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Edgeworth Price Cycles, Cost-based Pricing and Sticky Pricing in Retail Gasoline Markets

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Abstract

This paper examines dynamic pricing behavior in retail gasoline markets for 19 Canadian cities over 574 weeks. I find three distinct retail pricing patterns: 1. standard cost-based pricing, 2. sticky pricing, and 3. steep, asymmetric retail price cycles that, while seldom documented empirically, resemble those of Maskin & Tirole [1988]. I use a Markov switching regression to estimate the prevalence of the regimes, the pattern of markup in each, and the structural characteristics of the price cycles themselves. Retail price cycles prevail in over 40% of the sample. I show they are more prevalent in markets and at times where there is a greater penetration of small, independent firms. The cycle is accelerated and amplified in markets with very many small firms. In markets with few small firms, sticky pricing is dominant. Each of these findings is consistent with the theory of Edgeworth Cycles. I discuss both welfare and policy implications of such pricing behavior, and compare the Canadian experience with that of seemingly similar retail gasoline markets in the United States.

JEL Classification L13, L41, L81

"This is why marketers and individual retailers watch one another's price signs like hawks. When one competitor lowers the price, others follow right away. Consumers have the impression that the prices all change in unison, but they don't – it's a rapid chain reaction. Eventually, prices spiral down to the point where the margin disappears altogether, until one competitor restores the price." – Roger Purdie, V.P. Imperial Oil Canada, 2000.

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1 Introduction

In a retail industry where many firms sell a homogeneous good, one might expect firms to simply set retail price equal to wholesale price plus the marginal cost of retailing. However, in retail gasoline markets in Canada, three different pricing phenomena can be seen. The first pattern is one in which prices cycle rapidly and in a strongly asymmetric way. The cycle begins with a large price increase from one week to the next, and is followed by a gradual decline in price over the next several weeks. It then repeats over and over. These cycles, seldom documented empirically, appear similar to the theoretical "Edgeworth Cycles" of Maskin & Tirole[1988]. In contrast, the second pattern is one in which prices remain fixed for months at a time. A more normal pricing pattern in which retail prices more closely follow wholesale prices is the least common pattern of the three.

In this paper, I use a panel set of 19 cities over 574 weeks (January 1989 to December 1999) to explore these three phenomena in two stages.

The first objective is simply to develop an empirical framework to separate out the three patterns, measure the prevalence of each, and then measure the structural characteristics of the cycles themselves, such as period, amplitude, and asymmetry. I show that a Markov switching regression technique, adapted from Cosslett & Lee[1985] and Ellison[1994], is well suited to this. I find cycling activity in 43% of the sample, sticky pricing in 30% and normal pricing in 27%. The cycles are strongly asymmetric, with prices first rising for 1.3 weeks and then falling for 2.5 weeks on average. The average amplitude is 3.1 cents per liter, or 60% of the average markup during cycling activity.[1] I also find much heterogeneity in cycle prevalence and characteristics both within and across cities.

The second objective is to show that not only do these cycles appear like Edgeworth Cycles but that their prevalence and characteristics change with the competitive environment in ways predicted by the theories of Edgeworth Cycles (Maskin & Tirole[1988] and Eckert[2003]). In particular, I focus on the effect of small independent firms and show that cycles are significantly more prevalent and are significantly taller, faster, and *less* asymmetric when there is greater penetration of small independents. Each of these results is consistent with the theories of Edgeworth Cycles. Moreover, the result is robust when controlling for market size and service outlet density, and also when using alternate measures of small firm penetration.

I follow with a short welfare analysis and show that cycling behavior is associated with lower markups. Interestingly, the asymmetric nature of the cycles themselves may account for the reverse perception by many consumer groups. I also consider and rule out several alternate explanations for the observed phenomenon. Finally, I conclude with a short comparison between Canadian and US markets and between gasoline and other product markets. We might have

[1] Currency in Canadian dollars unless otherwise stated. On average over the sample period, CDN$1 = US$0.70. Thus, 3.1¢/liter CDN = 8.2¢/gallon US.

Figure 1: Windsor Rack and Retail

expected to see these patterns in U.S. gasoline markets or in other product markets and yet it currently seems we do not.

Section 2 previews the results in graphs and preliminary statistics. Section 3 discusses the related literature and Section 4 lays out my empirical framework. A short discussion of the data is in Section 5. In Section 6, I report results on the prevalence of retail price cycles, sticky pricing and normal pricing and construct estimates of the structural characteristics of the cycle. I examine the impact of small independent firms on cycle prevalence and structural cycle characteristics in section 7. In Section 8, I conduct the welfare analysis and discuss alternate hypotheses for the cycles and Section 9 concludes.

2 Data at a Glance

Examination of wholesale and retail prices over time across Canadian cities reveals sharp differences in pricing behavior. To illustrate, figures 1, 2, and 3 show the average wholesale price (the "rack" price) and the average tax-exclusive retail price series for three cities over subsets of the sample: Windsor, St. John's, and Ottawa.[2] The data are average spot prices recorded at the same time each week, in Canadian cents per liter, and the same wholesalers and the

[2] The cities and time periods were chosen as good examples of each pattern. In particular, the time period for St. Johns (the middle third of the time series instead of the first third) was chosen to emphasize price stickiness even during a period of relatively volatile rack prices.

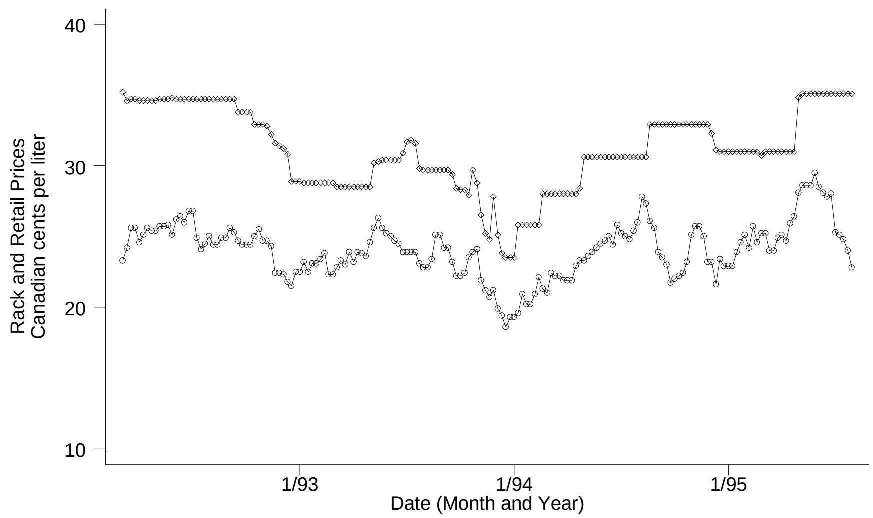

Figure 2: St. John's Rack and Retail

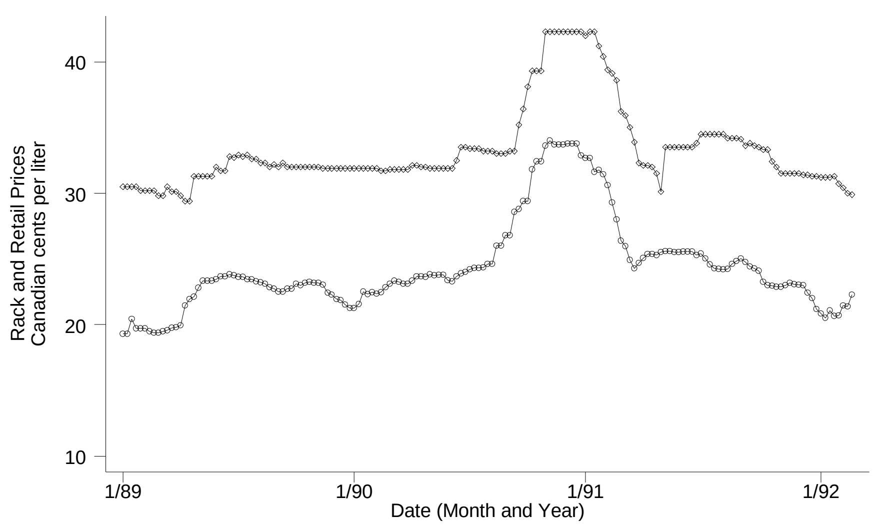

Figure 3: Ottawa Rack and Retail

same retail service outlets are polled each time.

The retail price series shown for Windsor exhibits a rarely documented but visually striking cyclical pattern that does not appear in wholesale prices. When the retail price gets too near the rack price, retail prices rise suddenly by more than three cents on average and often greater than five cents. On average, it triples the rack-retail markup. The retail price then falls gradually by a small amount each week until the price is sufficiently low that the cycle begins anew.

In contrast, retail prices remain sticky in St. John's in the mid 1990s for months at a time, in spite of fluctuating rack prices. In the Ottawa series, we observe signs of a more normal pattern where retail prices roughly follow wholesale prices. Neither show signs of cycles.

It is not just volatility but the strong asymmetry that is distinctive about these cycles. As a preliminary look at the extent of asymmetry in all sample markets (rather than just the selected graphs), I report basic summary statistics on rack prices, retail prices, and markups, and on per-week price changes and price "runs" in table 1. A "run" is defined as the number of weeks of consecutive same-sign price changes.

Over the full sample, the average week-to-week retail price increase (2.01 cpl) is significantly greater than the average decrease (1.18 cpl). I report both the usual two-sample t-statistic and the P-value from the more comprehensive Kolmogorov-Smirnov distribution test.[3] There are highly significant asymmetries in retail prices but none in rack prices.

Similarly, the mean length of a run down in retail prices (1.94 wks) is significantly longer than the mean length of a run up (1.36 wks). While it is rare to observe runs up of more than two weeks, runs down of four to eight weeks are common. Rack price runs, in contrast, do not show signs of asymmetry.

These simple statistics are suggestive but not sufficient for my purposes. They cannot separately identify individual price movements within an Edgeworth-like cycle from those within a normal cost-based pricing pattern, and therefore one cannot use them to compute the prevalence of cycles per se or their structural characteristics (or the influence of small independents on cycles).

3 Theory and Literature

The price cycles observed in these cities are similar in appearance to the theoretical "Edgeworth Cycles" of Maskin & Tirole[1988]. In their paper, Maskin & Tirole consider a dynamic Bertrand price setting game under which two equal sized firms produce homogenous goods under constant costs. Firms set prices alternately (along a finite price grid), and each responds to its opponent's action from the previous period. Firms split demand if prices are equal and the lower priced firm captures the entire market if not equal. The authors show that even under identical supply and demand conditions there are two distinct sets of Markov perfect Nash equilibria (MPE).

[3] The null hypothesis of the K-S test is that the distribution of retail price increases is the same as that of (the absolute value of) retail price decreases.

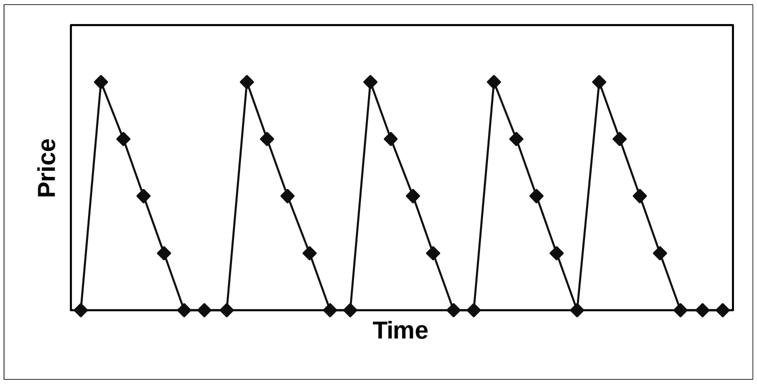

Figure 4: Edgeworth Cycle

The first set of MPE is the familiar focal price (or focal markup) equilibria supported under threat of retaliation. The sticky pricing we observe is consistent with a focal price and the normal pricing observed in the data could come from a standard, possibly competitive markup over the wholesale price.

The strong cyclical pattern observed in many cities appears consistent with the second type of dynamic equilibria. Maskin & Tirole call these "Edgeworth Cycles" and they operate as follows. In the longer downward portion of the cycle, firms repeatedly undercut one another by one notch on the grid in order to gain a larger market share. When price reaches marginal cost, each firm has a positive probability of raising its price back to the "top" of the cycle. A war of attrition results as each waits for the other to go up first. When one firm does, the other immediately follows and price undercutting begins anew. Figure 4 shows an example of a time path of cycling prices in their model.

One limitation of the Maskin & Tirole analysis is that the two firms are identically sized. Eckert[2003] extends the theoretical model to the case of firms of different sizes, where a firm of a larger "size" simply means it receives a larger fraction of consumers when prices are identical. When prices are unequal, it is assumed the lower priced firm (whether it is the large or small firm) can and does serve the entire market itself. As a result, the smaller the firm, the greater the incentive to undercut. The author concludes that when the two firms are sufficiently different in size, only Edgeworth cycling can exist. A focal price equilibrium cannot.

The shape of the cycle is also affected when firms are of different size. When the small firm undercuts, a sufficiently large firm is more likely to match the small firm's price rather than further undercut it. By matching, the large firm receives a higher price than by undercutting, and it serves almost the entire market anyway. As a result, the downward portion of the cycle progresses more slowly and the cycle appears more asymmetric when the large firm is very large.

The setting of these models lends well to Canadian gasoline retailing markets.

Gasoline is relatively homogeneous, frequently purchased, and firm level demand is highly-elastic.[4] Retail prices of regular gasoline are displayed on tall billboards – easy for consumers to compare and easy for competing firms to monitor. Menu costs are absent: in some markets, retail prices can change several times a day. Discussions with regional managers also suggest that an alternating moves game – where each firm monitors and then responds to changes by other firms – is an appropriate description of behavior.

It should be noted, however, that gasoline retailers are capacity constrained. A single small firm with few retail outlets can steal only a negligible fraction of the market by undercutting and is easily ignored by the large firm. Only when there are many such firms, individually small but collectively large, will more widespread undercutting steal enough market share to induce a price match or further undercut from the large firm, and thus generate price cycling. Moreover, with a sufficiently large number of small firms, one expects that the response from the large firm will be a further undercut rather than a match. This is because the large firm (which is not so large anymore) will no longer serve almost the entire market by matching and, as suggested by the theory, will find it more profitable to undercut.

The second objective of this paper is to test these propositions. I expect greater prevalence of retail price cycles in markets when there is a greater penetration of small independent firms and less sticky pricing. Where cycles exist, I expect a greater number of small or independent firms to speed up the downward portion and therefore the cycle itself and generate cycles that appear *less* asymmetric.

A great deal of empirical work has been done with respect to retail pricing in gasoline markets in the U.S., Canada, and elsewhere but few papers have specifically addressed asymmetric price cycles of this nature.

For the United States, Allvine & Peterson[1974] note similar patterns in some western U.S. cities in several episodes in the 1960s and early 1970s. They argue that the sudden halt to price cycling in these cities in 1972 may have been the result of suffocation of wholesale supplies to independent retailers in advance of the oil shortage of 1973, but no empirical analysis is performed. In a short note, Castanias & Johnson[1993] note the Edgeworth-like appearance of the cycles in Los Angeles from 1968 to 1972, and present simple summary statistics on price changes and runs (like table 1).

In Canada, the cycles have been known to industry and government observers for some time but only a few published academic papers exist.[5] Most

[4] High firm-level price elasticity is an important factor. Imperial Oil reports claim that many consumers do respond to differences as low as 0.2 cents per liter. (Majors generally only price in odd decimals so 0.2 is the minimum undercut.) Perhaps additional utility is being gained from paying the lowest price, since savings would only be about a dime on a fillup. My own anectodal evidence suggests than a difference of 1 cpl at two nearby Toronto stations (*very* rare and very brief) indeed has a large impact on volumes.

[5] Slade[1987, 1992] examines a price war in Vancouver in the summer of 1983 but it is different than the repeated, high-frequency price cycles analyzed here. The price war appears isolated in an era of stable prices and is postulated to have occurred because of an unan-

closely related to this work is Eckert[2003] who motivates his theoretical model (described above and found in that paper) with some interesting correlations between overall price rigidity and concentration ratios in these retail gasoline markets. The rigidity variable is defined as the fraction of times prices did not change from week to week within each year within a given city, and the concentration ratios are based on year-end station counts for 19 cities and 6 years.

The current paper improves upon the empirical exercise in that paper in several important respects. First, the rigidity variable cannot make the necessary distinction between price changes that are the result of asymmetric Edgeworth-Cycle-like behavior – which are of special interest – and prices that are not rigid for other reasons, such as occurs in a normal, symmetric pricing regime.[6] My empirical framework specifically separates out the three distinct pricing phenomena, isolates the asymmetric cycles in particular, and can directly estimate their prevalence. Secondly, the framework can estimate the detailed characteristics of the cycles it identifies which is of interest in its own right.[7] Thirdly and more importantly, both of these features allow a more complete and multi-pronged test of the relationships predicted by the theory: with increasingly more small independent firms, 1. Edgeworth Cycles (as opposed to moving prices) should be more prevalent, 2. the upward portion should be unaffected, 3. the downward portion and therefore 4. the cycle itself should progress more rapidly and finally 5. the cycle should be less asymmetric.

I am aware of two other recent empirical papers that examine individual Canadian cities during a period of strong retail price cycles throughout. Using weekly average price data for the city of Windsor from in the early 1990s, Eckert[2002] shows that the nature of the price cycle results in rack price increases being passed through to retail prices more quickly than decreases. This contrasts earlier studies by Hendricks[1996], Lerner[1996], and Godby et. al[2000] that included non-cycling cities. While the large literature on asymmetric rack-retail passthrough in the U.S. and elsewhere (Borenstein, Gilbert, & Cameron[1997] and many others) typically assume reversion to a single long-run steady-state retail price and are conducted for markets that are known *not* to exhibit retail price cycles, the existence of cycles suggests a new potential source for passthrough asymmetry.

Secondly, Noel[2003] uses a self-collected 12-hourly price data for twenty-two service stations in the city of Toronto over four months to test the reactions of large vertically integrated chains and small independents along the cycle in a strongly cycling environment. Without variation in market structure, the author still shows that both large and small firms are important to cycle gener-

ticipated demand shock. In those papers, the author reports evidence of tacit collusion and found that rivals respond more quickly to price increases by a major firm than to decreases while the opposite was true for reactions to independents. I limit my literature review here to papers about repeated, asymmetric Edgeworth-like price cycles.

[6] Prices may also be volatile for other reasons, or display an asymmetry that is opposite in direction to that suggested by the theory.

[7] Most notably, to confirm the existence and direction of the asymmetry.

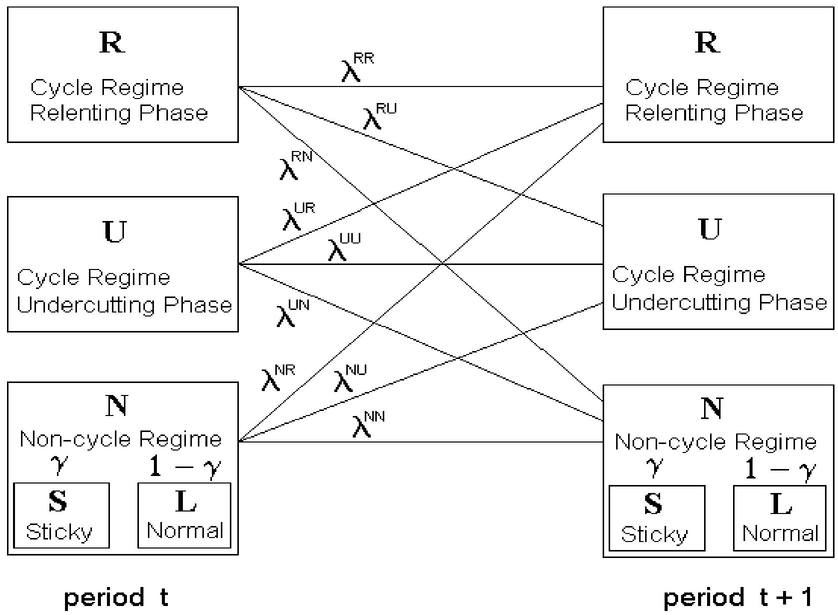

Figure 5: Regimes and Switching Probabilities

ation and in opposite ways. Price competition is intensified and, consistent with the theory of Edgeworth Cycles, small independents are more likely to initiate price undercutting while large integrated firms are more likely to initiate price resetting.

4 Empirical Framework

The first objective of this paper is to build measures of the prevalence of each pattern and of cycle characteristics directly from parameter estimates. I do this by taking nonlinear transformations of the parameters produced from a Markov switching regression.

The Markov structure is important in identifying cycles since it allows for serial correlation in the estimated regimes. The challenge is that the true underlying regimes are really unobservable and cycle and non-cycle price movements can look identical to the econometrician, even in the absence of sampling error. The Markov structure helps overcome this by incorporating both current and past information into regime categorization. For example, an observed price decrease of a given size is more likely to be considered part of the (downward) undercutting phase of a cycle if we believe the market was in an undercutting phase in the previous period. It is less likely to be considered part of the undercutting phase if we believe the market was in a normal or sticky pricing pattern in the previous period. A regular switching regression, which relies only on information contained in the current observation, has no such memory feature.

Of course, it would necessarily be subjective to classify cycles and their characteristics by eyeballing the price series or selecting minimum and maximum cutoffs. That in mind, eyeballing the results ex post suggests the model categorizes data reasonably well.

Guided by the time series, I model the retail gasoline industry as one in which a given market can be in one of three top-level regimes at a given point in time. They are

1. the relenting phase of the cycle (regime "R"),
2. the undercutting phase of the cycle (regime "U"),
3. the non-cycle price regime (regime "F", for focal).

and I later model the switching probabilities between each pair. I further subdivide the third regime – the non-cycle price regime – into two subregimes:

3a the non-cycle price regime – normal pricing (regime "F", subregime "N")

3b the non-cycle price regime – sticky pricing (regime "F", subregime "S")

and allow switching between these. Placing non-cycling activity into a single top-level regime is to make the parameter estimation manageable and allow me to concentrate on the asymmetric price cycles which are of primary interest.[8]

Figure 5 outlines the structure of the model.

4.1 The Regimes

The first two regimes capture price evolution within the cycle: the relenting phase (regime "R") and the undercutting phase (regime "U"). The portion during which I anticipate finding prices that rise sharply in a short time I call the relenting phase and the portion during which I anticipate finding prices that gradually fall I call the undercutting phase. However, it is important to note that the form of these within-regime regression equations is completely symmetric in each case and no *a priori* restrictions are imposed on the sign or minimum size of price changes.[9] Nothing in the setup tips the model toward finding any hypothesized asymmetry (in either direction).

[8] Also for computational reasons, I do not separately model adjustments in the sticky pricing regime. To the extent that adjustments reestablish a standard markup (which can vary by market and year) and are in part triggered by movements in rack price, combining normal and sticky pricing into a single regime helps classify these into normal pricing. More on computation in the appendix.

[9] This feature means the model is free to classify, for example, a (small) price increase or zero price change as part of the undercutting phase if the estimated switching probabilities and history of play suggest it.

Specifically, in periods of cycling, I model market m at time t as evolving according to the function

$$\Delta RETAIL_{mt} = X^i_{mt}\beta^i + \varepsilon_{mt}, \quad i = R, U \tag{1}$$

where $\Delta RETAIL_{mt}$ is the first difference of the retail price, $(X^i_{mt})'$ is an $K^i \times 1$ vector of explanatory variables, β^i is a $K^i \times 1$ vector of parameters and ε_{mt} is a normally distributed error term with mean zero and variance σ^2.[10]

Setting the X^i to a vector of ones, for example, allows a simple estimation of the average price changes in each phase of the cycle (since non-cycle periods have now been isolated and excluded) and will contribute to measuring the vertical characteristics. When I include variables that capture the penetration of small independent firms and other demand variables into X^i in section 7, the vertical dimension is allowed to evolve with changes in these variables.[11]

In the "normal pricing" subregime (subregime "N") of the non-cycling regime, I anticipate retail prices following movements in wholesale price more closely, perhaps with a lag. I model this subregime as:

$$RETAIL_{mt} = X^N_{mt}\beta^N + \varepsilon_{mt} \tag{2}$$

where $RETAIL_{mt}$ is the retail price, $(X^N_{mt})'$ is a $K^N \times 1$ vector of explanatory variables, β^N is a $K^N \times 1$ vector of parameters and ε_{mt} is normally distributed. In all specifications discussed below, the rack price, and dummies for city, month, and year are included in the X^N.

In the sticky price subregime (regime "S"), prices do not change from the previous week, so simply

$$RETAIL_{mt} = RETAIL_{m,t-1} \tag{3}$$

with no error term.

4.2 The Switching Probabilities

There are nine Markov switching probabilities in total, from and to each of three top-level regimes. Let I_{mt} be the indicator function equal to "R", "U", and "F" when market m at time t is in the relenting phase, the undercutting phase, and the non-cycle regime respectively. I model the probability that a market switches from regime i in period $t-1$ to regime j in period t with the logit form:

$$\begin{aligned} \lambda^{ij}_{mt} &= \Pr(I_{mt} = j \mid I_{m,t-1} = i, W^i_{mt}) \\ &= \frac{\exp(W^i_{mt}\theta^{ij})}{1 + \exp(W^i_{mt}\theta^{iR}) + \exp(W^i_{mt}\theta^{iU})}, \quad i = R, U, F, \quad j = R, U \end{aligned} \tag{4}$$

[10] In the relenting phase, price returns to the "top" of the cycle, which in turn depends on the current rack price. To account for this, I add a cycle position variable to X^R later in the paper.

[11] Particulars of each specification are discussed together with results in later sections.

and $\lambda_{mt}^{iF} = 1 - \lambda_{mt}^{iR} - \lambda_{mt}^{iU}$, $i = R, U, F$ to satisfy the adding up constraint. Call Λ_{mt} the 3×3 switching probability matrix whose ijth element is λ_{mt}^{ij}. Each $(W_{mt}^{i})'$ is an $L^i \times 1$ vector of explanatory variables that affects switching out of regime i and θ^{ij} is an $L^i \times 1$ vector of parameters. Note that the same set of explanatory variables appear in W^i for each j within a given i to avoid an Independence of Irrelevant Alternatives type constraint on the remaining probabilities.[12]

Setting the W^i to a vector of ones, for example, yields estimates for average switching probabilities which I use to measure the horizontal characteristics of the cycle. When I include variables that capture the penetration of small independent firms and other demand variables into W^i in section 7, the horizontal dimension is allowed to evolve with changes in these variables.

Conditional on a non-cycle regime, let the indicator variable J_{mt} equal to "N" and "S" when the market is in the normal pricing and the sticky pricing subregimes respectively. I model the probability of being in subregime "S", conditional on being in a non-cycle pricing regime, with the logit form:

$$\Pr(J_{mt} = \text{“}S\text{”} \mid I_{mt} = \text{“}F\text{”}, V_{mt}) = \gamma_{mt} = \frac{\exp(V_{mt}\zeta)}{1 + \exp(V_{mt}\zeta)} \tag{5}$$

where $(V_{mt})'$ is a $Q \times 1$ vector of explanatory variables and ζ is an $Q \times 1$ vector of parameters.

The core model parameters $(\beta^i, \theta^{ij}, \zeta)$ in each upcoming specification are simultaneously estimated by the method of maximum likelihood. Numerical methods are used to calculate robust Newey-West standard errors on the core estimates. Estimates of the switching probabilities, cycle characterisics, and partial derivatives are derived by joint non-linear transformations of the core parameter estimates or by simulation when noted. Standard errors for derived parameter estimates are calculated using the multivariate delta method or via simulation. Further detail is in the appendix.

4.3 Prevalence and the Anatomy of a Price Cycle

By combining the switching probabilities and the within-regime parameters, I can now derive formulae for the prevalence of each regime and for the structural characteristics of the cycles.

For example, the prevalence of the three top-level regimes is simply $z = (z^R, z^U, z^F)'$ where z solves

$$\Lambda' z = z, \quad z \neq 0 \tag{6}$$

and Λ' is the transpose of the switching probability matrix. It is straightforward to check that z is the eigenvector of the transposed switching probability

[12] For example, if variable x is included in λ^{iR} but not λ^{iU}, a change in x that increases λ^{iR} forces a compensating decrease in both λ^{iU} and λ^{iF} according to their proportions.

matrix corresponding to an eigenvalue of one. Within the non-cycle regime, the prevalence of sticky pricing is just γz^F and of normal pricing it is $(1-\gamma)z^F$.

Turning to the structural characteristics of the cycle, the expected period of the cycle, or the distance between consecutive troughs, is just the expected length of a relenting phase plus the expected length of an undercutting phase. Since the probability of "switching" from regime i in period $t-1$ to the same regime again in period t is λ^{ii}, I derive the expected duration of regime i as

$$E(duration\ of\ regime\ i) = \frac{1}{1-\lambda^{ii}} \tag{7}$$

and the expected period of the cycle as

$$E(period) = \frac{1}{1-\lambda^{RR}} + \frac{1}{1-\lambda^{UU}} \tag{8}$$

To derive the amplitude of the price cycle, I multiply the expected duration of the relenting phase with the expected relenting phase price change. One could also the undercutting phase to calculate the vertical fall (rather than the vertical rise) and the long term stationarity of prices over the sample period ensures these measures are about the same. Therefore, I calculate expected amplitude as

$$E(amplitude) = \frac{\alpha^R}{1-\lambda^{RR}} \text{ or } \frac{-\alpha^U}{1-\lambda^{UU}} \tag{9}$$

where $\alpha^R = E(\Delta RETAIL_{mt} \mid X^R_{mt})$ is the expected per week price change in a relenting phase and α^U is similarly defined.

One of the most interesting characterisics of the cycles is their asymmetry. There are two dimensions on which to measure this: horizontally and vertically. I define "horizontal asymmetry" as the ratio of the duration of the undercutting phase to the duration of the relenting phase:

$$E(horizontal\ asymmetry) = \frac{1-\lambda^{RR}}{1-\lambda^{UU}} \tag{10}$$

and "vertical asymmetry" as the (negative of the) ratio of the average price change in an relenting phase to the average price change of the undercutting phase:

$$E(vertical\ asymmetry) = \frac{-\alpha^R}{\alpha^U} \tag{11}$$

Again, the long run stationarity of prices ensures this measures to be roughly the same.

Finally, one might also be interested in the average duration of a complete cycling spell, which I calculate as

$$E(spell\ duration) = \frac{z^R + z^U}{z^R * \lambda^{RF} + z^U * \lambda^{UF}} \tag{12}$$

and the expected number of consecutive cycles that make up the spell:

$$E(\#\ consecutive\ cycles) = \frac{E(spell\ duration)}{E(period)} \tag{13}$$

Recall that these measures will yield average values of prevalence and characteristics when X^R, X^U, W^i, and V are columns of ones. Later, I allow them to covary with the penetration of small independents and other demand variables by building up the X^i, W^i, and V.

5 Data

I examine 19 major Canadian cities for the period beginning the first week of January, 1989 and ending the last week of December, 1999. Data were collected on retail gasoline prices, wholesale (rack) prices, outlet populations and other ancillary information.

Retail gasoline prices, $RETAIL_{mt}$, are the tax-exclusive prices for regular unleaded 87 octane gasoline, in Canadian cents per liter. Retail price data come from weekly surveys by the Ministry of Natural Resources of Canada, M.J. Ervin & Associates, and by the Ontario Ministry of Energy. The same set of service outlets are surveyed within each city at the same time each Tuesday morning and the average price across outlets is recorded.[13]

The wholesale price I use is the average spot rack price, $RACK_{mt}$, in each city for unbranded regular gasoline sold at the city terminal. The average is across major wholesalers, and it is reported weekly by the Bloomberg Oil Buyer's Guide (OBG), matching the retail price data.[14]

Measures of small firm penetration were constructed from bimonthly data on firm-specific outlet counts, which were purchased from Kent Marketing Ltd.[15] Populations and land areas were obtained from Statistics Canada.

Before discussing the results, I mention several data issues. Because retail price data is weekly, if it is true that the relenting phase is generally completed in less than a week, the duration of that phase will be somewhat overestimated

[13] M.J. Ervin & Associates picked up the pricing survey the same week the federal ministry discontinued it using mostly the same methodology and stations. The stations are branded self-service stations and number from from four to ten depending on the city. Rarely, a station will need to be replaced because of exit or other reasons. The Ontario Ministry of Energy survey is generally more comprehensive, and the number varies by city, but the stations are again the same each week. Both the Ontario Ministry of Energy and the federal Ministry of Natural Resources (M.J.Ervin after 1997) samples include Toronto and Ottawa during the period. There are no systematic differences in the two series.

[14] As a check, I also estimated the model using rack prices obtained from the Oil Price Information Service (OPIS), with direct station delivered prices from OBG, and with bulk wholesale purchase prices for the two cities that post them, all with similar results. There are between one and four wholesalers for any rack point. For cities that are not rack points, the nearest rack point is used.

[15] Second or "fighting" brands operated by major firms have been grouped as majors. Grouping these as independents do not change results.

(since it is left censored at one week) and the amplitude underestimated (since undercutting is expected in the days before and the days after.)[16] This works against finding strong, asymmetric cycles and my results may then be a lower bound. In the extreme case, one worries that cycles with a period of a week or less may be missed entirely. Fortunately, missing fast cycles does not appear to be a problem. Noel[2003] closely tracks cycles in Toronto, where they are especially fast, and which *did* have a period of about a week in early 2001. The city was selected specifically because of its fast cycles both at the time and throughout much of the sample. One finding is that cycles do not follow a day-of-the-week pattern – each Tuesday morning, prices could be very high or very low. The result is that fast cycles appear in the weekly datset here as extremely volatile week-to-week price changes (in contrast to rack prices) and *not* as normal pricing patterns. Accordingly, the Markov switching framework performs quite well. For Toronto for example, it classifies 84% of periods as cycles overall and better than 98% cycles in five of the last seven years, a time when cycles were well known to dominate. The issue is less a concern in other markets but where very fast cycles appear (and are often interspersed in a series of cleaner ones), the distinction between cycles and normal pricing is more clear.

Another issue is that, if the relenting phase is short but on or over a Tuesday, I may observe the average price of some firms that have relented and others that have not. The relenting phase duration would be measured at two weeks.[17] For undercutting phases which generally take many weeks to complete, this is less of an issue. As before, these data frequency issues will work against finding tall, asymmetric retail price cycles and my results may again represent a lower bound.

I model retail gasoline as a non-durable good. While it is possible for consumers to attempt to predict cycle troughs and stockpile large quantities of gasoline at low prices, my casual observation is that consumers do not and tend to simply fill up their tank when they run low.[18] To the (very) limited extent that consumers might time their purchases, the Coase conjecture would suggest a speeding up of the cycles.

I use the rack price as my measure of the wholesale price. This is the per liter cost of wholesale gas without the right to resell it under a branded name (and may not include additives in the branded version.) Small independents typically buy wholesale at a small discount off rack (three quarters of a cent is large) but for my purposes it is simply important to note that the size of the discount does not cycle or rapidly fluctuate.[19] Large firms are integrated into refining and retailing and they own and operate some of their branded retail

[16] Note that the theory does not make and I do not test predictions about amplitudes .

[17] In the theory, the periods are very short (discount rates near one) and relenting phase in fact does take two of these short periods. Noel[2003] that a period in Toronto is as short as a few hours. One firm raises price in the first, the second firm follows in the second. With more firms, it may take a few more of these short periods to complete a relenting phase and the chance of sampling part way through it can be somewhat larger.

[18] See Hendel & Nevo [2002] and Hendel & Nevo [2003] for consumer stockpiling behavior the grocery context.

[19] It was worth noting that there are only a few large wholesalers selling in this market.

outlets while leasing others outlets (or just the brand name) to private dealers. For outlets operated by a dealer, transactions occur at contract prices (instead the rack) and these are not publicly available. For outlets operated by the firm, no market transaction ever takes place. Given this, the rack price is the best available measure of the wholesale price. Lerner[1996] among others further argues the (discounted) rack price measures the wholesaler's opportunity cost of wholesale gasoline sold to dealers. Because of close and readily available U.S. sources of wholesale gasoline that constrain local wholesalers (for example, see Hendricks[1996]), the rack price is reasonably modeled as exogenous to retail price setting in Canadian markets.

Finally, it is important to be clear about who controls retail prices. A private dealer that leases and operates one branded station, for example, has different incentives than a large integrated firm that sets prices at all its stations. For my largely urban sample, the wide majority of major branded outlets and independent chain outlets are in fact centrally controlled and prices set at the firm's municipal or district office. Hence, concepts of "large" and "small" firms are meaningful.

6 A Description of Retail Price Cycles

I now return to my first objective and begin with a simple empirical description of the prevalence of the three regimes and of the anatomy of the price cycle. To do this, I first need to introduce the basic descriptive specifications and present the core results – the within-regime parameter estimates and the switching probabilites – from which to build that description.

6.1 The Regimes

The within-regime regression results are in table 2. The basic specification is (1) in which the X^R, X^U, W^i, and V are all vectors of ones. In other words, the expected price changes in the two cycle regimes ($\alpha^i = E(\Delta RETAIL_{mt} \mid X^i_{mt}),\ i = R, U$), all nine switching probabilities ($\lambda^{ij},\ i, j = R, U, F$), and the probability of sticky pricing conditional on not cycling (γ) are all constants. This specification simply yields a single "average" measure of the prevalence vector z and of cycle characteristics. In the non-cycle normal pricing regime, the retail price depends on the current rack price and city, month, and year dummy variables.

The expected price change in the relenting phase is 2.40 cpl and it is -1.26 cpl in the undercutting phase. In the non-cycle regime, the coefficient on $RACK$ is 0.800 and sticky pricing prevails just over half the time.

The only change in specification (2) is that I add city, month, and year dummies to the relenting and undercutting phase equations as well. Results are similar. Dummies are not reported in the table, but it is noteworthy that the monthly dummies for the two cycle regimes (which capture the majority of variation in sales volumes) are all insignificant.

For specification (3) I add the current rack price and six lags of the rack price to specification to the all within-regime equations (except sticky prices). This accounts for possible inventory effects on the passthrough rate of rack price shocks into retail prices, although I do not expect inventory effects to be a concern.[20] The sum of the rack coefficients is not significantly different from zero in each of the two cycle regimes. In the non-cycle regime, the coefficient rises from 0.800 (in (1)) to 0.937 showing that 80.0% of rack price shocks is passed into retail prices in the same week and an extra 13.7% is passed through in the following six weeks.

6.2 Switching Probabilities

Table 3 shows the switching probabilities from the same three descriptive specifications. In each case, the switching probabilities are just constants so $\lambda_{mt}^{ij} = \lambda^{ij}$ and thus $\Lambda_{mt} = \Lambda$.

Consider specification (1). A market currently experiencing a relenting phase has only a 23% probability of staying in a relenting phase the following week ($\lambda^{RR} = 0.23$). More than three times as large is the probability that the cycle has peaked and the undercutting phase begins again ($\lambda^{RU} = 0.73$). Only rarely does a market switch from a relenting phase to a non-cycle regime ($\lambda^{RF} = 0.04$).

A market currently experiencing an undercutting phase has a 59% chance of continuing in that undercutting phase the next week and a 33% chance of switching back to a relenting phase. Switching into a non-cycle regime occurs with 8% probability.

When in a non-cycle regime, a market continues in the non-cycle regime the next week with a 95% probability.

The switching probabilities are similar in specifications (2) and (3).

6.3 Prevalence and the Anatomy of a Price Cycle

Using the formulae above, I now construct a description of the three pricing patterns and of the characteristics of price cycles. I begin with results on the prevalence of the regimes as reported in table 4.

Again, return to specification (1). On a nationwide basis over the eleven year sample, I find the price cycling regimes in the study markets in 43% of the sample. The relenting phase accounts for 13% and the undercutting phase for 30%. This suggests asymmetry, a point to which I will return.

Sticky pricing was also very prevalent, occuring in 30% of the sample. This is not the result of flat rack prices – conditional on sticky pricing, the wholesale price changed over 70% of the time, by 0.54 cpl on average. I find normal pricing in 28% of the sample.

In specification (2), where city and time dummies in the two cycle regimes allow those equations to fit the data, I find price cycling in 47% of periods.

[20] Hendricks[1996] found lags in crude-rack passthrough but relatively quick passthrough in rack-retail. See Borenstein & Shepard[2002] and references for a discussion of passthrough lags in the U.S.

Specification (3), which includes current and lagged rack prices, yields results similar to specification (1).

These results argue that retail price cycles and sticky pricing are both real and prevalent phenomena in these markets.

But are these cycles asymmetric and repeated over and over as the theory of Edgeworth Cycles would suggest, or is it simply volatile prices that I have captured? To differentiate between these, I show that the detected cycles indeed have a particular shape. I describe that shape along three main dimensions of interest: cycle period, amplitude, and asymmetry. Results are in table 5.

Along the horizontal dimension, I calculate the period of a typical cycle at 3.75 wks using specification (1). This consists of a relenting phase of 1.30 wks followed an undercutting phase of 2.44 wks on average. Note that the relenting phase duration is close to one as predicted.[21]

Vertically, the amplitude of the cycle is 3.13 cpl (relenting phase calculation) or 3.08 cpl (undercutting phase calculation). This represents a large impact on firm margins: the amplitude of this price cycle is 60% of the average retailer markup in cycles, or 86% of the average markup at the bottom of the cycle.[22]

The asymmetry of the cycles is perhaps the most defining feature captured by the Markov switching regression framework. I report the horizontal asymmetry as 1.89 and the vertical asymmetry as 1.91. That is, the average duration of an undercutting phase is almost twice as long as that of a relenting phase and the average weekly price increase is almost twice as large as the average weekly price cut. These are both significantly greater than one at a very high level of significance.

I conclude that the retail price cycles are tall (relative to markups), relatively fast, and highly asymmetric in the direction that is consistent with the theories of Edgeworth Cycles. They are also repeated over and over – the average cycling spell lasts 14.51 wks. The average duration of a non-cycle price regime, for comparison, is 19.3 weeks.

Looking beyond average prevalence and the typical price cycle, we observe much heterogeneity across cities and over time. Using specification (1), I report in table 6, for each city, the prevalence of cycling activity over the full sample (column 1), each of its component phases (columns 2 and 3), normal pricing (column 4) and sticky pricing (column 5). In the last two columns I report the prevalence of price cycling in the most active year (maximum) and least active year (minimum) for that city. In Toronto, a dense and highly competitive

[21] Data from Noel[2003] suggest than the marketwide relent in Toronto in 2001 takes about a day and a half and individual stations generally do not relent on a weekend. Therefore, there would be a 1.5/5 or 30% chance that a relent is midway on a Tuesday morning. If the dataset used in that paper (twice-daily) were instead sampled weekly, it would generate a relenting phase duration of about 1.3 periods.

[22] As the two measures of amplitude are never significantly different from one another in any given specification, I report only the relenting phase calculations in the table. Also, since the rack price does not capture all marginal costs of retailing, the figure of 60% (or 86%) may be a lower bound.

market, retail gasoline prices cycled in 84% of periods in the full sample. In St. John's, a market dominated by a few majors, cycling occurs in only 15% of periods. Between these two extremes are cities that experienced retail price cycling activity over certain stretches, and none over others. The prevalence of sticky pricing and normal pricing varies greatly across markets and over time as well, as do the characteristics of the cycles themselves. In the following section, I turn to an examination of this heterogeneity and how the penetration of small independent firms contributes to it.

7 Industry Structure and Price Cycles

The theory of Edgeworth Cycles suggests that a greater penetration of small firms will increase the prevalence of Edgeworth Cycles specifically (in contrast to simply increasing the volatility of prices). Moreover, it predicts that a larger number of small firms will affect cycle characteristics in particular ways: the relenting phase duration should be unaffected, the undercutting phase duration and therefore the cycle period should become shorter and finally the cycle should be less asymmetric. The second objective of this paper is to establish an empirical relationship between small independents and each of these characteristics consistent with the theory.

Such findings would have two implications. First, they would provide evidence that we are observing the Edgeworth Cycle phenomenon – oftentimes considered only a theoretical artifact – in actual real world practice. Second, that undercutting behavior by small firms triggers such a cycle suggests that consumer welfare may improve from increased competition under a cycling regime. This would contrast the belief by many local consumer groups who, for reasons explained below, point to the volatility in prices in these markets as evidence of collusion.

7.1 Striking the Bottom

First, a short digression. As undercutting pushes the retail price closer to the rack price, profits shrink and the incentive to reset the cycle grows stronger. That is, λ^{UU} should fall and λ^{UR} should rise. Conversely, when the relenting phase pushes the price high above marginal cost, the switching probabilities should shift to favor a new undercutting phase (λ^{RR} falls, λ^{RU} rises.)

I use the difference between the lagged retail price and the current rack price, $RETAIL_{m,t-1} - RACK_{mt}$, as my measure of the distance to the bottom of the cycle. Call this measure "$POSITION$" with city and time fixed effects subtracted away. Hereafter, I allow all switching probabilities out of the relenting phase and out of the undercutting phase to depend on $POSITION$ by adding it to the W^R and W^Umatrices.

Specifications (4) and (5) repeat specifications (1) and (2) with this change. In table 7, I report the partial derivatives of the switching probabilities with respect to $POSITION$. Looking at specification (4), the probability of remaining in an undercutting phase is significantly and sizably smaller when $POSITION$ is smaller ($\frac{\partial \lambda^{UU}}{\partial POSITION} = 0.04.$) and the probability of switching to a relenting phase increases likewise. If starting in a relenting phase, the probabilities change only slightly, as the probability of having two consecutive relenting phases is always quite small. The results in specification (5), where city and time dummies are included in the two cycle regimes, are similar.

Making switching probabilities depend on cycle position allows better molding to the data, but simulation techniques are now required to obtain coefficient estimates. Previously the focus has been on intuitive and analytic derivations of prevalence and characteristics and so I postponed this until now. Repeating the previous analyses with $POSITION$, or repeating the following analysis without does not appreciably change results.

7.2 Small Independents, Prevalence and the Anatomy of a Price Cycle

I return to my second objective. Since there are four large integrated firms in most markets (that differ from market to market), variation in the penetration of small firms is well captured by the fraction of stations operated by all *except* the largest four firms. I call this measure SMALLINDEX, simply equal to one minus the four firm concentration ratio.[23]

Demand side factors may also be important to the "success" of price cycling activity. Greater local market size increases the short term demand gain from undercutting and should lead to more prevalent cycling. I use the driving age population per retail outlet (POP/RO, measured in thousands of people per outlet) to capture this.

Where stations are densely situated, consumers can more easily price compare to find the lowest price, which again increases the short term gain from undercutting and should lead to more prevalent cycling. I capture the spatial density of retail outlets (DENSITY, measured in outlets per square kilometer) to proxy for consumers' search costs.[24]

Summary statistics for the competitive environment variables are reported in table 8. There is much variation across markets and within markets over time. SMALLINDEX, for example, ranges for a low of 0.09 to a high of 0.53 across the full sample.

I allow SMALLINDEX, POP/RO, and DENSITY to enter the system through three transmission mechanisms. First, they enter directly into the X^R and X^U matrices in the price change equation (1) which allows them to covary with α and the vertical dimensions of the cycle. Second, they enter into the W^i matrices in the switching probability equation (4) which allows them to covary with the

[23] A large firm is defined by the number of retail outlets operated in a given market and time.

[24] Noel[2003] prevents evidence that, at least for Toronto, the relevant market is at the city level. The resetting behavior by large firms (at all its stations at roughly the same time) and the uniformity of independent locations effectively ties any "local, intersection-sized" submarkets together.

λ^{ij},with the horizontal dimensions of the cycle and with the prevalence of the regimes. Third, they enter into V in the non-cycle regime switching equation which allows them to covary with γ, the fraction of sticky prices conditional on non-cycling regime.[25]

Results are reported in table 9 and described below. Specification (6) adds only the SMALLINDEX variable to specification (4). Specification (7) adds all three competitive variables to specification (4). (Recall that specification (4) in turn was built from the basic specification (1) by adding the $POSITION$ variable to the switching probabilities.)

As always, rack prices and a full set of city and time dummies are included in the normal pricing subregime. Adding city and time dummies and rack prices to the cycle regimes (like specification (2)) or a full lag structure on rack prices for all regimes (like specification (3)) also have no appreciable effect on the results.

Because $POSITION$ is always changing along the path of the cycle, simulation techniques described in the appendix are hereafter required. In each cell of table 9, I report the partial derivative of the characteristic listed in the given *row* with respect to the competitive variable listed in the given *column*. (Each column represents a different RHS variable, each row a different LHS variable.) Standard errors are in parentheses. I also report the pseudo P-value equal to the fraction of simulation runs (out of 1000) that resulted in an estimate with the sign opposite that of the estimated mean partial derivative.

First, I find when there is a *greater* penetration of small firms, there is a substantially *higher* prevalence of Edgeworth-like price cycles. The coefficient on $SMALLINDEX$ is statistically significant and 0 out of 1000 simulations reported the incorrect sign in either specification. For specification (6), an increase in $SMALLINDEX$ of 0.035, or 10% from its mean, is associated with an increase in the prevalence of price cycling by 0.036, or 8.6% of its mean. From minimum up to maximum values of $SMALLINDEX$ in the data, the estimated increase in the fraction of periods cycling is 0.46 (or 107% of its mean.) Normal pricing also becomes a little more common. Sticky pricing, in contrast, is much less common with more small firms. These results are consistent with the theory of Edgeworth Cycles. More than just a reaffirmation of a simple concentration-price rigidity relationship, this result shows that retail price *cycles* – similar in structure to those of Maskin-Tirole – are more prevalent when there is a greater penetration of small firms.

The theory of Edgeworth Cycles goes on to predict how the structural characteristics of the cycle are shaped when there is greater penetration of small firms. The framework developed here can test for these relationships as well. Continuing with specification (6), I find a statistically significant and negative rela-

[25] Note that there is little concern over endogeneity of the concentration variable in this setting. SMALLINDEX is an explanatory variable only of price changes, never of price levels. It is difficult to imagine the reverse causality in which the presence of a price cycle in gasoline markets vis-a-vis sticky or normal prices and the specific shape of that cycle will encourage new entry rather than the reverse, or to identify other unobservables both relevant and correlated with the error term.

tionship between $SMALLINDEX$ and the duration of the undercutting phase – that is, the undercutting phase progresses more rapidly when there are more small firms present. However, I find *no* relationship between $SMALLINDEX$ and the length of the relenting phase. Both of these findings are consistent with the theory of Edgeworth Cycles. According to the theory, the faster undercutting phase occurs because the large firm (which is not as large anymore) will rather respond to undercutting by small firms with another undercut, rather than matching price. By undercutting, the large firm again captures the entire market. The relenting phase, which naturally occurs very quickly, remains largely unaffected.

This combination of results in turn has implications for the period of the cycle and its asymmetry. The combination of a shorter undercutting phase and an insignificantly different relenting phase results in a shorter period. Consistent with the theory, I find that cycles progress significantly faster when there is a greater penetration of small firms.

Finally, I return to the defining feature of the price cycles – their asymmetry. According to the theory, the cycles will appear less asymmetric because the undercutting phase is more rapid while the relenting phase is unaffected (but still shorter than the undercutting phase). Of course, this is exactly what we observe. Using horizontal asymmetry as the measure, I find a negative relationship between $SMALLINDEX$ and cycle asymmetry significant at the 5% level. Using vertical asymmetry instead, the relationship is again negative and similar in magnitude and significant at the 10% level.

The theory does not make predictions as to how small firms influence the amplitude of the cycles, and many different amplitudes are in equilibrium even for the same market structure. In my sample, I simply note that amplitude is positively related to the penetration of small firms.

In specification (7), I control for the influence of market size and outlet density on outcomes. The effects of $SMALLINDEX$ on the prevalence of cycling activity, sticky pricing and normal pricing are equally strong. However, the effect of $SMALLINDEX$ on cycle characteristics is made even stronger and the coefficients on the duration the undercutting phase, cycle period, and asymmetries roughly double. In particular, the negative relationship between $SMALLINDEX$ and asymmetry, horizontally and vertically, are now statistically significant at the 1% and 2% levels respectively. The coefficient on amplitude is no longer significant.

As expected, greater market size and higher outlet density themselves are associated with a significantly greater prevalence of cycling activity and significantly less sticky pricing. A 10% increase in the driving age population per retail outlet from its mean is associated with an increase in cycling prevalence of 0.024 (5% from the mean) and a decrease in the prevalence of sticky prices by a similar amount.[26] A 10% percent increase in outlet density from its mean is associated with an increase in cycling prevalence by 0.012, or just 2.8% from

[26] Using total, rather than per outlet, driving age population yields the same-signs but weaker coefficients, consistent with the notion that firms are capacity constrained.

the mean.

I find a statistically significant and negative relationship between market size and the duration of the undercutting phase and again no relationship with the duration of the relenting phase. Greater market size is also associated with significantly faster and less asymmetric cycles. The relationship between density and cycle characteristics all have the correct sign but are generally insignificant and (adjusting for means) much weaker than that those involving market size or small firms.

The first key conclusion of this section is that there is a significant and positive relationship between the penetration of small firms and the prevalence of retail price cycles and there is a significant and negative relationship between small firms and the prevalence of sticky pricing. Secondly, with increasingly more small firms, the undercutting phase of cycle is faster, the period is shorter, and the cycles appear *less* asymmetric. Each of these findings is consistent with the theory of Edgeworth Cycles.

7.3 An Example

To get a sense for what "typical" price cycles look like under different market environments, I report examples of cycle and non-cycle characteristics in table 10 for different values of $SMALLINDEX$ and the driving age population per outlet (POP/RO). Specification (7) is used. Given its small effect, density is set equal to its mean in each case. As one moves from left to right, $SMALLINDEX$ and POP/RO each increase by one standard deviation per column. Column (b) corresponds to the means.

As markets become larger and less concentrated, moving from left to right, there is a much higher prevalence of retail price cycles, from only 29% of periods in the first column up to 64% of periods in the last. Sticky pricing activity falls as rapidly.

The duration of the relenting phase is roughly constant while the undercutting phase grows shorter. As a result, retail price cycles that are sharply asymmetric when markets are small and concentrated become less asymmetric as markets grow and small firms become more influential. Cycles also become faster and taller.

To check the robustness of my results to the choice of the concentration ratio, I repeat the specifications (6) and (7) using several alternate measures.

In table 11, I use the actual percentage of outlets operated by independents ($INDEP$). Independents are those firms that do not have upstream refining capability and range from mom and pop stores to medium sized chains. The results are similar to before. I also estimated the model with the five firm and six firm concentration ratios and the Herfindahl index in place of CR4 in the $SMALLINDEX$ calculation, and again find similar results.

I also experimented with a separate concentration variable for large department and convenience stores who retail gasoline as a loss leader or ancillary business. There is a strong correlation between the presence of these independents and traditional independents in the dataset, and no additional effect of such retailers could be separated out.

8 Discussion

8.1 Welfare

In past years, some of the most vocal consumer concern have been in cities where retail price cycles are strong. These groups often point to the large marketwide retail price increases as evidence of anti-competitive behavior and reduced welfare. Complaints to federal and provincial competition authorities also cite the speed and synchonicity of these price increases across stations and the lack of a justifying increase in wholesale prices. While these increases are widely reported in the public press, it is interesting that the small and gradual daily price cuts during the undercutting phase of the price cycle receive no fanfare. This has in part led to the popular impression that gasoline prices are "always going up" in cycling markets when in reality they are almost always going down.

The question remains: are Edgeworth-like cycles a symptom of lower or higher welfare vis a vis sticky pricing? A simple comparison of (tax-exclusive) average markups over the full sample shows that markups are *lower* under price cycling than under sticky pricing or normal pricing.

To control for differences across cities and over time, I compare markups across each pair of regimes within each city-year combination. I report a weighted average across city-year combos where the weight is the squared prevalence of the lesser prevalent regime in the pair. Comparing sticky pricing regimes and cycle regimes, I find markups are 1.02 cents per liter *higher* under sticky pricing regimes than under cycling regimes. Normal pricing markups are 0.96 cents higher than cycling markups.[27] Unless consumers are unrealistically averse to short term gas price volatility, the lower average markups in periods of cycling increase consumer welfare. To the extent that consumers can time purchases to periods of low prices, the gain is even greater.

A rough back-of-the-envelope calculation gives a sense for magnitudes. To be conservative, assume consumers in cycling markets do not time their gasoline

[27] The weights ensure that comparisons are driven by city-year combos that have a good mix of each of the two regimes. Alternately, one could just exclude city-year combos that have fewer than a given number of each type. Using only city-year combos where each regime appears in at least 20% (10%) of periods, sticky pricing markups are 1.05 (0.83) cents greater than cycle markups in the 36% (61%) of city-years that remain, and normal pricing markups are 0.94 (0.91) cents greater than cycle markups in the 35% (68%) of city-years that remain. The difference between non-cycle markups and cycle markups ranges from 0.96 when all city-years are included to 1.18 cents when requiring 20% of each type (and 56% of city-years remain.)

purchases and pay the average price overall. Assume perfectly inelastic aggregate demand over the relevant price range. The approximate average annual output is 3.5 million liters for each of the 3750 stations in the final year of my 19 city sample. If all current sticky and normal pricing periods were replaced with periods of cycling activity, all else equal, consumer expenditures on gasoline would fall by $75 million a year in the sample cities. If instead all current cycling activity were replaced with sticky and normal pricing in their current proportions, consumers in the sample cities would have to pay $55 million a year more.

With approximately 13,000 stations nationwide each serving an average of 2.5 million liters annually, the difference in expenditure between a situation of only cycling behavior and a situation with sticky and normal pricing in their current 15:14 ratio would be $322 million. For comparative reference, there were 180,000 outlets in the U.S. in 1999.

8.2 Alternate Explanations

Other explanations for the cycles observed here, such as changing station inventories or demand fluctuations, are easily dispelled. One argument is that an asymmetric cycle can occur if firms vary pump prices as their underground supply tanks empty. However, the direction of prices goes the wrong way – one would expect a gradual rise in prices followed by a sudden fall. Of course, firms can and do endogeneously set their delivery schedules to avoid shortages and the typical ten day interval between deliveries rarely matches the period of the cycle. Secondly, inventory issues cannot explain the synchronicity of price jumps across stations within a given market.

Market demand fluctuations do not appear to be the source either. This would strangely require demand to shift downward gradually week and week before suddenly rebounding (and then repeating). While the typical cycle is a bit less than a month (and varies greatly across markets), the relenting phase can occur any week of the month. It is also not clear why different markets would possess cycles of different periods under this explanation.

8.3 Other Markets

This study has concentrated on the price of regular gasoline, which comprises approximately 89% of all retail gasoline sold. Prices on higher grades are not posted on billboards but are often set above regular by a set formula and so unsurprisingly I find cycling patterns in both midgrade and premium fuel prices as well. The patterns are slightly weaker, however, perhaps because the much lower sales volume reduces the gain from undercutting.

Diesel fuel shows no signs of such cycling at all. This is interesting since the vast majority of diesel sales are by national or large regional firms with cardlock facilities for large trucks and transports. Independents have a negligible effect on the diesel market. For other low volume products for which I have data, such as propane, there are no signs of asymmetric pricing.

There remains the question of why cycles are so common in Canada but, except for several western cities in the 1960s and 1970s, have not occurred in the United States. Cycles appear to be best generated in markets with numerous small undercutting independents and at least one very large major firm capable of resetting the cycle. In some U.S. markets, there may be too few aggressive independents, or the more decentralized control of prices at branded outlets may make price resetting difficult. Perhaps historical price cycling in Canada has created price hypersensitivity of otherwise similar consumers in that country, which increases the propensity of cycles there. These are directions of future research. It remains to be seen if the situation in the U.S. will continue. According to the Energy Information Administration, there has been "ferocious" rate of growth of independents in the U.S. throughout the 1990s,[28] which may again create conditions prone to price cycling activity.

Finally, I am not aware of similar Edgeworth-like cycles currently in other product markets. However, the interested observer can look across markets for certain characteristics that may lend to cycling activity. For example, markets with many small firms alongside at least one large firm capable of coordinating marketwide price increases are more likely to experience cycles. The product itself would likely be relatively homogeneous, highly elastic at the firm level, non-durable (in practice if not in principle), and frequently purchased. Consumer switching costs and firm menu costs should also be close to zero. Whether more cycling markets appear remains to be seen.

9 Conclusion

In this paper, I present evidence that retail price cycles, similar to the theoretical Edgeworth Cycles in appearance and behavior, are a real and prevalent phenomenon in Canadian retail gasoline markets. Using the parameter estimates from a Markov switching regression framework, I estimate measures of prevalence and build a description of the characteristics of cycles themselves. I identify repeated price cycling behavior in 43% of periods in the sample, sticky pricing in 30%, and normal cost-based pricing in 27%. Beyond volatile prices, I show that these cycles have a specific shape that is consistent with the theory – they have an expected amplitude of over three cents per liter, an expected period of just under four weeks, and are significantly asymmetric. Prices rise quickly from one week to the next and then begin to fall gradually over the next two to three weeks.

The theories of Edgeworth Cycles further suggest that a greater penetration of small firms should lead to more cycling activity and less sticky pricing. Moreover, the duration of the relenting phase of the cycle should be unaffected, the duration of the undercutting phase shortened and therefore the cycles should be more rapid and less asymmetric. Allowing the horizontal and vertical dimensions of the cycle to vary with a small firm concentration variable, I confirm

[28] See http://www.eia.doe.gov/emeu/finance/sptopics/restructure/highlite4.html

each of these relationships. My results are robust when controlling for market size and outlet density and when using alternate measures of concentration.

A short welfare analysis that shows consumers are better off in cycling markets stands in contrast with the public perception of competition between cycling and non-cycling markets. In strong cycles, the largest jumps in price are widely reported in the popular press but the daily price cuts of the undercutting phase, which are small and gradual, receive no attention. This seems to have led to the popular impression that gasoline prices are "always going up" in cycling markets when, in fact, they are almost always going down. It is true that some market power is necessary for a firm to effectively reset the price higher, but unlike sticky pricing markets, the many small firms in cycling markets keep bringing the price back down. The volatility that has generated so much controversy, relative to the alternative, is a benefit to consumers.

A Appendix

The Markov framework estimates switching probabilities directly (at the top level), rather than the probability of being in a given regime. The probability of firms actually being in regime j in market m at period t is given by the recursive relationship:

$$\Pr(I_{mt}) = \sum_{Im,t-1=R,U,F} (\Pr(I_{mt} \mid I_{m,t-1}) * \Pr(I_{m,t-1})) \tag{14}$$

where $\Pr(I_{mt} \mid I_{m,t-1})$ is called λ_{mt}^{ij} in the text.

Switching probabilities and within-regime parameters are estimated jointly and simultaneously by maximum likelihood. Let $\phi(\cdot)$ be the normal density function and define

$$G(y, I, W, X) = \prod_{t=1}^{T} g^{I_{mt}}(y_{mt}^{I_{mt}} \mid X_{mt}^{I_{mt}}) * \prod_{t=2}^{T} \Pr(I_{mt} \mid I_{m,t-1}, W_{mt}^{I_{mt}}) * \Pr(I_{m1} \mid W_{m1}^{I_{m1}}) \tag{15}$$

where $g^{I_{mt}}(\cdot) = \phi(\cdot)$ for $I_{mt} = R, U$. For $I_{mt} = F$,

$$\begin{aligned} g(y_{mt}^F \mid X_{mt}^F) = \quad & \Pr(J_{mt} = N \mid I_{mt} = F, V_{mt}, W_{mt}^F) * \phi(y_{mt}^F \mid X_{mt}^F) \\ + \quad & \Pr(J_{mt} = S \mid I_{mt} = F, V_{mt}, W_{mt}^F) * D(p_{mt} - p_{m,t-1}) \end{aligned} \tag{16}$$

where $D(\cdot)$ is an indicator function equal to one if its argument is equal to zero, and equal to zero otherwise. Note that $y_{mt}^{I_{mt}}$ in each case is just the left hand side of equations 1 or 2 and $\Pr(J_{mt} = S \mid I_{mt} = F, V_{mt}, W_{mt}^F)$ is called γ_{mt} in the text. The log likelihood function is given by

$$L = \ln \left\{ \sum_{I_{MT}=R,U,F} \cdots \sum_{I_{m1}=R,U,F} \left[\prod_{m=1}^{M} G(y, I, W, X) \right] \right\} \tag{17}$$

The likelihood function as written is computationally intractable and so is computed by means of a recurrence relation, as described by Cosslett & Lee [1985]

$$Q_{mt}(I_{mt}) = \sum_{I_{m,t-1}=R,U,F} g^{I_{mt}}(y_{mt}^{I_{mt}} \mid X_{mt}^{I_{mt}}) * \Pr(I_{mt} \mid I_{m,t-1}, W_{mt}^{I_{mt}}) * Q_{m,t-1}(I_{m,t-1}) \tag{18}$$

where $Q_{m1}(I_{m1})$ are chosen starting within-regime probabilities. Then the likelihood function is computed by

$$L = \sum_{m=1}^{M} \sum_{t=1}^{T} \ln \left(\sum_{I_{mt}=R,U,F} Q_{mt}(I_{mt}) \right) \tag{19}$$

Newey-West standard errors are computed for the core MLE parameters. All derived parameters and their standard errors in section 6 are found using the delta method.

The grouping of normal and sticky pricing into a single regime greatly reduces computational burden. The number of free switching probabilities is reduced from 12 to 7 (including γ) vis-a-vis a four top-level regime model and the number of parameters (θ and ζ) is reduced by as much as 26. There are 82 parameters in the last specification and convergence on a 700MHz processor takes approximately three days.

In section 7.1, partial derivatives of λ^{ii} and λ^{ij} with respect to an element in W^i (whose coefficient in λ^{ij} is θ_1^{ij}) are

$$\frac{\partial \lambda^{ij}}{\partial W^i} = \lambda^{ij} \left[\theta_1^{ij} - \theta_1^{ij} \lambda^{ij} - \theta_1^{ik} \lambda^{ik} \right], \ \forall \ i = R, U, F, \ j = R, U, \ k \neq j \neq F \tag{20}$$

and

$$\frac{\partial \lambda^{iF}}{\partial W^i} = -\theta_1^{iR} \lambda^{iR} \lambda^{iF} - \theta_1^{iU} \lambda^{iU} \lambda^{iF}, \ \forall \ i = R, U, F \tag{21}$$

Due to the cycle-position-dependent switching probabilities, partial derivatives of each characteristic with respect to competitive variables must be computed by simulation in section 7 if that characteristic depends on the switching probabilities. For consistency, all estimates were found by simulation.

I conducted 2K sets of simulations $S = \{S^{11}, S^{12}, S^{21}, S^{22} ..., S^{K1}, S^{K2}\}$ for each regression, where K is the number of included competitive variables. Each set contained 1000 individual simulations S_i^{kj}, $i = 1..1000,\ j = 1..2,\ k = 1..K$. For each competitive variable k, I conducted two simulations sets $S^{k1}$and S^{k2}. For the first simulation set S^{k1}, variable k was set equal to $\overline{x}_k - \Delta$ where $\overline{x}_k$ is the sample mean of variable k and Δ is small and positive. In the second, the mean of variable k was set to $\overline{x}_k + \Delta$. Other included competitive variables $s \neq k$ were set equal to their respective sample means $\overline{x}_s$. Actual rack prices were used. For each i, a vector of parameter values was drawn from the multivariate normal distribution of the core MLE estimates (using the Cholesky decomposition and transformation.) Then, for each S_i^{kj}, a retail price series was generated forward

100,000 periods. Estimates of prevalence and cycle features, etc. were calculated in the obvious way (since the current regime is known.) Each partial derivative of each characteristic with respect to changes in variable k was calculated from the difference in characteristics estimates across $S_i^{k1}$and S_i^{k2} for a given i, $i = 1..1000$ (and divided by 2Δ). The mean and standard error of each partial derivative is then found by bootstrapping.

The standard errors capture both the error in the core MLE estimates and also the error inherent in the price generation process. It is the former that is relevant. To test the degree of intrusion of the latter, I compare estimates from the core estimation that do not depend directly on switching probabilities with those from the simulations (such as within-regime price changes α^i and sigma σ). The standard errors in the simulation (at 100,000 periods) are slightly larger than those from the core parameters and therefore standard errors reported in the tables are taken as conservative.

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Table 1: Rack and Retail Price Changes and Runs

FULL SAMPLE

	Price Decreases		Price Increases			K-S
	Number	Average	Number	Average	t-stat	P-value
Retail	4092	1.180	2558	2.010	-20.668	0.000
Rack	2436	0.588	2568	0.595	-0.491	0.337
	Runs Down		Runs Up			K-S
	Number	Average	Number	Average	t-stat	P-value
Retail	2110	1.939	1819	1.360	14.430	0.000
Rack	1135	2.193	1219	2.212	-0.291	0.787

BY CITY (19 Cities)

	Difference in Price Changes		Difference in Run Durations	
	# signif. t-tests	# signif. K-S tests	# signif. t-tests	# signif. K-S tests
Retail	19/19	19/19	9/19	9/19
Rack	0/19	0/19	0/19	0/19

OTHER SUMMARY STATISTICS

	Mean	Std.Dev.	Min	Max	Mean (US ¢/gal.)
Retail Price	29.51	4.45	6.8	48.0	78.1
Rack Price	23.05	3.45	13.4	38.5	61.0
Markup	6.45	3.02	-14.1	14.7	17.1

Prices in Canadian cents per liter except as noted.

Table 2: Within-Regime Results

Specification	(1)	(2)	(3)
CYCLE: RELENTING PHASE (dependent var = $\Delta RETAIL_{mt}$)			
$E(\Delta RETAIL_{mt} \mid I_{mt} = \text{"}R\text{"})$	2.403	2.300	2.442
at cycle averages	(0.091)	(0.085)	(0.097)
Constant	2.403	-	2.162
	(0.091)	(-)	(0.463)
$\Sigma RACK$			0.012
			(0.021)
City/month/year dummies	N	Y	N
CYCLE: UNDERCUTTING PHASE (dependent var = $\Delta RETAIL_{mt}$)			
$E(\Delta RETAIL_{mt} \mid I_{mt} = \text{"}U\text{"})$	-1.259	-1.149	-1.290
at cycle averages	(0.062)	(0.061)	(0.063)
Constant	-1.259	-	-1.111
	(0.062)	(-)	(0.297)
$\Sigma RACK$			-0.007
			(0.012)
City/month/year dummies	N	Y	N
NON-CYCLE REGIME (dependent variable = $RETAIL_{mt}$)			
RACK	0.800	0.804	0.937
($\Sigma RACK$ in (3))	(0.030)	(0.031)	(0.019)
Fraction Sticky Prices	0.515	0.547	0.491
	(0.023)	(0.022)	(0.020)
City/month/year dummies	Y	Y	Y
σ^2	0.714	0.553	0.710
	(0.076)	(0.058)	(0.067)

Standard errors in parentheses calculated by delta method.

Table 3: Switching Probabilities

Specification:	(1)	(2)	(3)
λ^{RR}: R $\rightarrow$ R	0.233	0.238	0.229
	(0.014)	(0.013)	(0.014)
λ^{RU}: R $\rightarrow$ U	0.730	0.725	0.735
	(0.016)	(0.015)	(0.014)
λ^{RF}: R $\rightarrow$ F	0.038	0.036	0.035
	(0.010)	(0.009)	(0.009)
λ^{UR}: U $\rightarrow$ R	0.327	0.313	0.338
	(0.014)	(0.014)	(0.013)
λ^{UU}: U $\rightarrow$ U	0.592	0.600	0.590
	(0.014)	(0.013)	(0.014)
λ^{UF}: U $\rightarrow$ F	0.082	0.085	0.070
	(0.009)	(0.011)	(0.007)
λ^{FR}: F $\rightarrow$ R	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)
λ^{FU}: F $\rightarrow$ U	0.052	0.063	0.042
	(0.006)	(0.008)	(0.004)
λ^{FF}: F $\rightarrow$ F	0.948	0.935	0.957
	(0.006)	(0.008)	(0.004)

Standard errors in parentheses calculated by delta method.

Table 4: Prevalence of Regimes – Full Sample

Specification:	(1)	(2)	(3)
Fraction Cycling	0.428	0.475	0.410
	(0.046)	(0.045)	(0.050)
Fraction Relenting	0.126	0.136	0.123
	(0.017)	(0.017)	(0.018)
Fraction Undercutting	0.302	0.339	0.286
	(0.029)	(0.028)	(0.031)
Fraction Non-cycle	0.573	0.525	0.590
	(0.046)	(0.045)	(0.050)
Fraction Normal	0.278	0.239	0.300
	(0.022)	(0.021)	(0.024)
Fraction Sticky	0.295	0.287	0.290
	(0.023)	(0.023)	(0.024)

Standard errors in parentheses calculated by numerical methods.

Table 5: Key Cycle Characteristics

Specification	(1)	(2)	(3)
CYCLE CHARACTERISTICS			
Relenting Phase Duration	1.303	1.312	1.297
	(0.024)	(0.023)	(0.023)
Undercutting Phase Duration	2.449	2.504	2.441
	(0.083)	(0.082)	(0.085)
Cycle Period	3.752	3.816	3.738
	(0.088)	(0.088)	(0.091)
Horizontal Asymmetry	1.889	1.907	1.882
	(0.075)	(0.074)	(0.078)
Cycle Amplitude	3.131	3.018	3.168
(relenting phase calculation)	(0.109)	(0.101)	(0.125)
Vertical Asymmetry	1.909	2.002	1.893
	(0.062)	(0.060)	(0.070)
Cycle Spell Duration	14.51	13.93	16.62
	(3.32)	(3.31)	(3.90)
City/month/year dummies	N	Y	N
NON-CYCLE REGIME CHARACTERISTICS			
Fraction Sticky Prices	0.515	0.547	0.491
cond. on non-cycling	(0.023)	(0.022)	(0.020)
Non-cycle Spell Duration	19.31	15.46	23.56
	(2.379)	(1.975)	(2.622)
City/month/year dummies	Y	Y	Y

Standard errors in parentheses calculated by delta method.

Table 6: Prevalence of Regimes by City (Specification 1)

	Full Sample Prevalence of:					Min.	Max.
City:	Cycling	Rel.	Und.	Norm	Sticky	Cycling	Cycling
Vancouver	0.437	0.100	0.327	0.300	0.272	0.05	0.98
Calgary	0.347	0.087	0.260	0.344	0.309	0.11	0.84
Edmonton	0.401	0.094	0.308	0.293	0.305	0.11	0.74
Regina	0.329	0.075	0.244	0.263	0.417	0.05	0.85
Winnipeg	0.236	0.040	0.197	0.289	0.475	0.03	0.56
Toronto	0.839	0.359	0.480	0.146	0.014	0.58	0.99
Ottawa	0.621	0.223	0.398	0.213	0.165	0.04	1.00
London	0.476	0.114	0.362	0.354	0.169	0.07	0.89
Windsor	0.713	0.238	0.474	0.247	0.040	0.32	0.90
Sudbury	0.557	0.169	0.388	0.296	0.146	0.03	0.94
Sault Ste. Marie	0.307	0.063	0.244	0.346	0.346	0.05	0.61
North Bay	0.373	0.097	0.274	0.349	0.277	0.06	0.83
Thunder Bay	0.312	0.076	0.235	0.373	0.314	0.17	0.64
Timmins	0.229	0.041	0.188	0.288	0.482	0.07	0.46
Montreal	0.665	0.224	0.441	0.179	0.156	0.02	0.99
Quebec City	0.632	0.231	0.402	0.200	0.168	0.06	1.00
Saint John	0.317	0.082	0.235	0.267	0.415	0.07	0.65
Halifax	0.265	0.049	0.216	0.242	0.493	0.04	0.64
St. John's	0.147	0.033	0.113	0.229	0.623	0.02	0.32

Min. Cycling is fraction of cycling periods in least active year (of 11 years.)
Max. Cycling similarly defined. Rel.=Relenting, Und=Undercutting, Norm=Normal

Table 7: Partial Derivatives of Switching Probabilities w.r.t. POSITION

Specification:	(4)	(5)
λ^{RR}	-0.012	-0.009
	(0.003)	(0.004)
λ^{RU}	0.002	0.000
	(0.008)	(0.011)
λ^{UR}	-0.040	-0.045
	(0.006)	(0.005)
λ^{UU}	0.040	0.046
	(0.006)	(0.005)

Each entry is $\frac{\partial \lambda^{ij}}{\partial POSITION}$ calculated at average cycle position.
Standard errors in parentheses calculated by delta method.

Table 8: Summary Statistics – Competitive Variables

	Mean	Std.Dev.	Minimum	Maximum
SMALLINDEX	0.356	0.099	0.090	0.533
INDEP	0.332	0.121	0.007	0.585
POP. PER OUTLET	1.843	0.659	0.802	4.166
OUTLET DENSITY	0.443	0.314	0.050	1.288

Population in thousands. Outlet density is total number of outlets per square kilometer.

Table 9: Effects of Competitive Variables on Prevalence and Cycle Features

Specification:	(6)	(7)		
	SMALLINDEX	SMALLINDEX	POP/RO	DENSITY
Prevalence of Cycles	1.039	0.956	0.132	0.261
	(0.235)	(0.223)	(0.042)	(0.100)
	[0.000]	[0.000]	[0.000]	[0.003]
Prevalence of Sticky Pricing	-1.456	-1.519	-0.132	-0.210
	(0.121)	(0.101)	(0.036)	(0.054)
	[0.000]	[0.000]	[0.000]	[0.000]
Prevalence of Normal Pricing	0.417	0.562	-0.000	0.049
	(0.121)	(0.151)	(0.025)	(0.046)
	[0.000]	[0.000]	[0.475]	[0.138]
Duration of Relenting Phase	-0.261	-0.361	0.002	-0.049
	(0.366)	(0.352)	(0.040)	(0.112)
	[0.227]	[0.148]	[0.480]	[0.338]
Duration of Undercutting Phase	-2.125	-4.162	-0.632	-0.475
	(0.829)	(1.121)	(0.132)	(0.331)
	[0.004]	[0.000]	[0.000]	[0.078]
Period	-2.387	-4.524	-0.630	-0.524
	(0.951)	(1.161)	(0.139)	(0.356)
	[0.004]	[0.000]	[0.000]	[0.070]
Horizontal Asymmetry	-1.238	-2.583	-0.481	-0.284
	(0.772)	(1.036)	(0.112)	(0.295)
	[0.053]	[0.006]	[0.000]	[0.168]
$E(\Delta RETAIL \mid$ "R"$)$ (Relenting Phase)	1.800	1.381	0.096	0.498
	(1.047)	(0.914)	(0.104)	(0.362)
	[0.043]	[0.076]	[0.172]	[0.080]
$E(\Delta RETAIL \mid$ "U"$)$ (Undercutting Phase)	-1.631	-1.907	-0.309	-0.476
	(0.502)	(0.457)	(0.068)	(0.178)
	[0.000]	[0.000]	[0.000]	[0.003]
Amplitude (relenting phase calculation)	2.473	1.430	0.227	0.615
	(1.147)	(1.095)	(0.144)	(0.432)
	[0.011]	[0.097]	[0.058]	[0.080]
Vertical Asymmetry	-1.020	-1.852	-0.408	-0.338
	(0.762)	(0.855)	(0.111)	(0.270)
	[0.082]	[0.014]	[0.000]	[0.091]
Fraction Sticky Prices Conditional on Non-cycling (γ)	-1.742	-1.864	-0.123	-0.117
	(0.182)	(0.015)	(0.002)	0.006
	[0.000]	[0.000]	[0.000]	[0.000]

Cell contains $\frac{\partial(ROW)}{\partial(COLUMN)}$,standard errors in parentheses, pseudo P-values (equal to fraction of simulation pairs that yield wrong sign) in square brackets.

Table 10: Effects of Competition: An Example (Specification (7))

	(a)	(b)	(c)
SMALLINDEX	0.100	0.356	0.455
POP PER STATION	1.183	1.842	2.501
Prevalence	0.291	0.401	0.639
of Cycles	(0.011)	(0.017)	(0.021)
Prevalence	0.521	0.286	0.083
Sticky pricing	(0.018)	(0.015)	(0.008)
Prevalence	0.188	0.313	0.278
Normal pricing	(0.035)	(0.041)	(0.040)
Duration of	1.311	1.348	1.254
Relenting Phase	(0.031)	(0.023)	(0.034)
Duration of	3.404	2.746	2.049
Undercutting Phase	(0.105)	(0.064)	(0.025)
Period	4.716	4.095	3.303
	(0.110)	(0.073)	(0.038)
Horizontal	2.596	2.036	1.633
Asymmetry	(0.099)	(0.056)	(0.029)
$E(\Delta RETAIL \mid$ "R")	1.971	2.306	2.650
(Relenting Phase)	(0.072)	(0.050)	(0.034)
$E(\Delta RETAIL \mid$ "U")	-0.764	-1.214	-1.663
(Undercutting Phase)	(0.031)	(0.030)	(0.025)
Amplitude	1.851	3.094	3.324
(Rel. phase calculation.)	(0.113)	(0.077)	(0.050)
Vertical	2.583	1.900	1.593
Asymmetry	(0.154)	(0.061)	(0.030)
Cycle Spell	5.203	11.826	32.959
Duration	(0.202)	(0.642)	(2.448)
Non-Cycle	16.033	17.624	18.530
Duration	(0.494)	(0.873)	(1.218)
Fraction of Sticky	0.735	0.477	0.230
Prices (Non-Cycle)	(0.005)	(0.006)	(0.006)

Column (b) at means. Population in thousands.

Table 11: Effects of Competitive Variables on Prevalence and Cycle Features

Specification:	(8)	(9)		
	INDEP	INDEP	POP/RO	DENSITY
Prevalence of Cycles	0.758	0.832	0.076	0.347
	(0.296)	(0.237)	(0.077)	(0.120)
	[0.000]	[0.000]	[0.161]	[0.006]
Prevalence of Sticky Pricing	-1.178	-1.217	-0.071	-0.261
	(0.124)	(0.100)	(0.034)	(0.055)
	[0.000]	[0.000]	[0.028]	[0.000]
Prevalence of Normal Pricing	0.420	0.384	-0.004	-0.085
	(0.241)	(0.150)	(0.043)	(0.066)
	[0.035]	[0.003]	[0.446]	[0.103]
Duration of Relenting Phase	-0.242	-0.684	0.025	-0.109
	(0.293)	(0.587)	(0.044)	(0.207)
	[0.184]	[0.180]	[0.268]	[0.330]
Duration of Undercutting Phase	-2.073	-3.704	-0.439	-0.816
	(0.951)	(0.951)	(0.136)	(0.351)
	[0.013]	[0.000]	[0.000]	[0.008]
Period	-2.316	-4.389	-0.414	-0.926
	(1.036)	(1.100)	(0.136)	(0.382)
	[0.012]	[0.000]	[0.000]	[0.006]
Horizontal Asymmetry	-1.236	-1.762	-0.377	-0.482
	(0.785)	(0.834)	(0.142)	(0.457)
	[0.060]	[0.011]	[0.005]	[0.138]
$E(\Delta RETAIL \mid \text{“}R\text{”})$ (Relenting Phase)	0.242	0.708	0.059	0.704
	(1.089)	(1.047)	(0.130)	(0.441)
	[0.398]	[0.246]	[0.326]	[0.049]
$E(\Delta RETAIL \mid \text{“}U\text{”})$ (Undercutting Phase)	-0.712	-1.086	-0.439	-0.684
	(0.462)	(0.539)	(0.135)	(0.174)
	[0.055]	[0.023]	[0.000]	[0.000]
Amplitude (relenting phase calculation)	0.107	0.277	0.237	0.824
	(1.394)	(1.188)	(0.159)	(0.433)
	[0.457]	[0.406]	[0.071]	[0.026]
Vertical Asymmetry	-0.872	-1.107	-0.368	-0.510
	(0.805)	(0.714)	(0.107)	(0.397)
	[0.139]	[0.060]	[0.000]	[0.091]
Fraction Sticky Conditional on Non-cycling (γ)	-1.420	-1.411	-0.062	-0.173
	(0.184)	(0.013)	(0.001)	(0.006)
	[0.000]	[0.000]	[0.000]	[0.000]

Cell contains $\frac{\partial(ROW)}{\partial(COLUMN)}$, standard errors in parentheses, pseudo P-values (equal to fraction of simulation pairs that yield wrong sign) in square brackets.