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B. Starr McMullen

In this study, I test for tacit collusion in retail gasoline markets by testing for sticky downward pricing and price leadership. Using an extensive dataset consisting of twenty-five gasoline markets located in the greater Willamette Valley region of Oregon, I find evidence of sticky downward pricing in every market. I also find strong evidence that suggests several firms are using a price leader to coordinate prices. Further analysis suggests that the firms using a price leader to coordinate prices do not earn a greater average margin when compared to firms that do not coordinate prices with a price leader. Using past estimates of own-price elasticity for retail gas stations, I project the profit-maximizing price that station could charge and find that it is below the observed price charged by every station in every market. This result suggests that the tacit collusion observed in these markets is not an attempt by gas station managers to earn anti-competitive profits.

Tacit Collusion: Evidence of Price Leadership and Sticky Downward Pricing in Retail Gasoline Markets

by

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APPROVED:

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Major Professor, representing Economics

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Chair of the Department of Economics

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Dean of the Graduate School

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Scott P. Russell, Author

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Introduction:

On March 16, 2005 Oregon had the 4th highest gas prices in the nation, ranking behind only California, Nevada, and Hawaii according to a report by the Associated Press (AP 2005). In fact, on this date the average price of gas in Oregon was $0.30 higher on the same date previous year. When adjusted for inflation, the real price of gasoline is higher now than it was during the gas crisis of the early 1980's. Growing concern over the seemingly collusive behavior of gasoline retailers has arisen, as politicians have been taking an active approach toward the root of the high gas prices. Gas prices were a main issue the 2004 presidential race (Balz 2004), as the challenger blasted the incumbent for not doing anything to alleviate the record high price of gasoline.

Several studies have found evidence of sticky downward pricing in gasoline markets and suggest that this is evidence of tacit collusion. While industry level trends are useful as a first step, very few of these studies attempt to model the form of tacit collusion that causes the price stickiness. The majority of these papers use data that are collected monthly and represent a macroeconomic view of the gasoline industry.

Using an extensive pricing survey that spans several local markets in the Willamette Valley region of Oregon, this paper takes the sticky pricing literature to the next level by testing not only for sticky downward pricing, but testing explicitly for a well known form tacit collusion that one might expect to see in retail gasoline markets. In addition to sticky downward pricing, I find evidence of price leadership among several of the retail outlets in this sample.

This paper also investigates the spatial characteristics of the gasoline markets to determine if certain regional aspects help to determine the margin that a particular gas station is able to earn. It appears that isolated regions lend themselves to higher prices due to a lower market concentration, consistent with economic theory. It remains unresolved, however, who captures the extra margin; the retailer, or the major oil company.

It is important to distinguish the separation between the retail gas station owner and the major oil companies. In general, retail outlets are independently owned franchises that purchase wholesale gasoline from a major oil company. The individual stations are price takers, and inspection of the price-cost margins earned by retail gas station owners suggest that they do not share in the oil companies' extraordinary profits. It also appears that retail station owners are earning a margin that is less than optimal when one considers the individual market demand that each station faces.

The hypothesis that price leadership leads to higher margins than other, undetected forms, of sticky downward pricing is tested and rejected. I also propose evidence that suggests that even though firms are exhibiting behavior that is consistent with models of tacit collusion, namely sticky downward pricing and price leadership, the firms in the markets that I analyze are not charging the optimal price that they could charge given the market and own price elasticity estimates calculated for gasoline. These elasticity estimates will be discussed in detail in the literature review.

This paper is divided into sections as follows: First, an extensive literature surveys the prior studies that characterize gasoline markets. Second, an overview of the theory of oligopoly pricing briefly outlines models of tacit collusion, in particular a model of price leadership is proposed for the retail gasoline market. Third, the dataset is explained in detail and an empirical model is proposed to detect price leadership and sticky downward pricing. Fourth, additional tests are conducted to determine the regional characteristics that contribute to the price of gasoline.

Finally, the results of the empirical analysis are presented and their implications are discussed.

Literature Review:

Economists have used gasoline markets as testing grounds for theories regarding tacit collusion, sticky prices, elasticities, price wars, and spatial differentiation. One of the consistencies within the literature is that no one theory of pricing behavior fully explains all gasoline markets. Instead, each individual market appears to behave differently. Several theories are supported, but depending on the market in which gasoline is sold, the behavior of the agents can be quite different from one region to the next. This review looks at several lines of research and points out the most substantial studies in each area.

Borenstein and Shepard (1996) study several gasoline markets in the US and find evidence that firms are behaving in a way that is consistent with tacit collusion. When firms tacitly collude, they are acting in a profit maximizing way in which they realize that their own price cuts will be quickly matched by their competitors, and therefore engage in tacit collusion by not aggressively cutting prices. Collusion, on the other hand, is the practice of firms agreeing to set their own prices at the monopoly level. Given the relatively low price-cost markup, or margin, by gasoline retailers, it is immediately apparent that gasoline retailers are not acting as a joint-profit-maximizing monopoly. Marvel (1978) observes that a retail gasoline cartel would be nearly impossible to sustain in retail gasoline markets due to the highly informed gasoline consumer. A member of the cartel would be rewarded greatly by deviating from the monopoly price. This does not rule out models of tacit collusion, where firms engage in soft price competition.

Borenstein and Shepard (1996) exploit a supergame model, where soft price competition is supported by repeated interaction. Retail station managers realize that by cutting their own price, their opponent will react by cutting their price as well.

Cutting one's own price therefore does not lead to the increase in demand that the manager had hoped for, simply a lower margin on every gallon of gasoline sold.

Borenstein and Shepard (1996) predict and find that current margins are positively related to the expected next period demand and negatively related to the expected next period costs. This is consistent with their tacit collusion supergame model, where firms are able to anticipate reactions to their own price and therefore don't engage in fierce price competition. They also find evidence that prices are *sticky* or quick to increase and slow to decrease.

Davis and Hamilton (2004) also find evidence of sticky prices. They test whether or not menu costs are a valid explanation of the lags that are present in retail gasoline markets. Their findings reject the menu cost explanation. This is not surprising due to the fact that a gas station manager exerts little effort to change gas prices. Changing the retail price of gasoline involves putting new prices up on a price board, and entering a few keystrokes into a computer. The authors suggest that retail gasoline pricing depends on how consumers and competitors will react to a firms own price change. Evidence is found that prices appear to reflect strategic consideration of how consumers and competitors will react to price changes, consistent with studies such as Schendel and Balestra (1969), Slade (1987), Borenstein and Shepard (1996), and others.

In an effort to further explain the root of the sticky retail gasoline prices, several studies have examined the rate at which upstream cost shocks are realized in various downstream markets in the petroleum industry. Theories proposed by Borenstein, Cameron, and Gilbert (1997) suggest that lags in these pass-through rates can indicate market power in downstream markets. A related study by Asplund, Eriksson, and Friberg (2002) uses a model similar to the Borenstein et al (1997) model and finds similar results in the Swedish retail gasoline market. In a separate paper, Borenstein and Shepard (2002) find that firms that sell branded gas have even stickier prices than unbranded firms, suggesting that market power is positively correlated with sticky downward pricing patterns.

Borenstein et al (1997) study the pass-through rates for cost shocks in the crude oil market as they trickle down to the retail gasoline market. The speed at which a cost shock to the price of crude oil makes its way downstream to the wholesale and retail gasoline markets depends on the nature of many intermediate transactions, and the margin associated with each transaction.

Crude oil is sold to refiners, who in turn use this raw material to make gasoline and other petroleum products (diesel, kerosene, stove oil, etc.). This generic gasoline can then be sold as unbranded gasoline, or else it is mixed with certain additive packages to create branded gasoline (Chevron, Texaco, Shell, etc.). Gasoline is then sold to retail outlets directly from the refiner, or it is sold through jobbers, or middlemen between the refiner and the retailer. Depending on the steps taken, there could easily be two or three transactions that have taken place between the refinery and the retailer (Borenstein et al 1997).

Several theories have been proposed to explain this asymmetric, or sticky, downstream price adjustment to cost shocks. Borenstein et al (1997) suggest that reconfiguring a refinery to adjust immediately to a change in crude oil price would be very costly, and that long-run cost changes to the wholesale price of gasoline are gradually realized as refineries slowly adjust output to accommodate changing markets for various petroleum products. Refineries are also able to hold up to 25 days worth of inventories, suggesting that it would be much easier to accommodate negative shocks to crude oil prices than positive shocks (Borenstein and Shepard 2002). Consider the example given by Borenstein et al (1997) pp. 327 to explain price stickiness in wholesale gasoline markets:

> If half of all world oil reserves suddenly disappeared, the long-run competitive price of gasoline would increase greatly, and consumption would decrease greatly. Oil companies could accommodate that change quickly by raising gasoline prices. Since refinery production schedules cannot be adjusted immediately – such responses generally take at least two to four weeks to implement – the result would be a short-run building of finished gasoline inventories. In contrast, if world oil reserves doubled overnight, the short-run response in the gasoline market would be limited by available supplies of finished gasoline.

This argument hinges on the asymmetry between the short-run costs of increasing and decreasing inventories. These costs of changing refinery output are examined and further empirical evidence is found to support this example in a later work by Borenstein and Shepard (2002).

Borenstein et al (1997) find that there is asymmetry between cost increases and decreases along nearly every transaction point between crude oil and retail gasoline prices. Prices are observed to respond quite quickly to positive cost shocks and to respond slower to negative cost shocks. The one transaction that doesn't appear to be sticky is the transaction between the spot (or commodity) price of generic gasoline, and the wholesale price of gasoline. Borenstein et al (1997) find that the adjustment of these two prices is nearly instant, and stickiness is not observed in this transaction. Cost-shock stickiness is detected, however, between crude oil price and wholesale gasoline price, and also wholesale gasoline price and retail gasoline price.

Borenstein and Shepard (2002) extend the theories presented in Borenstein et al (1997) to test for market power between branded and unbranded gasoline at the wholesale level. In this paper, the pass-through rate of crude oil cost shocks is examined in the futures market for gasoline. Borenstein and Shepard (2002) test two different theories that explain sticky-pass-through costs. The first theory they consider is one of supply-adjustment cost, where changing output is costly for the producer. The second theory they consider is one based on models explaining the difference between the market-clearing price, and the actual price paid for the transaction. Because the futures markets in the US are highly scrutinized and little opportunity for arbitrage exists, any lags present in the futures market will be associated with supply adjustment costs, and not other forms of cost adjustment (Borenstein and Shepard 2002).

Because it is costly for refiners to immediately adjust to shocks in the price of crude oil, this price stickiness shows up in the futures market for wholesale gasoline. Refinery output is set by solving a complex algorithm that takes into account future expected demand for various petroleum products and the expected future cost of crude oil. Changing refinery output is costly and refineries operate at maximum productivity when output levels are held constant. It is therefore cost effective for refiners to slowly adjust to the long-run price of crude oil due (Borenstein and Shepard 2002).

Borenstein and Shepard (2002) find that there is asymmetry in the actual price charged for wholesale gasoline compared to the market-clearing price predicted by the futures market for branded and unbranded wholesale gasoline. The price of branded wholesale gasoline is found to respond slower than unbranded wholesale gasoline both to positive and negative cost shocks to crude oil. This asymmetry of adjustment rates between branded and unbranded products can be explained by the different characteristics of the gasoline retailer purchasing each type of product. Branded retailers often operate under contracts, where they are guaranteed a certain price for a short period of time. Unbranded retailers often don't operate under these contracts, and are able to buy from the least expensive wholesaler. Unbranded retailers are able to sell any brand of gasoline at their stations because they don't advertise any particular brand. Branded retail stations are required to sell the brand that they advertise, and are therefore captive in the short-run to buy their respective branded gasoline from their contracted wholesaler (Borenstein and Shepard 2002). This leads to fiercer price competition between the unbranded wholesalers due to the high substitutability of their products to retailers selling unbranded gasoline at retail stations.

Johnson (2002) compared the markups between diesel and gasoline and noticed that diesel often had a lower price-cost markup than gasoline. Retail gasoline was observed to have stickier prices than retail diesel. This can be partially attributed to the nature of the consumers for gasoline and diesel. Diesel is purchased mainly by large trucking companies that spend considerable effort tracking the price of diesel. Because each individual truck uses a tremendous amount of diesel when compared to the gasoline used in an automobile, a few cents saved per gallon of diesel to the trucking firm can add up very quickly. Combined with the fact that most trucking firms own several trucks, the expected payoff from searching for the cheapest diesel is much higher when compared to the expected payoff to the individual automobile user that fills up a couple of times per month (Johnson 2002).

Borenstein (1991) examines the markets for leaded and unleaded gasoline after noticing that the price-cost markup on unleaded gasoline was usually higher than the markup on leaded gasoline. Results were inconclusive as to why retailers charged different markups, but empirical evidence suggested that the average income of the leaded gasoline purchaser was lower, leading to a higher elasticity of demand for leaded gasoline and therefore price cutting took place between retailers.

The elasticity of demand for gasoline has been a topic of interest to energy economics, transportation economics, and industrial organization. Studies of gasoline elasticities in energy and transportation economics usually deal with the elasticity of demand for gasoline as a commodity. Aggregate gasoline demand has been found to be highly inelastic (Goodwin 1992, Nicol 2003, Graham and Glaister 2003). Studies of gasoline elasticity in the industrial organization literature have dealt mostly with the cross-price elasticity of demand for individual retailers' products. Estimates of cross price elasticity of demand for gasoline brands have been found to be elastic to varying degrees, depending on the market conditions (Slade 1987, and Barron, Umbeck, and Waddell 2003).

Because gasoline is not highly substitutable, at least in the short-run, it is not surprising that several studies have found the price elasticity of demand for gasoline to be extremely inelastic. Estimates vary, depending on the method of calculation, but the most common estimates of aggregate income and price elasticity of demand for gasoline is roughly 0.5 (Goodwin 1992, Nicol 2003, Graham and Glaister 2003).

In the short run, gasoline is found to be even more inelastic. Goodwin (1992) surveys the literature, noting that most studies have found the short-run price elasticity of demand for gasoline to be 0.28, and long-run estimates are between 0.71 and 0.84. Graham and Glaister (2003) re-survey the gasoline elasticity literature and note that the average short-run price elasticity of demand for gasoline is 0.27 and the long-run estimates range between 0.54 and 0.96, depending on the study. Graham and Glaister (2003) point out that European price elasticity of demand estimates are usually closer to unity than in the U.S., where the price elasticity of demand for gasoline ranges between 0.27 and 0.8 for the short-run and long-run respectively.

In both Goodwin (1992) and then later in Graham and Glaister (2003), the authors note that depending on the country the study takes place in, and the methodology employed, price elasticity of demand estimates for gasoline in the U.S. can vary. One consistency in all studies is that the short-run price elasticity estimates are lower than the long-run estimates.

These inelastic estimates of gasoline demand are not surprising. Commuters are unable to change travel patterns in the short-run, and the majority of people don't deviate from their current patterns if they expect the price level to decline in the future. As long as the long-run price of gasoline remains below a threshold level that makes it uneconomical to drive, commuters are likely to continue their driving patterns. If prices stay above threshold levels in the long-run, commuters will find alternate ways to work, such as public transportation, or else they will move closer to their work. Goodwin (1992) suggests that gasoline price manipulation is a good public policy tool if the goal is long-run traffic congestion relief, as the number of car owners will decline if prices are raised above a threshold level in the long-run.

In a field experiment, Barron, Umbeck, and Waddell (2003) were given control over 54 stations in Los Angeles, San Diego, and San Francisco. The California legislation had raised the question, "why are gasoline prices in Los Angeles substantially higher than both San Diego and San Francisco?" The purpose of this study was to examine how gas station retailers responded to exogenous changes in rival stations' prices, and to see if that relationship changed with the density of sellers in a particular region. Prices were changed at random at the control stations, and the responses of all stations within a 2-mile radius of the control station were recorded.

Barron et al (2003) found a direct link between the number of sellers in the retail gasoline market and the individual retailer's price elasticity of demand. As the density of sellers increases, the price elasticity of demand is also observed to increase. Regions with low, medium and high densities had respective own-price elasticities of demand of 1.4, 2.1, and 3.8 respectively. To answer the question of the California legislators, Los Angeles had the lowest station density and therefore the least competitive markets.

Barron et al (2003) also found that the stations' reactions to their random price changes were only partial – their random price changes at the control stations were not matched one-for-one by rival stations. It is also worth noting that reactions appeared to be inversely related to station density: As the number of stations in the area increased, the more likely they were to ignore the random pricing of the control station.

Gas Wars are a phenomenon where two or more stations aggressively undercut each others prices in order to increase their share of the market. Several studies have studies such phenomenon; Shendel and Balestra (1969), Slade (1987) Castinas and Johnson (1993), and Netz and Taylor (2002). While the markets that I consider show no evidence of gas wars, the topic is an interesting one, and an overview of this literature seems appropriate.

The gas war phenomenon is one that is at odds with models of soft price competition proposed by Borenstein and Shepard (1996), Borenstein, Cameron, and Gilbert (1997), Davis and Hamilton (2004), and Eckart and West (2004). However, given the high cross-price elasticity of demand for gasoline found in studies such as Barron et al (2003), depending on the thought processes of the individual agents, gas wars are an equilibrium market reaction, given the right market conditions. This next section discusses gas wars and the motivating factors that contribute to their occurrence.

Shendel and Balestra (1969) examine profit maximization conditions for an individual gas station and theorize that in some cases it may be profit maximizing to initiate a gas war. It is important to recognize that Shendel and Balestra (1969) divide all stations into two categories: Branded and unbranded stations.

Firms maximize profits with respect to individual station demand. In this model, if a firm expects greater profit by undercutting a rival, that firm will initiate a price cut. If the firm doesn't expect to receive a greater profit by price cutting, the firm will not initiate a price cut. Empirical evidence shows that price cuts are often lead by the unbranded firm. This could be because unbranded firms are able to purchase gasoline from the wholesaler offering the cheapest price, while their branded competitors are locked into long-term contracts that require the branded retailer to purchase their wholesale gasoline from a particular refinery. This would suggest that unbranded retailers have a cost advantage over their branded competitors, and thus Schendel and Balestra (1969) provide a viable theory explaining gas wars.

Slade (1987) continues the study of gas wars using an extensive dataset that includes price, variable cost, and volume for a number of competitors in the Vancouver, Canada area. Such availability of good data allows estimates of individual station demand and reaction functions.

Slade (1987) categorizes the urban Vancouver market as an oligopoly where price is the strategic variable. Secret undercutting by rivals is impossible due to the ease in which rival prices can be monitored. Slade (1987) also argues that competitors can at least implicitly monitor each others' volume of sales by observing the number of customers present at a location, and adjust prices accordingly.

One major difference in Slade's (1987) dataset and the one that I use is the volatility of the wholesale price of gasoline. In the mid-1980's, excess refining capacity in the world oil markets lead to excess supply in the market for gasoline. Slade (1987) concludes that this is the likely source of the gas wars. In the period from 2003-2005, the wholesale price of gasoline is much more volatile, which could explain why the results of my study are different from the gas war literature.

Castinas and Johnson (1993) continue the study of gas wars using a weekly dataset from Los Angeles. With few exceptions, the price increases are sharp and price decreases are gradual. Pricing patterns such as this can be explained by the Edgeworth Cycle model which suggests:

1. A firm's pricing decision depends only on other firms' current prices.
2. Each firm undercuts each other until the competitive price is reached.
3. One firm relents and restores a higher price.
4. The cycle begins anew.

The dataset of Castinas and Johnson (1993) exhibits a relatively constant wholesale price of gasoline, and consistent with Slade (1987). Empirical results from this study suggest that the Los Angeles market in the 1980's is not well explained by interrelationships between retail and wholesale prices.

In a more current study, Eckart and West (2004) criticize the use of the traditional Edgeworth Cycle model, saying that it doesn't take into account spatial differences between retail outlets. Eckart and West (2004) suggest that a spatially differentiated model might better account for retail margins than a model where spatial differences are not accounted for. If gas stations can keep their gas from being viewed as perfectly substitutable by a rival station's gas, they can charge a price above the perfectly competitive outcome and earn a margin. Models of spatial differentiation take into account not only the physical location of the station, but product differences such as service quality, brand name, and amenities offered at the gas station (car was, automotive shop, mini-mart, etc.).

Using daily observations over a five month period, Eckart and West (2004) test a number of different station attributes and their effect on market power. Regression analysis suggests that branded gasoline is favored by consumers over unbranded gasoline. Consumers are also willing to pay more for gas if the station has an adjacent car wash. Their empirical evidence also suggests that the number and type of stations in a region dictate the price a retail station can charge for gas. If there is a high density of "aggressive firms" in a region, this will lead to lower prices.

One peculiarity of this study was the observation that when several stations were controlled by the same manager in an aggressive region, that manager would often use the station closest to the aggressive competitor as a barrier between the aggressor and other stations. In a joint profit maximization situation, the insulating station will look unattractive to customers, but stations further away from the aggressive firm will look more attractive because they are not located within eyeshot of the low price competitor. While their empirical evidence doesn't fully support this hypothesis, it offers an interesting perspective.

Netz and Taylor (2002) also examine spatial decisions by gasoline retailers by studying location patterns. This study finds that the demand for gasoline at a particular station is positively affected by traffic flow in a given area. This is supported by their observation that most people won't drive all over town searching for the cheapest gasoline before they buy, if the cheapest station isn't known *a priori*, so long as the price appears to be "reasonable" given past knowledge of prices.

Netz and Taylor (2002) study the location patterns of gas stations as 1990's Los Angeles real estate prices skyrocketed. As income in a given area increased, the elasticity of demand for gasoline is seen to decrease. Also, as area income increased, property values also increased. Raising real estate values lead to the closing of gas stations in favor of more lucrative properties, which added to the market power of stations that chose to stay open. Stations that survived the rationalization period in parts of Los Angeles now have a natural monopoly, as it would be far too expensive for a new competitor to build a gas station in the area.

Van Meerbeeck (2003) also studies spatial differentiation and the corresponding prices of gas stations. In Belgium, the government regulates the maximum daily price that a gas station can charge. Not all stations are able to charge the maximum daily price. Van Meerbeeck (2003) finds that in areas where a station is isolated, and there is a high traffic flow such as highway locations, stations are able to charge the maximum daily price. These types of locations are the only ones that enjoy the maximum daily price. In areas where station density is higher, stations are much more competitive and prices well below the maximum daily price are observed (Van Meerbeeck 2003).

Hastings (2004) looks at spatial differentiation in gasoline stations, and whether or not vertically integrated branded stations (refinery owned retail outlets) charge a different markup than independently owned stations using the same brand name. When a branded retailer bought a smaller, unbranded retailer, the average gas price in the area rose. The rise in average area price is attributed to the decreased market share of the unbranded stations left in the area, and the increased market share of the branded stations in the area. Whether the stations were vertically integrated stations or independently owned was concluded to be unimportant. Consistent with Schendel and Balestra (1969), Hastings (2004) suggests that the presence of unbranded firms leads to more severe price competition.

Similar to Hastings (2004), Anindya (2005) studies how the market share of branded and unbranded retailers affects the average area price. In this study, a model of a dominant firm with a competitive fringe is employed. The branded retailers take the role of the dominant firm, and the unbranded retailers take the role of the competitive fringe. Empirical evidence suggests that the competitive fringe is less efficient than the dominant firm, and that the market share of the competitive fringe has a positive effect on area price. The competitive fringe is unable to realize economies of scale, and therefore has higher costs than the dominant firm. These positive effects on price are outweighed by the negative effect on price that a decrease in the monopoly power of the dominant firm has.

Eckart and West (2005) study the role of spatial distancing between stations and the rationalization of gas stations in Vancouver, Canada. The authors investigate reasons why rationalization occurs, i.e. why some stations stay open and others close. They find that some stations close not only to individual profit maximizing conditions, but to joint profit maximizing conditions. Stations that might have been profitable closed during this period, likely because a manager in control of several stations believed that by closing one station, demand would be shifted to the station that remained open, and they could thus minimize joint costs and maximize joint profits.

This paper is similar to the sticky pricing literature as I attempt to model how gas station managers react to changes in their competitors' margins. Instead of looking at pass through rates of wholesale gas to retail gas, this paper uses models of oligopoly pricing to develop and test a model of price leadership. In the next section, I review models of oligopoly pricing and propose a model of price leadership as a method of tacit collusion that could be used in retail gasoline markets. After the theory section, I describe the dataset and the model used to test for price leadership in retail gasoline markets.

Oligopoly Pricing:

Oligopoly pricing theory offers insight into the grey area between the completely uncooperative and completely cooperative actions that firms can take. Completely uncooperative actions, as illustrated in the classic Prisoners' Dilemma, suggest that firms are always in their best interest to play the safest strategy. On the other hand, if firms are allowed to meet and agree to fix prices, they are likely best off forming a cartel and colluding explicitly. These two solutions offer some insight into the real world; however, oligopoly pricing theory is needed to explain the countless outcomes that exist between completely cooperative behavior, and completely uncooperative behavior.

The need for oligopoly pricing theory comes from the reality that firms interact repeatedly with each other. In retail gasoline markets, station managers interact continuously as prices are easily changed in response to a rival's price changes. The solution offered by the classic Bertrand pricing game with homogonous products, suggests that gas stations should set their price equal to marginal cost, and that any other price would yield zero demand. This solution is somewhat unattractive because gas station managers differentiate themselves on brand, location, and service qualities. Also, it doesn't take into account that firms are generally better off by colluding to some degree.

The alternate solution, offered by a cartel model, suggests that gas station mangers should explicitly agree on a monopoly price and split the profits. While this may be attractive, it can be immediately discarded due to the illegality of this type of behavior in the United States. Cartel theory also suggests that the expected gain from deviation must be considered. If the expected gain from deviation is large enough, and monitoring is imperfect, cartels are always doomed to fail.

The middle ground between the Prisoners' Dilemma and the cartel solutions comes from the long standing suggestion by economists that intelligent managers should be able to figure out ways to earn profits somewhere between zero and the monopoly level (Vives 1999). Repeated interaction should induce some sort of "truce" between firms that does not necessarily have to be at the monopoly level. This sort of thought process lead to the development of folk theorems, or a class of theorems that generally suggest that there exist a set of actions that yield payoffs greater than the single-staged Nash payoffs that can be supported as equilibrium actions (Vives 1999).

In the retail gas market, the true nature of the game is a dynamic one in which firms are always aware of each other's prices and can change prices at any given moment. For simplicity, suppose that this game can be modeled as a static game, in which firms compete repeatedly an infinite number of times. By extending the number of interactions to an infinite horizon, firms are unable to predict the last period of play and cheat because of the lack of future punishment periods.

To support tacit collusive activity two conditions must hold. First, firms must believe that the stream of profits earned by tacitly colluding exceeds the stream of profits earned by playing the Nash equilibrium strategy repeatedly. The second condition that must be true for firms to collude is that the expected payoff from deviation from the tacitly collusive agreement must be less than playing the tacitly collusive strategy repeatedly. This second condition can be maintained through use of trigger strategies and credible threats to punish firms deviate from the cooperative actions.

The next section develops a model of price leadership that might emerge in retail gasoline markets. Price leadership suggests that in an environment where costs are constantly changing, firms may use a price leader to coordinate pricing behavior. Coordinating pricing behavior through use of a price leader lets rivals know that price movements are cooperative, rather than competitive, in nature.

Price Leadership:

Models of tacit collusion have been criticized due to the fact that is hard to cooperate with rivals when either input costs or demand for products is changing. To get around signaling problems, firms will sometimes use a price leader. In a price leadership model, one firm takes the role of the price leader, and the other firm(s) takes the role of the price follower(s). It is implicitly agreed that all changes in price will be first made by the price leader and followed by the price follower(s). It is important for all price changes to be instigated by the price leader, or else this could lead to pricing wars in which firms revert to the Nash equilibrium price.

In the gasoline market, the cost of wholesale gasoline is extremely volatile. When costs are volatile, firms would likely interpret cost-based price changes as non-competitive price movement. If station managers in markets were to make non-cost based price movements, these price changes may be seen as competitive. To clearly signal to other station managers that a margin change is appropriate, where margin is price-cost markup, station managers in a market may establish a price leader. The practice of setting price is identical to setting margin in retail gasoline markets. Margin setting and price setting are taken to mean the same thing throughout the remainder of this paper.

To motivate a price leadership model, it is important to note that in retail gasoline markets, rivals' prices, costs, and demands are fairly transparent. Prices are easily monitored because gas stations post prices on large signs easily accessible to motorists and rivals. Cost information can be obtained quite easily from private data companies that keep track of wholesale prices for all brands of gasoline. Finally, Slade (1987, 1992) suggests that demand for each station is known implicitly by rival firms through monitoring the number of cars fueling at each station.

Each retail gas station enjoys some form of market power based on brand, location, service quality, and amenities offered in addition to gas (Netz and Taylor 2002, Van Meerbeek 2003, Hastings 2004, etc). It is therefore reasonable to assume that gas stations will consider rival firms exercising their market power as consistent with cooperative pricing behavior as long as they don't attempt to deviate from their established relative price.

Let the retail gasoline market be modeled similar to the model of Slade (1987):

1. There are m firms in the market, and each firm knows every other firm's costs.
2. Firms set price in each period. The number of periods, n, is infinite. A discount rate of $\delta<1$ ensures that the sequence of profits converges as n approaches infinity.
3. Past history of price choice for every firm is known by each firm.
4. Each firm implicitly knows the underlying demand for each brand of gasoline for any vector of market prices. This demand is downward sloping, and of functional form:

$$D_i(p, g(x)) \tag{1}$$

Where: D_i = the demand for station i's gasoline.

p = the vector of m prices $(p_1, p_2, \ldots, p_m)$, where p_i is included as the price of the i'th station. $p \in [\underline{p}, \overline{p}]$, where $\underline{p}$ represents the vector of non cooperative prices and $\overline{p}$ represents the vector of prices that cause $D_i = 0$.

g(x) = function of consumer gasoline taste. Exogenous.

The inclusion of $\overline{p}$, captures the extremely competitive nature of the gasoline industry. Because retail gasoline markets are local markets, they have to price in such a way as to keep customers from traveling to another market to buy gasoline. Recall that gas prices are very transparent to the consumer, and they will likely travel to a different market to buy gasoline if p = $\bar{p}$. For example, if the *m* firms were to attempt to set p = the monopoly vector of prices, p_m, they would run the risk that p_m = $\bar{p}$ and customers would simply refuse to buy gasoline from any station in the market.

Suppose that all firms attempt to maximize their stream of profits by solving the problem:

$$\underset{p_i}{Max}\sum_{t=1}^{\infty}\pi_t\delta^t \tag{2}$$

$$\pi_{t,i} = (p_i - c_i)D_i(p, g(x)) - F_i \tag{3}$$

Where:

δ = Discount rate attached to future profits. $\delta < 1$ for simplicity.

c_i = Marginal cost of firm *i.*

F_i = Fixed costs of firm *i.*

Because equation (2) is a function of not only station *i*'s price, but all *m* prices in the market, oligopoly theory suggests that firms in a market such as this may be motivated to tacitly collude and earn a margin on each gallon of gasoline. To avoid confusion, and to simplify the argument, assume that δ is of a value that would make cooperative pricing worthwhile to all firms (Vives, 1999).

Given that firms have nearly complete information regarding competitors' prices, costs, and demand for all *m* brands of gasoline, one would expect station managers to take into account past history of rivals, along with their expected future actions. Because smart station managers expect their competitors to react to their own price changes, they must take these reactions into account before setting their own price.

Models of price leadership suggest that firms in a market will sometimes use a price leader to signal the appropriate prices to avoid confusion about the appropriate price to set (Besanko et al 2000). Perhaps the price leading firm is more market savvy. The price leader might have a better understanding of the underlying market demand, or perhaps they are the most adventurous of the firms in the market. Perhaps the price leader changes price to get a feel for current market demand conditions. An aggressive firm could also establish that unless rivals are willing to follow their lead, they will punish with trigger strategies such as setting price equal to (or below) marginal cost. There are several ways to establish a price leader; each of them is case specific. For simplicity, I do not concentrate on *how* a price leader emerges, I only model what price leadership *would* look like after it has been established.

In the retail gasoline market, costs are constantly changing. Suppose, therefore, that firms not only know each others' retail prices, but they know each others' margins. Suppose, for reasons unknown, the price leader plays one of two strategies:

$S1_L$: With probability = p, set margin = k.

$S2_L$: With probability = 1-p, set margin = k + ε.

Where k is equal to some constant and ε is a random disturbance term that could reflect the leader firm reacting to some exogenous shift in market demand.

Suppose that all firms that are following the leader adopt the following strategy:

$S1_F$: Set margin = $\alpha M_L + c$.

$S2_F$: Set margin = Ω = Margin independent of leader's margin.

Where M_L is the margin set by the leader firm in the previous time period, and c is a constant that represents the distance between the leader's margin and the optimal difference from the leader based on station characteristics and market demand. The parameter, α, represents the proportion of the leader's margin that the follower captures. This could be though of as a "rule of thumb" pricing mechanism, where a station manager decides to set their own margin as a function of the leader's margin, plus some constant amount. If a price following firm does not believe that following the price leader is the best decision, they revert to their own profit-maximizing margin, denoted Ω.

A linear relationship is likely to be appropriate because it is unlikely for station managers to solve a complex relationship between their own price and all of their rivals' prices. It is more likely that station managers know how much more (or less) of a margin they are able to earn relative to every other firm in the market. The next section describes the dataset used for empirical analysis and offers a model to test for price leadership in retail gasoline markets.

Data Description:

The empirical section of this paper uses a unique dataset that consists of local, market level, gas prices and regional wholesale gasoline prices. The first dataset is a unique market pricing survey that a multi-station, multi-branded retail gasoline firm collected twice weekly to keep track of its competitors' pricing trends. These proprietary data were given for use under the condition that individual stations and markets were not to be named explicitly in this paper. The second dataset comes from the U.S. Energy Information Administration, a branch of the U.S. Department of Energy. This second dataset consists of the Pacific Northwest spot price of wholesale gasoline. The Pacific Northwest spot is used as a proxy for marginal cost. The rational for using wholesale spot price will be explained below.

The pricing survey used in this analysis of retail gasoline price competition is unique for several reasons. First, and most importantly, stations in the twenty-five markets that I analyze come presorted into competitive markets. Most studies suffer from the need to sort firms into markets based on the assumptions of the researcher. This approach could improperly include or exclude relevant competitors.

The pricing survey was collected every Monday and Thursday over varying time periods for each market. The longest price survey spans a time period of 32 months, and the shortest spans a time period of 20 months. See Table 1. All markets considered in this analysis exhibit a smooth pricing pattern, which suggests that Edgeworth Cycles are not present in these markets.

Table 1: Individual Market Descriptive Statistics.

Market Code	Observation Starting Date	Observation Ending Date	Number of Observations	Number of Gas Stations
A	11/17/2003	7/11/05	172	5
B	10/02/2003	9/26/05	207	3
C	10/02/2003	9/26/05	207	4
D	2/3/2003	9/26/05	276	4
E	2/3/2003	9/26/05	276	5
F	2/3/2003	9/26/05	276	6
G	2/3/2003	9/26/05	276	4
H	2/3/2003	9/26/05	276	2
I	2/3/2003	9/26/05	276	3
J	2/3/2003	7/11/05	254	4
K	11/13/2003	9/26/05	195	4
L	11/13/2003	6/13/05	165	9
M	4/01/2004	9/26/05	156	5
N	11/13/2003	9/26/05	195	8
O	11/13/2003	9/26/05	195	3
P	11/13/2003	9/26/05	195	4
Q	10/16/2003	9/26/05	203	7
R	10/16/2003	9/26/05	203	3
S	10/16/2003	9/26/05	203	4
T	10/16/2003	7/28/05	203	6
U	10/23/2003	4/28/05	158	2
V	10/23/2003	9/26/05	201	4
W	10/23/2003	9/26/05	201	2
X	10/23/2003	9/26/05	201	3
Y	10/23/2003	9/26/05	201	4
Total:	**2/3/2003**	**9/26/05**	**5371**	**108**

The Pacific Northwest spot price represents the average price of large volume wholesale gasoline transactions that took place on each day. These data are collected weekly, and the series is adjusted to twice weekly to match the price survey data. The Pacific Northwest spot price is used as a proxy for marginal cost for each firm. It has been shown that the cost adjustment period from spot gasoline to wholesale gasoline is nearly instantaneous by Borenstein et al (1997). In reality, each firm has slightly different wholesale costs, but such cost information is unavailable for all firms. For simplicity, I assume that the relative markup of each brand is constant in each period.

Daily margin is calculated by taking the daily price of the *i*'th firm at time *t* and subtracting the spot price at time *t*, along with a constant \$0.464 per gallon to represent per gallon transportation costs and taxes incurred by each firm. State and Federal gasoline tax is a constant \$0.424 per gallon. According to the firm that supplied the pricing data, all stations located within these markets are charged a market rate of \$0.04 per gallon for delivery. Margin is therefore calculated as:

$$M_{i,t} = price_{i,t} - spot_t - 0.464$$

Where:

$M_{i,t}$ = The margin of firm *i* in time *t*.

$price_{i,t}$ = The retail price charged by firm *i* in time *t*.

$spot_t$ = The wholesale price of gasoline in time *t*.

t = Monday and Thursday of each week.

By modeling margin, price changes that are made to keep a constant markup over cost can be distinguished between price changes that represent a higher (lower) margin. This approach is attractive because it lets me consider only price changes that are the most likely to be scrutinized most by station managers in the markets. If managers are making cost-based changes, rival managers will likely not interpret these as either aggressive actions or signals that a new margin should be earned given the market demand.

The Model:

Most studies dealing with pricing competition have looked at contemporaneous changes in market prices. This paper takes a slightly different approach by modeling current margins for each firm based on their knowledge of past margins earned by each firm in the market. This approach is attractive for several reasons. First, by taking into account that each firm in the retail gasoline market is able to learn the pricing patterns of each of its competitors, I am able to model a specific form of tacit collusion in which the station managers are able to send signals to each other concerning the appropriate margin to earn given the current state of gasoline demand. Second, I am able to avoid the problem of endogenous variables by modeling current margin based on past history (Harvey, 1993, Kennedy 2003). Third, this approach takes into account that a signal sent by a firm might not be believable instantly by its rivals, and that for a margin change to be seen as deliberate, such a move would need to remain in effect for one whole period (one period is 3.5 days) to let competitors know that the firm is adjusting its margin deliberately.

The traditional price leader model suggests that through repeated interaction, firms may assume the role of price leaders while others assume the role of price followers (Vives, 1999; Besanko, Dranove, and Shanley 2000). Consider a model of price leadership where the strategic choice variable is margin. Firms assume either the role of "margin leader" or "margin follower" based on repeated signaling and previous successful past tacit collusive efforts. Therefore, in a given market with m competitors, each firm has self selected itself into one of two categories: margin leaders or margin followers. I denote M_L as "margin leader" and M_F as "margin follower".

This price leadership can be tested empirically using the following vector autoregression (VAR):

$$M_{i,t} = \alpha_i + \sum_{j=1}^{m} \sum_{k=1}^{3} \theta_{i,j} M_{j,t-k} + \Psi_i Inc + \beta_i Dec + \varepsilon \tag{4}$$

$M_{i,t}$ = Margin of firm i at time t.

Inc = Increasing spot. Dummy variable equal to unity if $Spot_t > Spot_{t-1} > Spot_{t-2}$.

Dec = Decreasing spot trend. Dummy variable equal to unity if $Spot_t < Spot_{t-1} < Spot_{t-2}$.

$\theta_{j,t-k}$ = parameter that captures the reaction of firm i to margin changes of each of the m firms. Note that $j=i$ is an AR(t-k) term. For $j \neq i$, this parameter captures the reaction of firm i to changes in firm j's past period margins.

α_i, Ψ_i, and β_i are firm specific parameters to be estimated.

ε is a normal and i.i.d. error term.

Gas station managers likely set their own margin based on a proportion of the leader's margin, along with a constant that represents their own niche in the market. Therefore, a linear relationship of the margins suggested by equation (4) is justified. The work of Slade (1987) and Barron et al (2003) also suggests that a linear relationship between retail gas prices is appropriate.

Equation (4) is estimated by OLS for the m firms in each market. Using a VAR sidesteps the possibility of endogenous variables due to the fact that only lagged values appear in every equation. Standard time-series diagnostic tests including; inspection of the autocorrelation functions, inspection of the partial autocorrelation functions, and the Ljung-Box Q-statistics strongly suggest that the error term is white-noise (Harvey 1993).

Each system of equations generated by (4) is inspected for price leaders and price followers in each market. Interpretation of (4) is relatively straight forward. If the *i*'th firm is taking the role of M_F, I expect $\theta_{i,j}$ to be significant for the *j*th firm taking the role of M_L. If firms *i* and *j* are not acting as followers and a leaders, then the parameter $\theta_{i,j}$ will be insignificant. Negative values of $\theta_{i,j}$ would suggest that stations in the market are reacting aggressively toward margin changes by competitors.

To check for sticky downward pricing, dummy variables are included to signal whether input costs are in an increasing or decreasing trend. If sticky downward pricing is present, I expect the value of β_i to be positive. This method of sticky price detection is similar to the approach used by studies such as Borenstein et al (1997), and Borenstein and Shepard (1996; 2002). Borenstein et al (1997), and others, have suggested that margins may be lower when costs are increasing. If this is the case, Ψ_i should be negative. This would imply that there is some implicit price competition stemming from station managers not wanting to be the first one to raise their price. Asplund et al (2000) found that consumers were especially unfavorable to price increases. This result would suggest that firms may take a short-run loss (lower margin) to keep their customer base complaisant.

The estimation output was very robust for all markets regardless of the number of lagged margins considered. Nearly every firm responded within one period to a margin change by a competitor, regardless of the number of lagged periods considered. One would expect that in a relatively low margin industry such as retail gasoline, signals would need to be interpreted fairly quickly to induce tacit collusion. Lags of length three are reported, however reporting lags of different lengths did not substantially change the results. The robustness of the VAR (4) reinforces the hypothesis that firms do in fact use signaling in retail gasoline markets

Results:

The VAR (4) was estimated in twenty-five markets, for a total number of 108 separate equations. After interpreting the results, twelve of twenty-five markets exhibited significant coefficient estimates that are consistent with price leader theory, while twenty-four of twenty-five markets exhibited evidence of sticky downward pricing. Estimation output for all markets can be found in Appendix A, Tables 3 through 27. The markets that exhibited leader-follower pricing patterns are summarized in Appendix B, Table 28.

No single brand of gas stood out as the margin leader in all markets. In fact, there are several cases of a brand being a margin leader in one market, a margin follower in another market. Consider markets P and B: Brand 7 is the price leader in market P, but in market B, Brand 7 is a follower of Brand 1. This should not come as a surprise as the manager of the station selling Brand 7 in market P is not likely to manage the station selling Brand 7 in market B

Each market had a margin leader with different characteristics. In some markets, the firm that earned the lowest average margin led the margin changes, while other markets the firm with the highest average margin led the margin changes. Estimation results suggest that the brand of fuel sold is not important when choosing a margin leader. This result would suggest that individual managers dictate whether or not to establish margin leadership.

Several textbooks suggest that tacit collusion is more easily sustained as the number of firms in the market decreases, for example Vives (1999) and Besanko et al (2000). This hypothesis does not appear to be supported by the estimation results. There are some markets with relatively few gas station that do not appear to be exhibiting a leader-follower pattern, while there are other markets with relatively many gas station that do exhibit leader-follower patterns. This could be due to the fact that margins are observed twice weekly, instead of daily. If station managers had a well-defined leader and placed a lot of faith in their leader's signals, they could possibly adjust their margins within a few hours of the leader's signal. This speedy response would not be detected in the sample that I use for this paper. Due to frequency of the data available, alternating pricing decisions made on the same day would be seen as contemporaneous price changes. Only leader/follower behavior that results in following firms adjusting margins at least one day later are detected by equation (4). If the margin-following firms adjust their margins on the same day as the leader, equation (4) will not detect these types of patterns. A dataset with more frequent observations would be required to detect leader/follower behavior taking place quite frequently. Eckart and West (2004) suggest that to truly capture the nature of retail gasoline pricing patterns, one should employ a dataset that consists of multiple observations per day.

Regression results also reveal that twenty-four of twenty-five markets had statistically significant dummy variables at the 5% level; the majority of the parameter estimates were significant at the 1% level. The significance of the dummy variables supports the hypothesis that gasoline retailers earn higher margins in periods when costs are falling and margins are less when costs are raising. This evidence of sticky pricing is consistent with the results of Borenstein et al (1997), Borenstein and Shepard (1996; 2002), Slade (1987) and others. Sticky downward pricing is a more general form of tacit collusion. Sticky downward pricing arises from firms implicitly agreeing (for reasons unknown) to lower prices slowly in response to cost decreases.

The estimation results presented in the Appendix A suggest that nearly all gas stations are able to earn an additional \$0.055 per gallon when their costs are in a decreasing period and earn \$0.045 per gallon less when their costs are increasing. While individual markets are not directly comparable to each other, due to the different time periods for which data are available for, stations generally earned an extra \$0.05-\$0.06 when costs were in a decreasing period and \$0.04-\$0.05 less when costs were in an increasing period. See Appendix A for details.

The significance of the dummy variable Dec suggests that nearly every market exhibited some form of tacit collusion, as margins appear to be higher when costs are decreasing. Brands in the markets that do not exhibit leader-follower pricing patterns could still very well be tacitly colluding in ways that are not detected by the use of equation (4). For example, a profit maximizing retail station would respond very quickly to a cost increase, otherwise their short term profits would be negative. Managers do not want to decrease prices initially. Over time, brands will face shocks in gasoline demand, and the incentive to price cut becomes even greater. As the incentive to price cut increases, brands slowly price-cut each other until another cost increase is realized in the market. The significance of the dummy variable Dec suggests that firms in the markets that I analyze are engaging in "soft price competition" hypothesized by Borenstein et al (1997). The significance of the variable Inc suggests that firms are reluctant to raise price when costs are increasing, suggesting some form of implicit price competition is also present in these markets.

Some parameter estimates were negative. These negative estimates suggest that station managers in these markets may be engaging in price competition instead of tacit collusion. For example, if Station A were to raise their margin, Station B might be best off by choosing not to collude by also raising margin, and therefore maximize their profits by lowering margin slightly and increasing the demand for their gasoline. This could be one explanation of the negative signs present in the results. Another possible explanation could be that the true relationship between margins is not linear.

To test whether or not stations that are engaging in price leadership patterns earn a greater margin than stations that do not engage in these practices, I regressed the average margin earned by each station on several station characteristics.

$$\overline{M_i} = \beta_0 + \beta_1 MAV + \beta_2 ISO + \beta_3 F + \beta_4 L + \beta_5 IS + \beta_6 MET + \beta_7 TT\ \beta_8 UB + \varepsilon \qquad (5)$$

Where:

$\overline{M_i}$ = The average margin of the ith station between 4/1/04 and 4/28/05. This date range is consistent for all markets.

MAV = Dummy equal to one if station is a "maverick" brand, a well-known low-price firm, known as a aggressive pricer. (Eckart and West 2004).

ISO = Dummy equal to one if the station is located on the Oregon Coast.

F = Dummy equal to one if the station exhibited a margin follower patterns.

L = Dummy equal to one if the station exhibited margin leadership patterns.

IS = Dummy equal to one if the station is located on an interstate exit ramp

MET = Dummy equal to one if the station is located in a city with population > 100,000

TT = Dummy equal to one if the station sells "top tier" branded gasoline (www.toptier.com).

UB = Dummy equal to one if the station sells unbranded gasoline.

TABLE 2: Average Station Margins Regression Output.

Dependent Variable: $\overline{M_i}$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.1682**	0.0143	11.764	0.0000
MAV	-0.0845**	0.0171	-4.9281	0.0000
ISO	0.0727**	0.0143	5.0584	0.0000
F	0.0064	0.0088	0.7250	0.4701
L	0.0099	0.0121	0.8202	0.4140
IS	0.0383*	0.0167	2.2896	0.0242
MET	-0.0131	0.0089	-1.4777	0.1427
TT	0.0203	0.0124	1.6356	0.1051
UB	-0.0474**	0.0156	-3.0442	0.0030

* = significant at the 5% level
** = significant at the 1% level

The regression results reported in Table 2 are consistent with what one would expect to find in the retail gasoline market. Consistent with prior research, firms selling fuel with a perceived lower quality charge less for their gasoline than do other "major" brands of gasoline. Eckart and West (2004) noticed that a certain "major" brand had a reputation of being the lowest priced gasoline, this firm is included in the regression as MAV because the study by Eckart and West (2004) suggested that this particular brand behaved like a maverick due to their cutthroat pricing behavior.

The variable TT is used as a quality indicator to test whether or not stations selling gasoline on the "top tier" list earn a greater margin when compared to other brands of gasoline that do not appear on the list. TT is almost significant at the 10% level, and suggests that "top tier" branded stations can capture an additional two cent margin when compared to station not on the "top tier" list.

The variable MET is used to capture two market characteristics. First, MET captures the higher station density observed in the larger population regions. As station density increases, one would expect market power to decrease. Second, MET captures the additional benefit of lowering one's price. Because there are many more people living in large cities, the expected gain from undercutting rivals increases. Met is significant at the 14% level, suggesting that the average margin earned in large cities is lower than average. The low statistical significance of this variable could be due to the fact that some markets within a greater metro region could in fact be somewhat isolated and therefore capture a greater margin.

The variable ISO is used to capture the isolated nature of the coastal communities relative to the other cities in this sample. Because of the increased cost incurred by customers wishing to drive to an alternate market to purchase gasoline, one would expect the value of $\bar{p}$ to be larger in these cities, and therefore the average margin earned should be larger in coastal cities. Consistent with theory, the average margin earned by coastal stations is about $0.07 greater than other stations in the sample.

The variables L and F were included to test whether or not firms exhibiting margin leadership or margin follower patterns were able to earn an average margin that is greater than the average margin earned by firms not exhibiting this type of pricing behavior. Both estimates are statistically insignificant. This is not surprising, due to the fact that twenty-five of twenty-six markets exhibited signs of sticky downward pricing, which suggests some other form of tacit collusion is present. This evidence suggests that firms identifying in margin leader/follower patterns do not earn a greater margin than firms engaging in tacit collusion that is undetectable by equation (4).

Discussion:

Many studies have attempted to explain the pricing patterns in various retail gasoline markets. While most past studies have looked to contemporaneous price changes for insight into pricing behaviors, this paper breaks that tradition by looking at how past choices of margin dictate present choices of margin. All but one of the retail gasoline markets examined in this paper exhibited signs of tacit collusion in the form of earning higher margins when costs are decreasing and lower margins when costs are increasing. This result is consistent with the findings of Borenstein et al (1997), Borenstein and Shepard (2002, 1996).

Twelve of the twenty-five markets exhibited strong evidence that the station managers in those markets were able to coordinate their respective margins through the use of a margin leader. In the markets where margin leadership was detected, firms did not necessarily earn a greater margin than firms in markets where such leadership was absent.

It is important to point out that the margins calculated in this study are not necessarily an accurate measure of the actual margin earned by each firm. The margins reported in this paper only reflect the difference between the price charged and the marginal cost of wholesale gasoline. In reality, the dealer tank wagon (DTW) price, or the price that retail stations pay for delivered wholesale gasoline, is higher than the wholesale spot price by several cents (Borenstein et al 1997). Senator Ron Wyden (1999) investigated the pricing behavior of the major oil companies and found that they practiced price discrimination between regions. This suggests that retail gas station owners are price takers at the wholesale level.

Market power in the gasoline industry is of concern due to relatively low market elasticities estimated for gasoline as a commodity. Suppose that all of the gas station managers were able to meet and agree to charge the monopoly price. Given the market elasticity estimate of 0.28 for gasoline (Goodwin 1992, Graham and Glaister 2003), this would suggest that a monopoly price of gasoline would be more than double what it is today. To illustrate, take the market elasticity of estimate 0.28 proposed in the literature. This would suggest that a 50% increase in the price of gasoline would be roughly met with a decline in demand of only 14%, and a 100% increase in the price of gasoline would be met with a decline in demand of 28%. If a cartel could be formed, retail managers could charge over $4.00 per gallon and only lose 28% of their business. Depending on the slope of the demand curve, the short-run monopoly price of gasoline could be extremely high.

In reality, cartels of this type would be extremely hard to keep in tact. First off, any station that deviated from the monopoly price would be greatly rewarded with lines of people waiting to buy gas from that station. Second, it is unlikely that the legislature would stand for monopoly pricing on something as important to the economy as gasoline. Barron et al (2003) suggest that the own-price elasticity values for retail gasoline are between 1.8 and 3.8. The inverse elasticity rule of pricing (Nicholson 2002) is given by:

$$\frac{p-c}{p}=\frac{1}{\eta} \tag{6}$$

Where:

p = price to be charged

c = marginal cost

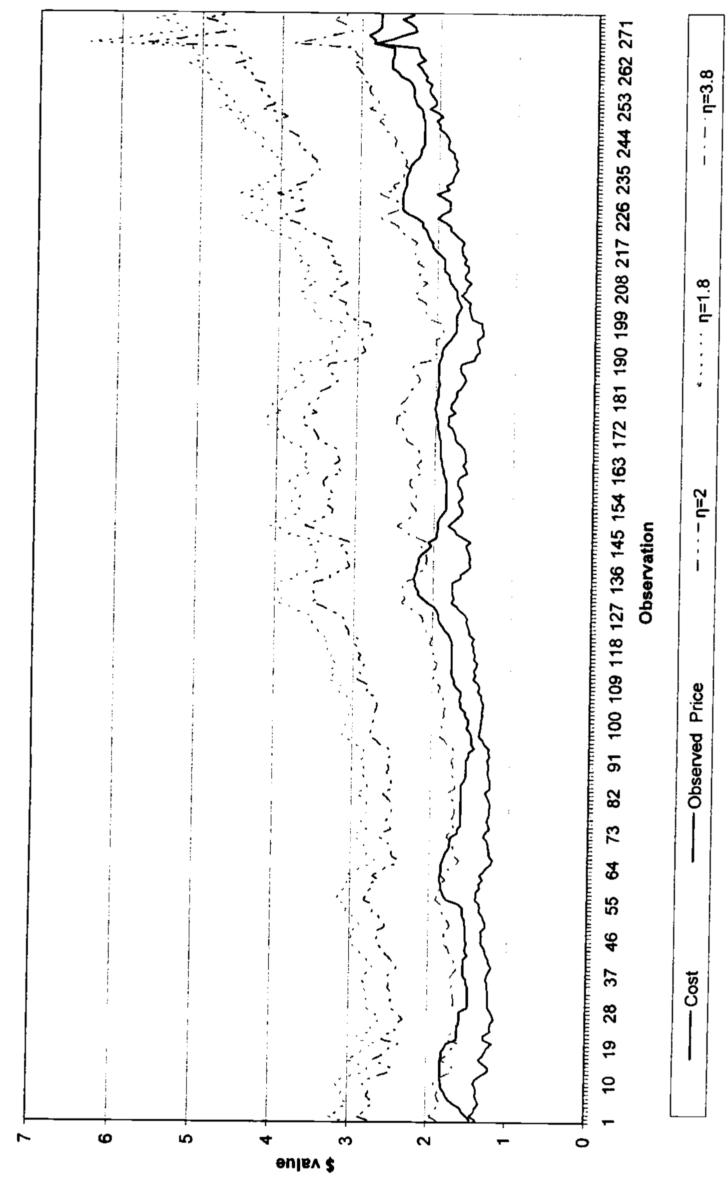
η = the price elasticity of demand

Firms could therefore maximize profits by setting price equal to:

$$p=\frac{\eta c}{\eta-1} \tag{7}$$

Unbranded fuel has the least mark-up of all fuels. Chart 1 shows the observed price charged by a station selling unbranded gasoline in market E compared to the optimal price that should be charged if that same firm was using the inverse elasticity rule given by (7). Notice that the observed price is much smoother than the price suggested by (7). Also, the price projected by (7) for the lowest elasticity estimate proposed by Barron et al (2003) suggests that the maximum price charged should over \$5 in some instances, while the actual price charged is under \$3. The price of \$5 per gallon is less than the monopoly price would be, given the extremely low estimates for market demand elasticity. The rule of thumb proposed by (7) cannot be used for inelastic regions of the demand curve, as this would imply that marginal cost is negative (Nicholson 2002, page 340). This makes it impossible to use (7) to project the monopoly price of gasoline. The projected prices observed in Chart 1 suggests that firms are not taking full advantage of their market power, let alone colluding to gain even more market power.

Chart 1:
Actual Price Charged v.s. Optimal Price Charged



To further investigate the pricing patterns of retail gas stations, one would need to collect daily price observations to detect all forms of tacit collusion. Using twice weekly observations was useful in categorizing the form of tacit collusion exerted in about half of the markets and detecting sticky downward pricing in the majority of the markets. The model that I used to detect margin leadership was successful in twelve of twenty-five markets; however another fourteen markets exhibited evidence of tacit collusion of some unknown form. A similar dataset with more frequent observations would be useful to better approximate the reactions of gas station managers to rival managers' price changes.

Granger Causality tests may yield stronger insight into the reaction functions of the firms. However, Granger Causality tests are costly in terms of computational power. Even if stronger evidence of price leadership could be uncovered, such evidence should not be cause for policy makers to investigate these retail gasoline markets for collusion. If station managers had appeared to be pricing at a level above the optimal level, proposed by the inverse elasticity rule (7), then policy makers would have reason to be concerned about the pricing practices of retail gas station managers.

Conclusion:

This paper examines twenty-five retail gasoline markets in the Willamette Valley region of Oregon and finds evidence that firms in these markets are tacitly colluding in the sense they earn a higher profit when prices are decreasing and earn a lower profit when prices are increasing. This finding is consistent with previous studies involving tacit collusion and sticky pricing in gasoline markets.

The results of this paper suggest that even when gas station managers are exhibiting behavior that is consistent with tacit collusion, their margins are far from lucrative. The average per gallon margin earned between the wholesale and retail markets is between \$0.06 and \$0.30, depending on the brand of fuel. It is impossible to determine from this dataset the proportion of the margin that the refiner, the jobber, and the retailer earned. Borenstein and Shepard (1996) suggest that the actual margin earned by the retailer is around $0.08 per gallon, before operating expenses are paid. The report by Senator Wyden (1999) suggests that firms are price takers at the wholesale level, and the margin discrepancies observed between regions could in fact be the result from major oil companies charging different prices to retailers in different regions. The data used in this paper would not detect this.

The inverse elasticity rule (7) suggests that firms are not taking full advantage of their market power given the elasticity estimates of Barron et al (2003). This would suggest that the collusion detected in these retail gasoline markets is in fact tacit collusion. Firms in these markets do not appear to be taking full advantage of their own price elasticities, let alone colluding to gain even more market power. These observations would suggest that efforts by the legislation to stop tacit collusion on the part of the retail gas stations themselves would be misplaced.

Margin leadership can explain the form of tacit collusion in several of the markets, but does not explain the tacit collusion found in the other markets. Further research into the market conduct would need to be undertaken before the form of tacit collusion could be characterized in these markets. Markets exhibiting patterns of margin leadership do not appear to earn greater a margins than those markets that do not exhibit margin leadership, suggesting that margin leadership does not lead to higher margins than the undetectable forms of tacit collusion in retail gasoline markets.

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APPENDICES

Appendix A: Estimation Output.

Tables 3-27 are estimation output of equation (4) for all markets.

$$M_{i,t} = \alpha_i + \sum_{j=1}^{m} \sum_{k=1}^{3} \theta_{i,j} M_{j,t-k} + \Psi_i Inc + \beta_i Dec + \varepsilon \qquad (4)$$

- Margins are reported in the estimation output as MBRAND #, where # is the numerical code for each brand of gasoline. Brand codes are consistent across markets, i.e. Brand 1 in Market A is the same brand as Brand 1 in Market B.
- The dependent margin, $M_{i,t}$, is listed at the top of each column.
- The independent variables $M_{j,t-k}$, *Inc*, and *Dec* appear as the first entry of each row. The lag values, k = 1, 2, 3 appear in parentheses. For example: In Market Y, Brands 2, 4, and 7 all follow one period lagged margin changes by Brand 1. See Table 27.

* = significant at the 5% level.
** = significant at the 1% level.
*** = significant at the 10% level.

Table 3: Estimation Output for Market A
Included observations: 169

	MBRAND 1	MBRAND 2	MBRAND 3	MBRAND 4	MBRAND 5
MBRAND 1(-1)	1.078939	0.780553	0.923379	0.657514	0.682002
MBRAND 1(-2)	0.762543	0.601568	0.684821	0.625846	0.724321
MBRAND 1(-3)	0.599324	0.578756	0.552626	0.552093	0.520944
MBRAND 2(-1)	0.534977*	0.695265**	0.554975*	0.518651*	0.532242*
MBRAND 2(-2)	0.370257	0.454088***	0.222084	0.359359	0.396415
MBRAND 2(-3)	-0.115631	0.037814	-0.149655	-0.103032	-0.057122
MBRAND 3(-1)	-0.210837	0.013861	0.300880	-0.212713	-0.210660
MBRAND 3(-2)	-0.616194*	-0.355701	-0.371474	-0.605064*	-0.610376*
MBRAND 3(-3)	-0.022325	-0.226714	0.020605	-0.016290	-0.109651
MBRAND 4(-1)	-0.445600	-0.299353	-0.569599	0.010478	-0.372001
MBRAND 4(-2)	-0.437673	-0.494412	-0.515384	-0.415627	-0.321935
MBRAND 5(-1)	-0.147631	-0.357501	-0.351709	-0.155450	0.163719
MBRAND 5(-2)	-0.330168	-0.419766	-0.327805	-0.222189	-0.380473
MBRAND 5(-3)	0.536095	0.316756	0.283445	0.472479	0.486950
C	0.022172	-0.002654	-0.017085	0.021712	0.014255
INC	-0.045363**	-0.036632**	-0.042388**	-0.046059**	-0.044215**
DEC	0.053694**	0.061560**	0.059738**	0.049324**	0.048339*
R-squared	0.788193	0.805640	0.804025	0.786363	0.787539
Adj. R-squared	0.764347	0.783759	0.781962	0.762312	0.763619
F-statistic	33.05365	36.81824	36.44164	32.69457	32.92460

Table 4: Estimation Output for Market B
Included observations: 204

	MBRAND 1	MBRAND 4	MBRAND 7
MBRAND 1(-1)	0.858327**	0.464281*	0.478315*
MBRAND 1(-2)	-0.081013	-0.232735	-0.243103
MBRAND 1(-3)	0.182331	0.057620	0.036900
MBRAND 4(-1)	0.609970	0.526221	0.550168
MBRAND 4(-2)	0.434082	0.041992	0.048395
MBRAND 4(-3)	0.957484	0.846975	0.860843
MBRAND 7(-1)	-0.557624	-0.075192	-0.119433
MBRAND 7(-2)	-0.663962	-0.118242	-0.117299
MBRAND 7(-3)	-0.914193	-0.675463	-0.663026
C	0.041219**	0.048601**	0.049435**
INC	-0.042518**	-0.044710**	-0.046384**
DEC	0.058120**	0.056398**	0.056572**
R-squared	0.776940	0.764177	0.764069
Adj. R-squared	0.764161	0.750666	0.750552
F-statistic	60.79595	56.56086	56.52708

Table 5: Estimation Output for Market C
Included observations: 204

	MBRAND 6	MBRAND 15	MBRAND 1	MBRAND 7
MBRAND 6(-1)	0.885345**	0.613382**	0.239299	0.163284
MBRAND 6(-2)	0.303086	0.336796	0.472329***	0.426935***
MBRAND 6(-3)	0.067922	-0.092551	-0.232176	-0.108065
MBRAND 15(-1)	0.054696	0.190186	-0.015379	-0.031212
MBRAND 15(-2)	-0.333362	-0.372390	-0.598846*	-0.488817*
MBRAND 15(-3)	-0.137739	-0.051638	0.021974	-0.006964
MBRAND 1(-1)	-0.208390	-0.081083	0.600009**	0.156619
MBRAND 1(-2)	-0.104294	-0.193304	-0.062160	-0.287446
MBRAND 1(-3)	0.477288*	0.565975**	0.582653**	0.314080
MBRAND 7(-1)	0.239499	0.240920	0.091207	0.617594**
MBRAND 7(-2)	-0.244716	-0.148240	-0.140572	-0.016242
MBRAND 7(-3)	-0.185460	-0.178354	-0.143790	0.057085
C	0.049401*	0.062416**	0.063622**	0.074739**
INC	-0.046866**	-0.050441**	-0.044848**	-0.039837**
DEC	0.043003*	0.038694*	0.047109*	0.054123**
R-squared	0.806801	0.798023	0.798821	0.769064
Adj. R-squared	0.792489	0.783062	0.783918	0.751958
F-statistic	56.37596	53.33935	53.60429	44.95777

Table 6: Estimation Output for Market D
Included observations: 273

	MBRAND 6	MBRAND 1	MBRAND 4	MBRAND 7
MBRAND 6(-1)	0.901276**	0.107366	0.125553	0.096873
MBRAND 6(-2)	0.001513	0.082918	0.053107	0.101523
MBRAND 6(-3)	0.063593	-0.084222	-0.034114	-0.060691
MBRAND 1(-1)	-0.320860	0.391613***	-0.121820	-0.017596
MBRAND 1(-2)	0.093047	0.067140	-0.199977	-0.034750
MBRAND 1(-3)	0.398054***	0.422100***	0.454124*	0.269469
MBRAND 4(-1)	0.563614*	0.304623	0.577566*	0.323760
MBRAND 4(-2)	-0.305848	-0.451613	-0.207157	-0.368006
MBRAND 4(-3)	-0.610913*	-0.474156***	-0.511543***	-0.534779***
MBRAND 7(-1)	-0.190729	0.112660	0.327351	0.504780***
MBRAND 7(-2)	-0.108457	0.011284	0.102912	0.026523
MBRAND 7(-3)	0.368975	0.342238	0.283472	0.548896***
C	0.033713***	0.063606**	0.060453**	0.055510**
INC	-0.041334**	-0.041206**	-0.039148**	-0.040412**
DEC	0.055316**	0.054239**	0.057937**	0.059818**
R-squared	0.846124	0.819455	0.830372	0.834797
Adj. R-squared	0.837774	0.809658	0.821168	0.825833
F-statistic	101.3339	83.64318	90.21280	93.12254

Table 7: Estimation Output for Market E
Included observations: 273

	MBRAND 6	MBRAND 1	MBRAND 4	MBRAND 7
MBRAND 6(-1)	0.716028**	0.141059	0.326925	0.275439
MBRAND 6(-2)	-0.421917***	-0.436727***	-0.523668***	-0.516983***
MBRAND 6(-3)	0.066792	-0.043934	-0.150832	-0.139730
MBRAND 1(-1)	-0.215669	0.186943	-0.088089	-0.071079
MBRAND 1(-2)	-0.096375	0.104198	-0.132405	-0.214872
MBRAND 1(-3)	0.532849**	0.482083*	0.547909**	0.555085**
MBRAND 4(-1)	0.163525	0.182866	0.349678	0.024599
MBRAND 4(-2)	0.045178	0.010125	0.261010	0.129875
MBRAND 4(-3)	0.242379	0.210372	0.159332	0.218646
MBRAND 7(-1)	0.261777	0.358868	0.304631	0.656375*
MBRAND 7(-2)	0.173005	0.047339	0.108513	0.311399
MBRAND 7(-3)	-0.564965***	-0.403950	-0.299179	-0.368657
C	-0.014586	0.023089	0.008707	0.004594
INC	-0.050561**	-0.040851**	-0.048154**	-0.045759**
DEC	0.064401**	0.066810**	0.064049**	0.063762**
R-squared	0.854946	0.819567	0.835162	0.836804
Adj. R-squared	0.847075	0.809776	0.826218	0.827949
F-statistic	108.6179	83.70645	93.36971	94.49460

Table 8: Estimation Output for Market F
Included observations: 273

	MBRAND 1	MBRAND 8	MBRAND 9	MBRAND 4	MBRAND 7	MBRAND 6
MBRAND 1(-1)	0.122207	-0.531631*	-0.475817*	-0.191424	-0.399310***	-0.331589
MBRAND 1(-2)	0.125213	-0.182892	-0.157863	-0.214488	-0.046199	-0.224681
MBRAND 1(-3)	0.757549**	0.783990**	0.669469**	0.697874**	0.706381**	0.660472**
MBRAND 8(-1)	-0.048138	0.624853	-0.066765	-0.069344	-0.102346	-0.014310
MBRAND 8(-2)	0.051922	0.088944	-0.109082	-0.001776	0.026540	-0.047577
MBRAND 8(-3)	-0.191061	-0.176316	-0.067192	-0.116295	-0.121141	-0.146796
MBRAND 9(-1)	0.185217	0.174803	0.607887	0.153719	0.136349	0.226693
MBRAND 9(-2)	-0.323873	-0.355245	-0.267205	-0.403290	-0.426184***	-0.366530
MBRAND 9(-3)	0.074895	0.204689	0.268250	0.072573	0.148366	0.139706
MBRAND 4(-1)	0.734987**	0.773779**	0.793838**	1.121559**	0.970683**	0.740673**
MBRAND 4(-2)	0.222148	0.402353	0.369430	0.425300	0.225765	0.458643
MBRAND 4(-3)	-0.202577	-0.243399	-0.199203	-0.168170	-0.158548	-0.190283
MBRAND 7(-1)	-0.349151	-0.446440***	-0.385315	-0.377957	-0.053777	-0.520119*
MBRAND 7(-2)	-0.273921	-0.256139	-0.215006	-0.193089	-0.122772	-0.240851
MBRAND 7(-3)	-0.362325	-0.382420	-0.363057	-0.331811	-0.343731	-0.290459
MBRAND 6(-1)	0.158714	0.296304	0.441669	0.221174	0.318098	0.796859**
MBRAND 6(-2)	-0.031775	-0.036273	0.046386	0.097798	0.023289	0.122870
MBRAND 6(-3)	0.119893	0.015498	-0.098206	0.055035	-0.012456	0.028226
C	0.051080**	0.032271***	0.027800	0.044089**	0.050540**	0.020262
INC	-0.045692**	-0.044569**	-0.048678**	-0.042323**	-0.048114**	-0.046396**
DEC	0.065961**	0.056115**	0.064309**	0.073679**	0.066476**	0.068352**
R-squared	0.816532	0.820468	0.849738	0.830708	0.827941	0.849775
Adj. R-squared	0.801971	0.806219	0.837812	0.817273	0.814285	0.837853
F-statistic	56.07685	57.58242	71.25350	61.82781	60.63054	71.27428

Table 9: Estimation Output for Market G
Included observations: 273

	MBRAND 1	MBRAND 2	MBRAND 9	MBRAND 7
MBRAND 1(-1)	0.580905*	0.119167	0.148912	0.149660
MBRAND 1(-2)	-0.288063	-0.259413	-0.296924	-0.273522
MBRAND 1(-3)	0.465610*	0.431692***	0.398217	0.457183***
MBRAND 2(-1)	-0.169156	0.319959	0.107031	-0.147787
MBRAND 2(-2)	-0.350018	-0.400083	-0.323241	-0.427312
MBRAND 2(-3)	0.073053	0.393700	0.120606	0.055654
MBRAND 9(-1)	0.491244*	0.491617***	0.736351**	0.607128*
MBRAND 9(-2)	0.026582	0.130712	0.176751	0.041215
MBRAND 9(-3)	-0.243798	-0.419570***	-0.236028	-0.329948
MBRAND 7(-1)	0.014577	0.040282	-0.043087	0.334189
MBRAND 7(-2)	0.320209	0.263477	0.197813	0.397884***
MBRAND 7(-3)	-0.057041	-0.193622	-0.067017	0.041735
C	0.048101*	0.009518	-0.001837	0.028456
INC	-0.045026**	-0.041945**	-0.044674**	-0.042655**
DEC	0.057411**	0.057808**	0.054311**	0.055327**
R-squared	0.859490	0.865904	0.868689	0.863987
Adj. R-squared	0.851866	0.858627	0.861563	0.856607
F-statistic	112.7266	118.9996	121.9141	117.0632

Table 10: Estimation Output for Market H
Included observations: 273
endpoints

	MBRAND 1	MBRAND 4
MBRAND 1(-1)	0.427557	0.010474
MBRAND 1(-2)	-0.427886	-0.618439*
MBRAND 1(-3)	0.784618**	0.667160**
MBRAND 4(-1)	0.506964***	0.940811**
MBRAND 4(-2)	0.183140	0.372044
MBRAND 4(-3)	-0.622454*	-0.508608*
C	0.035876**	0.031752**
INC	-0.041766**	-0.036993**
DEC	0.053488**	0.053633**
R-squared	0.826716	0.843625
Adj. R-squared	0.821465	0.838887
F-statistic	157.4384	178.0315

Table 11: Estimation Output for Market I

Included observations: 273

	MBRAND 1	MBRAND 2	MBRAND 7
MBRAND 1(-1)	1.493563**	1.129233**	1.281337**
MBRAND 1(-2)	-0.128469	-0.102046	0.017513
MBRAND 1(-3)	-0.086581	-0.036888	-0.450067
MBRAND 2(-1)	0.112092	0.396708	0.052266
MBRAND 2(-2)	0.384431	0.371256	0.336444
MBRAND 2(-3)	0.155309	0.274311	0.316824
MBRAND 7(-1)	-0.688663*	-0.645741*	-0.444169
MBRAND 7(-2)	-0.529370	-0.497362	-0.629892***
MBRAND 7(-3)	0.131930	-0.031725	0.355645
C	0.064330**	0.046451**	0.069526**
INC	-0.047414**	-0.050731**	-0.051124**
DEC	0.060276**	0.061955**	0.062269**
R-squared	0.855494	0.865561	0.849494
Adj. R-squared	0.849404	0.859895	0.843150
F-statistic	140.4683	152.7632	133.9222

Table 12: Estimation Output for Market J

Included observations: 251

	MBRAND 1	MBRAND 9	MBRAND 4	MBRAND 7
MBRAND 1(-1)	0.841286	0.701049	0.835746	0.826801
MBRAND 1(-2)	0.703325	0.724763	0.638621	0.406308
MBRAND 1(-3)	0.398421	0.034211	0.357980	0.208618
MBRAND 9(-1)	0.240969	0.613578**	0.140789	0.246059
MBRAND 9(-2)	-0.126313	-0.013067	-0.091245	-0.131298
MBRAND 9(-3)	-0.149492	-0.081410	-0.141594	0.027807
MBRAND 4(-1)	-0.392922	-0.687863	-0.359004	-0.632458
MBRAND 4(-2)	-0.786268	-0.861958	-0.769734	-0.533408
MBRAND 4(-3)	0.315536	0.519825	0.328493	0.334960
MBRAND 7(-1)	0.108816	0.210870	0.197665	0.438811
MBRAND 7(-2)	0.064807	0.014555	0.046990	0.059788
MBRAND 7(-3)	-0.345645	-0.256923	-0.313073	-0.361365
C	0.039067***	-0.000878	0.036820***	0.037539***
INC	-0.061322**	-0.064380**	-0.060003**	-0.057764**
DEC	0.058406**	0.057685**	0.058373**	0.059003**
R-squared	0.867335	0.875097	0.864050	0.872851
Adj. R-squared	0.859465	0.867688	0.855985	0.865308
F-statistic	110.2081	118.1049	107.1379	115.7203

Table 13: Estimation Output for Market K
Included observations: 121

	MBRAND 1	MBRAND 14	MBRAND 4	MBRAND 7
MBRAND 1(-1)	0.603795	-0.169631	-0.173321	-0.173680
MBRAND 1(-2)	0.097588	0.264009	-0.056642	0.248122
MBRAND 1(-3)	-0.138916	-0.019968	0.222423	-0.227868
MBRAND 14(-1)	0.111914	0.359180	-0.113185	-0.040974
MBRAND 14(-2)	0.631913	0.569440	0.757005	0.536003
MBRAND 14(-3)	-0.267203	-0.159327	-0.585524	-0.352018
MBRAND 4(-1)	0.672756***	0.977717**	1.429741**	0.733231***
MBRAND 4(-2)	-1.082744*	-1.081535*	-1.216627**	-1.152718*
MBRAND 4(-3)	-0.100292	0.070199	0.328975	0.151971
MBRAND 7(-1)	-0.309580	-0.063517	-0.037005	0.556940
MBRAND 7(-2)	0.138522	-0.010726	0.258327	0.153460
MBRAND 7(-3)	0.498303	0.117748	0.043810	0.414754
C	0.035638**	0.034301**	0.031773*	0.038056**
INC	-0.029451*	-0.025686***	-0.024615***	-0.028952*
DEC	0.021065	0.022423	0.024476	0.013751
R-squared	0.845732	0.846469	0.850297	0.846641
Adj. R-squared	0.825358	0.826191	0.830525	0.826387
F-statistic	41.50843	41.74385	43.00480	41.79932

Table 14: Estimation Output for Market L

Included observations: 162

	MBRAND 6A	MBRAND 6B	MBRAND 1A	MBRAND 1B	MBRAND 3	MBRAND 4	MBRAND 7	MBRAND 13
MBRAND 6A(-1)	0.315799	0.172126	-0.029874	-0.029916	0.317389	0.097471	0.045575	0.044714
MBRAND 6A(-2)	-0.187909	-0.113807	-0.386555	-0.218667	-0.288438	-0.310426	-0.370004	-0.353548
MBRAND 6A(-3)	-0.139966	-0.020684	0.113050	-0.048252	0.013563	0.007283	-0.129770	0.181062
MBRAND 6B(-1)	0.688047	0.754804	0.490398	0.540008	0.245840	0.305294	0.450738	0.280915
MBRAND 6B(-2)	-0.132118	-0.170146	-0.025142	-0.044742	0.006068	-0.055468	-0.029888	0.056250
MBRAND 6B(-3)	0.863453*	0.767202	0.598135	0.700626	0.555547	0.771558	0.848359	0.478813
MBRAND 1A(-1)	0.025040	0.014516	0.463970	0.116073	0.073387	0.173137	0.008697	0.214108
MBRAND 1A(-2)	-0.339875	-0.263348	-0.064589	-0.369474	-0.400696	-0.349055	-0.341645	-0.301316
MBRAND 1A(-3)	0.620224	0.506448	0.671628*	0.688171*	0.590198	0.632174*	0.637601	0.449935
MBRAND 1B(-1)	-0.189269	-0.193844	-0.198152	-0.007201	-0.407816	-0.522968	-0.427051	-0.602386
MBRAND 1B(-2)	0.267601	0.459756	0.420571	0.569990	0.667261	0.536503	0.622692	0.764069
MBRAND 1B(-3)	-0.671501	-0.718083	-0.856250*	-0.805297*	-0.776417	-0.821260*	-0.836082	-0.891848*
MBRAND 3(-1)	-0.201965	-0.190545	-0.110445	-0.216328	0.253045	0.058079	-0.121273	-0.242913
MBRAND 3(-2)	0.354861	0.379385	0.389850	0.392172	0.303962	0.330037	0.358888	0.447747
MBRAND 3(-3)	-0.764478**	-0.773190**	-0.899458**	-0.872551**	-0.639140**	-0.964656**	-0.925382**	-0.657786**
MBRAND 4(-1)	0.190010	0.159080	0.082492	0.186771	0.155543	0.450607	0.337760	0.119070
MBRAND 4(-2)	0.012940	-0.140809	-0.116015	-0.115048	-0.199241	0.033080	-0.113642	-0.356720
MBRAND 4(-3)	0.139993	0.325495	0.268832	0.244442	0.343979	0.189921	0.275978	0.303898
MBRAND 7(-1)	-0.179238	-0.103369	-0.062692	-0.011043	-0.047458	0.085435	0.309379	0.197245
MBRAND 7(-2)	0.345689	0.221730	0.257163	0.269439	0.222020	0.259813	0.278662	0.107326
MBRAND 7(-3)	-0.029990	-0.031362	-0.005916	-0.023223	-0.003667	0.059437	0.097959	0.045914
MBRAND 13(-1)	0.297813	0.324590	0.317021	0.353240	0.322351	0.280132	0.328599	0.869490**
MBRAND 13(-2)	-0.565749*	-0.601541*	-0.742060**	-0.734383**	-0.575600*	-0.720582**	-0.657797*	-0.582745*
MBRAND 13(-3)	0.116481	0.066459	0.242308	0.250816	0.076480	0.287397	0.168016	0.233084
C	-0.000478	0.001947	0.022473	0.021971	-0.001314	0.026049	0.026390	0.018669
INC	-0.049807**	-0.046817**	-0.042038**	-0.045703**	-0.047299**	-0.042772**	-0.053036**	-0.045676**
DEC	0.043089**	0.039658*	0.049865**	0.051843**	0.050789**	0.051216**	0.039984***	0.050628**
R-squared	0.860432	0.854688	0.860935	0.865482	0.847941	0.860423	0.837219	0.835139
Adj. R-squared	0.833552	0.826702	0.834152	0.839575	0.818656	0.833542	0.805869	0.803388
F-statistic	32.01037	30.53987	32.14487	33.40710	28.95436	32.00800	26.70524	26.30271

Table 15: Estimation Output for Market M
Included observations: 153

	MBRAND 6	MBRAND 1	MBRAND 8	MBRAND 7A	MBRAND 7B
MBRAND 6(-1)	0.725314***	0.299827	0.369238	0.238527	0.623846
MBRAND 6(-2)	-0.515515	-0.431809	-0.523739	-0.610563	-0.521317
MBRAND 6(-3)	0.097178	0.334867	0.132935	0.112304	0.235093
MBRAND 1(-1)	0.277314	0.678320**	0.178522	0.204195	0.206360
MBRAND 1(-2)	-0.059767	0.138643	-0.009687	0.024608	-0.164683
MBRAND 1(-3)	-0.018823	0.047230	-0.002747	0.019803	-0.013229
MBRAND 8(-1)	0.361699	0.179722	0.804787**	0.210505	0.068438
MBRAND 8(-2)	-0.056552	0.049162	-0.075656	0.050877	-0.029052
MBRAND 8(-3)	0.037204	-0.048253	0.041517	0.011005	-0.032000
MBRAND 7A(-1)	-0.368987	-0.036178	-0.294314	0.210662	-0.186249
MBRAND 7A(-2)	-0.168632	-0.139580	-0.089758	-0.047414	-0.036168
MBRAND 7A(-3)	-0.085989	-0.251491	-0.212484	-0.094142	-0.101147
MBRAND 7B(-1)	-0.063970	-0.231471	-0.149956	0.061953	0.192355
MBRAND 7B(-2)	0.469952***	0.123112	0.349256	0.261066	0.429439
MBRAND 7B(-3)	0.235078	0.119815	0.303876	0.204308	0.149563
C	-0.006977	0.067207	0.002423	0.022648	0.057852
INC	-0.058025**	-0.056901**	-0.064117**	-0.054195**	-0.051919**
DEC	0.076865**	0.078625**	0.064917*	0.074719**	0.075535*
R-squared	0.809439	0.824873	0.774857	0.786922	0.776653
Adj. R-squared	0.785442	0.802819	0.746506	0.760090	0.748528
F-statistic	33.73140	37.40396	27.33059	29.32773	27.61415

Table 16: Estimation Output for Market N

Included observations: 192

	MBRAND 6	MBRAND 1	MBRAND 2	MBRAND 9	MBRAND 4	MBRAND 7A	MBRAND 7B	MBRAND 12
MBRAND 6(-1)	0.673132*	0.162975	0.031396	0.533119***	0.284377	0.276865	0.243354	0.265974
MBRAND 6(-2)	-0.248070	-0.328867	-0.456603	-0.469018	-0.438622	-0.327913	-0.262057	-0.546425*
MBRAND 6(-3)	0.039535	-0.020117	0.107483	0.141247	0.029475	0.030440	-0.010516	0.008301
MBRAND 1(-1)	-0.469115	-0.040862	-0.718744*	-0.656307*	-0.590316***	-0.650252*	-0.514601	-0.467413
MBRAND 1(-2)	0.372348	0.461933	0.222800	0.564834	0.511928	0.374781	0.197874	0.114881
MBRAND 1(-3)	0.227673	0.582771***	0.536327	0.359107	0.262048	0.364662	0.360557	0.531938***
MBRAND 2(-1)	-0.064276	-0.027677	0.437157*	0.076265	0.005905	-0.007259	-0.020493	-0.043989
MBRAND 2(-2)	0.040447	0.016102	-0.021295	0.083807	0.047815	0.057633	0.069706	0.046337
MBRAND 2(-3)	-0.023677	-0.018993	0.311625	-0.063799	-0.025084	0.002633	0.038135	0.042176
MBRAND 9(-1)	0.512488***	0.537016*	0.536301*	0.656795*	0.505794*	0.592621*	0.524752*	0.470465***
MBRAND 9(-2)	-0.054125	0.032220	0.188630	0.224975	0.169595	0.082651	0.069427	0.273355
MBRAND 9(-3)	0.351969	0.337907	0.133162	0.303669	0.269086	0.225074	0.233823	0.109819
MBRAND 4(-1)	-0.101127	-0.156897	-0.094101	0.140002	0.261901	-0.118766	0.066181	-0.162739
MBRAND 4(-2)	0.276660	0.228269	0.031407	0.077469	0.423639	0.207910	0.282301	0.036633
MBRAND 4(-3)	-0.167434	-0.108376	-0.007301	-0.099252	-0.091971	-0.006196	-0.124123	-0.094764
MBRAND 7A(-1)	0.880205*	0.667611*	0.842016*	0.884243*	0.777718*	1.108658**	0.627781***	0.743518*
MBRAND 7A(-2)	-0.768278***	-0.666156***	-0.605455	-0.719529***	-1.025627*	-0.755407***	-0.845170*	-0.483126
MBRAND 7A(-3)	-0.340404	-0.530348	-0.627763	-0.499145	-0.328377	-0.463433	-0.240575	-0.304868
MBRAND 7B(-1)	-0.116558	0.048413	-0.207101	-0.233391	-0.051470	-0.049690	0.274278	-0.052070
MBRAND 7B(-2)	0.123765	-0.105569	0.310760	0.053935	0.010678	0.037294	0.183133	0.055133
MBRAND 7B(-3)	-0.093181	-0.085364	-0.240343	-0.120346	-0.012381	-0.040903	-0.111682	-0.106858
MBRAND 12(-1)	-0.462833	-0.416210	-0.097607	-0.576038*	-0.388437	-0.347945	-0.359168	-0.012863
MBRAND 12(-2)	-0.038741	0.126288	0.014127	-0.105501	0.071008	0.039343	0.041267	0.250823
MBRAND 12(-3)	0.186031	0.046164	0.066698	0.228218	0.085570	0.119999	0.083054	0.043436
C	0.036469	0.059459	0.085267*	0.037915	0.031550	0.042822	0.093178*	0.034763
INC	-0.043020**	-0.041133**	-0.053672**	-0.042183**	-0.030828**	-0.040923**	-0.039881**	-0.046174**
DEC	0.072078**	0.086029**	0.082605**	0.081861**	0.083507**	0.082252**	0.093531**	0.094033**
R-squared	0.803214	0.833633	0.730596	0.814880	0.828199	0.816571	0.827582	0.793477
Adj. R-squared	0.772205	0.807418	0.688144	0.785709	0.801127	0.787667	0.800413	0.760934
F-statistic	25.90281	31.79936	17.21011	27.93509	30.59283	28.25125	30.46054	24.38236

Table 17: Estimation Output for Market O

Included observations: 192

	MBRAND 1	MBRAND 4	MBRAND 7
MBRAND 1(-1)	0.918754*	0.567710***	0.358516
MBRAND 1(-2)	-0.315521	-0.361085	-0.469591
MBRAND 1(-3)	0.291180	0.244309	0.391382
MBRAND 4(-1)	0.310840	0.489681	0.189413
MBRAND 4(-2)	-0.003969	0.156149	-0.045497
MBRAND 4(-3)	-0.142952	-0.095542	-0.169389
MBRAND 7(-1)	-0.290887	-0.144638	0.377796
MBRAND 7(-2)	0.004533	-0.100084	0.187829
MBRAND 7(-3)	0.053667	0.061406	-0.001721
C	0.022838**	0.025639**	0.029285**
INC	-0.042122**	-0.040629**	-0.045611**
DEC	0.062367*	0.062821*	0.054618*
R-squared	0.809176	0.795748	0.771217
Adj. R-squared	0.797514	0.783266	0.757236
F-statistic	69.38870	63.75117	55.16117

Table 18: Estimation Output for Market P

Included observations: 192

	MBRAND16	MBRAND 1	MBRAND 2	MBRAND 7
MBRAND16 (-1)	0.498055**	-0.016077	0.073162	-0.091657
MBRAND16 (-2)	-0.239859	-0.213854	-0.126531	-0.104466
MBRAND16 (-3)	0.048547	-0.114310	-0.168739	-0.181539
MBRAND 1(-1)	-0.113121	0.555218	-0.243721	-0.167093
MBRAND 1(-2)	-0.074104	0.021467	-0.265443	-0.112080
MBRAND 1(-3)	0.201960	0.164614	0.288072	0.218871
MBRAND 2(-1)	0.107452	-0.093105	0.531297**	0.228477
MBRAND 2(-2)	-0.350362***	-0.242236	-0.261645	-0.487330*
MBRAND 2(-3)	0.298657	0.259993	0.270195	0.294503
MBRAND 7(-1)	0.386690	0.433262*	0.585397**	0.980873**
MBRAND 7(-2)	0.241920	0.117633	0.312650	0.357410
MBRAND 7(-3)	-0.324786	-0.124530	-0.252325	-0.193477
C	0.078317**	0.085398**	0.079647**	0.061261**
INC	-0.040526**	-0.050158**	-0.044383**	-0.038152**
DEC	0.068188**	0.056016**	0.049274*	0.053763*
R-squared	0.734114	0.790486	0.806391	0.824629
Adj. R-squared	0.713084	0.773914	0.791077	0.810757
F-statistic	34.90711	47.70090	52.65808	59.44902

Table 19: Estimation Output for Market Q
Included observations: 200

	MBRAND 10	MBRAND 6	MBRAND 1	MBRAND 4	MBRAND 7	MBRAND 11	MBRAND 5
MBRAND 10(-1)	0.327057	0.211579	0.004388	0.067404	-0.028354	0.063259	0.012813
MBRAND 10(-2)	-0.346734	-0.376959	-0.312496	-0.572901*	-0.524841*	-0.463086*	-0.313539
MBRAND 10(-3)	0.254011	0.043239	0.011410	0.233774	0.177588	0.029007	0.172213
MBRAND 6(-1)	0.378549***	0.773424**	0.161186	0.249994	0.355514***	0.205108	0.115361
MBRAND 6(-2)	0.038977	0.120928	0.136363	0.172125	0.136212	0.196831	0.004610
MBRAND 6(-3)	0.101640	0.322300	0.285635	0.116252	0.210410	0.167448	0.186828
MBRAND 1(-1)	-0.241529	-0.203243	0.664541	-0.247298	-0.325604	0.094632	0.074290
MBRAND 1(-2)	0.443344	0.484560	0.353893	0.325722	0.260388	0.176022	0.167078
MBRAND 1(-3)	-0.297506	-0.204308	-0.060104	0.010305	-0.020549	-0.137925	-0.109042
MBRAND 4(-1)	-0.213195	-0.219389	-0.304689	0.309879	-0.034870	-0.167201	-0.371814
MBRAND 4(-2)	0.221955	0.123734	0.114176	0.291682	0.077108	0.026660	0.235667
MBRAND 4(-3)	-0.036982	0.144934	0.234480	0.139069	-0.022407	0.169631	0.101416
MBRAND 7(-1)	0.355823	0.289497	0.226876	0.253780	0.579478*	0.164660	0.429276***
MBRAND 7(-2)	-0.011493	0.050581	0.011395	0.093666	0.359524	0.046094	0.052563
MBRAND 7(-3)	-0.123119	-0.338000	-0.347222	-0.309834	-0.282357	-0.231718	-0.321691
MBRAND 11(-1)	0.287777	0.048940	0.194718	0.253765	0.239864	0.685861**	0.149217
MBRAND 11(-2)	-0.230939	-0.335053	-0.263141	-0.250278	-0.210376	-0.030298	-0.370472
MBRAND 11(-3)	0.097831	0.126991	-0.016096	-0.102323	0.032963	0.093522	0.069752
MBRAND 5(-1)	-0.058574	-0.040513	-0.163380	-0.058253	0.048513	-0.219039	0.317007
MBRAND 5(-2)	-0.371299	-0.376933	-0.334617	-0.369441	-0.390596***	-0.256757	-0.143885
MBRAND 5(-3)	0.106648	0.012210	0.047281	0.052598	0.020271	0.030832	0.149833
C	0.097186**	0.106592**	0.134253**	0.127081**	0.122097**	0.130248**	0.143860**
INC	-0.040713**	-0.045446**	-0.045843**	-0.055461**	-0.042749**	-0.041839**	-0.051826**
DEC	0.05119**	0.060648**	0.056112**	0.058361**	0.057990**	0.061631**	0.054469**
R-squared	0.797275	0.803211	0.794510	0.797673	0.794371	0.790479	0.676280
Adj. R-squared	0.770783	0.777494	0.767656	0.771232	0.767499	0.763099	0.633976
F-statistic	30.09440	31.23293	29.58645	30.16863	29.56130	28.87011	15.98609

Table 20: Estimation Output for Market R
Included observations: 200

	MBRAND 6	MBRAND 1	MBRAND 4
MBRAND 6(-1)	0.470115*	0.192320	0.321453
MBRAND 6(-2)	0.308050	0.159352	0.250977
MBRAND 6(-3)	0.082860	0.106797	0.031794
MBRAND 1(-1)	-0.105898	0.548235	-0.070639
MBRAND 1(-2)	-0.482948*	-0.290906	-0.500657**
MBRAND 1(-3)	0.189038	0.187201	0.177163
MBRAND 4(-1)	0.503965**	0.068958	0.621738**
MBRAND 4(-2)	-0.143619	-0.094467	-0.081164
MBRAND 4(-3)	-0.069938	-0.123987	-0.009191
C	0.142880**	0.228762**	0.214453**
SPOT	-0.056705**	-0.080096**	-0.069425**
INC	-0.049122**	-0.048977**	-0.040300**
DEC	0.045862**	0.049310**	0.050767**
R-squared	0.807288	0.802077	0.803127
Adj. R-squared	0.794922	0.789376	0.790494
F-statistic	65.28019	63.15098	63.57099

Table 21: Estimation Output for Market S
Included observations: 200

	MBRAND 9	MBRAND 4	MBRAND 7	MBRAND 12
MBRAND 9(-1)	0.744428*	0.044431	0.406278	0.608895*
MBRAND 9(-2)	-0.075136	-0.115504	-0.175242	-0.234877
MBRAND 9(-3)	0.490359	0.651493*	0.355563	0.416153
MBRAND 4(-1)	-0.109395	0.601998**	-0.124688	-0.166854
MBRAND 4(-2)	0.036944	0.104143	0.036128	0.040903
MBRAND 4(-3)	0.069310	0.079723	0.067391	0.032932
MBRAND 7(-1)	0.145338	0.113055	0.491452**	0.146897
MBRAND 7(-2)	-0.032484	-0.228661	-0.018233	-0.129560
MBRAND 7(-3)	-0.161193	-0.200064	-0.041760	-0.123383
MBRAND 12(-1)	0.105941	0.103307	0.117985	0.249038
MBRAND 12(-2)	-0.182170	-0.058073	-0.110388	0.092157
MBRAND 12(-3)	-0.267949	-0.354736	-0.218605	-0.208716
C	0.069691*	0.121252**	0.100462**	0.090120*
INC	-0.046474**	-0.032385*	-0.050362**	-0.040782**
DEC	0.056994**	0.059313**	0.043881*	0.053984**
R-squared	0.787351	0.787206	0.772972	0.764231
Adj. R-squared	0.770015	0.769859	0.754464	0.745011
F-statistic	45.41826	45.37910	41.76473	39.76176

Table 22: Estimation Output for Market T

Included observations: 200

	MBRAND 10	MBRAND 1A	MBRAND 1B	MBRAND 1C	MBRAND 8	MBRAND 7
MBRAND 10 (-1)	0.396351***	-0.184175	-0.130124	-0.188058	-0.127986	-0.107569
MBRAND 10(-2)	0.283443	0.336368	0.283152	0.267910	0.236900	0.312979
MBRAND 10 (-3)	-0.102690	-0.190793	-0.218488	-0.182471	-0.364067	-0.353805***
MBRAND 1A(-1)	-0.087580	0.662604	0.103868	0.252946	-0.059735	0.250794
MBRAND 1A(-2)	0.050619	0.034707	-0.037550	0.022773	0.051906	-0.230204
MBRAND 1A(-3)	0.170308	0.281018	0.262484	0.141975	0.245598	0.409874
MBRAND 1B(-1)	0.058424	0.434734	0.821498**	0.317172	0.480524	0.493709***
MBRAND 1B(-2)	-0.007745	-0.195087	0.005830	-0.258531	-0.203660	-0.361513
MBRAND 1B(-3)	-0.259210	-0.393598	-0.403978	-0.342937	-0.405087	-0.287718
MBRAND 1C(-1)	0.495769***	0.234603	0.247315	0.651546*	-0.080614	-0.108709
MBRAND 1C(-2)	-0.600970***	-0.606662***	-0.585604***	-0.394647	-0.549718	-0.519848
MBRAND 1C(-3)	0.372458	0.531031***	0.573141***	0.617045*	0.756659*	0.741936**
MBRAND 8(-1)	0.165018	0.015493	0.058709	0.106450	0.833983**	-0.006781
MBRAND 8(-2)	0.064610	-0.018494	-0.029171	-0.040947	0.086595	0.090607
MBRAND 8(-3)	-0.051656	-0.011589	0.061470	0.028197	0.037545	-0.073260
MBRAND 7(-1)	-0.131229	-0.283210	-0.154665	-0.233932	-0.093069	0.422138
MBRAND 7(-2)	-0.030167	0.158719	0.119742	0.124078	0.008275	0.326586
MBRAND 7(-3)	0.094563	0.004262	-0.072352	0.006960	-0.035757	-0.156156
C	0.055443**	0.044830**	0.047469**	0.051170**	0.042540*	0.048985**
INC	-0.046840**	-0.045311**	-0.040872**	-0.047445**	-0.043442**	-0.049722**
DEC	0.057459**	0.060966**	0.058093**	0.059184**	0.054194**	0.059783**
R-squared	0.800309	0.772880	0.825641	0.797500	0.783051	0.788207
Adj. R-squared	0.777998	0.747504	0.806159	0.774874	0.758811	0.764543
F-statistic	35.86934	30.45651	42.38080	35.24751	32.30387	33.30830

Table 23: Estimation Output for Market U
Included observations: 155
endpoints

	MBRAND 1	MBRAND 4
MBRAND 1(-1)	0.764671**	0.279013***
MBRAND 1(-2)	0.165227	-0.205264
MBRAND 1(-3)	-0.037530	0.161792
MBRAND 4(-1)	0.080894	0.556196**
MBRAND 4(-2)	-0.33869*	0.060109
MBRAND 4(-3)	0.208375	0.069366
C	0.039055**	0.012190
INC	-0.042134**	-0.049220**
DEC	0.045723**	0.043805**
R-squared	0.794693	0.818775
Adj. R-squared	0.783444	0.808845
F-statistic	70.64148	82.45365

Table 24: Estimation Output for Market V
Included observations: 198

	MBRAND 1	MBRAND 4A	MBRAND 4B	MBRAND 4C
MBRAND 1(-1)	0.399615**	-0.109159	-0.155914	-0.159286
MBRAND 1(-2)	0.260432**	-0.114976	-0.199715	-0.195901
MBRAND 1(-3)	-0.014427	0.069968	0.028102	0.025351
MBRAND 4A(-1)	0.226631**	0.435130**	-0.091697	-0.088534
MBRAND 4A(-2)	-0.007767	-0.216221	-0.246489	-0.242297
MBRAND 4A(-3)	-0.064033	0.542379**	0.443605*	0.433560*
MBRAND 4B(-1)	0.652180	0.780108	1.356001	1.440217
MBRAND 4B(-2)	0.034684	-0.927891	0.479256	0.544965
MBRAND 4B(-3)	0.292767	-0.084260	-1.996590	-1.933393
MBRAND 4C(-1)	0.097221	-0.208890	-0.224502	-0.312246
MBRAND 4C(-2)	-0.396435	0.901990	-0.423971	-0.493247
MBRAND 4C(-3)	-0.493133	-0.244615	1.864458	1.807038
C	-0.006020	0.053771**	0.020856	0.021812
INC	0.000925	-0.013451	-0.003737	-0.003308
DEC	-0.001742	0.053110*	0.050226*	0.051397*
R-squared	0.987792	0.777275	0.805634	0.803671
Adj. R-squared	0.986858	0.760236	0.790764	0.788651
F-statistic	1057.619	45.61715	54.18005	53.50784

Table 25: Estimation Output for Market W

Included observations: 198

	MBRAND 1	MBRAND 7
MBRAND 1(-1)	0.371564*	0.236297
MBRAND 1(-2)	0.048205	-0.386440*
MBRAND 1(-3)	0.468687**	0.246217
MBRAND 7(-1)	0.560134**	0.736629**
MBRAND 7(-2)	-0.336144**	0.045070
MBRAND 7(-3)	-0.271962	-0.053149
C	0.040748**	0.032429**
INC	-0.052340**	-0.045626**
DEC	0.048003**	0.048171**
R-squared	0.798455	0.779549
Adj. R-squared	0.789924	0.770217
F-statistic	93.59457	83.54148

Table 26: Estimation Output for Market X

Included observations: 198

	MBRAND 10	MBRAND 6	MBRAND 1
MBRAND 10(-1)	-0.042202	-0.558911	-0.252694
MBRAND 10(-2)	-0.114766	-0.257705	-0.290199
MBRAND 10(-3)	0.287100	0.208769	0.149372
MBRAND 6(-1)	0.310528*	0.765210**	0.311396*
MBRAND 6(-2)	-0.167997	-0.061665	-0.141952
MBRAND 6(-3)	0.145858	0.320487	0.172519
MBRAND 1(-1)	0.581821*	0.702287**	0.783606**
MBRAND 1(-2)	0.036588	0.035750	0.186846
MBRAND 1(-3)	-0.249650	-0.363270	-0.122216
C	0.028946	0.017333	0.051299**
INC	-0.050846**	-0.044833**	-0.059241**
DEC	0.040094*	0.050845*	0.042585*
R-squared	0.764245	0.771365	0.779373
Adj. R-squared	0.750303	0.757844	0.766325
F-statistic	54.81409	57.04770	59.73196

Table 27: Estimation Output for Market Y

Included observations: 198

	MBRAND 1	MBRAND 2	MBRAND 4	MBRAND 7
MBRAND 1(-1)	0.945170**	0.570009***	0.575731***	0.729080*
MBRAND 1(-2)	-0.281691	-0.243402	-0.265609	-0.345418
MBRAND 1(-3)	-0.108213	-0.337671	-0.302478	-0.166606
MBRAND 2(-1)	0.114501	0.022556	0.039237	0.112108
MBRAND 2(-2)	0.015828	-0.001770	-0.003753	0.049941
MBRAND 2(-3)	0.028270	-0.001156	0.014155	0.066709
MBRAND 4(-1)	-0.181297	-0.021729	-0.030215	-0.303403
MBRAND 4(-2)	0.244348	0.425086	0.415123	0.328908
MBRAND 4(-3)	-0.266857	-0.085917	-0.074096	-0.274123
MBRAND 7(-1)	0.082469	0.385894	0.368343	0.389193
MBRAND 7(-2)	-0.306774	-0.452017	-0.442177	-0.311749
MBRAND 7(-3)	0.539513	0.576646	0.544753	0.542056
C	0.033497**	0.021974***	0.023032***	0.030583**
INC	-0.037127**	-0.036988**	-0.039670**	-0.033409*
DEC	0.055824**	0.055283**	0.055256**	0.054675**
R-squared	0.785177	0.782600	0.784642	0.769397
Adj. R-squared	0.768742	0.765968	0.768166	0.751755
F-statistic	47.77594	47.05464	47.62481	43.61215

Appendix B: Markets Exhibiting Strong Leader-Follower Pricing Patterns.

Market A:
Brands Present: 1, 2, 3, 4, 5
Leader Brand: Brand 2
Followers of Brand 2: 1, 3, 4, 5

Market B:
Brands Present: 1, 4, 7
Leader Brand: Brand 1
Followers of Brand 1: Brands 4, 7

Market F:
Brands Present: 1, 4, 6, 8, 9, 7
Leader Brand: 4
Followers Brand of 4: 1, 6, 7, 8, 9
Leader Brand: 1
Followers of Brand 1: 4, 6, 7, 8, 9

Market G:
Brands Present: 1, 2, 7, 9
Leader Brand: 9
Followers of Brand 9: 1, 2, 7

Market I:
Brands Present: 1, 2, 7
Leader Brand: 1
Followers of Brand 1: 2, 7

Market K:
Brands Present: 1, 4, 7, 14
Leader Brand: 4
Followers of Brand 1: 1, 7, 14

Market N:
Brands Present: 1, 2, 4, 6, 7a, 7b, 9, 12
Leader Brand: 9
Followers of Brand 9: 1, 2, 4, 6, 7a, 7b, 12
Leader Brand: 7a
Followers of Brand 7a: 1, 2, 4, 6, 7b, 9, 12

Market P:
Brands Present: 1, 2, 7, 16
Leader Brand: 7
Followers of Brand 7: 1, 2

Market V:
Brands Present: 1, 4a, 4b, 4c
Leader Brand: 4a
Followers of Brand 4a: 1, 4b, 4c

Market W:
Brands Present: 1, 7
Leader Brand: 7
Follower of Brand 7: 1

Market X:
Brands Present: 1, 6, 10
Leader Brand: 6
Followers of Brand 6: 1, 10
Leader Brand: 1
Followers of Brand 1: 6, 10

Market Y:
Brands Present: 1, 2, 4, 7
Leader Brand: 1
Followers of Brand 1: 2, 4, 7