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ABSTRACT

Some gasoline markets exhibit remarkable price cycles, where price spikes are followed by a string of small price declines until the next price spike. This pattern is predicted from a model of competition driven by Edgeworth cycles, as described by Maskin and Tirole. We extend the Maskin and Tirole model and empirically test its predictions with a new dataset of daily station-level prices in 115 US cities. One innovation is that we also examine cycling within cities, which allows controls for city fixed effects. Consistent with the theory, and often in contrast with previous empirical work, we find that the least and most concentrated markets are much less likely to exhibit cycling behavior; and the areas with more independent retailers that have convenience stores are more likely to cycle. We also find that the average gasoline prices are relatively unrelated to cycling behavior.

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I. Introduction

Tremendous variation exists in the pricing strategies chosen by different businesses and how market prices dynamically evolve in different industries. Although a long literature in industrial organization identifies different equilibrium pricing strategies, in many cases the models do not make clear predictions as to why firms might choose one set of strategies in one competitive environment and choose a different set of strategies in another competitive environment.

In this paper, we revisit the study of Edgeworth cycles in retail gasoline markets: a remarkable pattern in prices over time when price spikes are followed by slow reductions until the next spike. We extend the theory proposed by Maskin and Tirole (1988) in two novel ways. First, we allow for loyal consumers who, due to geographic differentiation, brand loyalty or unobservable preference, do not switch to competitors offering marginally lower prices. Second, we allow firms to earn profits from goods complementary to the primary good upon which firms compete. These two additions provide conditions under which competitors may find it more profitable to adopt cycling strategies rather than cost-based pricing strategies. We then empirically test the predictions of the model using a significantly larger dataset than previous studies: daily, station-level prices for 115 US metropolitan areas. One innovation in the paper is that we also examine cycling within cycling and non-cycling metropolitan areas, which allows us to control for fixed characteristics in models estimated at the ZIP code level.

Maskin and Tirole first specified a dynamic game in which firms played Edgeworth cycle strategies in equilibrium. The model considers a dynamic Bertrand game in which two identical competitors sequentially choose from a finite grid of prices.

Maskin and Tirole prove that if the discount rate is sufficiently high, an equilibrium exists in which firms play strategies which generate Edgeworth cycles. In these equilibria, if the opponent's price is greater than marginal cost, the firm selects the price that just undercuts her opponent's price. If the opponent was pricing at marginal cost, with some probability the firm relents, choosing a much higher price and allowing the cycle of undercutting to begin again. In such an equilibrium, the market clearing price slowly falls to marginal cost until one firm stochastically relents, which results in a price spike.

Several papers empirically document Edgeworth cycles in retail gasoline markets. Eckert (2003) extends the model proposed by Maskin and Tirole by introducing heterogeneity in the market participants. Unlike the Maskin and Tirole model in which firms split the market if they chose identical prices, Eckert considers the case in which one firm obtains greater than half of the market when both firms choose identical prices. Although cycle equilibria exist for all splits of the market, Eckert proves that as one firm's proportion of demand when identical prices are chosen rises, the firm has a greater incentive to match rather than undercut her competitor's prices. As a result, the speed at which prices fall, and the length of the undercutting phase, are negatively related to the asymmetry between the two participants.[4] Eckert analyzes city-level prices for 19 Canadian cities and finds that market penetration of independent gasoline retailers is negatively correlated with price rigidity, consistent with the results from his theoretical model.

[4] Eckert also shows that constant price equilibrium, which we do not consider in this paper, only exists when firms are of relatively similar sizes.

Drawing on the theoretical results of Eckert, Noel (2007a) applies a Markov switching regression to estimate the length of the undercutting and relenting phases as well as the transition probabilities. Using ten years of weekly, city-level data for 19 Canadian cities, Noel finds that as independent retail station market share increases, more markets exhibit cycling behavior, a result that supports the predictions of Eckert's model. Lewis (2008) finds that prices fell more quickly in Edgeworth cycle markets than in non-cycling markets following the Hurricane Rita price spike. In addition, he finds a similar relationship between independent retailer penetration and price cycling as Noel (2007a), using city-level data for 83 US cities.

A second set of papers examine the characteristics of Edgeworth cycles using station-level data within particular markets. For example, Noel (2007b) estimates cycle attributes using semi-daily data on 22 retail gasoline stations in Toronto, Canada and Atkinson (2008) examines hourly data for 27 retail gasoline stations in Guelph, Canada. Both Noel and Atkinson study the behavior of participants in price cycles and examine which firms in each market are most likely to relent at the bottom of the cycle. They tend to find that larger firms are more likely to initiate the relenting phase, whereas smaller firms are more likely to undercut.

The remainder of the paper is organized as follows: section 2 offers the extensions to the Maskin and Tirole model of Edgeworth cycles; section 3 describes the data; section 4 reports the empirical models and results; and section 5 concludes.

II. Model

Consider a dynamic game in which N firms sequentially choose from a discrete set of possible prices. We define p_{it} as firm i's choice of price at time t, p_{-it} as the vector of prices of firm i's competitors, and p_t as the vector of all firm prices at time t. Following Maskin and Tirole, we focus on Markov perfect equilibria to the game, given by a set of N reaction functions, $\{R_i(p_{-it})\}$. For each vector of opponent's prices, $R_i(p_{-it})$ maximizes firm i's expected current and future profits assuming all firms continue to play their reaction functions. We specify firm i's profits in period t as

$$\Pi_{it} = (p_{it} - c_i)[\alpha_i + \beta_i(p_t)]q(p_{it}) + \gamma_i[\alpha_i + \beta_i(p_t)] \qquad (1)$$

The first term in the profit function corresponds to sales of the primary good for which firm i sets price p_{it}. The second term corresponds to additional profits accrued from the proportion of consumers who purchase from firm i through sales of secondary goods. In the context of retail gasoline stations, the first term corresponds to purchases of gasoline, and the second term corresponds to purchases of other goods and services offered by an affiliated convenience store or service station. Implicitly, we assume that firms attract customers on the basis of the posted price of the primary good (gasoline), and in some cases, may accrued additional profits from the secondary good (c-store sales).

In our model, we distinguish two types of consumers. We let α_i denote the proportion of consumers "loyal" to firm i, who always purchase from firm i regardless of the price firm i chooses to set. We do not distinguish whether a consumer is "loyal" as a result of brand loyalty, geographic proximity or some unobservable preference. We treat each source of loyalty as equivalent in our model, although in the empirical section, we distinguish between loyalty arising from a preference for branded gasoline and loyalty arising from geographic differentiation. $\beta_i(p_t)$ denotes the proportion of consumers who will switch firms in response to the relative prices offered by the firms. We assume, without loss of generality, that all consumers are either loyal to a single firm or switch firms depending on the relative prices – that is, for all vectors p_t, $\sum_i \alpha_i + \beta_i(p_t) = 1$. By definition, we assume that if firm i has the highest price of the N firms, $\beta_i(p_t)=0$. Furthermore, we define $\overline{\beta}_i$ as the value when firm i has the lowest price of the N firms: the highest value $\beta_i(p_t)$ can take. Finally, we let p_i^* denote the price that maximizes profits from loyal consumers. This framework is a significant generalization of that used in the previous literature. Maskin and Tirole consider a duopoly in which $\alpha_i=0$, $\gamma_i=0$, $\beta_i(p_i,p_j)$ is equal to either zero, one-half or one depending on whether p_i is greater than, equal to or less than p_j. Eckert allows an asymmetric split of the market when firms choose identical prices. Following Maskin and Tirole, we use $V_{it}(p_{-it})$ to denote firm i 's expected profits when it is about to choose prices and firms play Markov perfect equilibrium strategies $\{R_1(p_{-1t}), R_2(p_{-2t}),\ldots, R_N(p_{-Nt})\}$ thereafter.[5] For notational convenience, let $V_{it}^{\alpha}(p_{-it})$ and $V_{it}^{\beta}(p_{-it})$ denote the expected profits from gasoline sold to loyal customers and to firm-switching customers when the firm i plays $R_i(p_{-it})$. Let $W_{it}^{\alpha}(p_{-it})$ and $W_{it}^{\beta}(p_{-it})$ denote the expected c-store or service station profits when the firm i plays $R_i(p_{-it})$.

We begin by characterizing the relationship between parameters α_i, β_i, and γ_i, and the expected profits earned by cycling and non-cycling firms. We prove that as the share of "loyal" customers rises, the expected profits from playing a constant price strategy rise

[5] Multiple Markov perfect equilibria (MPE) may exist - the value function depends on the particular MPE.

more quickly than the expected profits from playing a cycling strategy. Furthermore, if α_i is sufficiently high relative to $\overline{\beta}_i$, we prove that playing p_i^* strictly dominates all strategies exhibiting cycling behavior. Second, we show that as γ_i increases, a firm will be more willing to play a strategy exhibiting cycling behavior. For brevity, we include proposition proofs in the appendix.

Proposition 1: Let $\{R_1(p_{-1t}), R_2(p_{-2t}),\ldots, R_N(p_{-Nt})\}$ be a set of reaction functions exhibiting cycling behavior. As α_i increases, the expected profits earned by firm i by playing strategy $R_i(p_{-it})$ increase less quickly than the expected profits associated with always playing p_i^*.

Corollary 2: There exist values of α_i and $\overline{\beta}_i$ such that firm i would prefer to always play p_i^* rather than play $R_i(p_{-it})$.

As the share of "loyal" customers rises, the profits associated with playing the constant price strategy, p_i^*, rise more quickly than the profits associated with playing any cycling strategy. Corollary 2 proves that if a firm has a sufficiently high proportion of loyal customers, choosing the optimal static price for the loyal customers will dominate any cycling strategy. Thus, if a dominant firm in a market enjoys a sufficiently great geographic or brand advantage over a smaller rival, the larger firm may find that pricing to maximize profits from "loyal" customers strictly dominates any strategy involving cycling, and the smaller firm would then capture the majority of the firm-switching customers. Our finding, that a dominant firm with a substantial number of "loyal" customers may be reluctant to participate in cycles, contrasts with the theoretical results in Eckert (2003). He finds that if the dominant firm earns a sufficiently large split of the market when firm prices are identical, but does not enjoy any customer loyalty, the only MPE is one exhibiting cycling behavior. .

Proposition 3: Let $\{R_1(p_{-1t}), R_2(p_{-2t}),\ldots, R_N(p_{-Nt})\}$ be a set of reaction functions exhibiting cycling behavior. As γ_i increases, the expected profits associated with playing a strategy exhibiting cycling behavior increase more quickly than the expected profits associated with always playing p_i^*.

Firm willingness to play a cycling strategy rather than p_i^* depends on whether the profits gained by attracting firm-switching customers exceed the profits lost from suboptimally pricing to loyal customers.

The Propositions provide several predictions about the characteristics of cycling and non-cycling firms.[6] Although Propositions 1 and 3 do not necessarily imply a monotonic relationships between cycling propensity, the proportion of "loyal" customers (α_i), and profits accrued through the sales of the secondary good (γ_i), the results do suggest that potential benefits to cycling are less pronounced for firms enjoying geographic differentiation or brand loyalty or for firms deriving little profit from the secondary good. In addition, Proposition 1 suggests that firms for which loyal customers are a large proportion of demand are more likely to prefer a constant price to a strategy

[6] Although, in this paper we focus on cycling behavior, the proposition holds for any alternative reaction function chosen by firm i.

involving cycling.[7] In the context of retail gasoline stations, we would expect that retail stations with substantial brand loyalty or substantial geographic advantage would be less likely to choose a strategy involving cycling. If brand loyalty is greater for branded stations than independents, independents with substantial market presence may be more willing to choose strategies exhibiting cycling behavior than comparably-sized branded firms. Moreover, if branded stations compete for a subset of consumers, we expect that markets with more than one branded station are more likely to participate in cycling behavior. Finally, if proximity to other retail stations erodes a station's ability to extract a geographic rent from "loyal" customers, retailers in high station-density locations may be more likely to participate in cycles than retailers in locations with relatively few stations.[8]

Proposition 3 predicts that retailers deriving profits from goods other than the good whose price attracts customers to a particular location would be more likely to use a strategy involving cycling. In particular, in the context of retail gasoline, we would expect that retail stations with convenience stores would be more likely to participate in cycling behavior than retail stations without c-stores.

The previous propositions also suggest how the characteristics of the cycles might be related to observable firm characteristics. Specifically, a firm might be willing to play some but not all strategies exhibiting cycling behavior. Conditional on playing a cycling strategy, we would expect firms with a greater proportion of loyal customers to

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[7] In a two firm market, a competitor of a non-cycling firm would undercut the price of the non-cycling firm. With more than two firms, though, the proposition does not rule out cycling behavior on the part of a subset of market participants. With N>2, equilibria may exist in which firms with few loyal customers choose cycling strategies while firms with more loyal customers choose strategies in which they play p_i^*.
[8] Noel (2007) intuits this relationship and finds evidence consistent with station density increasing the likelihood of behavior consistent with Edgeworth cycles.

be less likely to play higher-amplitude cycling strategies, in which a firm cuts price significantly below p_i^* during the undercutting phase and sets substantially above p_i^* when relenting. Higher amplitude strategies price less optimally for the loyal customers. – thus, as the proportion of loyal customers increases, the lost-profit associated with suboptimal pricing to loyal customers is more likely to outweigh the profit gained through competing for the firm-switching customers. Furthermore, if a firm with a large proportion of loyal customers participates in a cycling equilibrium with a firm that has a smaller proportion of loyal customers, the former may be more likely to relent when prices are low.

Our model's predictions of cycle characteristics such as its amplitude are consistent with empirical observations in Noel (2007a), which were unpredicted by Eckert (2003). In markets with a large independent presence (markets in which β_i tends to be larger relative to α_i), Noel finds that market cycles have greater amplitude. In addition, he finds evidence that brand-name firms, which plausibly have a higher proportion of loyal customers, are more likely to relent at the bottom of a price cycle.

Empirical Predictions

Since we examine average prices at the MSA and ZIP code levels, we translate our predictions about station-level behavior up to what we expect to see at higher levels of aggregation. Based on our model predictions, we first predict that areas with independent stations and, especially independent stations with convenience stores, would be most likely to exhibit cycling behavior. If customers have a preference for branded gasoline, we also expect that cycling behavior would be more prominent in areas with more than one branded station. A branded station may be less likely to suboptimally price to consumers idiosyncratically preferring branded gasoline, absent a nearby branded competitor.

Cycles at the city level would reflect coordination over a large number of stations. We anticipate that this will be more likely in concentrated markets. In addition, as concentration rises, branded firms may have less incentive to participate in cycles with small market share independents. This suggests a relationship between concentration and observable cycling behavior where the least and most concentrated markets are less likely to cycle.

III. Data Description

The empirical analysis uses a dataset of daily gasoline prices across 115 metropolitan statistical areas (MSAs) in the Midwest and Northeast U.S. from April 1, 2000 to March 31, 2001.[9] These data were collected at the station level by the Wright Express Financial Services Corporation, a leading provider of payment processing and financial services to commercial and government car, van and truck fleets in the United States. Their Oil Price Information Service (OPIS) provides pricing information to the industry and transportation companies.

In addition to the retail price, OPIS data include a measure of each station's wholesale price. This is a rack price—the price at the terminal—from the nearest

[9] Metropolitan areas include an urban core with a population of at least 50,000, as well as surrounding counties tied economically through driving patterns—a definition well suited to studying gasoline markets. The data include stations in the Midwest, where there was a large price spike in the Spring of 2000, as well as eastern states as a comparison, including Arkansas, Connecticut, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, New York, Ohio, Pennsylvania, Rhode Island, Tennessee, Virginia, West Virginia, Wisconsin and Washington, DC.

refinery that produces the regulatory formulation of gasoline used by the station. These regional prices also vary by brand of gasoline, and the data include these brand-specific wholesale prices. This wholesale price may differ from the internal transfer price paid by refiner-owned stations. It may also differ from the station's actual wholesale price in that it does not include volume discounts or delivery charges.[10]

The OPIS data also include the street address of the station. US Census of Population data at the ZIP code level in 2000 were matched to the stations, including median household income, population, and commuting behavior. Race and educational attainment measures were also collected. In addition, the 2000 US Census ZIP Code Business Patterns database records the number of gasoline stations in each ZIP code.

One advantage of the OPIS data is that measurement error should be minimized, as the prices are recorded electronically from their clients' charge cards.[11] A cost of using credit card transactions is that they are only available for stations visited by a card holder, which results in missing data especially on weekends. Over 33,000 stations are found at least once over the year in our data, and theses stations provide a fairly accurate measure of brand coverage in a city. When comparing stations in the pricing survey and those in the Census Business Patterns data at the MSA level, then average number of stations is 262 and 274, respectively. At a smaller scale, the median ZIP code had three quarters of the stations surveyed.[12]

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[10] Volume discounts are common for branded gasoline at the wholesale level. Estimates with and without controls for wholesale price are discussed below.
[11] Further information on the methodology is available in Doyle and Samphantharak (2008) and at http://opisnet.com/methodology.asp
[12] To explore the types of ZIP codes that have better coverage in the pricing sample, the ZIP code count of the number of stations in the sample was regressed on the observable characteristics in Table 1. The main result is that more populous ZIP codes are associated with more station surveyed, controlling for the number of stations in the Census data.

Edgeworth cycles are characterized by gradual downward price movements, as firms marginally undercut competitors' prices, followed by a price spike. To empirically categorize geographic areas as cycling versus non-cycling, the median daily change in the retail price is considered, as in Lewis (2007). In particular, the daily change in retail price was calculated for each station with at least two consecutive days of data, and then the median of this daily price change at the MSA or ZIP code level was calculated. In cycling markets, we would expect the median price change to be negative, reflecting the greater number of days of falling prices as opposed to the sudden jump in price in the relenting phase. To ensure that the changes represent movements of a common set of stations, only stations that were present for at least 200 days over the year were included in these calculations, although the results were similar when all of the information was used.

In practice, we found that OPIS data can characterize cycling behavior at the MSA and ZIP code levels, but they are not precise enough to characterize cycling at the station level. Furthermore, even in locations where cycling exists, it is difficult to observe which station relents at the bottom of the cycle, as the change likely happens at a higher frequency than our daily data can capture. Rather than estimate cycling behavior at the station-level, we aggregate up to the MSA and ZIP code levels.

The two main measures of market structure are the fraction of stations that are independent and measures of the brand concentration in the market. Independent stations are not affiliated with a particular oil refiner, and they were identified in our sample by investigating the brand name. The Society of Independent Gasoline Marketers of America (SIGMA) publishes its member list, which provides one measure of whether the brand was independent, and the remaining brands were investigated individually. We further categorized independents based on the proportion of their retail outlets with an attached convenience store, as reported in trade press, websites and regulatory filings. Of the 45 independent brands observed in our data, twenty-six brands operate convenience stores at more than half of their retail outlets.

In terms of the brands, one feature of gasoline markets is that some stations may be owned by the refiner, while others are franchises. Unfortunately, the data do not allow us to separate these two groups. Further, when we characterize brand shares, no quantity data are available at the daily level. Instead, the fraction of stations in our sample of a particular brand is used in calculating the 3-brand concentration ratio and the brand HHI. Again, the station concentration of each brand appears fairly accurately measured, as the number of stations ever surveyed in each area is similar to Census measures.

IV. Empirical Models and Results

A. Edgeworth Cycles across Cities

As mentioned, we calculate the median daily price change for each of our geographic areas following Lewis (2008) and for ease of interpretation, we apply a cutoff below which an area is classified as exhibiting cycling behavior. As a first look, we ranked the MSAs in our sample by their median daily changes of average retail price. Figure 1 shows the average retail and wholesale price over time in 4 cities: the city with the smallest (i.e. largest negative) median change in retail price (Toledo, OH: median change equal to $-0.0124), a city near the median of the daily price change distribution (Detroit, MI: $-0.0014), and two cities city near the top of the ranking (Lincoln, NE, and

Johnstown, PA). In the top 3 graphs, a large price spike in the Spring of 2001 common to stations in the Midwest dominates the first few months of the series. This spike was partially due to a mandated reformulation and subsequent shortages (for more detail, see Doyle and Samphantharak, 2008). Later in the summer and the rest of the year, some of the cities in the Midwest reveal small decreases in price followed by sudden increases. For Toledo, Detroit, and Lincoln, the wholesale price movements are nearly identical, but the Toledo market has what appear to be Edgeworth cycles and the other two do not. Johnstown does not have the spike in April 2000, nor does it exhibit cycling behavior. It appears that the median price change measure reveals which cities tend to cycle. In particular, cities with a median price decline of -0.005 or more appear to exhibit cycling behavior, and this cutoff will be used in the analysis to compare cycling and non-cycling cities.[13]

Table 1 compares the characteristics of the 20 cycling MSAs with the 95 non-cycling MSAs in our sample The first row shows that this price change in the cycling MSAs is negative—a median decline of 0.8 cents per day—whereas non-cycling MSAs show median price change close to zero. The average retail and wholesale prices are similar across the two groups, with retail prices during this time period close to $1.50 per gallon. Much of the difference between retail and wholesale price is comprised of the state and federal taxes on gasoline.

In terms of the fraction independent and brand HHI, the cycling and non-cycling cities feature similar measures. This similarity masks a nonlinearity in the data that the most (and least) concentrated markets are less likely to feature cycling. The fraction of

[13] Appendix Figures A1A and A1B show retail and wholesale prices over time for the cutoff city at -0.005 and a city with a median change in retail prices of -0.004.

stations that are independent with convenience store operations does appear positively related to cycling in the raw means, with these types of stations making up 15% of cycling-city stations and only 9% of stations in non-cycling cities.

When US Census characteristics are considered, non-cycling MSAs include the largest cities and have higher average population density levels (1600 per square mile vs. 1400). Cycling cities also have more stations on average (271 vs. 255). The median household income is slightly higher in the average cycling city as well ($41,400 vs. $40,600).

Among the employed population, commuting patterns are similar across the two groups. Most workers drive to work alone, with slightly higher rates in cycling cities (83 vs. 80%). Meanwhile, the cities are similar in terms of racial composition. Among adults over the age of 25, the high school dropout rates are the same on average across the two groups. The percent with college education is higher in the non-cycling MSAs (23% vs. 21%). Overall, the cycling and non-cycling MSAs appear similar, with the non-cycling MSAs including the largest cities.

Cycling & Brand Concentration

In the model, the price elasticity of customers varies by firm, with some firms enjoying more brand loyalty or geographic advantage than others. One way that we characterize the potential for brand loyalty is by comparing independent stations with the refiner-affiliated brands such as Exxon or Citgo that invest more heavily in brand identification. Further, the model suggests that in markets that are highly concentrated the top firms will have less incentive to enter the cycle, and in highly competitive markets, the tacit collusion necessary to support cycling may break down. As a first look at these implications, Table 2 compares the cycling behavior across MSAs that vary by their fraction of stations that are independent or their brand concentration levels.

Panel A groups MSAs into quartiles based on the fraction of independent stations. The bottom quartile has 4% of stations that are independent on average, whereas the top quartile averages 35% of stations that are not affiliated with an oil refiner. The relationship between the fraction independent and cycling behavior has a marked invese-U shape: 31% of cities in the middle two quartiles exhibiting cycling, whereas few cities in the bottom or top quartile are found to cycle. This result is in contrast with the previous evidence that compared 19 cities in Canada and found that more independent stations were associated with a higher likelihood of cycling behavior (Noel, 2007a).

Panel B shows that a greater proportion of stations that are independent does appear to be related to cycling when those independents are also convenience store operators. The bottom two quartiles of cities here do not exhibit cycling at all. For the top two quartiles of cities based on the fraction of independent stations with convenience store operations, 41% and 29% are found to cycle, respectively.

As the fraction of independent stations grows, this may represent a more competitive market. To investigate the relationship between concentration and cycling directly, Figure 2 considers the 1-brand concentration ratio and the 3-brand concentration ratio. Local-linear regression estimates of the cycling indicator on these concentration measures are reported. As the largest brand gets larger, the likelihood of cycling in the city decreases. This is consistent with a reduced incentive by a dominant firm to engage in an Edgeworth cycle. 3-brand concentration ratio shows a distinctive inverse-U shape with regard to cycling. It appears that cycling is much less likely in cities with either a high or low level of concentration.

Panel C of Table 2 further explores this relationship between concentration levels and cycling in terms of HHI measured using the share of stations in the area (similar results are found when the 3-brand concentration ratio is used instead). 14% of the markets in the least concentrated MSAs and 11% of the most concentrated MSAs can be categorized as cycling, compared to 31% in the 3rd quartile.[14] These measures could be related to the fraction of independent stations to the extent that large independent brands are driving both measures. In practice, more independent stations are associated with less concentrated markets.[15]

These raw comparisons do not take into account differences between the MSAs. Table 1 showed that cycling and non-cycling MSAs are similar, but the relationship between cycling and concentration may be affected by the demand characteristics in the area. To test the relationship between cycling behavior and the fraction of independent stations or brand concentration, controlling for the demographic characteristics of the MSAs, the following model is estimated for MSA *m*:

$$Y_m = \gamma_0 + \gamma_1 I_m + \gamma_2 \mathrm{H}_m + \gamma_3 \mathrm{X}_m + \varepsilon_m \qquad (2)$$

where Y_m is a measure of the cycling behavior of the MSA, either the cycling indicator or the median daily change in the retail price; I_m measures the fraction of independent stations in the MSA; H_m is a vector of indicator variables equal to one if the MSA is in a particular quartile of the HHI distribution and zero otherwise; X_m is a vector of the

[14] Similarly, the 3 brand concentration ratio (not shown) increases from 0.27, 0.49, 0.57, and 0.70 from the bottom to the top quartile, and the fraction of cities that cycle in each quartile is 13%, 18%, 29%, and 11%.
[15] Pair-wise correlations between the fraction of independent stations vs. HHI and between the fraction of independent stations vs. the top 3 brand concentration are -0.14 and -0.27, respectively.

MSA's characteristics described in Table 1, including the demographic controls and the median change in the wholesale price. The model is estimated with OLS to compare conditional means, although the results for are similar when probit models are used to estimate the model when the dependent variable is the cycle indicator.

Panel A of Table 3 reports the results when the indicator for cycling is the dependent variable, and Panel B reports the results for the median change in daily prices—the measure used to define the cycling indicator. This measure allows all of the information in the daily change to be used in estimating the relationships, although the relationships are similar in both Tables.

Column (1) shows a lack of a linear relationship between the fraction of stations that are independent in a city and cycling behavior, whereas Column (2) shows that the greater the proportion of stations that are independent with significant convenience store operations increases, so does the likelihood of cycling. To consider the nonlinearity shown in Table 2, Column (3) reports estimates from a model that includes indicators for the quartiles of the fraction of stations that are independent. Here, the bottom quartile is less likely to cycle compared to the top quartile, although the difference is not statistically significant. As in Table 2, the middle two quartiles are where cycling behavior is found most likely to occur. Column (4) shows that across cities that vary by their fraction of stations that are independent with significant convenience store operations, the top two quartiles are much more likely to cycle.[16]

Columns (5) shows that the areas most likely to cycle are those where the concentration measure is in the 3rd quartile, confirming the unconditional results shown in

[16] These results were robust to categorizing stations as independent if they were SIGMA members, as opposed to the measure in the main results which involved investigating each brand name.

Table 2. Columns (6) and (7) include both the fraction independent measures and the HHI quartile indicators, and both results are robust. In particular, the 3rd quartile in terms of brand HHI is associated with a 22-25 percentage-point higher likelihood of cycling compared to the most concentrated MSAs (s.e. = 0.11). With 17% of cities found to cycle, this is a large difference.

In terms of the control variables, the demographic characteristics of the cities are largely unrelated to cycling behavior (see Appendix). In particular, median daily changes in our wholesale price measure are unrelated to cycling. The greater proportion of workers who drive to work alone is (weakly) positively related to cycling behavior.

These results suggest that cycling behavior is less likely to occur in the most competitive markets with the most independent stations—a situation when coordination may be infeasible. Further, in the most concentrated markets, it may not be in the interest of the dominant firms to enter the cycle. Rather, it is in the markets where the top 3 brands represent 50-60% of the market where we are seeing the cycling behavior most pronounced.

Price Effects

One question that arises is whether cycles result in lower or higher average prices. A complication is that cycling is related to the competitive nature of the market, which is predicted to affect prices as well. To consider the relationship between cycling and prices, controlling for market concentration, the following model is estimated for market *m*:

$$P_m = \gamma_0 + \gamma_1 C_m + \gamma_2 I_m + \gamma_3 \mathrm{H}_m + \gamma_4 \mathrm{X}_m + \varepsilon_m \qquad (3)$$

where P_m is the average retail price in the city, C_m is a cycling indicator, I and H are measures of the market structure as above, and X is a vector of controls including the average wholesale price in the market.

The results are reported in Table 4, and cycling is weakly related to lower prices. A cycling city is found to have lower prices by 1 to 2 cents per gallon on average (s.e.=0.01). It appears that the cycling cities have cycles that spend roughly equal time above and below the price levels in non-cycling cities.

Controlling for cycling behavior, the fraction of independent stations is associated with higher prices in the area, whereas the fraction of independent stations with c-store operations is associated with lower prices. Meanwhile, HHI in the area is associated with higher prices: cities in top quartile in terms of brand concentration have prices that average approximately 5 cents per gallon. This result is robust to controls, with income level and wholesale price positively related to the retail price (see Appendix). With markups generally on the order of 5 cents per gallon in the Midwest (Brannon, 2003), such a difference appears economically significant.

B. Edgeworth Cycles Within Cities

The "rockets and feathers" pattern of prices at the city-level suggests that competition is at the city level as well. Otherwise, if stations competed in this way across the street from one another and had different cycle frequencies, it would be difficult to detect the cycles at the city level. Instead, we find the jump in prices occurs on the same dates across cities. Given that MSAs are defined by commuting patterns, pricing pressure is likely transmitted across the MSA. The original Maskin and Tirole model evokes images of gasoline stations competing on a street corner, however, and we investigate whether cycling can be characterized at a smaller unit of analysis: the ZIP code level.

An advantage of investigating cycling behavior within cities is that we can control for fixed characteristics of MSAs that are difficult to control but may be related to both cycling behavior and market concentration, such as the regulatory environment. The fixed effects also control for regional factors, as cycling is found in the Midwest and not in the Northeast of the U.S. That said, store locations are chosen with future competition in mind, and convenience store operators, for example, may select areas within cities that are more prone to cycling behavior for reasons other than their pricing strategies.

To consider the source of Edgeworth cycles within and across cities, we compared 5900 ZIP codes to describe the determinants of cycling at a smaller unit of analysis. To identify ZIP codes that cycle there are two data issues. First, the ZIP code data are more likely to suffer from missing data problems compared to measures of prices at the city level. The main results include all of the ZIP codes in the data, but results are similar when the data are restricted to ZIP codes with observations in at least 200 days out of the year. Second, it is useful for ease of interpretation to categorize ZIP codes as cycling or non-cycling, and we visually inspected the data to arrive at a median change in retail price cutoff of -0.002.[17] Again, the results are similar when we use the median change in retail price itself rather than the dichotomous indicator for cycling, as well as when the cutoff remained -0.005.

The empirical models for ZIP code z in MSA m take the following form:

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[17] The city analysis used a cutoff of -0.005. Appendix Figures A2A and A2B show the time series of retail and wholesale prices for all ZIP codes that are categorized as cycling vs. those that are categorized as not cycling using the -0.002 cutoff.

$$Y_z = \gamma_0 + \gamma_1 W_z + \gamma_2 X_z + \delta_{m(z)} + \varepsilon_z \qquad (4)$$

where Y is an indicator for cycling behavior or average price in the ZIP code and W is a characteristic of the ZIP code of interest from the theoretical model, such as the presence of an independent station with a convenience store or the presence of dominant firm. The results are shown with and without controls for ZIP Code characteristics taken from the US Census of Population in 2000, X, and with and without MSA fixed effects. The models reported are estimated using OLS, although nearly identical results are found with probit models. For comparability with the earlier results and the dependence of pricing within a larger MSA market, the standard errors are clustered at the MSA level.

Table 5 reports the results for cycling behavior at the ZIP code level. Panel A considers the presence of an independent station (either with or without major convenience store operations), with the excluded category ZIP codes with no independent stations. 38% of ZIP codes have an independent gasoline station, and 21% have a convenience-store independent. Column (1) includes no control variables and the presence of an independent gasoline station with significant convenience store operations is a large predictor of cycling in the ZIP code. Compared to a mean of 13%, the presence of at least one such station is associated with a 31 percentage point increase in the likelihood of cycling (38% of ZIP codes with a convenience-store independent are found to cycle compared to 6.5% of ZIP codes with no such station), and the result is robust to the addition of controls. The presence of an independent without convenience store operations is negatively related to cycling, although this result is less robust to the inclusion of MSA fixed effects. Columns (3) and (4) report models with MSA fixed effects, and the estimates are identified from differences in the independent store locations within an MSA. The convenience-store results are generally similar when we compare ZIP code cycling within cities.

Column (4) restricts the analysis to within city comparisons of ZIP code cycling, conditional on the MSA cycling as defined earlier. We find that 42% of the stations in our cycling cities are in ZIP codes that are also found to cycle. Again, having an independent with convenience-store operations in the ZIP code is positively related to ZIP code cycling within the city, with a similar coefficient of 0.31, but compared to a different baseline of 43%. Independent stations without a convenience store are also positively related to ZIP code cycling (coefficient of 0.12). In terms of covariates, the median change in wholesale prices is not related to cycling, consistent with cycling being a retail market phenomenon (see Appendix). Taken together, it appears that convenience-store independents are associated with an increased likelihood that a city cycles, and once a city cycles any independent station is associated with aggressive pricing strategies.

Section 2 suggested that there should be a nonlinear relationship between brand concentration and cycling, and this was found for the cross-city comparisons in Table 3. Panel B of Table 5 further investigates this relationship by considering whether having only one “top brand” in the ZIP code reduces the likelihood of cycling compared to having two top brands. “Top brands” are defined as the two brands with the highest station shares in the city. If only one top player is in the ZIP code, it may have a higher fraction of loyal consumers who live or work nearby and they may eschew the costs of engaging in Bertrand-style price movements. The results in Panel B report estimates from models similar to Panel A, but with indicators that one or both of the top 2 brands in the city are in the ZIP code, with the excluded category ZIP codes with neither of the top 2 brands. The results show that having both of the top 2 brands is a much stronger positive relationship with cycling than having just one, consistent with the notion that it takes at least two to play the game. This result is robust to controls, including MSA fixed effects.[18] These results provide compelling evidence that the observed cycles are indeed a product of competitive forces among large players, as opposed to some (unobserved) mechanical process that leads to price spikes.

The last set of results replicates the retail price results and are shown in Table 6.[19] As in Table 4, cycling is associated with modest reductions in price (between 1 and 3 cents on average, compared to an average gas price at the time of $1.52). It appears that cycling results in prices that are more volatile, but are similar to non-cycling cities on average. Meanwhile, the presence of an independent gasoline station in the ZIP code, or a top brand, is relatively unrelated to the average price in the ZIP code.

Limitations

The MSA results are cross-sectional relationships with the usual caveats that areas with cycling behavior may simply differ compared to areas without cycling behavior. The observable characteristics look similar across the groups, however, with the exception that the largest cities do not appear to cycle. Results are similar when cities of

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[18] Other measures of brand overlap in a city were considered. Similar results are found when more than the top 2 brands are considered, with the presence of only one of the top 3 or 5 brands being associated with significantly less cycling behavior. Cycling by brand was also considered, although missing data limitations make this type of comparison less compelling.

[19] The number of observations is slightly different in Table 6 compared to Table 5 due to missing data for the change in wholesale price in the set of controls used in Table 5. Results are nearly identical when this variable is excluded and the same sample is used for both Tables.

greater than 2 million populations are excluded. Also, the results are similar when MSA fixed effects are included.

Second, the data are limited by the frequency of missing observations, especially for weekends. Aggregate city level data should categorize cities that cycle versus those that do not. In addition, the results are similar when the sample is limited to stations that are frequently seen in the data. In addition, it appears that our sample has sufficient coverage over the course of the year to characterize brand concentration.

Another limitation is the lack of quantity data results in measures of concentration at the station-share level rather than the usual market share for each brand. To the extent that station shares reflect some minimum quantity before a franchise is allowed to open, it seems likely that such station shares are sufficiently highly correlated with quantity shares to serve as a reliable proxy for HHI. In any event, the station shares provide slightly different measure of concentration, but one that reflects geographic coverage of the brands.

Last, the cycling behavior is found in the Midwest, largely in Ohio, Michigan, Indiana, and Illinois. The shape of the relationships described in the larger sample is robust to limiting the sample to stations only in the Midwest, and we find that the cities in the eastern U.S. provide a useful comparison group.[20]

V. Conclusion

Retail gasoline markets are unique in that the price for the product is broadcast for all to see, including competitors. This facilitates price competition, and a striking feature

[20] In our sample, Midwest states are Indiana, Illinois, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, and Wisconsin.

of these markets is that some exhibit what appear to be Edgeworth cycles. A refinement to the Maskin-Tirole model that allows firms to retain some customers even when they are underbid suggests that markets with dominant firms may not have the incentive to enter such a cycle. Further, a necessary condition for such tacit collusion is that the firms have some market power, and the least concentrated markets may not be able to support such cycles either.

The empirical results use a dataset of daily prices across 115 cities to describe the types of cities that exhibit cycling behavior. 17% of cities in our sample have price cycles. In contrast to previous evidence, cities with more independent stations are found less likely to cycle. When independent stations with significant convenience store operations are considered, however, a greater proportion of such stations is related to cycling. This relationship with convenience-store independents and cycling behavior is found within cities as well, with ZIP codes with such stores much more likely to have cycling. Given the complementary goods and the price salience of the gasoline price, these stations may have an incentive to engage in price reductions that can lead to the cycling behavior.

It appears that the main observable characteristics that characterize which Midwestern cities exhibit Edgeworth cycles is the extent to which the market is concentrated: the least and most concentrated cities are less likely to cycle. Meanwhile, cycling behavior is not found to result in higher or lower retail prices. These results are found controlling for city characteristics such as income levels, commuting patterns, changes in wholesale prices, as well as models that included MSA fixed effects and identified the relationships across ZIP codes in the same city.

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Appendix

Proposition 1 Proof: Let $\{R_1(p_{-1t}), R_2(p_{-2t}),\ldots, R_N(p_{-Nt})\}$ be a set of reaction functions exhibiting cycling behavior and consider the derivative with respect to α_i of firm i's expected profits earned by playing $R_i(p_{-it})$ and by playing p_i^*. Since p_i^* maximizes profits from the share of "loyal" customers, α_i ,

$$\frac{\partial E\left[\sum_{t=0}^{\infty}\delta^t(p_i^*-c_i)\alpha_i q(p_i^*)\right]}{\partial\alpha_i} > \frac{\partial V_{it}^{\alpha}(p_{-it})}{\partial\alpha_i} \quad . \tag{2}$$

Thus, a change in the share of loyal customers increases the profits associated with playing p_i^* more than the profits associated with playing $R_i(p_{-it})$.

Corollary 2 Proof: Let $R_i(p_{-it})$ be a reaction function exhibiting cycling behavior and consider a deviation from $R_i(p_{-it})$ to a strategy in which the firm always plays p_i^*. Let $V_{it}^{\alpha}(p_{-it})$ and $V_{it}^{\beta}(p_{-it})$ denote the expected profits from loyal customers and firm-switchers when firm i plays $R_i(p_{-it})$.[21] Define $\hat{p}_i$ as the constant price which provides the firm the same expected profits from loyal customers as the cycling equilibrium[22]. By definition, $\hat{p}_i$ solves

$$E\left[\sum_{t=0}^{\infty}\delta^t(\hat{p}_i-c_i)\alpha_i q(\hat{p}_i)\right] = V_{it}^{\alpha}(p_{-it}) \tag{3}$$

A firm will prefer to play p_i^* to $R_i(p_{-it})$ if and only if

$$E\left[\sum_{t=0}^{\infty}\delta^t(p_i^*-c_i)[\alpha_i+\beta_i(p_i^*,p_{-it})]q(p_i^*)\right] \geq V_{it}^{\alpha}(p_{-it}) + V_{it}^{\beta}(p_{-it}) \tag{4}$$

[21] For expositional purposes, we assume that $\gamma_i=0$ – we find an identical result allowing $\gamma_i>0$.

[22] Note that $\hat{p}_i$ is a function of both the vector of reaction functions as well as the vector of starting prices.

Consider $\alpha_i, \overline{\beta}_i \in (0,1)$ satisfying

$$\frac{\overline{\beta}_i}{\alpha_i} = \frac{(p_i^* - c_i)q(p_i^*) - (\hat{p}_i - c_i)q(\hat{p}_i)}{(\hat{p}_i - c_i)q(\hat{p}_i)} \quad (5)$$

Rearranging (4), we have

$$\sum_{t=0}^{\infty} \delta^t (p_i^* - c_i)\alpha_i q(p_i^*) = \sum_{t=0}^{\infty} \delta^t (\hat{p}_i - c_i)\alpha_i q(\hat{p}_i) + \sum_{t=0}^{\infty} \delta^t (\hat{p}_i - c_i)\overline{\beta}_i q(\hat{p}_i) \quad (6)$$

The left hand side of (6) is the expected profits earned from loyal consumers by a firm playing p_i^* in all periods. The first term on the right hand side is equal to $V_{it}^{\alpha}(p_{-it})$ and the second term in the right hand side is strictly greater than $V_{it}^{\beta}(p_{-it})$ by definition of $\overline{\beta}_i$. Thus, values of α_i, $\overline{\beta}_i$ satisfy condition (5) implying that firm i prefers to play p_i^* to $R_i(p_{-it})$.

Proposition 3 Proof: Consider a firm choosing between $R_i(p_{-it})$ and p_i^*. By definition, the derivative of profits associated with playing p_i^* and $R_i(p_{-it})$ with respect to γ_i are respectively,

$$E\left[\sum_{t=0}^{\infty} \delta^t (\alpha_i + \beta_i(p_i^*, p_{-it}))\right] \quad (7)$$

$$\frac{\partial W_{it}^{\alpha}(p_{-it})}{\partial \gamma_i} + \frac{\partial W_{it}^{\beta}(p_{-it})}{\partial \gamma_i} \quad (8)$$

Noting that $\frac{\partial W_{it}^{\alpha}(p_{-it})}{\partial \gamma_i} = E\left[\sum_{t=0}^{\infty} \delta^t (\alpha_i)\right]$, the difference in the derivative of profits is given by the relative proportion of firm switching consumers obtained by p_i^* and $R_i(p_{-it})$. Since playing cycling strategy $R_i(p_{-it})$ allows a firm to obtain a greater proportion of firm-switching customers than playing p_i^*, for which firm i receives $\beta_i(p_i^*, R_{-it}(p_i^*))$, an increase in γ_i has a greater effect of firm profits when the firm plays a cycling strategy than when the firm plays a non-cycling strategy.

Table 1: Selected Statistics, MSA Level

Variable		Cycling MSAs (Number of Obs. = 20) Mean	Std. Dev.	Min	Max	Non-Cycling MSAs (Number of Obs. = 95) Mean	Std. Dev.	Min	Max
Gasoline Prices	Median Daily Change in Retail Price	-0.008	0.002	-0.012	-0.005	-0.002	0.001	-0.005	0.000
	Average Daily Retail Gas Price	1.48	0.04	1.40	1.54	1.49	0.07	1.37	1.66
	Average Daily Wholesale Gas Price	0.93	0.02	0.91	0.97	0.93	0.03	0.88	1.00
Gasoline Stations	Number of Stations	272	237	33	969	255	388	15	2337
	Fraction of Independent Stations	0.18	0.08	0.10	0.38	0.17	0.13	0	0.68
	Fraction of Independent Stations w. Conv. Store	0.15	0.05	0.08	0.31	0.09	0.11	0	0.64
Brand Concentration	HHI	1119	349	334	1617	1168	701	55	3082
	Fraction of Top Three Brands	0.51	0.09	0.280	0.638	0.50	0.19	0.105	0.957
Census Characteristics	Population Density (per sq. mile)	1420	737	408	3020	1583	2307	177	20216
	Median Income (Thousand $)	41.399	3.058	34.222	46.116	40.573	5.821	28.117	54.751
Commuting (of Working Population)	Drive alone	0.83	0.02	0.795	0.857	0.80	0.046	0.547	0.87
	Public Transportation	0.01	0.01	0.003	0.040	0.02	0.033	0.002	0.27
Race (of Total Population)	White	0.85	0.04	0.78	0.93	0.86	0.10	0.52	0.97
	Black	0.10	0.03	0.04	0.16	0.08	0.08	0.00	0.43
	Hispanic	0.03	0.02	0.01	0.06	0.03	0.03	0.00	0.18
Education (of Population over 25 years old)	Less than Highschool	0.17	0.02	0.11	0.20	0.17	0.04	0.07	0.32
	Some College	0.28	0.03	0.23	0.34	0.26	0.04	0.18	0.33
	College	0.21	0.05	0.12	0.30	0.23	0.07	0.11	0.46

Table 2: Mean of Cycle and Median Difference in Daily Retail Prices

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: By Fraction of Independent Stations					
1st Quartile					
Cycle	29	0	0	0	0
Median Difference in Daily Retail Prices	29	-0.002	0.001	-0.004	0.000
Fraction of Independent Stations	29	0.041	0.026	0.000	0.079
2nd Quartile					
Cycle	29	0.310	0.471	0	1
Median Difference in Daily Retail Prices	29	-0.003	0.003	-0.010	0.000
Fraction of Independent Stations	29	0.119	0.020	0.079	0.152
3rd Quartile					
Cycle	29	0.310	0.471	0	1
Median Difference in Daily Retail Prices	29	-0.004	0.004	-0.012	0.000
Fraction of Independent Stations	29	0.197	0.031	0.153	0.256
4th Quartile					
Cycle	28	0.071	0.262	0	1
Median Difference in Daily Retail Prices	28	-0.002	0.002	-0.006	0.000
Fraction of Independent Stations	28	0.350	0.095	0.258	0.679
Panel B: By Fraction of Independent Stations w/ Convenience Store					
1st Quartile					
Cycle	29	0	0	0	0
Median Difference in Daily Retail Prices	29	-0.001	0.001	-0.003	0.000
Fraction of Independent Stations w/ Conv. Store	29	0.002	0.004	0.000	0.012
2nd Quartile					
Cycle	29	0	0	0	0
Median Difference in Daily Retail Prices	29	-0.002	0.001	-0.004	0.000
Fraction of Independent Stations w/ Conv. Store	29	0.042	0.019	0.013	0.081
3rd Quartile					
Cycle	29	0.414	0.501	0	1
Median Difference in Daily Retail Prices	29	-0.004	0.003	-0.010	0.000
Fraction of Independent Stations w/ Conv. Store	29	0.114	0.021	0.082	0.146
4th Quartile					
Cycle	28	0.286	0.460	0	1
Median Difference in Daily Retail Prices	28	-0.003	0.003	-0.012	0.000
Fraction of Independent Stations w/ Conv. Store	28	0.241	0.106	0.147	0.641
Panel C: By HHI of Brands					
1st Quartile					
Cycle	29	0.138	0.351	0	1
Median Difference in Daily Retail Prices	29	-0.002	0.002	-0.010	0.000
HHI	29	373	223	55	683
2nd Quartile					
Cycle	29	0.138	0.351	0	1
Median Difference in Daily Retail Prices	29	-0.003	0.003	-0.009	0.000
HHI	29	964	125	684	1167
3rd Quartile					
Cycle	29	0.310	0.471	0	1
Median Difference in Daily Retail Prices	29	-0.004	0.003	-0.012	0.000
HHI	29	1308	87	1170	1466
4th Quartile					
Cycle	28	0.107	0.315	0	1
Median Difference in Daily Retail Prices	28	-0.002	0.003	-0.010	0.000
HHI	28	2022	471	1484	3082

Table 3: Competition and Cycling

Panel A: Dependent Variable = Dummy Variable for Cycling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraction Independent	0.0616					-0.0150	
	(0.29)					(0.27)	
Fraction Independent with Convenience Store		0.773*					0.724*
		(0.39)					(0.40)
Fraction Independent, Dummy for 1st Quartile			-0.110				
			(0.088)				
Fraction Independent, Dummy for 2nd Quartile			0.216*				
			(0.11)				
Fraction Independent, Dummy for 3rd Quartile			0.176*				
			(0.098)				
Fraction Independent with Convenient Store, Dummy for 1st Quartile				-0.323***			
				(0.098)			
Fraction Independent with Convenient Store, Dummy for 2nd Quartile				-0.266***			
				(0.092)			
Fraction Independent with Convenient Store, Dummy for 3rd Quartile				0.0969			
				(0.13)			
HHI, Dummy for 1st Quartile					0.122	0.123	0.0645
					(0.11)	(0.11)	(0.11)
HHI, Dummy for 2nd Quartile					0.0767	0.0776	0.0232
					(0.11)	(0.11)	(0.11)
HHI, Dummy for 3rd Quartile					0.253**	0.253**	0.218*
					(0.11)	(0.11)	(0.11)
Observations	115						
R-squared	0.18	0.21	0.28	0.35	0.23	0.23	0.25

All models include full controls. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 3: Competition and Cycling, Cont.

Panel B: Dependent Variable = Median Daily Price Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraction Independent	0.000892					0.00163	
	(0.0019)					(0.0017)	
Fraction Independent with Convenience Store		-0.00711**					-0.00672**
		(0.0028)					(0.0028)
Fraction Independent, Dummy for 1st Quartile			-0.0000253				
			(0.00067)				
Fraction Independent, Dummy for 2nd Quartile			-0.00156**				
			(0.00072)				
Fraction Independent, Dummy for 3rd Quartile			-0.00183***				
			(0.00069)				
Fraction Independent with Convenient Store, Dummy for 1st Quartile				0.00307***			
				(0.00072)			
Fraction Independent with Convenient Store, Dummy for 2nd Quartile				0.00162**			
				(0.00069)			
Fraction Independent with Convenient Store, Dummy for 3rd Quartile				-0.000416			
				(0.00086)			
HHI, Dummy for 1st Quartile					-0.000771	-0.000890	-0.000239
					(0.00080)	(0.00080)	(0.00079)
HHI, Dummy for 2nd Quartile					-0.000932	-0.00103	-0.000436
					(0.00080)	(0.00079)	(0.00079)
HHI, Dummy for 3rd Quartile					-0.00192**	-0.00198**	-0.00160**
					(0.00079)	(0.00079)	(0.00077)
Observations	115						
R-squared	0.23	0.28	0.31	0.43	0.28	0.28	0.33

All models include full controls. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 4: Cycling, Competition and Retail Prices

Dep. Var. MSA Average Retail Price	(1)	(2)	(3)	(4)	(5)
cycle	-0.0284**	-0.0150	-0.0181	-0.0184	-0.0164
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Fraction Independent				0.0889**	
				(0.040)	
Fraction Independent with Convenience Store					-0.0318
					(0.038)
Fraction Independent, Dummy for 1st Quartile	-0.0426**				
	(0.018)				
Fraction Independent, Dummy for 2nd Quartile	-0.0156				
	(0.013)				
Fraction Independent, Dummy for 3rd Quartile	-0.0138				
	(0.012)				
Fraction Independent with Convenient Store, Dummy for 1st Quartile		0.0505***			
		(0.013)			
Fraction Independent with Convenient Store, Dummy for 2nd Quartile		-0.0171			
		(0.012)			
Fraction Independent with Convenient Store, Dummy for 3rd Quartile		0.0127			
		(0.0097)			
HHI, Dummy for 1st Quartile			-0.0545***	-0.0607***	-0.0524***
			(0.015)	(0.015)	(0.016)
HHI, Dummy for 2nd Quartile			-0.0309**	-0.0364**	-0.0287*
			(0.014)	(0.014)	(0.015)
HHI, Dummy for 3rd Quartile			-0.0194	-0.0225	-0.0184
			(0.014)	(0.014)	(0.014)
Observations	115				
R-squared	0.61	0.70	0.64	0.65	0.64

All models include full controls. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

Table 5: Cycling At the ZIP Code Level

Panel A: Presence of an Independent Station in ZIP

Dependent Variable: ZIP Code Cycle	(1)	(2)	(3)	(4)
Presence of an Independent with Convenience Store	0.314	0.284	0.219	0.309
	(0.040)**	(0.035)**	(0.031)**	(0.038)**
Presence of an Independent without Convenience Store	-0.045	-0.047	0.013	0.122
	(0.015)**	(0.017)**	(0.011)	(0.053)*
Full Controls	No	Yes	Yes	Yes
MSA Fixed Effects	No	No	Yes	Yes
Cycling MSAs only	No	No	No	Yes
Observations	5900	5722	5722	1019
R-squared	0.15	0.18	0.34	0.39
Mean of Dependent Variable	0.134	0.138	0.138	0.427

Panel B: Presence of Major Brands

Dependent Variable: ZIP Code Cycle	(1)	(2)	(3)	(4)
Presence of 1 of the Top 2 City Brands	0.051	0.044	0.047	0.140
	(0.016)**	(0.015)**	(0.016)**	(0.033)**
Presence of Both Top 2 City Brands	0.204	0.171	0.163	0.435
	(0.038)**	(0.033)**	(0.031)**	(0.039)**
Full Controls	No	Yes	Yes	Yes
MSA Fixed Effects	No	No	Yes	Yes
Cycling MSAs only	No	No	No	Yes
Observations	5900	5722	5722	1019
R-squared	0.06	0.11	0.32	0.41
Mean of Dependent Variable	0.134	0.138	0.138	0.427

Standard errors in parentheses, clustered at the MSA level *** p<0.01, ** p<0.05, * p<0.10

Table 6: Retail Prices & Cycling At the ZIP Code Level

Panel A: Presence of an Independent Station in ZIP

Dependent Variable: Average Retail Price	(1)	(2)	(3)	(4)
ZIP Code Cycle	-0.034	-0.023	-0.011	-0.014
	(0.007)**	(0.006)**	(0.004)**	(0.003)**
Presence of an Independent with Convenience Store	-0.036	-0.023	-0.014	-0.007
	(0.014)**	(0.007)**	(0.002)**	(0.002)**
Presence of an Independent without Convenience Store	0.034	0.020	-0.014	-0.012
	(0.015)*	(0.006)**	(0.002)**	(0.003)**
Full Controls	No	Yes	Yes	Yes
MSA Fixed Effects	No	No	Yes	Yes
Cycling MSAs only	No	No	No	Yes
Observations	5900	5825	5825	1033
R-squared	0.10	0.48	0.79	0.56
Mean of Dependent Variable	1.523	1.522	1.522	1.485

Panel B: Presence of Major Brands

Dependent Variable: Average Retail Price	(1)	(2)	(3)	(4)
ZIP Code Cycle	-0.054	-0.034	-0.014	-0.017
	(0.012)**	(0.007)**	(0.005)**	(0.003)**
Presence of 1 of the Top 2 City Brands	0.0001	-0.004	-0.006	-0.002
	(0.005)	(0.004)	(0.002)**	(0.002)
Presence of Both Top 2 City Brands	-0.001	-0.002	-0.009	-0.001
	(0.007)	(0.005)	(0.003)**	(0.003)
Full Controls	No	Yes	Yes	Yes
MSA Fixed Effects	No	No	Yes	Yes
Cycling MSAs only	No	No	No	Yes
Observations	5900	5825	5825	1033
R-squared	0.05	0.46	0.79	0.55
Mean of Dependent Variable	1.523	1.522	1.522	1.485

Standard errors in parentheses, clustered at the MSA level *** p<0.01, ** p<0.05, * p<0.10

Appendix Table A1: Covariates for Selected Models

	Geographic Level:	MSA	MSA	ZIP	ZIP
	Dependent Variable:	Cycle	Retail Price	Cycle	Retail Price
		(1)	(2)	(3)	(4)
Main Explanatory Variables	Fraction Independent	0.724*	-0.0318		
	with Convenience Store	(0.40)	(0.038)		
	Cycle		-0.0164		-0.014
			(0.012)		(0.003)**
	Presence of an Independent			0.309	-0.007
	with Convenience Store			(0.038)**	(0.002)**
	Presence of an Independent			0.122	-0.012
	without Convenience Store			(0.053)*	(0.003)**
	HHI, Dummy for 1st Quartile	0.0645	-0.0524***		
		(0.11)	(0.016)		
	HHI, Dummy for 2nd Quartile	0.0232	-0.0287*		
		(0.11)	(0.015)		
	HHI, Dummy for 3rd Quartile	0.218*	-0.0184		
		(0.11)	(0.014)		
Census Controls at	Population Density (pop/square mile)	0.0000530	-0.00000241	0.00000628	0.000000394
MSA or ZIP Code Levels		(0.000042)	(0.0000061)	(1.94E-05)	(9.37E-07)
	Median Household Income	0.00125	0.00380***	-0.00000742	4.31E-08
		(0.0078)	(0.0010)	(2.23E-06)	(3.15E-07)
Race / Ethnicity	White	-0.0168	-0.282	-3.114	-0.055
		(3.22)	(0.49)	(1.358)*	(0.044)
	Black	0.927	-0.511	-3.147	-0.040
		(3.13)	(0.50)	(1.460)*	(0.043)
	Hispanic	-0.691	-0.588	-2.937	-0.045
		(3.91)	(0.57)	(1.631)	(0.061)
Education	Less than High School	-0.172	0.297	-1.647	0.096
(Among those >25 years old)		(1.37)	(0.19)	(0.265)**	(0.029)**
	High School Graduate	1.262	0.468***	-2.211	0.103
		(1.41)	(0.17)	(0.376)**	(0.034)**
	College	-0.412	-0.186	-1.033	0.124
		(0.91)	(0.11)	(0.416)*	(0.032)**
Commuting Patterns	Drive Alone	5.835*	0.577	4.667	-0.024
(Among working population)		(3.44)	(0.48)	(1.000)**	(0.113)
(work from home, excluded)	Car Pool	-1.303	-1.258*	4.291	-0.100
		(4.77)	(0.66)	(1.162)**	(0.129)
	Public Transportation	1.303	1.258*	3.435	-0.054
		(4.77)	(0.66)	(1.684)	(0.066)
	Other Transport	5.685	1.674***	2.524	0.046
		(4.00)	(0.59)	(1.044)*	(0.129)
	Median Change in Wholesale Price	-138.1		-2.864	
		(135)		(2.718)	
	Average Wholesale Price		1.069***		0.516
			(0.22)		(0.190)*
	Full Controls	Yes	Yes	Yes	Yes
	MSA Fixed Effects	N/A	N/A	Yes	Yes
	Cycling MSA	N/A	N/A	Yes	Yes
	Observations	115	115	1019	1033

Column (1) is the model reported in Table 3A, Column (7); Column (2) is the model reported in Table 4, Column(5); Column (3) is the model reported in Table 5 Column (4); and Column (4) is the model reported in Table 6, Column(4); The difference in the number of observations in Columns (3) & (4) is due to missing change-in-wholesale-price data in Column (3); *** p<0.01, ** p<0.05, * p<0.10

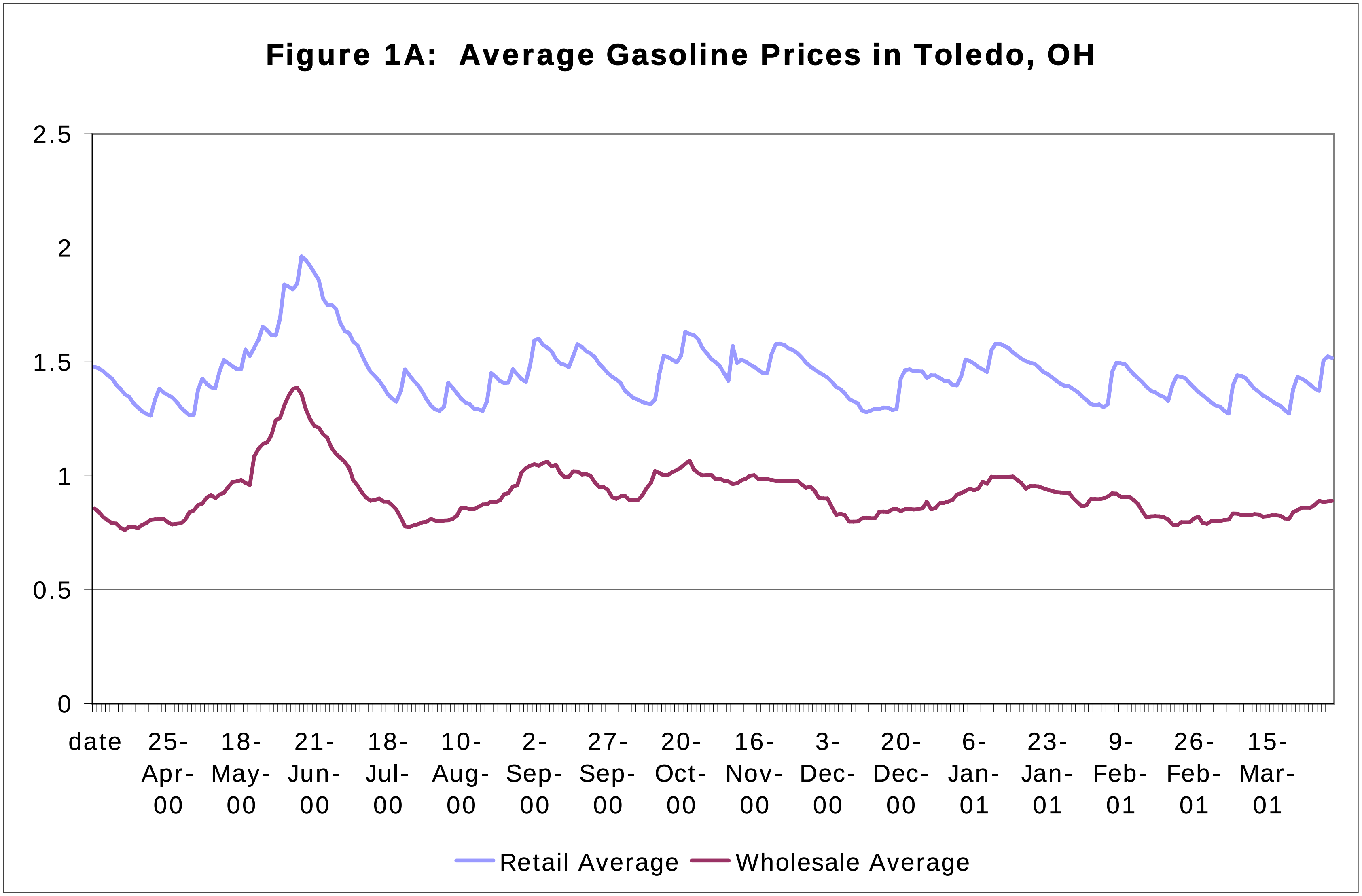
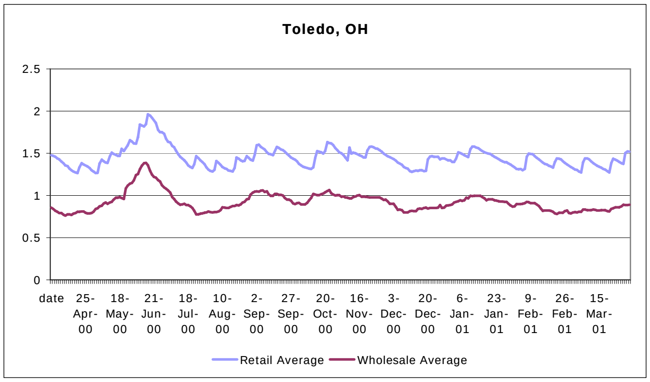
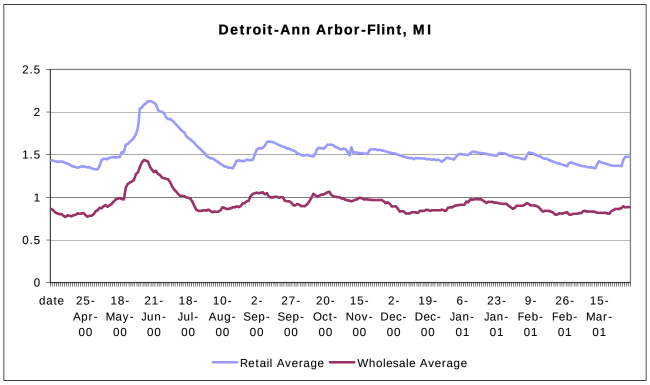
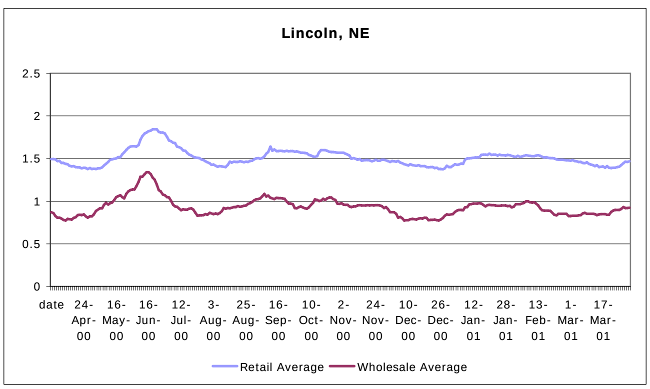


Figure 1A: Average Gasoline Prices in Toledo, OH
2.5
2
1.5
1
0.5
0
date
25-Apr-00
18-May-00
21-Jun-00
18-Jul-00
10-Aug-00
2-Sep-00
27-Sep-00
20-Oct-00
16-Nov-00
3-Dec-00
20-Dec-00
6-Jan-01
23-Jan-01
9-Feb-01
26-Feb-01
15-Mar-01
Retail Average
Wholesale Average

Figure 1B Gasoline Price Movements







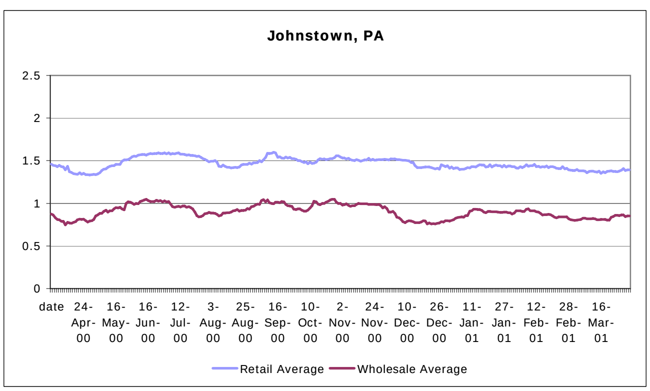


**Figure 2A: Likelihood of Cycling vs.
1 Brand Concentration Ratio**

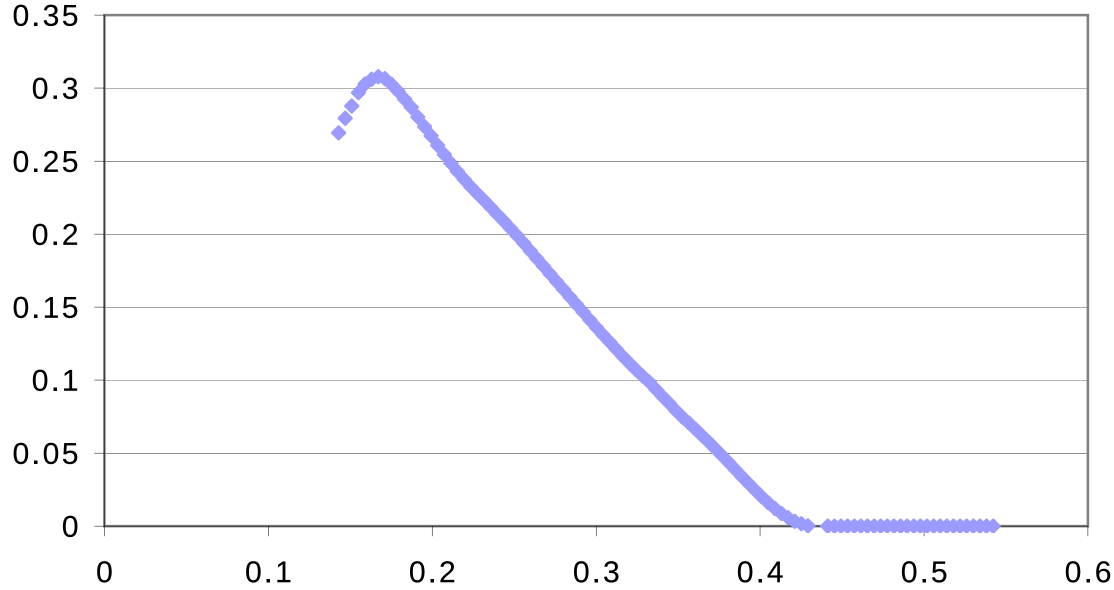
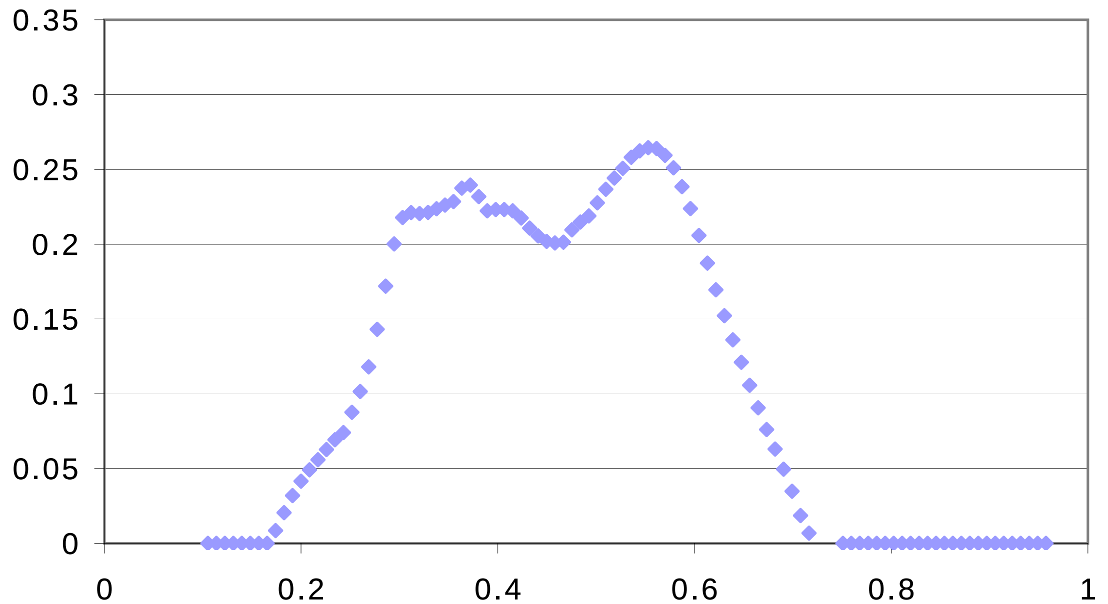


**Figure 2B: Likelihood of Cycling vs.
3-Brand Concetration Ratio**



Local linear regression estimates, with a pilot bandwidth of 0.05. Concentration ratios use the share of stations in a city that belong to a particular brand. N=115 MSAs.

Figure A1A: Retail & Wholesale Prices over Time Cutoff City with Median Change in Retail Price At the Cutoff: -0.005

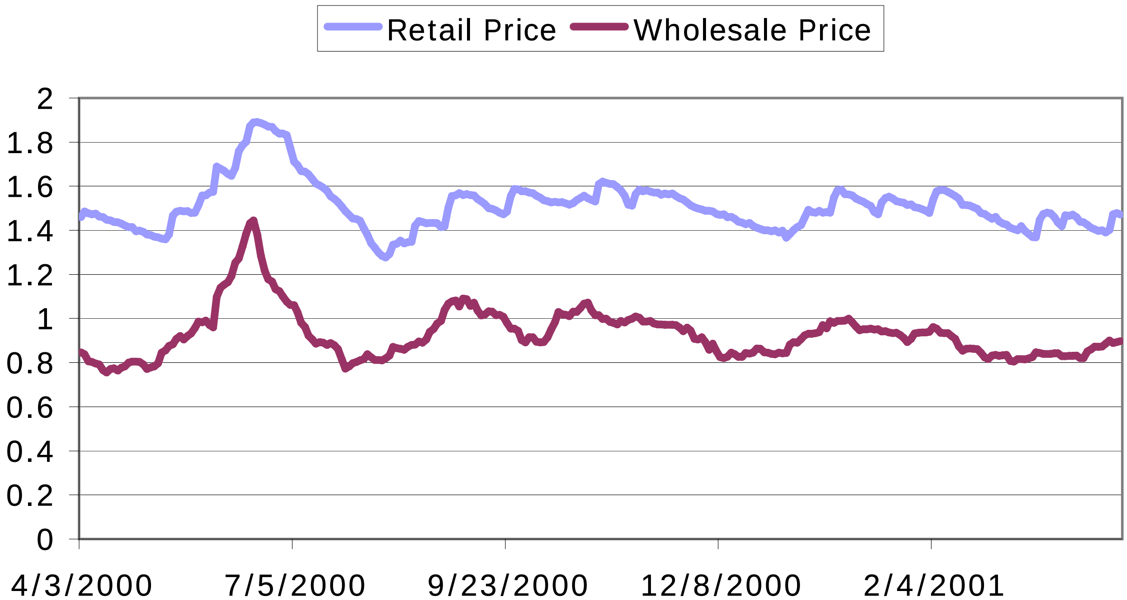
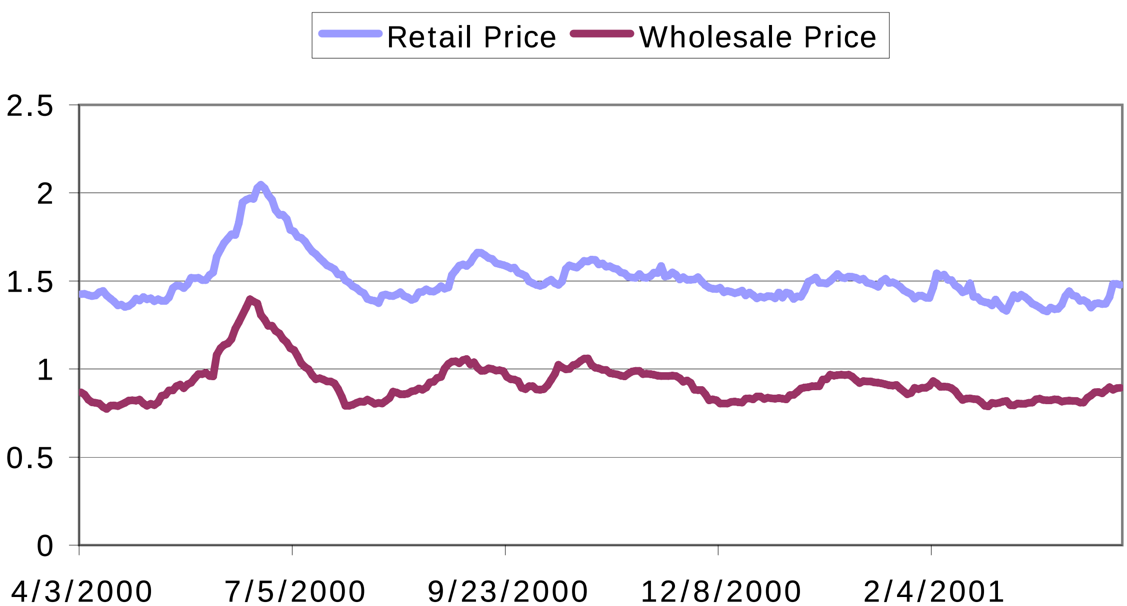
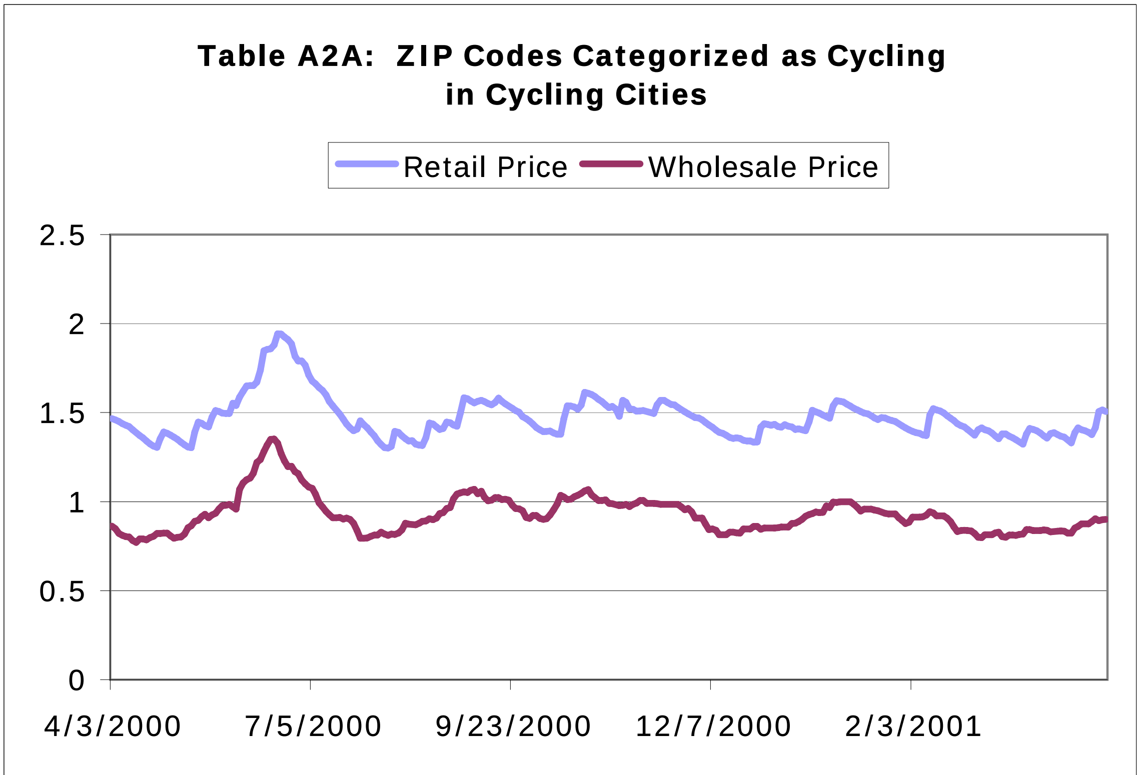
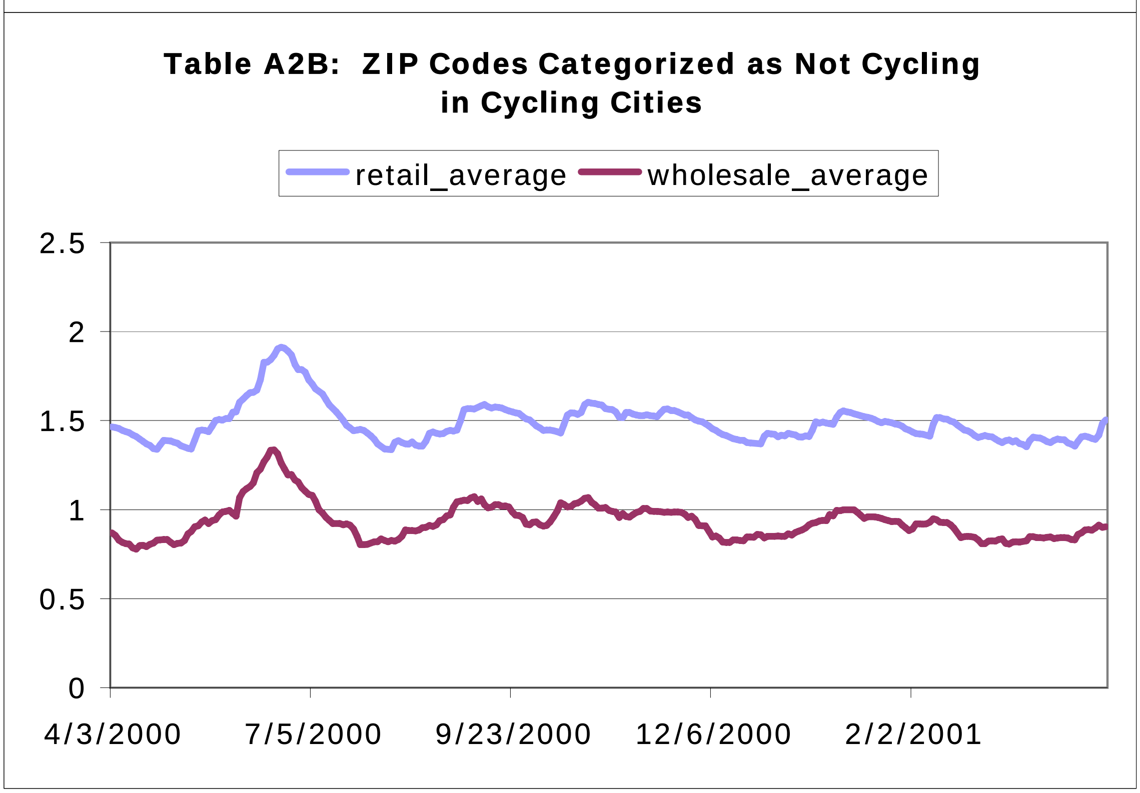


Figure A1B: Retail & Wholesale Prices over Time City with Median Change in Retail Price at An Alternative Cutoff: -0.004







Figures pooled data across all cycling cities, using ZIP codes with at least 200 days of data over the course of the year. Cycling indicator equals 1 if the median change in retail price in the ZIP code is less than -0.002.