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Edgeworth Price Cycles in Gasoline: Evidence from the U.S.*

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Abstract

Studies of gasoline prices in multiple countries have found a repeated sequence of asymmetric cycles where a sharp price increase is followed by gradual decreases. This price pattern is linked to Maskin & Tirole's (1988) theoretical duopoly pricing game that produces a similar pattern, Edgeworth price cycles. We examine data on average daily city-level retail gasoline and diesel prices for 355 cities in the U.S. from 2001-2007 using multiple methods to identify price cycles. We show that a relatively small number of U.S. cities concentrated in a number of contiguous upper Midwestern states evidence Edgeworth cycle-like pricing behavior. Within our data set cities tend to either cycle in all years or they do not cycle at all. We examine prices in cycling and non-cycling cites controlling for other factors and find consumers are no worse off, and likely better off, on average, in cycling than non-cycling cities. Finally, unlike previous studies, we find that some vertically integrated (branded) retail gasoline stations are themselves potentially important drivers of the scale and scope of cycling in retail gasoline prices.

JEL Codes: D4, L44, L81

Key Words: Retailing, Petroleum industry, Pricing, Gasoline, Dynamic oligopoly, Edgeworth price cycles

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1 Introduction

A number of recent studies have found a repeating asymmetric, cyclical pattern in retail gasoline prices which can be described as a sharp and relatively large price increase followed by smaller and more gradual price decreases.[1] This type of pricing pattern corresponds with that predicted by Maskin & Tirole (1988) in their theoretical Edgeworth (price) cycle model. Their model examines a sequential pricing game between two firms selling a homogenous good. A large price increase, or "restoration," by one firm is followed by the other firm with subsequent decreases, or "cheating," until the price is close to marginal cost and there is another restoration. This model implicitly suggests some form of price leadership and tacit collusion.

In the recent literature, Edgeworth cycles are typically *identified* in one of two ways: either through (1) "casual empiricism," *i.e.*, eyeballing the data; or (2) a replicable statistical measure. Many of these statistical measures essentially parameterize some portion of the eyeball test, *e.g.*, a description of the median price change or the number of consecutive periods with price decreases relative to consecutive increases. A few papers, including Noel (2007a, 2007b) and Eckert (2002), use a Markov switching model to examine the probability of regime changes, *e.g.*, whether the probability of staying in the price decrease regime is greater or less than the probability of staying in the price increase regime.

One issue in the literature is the competing methods for identifying price cycles and whether the methods lead to the same conclusions. We use multiple parameterizations of the eyeball test as well as a Markov switching model to identify price cycling. These methods generally lead to the same results.

A second issue in the cycling literature is how widespread and persistent price cycling is in the U.S.[1] We examine retail pricing data for 355 cities in the U.S. using daily prices for over a six year period from 2001-2007. Recent studies examining cycling in U.S. cities use significantly

[1] For studies of Edgeworth cycles in gasoline using Canadian data see Eckert (2002), Eckert (2003), Eckert & West (2004a, 2004b), Noel (2007a, 2007b), Atkinson (2009), for studies using Australian data see Wang (2007, 2009).

less data.[2] We show that a relatively small number of U.S. cities evidence Edgeworth cycle-like pricing behavior. Our results confirm that cycling cities are concentrated in a number of contiguous upper Midwestern states: Michigan, Ohio, Indiana, Illinois, Kentucky, and Missouri. We also find that cities tend to either be cycling or not. In other words, within our data set cities tend to either cycle in all years or they do not cycle at all.

The third and largest issue in the cycling literature is what causes cycling. The causes of cycling are generally examined indirectly by examining attributes of cycling cities either on their own or in relation to attributes of non-cycling cities. Recent research on U.S. cities has examined factors such as the concentration of independents (Lewis, 2009a), concentration of independents with convenience stores and number of major brands (Doyle *et al*., 2010), and possible price leadership by independents (Speedway and QuikTrip) in the Midwest (Lewis, 2009b). Using data on ownership concentration, our results suggest that higher concentration of company-owned-and-operated cites is correlated with more cycling.

A related issue that has only been touched upon in recent work is whether cycling is ultimately harmful to consumers. In the research concerning Australia and Canada, cycling has been in a number of cases the outcome of explicit collusion.[3] In papers examining cycling in the U.S., there have been suggestions that cycling is the outcome of price leadership (Lewis, 2009b), which would suggest a lack of competition. Doyle *et al.* (2010) find that cycling tends to occur in markets with mid-level concentration and that cycling cities may have no different prices than non-cycling cities. We examine prices in cycling and non-cycling cites controlling for other factors and find consumers are no worse off, and likely better off, on average, in cycling than non-cycling cities. This is a unique finding and is inconsistent with cycles in the U.S. arising from

[2] Doyle *et al*. (2010) examine one year of data for 115 metropolitan areas. Lewis (2009a) examines 85 cities over 18 months and Lewis (2009b) examines data for 280 cities for somewhat less than 4 years but uses a 3 day moving average of retail prices.

[3] For papers finding Edgeworth cycles resulting from explicit collusion, *see* Wang (2008, 2009), and Erutku & Hildebrand (2010).

tacit collusion unless non-cycling cities are either less competitive or have significantly different costs.

The next section of the paper describes previous papers examining Edgeworth cycles in gasoline. The third section of the paper reviews the data used in this study. The fourth section details our price cycling identification strategies and discusses the results. The fifth section examines possible causes of cycling and possible consumer effects. The sixth section of the paper presents conclusions and recommendations.

2 Literature review

Most prior studies examining Edgeworth cycles in retail gasoline prices have looked at Canadian or Australian data, and in a number of cases cycling is associated with either suggested or confirmed tacit or explicit collusion. Erutku & Hildebrand (2010) examine cartel behavior in Quebec. The gasoline pricing pattern observed in these multiple cities and towns in Quebec had large increases followed by slow price declines. The collusion was explicit (phone calls to set price) during the price increase portion of the cycle but tacit (no communication) during the decreasing portion of the cycle. Similar to the Canadian episode(s), Wang (2008) describes similar cycling and collusion in Ballarat, Australia, in 1999-2000. Using pricing information along with evidence presented at trial, Wang finds that the price cycling pattern was a result of collusion by gas stations. Wang (2007, 2009) examines gasoline prices in Perth, Australia, and also detects price cycles. These cycles seem to be the outcome of a regulation that requires each station to report tomorrow's price to the government today and not deviate from the reported price. Wang concludes that his results highlight the importance of price commitment in tacit collusion.

Other authors have examined Canadian data and found price cycles in at least some of the cities examined, but have not linked cycling explicitly to a lack of competition. Noel (2007b) finds that cycling behavior is more prevalent in cities that have relatively more small firms.

Eckert (2003) makes a similar observation. Noel (2007a) finds that in Toronto price increases tend to be led by the larger firms and price decreases tend to be led by smaller firms. Eckert (2002) shows that the cycles may be caused by asymmetric pass through of wholesale cost shocks. Atkinson (2009) examines prices in Guelph, Ontario, and finds very distinct, recurring price cycles. All these papers generally examine one or two cities, with the exception of Eckert (2003), who looks at 19 Canadian cities.

In terms of evidence of price cycling in U.S. cities, Allvine & Patterson (1974) describe a "yo-yo pattern" (p. 243) in prices for a number of mostly western U.S. cities at various intervals between 1971-1973. The cycles in each city end sometime in 1972 or 1973, which coincided with the lead up to the 1973 oil shortage. Castanias & Johnson (1993) present some summary statistics on price cycles in Los Angeles between 1968-1975 which show a similar pattern. Thus, cycling is not a recent phenomenon.

With more recent U.S. price data, Lewis (2009a) examines the price reaction of cycling and non-cycling cities to the 2005 hurricanes. Using 18 months of data from 2004-2005 covering 85 cities in the Eastern half of the U.S., he finds that price cycling cities are concentrated in the Midwestern U.S. and tend to be associated with higher concentrations of independent gas stations. He also finds that cost changes are passed through more quickly in cities where retail gasoline prices follow an Edgeworth price cycle pattern and no difference in the average retail markup (based on unbranded rack prices) in cycling and non-cycling cities.

Doyle *et al.* (2010) examine 115 U.S. cities for cycling for a one year period from 2000-2001. Lewis (2009b) examines 280 U.S. cities for cycling between 2004-2008 using a three day moving average for prices. Both of these papers note that price cycling is generally concentrated in the Midwest. Doyle *et al*. focus on concentration of independent gas stations with convenience stores and the presence of brands as potential explanations for the prevalence of price cycling. Their main finding is the most concentrated and the least concentrated markets are less likely to cycle. They also find some evidence that cities with at least two major brands present are more

likely to cycle. Doyle *et al.* also find no effect on average retail pricing, *i.e.*, prices in cycling cities are not higher than in non-cycling cities. Lewis (2009b) suggests that price leadership and coordination by independent gas stations with centralized city-wide pricing, Speedway and Quik Trip, generates the cycling pattern in many Midwestern cities. He also examines Speedway data to show that in a number of cities Speedway tends to lead the price increases. Lewis & Noel (forthcoming) examine asymmetric pass through in 90 cities, some cycling and some not, and find that cycling cities have quicker pass through of cost changes from wholesale to retail than non-cycling cities, which is a similar conclusion to Lewis (2009a).

3 Data

We have data on daily average regular grade retail gasoline prices for 355 cities from October 25, 2001, to December 31, 2007. For 20 select cities we also have daily wholesale (rack) prices for branded and unbranded gasoline and diesel fuel. These price data come from the Oil Price Information Service (OPIS). OPIS collects data on retail and wholesale prices in a large number of cities in the U.S. The retail data are generated from a sample of retail outlets that accept fleet/credit cards. In general more than 50 percent of stations in any city are observed on any given day. We subtract the gasoline taxes from the retail data.

One advantage of studying gasoline retailing is that some measures of marginal cost, *e.g.*, wholesale or "rack" prices for branded and unbranded gasoline, are observable to researchers.[4] Variations in wholesale gasoline prices across areas and over time might play a role in explaining retail cycling. Gas stations that purchase branded gas at the rack are owned and operated by individuals who, in essence, operate franchises. Other firms (sometimes the same firms selling branded gasoline, sometimes firms acting purely as distributors) will post unbranded prices for

[4] The wholesale distribution point of gasoline is referred to as the "rack," which is the point at a terminal where trucks obtain gasoline for retail stations.

gasoline that will be sold at stations unaffiliated with a brand. There are, however, two other channels of retail gasoline distribution for which marginal cost are unobserved.

Stations that are owned and operated by a refiner (*i.e.*, completely vertically integrated) "pay" an unobserved transfer price for gasoline. There are also a significant number of "lessee-dealer" stations. These stations are owned by the refiner but are operated by separate entities. These stations pay a dealer tank wagon (DTW) price which is determined by the refiner and unobservable to the public. In addition, the wholesale price paid by different lessee-dealers operating in the same metropolitan area may vary.[5] Thus, at a given time, there may be a number of different wholesale prices across stations within the same region and the marginal cost may change from branded to unbranded over time. It is, therefore, difficult to control for the various types of wholesale prices with the limited observable wholesale prices but for a sample of cities where we have rack prices, we examine the possibility the wholesale prices cause retail price cycles.

In addition, these multiple ownership relationships make examining market structure in cycling cities and non-cycling cities more difficult. In order to examine the relationship between price cycling and the various market attributes of cycling and non-cycling cities, we purchased data from New Image Marketing, Ltd. on brand market shares and ownership structure within the brands. We purchased these data for 29 cities (16 cycling and 13 non-cycling) cities. This market share and ownership information was gathered by conducting a census of gasoline stations in these cities.

4 Retail gasoline price cycles in U.S. cities

4.1 Identifying price cycles

The identification of Edgeworth price cycles begins with reference to the price pattern described in Maskin & Tirole (1988), which is a sharp price increase followed by smaller and

[5] *See* Meyer & Fischer (2004) for an extensive discussion of lessee-dealer pricing and zone pricing.

more sustained price decreases, which together form a saw-tooth pattern. In our sample, some cities' gasoline prices have a pattern very similar to the Edgeworth price cycle pattern and some do not. For example, in Figure 1, we plot the average daily retail price of gasoline in St. Louis, Missouri, and Newark, New Jersey, in 2007. While the two price series have a correlation coefficient of 0.95, St. Louis repeatedly exhibits a saw-tooth pattern while Newark has relatively smooth price trends.

Castanias & Johnson (1993), Eckert (2002), Eckert & West (2004a, 2004b), Wang (2005, 2007, 2008), Noel (2007a, 2007c), and Atkinson (2009), all rely on "casual empiricism"[6] to identify cycling cities, *i.e.*, an eyeball test. While this identification method is not based on a formal statistical rule, these researchers have identified a number of traits in price patterns that suggest an Edgeworth price cycle.

For instance, Castanias & Johnson (1993) make use of positive and negative "runs" (*i.e.*, continuous price changes in the same direction) to describe how Los Angeles gas prices from 1968-75 followed a saw-tooth pattern. Similarly, Eckert (2002) makes use of runs to describe how retail prices in Windsor, Ontario, from 1989-94 followed an asymmetric, cyclical pattern while wholesale prices did not. Eckert & West (2004a) make use of the fact that prices that have Edgeworth cycles will tend to have negative average first differences and less frequent first differences equal to zero. Similarly, Wang (2005) indexes for price rigidity at specific gas stations using the average number of days in which a station's price does not change. Noel (2007a, 2007c) uses a Markov switching model to classify prices as either on the upswing portion (*i.e.*, relenting phase) or downswing portion (*i.e.*, undercutting phase) of an Edgeworth cycle.

More recent research has identified cycling cities using either a statistical measure that parameterizes some portion of the Edgeworth pattern or estimating transition probabilities. Eckert (2003) counts the number of first differences in retail prices that are equal to zero. Cities with a relatively low count of zeros are considered price cycle cities. Lewis (2009a, 2009b) uses the

[6] This is the term used by Eckert & West (2004a).

median value of retail price changes to detect price cycles. Cities with a median less than -0.2 cents (Lewis, 2009a) are considered price cycle cities. Doyle *et al*. (2010) also use the median value of retail price changes but use a more stringent cutoff of -0.5 cents. Finally, Noel (2007b) uses a Markov switching model based on transition probabilities to classify a city-period as cycling or non-cycling.

In determining the best approach to identify cycling cities, we focus on two principal characteristics of Edgeworth cycles: (i) frequent price decreases relative to increases and (ii) smaller price decrease amounts relative to increase amounts. To that end, we use three statistical measures to encapsulate these characteristics. *First*, we average the ratio of days with a price decrease to days with a price increase across all the cycles within a city over the sample period, *i.e*., the ratio of down-to-up days, where higher values suggest an Edgeworth pattern.[7] *Second*, we average the ratio of the average daily price increase amount to the average daily price decrease amount across all the cycles within a city over the sample period, *i.e*., the ratio of price increases-to-decreases, where a higher (absolute) value suggests an Edgeworth pattern. *Third*, like Doyle *et al*. (2010) and Lewis (2009a, 2009b), we calculate the median change in the daily price, where lower values suggest an Edgeworth pattern.

In addition to the statistical measures, we use a Markov switching model based on Neftçi (1984) where we estimate two transition probabilities: (a) the probability of three continuous days of price increases and (b) the probability of three continuous days of price decreases. If (a) < (b) and the two probabilities are significantly different, then the city is considered a cycling city under the Markov approach.[8]

[7] We define a price cycle as a period when there is a price increase, or increases, followed by either a price decrease(s) or no change(s) in price. After observing at least one price decrease, whenever the next price increase occurs, then a new cycle begins.
[8] *See* the Appendix for details on the Markov switching model.

4.2 The extent of retail gasoline price cycles in the U.S.

In order to use information from all three statistical measures, we first calculated an overall rank for each of the 355 cities based on the average rank across the three measures, *i.e.*, the ratio of down-to-up days, the ratio of price increases-to-decreases, and the median change in the daily price.[9] In Table 1, we list the top 10 percent of the cities in the sample that best conform to a price cycle pattern using the overall rank measure. Of these 35 cities, 10 are in Ohio (out of 15 total Ohio cities in the sample); 8 in Indiana (out of 13); 8 in Michigan (out of 9); 3 in Kentucky (out of 7); 2 in Missouri (out of 6); 2 in Illinois (out of 10); 1 in Kansas (out of 4); and 1 in Minnesota (out of 6). Overall, over a quarter of the cities in the top 10 percent are located in Ohio, and almost three-quarters of the cities in the top 10 percent are in Ohio, Indiana, or Michigan, all Midwest states. However, it is important to note that not all the cities in the states listed in Table 1 are classified as cycling cities. Specifically, the 35 cities in Table 1 represent exactly half of the total number of cities in our sample in the states listed in Table 1.[10]

Second, we address a question that prior research has been unable to answer given data limitations (*i.e.*, sample periods that are less than a year or two): do cities go in and out of price cycles? Table 2 takes the overall rank for the 35 cities in Table 1 and also presents the yearly rank for each city. This gives us six full years and a partial year (2001). Generally, the rank of the cities with regard to a cycling pattern stays relatively the same across the years. For instance, Indianapolis, Indiana, is the top cycling city in the overall sample and is in the top 5 each year. The other cities in the overall top 6 tend to remain in the yearly top 10 with some exceptions near the end of the sample. The overall top 7 through 15 cities tend to remain in the yearly top 25 with

[9] It should be noted that the median price change measure, which is the most prevalent of the three measures in the prior literature, is the least correlated with the other measures in terms of city rank. It has a correlation coefficient with the ratio of down-to-up days and the ratio of price increases-to-decreases of 0.73 and 0.49, respectively, for the 35 cities in Table 1. The correlation coefficient between the ratio of down-to-up days and the ratio of price increase-to-decrease is 0.86.

[10] Of the other 35 cities (not listed in Table 1) in the eight states, 25 are ranked in the top 25% while 30 are in the top 50%. The remaining 5 cities in the bottom 50% of the ranking are generally located on the border of non-cycling states or, in the case of Columbia, MO, right in the middle of the state given that Missouri borders Illinois and Kansas. The one exception is Topeka, KS, which is close to Kansas City, KS, which is ranked in the top 15%.

only a few exceptions. The remaining 20 cities tend to have a slightly higher yearly variance, but only marginally so.[11] Nonetheless, there are some notable movements in rank. Louisville, Kentucky, ranked as low as 28 in 2002 and as high as 2 in 2006. Similarly, Lexington, Kentucky, ranked as low as 30 in 2002 and as high as 1 in 2006. Wichita, Kansas, is ranked 27 overall but reached as high as 10 in 2006.[12] Even given these exceptions, there is arguably a remarkable degree of stability in price cycling patterns in these cities. Over the sample period, the annual average price of regular gasoline increased from $1.42 to $2.80 per gallon, yet the cities that had price cycles in 2001/2002 generally continued to have price cycles in 2007. There are no instances where a city went permanently from cycling to non-cycling, and *vice versa*, in a meaningful way.

One shortcoming of the above statistical approach is that there is no natural test (beyond an arbitrary cutoff value) to classify a city as cycling versus non-cycling. While this fact reflects the reality that cycling patterns range from an almost perfect Edgeworth cycle shape to an almost completely flat shape, it does not make for tractable analyses. On the other hand, the Markov switching model does lend itself to a natural test to determine whether a city is cycling or not. We identify a city as cycling if the probability of a negative run is greater than a positive run at the 10 percent level.[13] Figure 2 shows the percentage of cycling cities, identified by the Markov model, in each state relative to non-cycling cities. As shown on the map, most cycling cites identified by the Markov model are also in the Midwest, with three quarters of the cities in Michigan, Ohio, Indiana, and Illinois classified as cycling cities. There are also a high percentage of cycling cities

[11] The average standard deviation for the top 15 cities (across all the full years, 2002-2007) is 5.0 while the remaining 20 cities have a standard deviation of 6.3.

[12] These three cities, Louisville, KY; Wichita, KS; and Lexington, KY, represent the cities with the most variability in year to year rank in Table 2. The explanation for the variability somewhat differs between the three cities. For Louisville, KY, all three rank criteria have similar yearly variance. For Wichita, KS, and Lexington, KY, the rank criterion based on the ratio of ratio of down-to-up days stands out as the most important source of variation.

[13] More conservative tests would be a requirement of statistical significance at the 5 percent or 1 percent levels.

in West Virginia and Kentucky. With the exception of West Virginia, these are the same states which were identified in Table 1 using the more traditional, statistical approach.[14]

4.3 Cycling in select cities

In Table 3, we list the 20 cities for which we have wholesale and retail price data and characterize each city's retail price change patterns. Specifically, the first column provides the city's rank relative to the other cities in the larger 355 city data set. The table details the statistical characteristics of price cycles for each city over the entire sample period. We define a price cycle as a period when there is a price increase, or increases, followed by either a price decrease(s) or no change(s) in price. After observing at least one price decrease, whenever the next price increase occurs, then a new cycle begins.

For example, in Minneapolis(-St. Paul), Minnesota, the average price cycle lasted 8.6 days where prices increased an average of 2.1 days while prices decreased an average of 6.6 days. Thus, days with a price decrease outnumbered days with a price increase by a factor of 3.2. In absolute value, the average daily price increase was 3.6 times greater than the average daily price decrease. The median price change in Minneapolis was -0.95 cents. The average price, excluding all taxes, over the sample period was 160 cents.

In contrast, the average price cycle in Seattle(-Bellevue-Everett), Washington, lasted 6.7 days with approximately an equal number of days with an increase as with a decrease. In absolute value, the average price increase was only 1.1 times greater than the average price decrease. The median price change was -0.03 cents. The average price, excluding taxes, was 170 cents.

The results from Table 3 indicate that retail prices in Minneapolis(-St. Paul), St. Louis, Cleveland(-Lorain-Elyria), and Louisville have retail price patterns that are descriptively similar to Edgeworth price cycles. Each city has: (1) ratios of down to up days over 2.0; (2) ratios of

[14] Using the traditional approach, while outside of the top 10%, 3 of the 6 cities in West Virginia are ranked in the top 25%.

average daily price increases to decreases over 3.0 in absolute value; and (3) median daily price changes below -0.60 cents. Consequently, all four cities would be considered Edgeworth price cycle cities based on the cut-off for median price changes used in previous studies, *i.e.*, Doyle *et al.* (2010) and Lewis (2009b). The next two cities on the list in order of the cycling criteria are Detroit and Chicago. These two cities would not be cycle cities under the median first difference criteria used by Doyle *et al.* (2010) but would for Lewis (2009b).

We examined these twenty cities out of the 355 cities on which we have retail data because we were able to obtain detailed wholesale (rack) prices for these cities. We wanted to determine to what extent wholesale prices may be contributing to or causing retail price cycles. The last column of Table 3 presents the median unbranded rack price change for each city. In all cities the median unbranded rack price change was zero (rounded to two decimal points). The median price change for branded wholesale prices was zero as well.[15]

Using the Markov model to estimate transition probabilities, we see a similar ranking for the cycling cities. Table 4 shows the transition probabilities for the 20 select cities for regular and premium gasoline prices as well as diesel prices. The top four of the 20 cycling cities shown on Table 3, Minneapolis, St. Louis, Cleveland, and Louisville, have the lowest Wald *p*-values in Table 4, meaning the probability of cycling, greater runs of negative price changes, is the highest. The next two highest *p*-values are for Detroit and Chicago. Again, this mirrors the results in Table 3. An advantage of using the Markov model is the test giving the level of confidence to reject that the transition probabilities are the same.

The transition probabilities for premium gasoline are very similar to regular gasoline. The same six cities show cycling behavior in premium prices. This may not be surprising since many

[15] We also investigated whether controlling for wholesale prices in the 20 select cities explained the heterogeneous price patterns across the cities. First, we examined margins for both branded and unbranded gasoline and found that cities with price cycles also had margins that looked like Edgeworth cycles, which suggests that wholesale prices could not explain retail price cycling. Second, we examined the cycling patterns of residuals from numerous regressions controlling for various measures of wholesale prices and lags of wholesale prices. Again, cities with price cycles also had residuals that looked like Edgeworth cycles, although in some cases slightly diminished.

stations move the pricing of the three different octanes of gasoline in tandem. It is interesting, however, that retail diesel prices do not cycle in any of the twenty cities and, in general, the transition probabilities of three negative or three positives are very similar for these cities. The lack of retail diesel price cycles may be due to the fact that diesel sales are a small percentage of fuel sales at most gasoline stations and convenience stores.[16]

5 Explaining the presence of retail gasoline price cycles: station ownership characteristics

Several recent studies have examined the role that station characteristics (*e.g.*, Doyle *et al.*, 2010) or ownership structure (*e.g.*, Noel, 2007b; Lewis, 2009a) play in explaining the presence of retail gasoline price cycling. The latter studies focus primarily on the influence that "independents," *i.e.*, gasoline stations (or networks thereof) that are not affiliated with a refiner's brand. In general, these studies find that a larger number or proportion of independent stations in a local market correlates with the presence of price cycling and that these players tend to be the firms that initiate and "lead down" the market during the undercutting phase of the cycle.

While the presence or concentration of independent gasoline stations may be an important determinant of gasoline price cycling, it is possible that the concentration of branded (or vertically integrated) stations also plays a significant role. In particular, it may be the case that although independent stations tend to drive undercutting, integrated stations might largely explain the other side of the coin: namely, initiation of the relenting phase. The ability to lead market prices upwards after hitting the bottom of a cycle may be a function of being able to set prices simultaneously at a large number of stations.

Refiners set the retail prices posted at their branded retail stations either directly (via their company owned and operated stations) or indirectly through their setting of the DTW to lessee-

[16] The National Association of Convenience Stores (NACS) reports that in 2008 diesel sales were eight percent of fuel sales at convenience stores. *See* <http://www.nacsonline.com/NACS/News/FactSheets/Motor%20Fuels/Pages/MotorFuelSales.aspx>.

dealers. Higher concentrations (or a larger network) of these types of *branded* retail stations may *also* be required (*i.e.*, in addition to independent stations) to drive any retail cycling behavior. Furthermore, failing to account for the role of branded stations may lead one to overestimate the true effect that independent stations exert on explaining the presence of retail price cycling across areas. This section explores the relative contributions that independent versus integrated gasoline stations play in determining the presence of city-level retail gasoline price cycling.

We obtained data on the proportion of city-level retail gasoline sales made through stations of various ownership structures from New Image Marketing, Ltd. for 29 metropolitan areas (16 cycling and 13 non-cycling).[17] The following ownership structures/groups, indexed by O, are reflected in these data: (1) branded company owned and operated sites; (2) independent and branded jobber sites; and (3) lessee-dealer sites.[18] Let $s_{i,O}^{(f)} \in (0,1]$ denote the share of total retail gasoline sales made in city i through stations of "flag" (or brand) $f = 1,\ldots,F$ that are operated under ownership structure O.[19] Define

$$HHI_{i,O} = \sum_{f=1}^{F} (s_{i,O}^{(f)})^2 \in (0,1] \tag{1}$$

as the Herfindahl-Hirschman Index (HHI) of "within-group" (*i.e.*, stations of type O) retail gasoline sales in city i. The possible values of $HHI_{i,O}$ range from a maximum of 1.0 to a

[17] It was not possible to obtain the New Image data for the same year for all 29 cities. For 25 of the cities the census is from 2000 or 2001 with the remainder in 1999. Since the cities were consistently cycling and the brand and ownership shares tend to be stable, we do not see this limitation as problematic.
[18] Separate data for independent and branded jobber sites are not available.
[19] For example, in a given city i we might observe the following combinations of flags and ownership structures:

$$\{f = Shell; O = company\text{-}owned\text{-}and\text{-}operated\} \text{ (group 1)},$$

$$\{f = Chevron; O = jobber\} \text{ (group 2)},$$

$$\{f = Thrifty; O = independent\} \text{ (group 2)},$$

$$\{f = Chevron; O = lessee\text{-}dealer\} \text{ (group 3)}.$$

minimum based on the specific distribution of the relevant flag shares. The $HHI_{i,O}$ increases (approaches one) as the as the number of flags decreases or the disparity in the size between flags (holding the number of flags constant) increases.

Using the above HHIs we estimate the following cross-sectional probit regression:

$$\Pr(Cycle_i = 1) = \Phi(\alpha + \sum\nolimits_O \beta_O HHI_{i,O} + \Gamma X_i), \tag{2}$$

where $Cycle_i$ is an indicator taking a value of one if (based on the Markov switching model) city i is designated as a price cycling city and zero otherwise. The variable Φ denotes the standard normal distribution function, while α denotes the intercept term. By assumption, the regression error term under the above framework is $\varepsilon_{i,O} \sim N(0,1)$. The variable X_i denotes a vector of city-level Census demographic controls, which include median household income, population density, and total population measures, and Γ denotes a vector of coefficients. The β_O are the primary coefficients of interest. If $\beta_O > 0$, then a higher concentration of within-group sales pertaining to ownership structure O is positively correlated with the probability that retail gasoline price cycling occurs in city i, all else equal (and *vice versa*).

We also examine the natural log of the odds ratio (logistic transform) derived from the *p*-values of the city-specific Wald statistics obtained from the Markov switching model (which are denoted $p_{Wald,i}$) as an alternative dependent measure. The regression model in this framework is specified as:

$$\ln\left(\frac{p_{Wald,i}}{1 - p_{Wald,i}}\right) = \alpha + \sum\nolimits_O \beta_O HHI_{i,O} + \Gamma X_i + \varepsilon'_{i,O}, \tag{3}$$

where $\varepsilon'_{i,O} \sim N(0, \sigma^2 I)$ denotes the error term. Equation (3) is estimated via Ordinary Least Squares (OLS). This model provides a rough approximation of the "strength" at which a city cycles. Specifically, a strongly cycling city is associated with a "small" $p_{Wald,i}$, and as such, if

$\beta_O < 0$ then a higher concentration of within-group sales pertaining to ownership structure O is correlated with a stronger cycling effect.

Table 5 presents the results of estimating both the cycling indicator and log odds models. Columns (1) and (5) control only for the HHIs pertaining to company-owned-and-operated and independent/jobber stations. Columns (2) and (6) then add the HHI corresponding to the lessee-dealer stations. These latter results are presented separately since we lose seven observations for which data on lessee-dealer stations could not be obtained, and we only have 29 total potential observations to begin with. Columns (3) and (7) then add the covariates in X_i to the specifications in Columns (1) and (5), respectively, while Columns (4) and (8) do the same for Columns (2) and (6), respectively.

First consider the cycling indicator regressions in Columns (1)-(4). All of the reported Probit coefficient estimates are presented in terms of their marginal effects, with robust (heteroskedasticity-consistent) *z*-statistics in parentheses. The results consistently indicate that a an increase in the HHI of within-group sales of refiner *company-owned-and-operated* stations increases the probability of retail gasoline price cycling, and all of the coefficient estimates are statistically significant.[20] In Columns (1)-(3), a 100-point increase in the HHI implies that an increase of approximately 1 to 2 percentage points in the probability that a city exhibits cycling behavior, all else equal.[21] In Column (4), which represents the most fully specified model, the magnitude of the estimated marginal effect falls appreciably. Specifically, a 100-point increase in the HHI is predicted to result in a 0.04 percentage point increase in the probability that a city cycles.

The coefficient estimates pertaining to the HHI of independent and jobber sales are consistently and considerably larger in magnitude relative to those for the other ownership

[20] Note however, that we cannot reject the hypothesis that the slope coefficients are jointly equal to zero in Column (3). As such, due caution is warranted in interpreting those results.
[21] Note that the HHIs used in estimating the regressions presented in Table 5 are defined continuously on the unit interval (*i.e.*, the HHIs are scaled by 10,000).

groups; however, the coefficient estimates in Columns (1)-(3) are not statistically significant at conventional levels. The coefficient estimate in Column (4), however, is statistically significant at the 10 percent level and indicates that a 100-point increase in the independent/jobber HHI increases the probability of cycling by 0.3 percentage points. While small, the magnitude of this effect is substantially larger than that associated with company-owned-and-operated stations. Finally, most of the coefficient estimates on the demographic covariates are not statistically significant, the exception being median household income in Column (4). This latter result implies that cities with higher incomes will be more likely to exhibit cycling, which is consistent with Doyle *et al.* (2010).

The results obtained from estimating equation (3) in Columns (5)-(8) of Table 5 are seemingly consistent with those from the cycling indicator regressions. In each case the coefficient estimate on the company owned and operated HHI is negative (which, again, implies that a one unit increase in the variable is associated with a stronger cycling city) and statistically significant. Furthermore, the coefficient estimate on the lessee-dealer HHI is negative and statistically significant at the 10 percent level in Column (6) (whereas this variable is always insignificant in the cycling indicator regressions). In each individual specification the coefficient estimates on the jobber/independent HHIs are comparatively more negative, but never statistically significant.

Treating the results obtained from Columns (4) and (8) as our "preferred" specifications, the results imply that the concentration of independents/jobbers within cities tends to explain the presence of cycling but not the strength of its effect. The concentration of refiner-affiliated company-owned-and-operated stations, which arguably are those for which the upstream refiner has greatest control over the downstream retail price, explain both the likelihood of cycling (although to a much smaller degree than the concentration of independents/jobbers) as well as the strength of the cycling behavior. Thus, unlike previous studies, we find that some vertically

integrated (branded) retail gasoline stations are themselves potentially important drivers of the scale and scope of cycling in retail gasoline prices.

6 Average retail gasoline price differences across cycling and non-cycling cities

Many of the papers discussing price cycling in Australia and Canada have described or suggested either explicit or tacit collusion. The Maskin & Tirole (1998) model is one of dynamic oligopoly. Against this backdrop of less than perfect competition, there is the suggestion in Lewis (2009a) and Doyle *et al.* (2010) that prices may be no higher in cycle cities and pass through of cost changes may be more rapid in cities with price cycles than those without. We examine year-by-year whether retail prices are on average higher or lower in cycling than non-cycling cities.

Using the mean weekly retail prices—averaged over the course of a year—for all available OPIS cities, we examine by year whether higher or lower retail prices are associated with cycling. We identified a city as cycling using the aforementioned results and cutoff criteria of the Markov model. Letting i index cities, the cross-sectional regression model is given by

$$P_i = \alpha + \beta Cycle_i + \Gamma X_i + \eta_i \,, \tag{4}$$

which is estimated using Feasible Generalized Least Squares (FGLS) and assuming heteroskedasticity in the error structure of cities located within the same state. The variables α and η_i are the constant and error terms, respectively; all other variables represent coefficients.

The results of estimating two specifications are presented in Table 6 for each year from 2002 to 2007. The first is a baseline specification that only controls for whether the city is identified as cycling (through the cycling indicator $Cycle_i$). The second specification adds several key demographic variables—represented by the vector X_i in equation (4)—which have been shown in the literature to be correlated with gasoline price levels (including those considered in Table 6).

We find that without controlling for demographic variables cycle cities have lower prices relative to non-cycling cities in each of the six years in the data, with all of the cycle indicator coefficients being statistically significant at the 1 percent level. The magnitude of the cycling effect in the baseline specifications ranges from -1.1 to -8.1 cents per gallon. When controlling for the key demographic variables, we find negative and statistically significant price effects of being in a cycling city for four of the six years. In two other years the cycling indicator is negative and statistically insignificant. Only in 2002 is the cycling indicator coefficient positive, but it is not statistically significant in this case. And while there is some change on the coefficients on the demographic variables from year to year, they are generally of the same order of magnitude and significance across the six regressions.

Controlling for the demographic variables tends to reduce the size of the cycling coefficients (*i.e.*, move them in the positive direction). In the full specifications, the magnitude of the *statistically significant* cycling coefficients ranges from -1.0 to -5.1 cents per gallon, with an average effect of -2.9 cents per gallon. In order to gauge the economic significance of the latter estimate, consider the NACS report that:

> In 2006, a gasoline retailer's average gross margin (before expenses) was 13.9 cents per gallon . . . . After expenses, typical net profits are per gallon are a few cents per gallon, at most . . . NACS estimates that the average retailer had a net pretax profit of between one and two cents [per gallon] in 2007.[22]

Thus, a -2.9 cents a gallon retail price difference could translate into gross retail margins that were approximately 21 percent lower relative to non-cycling cities if wholesale costs and volumes are similar across cycling and non-cycling cities.

We conclude that the average price in a cycle city is not higher and, if anything, likely lower than in a non-cycling city. This result seems somewhat counterintuitive since Edgeworth price cycles are presumed to arise from an oligopolistic pricing game that others in the literature

[22] *See* <http://www.nacsonline.com/NACS/Resources/campaigns/GasPrices_2008/Pages/HowToGetGas.aspx>.

have linked to tacit collusion.[23] The results suggest that non-cycling markets may be relatively "less competitive" on average compared to cycling cities. The results also raise the question of why firms would continue to price in cycling patterns, or remain stuck in that equilibrium, given presumably higher prices in non-cycling cities. The answers to these questions are left for future research.

7 Concluding remarks

Our comprehensive analysis of retail price data from across the U.S. leads to the clear conclusion that retail price cycling is confined to the upper Midwest, mainly a five state region. While others in the literature have found gasoline price cycles in the Midwest, we examined a larger number of cities using multiple criteria to identify cycling. In addition we examined premium gasoline and diesel prices and found that premium prices cycled in the same cities as regular gasoline but diesel prices did not cycle. We also found, using 6 years of data that cities generally either cycle or they do not. We found no evidence in our data set of cities having periodic gasoline price cycles.

We used a number of criteria for classifying a city has having cyclical retail pricing. All the criteria generally lead to the same conclusion, with a few notable caveats. The median price difference criteria can lead to meaningfully different conclusions with slightly different levels for the threshold value. The Markov model gives a clearer cut off for classifying cycling and non-cycling cities.

With respect to the causes and consequences of gasoline price cycles, we find evidence that concentration of both independent/jobbers and branded refiner affiliated company-owned-and-operated stations are potentially important determinants of gasoline price cycles. More importantly, we find that cycling cites on average have no higher and in some cases lower retail prices. While additional research may lead to a more robust conclusion on this point, the current

[23] Erutku & Hildebrand(2010) and Wang(2008)

finding is disconnected from the dynamic model which is suggestive of tacit collusion and the literature examining tacit or explicit collusion in Canada and Australia. The puzzle of why price cycles exist if prices are no higher and seem to be lower in cycling cities is a topic for further research as well.

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Appendix: A Markov-switching model for identifying Edgeworth price cycles

We employ a Markov switching model based upon Neftçi (1984). Let $p_t^{(\ell)}$ denote the retail price in a given city during week t for $\ell = \{regular, premium, diesel\}$, which over time is assumed to follow a mean-zero linearly regular stationary process. Define $\{I_t\}$ as a second-order ("two-state") Markov switching process such that

$$I_t = \begin{cases} +1 & \text{if} \quad \Delta_t p_t^{(\ell)} > 0 \\ -1 & \text{if} \quad \Delta_t p_t^{(\ell)} \leq 0, \end{cases} \tag{5}$$

where Δ_t denotes the first-difference operator.[24] The associated transition probabilities, denoted λ_{ij} for $i, j = \{0,1\}$, are given by

$$\left.\begin{aligned} \lambda_{11} &= \Pr(I_t = +1 \mid I_{t-1} = +1, I_{t-2} = +1) \\ \lambda_{00} &= \Pr(I_t = -1 \mid I_{t-1} = -1, I_{t-2} = -1) \\ \lambda_{10} &= \Pr(I_t = +1 \mid I_{t-1} = +1, I_{t-2} = -1) \\ \lambda_{01} &= \Pr(I_t = -1 \mid I_{t-1} = -1, I_{t-2} = +1) \end{aligned}\right\}. \tag{6}$$

If a city's retail or wholesale gasoline price series exhibits sharp increases and gradual decreases as suggested by the Maskin & Tirole (1988) model of Edgeworth cycles, then $\{I_t\}$ remains in state -1 longer than it remains in state $+1$. In this case, the retail price cycle is said to be *asymmetric* and would imply $\lambda_{00} > \lambda_{11}$. If, on the other hand, the series is *symmetric* over the cycle then $\lambda_{00} = \lambda_{11}$.

Our objective is to obtain estimates of the transition probabilities given in Eq. (6). Let s_T denote a realization of $\{I_t\}$. The log-likelihood function is then given by

$$\begin{aligned} L(s_T, \lambda_{11}, \lambda_{00}, \lambda_{10}, \lambda_{01}, \pi_0) = \ln \pi_0 &+ \phi_{11} \ln \lambda_{11} + \psi_{11} \ln(1 - \lambda_{11}) \\ &+ \phi_{00} \ln \lambda_{00} + \psi_{00} \ln(1 - \lambda_{00}) \\ &+ \phi_{10} \ln \lambda_{10} + \psi_{10} \ln(1 - \lambda_{10}) \\ &+ \phi_{01} \ln \lambda_{01} + \psi_{01} \ln(1 - \lambda_{01}). \end{aligned} \tag{7}$$

The variable π_0 denotes the initial condition (*i.e.*, the probability of observing the initial two states), while the variables $\phi_{11}, \ldots, \psi_{01}$ represent the number of *observed* occurrences of the respective transitions throughout the sample period.

[24] As noted by Neftçi (1984, p. 314), an advantage of this procedure is that it can handle nonstationarity in the underlying data (*i.e.*, p_t) given that the implied I_t will often be plausibly stationary even when the former is not.

Neftçi argues that it is necessary to estimate π_0 when the number of observations contained in the relevant time series is small and when the initial state may contain useful information on the transition probabilities (*e.g.*, when the process I_t does not in fact start at $t = 1$, which is usually the case). Neftçi's paper develops a methodology for deriving the limiting probabilities of the initial conditions in terms of the transition probabilities.[25] If, however, the number of observations available in the sample is relatively large (*i.e.*, in an asymptotic sense) the initial state may be treated as a nuisance parameter (Billingsley, 1961). Since the number of daily city-specific price observations available in our dataset covers over a six year period (2001-2007), ignoring the influence of the initial condition is likely to be reasonable.[26] With $\pi_0 = 0$, the maximum likelihood estimates (MLEs) of the four unknown parameters $\Lambda = [\lambda_{00}, \lambda_{11}, \lambda_{10}, \lambda_{01}]'$ are obtained by setting the four score equations of the log-likelihood function equal to zero and solving the parameters in terms of the transition counts.[27] The general form of the score equations is given by

$$\frac{\partial L}{\partial \lambda_{ij}} = \frac{\phi_{ij}}{\lambda_{ij}} - \frac{\psi_{ij}}{1 - \lambda_{ij}} = 0. \tag{8}$$

Solving Eq. (8) in terms of λ_{ij} gives

$$\left.\begin{aligned} &\frac{\phi_{ij}}{\lambda_{ij}} = \frac{\psi_{ij}}{1 - \lambda_{ij}} \\ &\Rightarrow \phi_{ij}(1 - \lambda_{ij}) = \psi_{ij}\lambda_{ij} \\ &\Rightarrow \lambda_{ij}(\phi_{ij} + \psi_{ij}) = \phi_{ij} \\ &\Rightarrow \lambda_{ij} = \frac{\phi_{ij}}{\phi_{ij} + \psi_{ij}} = \hat{\lambda}_{ij} \end{aligned}\right\} \tag{9}$$

where $\hat{\lambda}_{ij}$ denotes the (approximate) MLE of λ_{ij}. The asymptotic variance of $\hat{\lambda}_{ij}$ is given by[28]

$$\sigma^2(\hat{\lambda}_{ij}) = \frac{\hat{\lambda}_{ij}(1 - \hat{\lambda}_{ij})}{\phi_{ij} + \psi_{ij}}. \tag{10}$$

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[25] *See* Neftçi (1984, pp. 326-327).

[26] Several studies that have relied upon a substantially smaller number of observations than are employed herein have demonstrated that estimating the initial condition along with the transition probabilities does not materially affect the magnitude of the latter when they are estimated alone. *See*, *e.g.*, Falk (1986) and McQueen & Thorley (1991). Further, a particular advantage of treating π_0 as a nuisance parameter comes from the considerable reduction in the computation burden of estimating the transition probabilities (Rothman, 2003). Specifically, ignoring the initial state variables does not require using nonlinear numerical methods to approximate the maximum of the log-likelihood function. Rather, as demonstrated below, closed-form analytical solutions for the maximum likelihood estimators are easily obtained.

[27] McQueen and Thorley (1991, p. 243).

[28] *See id.*, note 5.

Testing for the presence of Edgeworth price cycles (asymmetry) in gasoline prices involves testing the null hypothesis $H_0 : \lambda_{00} = \lambda_{11}$ against the (two-sided) alternative $H_1 : \lambda_{00} \neq \lambda_{11}$.

Hypothesis Testing

Neftçi demonstrates how the test for asymmetry can be evaluated by using the estimate of the transition probabilities to construct a confidence region (ellipsoid), the center of which corresponds to the MLEs of λ_{11} and λ_{00}. All points within the confidence ellipsoid represent the true value of the latter estimate for a given confidence level.[29] However, Sichel (1989) demonstrates that this procedure "has low power and is sensitive to noise" (p. 1259). Specifically, he shows that Neftçi's test may fail to identify asymmetry that is actually present, and instead applies an asymptotic *t*-test that appears to give higher power.

McQueen & Thorley (1991) test the symmetry hypothesis in their data by considering asymptotic Lagrange Multiplier, Likelihood Ratio, and Wald tests (all of which are approximately equal for large sample sizes). They note that: "The choice of test statistics is normally a matter of computational convenience" (p. 256). Again, the length of our time series data suggests that we can rely upon the direct analytical solutions for the MLEs and (asymptotic) variances of the Markov transition probabilities. This fact motivates the use of the Wald test since it uses the MLEs and asymptotic variance estimates of the *unconstrained* log-likelihood function, which correspond to the "unrestricted" estimates obtained by appealing to Eqs. (9) and (10). The computed value the Wald test under H_0 is given by:

$$\frac{(\hat{\lambda}_{00} - \hat{\lambda}_{11})^2}{\sigma(\hat{\lambda}_{11}) - \sigma(\hat{\lambda}_{00})} \sim \chi^2_{df=1}. \tag{11}$$

This test statistics is used to determine whether there is a statistically significant Edgeworth price cycling effect within a given city over the sample period.

[29] *See* Neftçi (1984, pp. 315-318) for the formula used to construct the confidence ellipsoid and further discussion of this test.

Figure 1

Regular Unleaded Retail Prices for St. Louis, MO, and Newark, NJ (1/2007 – 12/2007)

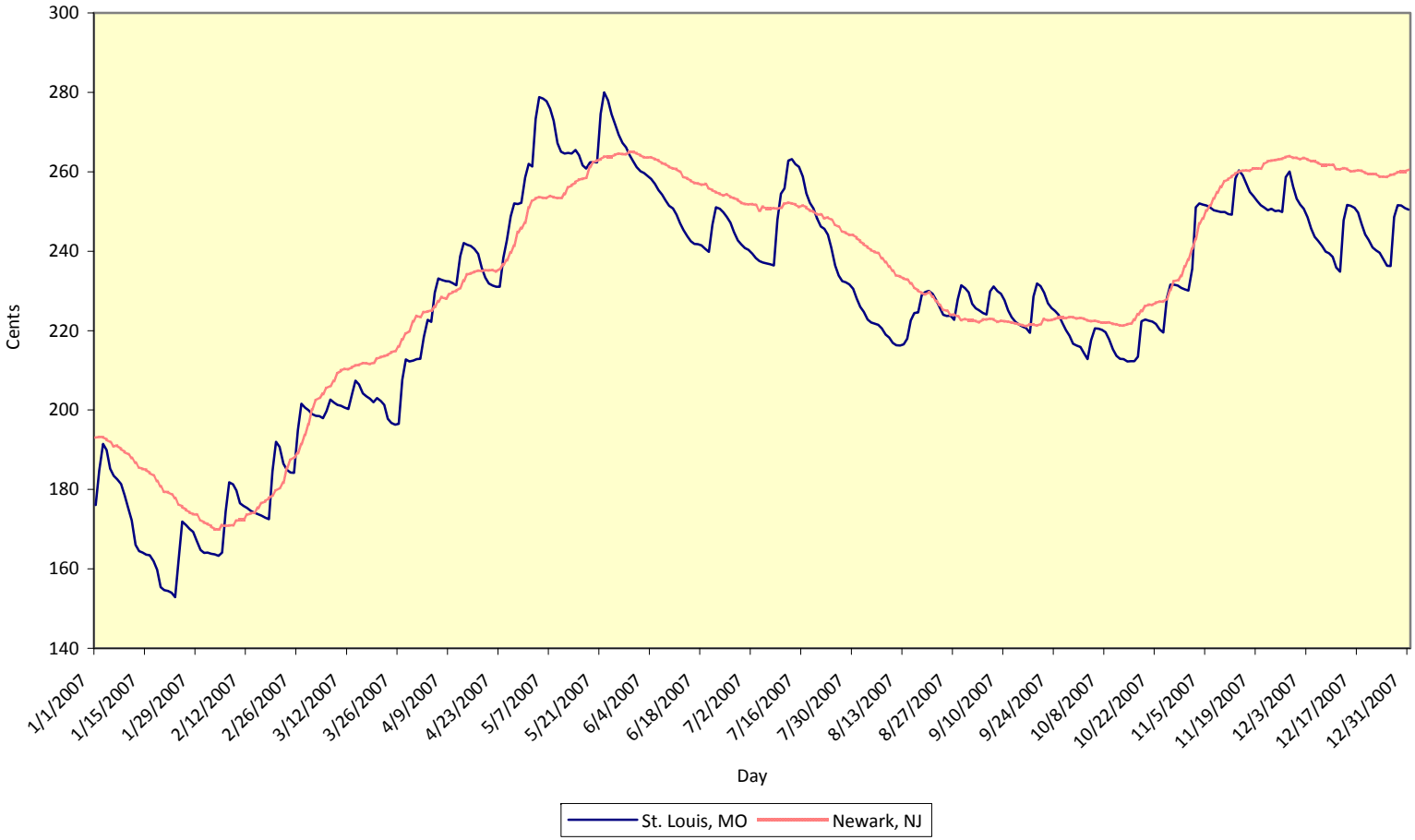

TABLE 1

TOP 10 PERCENT OF THE 355 CITIES IN TERMS OF CONFORMITY TO EDGEWORTH PRICE CYCLE PATTERN

				Rank by Criteria		
City	Syate	*Overall Rank*	Avg. Rank Across Criteria	Ratio of Down to Up Days	Ratio of Avg. Price Increase to Decrease	Median Price Change
Indianapolis	IN	*1*	3.0	1	2	6
Dayton-Springfield	OH	*2*	3.3	4	5	1
Columbus	OH	*3*	5.7	6	9	2
Toledo	OH	*4*	5.7	8	6	3
Cincinnati	OH	*5*	6.0	7	7	4
Minneapolis-St. Paul	MN	*6*	6.7	3	3	14
Saginaw-Bay City-Midland	MI	*7*	9.0	5	12	10
St. Louis	MO	*8*	9.7	2	1	26
Akron	OH	*9*	10.7	11	4	17
Lansing-East Lansing	MI	*10*	11.3	10	17	7
Grand Rapids-Muskegon-Holland	MI	*11*	11.3	12	10	12
Flint	MI	*12*	12.7	13	16	9
Cleveland-Lorain-Elyria	OH	*13*	13.3	16	11	13
Louisville	KY	*14*	13.3	9	13	18
Canton-Massillon	OH	*15*	13.7	14	19	8
Lexington	KY	*16*	15.3	15	20	11
Hamilton-Middletown	OH	*17*	17.0	23	23	5
Kalamazoo-Battle Creek	MI	*18*	18.0	18	14	22
Gary	IN	*19*	18.3	19	8	28
Fort Wayne	IN	*20*	19.3	20	15	23
Muncie	IN	*21*	20.7	21	25	16
South Bend	IN	*22*	21.0	17	21	25
Springfield	IL	*23*	23.3	24	26	20
Mansfield	OH	*24*	24.0	26	27	19
Elkhart-Goshen	IN	*25*	24.7	25	28	21
Lima	OH	*26*	25.7	30	32	15
Wichita	KS	*27*	27.3	22	18	42
Jackson	MI	*28*	28.7	27	35	24
Cincinnati	KY	*29*	29.7	29	33	27
Lafayette	IN	*30*	31.0	28	36	29
Bloomington-Normal	IL	*31*	34.0	33	39	30
Kansas City	MO	*32*	35.0	31	24	50
Ann Arbor	MI	*33*	35.3	34	34	38
Kokomo	IN	*34*	35.7	32	43	32
Detroit	MI	*35*	37.3	41	22	49

Figure 2: Percent of Cycle Cities by State

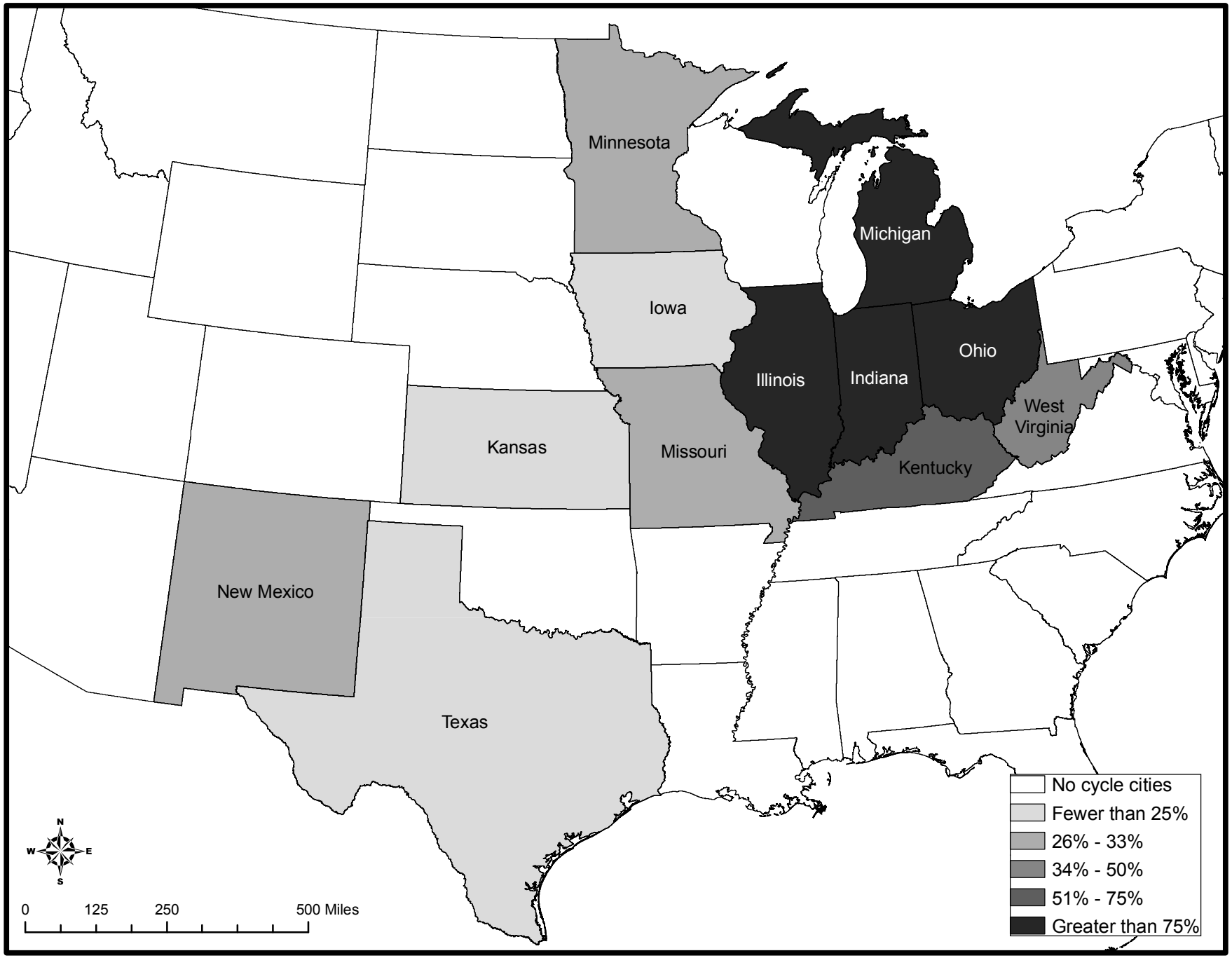

TABLE 2
TOP 10 PERCENT OF THE CITIES IN TERMS OF CONFORMITY TO THE EDGEWORTH PRICE CYCLE PATTERN BY YEAR

			Annual Rankings						
City	State	*Overall Rank*	2001	2002	2003	2004	2005	2006	2007
Indianapolis	IN	*1*	2	1	3	3	1	5	1
Dayton-Springfield	OH	*2*	19	5	1	1	7	3	12
Columbus	OH	*3*	7	2	4	4	12	8	5
Toledo	OH	*4*	3	3	2	6	4	19	16
Cincinnati	OH	*5*	8	7	10	2	6	9	7
Minneapolis-St. Paul	MN	*6*	1	8	5	10	9	7	6
Saginaw-Bay City-Midland	MI	*7*	4	9	14	14	8	4	8
St. Louis	MO	*8*	11	13	8	21	3	12	11
Akron	OH	*9*	16	19	16	5	17	11	9
Lansing-East Lansing	MI	*10*	5	10	15	11	11	6	2
Grand Rapids-Muskegon-Holland	MI	*11*	18	22	7	7	2	14	3
Flint	MI	*12*	6	6	9	13	13	16	22
Cleveland-Lorain-Elyria	OH	*13*	25	11	11	9	15	20	17
Louisville	KY	*14*	13	28	6	26	5	2	4
Canton-Massillon	OH	*15*	23	12	12	8	18	22	15
Lexington	KY	*16*	15	30	13	18	16	1	13
Hamilton-Middletown	OH	*17*	21	26	20	17	19	13	14
Kalamazoo-Battle Creek	MI	*18*	10	18	17	20	10	21	20
Gary	IN	*19*	9	24	23	12	14	15	18
Fort Wayne	IN	*20*	14	4	19	22	23	24	21
Muncie	IN	*21*	37	29	26	16	27	17	19
South Bend	IN	*22*	20	15	27	23	20	18	10
Springfield	IL	*23*	17	17	21	27	31	25	24
Mansfield	OH	*24*	31	21	24	15	28	26	33
Elkhart-Goshen	IN	*25*	36	16	25	24	24	27	23
Lima	OH	*26*	40	27	18	28	36	28	30
Wichita	KS	*27*	29	41	31	19	29	10	25
Jackson	MI	*28*	22	14	28	25	30	41	32
Cincinnati	KY	*29*	129	36	22	29	21	29	40
Lafayette	IN	*30*	44	25	29	30	33	35	27
Bloomington-Normal	IL	*31*	30	31	35	32	43	37	34
Kansas City	MO	*32*	33	37	38	33	35	23	49
Ann Arbor	MI	*33*	41	35	32	34	37	31	45
Kokomo	IN	*34*	96	39	40	31	41	47	31
Detroit	MI	*35*	24	38	34	36	39	34	57

= Indicates a ranking of 10 or lower

TABLE 3

RETAIL PRICE CYCLE STATISTICS – 20 SELECT CITIES

			Avg. Cycle Characteristics				Price Change			Levels (cents)		Wholesale
355 Rank	City	State	Cycle Length	Up Days	Down Days	Ratio Down to Up Days	Ratio Avg. Price Incr. to Decr.	Median	St. Dev	Mean	St. Dev	Unbranded Rack Median Price Ch.
6	Minneapolis-St. Paul	MN	8.6	2.1	6.6	3.2	-3.6	-0.95	3.15	160	56	0.00
8	St. Louis	MO	10.4	2.4	8.0	3.3	-4.0	-0.68	2.99	157	56	0.00
13	Cleveland-Lorain-Elyria	OH	7.8	2.0	5.8	2.9	-3.4	-0.96	3.07	156	55	0.00
14	Louisville	KY	8.3	2.1	6.3	3.1	-3.3	-0.83	3.39	163	58	0.00
35	Detroit	MI	8.2	2.9	5.3	1.8	-2.7	-0.29	1.79	155	56	0.00
42	Chicago	IL	7.2	2.5	4.6	1.8	-2.4	-0.27	1.38	163	57	0.00
63	Denver	CO	7.9	3.1	4.7	1.5	-1.5	-0.13	1.10	159	59	0.00
65	Atlanta	GA	9.6	4.1	5.5	1.3	-1.8	-0.10	1.57	155	59	0.00
70	Los Angeles-Long Beach	CA	9.8	4.1	5.6	1.4	-1.5	-0.11	0.97	174	57	0.00
95	Houston	TX	9.0	4.1	4.9	1.2	-1.6	-0.05	1.00	155	58	0.00
110	Phoenix-Mesa	AZ	8.7	3.9	4.7	1.2	-1.2	-0.07	1.04	170	56	0.00
115	Dallas	TX	7.3	3.4	3.9	1.1	-1.4	-0.04	1.04	157	57	0.00
119	New Orleans	LA	5.6	2.6	3.0	1.2	-1.3	-0.05	1.03	157	58	0.00
145	San Francisco	CA	6.0	2.7	3.2	1.2	-1.1	-0.06	0.99	184	54	0.00
146	Boston	MA	5.9	2.8	3.0	1.1	-1.4	-0.03	1.11	163	56	0.00
177	Salt Lake City-Ogden	UT	5.9	2.7	3.1	1.1	-1.1	-0.05	0.93	158	57	0.00
178	Fairfax	VA	5.9	2.8	3.0	1.1	-1.2	-0.02	1.19	160	57	0.00
208	Newark	NJ	5.3	2.6	2.7	1.0	-1.1	-0.01	1.08	165	57	0.00
219	Miami	FL	5.8	2.8	3.0	1.1	-1.1	-0.02	0.88	159	58	0.00
250	Seattle-Bellevue-Everett	WA	6.7	3.2	3.5	1.1	-1.0	-0.03	0.88	170	57	0.00

Notes: All figures correspond to retail prices for regular-grade gasoline.

TABLE 4
ESTIMATED MARKOV TRANSITION PROBABILITIES – 20 SELECT CITIES

	Regular Gasoline			Premium Gasoline			Diesel	
	MLE		Wald test	MLE		Wald test	MLE	
City	λ_{00}	λ_{11}	*p*-value	λ_{00}	λ_{11}	*p*-value	λ_{00}	λ_{11}
Atlanta	0.8408	0.7997	0.5120	0.7407	0.6886	0.4129	0.6059	0.6490
Boston	0.7097	0.7253	–	0.4887	0.5519	–	0.4632	0.5649
Chicago	0.8010	0.6013	0.0557	0.7204	0.5242	0.0722	0.5157	0.5806
Cleveland	0.8136	0.1966	0.0000	0.7712	0.2227	0.0000	0.4617	0.4974
Dallas	0.7981	0.8090	–	0.5621	0.5963	–	0.5609	0.6535
Denver	0.8432	0.7976	0.5441	0.5832	0.6020	–	0.5659	0.6172
Detroit	0.8273	0.6245	0.0483	0.7598	0.4396	0.0162	0.5643	0.5811
Fairfax	0.7093	0.7707	–	0.4386	0.5375	–	0.4135	0.4603
Houston	0.8643	0.8314	0.5336	0.5568	0.6169	–	0.5676	0.6722
Los Angeles	0.8758	0.8490	0.6593	0.6151	0.6776	–	0.5710	0.6003
Louisville	0.8433	0.3066	0.0001	0.7779	0.3162	0.0002	0.4312	0.5063
Miami	0.7260	0.7550	–	0.4583	0.5356	–	0.4414	0.4864
Minneapolis	0.8416	0.1655	0.0000	0.8036	0.3043	0.0019	0.5897	0.5882
New Orleans	0.7312	0.7206	0.8346	0.4161	0.4861	–	0.4751	0.5434
Newark	0.7256	0.7444	–	0.3973	0.4375	–	0.4459	0.4589
Phoenix	0.8544	0.8316	0.6480	0.6565	0.6705	–	0.5588	0.6292
Salt Lake City	0.7497	0.7786	–	0.4573	0.5000	–	0.5439	0.6296
San Francisco	0.7569	0.7670	–	0.4022	0.4960	–	0.3725	0.4534
Seattle	0.7967	0.7826	0.6965	0.4664	0.5772	–	0.5087	0.6184
St. Louis	0.8774	0.4076	0.0007	0.7297	0.4904	0.0334	0.5622	0.6443

Notes: The data correspond to daily city-specific average retail price data from September 25, 2001 to December 31, 2007. The variable λ_{11} (λ_{00}) denotes the MLEs of the transition probabilities associated with observing a positive (negative) retail price change in the current day conditional on observing positive (negative) price changes in the previous two days (*see* the Appendix for further detail). All MLEs reported above are statistically significant at the 1 percent level (estimated standard errors available upon request). The *p*-values are not shown for diesel prices since the relative magnitudes of the MLEs in this case suggest that cycling is never present.

TABLE 5

THE EFFECTS OF RETAIL-STATION OWNERSHIP STRUCTURE ON THE PRESENCE OF EDGEWORTH PRICE-CYCLES IN RETAIL GASOLINE MARKETING

	Dependent variable:							
	Cycle				$\ln\left(\frac{p_{Wald}}{1-p_{Wald}}\right)$			
Independent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI of within-group sales of refiner company owned & operated sites	1.511**	1.324*	1.550**	0.043**	-16.529**	-37.119***	-15.385**	-39.994***
	(2.37)	(1.81)	(2.36)	(2.53)	(2.60)	(3.74)	(2.14)	(3.87)
HHI of within-group sales of independent and jobber sites	5.148	6.284	5.32	0.299*	-21.917	-57.106	-20.371	-60.998
	(1.06)	(1.31)	(1.07)	(1.92)	(0.52)	(1.01)	(0.38)	(0.75)
HHI of within-group sales of lessee-dealers		0.238		0.030		-7.243*		-6.299
		(0.64)		(1.49)		(1.85)		(1.58)
Median household income			-1.96E-05	1.300E-06*			1.494E-04	2.180E-04
			(0.95)	(1.81)			(0.93)	(1.07)
Population density			-3.685E-04	-1.420E-06			0.001	-0.001
			(1.19)	(0.13)			(0.42)	(0.54)
Total population			2.364E-04	2.110E-05			0.004	0.008
			(0.26)	(0.88)			(0.53)	(0.80)
Constant					2.542	15.082*	-5.081	6.846
					(0.48)	(1.91)	(0.52)	(0.41)
Observations	29	22	29	22	29	22	29	22
Pseudo R^2	0.20	0.24	0.27	0.56				
p(Wald χ^2 - statistic) [H_0: All coefficients = 0]	0.059	0.308	0.063	0.020				
R^2					0.25	0.43	0.32	0.52
p(F-statistic) [H_0: All coefficients = 0]					0.044	0.000	0.069	0.005

Notes: The results in Columns (1)-(4) are from a Probit regression, while those in Columns (5)-(8) are from OLS. Probit coefficient estimates are expressed in terms of marginal effects. Absolute values of robust z-statistics (Columns (1)-(4)) and t-statistics (Columns (5)-(8)) in parentheses.
"*" = statistical significance at the 10 percent level in a two-tailed test
"**" = statistical significance at the 5 percent level in a two-tailed test
"***" = statistical significance at the 1 percent level in a two-tailed test

Table 6
Estimated Price Effects of Edgeworth Price Cycles in Retail Gasoline by Year (2002-2007)

	2002		2003		2004		2005		2006		2007	
Cycle	-1.130***	0.312	-3.244***	-1.003*	-3.575***	-1.944***	-5.107***	-3.584***	-8.056***	-5.151***	-2.879***	-0.320
	(3.73)	(0.77)	(6.95)	(1.86)	(8.51)	(3.72)	(12.07)	(6.39)	(17.65)	(9.68)	(5.40)	(0.53)
Median household income		3.066E-04***		0.001***		4.319E-04***		1.899E-04***		3.465E-04***		4.247E-04***
		(5.67)		(7.97)		(6.12)		(2.83)		(4.56)		(5.40)
Population density		0.001		3.436E-04		-0.001		-0.001		2.620E-05		-0.003*
		(0.55)		(0.27)		(0.82)		(0.81)		(0.03)		(1.75)
Total population		1.15E-07		2.15E-07		2.39E-07		1.42E-07		-1.21E-07		9.15E-08
		(0.84)		(1.28)		(1.38)		(0.93)		(0.73)		(0.47)
Percent urban		0.005		0.018		0.038		0.018		0.032		0.023
		(0.27)		(0.62)		(1.46)		(0.72)		(1.28)		(0.84)
Percent white		-0.334***		-0.533***		-0.431***		-0.409***		-0.412***		-0.481***
		(17.21)		(7.49)		(7.31)		(12.58)		(7.42)		(6.89)
Percent black		-0.416***		-0.739***		-0.592***		-0.475***		-0.548***		-0.730***
		(18.79)		(11.43)		(10.79)		(15.13)		(10.42)		(11.70)
Percent hispanic		-0.181***		-0.337***		-0.292***		-0.207***		-0.258***		-0.236***
		(7.38)		(8.13)		(7.15)		(5.74)		(7.02)		(5.82)
Percent drive alone		-0.909***		-1.509***		-1.465***		-1.018***		-1.321***		-1.183***
		(11.05)		(12.14)		(11.88)		(8.99)		(10.65)		(8.90)
Percent using public transportation		-1.433***		-2.194***		-2.030***		-1.761***		-1.331***		-1.718***
		(4.63)		(5.44)		(4.95)		(4.46)		(3.36)		(3.78)
Percent commuters with travel time > 30 min		-0.273***		-0.378***		-0.249***		0.014		-0.114		-0.322***
		(4.18)		(4.36)		(2.85)		(0.16)		(1.36)		(3.64)
Percent with less than high school education		0.007***		0.006*		0.005		0.003		0.004		0.005*
		(2.92)		(1.91)		(1.51)		(1.28)		(1.12)		(1.71)
Percent with high school diploma		0.042		-0.06		0.014		0.024		0.01		-0.015
		(0.57)		(0.59)		(0.15)		(0.25)		(0.10)		(0.15)
Percent with some college education		0.757***		0.603***		0.679***		0.719***		0.700***		0.773***
		(5.84)		(3.11)		(3.82)		(4.16)		(3.58)		(4.14)
Constant	92.926***	142.244***	113.207***	197.634***	140.856***	215.883***	182.375***	244.831***	211.839***	280.117***	233.650***	305.435***
	(466.61)	(45.64)	(451.77)	(28.97)	(527.18)	(35.44)	(725.74)	(56.24)	(945.39)	(47.79)	(879.65)	(45.40)
Observations	355	355	355	355	355	355	355	355	355	355	355	355
p (F-statistic) [H_0: All coefficients = 0]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Notes: All estimates are obtained using Feasible Generalized Least Squares (FGLS) assuming heteroskedasticity across cities within states. Absolute values of t-statistics are shown in parentheses. The excluded racial category is "other."
"*" = statistical significance at the 10 percent level in a two-tailed test
"**" = statistical significance at the 5 percent level in a two-tailed test
"***" = statistical significance at the 1 percent level in a two-tailed test