.0522)	0.776 (0.0491)
δ_1	x_{t-1}	—	1.22 (0.137)	1.09 (0.143)	1.09 (0.142)
δ_2	x_{t-2}	—	-0.540 (0.213)	-4.98 (0.195)	-0.497 (0.192)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.0177 (0.00411)	—	0.000971 (0.00136)	—
γ_2	$(s_{t-1} - s_{t-2})$	-24.14 (7.05)	—	-34.59 (6.32)	-34.37 (6.32)
γ_3	lagged duration	-0.00672 (0.00262)	—	-0.000292 (0.000865)	—
log lik		-435.01	-308.61	-290.44	-290.77
SBC		-448.90	-322.50	-314.75	-308.13
RV		0.3531	6.74	6.84	6.84
p-value		0.362	0.0000	0.0000	0.0000

Note: Standard errors are in parentheses

Table 1.9: ACB Estimation Results for the Bank of Japan (2nd subsample)

parameter	variable	probit	ACB(0, 1, 2)		
			(1)	(2)	(3)
ω	constant	-2.07 (0.0844)	-2.55 (0.526)	-3.14 (0.292)	-3.12 (0.280)
ρ	$G^{-1}(h_{t-1})$	————	-0.188 (0.242)	-0.398 (0.116)	-0.415 (0.111)
δ_1	x_{t-1}	————	1.13 (0.265)	1.30 (0.280)	1.34 (0.273)
δ_2	x_{t-2}	————	1.35 (0.393)	1.49 (0.285)	1.48 (0.285)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.000145 (0.00279)	————	0.00201 (0.00412)	————
γ_2	$(s_{t-1} - s_{t-2})$	16.60 (7.80)	————	26.82 (7.90)	28.47 (7.78)
γ_3	lagged duration	0.00242 (0.00148)	————	0.00132 (0.00199)	————
log lik		-162.03	-145.26	-138.62	-139.08
SBC		-176.65	-159.89	-164.22	-157.36
RV		-1.48	0.814	1.60	1.56
p-value		0.0694	0.2078	0.0548	0.0594

Note: Standard errors are in parentheses

Table 1.10: Ordered Probit Results for Federal Reserve and Bundesbank Intervention

parameter	variable	Federal Reserve	Bundesbank
π_1	magnitude of last intervention	0.0044 (0.00056)	0.0030 (0.00038)
π_2	$(\sigma_{t-1}^2 - \sigma^2)$	-0.0008 (0.00308)	-0.0039 (0.00269)
π_3	$spread_{t-1}$	0.6795 (0.2017)	—
π_4	$\Delta(s_{t-1} - s_{t-1}^*)$	-31.224 (9.8023)	-6.787 (8.5652)
c_1		-2.978 (0.2599)	-1.619 (0.1308)
c_2		-2.389 (0.2339)	-0.942 (0.1086)
c_3		-1.808 (0.2223)	-0.547 (0.1029)
c_4		-1.031 (0.2082)	-0.032 (0.1001)
c_5		-0.349 (0.1976)	0.538 (0.1046)
c_6		-0.046 (0.1947)	0.683 (0.1074)
c_7		0.438 (0.1955)	0.928 (0.1141)
c_8		1.061 (0.2065)	1.404 (0.1358)
c_9		1.644 (0.2346)	2.042 (0.1905)
log-lik		-318.98	-417.24
SBC		-366.01	-460.96

Notes:

magnitude of last intervention is the magnitude and direction of the last observed Federal Reserve intervention as of time $(t - 1)$
standard errors are in parentheses

Table 1.11: Ordered Probit Results for Bank of Japan Intervention

parameter	variable	full sample	1991-1995	1995-2001
π_1	magnitude of last intervention	0.0036 (0.00049)	0.0156 (0.00215)	0.00191 (0.000658)
π_2	$(\sigma_{t-1}^2 - \sigma^2)$	-0.0195 (0.00643)	-0.0110 (0.00840)	0.0015 (0.01473)
π_3	$(s_{t-1} - s_{t-2})$	-13.763 (8.3220)	19.425 (10.7703)	-46.924 (18.3392)
c_1		-2.350 (0.2121)	-2.252 (0.1974)	-1.267 (0.4085)
c_2		-1.333 (0.1301)	-1.178 (0.1482)	-0.262 (0.3861)
c_3		-0.514 (0.1026)	-0.358 (0.1393)	0.094 (0.3947)
c_4		0.190 (0.1003)	0.6976 (0.1520)	0.455 (0.4102)
c_5		0.957 (0.1178)	1.013 (0.1642)	0.719 (0.4288)
c_6		1.145 (0.1260)	1.524 (0.1957)	
c_7		1.448 (0.1438)	1.952 (0.2392)	
c_8		1.678 (0.1624)		
c_9		2.110 (0.2168)		
log-lik		-347.95	-253.70	-42.43
SBC		-394.98	-288.43	-71.68

Notes:

magnitude of last intervention is the magnitude and direction of the last observed Bank of Japan intervention as of time $(t - 1)$
standard errors are in parentheses

Figure 1.1: Number of Interventions Per Week for the Federal Reserve

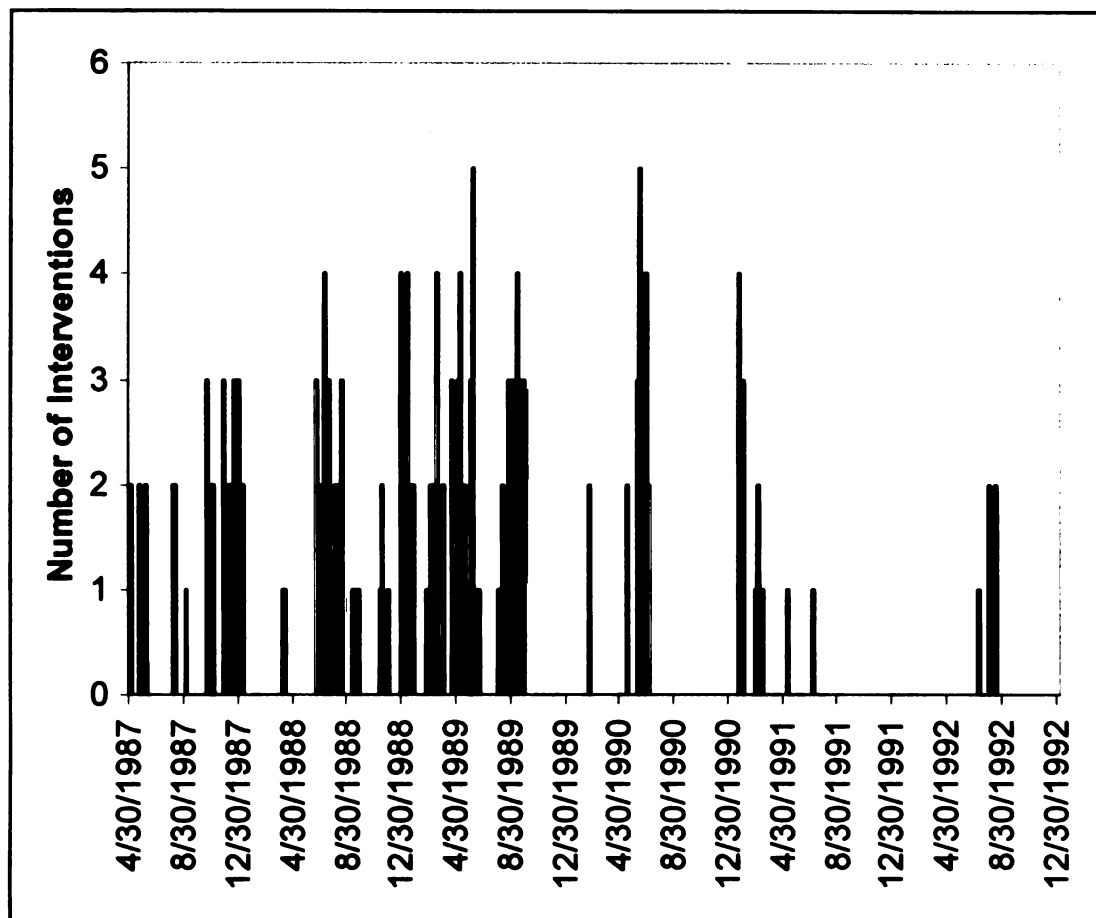


Figure 1.2: Number of Interventions Per Week for the Bundesbank

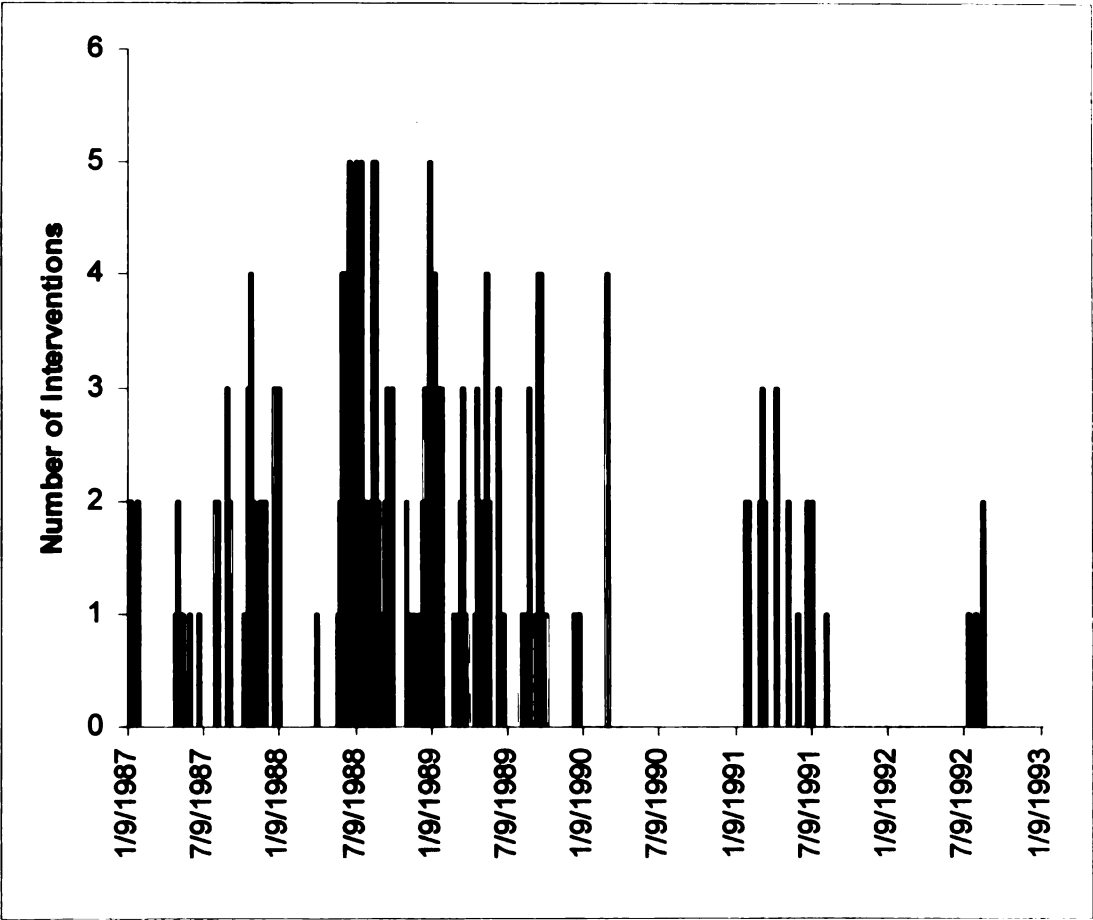


Figure 1.3: Number of Interventions Per Week for the Bank of Japan

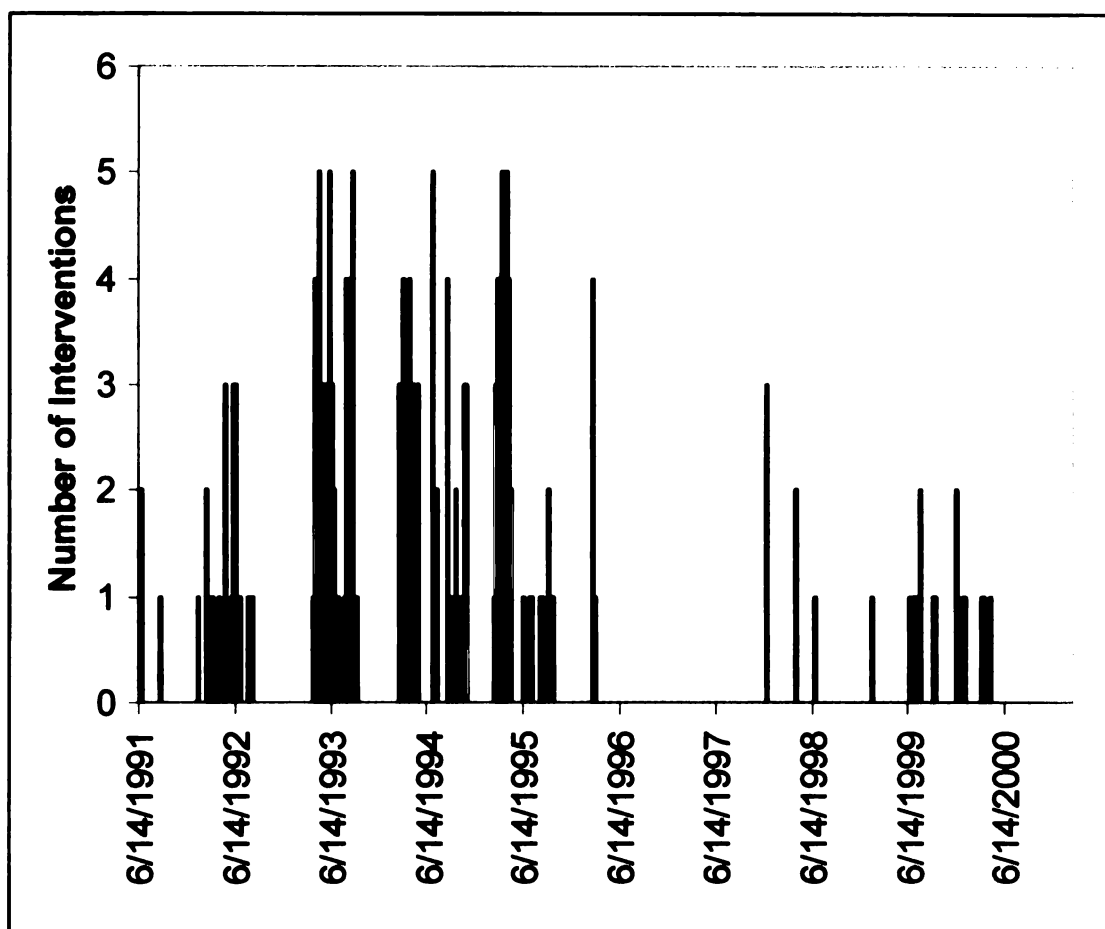
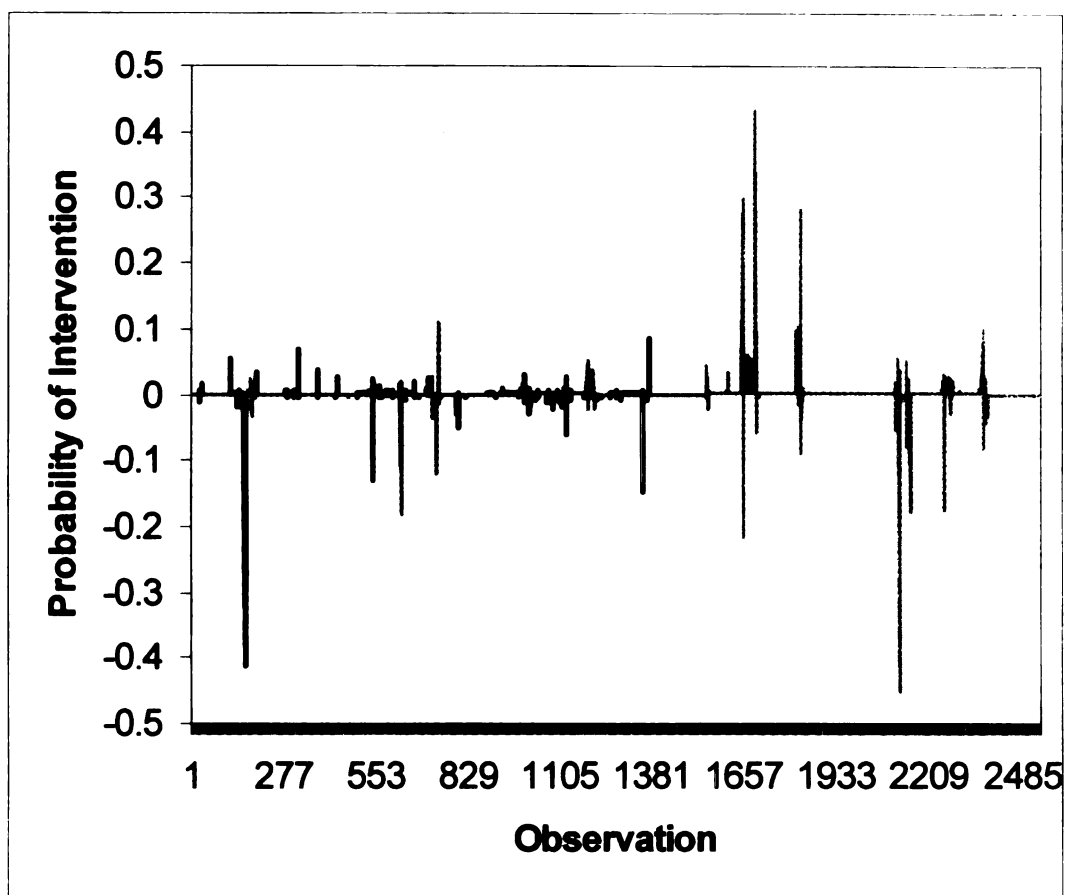
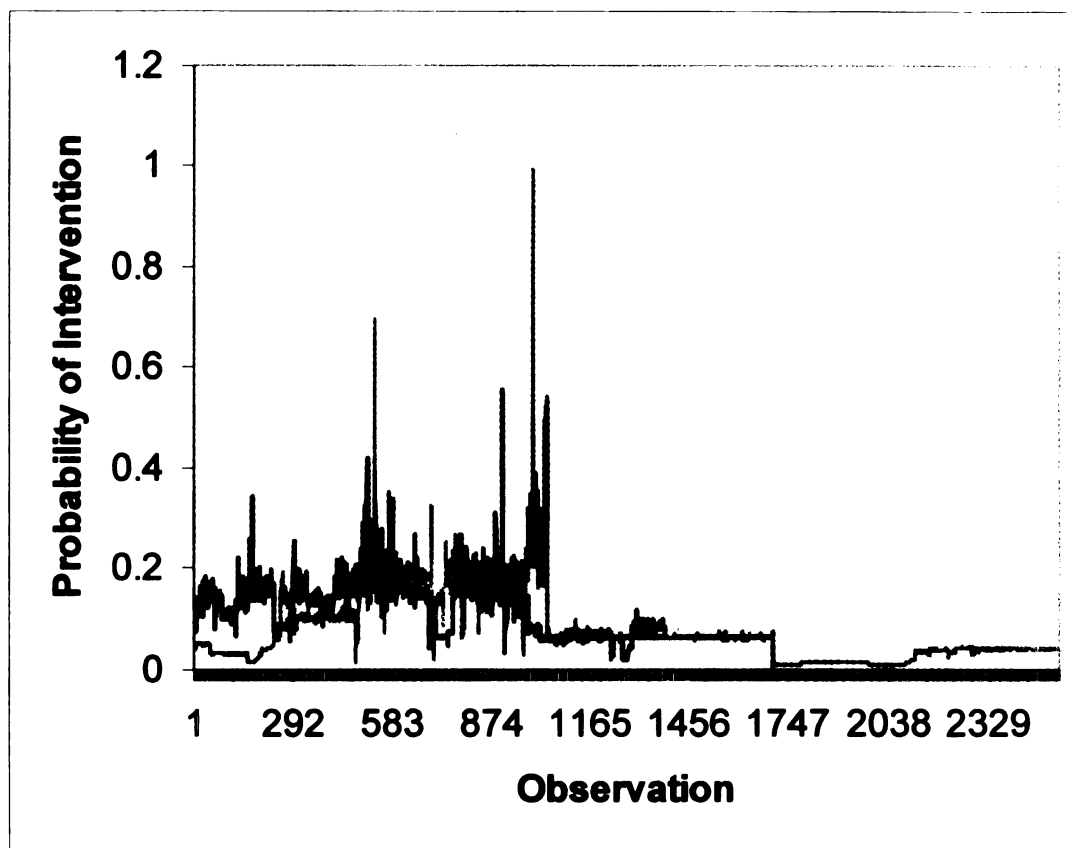


Figure 1.4: ACH Estimated Probability of Intervention for Federal Reserve and Bank of Japan (Without Smoothing Function)



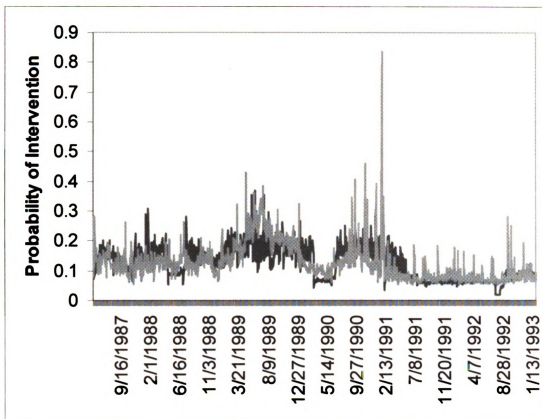
Black line: Federal Reserve; Grey Line: Bank of Japan

Figure 1.5: ACH Estimated Probability of Intervention for the Federal Reserve and Bank of Japan (With Smoothing Function)



Black line: Federal Reserve; Grey line: Bank of Japan

Figure 1.6: ACH (With Smoothing Function) and Probit Estimated Probability of Intervention for the Federal Reserve



Black line: ACH; Grey line: Probit

Figure 1.7: $ACB(0, 1, 2)$ Estimated Probability of Intervention for the Federal Reserve

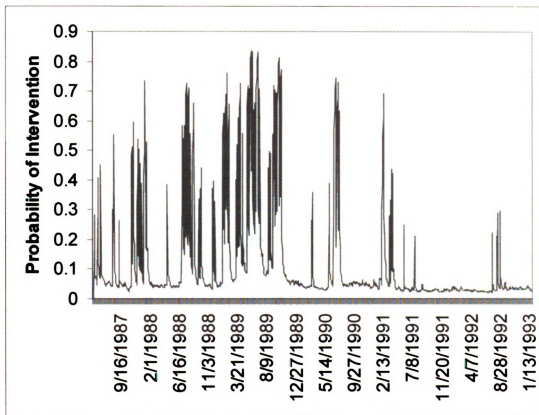
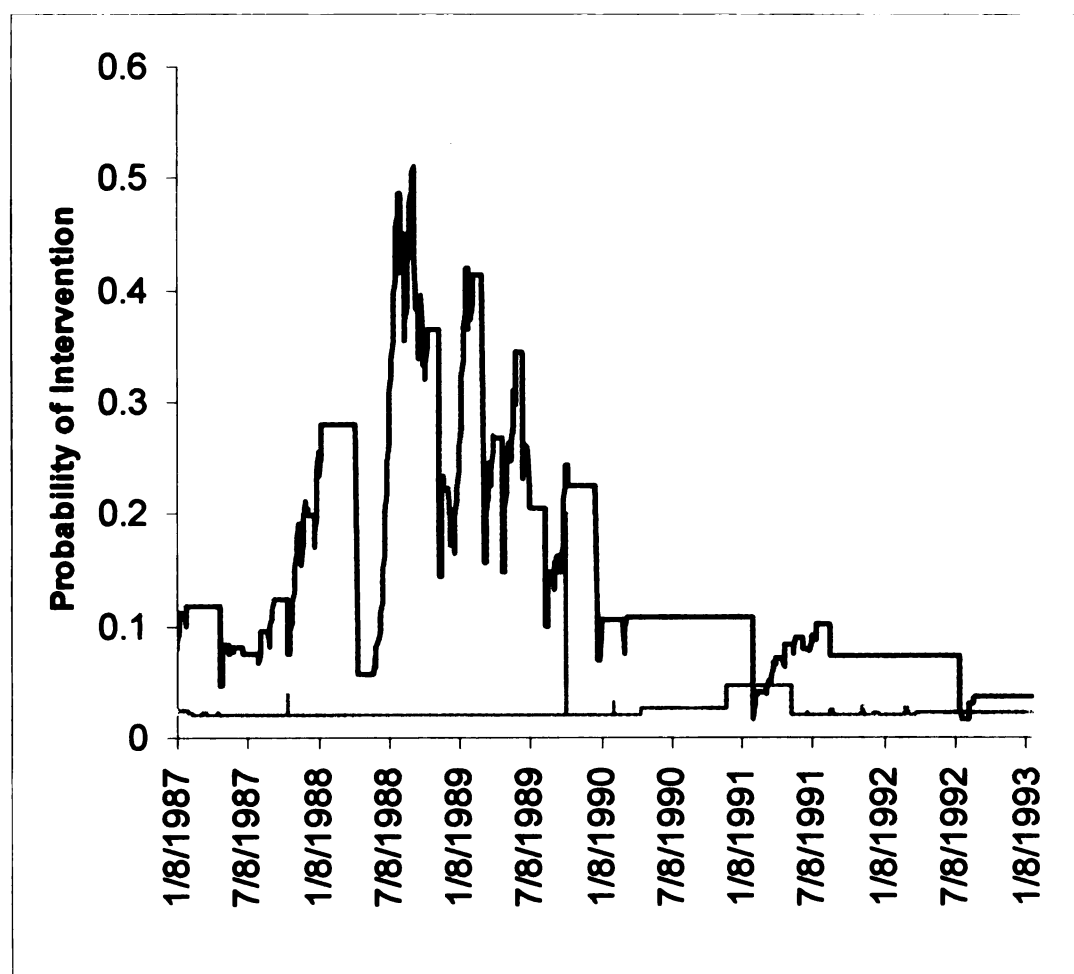


Figure 1.8: ACH (With Smoothing Function) and Probit Estimated Probability of Intervention for the Bundesbank



Black line: ACH; Grey line: Probit

Figure 1.9: $ACB(0,1,3)$ Estimated Probability of Intervention for the Bundesbank

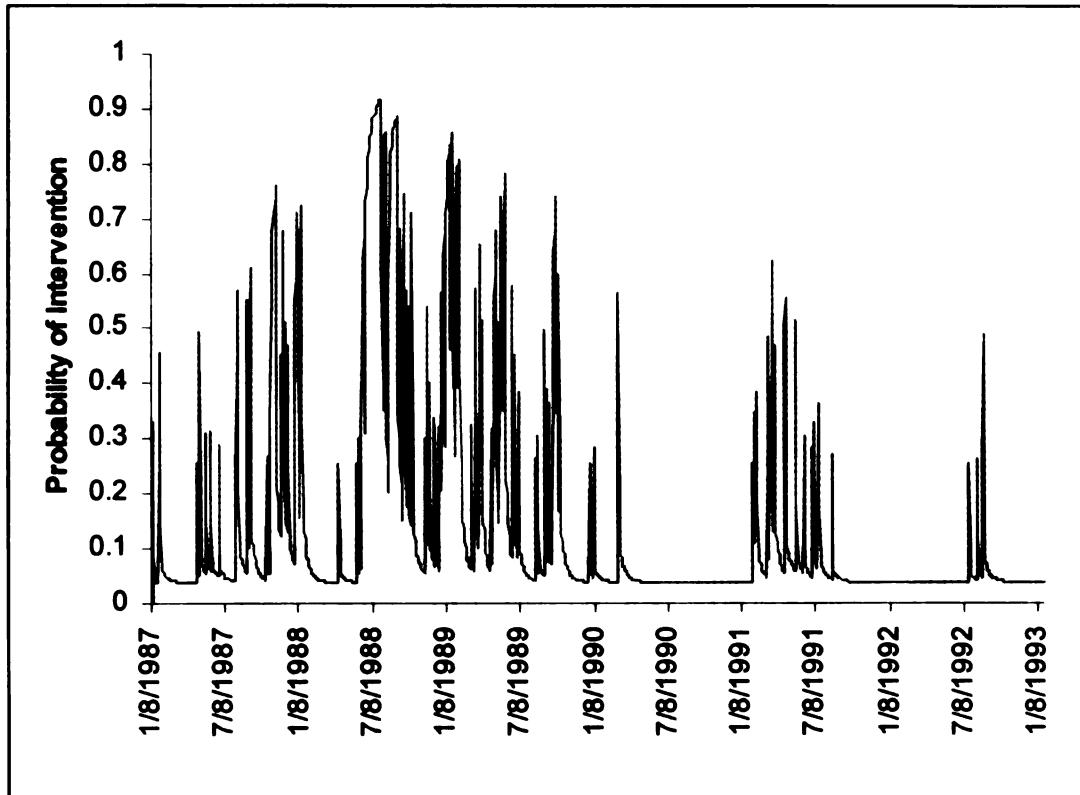
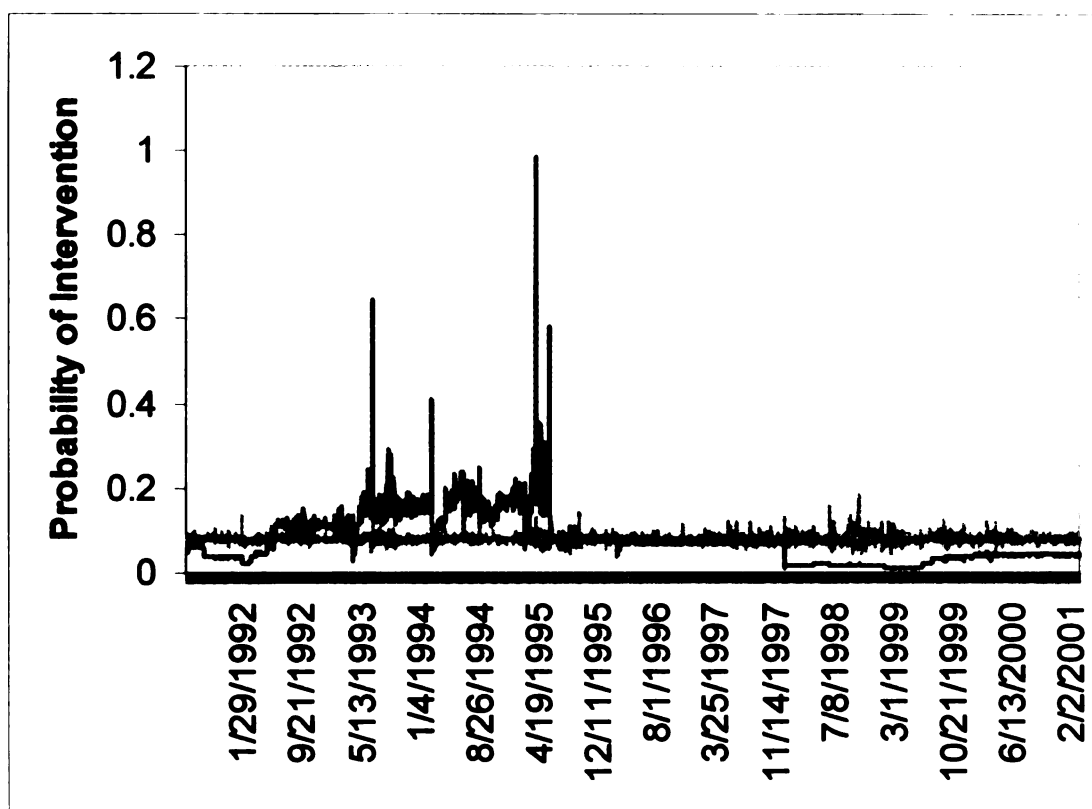
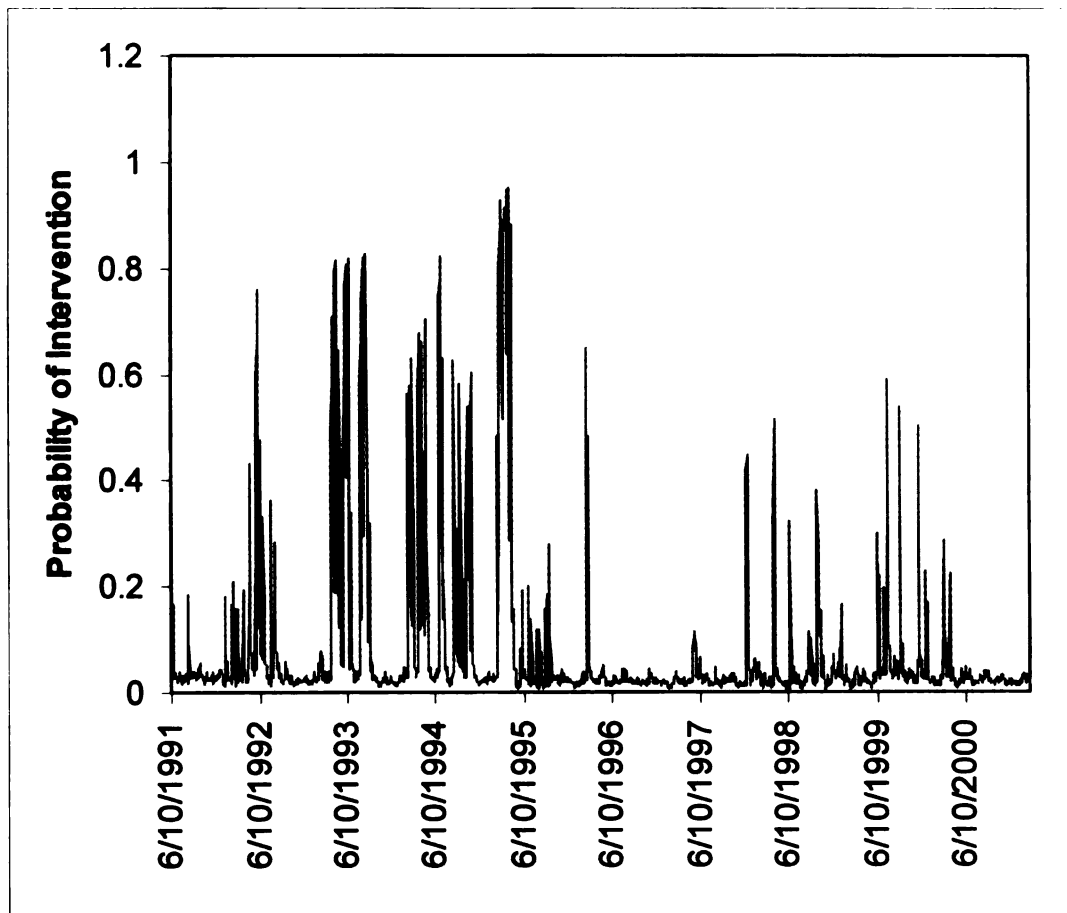


Figure 1.10: ACH (With Smoothing Function) and Probit Estimated Probability of Intervention for the Bank of Japan



Black line: ACH; Grey line: Probit

Figure 1.11: $ACB(0,1,3)$ Estimated Probability of Intervention for the Bank of Japan



Chapter 2: Why are Gasoline Prices Sticky? A Test of Alternative Models of Price Adjustment

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 obtaining and 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, while menu cost models suggest the probability of a price change should only depend on the current gap, models with information processing delays 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 alternative models of price stickiness based on the daily pattern of price adjustment of nine Philadelphia gasoline wholesalers. This data set provides a fertile 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 may be 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 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 in that 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 2.1). This positive correlation suggests past firm behavior may play an important role in explaining price stickiness.

Our work builds on Davis and Hamilton's (2004) investigation of price stickiness in Philadelphia's wholesale gasoline market. Their paper fits an explicit optimizing model of price dynamics (Dixit, 1991) to the data and investigates whether menu costs capture the dynamic adjustment of individual wholesalers to changes in the upstream price of gasoline. In addition, they estimate an atheoretical logit model and an Autoregressive Conditional Hazard (*ACH*) model and conclude 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 conclude that the menu cost model makes predictions that are "broadly consistent" with the data. In

contrast, we consider more general patterns of time dependence and ask whether they are consistent with the tell-tale predictions of three broad theories of price rigidities.

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 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, 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, 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, and 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.⁵ 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.⁶ 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 that 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 current or lagged 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 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 conveniently 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 costs 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 "menu cost"). 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). Naturally, 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), yet they can exert a large impact on the business cycle (Mankiw, 1985), especially in the face of large cost shocks (Fishman and Simhon, 2005).

Consider Dixit's (1991) menu cost model. 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 $t_1, t_2, \dots$ to change its price in order to minimize the objective function

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

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, $g e^{-\rho t}$, represents the fixed cost of the firm changing its price.

The Dixit model is unique 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.⁷ Defining $p^*(t)$ 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, DH show that the probability of a price change under the Dixit menu cost model is

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

where $\Phi(\cdot)$ is the standard normal c.d.f.⁸ The optimal decision rule is for the firm to change its price whenever $|p(t_{i-1}) - p^*(t_i)| > b$ where b is defined as

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

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), Mankiw (1985) and Sheshinski and Weiss (1977). 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 the 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

"Sticky information" 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. This implies a firm's probability of changing the price in consecutive days is very low.

Recent theoretical developments into 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. An implication of this model is that it predicts no asymmetry. 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 a 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. That is, consumers (retailers) are inattentive because the menu cost forces them to be.

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

- *Information processing delays would result in the probability of a price change responding strongly to past information.* Delays in the processing of information due to rational inattention 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 serial correlation.* 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, it is likely to remain inattentive for the following periods and to leave the price unchanged. 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 to 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 of 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 serial correlation 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 serial correlation.* 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.⁹

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 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,¹⁰ 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.¹¹

Table 2.2 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 useful to compare our data to those analyzed 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 (Chapter 3 of this dissertation) 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 2.2).¹² 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 test alternative theories of price adjustment, we utilize the Autoregressive Conditional Binomial (*ACB*) model.¹³ 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 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 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 $G^{-1}(h_{t+1}) = y_t \Leftrightarrow G(y_t) = h_{t+1}$. That is, $G^{-1}(\cdot)$ is a 1-1 mapping from h_{t+1} to $\mathbb{R}$.

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

$$h_{t+1} \equiv \Pr(x_{t+1} = 1 \mid x_t, x_{t-1}, \dots, x_1, z_t) \quad (4)$$

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

$$G^{-1}(h_{t+1}) = \omega + \sum_{j=1}^q \alpha_j (x_{t-j+1} - h_{t-j+1}) + \sum_{j=1}^r \beta_j G^{-1}(h_{t-j+1}) + \sum_{j=1}^s \delta_j x_{t-j+1} + \gamma z_t \quad (5)$$

where the probability of a price change is given by

$$h_{t+1} = G \left[\omega + \sum_{j=1}^q \alpha_j (x_{t-j+1} - h_{t-j+1}) + \sum_{j=1}^r \beta_j G^{-1}(h_{t-j+1}) + \sum_{j=1}^s \delta_j x_{t-j+1} + \gamma z_t \right] \quad (6)$$

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

$\theta = \{\omega, \alpha_1, \dots, \alpha_q, \beta_1, \dots, \beta_r, \delta_1, \dots, \delta_s\}$ obtained by maximizing the likelihood function

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

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

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

(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 $|P_{t-1} - P_{t-1}^*|$ as the absolute value of the previous day’s price gap and defining $|P_{w1(t)} - P_{w1(t)}^*|$ 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 $\mathbf{z}_{it} = (|P_{it} - P_{it}^*|)^t$ with

$$\mathbf{z}_{it} = [\theta_{it}, (1 - \theta_{it}), \theta_{it}(P_{it} - P_{it}^*), -(1 - \theta_{it})(P_{it} - P_{it}^*)]^t. \quad (9)$$

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 $(\theta_{it}(P_{it} - P_{it}^*))$ and negative $((1 - \theta_{it})(P_{it} - P_{it}^*))$ 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, sticky information, 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 on only the current value of the price gap. For this reason, the estimated coefficients on $|P_{t-1} - P_{t-1}^*|$ and $|P_{w1(t)} - P_{w1(t)}^*|$ 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 $\theta_t(P_t - P_t^*) = -(1 - \theta_t)(P_t - P_t^*)$.

- *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 $|P_{t-1} - P_{t-1}^*|$ 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 inattentive today. 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 $\theta_t(P_t - P_t^*) = -(1 - \theta_t)(P_t - P_t^*)$.
- *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,

$|P_{w1(t)} - P_{w1(t)}^*|$, 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, $|P_{w1(t)} - P_{w1(t)}^*|$ 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 Serial Correlation and the Dynamics of Price Adjustment

Estimation results for the $ACB(0, 1, 1)$ model reported in Table 2.3 suggests the presence of time dependence in 7 out of the 9 gasoline wholesalers in Philadelphia.¹⁴ 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, $|P_{t-1} - P_{t-1}^*|$, 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 the coefficient on $|P_{t-1} - P_{t-1}^*|$ at the 5% level for all but two firms.¹⁵ 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 last column of Table 2.3).

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 our 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, 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 $\mathbf{z}$ -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 2.6).

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.

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 ($G^{-1}(h_{t+1}) = G^{-1}(h_t) = G^{-1}(\bar{h})$). Solving equation (5) for $G^{-1}(\bar{h})$ gives:

$$G^{-1}(\bar{h}) = \frac{\omega + \gamma \bar{\mathbf{z}}}{1 - \beta} \quad (10)$$

where $\bar{\mathbf{z}}$ contains the averages of $|P_t - P_t^*|$ and $|P_{t-1} - P_{t-1}^*|$, respectively, and $x_t = 0$.¹⁶ Replacing this value for $G^{-1}(\bar{h})$ into our *ACB*(0,1,1) specification, we obtain the steady-state probability of a price change:

$$\bar{h} = G \left[\omega + \beta G^{-1}(\bar{h}) + \gamma_1 \overline{|P_t - P_t^*|} + \gamma_2 \overline{|P_{t-1} - P_{t-1}^*|} \right]$$

$$= G\left[\omega + \beta G^{-1}(\bar{h}) + (\gamma_1 + \gamma_2)|\overline{P - P^*}| \right] \quad (11)$$

Now, assume that at time $t = 1$, the price gap experiences a 10¢ one-time increase over the sample average so that $|P_1 - P_1^*| = |\overline{P - P^*}| + 10$. As we mentioned above, this shock can be interpreted as a result of an unexpected increase in the NYMEX price of gasoline while holding the desired markup for each firm constant. We then assume that the firm adjusts its price so as to set $|P_t - P_t^*| = |\overline{P - P^*}|$ 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

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

The response probability for the logit model can be computed by setting $\beta = \delta = 0$.

Therefore the simulated probability is given by¹⁷

$$h_t = \left\{ \begin{array}{ll} G\left[\tilde{\omega} + \tilde{\gamma}_1(|P_t - P_t^*| + 10) \right] & \text{for } t = 1 \\ G\left[\tilde{\omega} + \tilde{\gamma}_1|\overline{P - P^*}| \right] & \text{for } t \geq 2 \end{array} \right\}, \quad (13)$$

where a tilde ($\sim$) 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 2.1. For firms with $\beta > 0$, the pattern of adjustment implied by the ACB and the logit are generally similar.¹⁸ The probability of a price change rises immediately after the shock and then quickly returns to the initial level. This is evidence

against Rotemberg's partial adjustment hypothesis, as the estimates indicate that the likelihood of further adjustment is low. Notice in Table 2.3 that, for some of the firms, the coefficients on the current and lagged price gap are roughly equal and of 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 the probability is consistent with the idea of customers believing that it is fair for firms to raise prices in the face of cost shocks 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.¹⁹ 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 change 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 comparing 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 stickiness in prices.

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. In that case, the response probabilities for the *ACB* and the logit, respectively, would be given by:

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

and

$$h_t = G[\tilde{\omega} + \tilde{\gamma}_1(|P_t - P_t^*| + 10)] \quad \text{for } t \geq 1. \quad (15)$$

Figure 2.3 illustrates 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 a 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 3, 5, and 9 (see Table 2.6). 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 competitors.

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, $|P_{t-1} - P_{t-1}^*|$, to be statistically significant in the *ACB* specification, we explore the asymmetry of price adjustments by including one lag of the positive $(\theta_{it-1}(P_{it-1} - P_{it-1}^*))$ and negative $(-(1 - \theta_{it-1})(P_{it-1} - P_{it-1}^*))$ gaps in the set of explanatory variables given by equation (9). Table 2.4 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 2.4).

Lastly, another source of asymmetry here is that for all firms, the coefficient on $\theta_{it-1}(P_{it-1} - P_{it-1}^*)$ is larger than the coefficient on $-(1 - \theta_{it-1})(P_{it-1} - P_{it-1}^*)$, 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 2.4 plots the probability of a price change as the difference between P_{it} and P_{it}^* varies between -10 and +10 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 2.1 of DH.²⁰ The solid line is the asymmetric *ACB* found by setting $G^{-1}(h_t)$ to its averages and setting x_t 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 sticky information] 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 of a price change is strongly correlated with the previous day's, for 7 of the 9 firms. Second, Figure 2.1 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. Additionally, Figure 2.3 suggests 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 2.4 and Figure 2.4 suggest 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 2.4 and Figure 2.4 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 2.2 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 $|P_{t-1} - P_{t-1}^*|$ 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-contingent 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. However, the results for this additional variable are very similar to that for $|P_{t-1} - P_{t-1}^*|$.²² Thus, $|P_{last} - P_{last}^*|$ enters with the opposite side as implied by the inattentiveness model.

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 incentive to make large price decreases over large price increases. And, if retailers cannot match small price changes, wholesalers have 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 from (a) fairness concerns in everyday pricing, especially with regards to large price increase and (b) rational inattention, perhaps due to a menu cost farther down the supply chain, for very small price changes. The following section compares our results to what has been found in the literature.

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.

As we mentioned in section 2, DH began their investigation by fitting the Dixit menu cost model to the Philadelphia wholesale data. Although the model fits 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 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 2.2).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 2.5).

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 (*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 $u_{n-1}, u_{n-2}, \dots, u_1$, 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

$$h_{t+1} = \frac{1}{\psi_{N(t)} + \gamma' z_t} \quad (17)$$

where

$$\psi_n = \alpha \sum_{i=1}^{n-1} \beta^{i-1} u_{n-i} + \beta^{n-1} \bar{u} \quad (18)$$

and $\bar{u}$ 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 2.5, which reproduces DH's Table 2.3. Using both models, the authors find $|P_{it-1} - P_{it-1}^*|$ to be significant for only two firms (in contrast with the *ACB*, which finds it significant for seven firms), and $|P_{i,w1_{i(t)}} - P_{i,w1_{i(t)}}^*|$ significant for none (see Table 2.6). Additionally, since the *ACH* outperforms the atheoretical logit in terms of goodness of fit for only one firm (see Table 2.5), the authors find little evidence of time dependence in the price change decision. They conclude that "the history of prices matters for the probability 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 (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 2.7. 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 2.3.²⁶

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, $\ln(u_{N(t-1)} - 1)$, in the *ACB*. The second column of Table 2.7 reports the p-value for the test of the null hypothesis that the coefficient on $\ln(u_{N(t-1)} - 1)$ 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 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 2.7 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 2.5).

As a final comparison between the *ACH* and *ACB*, we conduct a Rivers and Vuong (2002) test of non-nested likelihoods, which is a time-series extension of the Vuong's (1989) test. Rivers and Vuong (2002) tests whether the (absolute value) of the *ACH* log-likelihood is greater than, less than, or equal to the *ACB* log-likelihood. Rivers and Vuong (2002) shows that the test statistic is distributed *Normal*(0, 1). The null hypothesis of the test is that the two models fit the data equally well, whereas the alternate hypothesis is that one model

fits the data better than the other. Thus, if the test statistic is statistically greater than zero at some critical value, the *ACH* is rejected in favor of the *ACB*, and vice versa if the test statistic is statistically less than zero. If the test statistic is not statistically different than zero, we cannot reject the null hypothesis, given the data.

The last column of Table 2.3 reports the results of this test. For 6 of the 9 firms we can reject the null hypothesis, at the 5% level or lower, that the two models fit the data equally well in favor of the alternate hypothesis that the *ACB* is preferred. Thus this, coupled with the likelihood ratio test statistic (second-to-last column of Table 2.3) of the *ACB* versus the logit offers evidence in favor of our dynamic *ACB* specification compared to the *ACH* and logit specifications in Davis and Hamilton (2004).

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, 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 customers with insufficient supplies. The latter concern results from wholesalers fearing that

a high price will cause its customers to switch brands when its 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 large and small changes in the price gap.

7. Conclusion

Why are wholesale gasoline prices sticky? In this paper we consider 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 posits 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 serial correlation 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 serial correlation of price change probabilities, the immediate pass-through of cost shocks (Figure 2.1), and finding that firms are more likely to make large price decreases over large price increases (Table 2.4 and Figure 2.4) 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 seems like a practical concern.

Notes

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.
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*).
5. According to Tappata (2006), Bacon (1991) was the first to use this term to describe the behavior of gasoline prices in Great Britain.
6. 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).
7. 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, this assumption is likely satisfied.
8. 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.
9. The nine wholesalers in our data set are Amoco, ARCO, BP, Chevron, Exxon, Gulf, Mobil, Sunoco and Texaco.
10. According to a search of gas stations on Verizon's superyellowpages.com

11. 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>).
12. 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.
13. This model is a calendar time version of the Autoregressive Conditional Multinomial (ACM) model of Engle and Russell (2005).
14. 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.
15. Given that the regressors are stationary and the number of lags are enough to capture serial correlation, likelihood ratio tests are valid.
16. 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.
17. 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.
18. 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.
19. 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.
20. Because the 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 2.4 indicates that the likely reason for this is asymmetry in the "small" for values of the gap close to zero.
22. As a result, we do not include them here, but are available upon request.

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

Table 2.1: Description of Price Changes

Firm	Number of Price Changes	Increase Following		Increase Following		Decrease Following		Decrease Following	
		Previous	Following	Previous	Following	Previous	Following	Previous	Following
1	270	102	22	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			

Table 2.2: 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

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 2.3: 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 (0.234)	-0.505** (0.145)	-0.184 (0.151)	-0.0364 (0.0386)	0.196** (0.0402)	-478.97	0.00070**	1.82 0.0344*
2	-0.110 (0.0595)	0.828** (0.117)	0.149 (0.0802)	0.107** (0.0350)	-0.102** (0.0331)	-529.43	0.0324*	0.968 0.1665
3	-0.0898 (0.0987)	0.368* (0.174)	0.320* (0.140)	0.296** (0.0551)	-0.247** (0.0525)	-512.83	0.0000**	2.33 0.0099**
4	-0.638 (0.272)	0.467* (0.239)	0.508** (0.174)	0.106* (0.0433)	-0.0680 (0.0581)	-405.37	0.00530**	2.26 0.0119*
5	-0.0992 (0.0513)	0.901** (0.0464)	0.202** (0.0900)	0.113** (0.0296)	-0.114** (0.0292)	-520.52	0.0000**	1.38 0.0838
6	-0.209 (0.129)	0.827** (0.105)	0.206 (0.121)	0.185** (0.0333)	-0.169** (0.0352)	-471.30	0.0183*	3.45** 0.0003
7	-0.0672 (0.0507)	0.899** (0.0608)	0.0686 (0.0696)	0.121** (0.0276)	-0.117** (0.0267)	-521.19	0.1136	1.59 0.0559
8	-0.868 (0.253)	-0.570* (0.256)	-0.00605 (0.210)	0.0223 (0.0467)	0.126** (0.0419)	-524.31	0.0990	2.11* 0.0174
9	-0.267 (0.101)	0.780** (0.0798)	0.259* (0.115)	0.157** (0.0321)	-0.141** (0.0330)	-432.65	0.0186*	2.09* 0.0183

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 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 2.4: 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 (0.1547)	-0.2068 (0.1566)	-1.7162** (0.2787)	-1.5107** (0.3082)	0.0120 (0.0910)	-0.0649 (0.0473)	0.2139** (0.0777)	0.1831** (0.0485)	-476.30	0.1485
2	0.5955 (0.1965)	0.0271 (0.1374)	-0.2568 (0.1570)	-0.0156 (0.1026)	0.1528** (0.0548)	0.1273** (0.0464)	-0.0877 (0.0573)	-0.1502** (0.0485)	-520.48	0.0005**
3	0.3775 (0.1965)	0.3093 (0.1396)	-0.1039 (0.1278)	-0.0628 (0.1362)	0.3601** (0.0855)	0.2574** (0.0695)	-0.2704** (0.0884)	-0.2490** (0.0609)	-510.75	0.2447
4	0.1989 (0.2480)	0.4609 (0.1747)	-1.2550** (0.3817)	-0.6091** (0.2257)	0.1222* (0.0587)	0.0623 (0.0570)	0.0421 (0.0799)	-0.0492 (0.0623)	-396.87	0.0007**
5	0.8715 (0.0517)	0.2622 (0.0984)	-0.1180 (0.0626)	-0.1460** (0.0566)	0.1347** (0.0441)	0.1420** (0.0386)	-0.1357** (0.0448)	-0.1419** (0.0382)	-520.52	1.0000
6	-0.2413 (0.2275)	0.3126 (0.1644)	-1.9085** (0.3541)	-0.8220** (0.2607)	0.1689** (0.0677)	0.0700 (0.0476)	0.1567* (0.0789)	0.0212 (0.0535)	-462.34	0.0005**
7	0.8485 (0.0751)	0.0309 (0.0821)	-0.0509 (0.0654)	-0.1281 (0.0666)	0.0826 (0.0474)	0.1587** (0.0406)	-0.0710 (0.0521)	-0.1507** (0.0392)	-515.71	0.0119*
8	-0.3144 (0.4717)	-0.0048 (0.0701)	-0.8584** (0.2434)	-0.6660 (0.4345)	0.0283 (0.0570)	0.0200 (0.0502)	0.1526* (0.0688)	0.0756 (0.0900)	-523.26	0.5519
9	0.7581 (0.0821)	0.2245 (0.1152)	-0.3476** (0.1280)	-0.1961* (0.0948)	0.1640** (0.0495)	0.1506** (0.0400)	-0.1286* (0.0504)	-0.1445** (0.0411)	-429.83	0.1305

Table 2.5: 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 2.6: Test for Significance of Additional Variables

Firm	$ P_{t-1} - P_{t-1}^* $	$ P_{w1(t)} - P_{w1(t)}^* $	$\{\theta_t, P_t - P_t^*\}$	$u_{N(t-1)-1}$	y_{t-1}^{other}
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*	0.0513	0.0000**
2	0.0348*	0.6390	0.0022**	1.000	0.0173*
3	0.0004**	0.6390	0.5273	0.1573	0.2687
4	0.2741	0.0769	0.0003**	0.9542	0.0000**
5	0.0000**	0.0931	0.7445	0.00130***	0.1517
6	0.1565	0.1345	0.0002**	0.2184	0.0000**
7	0.0181*	0.7290	0.2725	0.8559	0.0000**
8	0.0355*	1.0000	0.1281	1.000	0.0001**
9	0.0024**	0.2453	0.0537	0.1505	0.4371

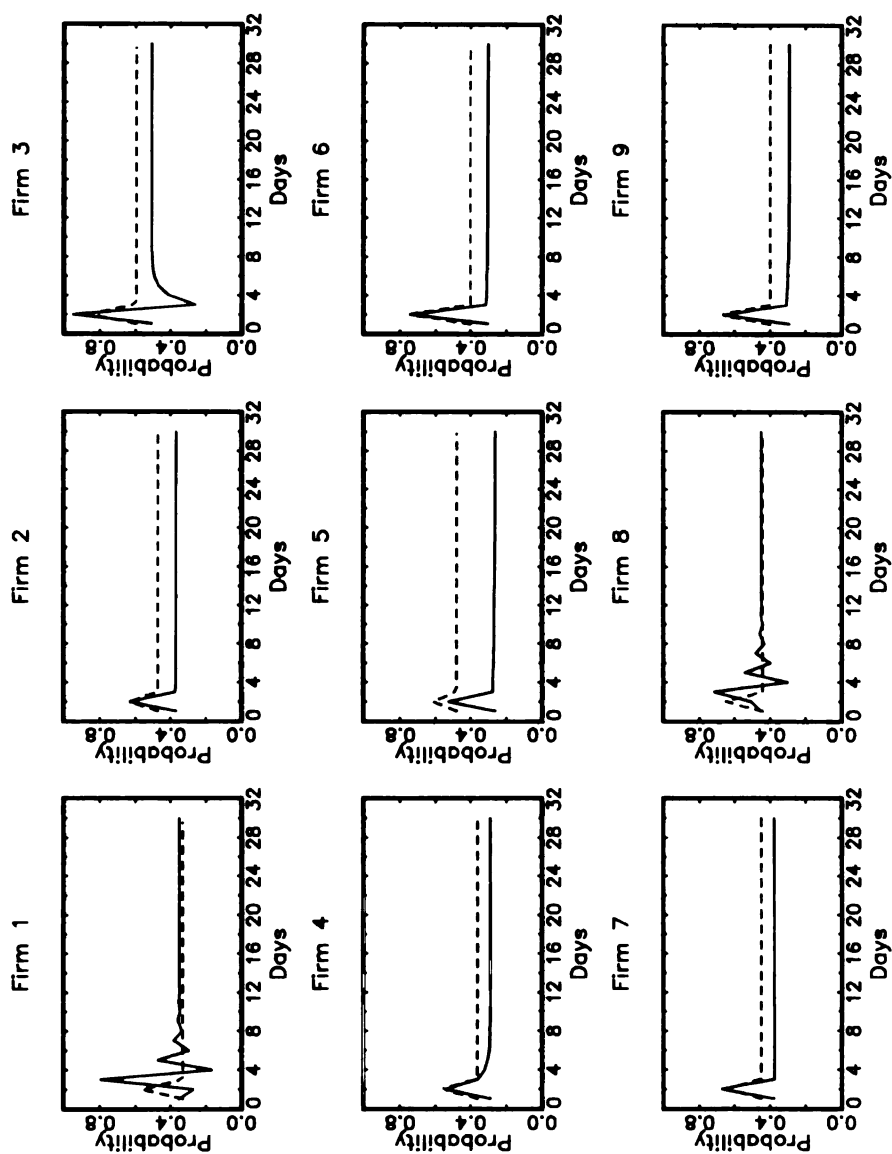
NOTES: Table reports p-value of test of null hypothesis that the indicated variable does not belong as an additional explanatory variable to the logit or ACH model. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

Table 2.7: Tests for Significance of the Duration

Firm	$\ln(u_{N(t)})$	$\ln(u_{N(t)-1})$	$u_{N(t)-1}$
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

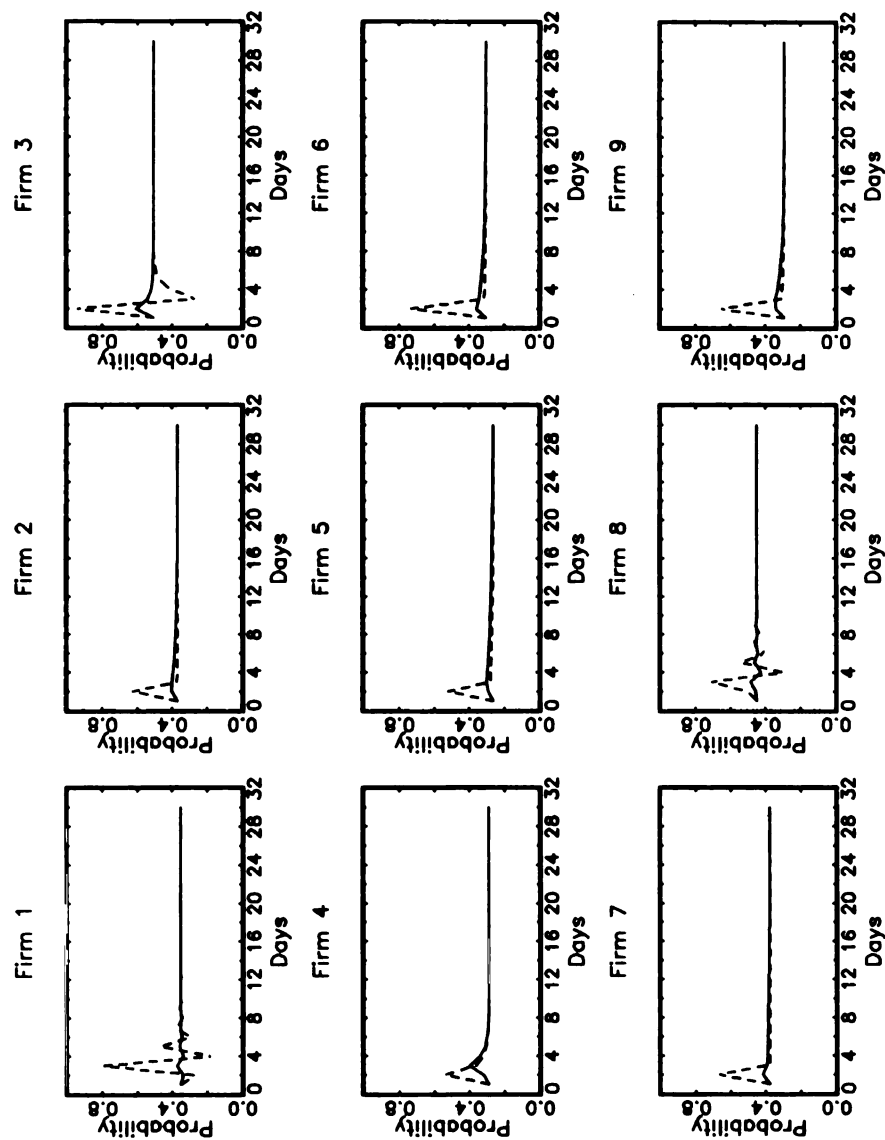
NOTES: Column 2 reports the p-value for the test of the null hypothesis that the natural log of the contemporaneous duration in the ACB-ACD model is zero. Column 3 reports the p-value for the test of the null hypothesis that the lagged duration is equal to zero in the logit model with the current price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

Figure 2.1: ACB and Logit Impulse Response Assuming the Firm Changed Its Price



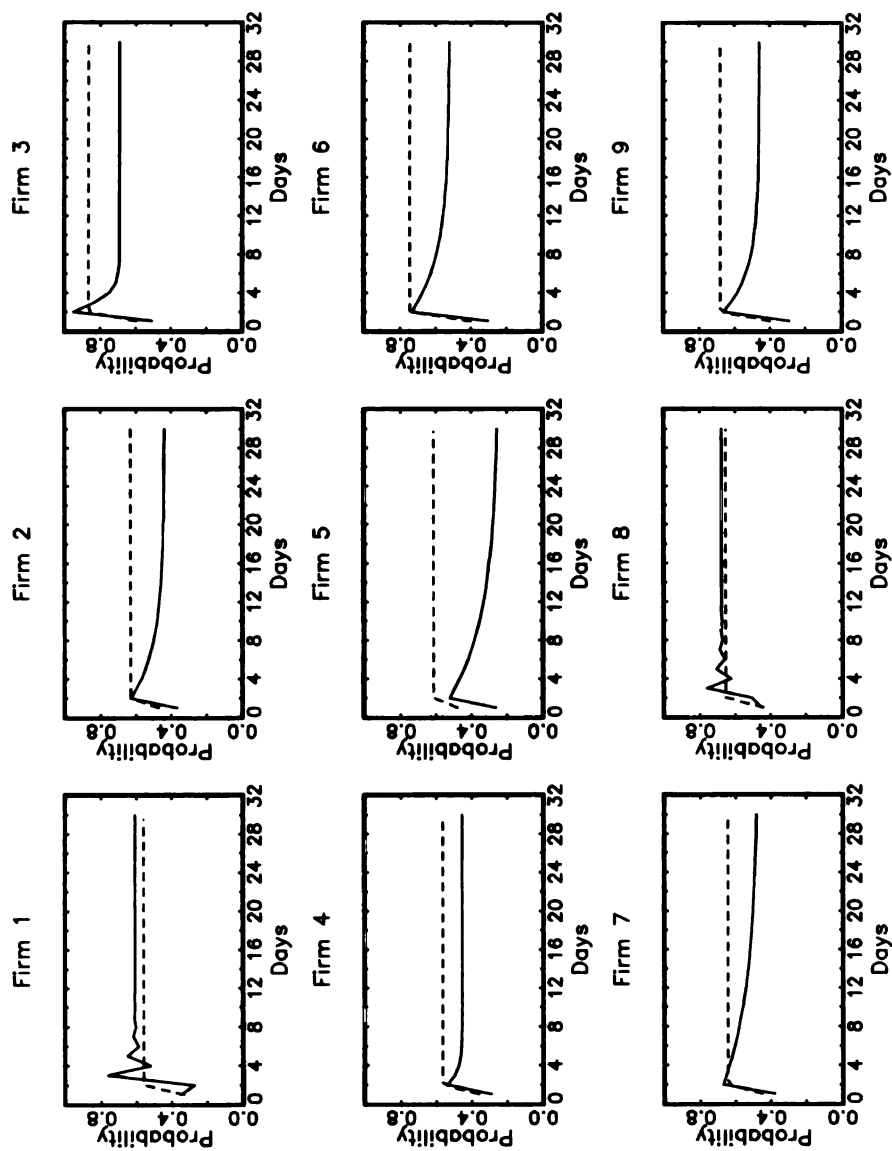
Dashed Line: logit Solid Line: ACB

Figure 2.2: ACB Impulse Response for a 1.36¢ and 10¢ Shock, Assuming the Firm Changed Its price



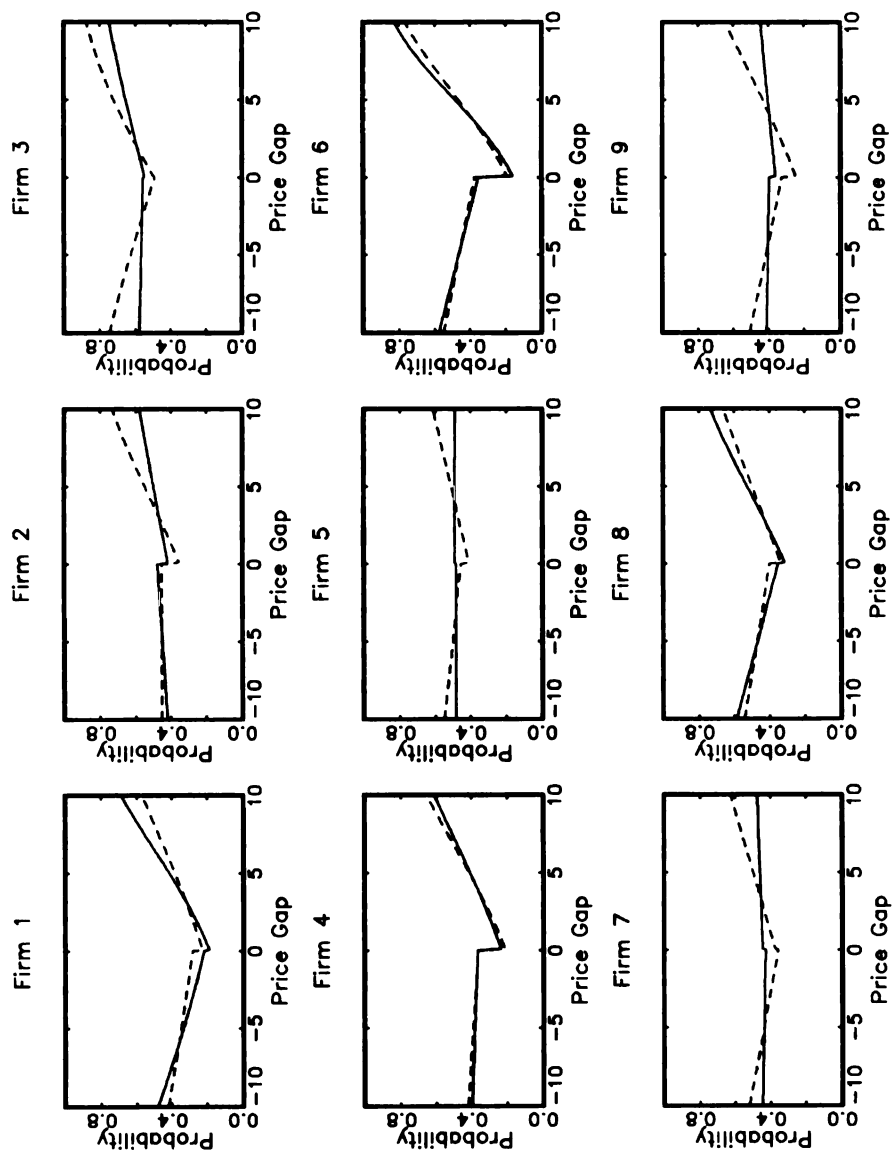
Dashed Line: 10¢ Shock Solid Line: 1.36¢ Shock

Figure 2.3: ACB and Logit Impulse Response Assuming the Firm Left Its Price Unchanged



Dashed Line: Logit Solid Line: ACB

Figure 2.4: Asymmetric ACB and Logit Estimated Probabilities



Dashed line: Logit; Solid Line: ACB

Chapter 3: Dynamic Pricing and Asymmetries in Retail Gasoline Markets: What Can We Learn About Price Stickiness?

1. Introduction

Many empirical macroeconomic studies find that the real effects of monetary policy shocks persist over several periods. Sims (1992) finds that an expansionary monetary policy shock leads to a "hump-shaped" effect on output, with the peak coming two years following the shock. In order to replicate these real effects in business cycle models, researchers have had to introduce the notion of price stickiness, or the failure of prices to fully adjust following a shock. Theoretical motivations for price stickiness range from firms paying a fixed cost (i.e. a "menu cost") in order to change their price (Barro, 1972, Sheshinski and Weiss, 1977, 1983; Mankiw, 1985), failures to instantly process information (Calvo, 1983; Mankiw and Reis, 2002; Reis, 2006), and strategic considerations (Rotemberg, 1983, 2002, 2006). In the industrial organization literature on gasoline prices, this latter motivation has taken the form of tacit collusion between retailers (Borenstein, Cameron, and Gilbert, 1997) and search costs (Johnson, 2002, Lewis, 2003). In the macroeconomic literature, price stickiness has often been conveniently abstracted to take the form of time dependence in that firms only adjust their prices after a certain amount of time has passed (Fisher 1979; Taylor 1979, 1980).

This paper explores the motivations for price stickiness by utilizing a unique data set consisting of observations of the daily retail and wholesale price of gasoline for 15 Philadelphia retail gasoline stations beginning in January 1, 2002 and ending in December

31, 2004. During this time period, the wholesale price of gasoline changed on approximately 40% of the days. Yet, the retail price only changed between 6.94% and 13.6% of the observations. This paper seeks to explain why retail price stickiness present in this market.

As in Davis and Hamilton (2004) and Davis (2004), we begin examining this question by fitting the data to the Dixit (1991) menu cost model that assumes that a firm incurs a fixed cost in changing its price. This implies that the firm allows its price to vary from the optimal price within a fixed threshold. We find that this model predicts larger price changes than what are actually observed, and fits the data worse than the other models examined. However, we find that if we allow the threshold to vary over time, a simple (s, S) model fits the data quite well and predicts a range of price stickiness of between 6¢ and 9¢ per gallon, a range consistent with the data.

We examine the motivations related to time dependence and asymmetry by fitting the data to the autoregressive conditional binomial (*ACB*) model.¹ We find statistical evidence that the history of price changes matters not only through the current gap between the actual and optimal price, but also through a lagged indicator variable taking the value of unity if the station changed its price on the previous day. Specifically, we find that the lagged indicator variable is significant at least at the 5% level for 9 of the 15 stations. Additional evidence of time dependence takes the form of the natural logarithm of the contemporaneous duration, or time between successive price changes, being significant at least at the 5% level for 7 of the 15 stations. Using the *ACB* framework, we find little evidence for information processing delays in the spirit of Calvo (1983), or for Rotemberg's (1982, 2002, 2006) strategic explanations in that the estimated coefficients on the variables that imply these explanations are largely insignificant.

Finally, we link the *ACB* to the variable threshold model by estimating the variable threshold model with the time dynamics that are significant in the *ACB*. An interesting asymmetric result is revealed: the time dynamics almost exclusively appear in the lower threshold (the threshold that the retail price must cross for it to be increased). Specifically, the lagged indicator variable is only significant at the 5% level for one station, and the contemporaneous duration is only significant at the 5% level for three stations in the upper threshold (the threshold the retail price must cross for it to be lowered). Neither is significant at the 1% level for any of the stations. However, in the lower threshold, the lagged indicator variable is significant at the 5% level or lower for 9 stations and the contemporaneous duration is significant for 7 stations. Largely, the stations with significant time dynamics overlap in the two models.

Additional asymmetry is revealed in the variable threshold model where the distance between the thresholds narrows when prices are rising and widens when prices are falling. Asymmetry in the *ACB* is revealed in that the majority of stations are more prone to raising their prices than lowering them for all values of the gap between the actual and the optimal price. Thus, linking the asymmetric *ACB* results with the variable threshold model suggests that retail gasoline prices are more flexible in the upward than downward direction. All in all, the time dependence and asymmetry found is broadly consistent with the idea of "search costs".

The paper is organized as follows. Section 2 discusses competing theoretical explanations of price stickiness. Section 3 describes the retail data set. Section 4 presents the estimation results for both the Dixit (1991) menu cost model and the variable threshold model. Section 5 presents the estimation results for the *ACB*. Section 6 links the variable

threshold model with the *ACB* and investigates asymmetry in the station's price change decision, and Section 7 concludes.

2. Theoretical Explanations of Price Stickiness

A menu cost in the spirit of Barro (1972) and Dixit (1991) suggests that a firm must pay a fixed cost in order to change its price. For example, if a restaurant wants to change the price of the food it serves, it must print new menus at substantial expense. The implication of a menu cost is that if the amount of additional profit resulting from the price change is less than the menu cost, the firm will elect not to change its price if it otherwise would, if there was no such friction (Mankiw, 1985). That is, price stickiness would result. Naturally, given the mechanics of changing the typical price, menu costs are estimated to be quite small. For example, Levy et. al. (1997) measures them to be 0.70% of total revenues for supermarket chains. However, such a small menu cost can exert a large impact on the business cycle (Mankiw, 1985), even in the face of large cost shocks (Fishman and Simhon, 2005). Thus, the finding of menu costs driving price stickiness in this market would have important implications for the business cycle.

Information processing delays have been incorporated into models of price stickiness in a variety of ways. Traditionally, models such as Sims (1998) and Mankiw and Reis (2002) have followed Calvo (1983) in positing that firms do not continuously react to information. That is, information is "sticky". Thus, price stickiness results from firms reacting to lagged, rather than current information. A newer class of models find that this behavior may be optimal. Rational inattention by producers (Reis, 2006) suggests that since it is costly for

firms to continuously obtain and process information, firms choose a price for their output and derive an optimal time to be inattentive. While they are inattentive, they receive no news about the state of the economy, until the inattentive period is over and it is time to plan again. Thus, price stickiness comes from firms failing to adjust to cost shocks while they are inattentive. An implication of Reis' model is that since firms are not aware of new information when it arrives, they do not respond asymmetrically to it. Information processing delays that result in price stickiness can also come from consumers. Levy et. al (2005) suggests that consumers are relatively insensitive to small price changes. As a result, prices are sticky downwards as producers do not make small price decreases, since doing so will not result in an increase in business. But, prices are flexible upwards as producers make have incentive to make small price increases, since consumers will not react to such an increase.

In the macroeconomic literature, strategic considerations have followed Okun's (1981) suggestion that markets do not immediately clear because firms are reluctant to raise prices "unfairly". Rotemberg (1982) derives a model where firms deliberately stretch out large price changes over a successive string of smaller price changes in order to avoid upsetting customers. Rotemberg's (2002, 2006) models of inflation where prices stickiness results from firms being reluctant to changing prices "unfairly" is an extension of Kahneman, Knetsch, and Thaler's (1986) study on the importance of fairness in price setting. In long term relationships, customers believe they are entitled to their "reference" (past) price and firms are entitled to their "reference" profit. When this reference profit is threatened, customers believe it is fair for a firm to raise its price in order to protect this profit, even passing on the complete loss unto them. However, customers believe that it is unfair for a

firm to raise its price when doing so results in a "windfall" profit, or profit over and above the reference profit. Thus, it is unfair for a firm to raise its price in response to an increase in demand and unfair for a firm to increase its price in order to ration a shortage. Absent a cost shock, if fairness explains the stickiness in this market, we should see firms attempting to maintain the status quo.

In the industrial organization literature on gasoline prices, strategic considerations often take the form of search costs or tacit collusion. Search costs such as Johnson (2002) and Lewis (2003) are really an information problem on the part of consumers. Since gasoline stations are spatially distributed, consumers cannot instantly observe the price at each station and must "search" in order to do so. A customer will search if he believes that the gains for search are greater than the costs of doing so (driving to another station and observing the price). If a customer sees a price increase at a station, he might conclude that prices have not increased elsewhere (since prices are sticky) and search. However, if he observes a decrease, he might conclude that the probability of finding an even lower decrease is low, and thus not search. The implication is that stations know this and have incentive to make prices sticky on the downward direction. Clearly, stations would like to hold off on making price increases to avoid consumer search. However, as pointed out in Johnson (2002) and Lewis (2003) and confirmed in Table 3.1, the retail margin is razor thin.² Thus, in the face of a wholesale cost shock, a station must raise its price to prevent margins from becoming negative even if it results in consumer search.

Borenstein, Cameron, and Gilbert (1997) suggest that prices may be sticky downward if firms are able to use past prices as "focal points" on which to collude. Thus, under focal point collusion, we should expect the current probability of a price change to be strongly

correlated with the past probability. Also, such collusion implies a degree of market power.³ As a result, stations with the largest market power should be the ones who can most easily collude and price asymmetrically (Johnson, 2002). As both Borenstein, Cameron, and Gilbert (1997) and Lewis (2003) point out, when collusion breaks down, prices should rapidly fall to their competitive levels. In aggregated data, this can look like a gradual decrease if submarkets where the collusion is breaking down are averaged together with submarkets where the collusion is holding. However, for *firm* level data (as used in this paper), we should see very sharp decreases in price on the firm level when the collusion breaks down.

3. Data

We purchased daily retail data for 270 retail gasoline stations for the city of Philadelphia starting at January 1st, 2002 and ending December 31, 2004 from the Oil Price Information Service (OPIS). We chose Philadelphia for several reasons. As Borenstein and Shepard (1996) point out, the price of wholesale gasoline accounts for about 85% of the retail price, with the other 15% coming from labor costs (for example, the clerks who work at the stations) and the transportation cost of delivering gasoline from the wholesale terminal to the retail outlet. Since Philadelphia has a terminal station, this latter cost should be minimal. Also, by choosing Philadelphia, we can compare our results to the results for the nine Philadelphia wholesalers in Davis and Hamilton (2004) and in Chapter 2 of this dissertation. We find that retail prices exhibit different dynamics than wholesale prices.

For each station in the data set, OPIS provides the retail price, the wholesale price, and the margin. The retail price is recorded whenever a fleet card is used to purchase gasoline.

A fleet card differs from a credit card in that it can only be used to purchase gasoline and not merchandise. Thus, a fleet card allows companies to "keep employees honest" by ensuring they only purchase gasoline with the company gas card. The wholesale price recorded is the rack price posted at the terminal closest to the retail station, which is also collected by OPIS on a daily basis. Thus, the wholesale price represents the station's replacement cost of gasoline. The margin is defined as the difference between the retail price, less taxes and transport, and the wholesale cost of gasoline.

The use of fleet cards for data collection poses an unfortunate issue: if no fleet card transaction takes place during a particular day, then the observation for that day is coded as missing. Thus, all of the stations in the data set have missing observations appear randomly throughout the sample. For this reason, we have to pare down our data set to 15 stations with relatively complete samples. Figure 3.1 shows the location of each of the 15 stations. As seen in the figure, the stations are rather uniformly spread out in the Philadelphia area (the right side of the river is New Jersey). Thus the common results that emerge are not likely to be tied to a common location characteristic shared by each station.

Out of these 15 stations, 14 of them are Sunoco stations and 1 is an unbranded station, or a station that is not tied to a specific name-brand of gasoline and consequently, can buy wholesale gasoline from whatever wholesaler it likes. For these stations, the periods of missing observations are very small in duration, the vast majority being under 5 days, and the retail price is often the same at the beginning and end of these periods. Thus, we follow Davis (2004) and impute the last value observed to each daily unobserved data point.⁴

Table 3.1 presents summary statistics for each of the 15 stations. Station 13, our unbranded station, has wholesale costs that are, on average, \$0.01/gallon less than the

Sunoco stations. Each station changes its price far less than the number of wholesale price changes, with 35.9% to 40.1% of the observations corresponding to a change in the wholesale price of gasoline, but only 6.94% to 13.6% corresponding to a change in the retail price.⁵ Thus, the phenomenon of price stickiness is present in this market. We also note that the unbranded station changed its price the most often, suggesting that the freedom to purchase wholesale gasoline from any wholesaler it chooses can lead to more flexible pricing.

Columns 7 and 8 of Table 3.1 present summary statistics on the magnitude of the price changes. On average, a station's price changed ranged from a low of 2.33¢ to a high of 3.78¢. Additionally, stations on more than one occasion changed their prices by a penny. Station 6 did so four times while station 13 did so 47 times. The summary statistics suggest that, on average, a station's price increase is small in magnitude. The last column of Table 3.1 indicates the number of competitors within a 1 mile radius of the station, which is the standard measure of competitiveness in the literature (Hastings, 2004). Thus, we use this as a proxy for the retail station's market power. Note that stations in the data set range from very competitive to not competitive, with many values in between.

4. Menu Costs

4.1 Fixed Threshold

We examine whether or not a fixed menu cost prevents a station from changing its price by estimating the Dixit (1991) menu cost specification. Such a menu cost is enough to prevent stations from changing their price more often than once per day, since in order to change their prices, stations must shut down their pumps (Kolsa, 2005).

Let $p(t)$ denote the natural logarithm of the price charged by the retail station, and $p^*(t)$ denote the natural logarithm of the optimal price. Following Davis and Hamilton (2004), we define $p^*(t)$ as the wholesale price plus a constant mark-up, defined as the average mark-up of the retail price over the wholesale price for the sample period. Following this methodology facilitates comparison of our retail dynamics with wholesale dynamics. The Dixit (1991) menu cost model posits that under continuous time, the firm chooses the dates $t_1, t_2, \dots$ to change its price in order to minimize the objective function,

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

where $p(t_0) = p^*(t_0)$ is given and $dp^*(t) = \sigma dW(t)$, for $W(t)$ standard Brownian motion. The term in parenthesis in equation (1) represents the cost borne by the firm by charging a price that differs from its optimal price, and the second term represents the cost to the station in changing its price. Dixit (1991) shows that the optimal decision rule is for the firm to change its price to the optimal price whenever $|p(t_{i-1}) - p^*(t_i)| = b$, with the optimal value of b given by,

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

Thus, b has the interpretation of being the percentage the firm lets the actual price deviate from the optimal one. Davis and Hamilton (2004) show that the probability of observing a price change under this specification is:

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

Defining the binary variable x_t to take the value of unity if we observe a price change at date t and zero otherwise, the log likelihood of observing the sample $\{x_1, x_2, \dots, x_T\}$ is

given by,

$$\sum_{t=1}^T \{x_t \log h_t + (1 - x_t) \log(1 - h_t)\} \quad (4)$$

Thus, the parameters in the optimal decision rule, b and σ , can be obtained by numerically maximizing this likelihood function.

Table 3.2 presents the estimates for this model. The fact that b and σ are significant at the 1% level for all stations suggests that this model fits the data well. Column 3 of Table 3.2 solves equation (2) for g/k . Davis and Hamilton (2004) show that g/k can be interpreted as the ratio of menu costs to total costs. Thus, we estimate the menu costs for our Philadelphia retail stations to vary between 0.31% and 2.64% of the total costs. This magnitude seems plausible, given the mechanics involved in changing the retail price.

Yet, a problem with these estimates is that b is "too big" compared to the data. Although this is not immediately observable from the table, consider the case of a price decrease. From equation (2), a station will decrease its price whenever $|p(t) - p^*(t)| > b$. Equivalently, we can write this as $\log\left(\frac{P(t)}{P^*(t)}\right) > b$, where the upper-case variables denote the actual and optimal price in levels rather than logs. Taking the exponential of both sides, a station will decrease its price if $P(t) > e^b P^*(t)$. Analogously, a station will increase its price if $P(t) < e^{-b} P^*(t)$.

Consider the case of the lowest estimated value of b , 0.215. Taking an optimal retail price of \$1.65 (which roughly corresponds to the average retail price), a station will not decrease its price unless $P(t) > \$2.05$ or increase it unless $P(t) < \$1.33$. Such a range would imply much larger average price changes than what are reported in Table 3.1. Intuitively, what these estimates of b suggest is that a station will not change its price unless

the actual price deviates from the optimal price by $b\%$. A value of 0.215 for b suggests that it takes a deviation of 21.5% to induce a price change. Thus, although the menu cost model fits the data well in terms of significance of the parameter estimates and the magnitude the g/k ratio, it fails in predicting when the price will change, since the range estimated by the menu cost model implies price change magnitudes much larger than what is observed in Table 3.1. This is also the case with wholesale prices (Davis and Hamilton, 2004) and later with retail prices in Newburgh, New York (Davis, 2004).

The Dixit menu cost model implies that the size of the threshold, b , remains fixed over time. However, previous studies suggest that the station's pricing decision is not constant over time, but depends on market conditions present when the pricing decision is made.⁶ Thus, rather than being fixed, it is likely that b varies over the course of the sample. To investigate this possibility, we estimate a variable threshold model in the following subsection.

4.2 Variable Threshold

The variable threshold model we consider is a (s, S) model similar to Slade(1999). In this model, the retail price is assumed to remain unchanged as long as it falls between a lower threshold, s_t^l , and an upper threshold, s_t^u . Thus, if $s_t^l \leq P_t \leq s_t^u$, the retail price is unchanged ($\Delta P_t = 0$). If P_t crosses one of the thresholds, the price is changed to $\Delta P_t = S_t - P_t$, where S_t is the target price. Thus, the retail price is lowered if it crosses the upper threshold and raised if it crosses the lower threshold. We approximate each threshold by a linear function in the form of:

$$s_t^m = k_t \eta^m + u_t^m \quad (5)$$

where $m = l, u$ and k_t contains the explanatory variables. Initially, we choose the explanatory variables as the wholesale price and margin for the station at time t , as well as a constant.⁷

Assuming that $u_t^m \sim \text{exponential}(0, 1)$, we estimate a version of an ordered logit model. Defining the dummy variables $d_t^l = 1$ if $\Delta P_t > 0$ and zero otherwise, the probability of a price increase is,

$$\begin{aligned} \text{prob}(\Delta P_t > 0 \mid k_t) &= \text{prob}(P_t < s_t^l \mid k_t) \\ &= \Lambda(k_t^l \eta^l - P_t) \end{aligned} \quad (6)$$

where $\Lambda(\cdot)$ denotes the logistic c.d.f. This is a logit and can be estimated by maximizing the likelihood function,

$$\sum_{t=1}^T \left\{ d_t^l \log[\Lambda(k_t^l \eta^l - P_t)] + (1 - d_t^l) \log[1 - \Lambda(k_t^l \eta^l - P_t)] \right\} \quad (7)$$

Following the same reasoning, the probability of a price decrease is,

$$\begin{aligned} \text{prob}(\Delta P_t < 0 \mid k_t) &= \text{prob}(P_t > s_t^u \mid k_t) \\ &= \Lambda(P_t - k_t^l \eta^l) \end{aligned} \quad (8)$$

which can be estimated by maximizing equation (7), replacing d_t^l with d_t^2 , where $d_t^2 = 1$ if $\Delta P_t < 0$ and zero otherwise.⁸ Thus, if $k_t^l \eta^l = k_t^u \eta^u$, prices are flexible at time t . If $k_t^l \eta^l < k_t^u \eta^u$, then there is some positive threshold at time t , indicating price stickiness.

Table 3.3 presents the estimates for both the lower and upper thresholds of the variable threshold model. All estimated coefficients are significant at a 1% level. The log-likelihood for each threshold indicates that this model represents an improvement over the Dixit (1991) in goodness-of-fit for all stations. The average distance between the threshold can be

calculated evaluating $\bar{k}_t' \eta^m$ for each threshold, where $\bar{k}_t'$ contains the average values of the explanatory variables and η^m are the estimated coefficients for $m = l, u$. The last column of Table 3.3 shows that on average, prices are sticky within a range of 6.62¢ to 8.27¢. Unlike the range implied by the Dixit (1991) model, this range seems plausible. For example, if the optimal price is \$1.65 and, on average, in the middle of the threshold,⁹ then the retail price would be sticky in a range of \$1.61 to \$1.69 (assuming an 8¢ threshold). Then, if the actual price is \$1.60, it would be increased by 5¢, a magnitude consistent with the summary statistics in Table 3.1. Thus, we can reconcile the data with a threshold model by allowing the size of the threshold to vary over time.

Neither the menu cost nor variable threshold model allow any role for time dynamics to influence a station's pricing decision. Time dependence may imply information processing delays or strategic considerations are responsible for the price stickiness, as these motivations imply a specific form of time dependence as well as asymmetry. The next section uses the *ACB* model to explore these alternative motivations.

5. Information Processing Delays and Strategic Interactions

A logit model containing a constant and the level of the price gap, $|P(t) - P^*(t)|$, as explanatory variables fits the data better than the Dixit (1991) model for all stations but one (the last column of Table 3.2). This logit model can be thought of as being an atheoretical menu cost model, as it assumes that the only relevant explanatory variable in inducing a price change is the current value of the price gap, but does not impose a specific functional form such as the Dixit model. Thus, we can use this logit model as a baseline to test for

dynamics and other motivations besides a menu cost, that may influence a station's pricing decision.

The autoregressive conditional binomial (*ACB*) model is a calendar time modification of the autoregressive conditional multinomial model of Engle and Russell (2005). The *ACB* model is a flexible specification that allows the current probability of a retail price change to depend on the history of price changes both through distributed lags of past price change probabilities and through lags of the binary dependent variable x_t .

Define the function $G(\cdot)$ is a strictly increasing, continuous c.d.f. To keep the *ACB* within the logistic framework, we elect to use the logistic c.d.f. for $G(\cdot)$. Since $G(\cdot)$ is strictly increasing, $G^{-1}(h_t)$ is a link function that is well-defined by $G^{-1}(h_t) = y_t \Leftrightarrow G(y_t) = h_t$. That is, $G^{-1}(\cdot)$ is a 1-1 mapping from h_t to $\mathbb{R}$, where, as before, h_t is the probability that the station changes its price on day t .

Defining the probability that the station changes its price on date t as:

$$h_t \equiv \text{prob}(x_t = 1 \mid x_{t-1}, \dots, x_1, z_{t-1}) \quad (9)$$

where, as before, x_t is a binary variable taking the value of unity if the retail price is changed on date t and z_{t-1} is a vector of exogenous variables known at time t . Then, the *ACB*(q, r, s) model is defined as

$$G^{-1}(h_t) = \omega + \sum_{j=1}^q \alpha_j (x_{t-j} - h_{t-j}) + \sum_{j=1}^r \beta_j G^{-1}(h_{t-j}) + \sum_{j=1}^s \delta_j x_{t-j} + \gamma z_{t-1} \quad (10)$$

where the probability of a price change is given by

$$h_t = G \left[\omega + \sum_{j=1}^q \alpha_j (x_{t-j} - h_{t-j}) + \sum_{j=1}^r \beta_j G^{-1}(h_{t-j}) + \sum_{j=1}^s \delta_j x_{t-j} + \gamma z_{t-1} \right] \quad (11)$$

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

$\theta = \{\omega, \alpha_1, \dots, \alpha_q, \beta_1, \dots, \beta_r, \delta_1, \dots, \delta_s, \gamma\}$ can be obtained by maximizing the likelihood function given by equation (4). Since $G(\cdot)$ is the logistic c.d.f., setting $q = r = s = 0$ and $z_{t-1} = |P_t - P_t^*|$, the $ACB(0,0,0)$ is equivalent to the baseline logit specification reported in Table 3.33. Thus, the ACB extends the logit framework to test for the presence of dynamics in a station's decision to change its price.

5.1 Testable Predictions

First, define the one day lag of the price gap as $|P_{t-1} - P_{t-1}^*|$ and the size of the gap remaining after the most recent correction as $|P_{w1(t)} - P_{w1(t)}^*|$, dated by $w1(t)$. The intuition for this latter variable is as follows: if a station is slowly adjusting its price when there is a gap between its actual and optimal price, the amount of this gap the station chooses to keep in place after a price change should contain information on subsequent price changes. For an additional measure of time dependence, we include the natural logarithm of the contemporaneous duration, $\ln u_{N(t)}$, in the ACB model.¹⁰ And, since competing explanations of price stickiness offer different prediction of asymmetry, replace the constant ω and $z_{t-1} = |P_t - P_t^*|$ in equation (11) with:

$$z_t = [\theta_t, (1 - \theta_t), \theta_t(P_t - P_t^*), -(1 - \theta_t)(P_t - P_t^*)]' \quad (12)$$

where the dummy variable θ_t takes the value of unity if $P_t - P_t^* \geq 0$ and zero otherwise. Separating the constant into a positive (θ_t) and negative ($1 - \theta_t$) component tests whether a firm is more or less likely to raise its price when the gap is small and negative than lower it when the gap is small and positive. Separating the gap into a positive ($\theta_t(P_t - P_t^*)$) and

negative $-(1 - \theta_t)(P_t - P_t^*)$) component tests whether a firm is more or less likely to raise its price when the gap is large and negative than lower it when the gap is large and positive.

Given the discussion in Section 2, we can use the *ACB* to make the following empirical predications with regards to information processing delays and strategic considerations:

- **Sticky information:** $\beta < 0$ and $\delta < 0$: If the probability of a price change was high yesterday and the firm elected to change its price, it is less likely to do so today. The coefficient on $|P_{t-1} - P_{t-1}^*|$ should be positive, indicating that a large gap yesterday increases the probability of a price change today, as information is processed with a delay.
- **Rational inattention by producers:** $\delta < 0$, indicating that if the firm changed its price yesterday, it is inattentive today and thus will not change its price. The coefficient on the contemporaneous duration should be positive. As the time between price changes becomes larger, the planning period draws to a close, increasing the probability of a price change. There should be no asymmetry "in the small" nor "in the large". That is, $\theta_t = (1 - \theta_t)$ and $\theta_t(P_t - P_t^*) = -(1 - \theta_t)(P_t - P_t^*)$.
- **Rational inattention by consumers:** Asymmetry "in the small" with $(1 - \theta_t) > \theta_t$; a firm is more likely to raise its price when the gap is small and negative than lower it when the gap is small and positive, since consumers are inattentive to such small price changes. No asymmetry "in the large", or $\theta_t(P_t - P_t^*) = -(1 - \theta_t)(P_t - P_t^*)$, as consumers are not inattentive to large price changes.
- **Partial adjustment:** $\beta > 0$ and $\delta > 0$, indicating that if the probability of a price change yesterday was high and the station changed its price, it should be likely to change it again today, since it is stretching out price changes. The coefficient on

$|P_{wl(t)} - P_{wl(t)}^*|$ should be positive as explained in the first paragraph of the subsection.

- **Fairness:** $\beta > 0$. Since customers are entitled to their "reference transaction", yesterday's probability of a price change should be positively correlated with today's. Price changes should be immediately passed through to customers. That is, $|P_{wl(t)} - P_{wl(t)}^*|$ should contain no additional predictive power for future price changes. Given that customers may believe that large price increases may be unfair, the only asymmetry "in the large" we should expect is: $\theta_t(P_t - P_t^*) < -(1 - \theta_t)(P_t - P_t^*)$. That is, retail stations may want to win customer loyalty by offering a big price decrease, but will be reluctant to lose customer loyalty by making a big price increase.
- **Search costs:** Prices should be more flexible in the upward direction relative to the downward direction: $(1 - \theta_t) > \theta$ and $\theta_t(P_t - P_t^*) > -(1 - \theta_t)(P_t - P_t^*)$. That is, we can expect asymmetry for all ranges of the price gap. Also, asymmetry should be present in most stations regardless of degree of market power (Johnson, 2002). Finally, we can expect $\delta < 0$ if stations want to avoid successive price increases, if such an increase induces consumer search.
- **Focal point collusion:** Like search costs, prices should be more flexible in the upward compared to the downward direction. But, the asymmetry should be most pronounced in the stations that are the least competitive. We should expect $\beta > 0$ as firms use past prices to collude on the current price and see sharp price decreases when collusion between stations breaks down.

5.2 ACB Results

Table 3.4 reports the results of the $ACB(0, 1, 1)$ estimation.¹¹ For 9 of the 15 stations, we can reject the null hypothesis that $\beta = \delta = 0$ at a 5% level of significance or lower (last column, Table 3.4). Thus, there is evidence that time dynamics play a role in the station's pricing decision. Notice from the table that these dynamics take the form of δ being negative and significant, meaning that if a station changed its price yesterday, it is less likely to do so again today. Thus, the assumption that prices remain fixed for a certain amount of time as in Fischer (1979) and Taylor (1979, 1980) seems to be relevant in this specific market.

Tests for the significance of the additional variables in the $ACB(0, 1, 1)$ as discussed in the previous subsection model are reported in Table 3.5. There is little evidence for either information processing delays or gradual adjustment explaining the price stickiness; the coefficients on $|P_{t-1} - P_{t-1}^*|$ and $|P_{w1(t)} - P_{w1(t)}^*|$ are only significant for 3 of the 15 stations. Additionally, from Table 3.4, β is insignificant for all station's but two. Thus, given our testable predictions and the insignificance of these variables, we can rule out sticky information, partial adjustment, and fairness as motivating the price stickiness.

Additional evidence of time dependence comes from the contemporaneous duration being significant for 7 of the 15 stations. However, the sign on the contemporaneous duration is the opposite of what would be expected in rational inattention by producers.¹² Additionally, the finding of asymmetry runs counter to the hypothesis of rational inattention by producers. We can reject the null hypothesis of the symmetric specification for 9 of the 15 stations.

Largely, these results agree with the results of Davis (2004) who applies a logit model with the same explanatory variables to a data set consisting of four Newburgh, NY gasoline

retailers. Davis estimates the coefficients on $|P_{t-1} - P_{t-1}^*|$ and $|P_{w1(t)} - P_{w1(t)}^*|$ to be insignificant for all stations. Thus, there is consistent evidence that the price stickiness exhibited in retail prices is not the result of information processing delays or partial adjustment. However, our methodology differs from his by introducing the time series terms in the *ACB*. As a result, we can rule out other motivations, such as fairness and rational inattention by producers, besides his two in accounting for the stickiness.

The *ACB* offers evidence of time dependence and asymmetry in a stations pricing decision. However, the insignificance of β and the coefficients on $|P_{t-1} - P_{t-1}^*|$ and $|P_{w1(t)} - P_{w1(t)}^*|$ cast evidence against sticky information, gradual adjustment, and fairness. The finding of asymmetry offers evidence against rational inattention by producers. To differentiate between the remaining motivations, we link the *ACB* with the variable threshold model and investigate the question of asymmetry in the following section.

6. Asymmetry

We begin the investigation of asymmetry by linking the *ACB* model with the variable threshold model by including the significant dynamics as uncovered by the *ACB* as explanatory variables in the threshold equations. Thus, we replace equation (5) with

$$s_t^m = k_t \eta^m + \delta x_{t-1} + \chi \ln u_{N(t)} + u_t^m \quad (13)$$

where, as before, k_t contains the wholesale price and margin at time t , x_{t-1} is an indicator variable taking the value of unity if the station changed its price at time $t - 1$, and $\ln u_{N(t)}$ is the natural logarithm contemporaneous duration between successive price changes. Recall from Table 3.5 that the *ACB* found these latter two variables to be significant for the majority

of the stations.

Tables 3.6 presents the results of this estimation for the lower threshold. Notice that δ , the coefficient on x_{t-1} , is significant at least at a 5% level for 8 stations. Also notice that δ is estimated to be negative, which is the same sign as in the *ACB* model. The interpretation for this in the *ACB* is that if a station changed its price yesterday, it is less likely to change it again today. Whereas in the variable threshold model, the negative sign suggests that if a station changed its price yesterday, it reduces today's lower threshold (see equation (13), replacing m with l). Recall that the retail price must cross this lower threshold to trigger a price increase. If a previous day's price change reduces today's lower threshold, it has the effect of increasing price stickiness. The retail price has to decrease even more than it otherwise would, in order for it to cross the lower threshold, which would then cause the station to raise its price. That is, $k'_t \eta^l$ becomes even less than $k'_t \eta^u$ following a price change yesterday. Thus, the results of the dynamic lower threshold in the variable threshold model overlap with the results of the *ACB*.

The coefficient on the contemporaneous duration, χ , is estimated to be negative and significant for 7 stations. The interpretation of this result is that the longer stations go without a price change ($u_{N(t)}$ large), the smaller the lower threshold becomes.¹³ Thus, as with δ , $k'_t \eta^l$ becomes even less than $k'_t \eta^u$ the longer the price remains unchanged, suggesting if a station is going to increase its price, it is going to do so right away.

Compare these results to the results for δ and χ in Table 3.7 for the upper threshold. Thus, we have evidence of asymmetry. Whereas δ and χ were significant for 8 and 7 stations respectively in the lower threshold, δ is only significant at a 5% level or less for 1 station and χ is only significant for 3 stations in the upper threshold. Thus, the dynamics found in the

ACB model almost exclusively come from price increases (the lower threshold), rather than price decreases (the upper threshold).

Figures 3.2-3.4 plot the fitted values of the thresholds over the sample with the retail price superimposed. Notice that the retail price stays within the upper and lower thresholds for all the stations, indicating a good fit for the model. These figures reveal an additional source of asymmetry: the distance between the thresholds narrows when the retail price is rising and widens when it is falling. That is, the retail price is more flexible when it is increasing than when it is decreasing.

Recall that Table 3.5 offered evidence of asymmetry in the *ACB* model (last column). Thus, we report the parameter estimates of the asymmetric *ACB* model in Table 3.8 to compare them to the asymmetry found in the variable threshold model. Table 3.8 reveals two sources of asymmetry. First, the negative constant is greater than the positive constant for the majority of stations (11 of 15). This indicates that a station is more likely to increase its price when the gap between the actual and optimal price is small and negative than raise it when the gap is small and positive. Second, the negative gap is greater than the positive gap for the majority of stations (10 of 15). This indicates that a station is more likely to raise its price when the gap is large and negative than lower it when the gap is large and positive. We also plot these asymmetric *ACB* parameters over a range of -20¢ to $+20\text{¢}$ for the gap in Figures 3.5 and 3.6. These figures clearly indicate the above result; stations are more likely to make price increases than decreases.

The *ACB* suggests that, all things equal, stations are more likely to make price increases over price decreases for all ranges of the price gap. That is, there is asymmetry "in the small" and asymmetry "in the large". This offers evidence against rational inattention by

consumers, as that hypothesis predicts only asymmetry "in the small", but not "in the large", because consumers will not be inattentive to large price increases. However, this asymmetry is consistent with both focal point collusion and search costs. But, three pieces of evidence favor search costs over focal point collusion. First, from Figures 3.2-3.4, there are no instances where prices rapidly fall where collusion breaks down. When they decrease, they tend to do so at a gradual rate, especially compared with increases. Whereas, if collusion was breaking down, prices should fall rapidly from their collusive level to their competitive level. Second, β is insignificant for all stations but two. If collusion was being sustained using past prices as focal points, we would expect the probability of a price change to be strongly correlated over time. Third, the asymmetry does not appear to be tied to market power. Comparing the last column of Table 3.5 with the last column of Table 3.1, we reject the null hypothesis of symmetry both for station 15, with zero competitors, and for station 2, with 12 competitors. And, for example, we reject the null hypothesis of symmetry for station 11 (nine competitors) but not for station 12 (also with nine competitors) or for station 10 (four competitors).

However, this evidence is consistent with search costs. When customers see a price decrease, they assign a small probability to finding an even lower decrease and thus choose not to search. Retailers know this and have incentive to make prices sticky on the downward direction. This downward stickiness is evidenced both by the asymmetry given in the *ACB* and in Figures 3.2-3.4. And, retailers are hesitant to raise prices, because doing so will give consumers incentive to search. Yet, since margins are thin, retailers must raise prices and endure customer search. However, the overlap between the *ACB* in δ being negative and significant with variable threshold model, where δ is negative and significant in *only* the

lower threshold, suggests that when a station raises its price, it is hesitant to do so again the next day. That is, a station prefers to raise its price once and endure search once, rather than raising prices over successive days and enduring successive days of search.

Interestingly, the asymmetry exhibited by Philadelphia retail prices differs from the asymmetry exhibited by Philadelphia wholesale prices as found by Davis and Hamilton (2004) using a logit model and in Chapter 2 of this dissertation using the *ACB*. Both of these studies find that, like retailers, wholesalers are more likely to small price increases compared to small price decreases. However, unlike retailers, wholesalers are more likely to make large price decreases compared to large price increases. And, the dynamics for Philadelphia retailers stand in sharp contrast to the dynamics for Philadelphia wholesale prices found in Chapter 2. Applying the *ACB* model to Davis and Hamilton's (2004) data set for Philadelphia gasoline wholesalers, Chapter 2 finds that dynamics for wholesale prices take the form of significance in β , rather than δ , and the contemporaneous duration is largely insignificant. Additionally, $|P_{t-1} - P_{t-1}^*|$ is found to be significant for 7 of the 9 wholesalers, but for only 3 of the 15 retailers. Thus, for wholesale prices, the dynamics of the wholesalers's pricing decision primarily comes from the past distribution of price changes and the lagged gap whereas the dynamics of the retailer's pricing decision primarily comes from the lag of the indicator variable and the contemporaneous duration.

The conclusion was for wholesale prices stickiness was fairness. Given the results of this paper, it appears that fairness is less of a concern for retail prices. Although curious on the surface, Kahneman, Knetsch, and Thaler (1986) offer insight on why this may be the case. Their framework applied to *long-term* relationships with many repeated transactions bound by long term contract, such as those between a employer and employee, or landlord and

tenant. Clearly, a gasoline wholesaler and retailer is such a relationship. However, a gasoline retailer and customer is not such a relationship. Obviously, there are no long term contracts binding a customer to a single retail station, and few customers purchase gasoline every day. In similar relationships in Kahneman et. al., people believed it was fair if others did not receive as favorable of a transaction as they did. That is, new customers were not entitled to the former customer's reference transaction. Thus, people who purchased gasoline at the lower price yesterday may not believe that others are entitled to purchase gasoline at that low price today. If this is the case, it is not surprising that fairness is less of a concern in the retail gasoline market, compared to the wholesale market.

7. Conclusion

In this paper, we have utilized a unique data set containing firm level observations for 15 Philadelphia retail gasoline stations and flexible methodology to test various explanations of price stickiness. We find that price stickiness in this data stems primarily from two sources. First, prices are stickier in the downward direction than the upward direction. The distance between the thresholds is much smaller when prices are rising than when they are falling (Figures 3.2-3.4) and stations are more prone to making price increases than decreases for all sizes of the gap between the actual and optimal price (Table 3.8, and Figures 3.5 and 3.6). Second, the significance of the lagged indicator variable in both the *ACB* and variable threshold models suggests that if a station changes its price today, it is less likely to do so again tomorrow. This indicates that prices are sticky following a previous price change in regards to a subsequent price increase.

We argue that these results are consistent with search costs such as those considered in

Johnson (2002) and Lewis (2004). Search costs suggest that firms are reluctant to make price increases because doing so induces consumer search, but thin retail margins often necessitate such a price increase. And, search costs suggest that prices will be sticky in the downward direction, as a small price decrease garners the same effect as a big price decrease due to consumer search behavior. Overall, we believe our results contribute to the understanding of retail gasoline pricing and which of the many competing explanations of price stickiness, both on the macro and micro level, is most consistent with what we observe on the firm level.

Notes

1. Because the model is a binomial calendar time version of the Autoregressive Conditional Multinomial model of Engle and Russell (2005), the model is called the Autoregressive Conditional Binomial (*ACB*).
2. Note that the margin given in Table 1 is defined as the *retail price – wholesale price – taxes – transport*. It does not take into consideration the other costs of running a station (such as wages, rent, utilities, etc.) Thus, the margin listed in Table 1 overstates the station's true profit margin.
3. In the literature, market power is usually defined as the number of competitors within a one-mile radius of the retail station. See, for example, Hastings (2004).
4. Our summary statistics are very similar to those in Davis (2004) for Newburgh, New York, indicating that the missing observations are not posing a major issue.
5. The frequency of wholesale adjustment is also consistent with the Philadelphia wholesaler data used in Davis and Hamilton (2004). Davis and Hamilton's data set includes daily observations from 9 Philadelphia gasoline wholesalers spanning January 1, 1989 to December 31st, 1991.
6. See, for example, Hosken, McMillan, and Taylor (2006).
7. Note that other than the constant, these are the same explanatory variables as the Dixit (1991) model, except without the assumption that the margin is equal to the average mark-up of the retail price over the wholesale price.
8. This differs from traditional ordered logit in that $\tilde{\kappa}_t^l \alpha^m$ can vary for $m = l, u$. This will prove vital in Section 5.
9. This appears to often be the case. See Figures 3.3 and 3.4.
10. We also estimate the *ACB* jointly with the autoregressive conditional duration (*ACD*) as in Engle and Russell (1998). The estimated results are very similar and available upon request.
11. We focus on the *ACB*(0,1,1) because for all but two stations, the Schwarz Bayesian Criteria (Schwarz, 1978) is minimized using this specification over an *ACB*(0,2,2) specification.
12. The estimated sign is negative. Estimates not reported, but available upon request.
13. The contemporaneous duration is also estimated to be negative in the *ACB* model (not reported). Available from the authors upon request.

Table 3.1: Summary Statistics

Station	Mean Price	Mean Rack	Mean Margin	Frequency of Price Change	Frequency of Rack Change	Mean Price Change	Number of Price Changes	Number of Competitors
1	165.82	100.57	18.59	0.0694	0.366	3.78	7	16
2	162.48	100.52	15.26	0.104	0.363	2.33	26	12
3	161.96	100.53	14.74	0.106	0.357	2.50	16	10
4	162.61	100.57	15.36	0.102	0.361	2.48	13	6
5	160.17	100.58	12.90	0.0915	0.360	2.86	14	6
6	162.06	100.59	14.78	0.0849	0.363	3.25	4	8
7	160.48	100.60	13.18	0.107	0.367	2.82	6	4
8	163.29	100.65	15.95	0.0851	0.359	3.45	10	7
9	164.90	100.59	17.61	0.0895	0.378	2.90	7	5
10	163.03	100.72	15.63	0.107	0.366	3.33	9	4
11	162.79	100.59	15.51	0.0969	0.378	2.75	10	9
12	164.39	100.61	17.10	0.112	0.362	2.59	15	9
13	156.29	99.46	10.13	0.136	0.401	3.55	47	6
14	158.60	100.69	11.12	0.124	0.364	2.53	27	5
15	161.60	100.63	13.74	0.106	0.348	2.59	16	0

Note: All prices and price changes are given in cents/gallon

Table 3.2: Estimation of the Dixit Menu Cost Model

Station	<i>b</i>	σ	<i>g/k</i>	log lik	obs.	logit
1	0.311** (0.0682)	0.161** (0.0393)	0.00968	-272.84	1095	-269.12
2	0.262** (0.0459)	0.151** (0.0296)	0.00520	-364.95	1095	-345.46
3	0.256** (0.0433)	0.148** (0.0280)	0.00484	-364.36	1093	-363.14
4	0.239** (0.0370)	0.135** (0.0238)	0.00402	-354.38	1094	-351.25
5	0.215** (0.0297)	0.115** (0.0187)	0.00310	-326.26	1093	-325.40
6	0.239** (0.0318)	0.125** (0.0197)	0.00435	-308.67	1095	-304.88
7	0.243** (0.0393)	0.140** (0.0255)	0.00415	-365.89	1094	-361.32
8	0.326** (0.0681)	0.179** (0.0410)	0.0105	-314.26	1093	-313.73
9	0.310** (0.0611)	0.172** (0.0373)	0.00895	-326.74	1095	-323.45
10	0.458** (0.192)	0.278** (0.122)	0.0264	-370.90	1091	-371.20
11	0.281** (0.0534)	0.158** (0.0377)	0.00658	-343.72	1094	-341.90
12	0.384** (0.112)	0.233** (0.0723)	0.0156	-382.85	1094	-381.47
13	0.248** (0.0458)	0.155** (0.0322)	0.00407	-431.14	1093	-426.19
14	0.327** (0.121)	0.207** (0.0802)	0.00921	-409.99	1096	-409.84
15	0.245** (0.0423)	0.141** (0.0273)	0.00426	-362.67	1094	-361.50

Note: Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level.

Table 3.3: Estimation of the Variable Threshold Model

Station	η_1^l	η_2^l	η_3^l	$\log \text{lik}^l$	η_1^u	η_2^u	η_3^u	$\log \text{lik}^u$	distance
1	41.074** (0.731)	1.045** (0.0069)	0.841** (0.0255)	-151.01	51.678** (1.085)	1.019** (0.0103)	0.859** (0.0224)	-123.70	8.27
2	42.727** (0.526)	1.0359** (0.0053)	0.766** (0.0282)	-196.71	51.404** (0.8550)	1.006** (0.0083)	0.888** (0.0166)	-168.00	7.53
3	41.888** (0.556)	1.045** (0.0061)	0.742** (0.0318)	-192.60	50.576** (0.0838)	1.013** (0.0081)	0.866** (0.0163)	-178.26	7.58
4	41.988** (0.557)	1.043** (0.0058)	0.761** (0.0286)	-190.31	51.084** (0.903)	1.013** (0.0088)	0.873** (0.0177)	-160.08	7.72
5	42.903** (0.565)	1.029** (0.0057)	0.752** (0.0318)	-181.32	48.926** (0.904)	1.029** (0.0096)	0.886** (0.0180)	-156.00	7.77
6	41.120** (0.637)	1.052** (0.0069)	0.704** (0.0339)	-154.22	49.481** (0.963)	1.032** (0.0104)	0.864** (0.0200)	-139.85	8.76
7	42.095** (0.550)	1.038** (0.0058)	0.759** (0.0294)	-190.86	51.471** (0.889)	1.008** (0.0079)	0.852** (0.0182)	-175.08	6.72
8	41.501** (0.604)	1.049** (0.0070)	0.746** (0.0319)	-169.61	52.397** (0.996)	0.998** (0.0087)	0.900** (0.0198)	-140.22	8.18
9	41.015** (0.615)	1.055** (0.0070)	0.791** (0.0262)	-192.00	50.735** (0.106)	1.031** (0.0109)	0.837** (0.0237)	-123.10	8.12
10	41.685** (0.520)	1.043** (0.0055)	0.835** (0.0210)	-241.79	50.086** (0.922)	1.018** (0.0089)	0.904** (0.0180)	-150.43	6.89

Table 3.3 (cont'd)

Station	η_1^l	η_2^l	η_3^l	$\log \text{lik}^l$	η_1^u	η_2^u	η_3^u	$\log \text{lik}^u$	distance
11	41.997** (0.576)	1.044** (0.0062)	0.737** (0.0313)	-176.11	50.280** (0.857)	1.013** (0.0083)	0.908** (0.0161)	-166.49	7.84
12	40.575** (0.597)	1.064** (0.0072)	0.741** (0.0301)	-196.95	50.649** (0.837)	1.014** (0.0079)	0.890** (0.0163)	-179.87	7.55
13	42.186** (0.568)	1.027** (0.0053)	0.806** (0.0257)	-204.63	50.194** (0.627)	1.003** (0.0058)	0.913** (0.0118)	-259.09	6.62
14	41.844** (0.541)	1.048** (0.0058)	0.596** (0.0455)	-200.21	50.467** (0.718)	1.004** (0.0066)	0.908** (0.0159)	-212.71	7.70
15	42.361** (0.556)	1.040** (0.0057)	0.711** (0.0339)	-188.21	50.847** (0.839)	1.008** (0.0078)	0.894** (0.0620)	-177.40	7.72

Notes: η_1^m is the threshold constant, η_2^m is the coefficient on the threshold wholesale price, η_3^m is the coefficient on the lower threshold margin, and $\log \text{lik}^m$ is the log likelihood for $m = l, u$. Asterisk (*) denotes statistical significance at the 5% level. Double-asterisk (**) denotes statistical significance at the 1% level.

Table 3.4: Estimation of the $ACB(0, 1, 1)$

Station	ω	β	δ	γ	log lik	LR
1	-2.610** (1.380)	0.194 (0.420)	-0.703 (0.591)	0.0647 (0.0359)	-268.26	0.4232
2	-2.835** (0.465)	-0.034 (0.153)	-1.120* (0.473)	0.088** (0.021)	-350.65	0.0221*
3	-2.270** (0.356)	0.099 (0.120)	-2.120** (0.723)	0.062** (0.017)	-354.43	0.0002**
4	-2.360** (0.732)	0.144 (0.256)	-0.954* (0.436)	0.072** (0.024)	-348.24	0.0493*
5	-3.080** (0.037)	-0.087 (0.101)	-2.550* (1.040)	0.088** (0.022)	-317.91	0.0006**
6	-2.680** (0.485)	0.134 (0.143)	-1.710* (0.733)	0.084** (0.020)	-300.26	0.0099**
7	-1.610** (0.489)	0.400* (0.176)	-0.675 (0.354)	0.055** (0.018)	-358.91	0.0898
8	-2.940** (0.553)	-0.045 (0.181)	-0.831 (0.527)	0.062** (0.022)	-312.11	0.1979
9	-2.960 (2.190)	-0.049 (0.784)	-0.366 (0.544)	0.069 (0.051)	-323.02	0.6505
10	-2.630** (0.448)	-0.205 (0.176)	-0.930* (0.428)	0.019 (0.020)	-367.99	0.0404*
11	-0.443 (0.258)	0.849** (0.092)	0.247 (0.154)	0.010 (0.007)	-340.89	0.3642
12	-4.360** (0.423)	-0.836** (0.152)	0.227 (0.179)	0.066* (0.027)	-380.91	0.5712
13	-2.680** (0.438)	-0.174 (0.172)	-0.764* (0.313)	0.074** (0.019)	-422.56	0.0265*
14	-2.570** (0.409)	-0.234 (0.154)	-0.904** (0.372)	0.038 (0.024)	-405.35	0.0112*
15	-2.780* (0.504)	-0.097 (0.177)	-1.320* (0.520)	0.071** (0.022)	-356.65	0.0078**

Notes: LR reports the p-value for the likelihood ratio test of the null hypothesis that the ACB reduces to the logit. Asterisk (*) denotes statistically significant at the 5% level. Double-asterisk (**) denotes statistically significant at the 1% level

Table 3.5: Test of the Significance of Other Variables in the $ACB(0, 1, 1)$ model

Station	$ P_{t-1} - P_{t-1}^* $	$P_{w1(t)} - P_{w1(t)}^*$	$\ln(u_{N(t)})$	$\{\theta_t, P_t - P_t^*\}$
1	0.9459	0.3588	0.1048	0.5805
2	0.1326	0.1278	0.0012**	0.0099**
3	0.1353	0.6949	0.0028**	0.1264
4	0.9162	0.8663	0.0068**	0.1375
5	0.0369*	0.0044**	0.4949	0.0017**
6	0.3874	0.2852	0.0739	0.0059**
7	0.2956	0.5535	0.0168*	0.1087
8	0.4226	0.1514	0.4900	0.0015**
9	0.1336	0.5258	0.5626	0.0000**
10	0.6841	0.3561	0.0953	0.0546
11	0.4465	0.9154	0.2876	0.0018**
12	0.0018**	0.6936	0.0812	0.0046
13	0.5653	0.0356*	0.0002**	0.1684
14	0.0184*	0.1081	0.0001**	0.0172*
15	0.2954	0.0342*	0.0011**	0.0078**

Notes: Table reports the p-value of the test of the null hypothesis that the indicated variable does not belong in the $ACB(0,1,1)$ specification that already includes the current gap. Asterisk (*) denotes statistical significance at the 5% level. Double-asterisk (**) denotes statistical significance at the 1% level.

Table 3.6: Estimation of the Dynamic Lower Threshold

Station	η_1^l	η_2^l	η_3^l	δ	χ	log lik
1	42.807** (1.087)	1.041** (0.0076)	0.834** (0.0257)	-2.036 (1.072)	-0.457* (0.199)	-145.93
2	43.393** (0.627)	1.035** (0.0055)	0.772** (0.0284)	-1.049* (0.511)	-0.243 (0.140)	-193.21
3	42.556** (0.738)	1.045** (0.0064)	0.742** (0.0323)	-2.610* (1.029)	-0.260 (0.186)	-184.74
4	41.612** (0.815)	1.048** (0.0069)	0.742** (0.0328)	-0.976 (0.506)	0.0918 (0.172)	-187.73
5	43.464** (0.715)	1.029** (0.0060)	0.747** (0.0326)	-11.755 (109.04)	-0.203 (0.167)	-171.79
6	42.260** (0.785)	1.051** (0.0073)	0.699** (0.0354)	-2.120** (0.799)	-0.449* (0.173)	-146.39
7	42.762** (0.622)	1.038** (0.0059)	0.752** (0.0303)	-0.473 (0.462)	-0.312* (0.137)	-188.38
8	41.900** (0.683)	1.049** (0.0071)	0.745** (0.0320)	-1.548* (0.747)	-0.148 (0.134)	-165.96
9	40.768** (0.714)	1.057** (0.0073)	0.784** (0.0270)	-0.552 (0.480)	0.0834 (0.139)	-190.98
10	42.322** (0.588)	1.043** (0.0056)	0.836** (0.0211)	-1.136* (0.492)	-0.297* (0.137)	-236.58
11	42.386** (0.609)	1.046** (0.0062)	0.732** (0.0324)	-0.722 (0.486)	-0.234 (0.143)	-173.96
12	40.424** (0.682)	1.065** (0.0076)	0.738** (0.0306)	-0.121* (0.378)	0.0468 (0.115)	-196.81
13	42.734** (0.708)	1.027** (0.0055)	0.799** (0.0265)	-0.983* (0.488)	-0.218* (0.160)	-201.64
14	42.728** (0.688)	1.047** (0.0062)	0.597** (0.0462)	-1.308** (0.481)	-0.370* (0.173)	-194.39
15	43.629** (0.691)	1.040** (0.0060)	0.706** (0.0353)	-2.084** (0.664)	-0.534** (0.185)	-178.21

Notes: η_1^l is the lower threshold constant, η_2^l is the coefficient on the lower threshold wholesale price, η_3^l is the coefficient on the lower threshold margin, δ is the coefficient on the lagged indicator variable, and $u_{N(t)}$ is the contemporaneous duration. Asterisk (*) denotes statistical significance at the 5% level. Double-asterisk (**) denotes statistical significance at the 1% level.

Table 3.7: Estimation of the Dynamic Upper Threshold

Station	η_1^u	η_2^u	η_3^u	δ	χ	log lik
1	53.069** (1.347)	1.021** (0.0109)	0.837** (0.0255)	0.366 (0.778)	-0.452* (0.225)	-121.42
2	51.374** (1.145)	1.005** (0.0088)	0.887** (0.0173)	12.152 (308.64)	0.0420 (0.1807)	-162.41
3	50.651** (0.958)	1.012** (0.0083)	0.884** (0.0167)	1.990 (0.103)	0.0181 (0.146)	-174.83
4	50.913** (1.127)	1.012** (0.0090)	0.868** (0.0185)	14.029 (291.44)	0.112 (0.203)	-153.20
5	49.444** (0.998)	1.029** (0.0095)	0.885** (0.0181)	1.270 (1.026)	-0.263 (0.192)	-153.91
6	50.390** (1.132)	1.032** (0.0106)	0.856** (0.0204)	11.583 (208.04)	-0.363* (0.181)	-134.75
7	52.851** (1.302)	1.001** (0.0089)	0.824** (0.0191)	1.403 (0.752)	-0.281 (0.199)	-171.43
8	52.951** (1.154)	0.995** (0.0090)	0.897** (0.0202)	0.634 (0.757)	-0.141 (0.147)	-139.35
9	50.968** (1.263)	1.029** (0.0114)	0.836** (0.0239)	1.315 (1.044)	-0.0399 (0.173)	-121.92
10	50.780** (1.080)	1.014** (0.0093)	0.907** (0.0183)	1.226 (1.025)	-0.234 (0.174)	-148.49
11	50.920** (1.104)	1.009** (0.0089)	0.912** (0.0162)	1.425 (1.026)	-0.172 (0.187)	-164.57
12	50.724** (0.876)	1.012** (0.0081)	0.890** (0.0165)	1.164 (0.743)	0.00177 (0.0711)	-178.17
13	49.163** (0.786)	1.007** (0.0064)	0.908** (0.0122)	1.069* (0.455)	0.338* (0.149)	-253.59
14	51.056** (1.037)	1.000** (0.0075)	0.911** (0.0160)	1.355 (0.735)	-0.139 (0.201)	-209.81
15	51.075** (0.953)	1.006** (0.0079)	0.893** (0.0164)	1.797 (1.027)	-0.0726 (0.174)	-174.50

Notes: η_1^u is the upper threshold constant, η_2^u is the coefficient on the upper threshold wholesale price, η_3^u is the coefficient on the upper threshold margin, δ is the coefficient on the lagged indicator variable, and $u_{N(t)}$ is the contemporaneous duration. Asterisk (*) denotes statistical significance at the 5% level. Double-asterisk (**) denotes statistical significance at the 1% level.

Table 3.8: Estimation of the Asymmetric $ACB(0, 1, 1)$

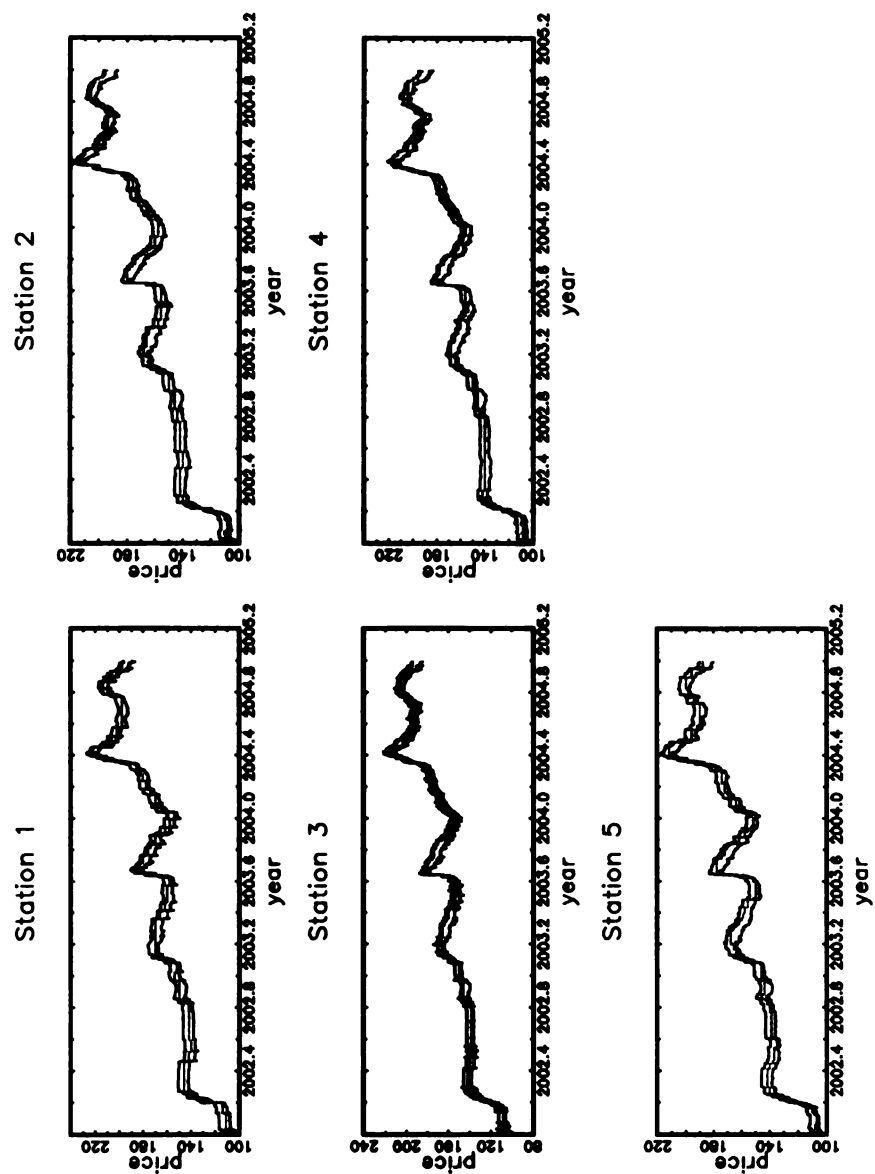
Station	β	δ	Pos const	Pos gap	Neg Const	Neg gap	log lik
1	0.2231 (0.4079)	-0.7048 (0.5867)	-2.7671 (1.4660)	0.0771 (0.0433)	-2.3785 (1.3031)	0.0541 (0.0383)	-267.72
2	-0.0050 (0.0489)	-1.1925 (0.4764)	-2.9748** (0.3440)	0.0795** (0.0254)	-2.9111** (0.3059)	0.1377** (0.0304)	-346.04
3	0.1103 (0.1199)	-2.1472 (0.7233)	-2.5583** (0.4500)	0.0713** (0.0240)	-2.2037** (0.3796)	0.0761** (0.0268)	-352.36
4	0.1563 (0.2634)	-0.9838 (0.4385)	-2.3980** (0.7747)	0.0647** (0.0242)	-2.4336** (0.7965)	0.1019** (0.0363)	-346.26
5	-0.0507 (0.1012)	-2.6187 (1.0356)	-3.5312** (0.5284)	0.0970** (0.0316)	-3.0731** (0.4119)	0.1446** (0.0352)	-311.52
6	0.1745 (0.1350)	-1.8564 (0.7329)	-2.7581** (0.5621)	0.0742** (0.0258)	-2.6493** (0.4887)	0.1202** (0.0281)	-295.13
7	0.4202 (0.1553)	-0.6979 (0.3524)	-1.8410** (0.5241)	0.0686** (0.0230)	-1.4413** (0.4198)	0.0513* (0.0204)	-356.69
8	0.0309 (0.2265)	-0.9305 (0.5283)	-3.5827** (0.8573)	0.0964** (0.0360)	-2.4008** (0.6449)	0.0556 (0.0288)	-305.61
9	0.6286 (0.1216)	0.1263 (0.2883)	-1.6257** (0.5419)	0.0600** (0.0230)	-0.6885** (0.2590)	0.0040 (0.0108)	-308.14
10	-0.1741 (0.1725)	-0.9640 (0.4275)	-2.7676** (0.5283)	0.0070 (0.0298)	-2.4915** (0.4439)	0.0408 (0.0278)	-365.08
11	0.4531 (0.3309)	-0.2904 (0.3768)	-1.6376 (1.0371)	0.0298 (0.0250)	-1.5869** (0.9198)	0.0676 (0.0384)	-334.55
12	0.4717 (1.1298)	-0.0387 (2.6599)	-1.7073 (3.4776)	0.0479 (0.1106)	-1.0197 (1.9168)	0.0066 (0.0201)	-375.52
13	-0.1427 (0.1737)	-0.7742 (0.3144)	-2.3587** (0.4871)	0.0500* (0.0224)	-2.9394** (0.4929)	0.1207** (0.0338)	-420.78
14	-0.2523 (0.1597)	-0.9100 (0.3797)	-2.5749** (0.5579)	0.0081 (0.0374)	-2.9526** (0.4841)	0.1317** (0.0447)	-401.29
15	-0.0611 (0.1677)	-1.3992 (0.5245)	-2.6364** (0.5122)	0.0426 (0.0261)	-3.0752** (0.5617)	0.1498** (0.0383)	-351.79

Notes: Asterisk (*) denotes constant and/or gap statistically significant at the 5% level.
Double-asterisk (**) denotes constant and/or gap statistically significant at the 1% level.

Figure 3.1: Map of Philadelphia Retail Stations

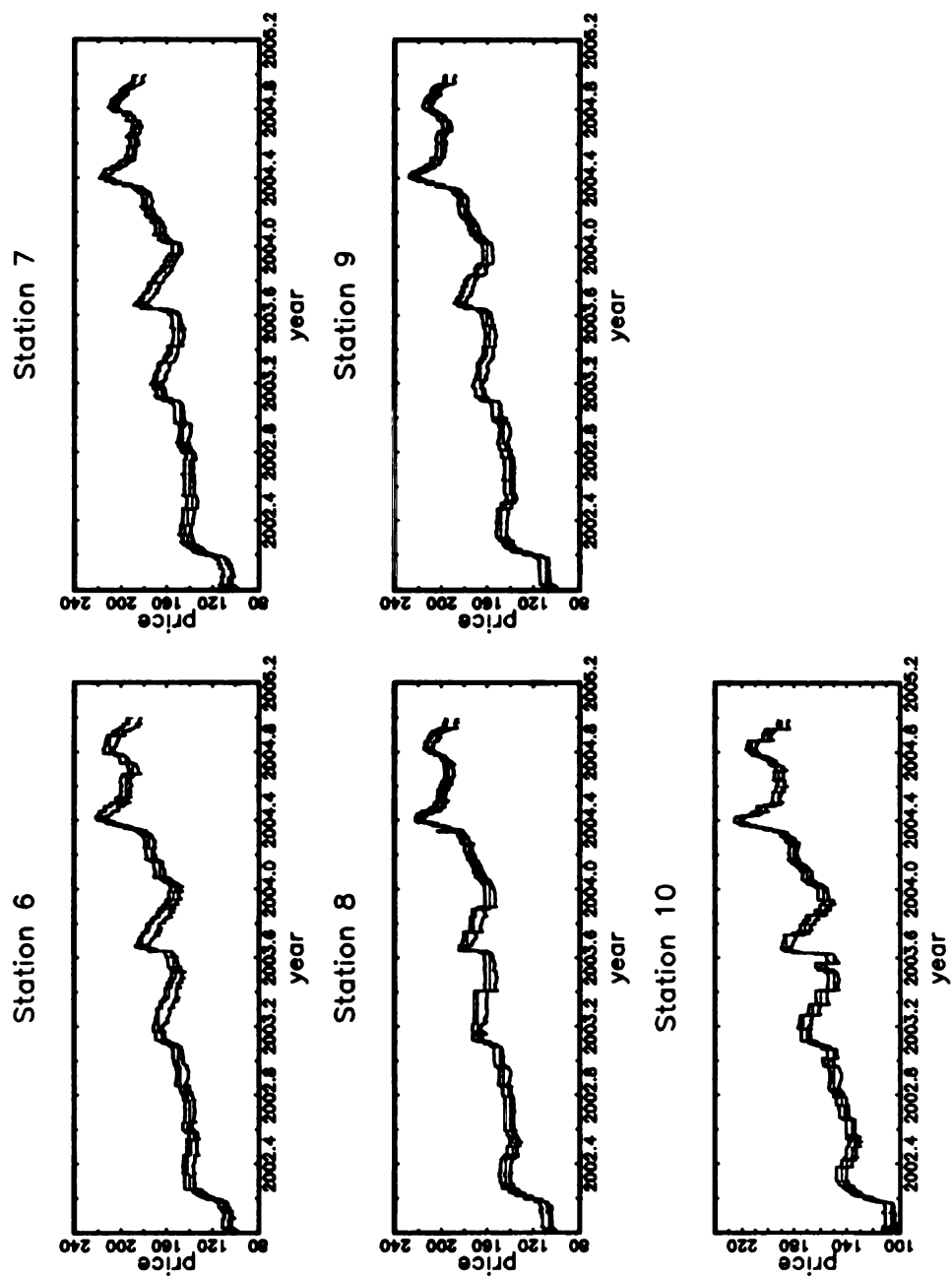


Figure 3.2: Fitted Thresholds for Stations 1-5



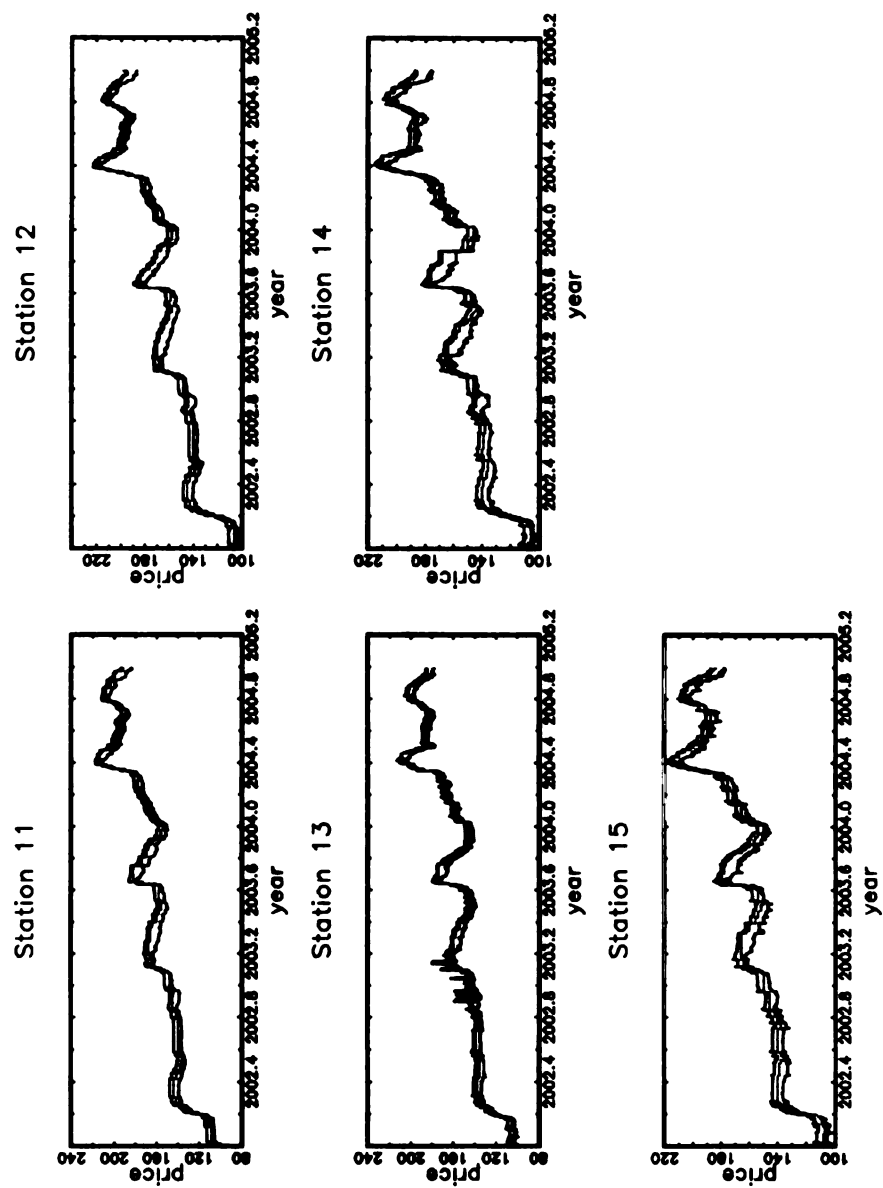
Black Line: Fitted Thresholds; Grey Line: Retail Price.

Figure 3.3: Fitted Thresholds for Stations 6-10



Black Line: Fitted Thresholds; Grey Line: Retail Price.

Figure 3.4: Fitted Thresholds for Stations 11-15



Black Line: Fitted Thresholds; Grey Line: Retail Price

Figure 3.5: Asymmetric ACB Estimated Probabilities for Stations 1-9

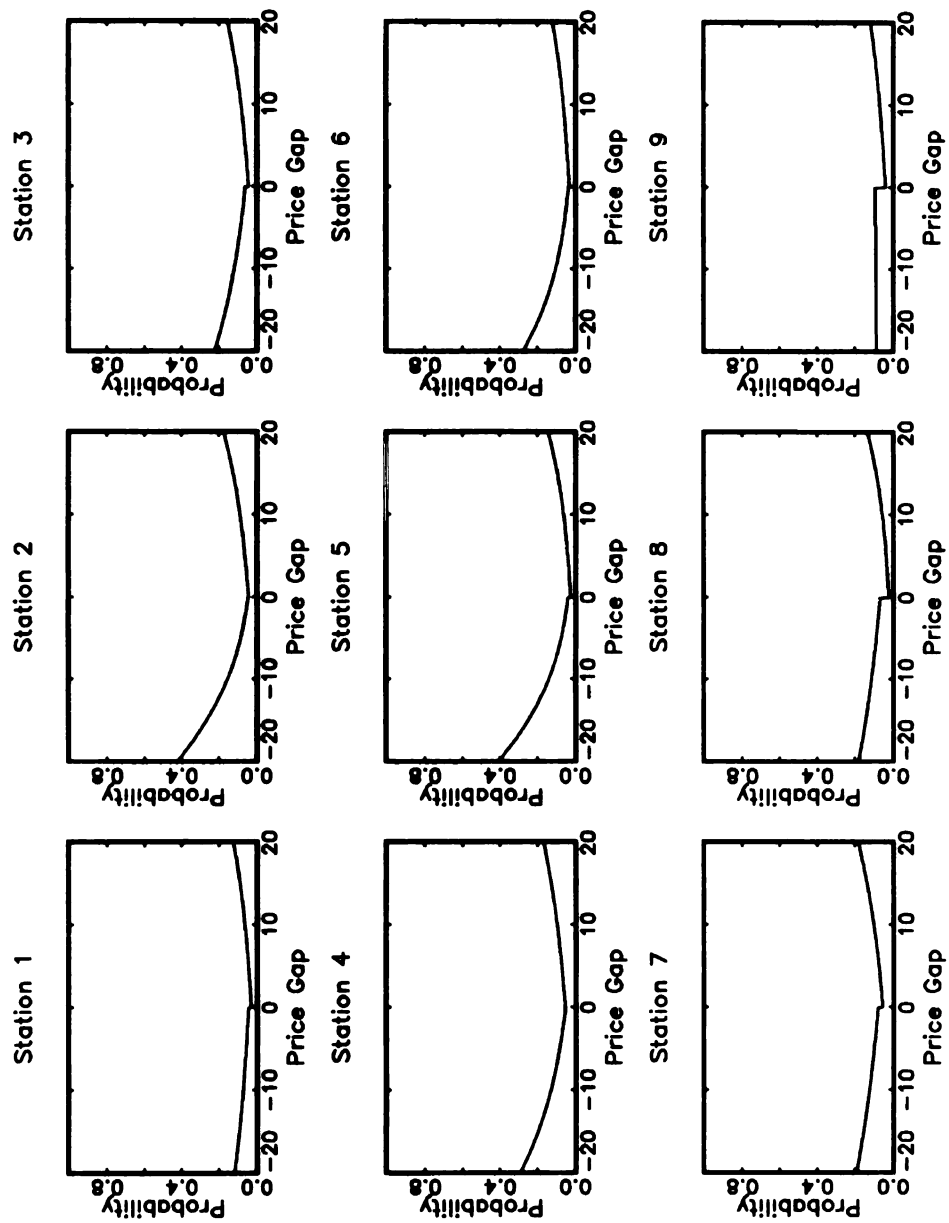
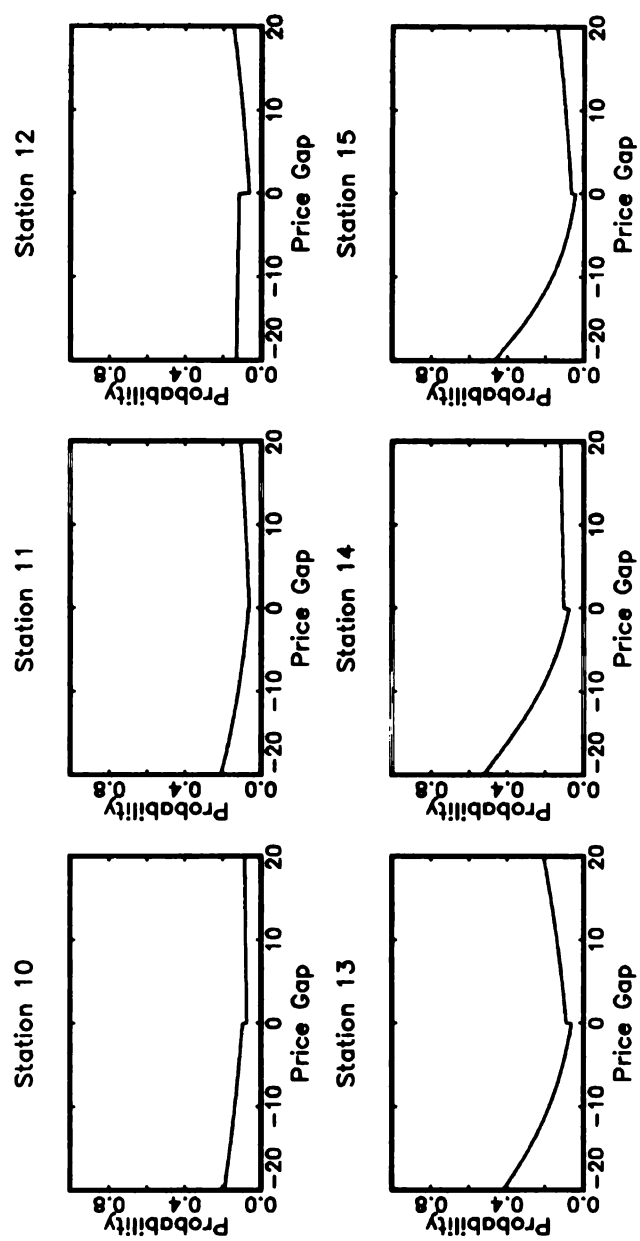


Figure 3.6: Asymmetric ACB Estimated Probabilities for Stations 10-15



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