An Empirical Study of Pricing Strategies in an Online Market with High-Frequency Price Information

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June 2010

Abstract: We study competition among a score of firms participating in an online market for a commodity-type memory module. Firms were able to adjust prices continuously and prices determined how the firms were ranked and listed (lowest price listed first), with better ranks contributing to firms' sales. Using a year's worth of hourly data, we document the pricing dynamics, cycles, and other patterns in this market. We then characterize empirically the factors which drive price changes, noting clear evidence of firm heterogeneity in the choice of pricing strategy. Finally, we develop a framework for simulating counterfactual market settings, using the simulations to examine counterfactuals involving different mixes of firms according to pricing strategies.

JEL Codes: L11, C73, D21, L81

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Acknowledgments: The authors are grateful to Hongkai Zhang for superb research assistance and to Glenn Ellison for a number of useful conversations.

1. Introduction

There is a vast and rich theoretical literature on the dynamics of repeated games. One conclusion of this literature is that many different market outcomes are possible. Full collusion, collusion on a focal price, cyclical markup patterns, and prices exactly tracking costs, are among the possibilities. This lack of a clear theoretical prediction suggests an important role for empirical analysis. In any particular setting, theory might suggest that certain outcomes are more or less likely, but the empirical documentation will ultimately be important. We are interested in the market outcomes in one particular empirical setting, an online market with a large number of firms, ranked by price, with highly visible and easy-to-change prices. We want to understand the effect that this transparency and immediacy has on the firms' abilities to maintain markups, and, more generally, the factors that affect firms' decisions to change prices. We also want to determine whether the particulars of our empirical setting can give rise to cyclical patterns, and, if so, of what variety.

The empirical literature on repeated games has often been hampered by the paucity of complete, high-frequency pricing data over long periods of time. Notable exceptions include work on the Joint Executive Committee railroad cartel by Porter (1983) and Ellison (1994), the Sugar Institute sugar cartel by Genesove and Mullin (2001), and British shipping cartels by Scott Morton (1997); research on Edgeworth cycles in retail gasoline pricing (Eckert and West 2004 and Noel 2007b among others), and more recent work on Edgeworth cycles in online advertising auctions by Edelman and Ostrovsky (2010) and Zhang (2010).[1] It is interesting to note that laws against collusion and other types of price fixing may have significantly hampered the study of pricing dynamics by academics because they have made the gathering of detailed pricing data by rivals a *de facto* suspicious activity. Regulated industries or industries in the process of deregulation,

[1]The data on the Joint Executive Committee, the Sugar Institute, and the British shipping cartels were gathered by the market participants in a pre-Sherman Act period where, because collusion was legal, gathering detailed pricing data on rivals would not have been viewed as suspicious. The retail gasoline pricing data used by Noel were painstakingly gathered by hand twice every day on a commute to and from work. The data on online advertising auctions were gathered by Yahoo! and Google, who were actually running the auctions.

such as the wholesale electricity market, often gather detailed pricing data, but these data may be less useful for the study of unfettered competition. Finally, there are many markets that might be ill-suited to the empirical study of repeated pricing games simply because of their institutional structure. Markets where prices are hard to change or hard to observe may yield less interesting pricing dynamics, for instance.

Web-scraping technologies, of course, have started to enhance the availability of pricing data. They have made detailed pricing data fairly easy to collect, and researchers have started to exploit them. Baye, Morgan, and Scholten (2004) is an excellent example of a study which used detailed pricing data collected on the web over a period of time, although their focus was not on the firms' repeated game strategies. We, too, have gathered most of our data by scraping firm and pricing data from a price search website for computer components. Furthermore, institutionally, we have a setting amenable to the empirical study of repeated games. In particular, we have identified 47 firms fairly active in selling a particular commodity-type memory module over the internet during one particular year. They list their prices for the item on a price search website and can change their listed prices at will. Prices are observable by all market participants. Wholesale costs are volatile, so firms must change their prices sometimes or they will either be selling at large losses or get bumped off the list of the twenty-four lowest prices. Consumers focus mostly on price-based rank of the firms when making their purchase decisions,[2] so firms are acutely aware of their rivals' prices. The transparency and immediacy of this empirical setting, along with the relative homogeneity of the products offered, have the potential to result in interesting pricing dynamics.

Our goal with this paper is three-fold. First, we want to document the pricing dynamics, cycles, and other patterns in this market. Second, we want to characterize empirically the factors which drive price changes, noting clear evidence of firm heterogeneity. Finally, we would like to develop a framework for simulating counterfactual market settings. In particular, we will

[2] See Ellison and Ellison (2009a) for demand estimates in this market.

examine counterfactuals arising from different mixes of the types of firms participating in the market, but we note that this framework is sufficiently flexible to allow for a large variety of types of counterfactuals.

One of the striking aspects of this market that we note is firm heterogeneity. Standard economic reasoning would suggest that our setting would engender homogeneity, not the heterogeneity we observe. For instance, the specific product on which we focus is fairly undifferentiated. We exploit the fact that the price search engine that mediates this market has predefined product categories, and we focus on one high-volume category, 128MB PC100 memory modules. The firms with the twenty-four lowest prices in this category are all selling generic, untested modules with unfavorable warranty and return terms. Furthermore, brand names of firms are relatively unimportant. Most consumers would have never encountered the names of any of these firms before. From talking to one of the business owners in the market, we gather that the competing firms are all small, share wholesale sources, and have similar sets of products. And yet we observe significant heterogeneity in the repeated game strategies that they seem to employ. We find this heterogeneity interesting enough to document, but we must remain largely agnostic about its origin. Even though the firms share wholesale sources, they might have different cost structures internally and may, therefore, face different marginal costs of fulfilling orders. They could enjoy different levels of managerial competence, which could account for the different strategies we observe. Finally, even if the firms were identical in all of these respects, it is possible that the heterogeneity we observe is simply the result of experimentation with different strategies or mixing. In fact, the business owner to whom we spoke acknowledged experimenting constantly with different website designs in addition to pricing strategies.[3]

Our paper proceeds in eight sections. Section 2 reviews the relevant literature. Section 3 offers additional details about the empirical setting. Section 4 describes the data set we use. Section 5 discusses how we classify firms into different "strategic clusters" to account for the

[3] In fact, he opened multiple websites selling identical products to facilitate this experimentation.

heterogeneity we observe. Section 6 presents and interprets our empirical model of firm pricing. Section 7 presents our simulations of counterfactuals of the mix of different strategic clusters. We conclude in Section 8.

2. Literature Review

The first part of this section provides a review of relevant theoretical papers in order to provide some background for our empirical work. The second part surveys the related empirical literature, highlighting our paper's contribution.

2.1. Theoretical Literature

The theoretical literature provides a mixed view on the ability of firms to sustain high margins in our market. The repeated-game literature (see e.g., Fudenberg and Maskin 1986) suggests that the monopoly outcome is sustainable if firms have a discount factor close enough to 1. In our market, firms could adjust price instantaneously, and these price changes are immediately registered to rivals along with customers, allowing rivals to respond to price cuts with their own. Translated back into a discrete-time setting, the period lengths in our market effectively are arbitrarily short and the discount factor arbitrarily close to 1, suggesting according to the Folk Theorem of Fudenberg and Maskin (1986) that full collusion is a possibility. Other factors that textbooks point to as facilitating collusion are also present in our market, including a homogeneous product and firms without glaring asymmetries among them (see Tirole 1988, Section 6.1, for a discussion).

On the other hand, other considerations may suggest that collusion is difficult, providing a rationale for the more competitive prices that we will end up observing. First, Fudenberg and Maskin's (1986) Folk Theorem indicates that collusion on the monopoly outcome may be a possibility but not a necessity, with a whole range of other outcomes possible, including marginal-cost pricing. How firms arrive at their repeated-game strategies and the market arrives at an equilibrium in the presence of this multiplicity of equilibria has been the subject of active research inspired by Axelrod's (1984) seminal work. A second factor hindering collusion is the relatively large number of firms in our market: hundreds of firms were listed on the price-comparison website (our data covers a smaller group of the 24 lowest-price firms each hour, for a total of 47 with significant presence during the sample period). For many reasons, collusion is harder to sustain with more firms.[4] Third, although in principle firms were able to adjust price instantaneously, in practice prices were not continuously changed, with lags of days or even weeks between price changes. Why firms showed inertia in price changes is in part the subject of our analysis. Davis and Hamilton (2004) offer four suggestions: menu costs, information-processing lags, customer acceptance, and strategic recognition of rival responses. To this list we would add a fifth: costs of continually monitoring market conditions, and computing best responses to these, leading to periods of inattention.

Interesting price patterns can emerge with staggered price setting in repeated games. The seminal paper in this area, Maskin and Tirole (1988), showed that if two firms set prices in alternating periods, there exist Markov-perfect equilibria exhibiting a focal price and also others exhibiting cycling prices (called Edgeworth cycles after Edgeworth 1925). Although we will not see marked Edgeworth cycles in our price series, firms' rankings in the price list will exhibit cycles for some firms reminiscent of Edgeworth cycles, and one of the goals of the analysis will be to characterize these rank cycles. Recent theoretical research has pointed to the robustness of the cycling equilibria. Wallner (1999) shows that Markov-perfect equilibria with price cycles can emerge even if the repeated game has a finite horizon. Eckert (2003) shows that while equilibria with cycling prices exist for a large range of firm sizes, focal-price equilibria require the two firms to be close enough in size. Work showing that asynchronous pricing will emerge

[4] Tirole (1988) provides a general discussion. Chowdhury (2008) shows that the unique equilibrium of a repeated game with convex costs (related to Edgeworth's capacity constraints) in which firms can choose price and quantity is a grid point above marginal cost if the number of firms is large enough.

in equilibrium includes Fishman (1992), Cahuc and Kempf (1999), and Lau (2001). Bhaskar and Vega-Redondo (2002) justify the restriction to Markov strategies, showing that all Nash equilibria must be in Markov strategies if agents have limited memory and strategies conditional on lengthening histories involve complexity costs. This paper is also related to the theme of limits to the reasoning and processing power of the price-setting agents mentioned in the previous paragraph as possibly leading to pricing inertia.

The price cycles that emerge in the literature cited in the previous paragraph are solely a function of firm strategy and not driven by fluctuations in market conditions. Of course, price cycles and other interesting movements may be generated by underlying fluctuations in demand and/or cost. Indeed these market fluctuations may affect the nature of firms' strategies, typically providing another factor hindering collusion (Tirole 1988). Classic papers on supergames in the presence of market fluctuations include Rotemberg and Saloner (1986), analyzing the case of observable shocks, and Green and Porter (1984), analyzing the case of unobservable shocks. Several more recent papers have added market fluctuations to repeated games with staggered pricing (Fishman 1992, Eckert 2004, Leufkens and Peeters 2008).

Much of the theoretical literature tends to focus on symmetric strategies, in contrast to our findings that firms adopt heterogeneous strategies that fall into identifiable clusters. The theory does suggest some rationales for heterogeneous strategies. Not knowing the strategies rivals are playing to say nothing of the best response to these strategies, different firms may be experimenting with different strategies, one or some of which may begin to emerge as dominant through survivorship or other evolutionary forces, along the lines of Axelrod (1984). In the model of Hansen *et al.* (1996), with duopolists in a Bertrand game with differentiated products, an unanticipated negative demand shock may elicit asymmetric responses as a decrease in one firm's price reduces the benefit to the other from changing its price, and it may decline to do so if price changes involve a fixed cost. In Lal and Matutes' (1989) model, manufacturers of a product bundle charge different prices for the individual components although the overall bundle is sold for the same total amount. This strategy allows firms to compete for different segments of the heterogeneous population of consumers with their differentiated products. Such strategies may be relevant for our market, because the product under consideration may be offered to induce consumers to buy other products along with it or as a substitute for it, so multiproduct strategies may be important in our market and may contribute to heterogeneity in strategies.

2.2. Empirical Literature

Our paper investigates the same market and uses the same data as Ellison and Ellison (2009a, 2009b). The focus of our paper is quite different, though. Ellison and Ellison (2009a) estimates demand in the market, but does not consider dynamic pricing patterns or firm interactions, which is the focus of the current study. Instead, we will use the demand estimates from that paper as an input into our analysis. Ellison and Ellison (2009b) also estimates aspects of demand to see how sensitive consumers are to sales-tax savings from purchasing online and whether consumers exhibit home-state "biases" in their purchasing.

The two empirical papers most closely related to ours both in substance and empirical setting are Edelman and Ostrovsky (2010) and Zhang (2010). They both document the occurrence of Edgeworth cycles in sponsored search, or online advertising, auctions. At first thought, the empirical settings seem quite different because those papers are studying bids in auctions, not prices set by firms in a market. On second thought, though, one can actually draw a very close analogy. In one case, firms are bidding on keywords, where a bid is the amount the advertiser pays for every click-through. Unlike a standard auction, the second, third, etc., highest bidders do not lose out in those auctions, though. They simply are allocated less desirable (*i.e.,* less likely to be clicked) spaces on the results pages. (Typically, the highest bidder is listed first on the page, the second highest second, and so forth.) Also unlike standard auctions, keyword auctions occur continuously in real time and advertisers can change their bids at will, just like a seller can change price in an online market. The analogy to our setting is the following: The price the firm sets to sell its product is like its bid for a favorable rank on the price search engine page and that rank determines the number of customers it receives, just like an advertiser's position on the results page determines click-throughs. We do not, in fact, find Edgeworth cycles in our price series, unlike Edelman and Ostrovsky (2010) and Zhang (2010), although our objective of documenting the pricing patterns that do exist is similar.[5]

As mentioned in the introduction, our paper is also related to a literature that tries to characterize interesting movements (and perhaps cycles) in retail gasoline prices, including Castanias and Johnson (1993), Eckert and West (2004), Noel (2007a, 2007b, 2008), Hosken, McMillan, and Taylor (2008), Atkinson (2009), Wang (2009), Lewis (2009), and Doyle, Muehlegger, Samphantharak (2010). Our hourly data is collected at a higher frequency than most of these studies, which mostly use daily data, an exception being Atkinson (2009), which uses bi-hourly observations. Also related is the literature on wholesale gas pricing. Borenstein, Cameron, Gilbert (1997) identify an asymmetry in price responses to cost rises versus falls.[6] Davis and Hamilton (2004) provide structural estimates of a menu-cost model. They find an adequate fit of the data, but some specific parameter values have implausible sizes, which they use as evidence in favor of alternative models of price inertia. Their preferred alternative is that firms keep prices constant in order to prevent undesirable strategic reactions by customers or rivals. They have a very specific menu-cost model (that of Dixit 1991), which does not nest the inattention story which we will consider as another alternative here. Lewis (2009) shows that temporary shocks may have long-lived strategic effects in the wholesale gas market.

Our finding of price dispersion is related to a much larger literature on this issue. Lach (2002) characterizes price dispersion for a cross-section of retail items sold in Israeli stores.

[5] Many advertisers in sponsored search auctions use automated bidding programs, which, combined with the first price auction format, leads to inherently unstable equilibria, according to Edelman and Ostrovsky. Very similar incentives would exist in our market, but our sellers do not use automated price-setting programs, which could be an important reason that we do not find Edgeworth cycles.

[6] A substantial literature, with many contributions by macroeconomists seeking to understand pricing over the business cycle, studies this issue of asymmetric price adjustments to market conditions. See Klenow and Malin (forthcoming) for a survey. In a study of strategies rather than price outcomes, Bhaskar, Machin and Reid (2002) survey over 70 owner-managed Scottish firms to determine how they respond to rivals.

Barron, Taylor, and Umbeck (2004), Hosken, McMillan, and Taylor (2008), and Lewis (2008) document price dispersion in retail gasoline. Perhaps closest to the present paper among these is Baye, Morgan, and Scholten (2004) because they document price dispersion in an online price comparison site, so a setting similar to ours.

More specifically we are interested not just in heterogeneity in price outcomes—price dispersion—but heterogeneity in strategies used in a dynamic game. Hosken, McMillan, and Taylor (2008) identify strategy heterogeneity in retail gasoline. Lewis (2008) also documents strategy heterogeneity, finding that his stylized facts are hard to reconcile with a single existing theory.

There is a literature, largely methodological at this point, on the structural estimation of dynamic games. The most prominent papers are Aguirregabiria and Mira (2007) and Bajari, Benkard, and Levin (2007). We see our paper as a complement to that literature in the following sense. Those models impose restrictions on firm behavior, that all firms' actions are consistent with Markov perfect equilibria, for instance, to back out certain structural parameters. We want to, instead, remain entirely agnostic about what type of equilibrium strategies (if any) firms are playing and instead focus on the empirical determinants of their actions, resulting markups, and so forth. Imposing those restrictions on firm behavior is neither necessary nor helpful for our exercise.

An experimental literature has investigated markets in which participants can adjust price continuously or nearly so (Millner, Pratt, and Reilly 1990, Davis and Korenok 2009). Another related experimental paper is Leufkens and Peeters (forthcoming), which studies a laboratory market in which prices are set dynamically with various commitment periods across treatments.

3. Empirical Setting

We look at the online market for computer components mediated by a price search engine called Pricewatch. This is an empirical setting examined also in two previous papers, Ellison and Ellison

(2009a, 2009b). We focus on aspects of the market and firm behavior that those papers largely abstracted away from, although details of the empirical setting discussed there will be important here as well. One should consult those papers for a more complete description.

During the period in which our data were collected, the Pricewatch universe was characterized by a large number of small, undifferentiated e-retailers selling memory upgrades, CPUs, and other computer parts. These retailers tended to do little or no adversiting, have rudimentary websites, receive no venture capital, and run efficient, profit-maximizing operations. They also tended to receive a large fraction of their customers through Pricewatch. Potential customers could use Pricewatch to locate a product in one of two ways. They could either type a technical product description, such as “Kingston PC2100 512MB,” into a search box, or they could run through a multilayered menu to select one of a number of predefined product categories, *e.g.,* clicking on “System Memory” and then on “PC100 128MB SDRAM DIMM.” In that case, they would receive back a list of products sorted from cheapest to most expensive in a twelve-listings-per-page format. These pre-defined categories may contain as many as 350 listings from 100 different websites. Figure 1 contains the first page of a typical list, that for PC100 128MB memory modules from October 12, 2000.

We will be focusing on the dynamic aspects of firm price-setting strategy, and it is worth noting that the Pricewatch lists exhibit substantial turnover from day to day and even from hour to hour. On average, five of the twenty-four retailers on the first two pages of the above-mentioned list will change their prices on a given day. Each price change typically moves several other retailers up or down one place on the list. Some websites are clearly big players that regularly occupy a position near the top of the Pricewatch list. From time to time one may observe a firm sitting in the first position for a week or more, but there is no rigid hierarchy.

Some of this turnover can be attributed to the technology used by Pricewatch and the various websites at the time. Pricewatch is a database-based system which relies on e-retailers’ updating their own prices in its database. Our impression is that all (or almost all) of the retailers were setting prices in Pricewatch manually in the time period we study. A typical retailer has dozens or hundreds of products listed in the Pricewatch database, making it impractical to constantly monitor one's place on each predefined product category and the current wholesale prices for each product. Instead, a retailer might manually examine its position on the most important Pricewatch categories a few times a day and might look at current wholesale prices at most once or twice a day.

4. Data

Our primary data source is prices downloaded from Pricewatch.com. We collected information on the twenty-four lowest price offerings, or the first two pages, in the category of 128MB PC100 memory modules.[7] In addition to the price, we downloaded the specific product name and the firm name, so that we could follow firm pricing strategies for specific products over time.[8] Due to the frequent turnover on the price lists, it was important to collect these data at high frequency, and, in fact, they were collected hourly from May 2000 to May 2001.[9]

In some calculations, we supplement the pricing data with proprietary data from a retailer who operates three websites listed on Pricewatch. This retailer provided us with daily wholesale acquisition cost data (which we have reason to believe is common to all retailers). Note that wholesale purchases are typically made every afternoon based on that day's retail orders, so little or no inventory is held. The retailer also provided us with sales data. We can use those data to calculate margins and markups as well as a proxy for product-level profit by firm conditional on current costs and a firm's Pricewatch position.

A large number of firms made brief appearances on the Pricewatch lists. Since we are interested in the dynamics of firms' pricing patterns, we only retained firms that were present for

[7]We collected price data on several different product categories from Pricewatch. We focus on this particular product category because it is the most active and highest volume category for which we have data.

[8]The products in this category are, physically at least, fairly homogeneous. We do treat it as a change in product offering when a firm changes the name of its product, though.

[9]We used Go!Zilla to carry out the downloads.

at least 1000 hours at some point during the year (approximately one-eighth of our time period) and changed price while staying on the list at least once. We also deleted the small number of firms who had multiple products on the first two pages of Pricewatch simultaneously. We were left with 47 firms that appear at some point during the year, with at most 24 present at any particular moment.

Based on these data, we created a number of variables to describe factors that might be important to firms' decisions about timing and magnitude of price changes. The rank of that firm on the Pricewatch list is an obvious candidate, but so would be factors like markup, length of time since its last price change, number of times a firm has been "bumped," or had its rank changed involuntarily, since its last price change, and so forth. Table 1 contains a description of these variables, and Table 2 lists their summary statistics.

Definitions of a few of the variables could use additional explanation. *Placement* is simply the fraction of the distance between the next lower-priced firm and the next higher-priced firm a particular firm is in price space. In other words, if three consecutive firms were charging $85, $86, and $88, the value for *Placement* for the middle firm would be 0.33, or $(86-85)/(88-85)$. *Density* is a measure of how crowded together firms are in price space in the immediate region around a particular firm. It is defined as the difference between the price of the next higher-priced firm minus the price of the firm three spaces below divided by 4. In other words, if five consecutive firms were charging $84, $84, $85, $86, and $88, the value for *Density* for the firm charging $86 would be 1, or $(88-84)/4$. *CostTrend* and *CostVol* were computed by regressing the previous two weeks of costs on a time trend and using the estimated coefficient as a measure of the trend and the square root of the estimated error variance as a measure of the volatility. The definitions of the remaining variables are self-explanatory.

Turning to Table 2, note first that the average price charged by our firms for a PC100 128MB memory module during this period was about $69 with a very large range, $21 up to $131. Most of this variation occurs over time, with prices typically above $100 at the beginning of the period and down in the \$20s by the end, mirroring a large decline in the wholesale cost of these modules. Note also the very low markups. On average, we see markups of 4% but see some as low as -35%! The explanation for the very low, often negative, markups is an add-on pricing business plan employed by the retailers. Discussion of this plan is a main focus of Ellison and Ellison (2009a).

5. Classifying Firms' Strategies

One of the striking characteristics of our data set was heterogeneity in firm strategies. Any empirical model of pricing behavior would have to accommodate this heterogeneity. Modeling pricing on a firm-by-firm basis would, of course, allow for arbitrary firm-level heterogeneity, but that analysis would sacrifice power, perhaps unnecessarily, and, more importantly, would result in a non-random sample selection, eliminating almost all of the less active firms due to too few observations. To balance those two concerns, we decided to categorize firms into classes, or what we will call "strategic clusters," as a prelude to empirically modeling their pricing behavior. To do so, we use the technique of cluster analysis.

Cluster analysis is a well-known tool in many other social sciences and sciences but is relatively unknown in empirical economics.[10] Therefore, a concise description makes sense here. We should begin by saying that we think of cluster analysis more as a handy tool to organize data as opposed to a statistical technique which produces useful estimates of anything or is optimal in any sense. With that in mind, we would define cluster analysis as a set of techniques used to assign objects, which are differentiated on multiple dimensions, to clusters which contain other, similar objects. In our case, the objects are firms, and we seek to assign them to clusters based on their strategic actions, such as how often they change their price, where on the price-sorted lists they tend to be, whether they change as a result of being bumped from their rank, and so

[10] A standard reference for cluster analysis is Romesburg (2004).

forth.[11] We think allowing for three clusters of firms is a nice balance between spanning most of the important firm heterogeneity we want to capture and still obtaining clusters large enough to analyze empirically with some confidence.

We started by standardizing the variables describing firm strategy to give them all a standard deviation of one. This step is common prior to performing a cluster analysis to prevent differences in the variable with the largest variance from dominating the assignment. Then we defined similarity (or dissimilarity) between two firms as the Euclidean distance in the space defined by the variables. Finally, we chose a method which defines similarity between clusters as a function of the sum of squared differences between all firms in the two clusters, Ward's method.

We performed an agglomerative cluster analysis, which first places every firm in its own cluster and proceeds iteratively by agglomerating the most similar clusters until, in our case, there are three. We used the standard Stata cluster anaysis command with the options described above. Table 3 contains the output of the clustering, both in terms of the number of firms which are assigned to each of three clusters and the average values of key variables within clusters. These averages provide an intuitive description, or shorthand, for each of the clusters. Cluster 1, for instance, could be characterized as the cluster of active firms who like to populate the highest spots (lowest ranks) on the price-sorted lists. These firms change prices often, tend to have low markups, and tend to not stray far from their preferred locations on the price-sorted lists. Cluster 2, the smallest cluster, is made up of firms with moderate prices and markups who are relatively inactive. In other words, these firms may target middle ranks but tend to get bumped far from their preferred spots before they bother to change their prices. Cluster 3 is higher-priced but more active than cluster 2. They prefer lower spots (higher ranks) on the price-sorted list and will change prices relatively often to maintain their preferred locations. To summarize, cluster 1 is low-priced and active, cluster 2 is mid-priced and inactive, and cluster 3 is high-priced and

[11] We used ten variables for the cluster analysis. The averages at the firm level of $Rank$ and $Markup$ were used, as well as firm averages conditional on a price change of $SinceBump$, $SinceChange$, and $NumBumps$. Finally, we used variables describing the fraction of time the firm spends in ranks 1-12, the firm's average price and rank changes, conditional on them being positive, and the same, conditional on them being negative.

fairly active.

This characterization is nicely illustrated in Figure 2. We chose one representative firm from each cluster and graphed both their prices and ranks for the month of August, 2000. Note that that month, like most of our months, is marked by falling wholesale prices, so a firm listing a particular price would tend to get bumped higher in rank as firms around it were lowering their prices in response to falling costs. Just as the means by cluster suggest, our representative firm from cluster 2 is between the lower price of the cluster 1 firm and the higher price of the cluster 3 firm. In addition, it is noticeably less active than either of its counterparts, changing price only twice during the month. As a result of its inaction, it is bumped up from a rank of 6 at the beginning of the month[12] to 14 by the end. Both the cluster 1 and cluster 3 firms are close to their initial rank at the end of the month. There is a notable difference between the firms from clusters 1 and 3 other than price level, though. The firm in cluster 3 is displaced further from its initial rank over the course of the month than the firm in cluster 1. It does, though, tend to regain its initial rank when it is bumped too far, unlike the firm from cluster 2.

An observant reader might notice phenomena in Figure 2 that resemble Edgeworth cycles, especially evident in the cluster 3 upper panel. They, in fact, look like upside-down Edgeworth cycles. Recall an Edgeworth cycle involves firms gradually decreasing prices to slightly undercut rivals and then reverting back to a high (monopoly) price after marginal cost has been reached. Although our cycles might bear some resemblance to Edgeworth cycles, their origin is entirely different. First, they are cycles in rank, not price, and rank is not something that firms can directly control. Second, our cycles result from inactivity, not the series of small price changes that give rise to Edgeworth cycles. Firms get bumped away from their desired rank—if cost is falling, they would typically be bumped to higher ranks—until they are sufficiently far to warrant the effort to change price and regain a desirable rank.

[12]It only enters on August 5 and is not present during the first four days of the month.

6. Modeling Firms' Price Changes

We use a two-stage model of firms' price-setting behavior. Each period t, corresponding to an hour in the dataset, the first stage involves each firm deciding whether to keep the same price from period $t-1$ or to change it. Over stretches of time, either because market conditions or rival actions have remained stable, or because the firm does not wish to exert effort of attending to current conditions just yet, the firm will decide not to change price. If it decides to change price in a certain period t, however, it moves to a second-stage decision about the size of the price change, including the direction of change (increase or decrease). We estimate the first-stage decision—timing of price change—using a probit specification, in which the dependent variable is an indicator equalling 1 if firm i changes its price between period $t-1$ and t and 0 if firm i keeps price the same. The results are reported in Table 4. We estimate the second-stage decision—size of price change—using an ordinary least squares regression in which the dependent variable is the proportional change in price: $\ln \mathit{Price}_{i,t} - \ln \mathit{Price}_{i,t-1}$. The results are reported in Table 5.

We estimate three separate models for each of the three strategic clusters of firms, thus allowing us to characterize the heterogeneous strategies across clusters and to reflect this heterogeneity in the simulations. In addition to these cluster-specific models, we present an initial model that combines all the firms in one model, as a sort of general summary of the "average" firm strategy. We present two specifications of each model. One is a parsimonious model that includes a small set of the most important variables which we believed to have a first-order effect on firms' pricing decisions: the two central pricing variables (*Markup* and *Rank*), and variables capturing the current spell without voluntary or involuntary movement in the price ranks (*SinceChange* and *SinceBump*, respectively). This is the specification that will be used to generate the simulations below, the parsimony helping to generate stable simulations which turn out to be difficult with the inclusion of less-important variables. To help provide a full characterization of firms' strategies from a descriptive perspective, we also estimate a rich specification that includes ten other variables which may potentially affect firms' pricing, albeit in a less powerful way. The rich specification includes additional controls for recent rival activity (*NumBumps*) and cost fluctuations (*CostTrend* and *CostVol*), the distribution of prices in the neighborhood of firm i (*Placement* and *Density*), and aspects of distribution of prices more globally (*LowPrice*, *AvgPrice*, *HighPrice*, and *AvgMargin*).

6.1. Timing of Price Change

Consider the results for the probit model of the timing of price change reported in Table 4. All results are presented as marginal effects for ease of interpretation, and all but the results for the markup variables (*Markup* and $Markup^2$) are scaled up by 10^3 for legibility. The combined probit involves over 170,000 observations, over 60% of which are for firms in strategic cluster 1 (the preponderance of observations due to the fact that almost half the firms are in cluster 1 and these firms tend to have more complete presence during the sample period). The combined probits in the first set of columns will generally be somewhere in the middle of the three clusters' results, but somewhat skewed toward the cluster-1 results. Reported standard errors are robust to heteroskedasticity and are adjusted to account for the possible non-independence across observations for the same firm.[13]

It should be noted that very few of the results for cluster 2 are statistically significant. This is true for two reasons. First, one of the central characteristics of the cluster is to adjust prices relatively infrequently. Hence there will not be much variation in the dependent variable to explain. Second, although the probits for cluster 2 include almost 10,000 observations, this is still only a tiny fraction (about 6%) of the overall sample. This is in fact a small sample once one recognizes that time-series observations for a single firm are not independent and that there are

[13] These are sometimes referred to as clustered standard errors, a usage of "cluster" which should be kept distinct from the strategic clusters used throughout this paper. Clustered standard errors adjust for the correlation among errors for a single firm, whereas a strategic cluster involves a group of firms identified by the methods of cluster analysis.

few price changes (showing up as 1's for the dependent variable) in the subsample. Overall, the pseudo-R^2 values are fairly low across the probits, only as high as 0.068 (i.e., 6.8%), evincing the difficulty in predicting the rare event of a price change in hourly data.

The marginal effect of *Markup* in the probits is difficult to discern directly because it enters as a quadratic to allow for possible nonlinear effects. To aid in interpretation, Figure 3 graphs the quadratic function associated with the marginal effects from the parsimonious specification. The dotted curve for the combined results, in particular its steep downward slope for negative margins, indicates that the average firm is very sensitive to large negative margins and likely to adjust their prices then. For example, a price-cost margin of –0.35, meaning that price is 35% below cost, leads the average firm to increase its probability of a price change in a given period by almost 0.009, that is, 0.9 percentage points. This may seem like a small increase in probability until one recalls that this is hourly data, and the probability of a price change in any given hour is quite low to begin with. The hourly marginal effect cumulates into a larger effect over longer time periods, implying that a 0.9 percentage point marginal effect is actually quite large. The effects for cluster-1 firms are even stronger, with a markup of –0.35 leading to a 0.010 (i.e., one full percentage point) increase in the probability of price change in an hour. Clusters 2 and 3 show some but much less sensitivity, reflecting the more general result that cluster 1 includes more responsive firms than the other clusters.

The fact that the curves for clusters 2 and 3 in Figure 3 pass through the origin and become negative for positive margins indicates that positive margins lead firms in these clusters to be slower to adjust prices. Evidently, firms in these clusters are willing to trade off increased margins for lower sales in this region. The curve for cluster 1 tells a different story. For all but the largest positive margins, positive margins have no effect on the firm's likelihood of changing prices, as can be seen from the curve for cluster 1 hovering close to the horizontal axis. For large, positive margins, the curve rises more steeply and becomes positive, indicating that the largest positive margins also lead the firm to adjust its prices, presumably because it is losing demand. For example, projecting out to a margin of 0.4 (price 40% above cost, which is slightly outside our data range), this margin would lead a cluster 1 firm to be 0.0025 (a quarter of a percentage point) more likely to change price in a given hour. The combined results given by the dotted curve are more muted than the cluster 1 results, implying that positive margins do not affect the timing of price changes on average.

The *SinceChange* variable is included to determine whether prices are adjusted according to a systematic schedule. Changing prices according to a systematic schedule, say every x periods, would show up as a positive coefficient on *SinceChange* as the firm would be increasingly likely to change price as the next scheduled date for changing price approached. Instead, we find a negative and statistically significant result for the combined and cluster-1 results and results that are still negative but smaller in magnitude for cluster 3. For these clusters, a firm's price changes tend to be bunched in time, followed by longer spells of inactivity than would be predicted by regular schedule. This finding supports an inattention model, but of a certain type, with the manager of each of these firms being drawn away from watching the market at random times for random durations, but then making rapid adjustments in periods he or she is allowed to attend to the market, as opposed to setting prices and then returning to revise them at consistent intervals, say once every other day. Cluster 2's results are essentially 0, indicating that pricing for these firms conforms more to a regular schedule. The examples in the lower panels of Figure 2 illustrate this pattern, with the representative firm from cluster 2 showing price changes at regular intervals but those for the other clusters being more scatter-shot.

SinceBump has a similar interpretation as *SinceChange*, but accounts for time since an involuntary as opposed to a voluntary movement in the price rankings. The results are generally similar to those for *SinceChange*, negative and statistically significant overall and for clusters 1 and 3 individually. The results are positive and statistically significant for cluster 2. One explanation is that given these firms are the most inert, and thus are unlikely to initiate price changes themselves, they must be careful at least to respond to changes in their ranking caused by other firms' activity.

The results for *Rank* are puzzling at first glance. We expected to see a positive marginal effect, with a high ranking motivating the firm to change its price to appear in a better position on the Pricewatch page. In the parsimonious specification for the combined probit, we see a negative and significant marginal effect of -0.193×10^{-3}. The magnitude of the effect falls with the inclusion of other variables in the rich specification, and indeed is positive for all the rich specifications for individual clusters, and is statistically significantly positive for cluster 3. Thus the disaggregated results are as expected.

The remaining variables enter the combined probit with the expected signs, although there is heterogeneity across groups in sign and significance in some cases. *NumBumps* has a positive marginal effect in the combined probit, consistent with the hypothesis that the more a firm has been displaced in the ranking by other firms' actions, the more likely the firm is to respond with a price change of its own. However, the result is not significant and differs in sign across some clusters. *Placement* has the expected negative sign in the combined probit, indicating that a firm that is well positioned relative to its neighbors in price space is less likely to want to change its price. The ideal placement (associated with the highest value of *Placement*) is one just below the higher-priced neighbor because this maximizes markup subject to keeping the firm's rank constant, and rank is an important determinant of demand in this market. However, the negative result is insignificant in the combined probit and only significant for cluster 2. *Density* has the expected positive sign, where firms are more likely to adjust prices if their price is close to a concentration of other firms'. Considering indexes of the "global" price distribution (*LowPrice*, *AvgPrice*, *HighPrice*), in the combined probit at least, the negative effect of *LowPrice* and the positive effect of *HighPrice* suggest that a spread in the range of prices increases the probability a firm adjusts prices. *AvgMargin* has a positive effect in all of the probits, significant in all but one. This is consistent with a model in which attention requires a fixed cost each period; the manager is more likely to expend this cost if the absolute level of margins is higher and so there are greater possible gains from price adjustments.

CostTrend is significantly positive for cluster 1. We interpret this as consistent with the results above for *Markup*, the difference being that *Markup* captures current conditions while *CostTrend* captures anticipated movements in margins. *CostTrend* will capture expectations of future margins to the extent that there is serial correlation in the cost series, so that increasing costs in the recent past are predictive of continuing cost increases. Cluster-1 firms respond to such anticipated cost increases, which would lead to negative margins if prices were not adjusted, as they do to negative current markups as described above. The opposite is true for a negative cost trend, which reduces the firms' probability of changing prices. But this is again similar to what was found with *Markup*, where positive margins were not found to affect the timing of cluster-1 firms' price changes. The cluster-2 and 3 results are smaller in magnitude and insignificant, consistent with our earlier finding that these other clusters did not respond as much to current margins as did cluster-1 firms. Finally, the positive effect of *CostVol* in the combined probit indicates that the average firm is more likely to adjust prices in the presence of recent cost volatility, but this effect is not significant in this or the disaggregated cluster probits.

6.2. Size of Price Change

Turn next to the results for the size of price change reported in Table 5. These ordinary least squares regressions were run on only the subset of observations for which there was a price change from the previous hour. This results in a much smaller sample because price changed in fewer than 1% of the observations. The cluster-2 regressions should be interpreted with particular caution because they include a mere 19 observations. For completeness we report results for this cluster, but for the parsimonious specification only.

The dependent variable is the change in log price, $\ln(\mathit{Price}_{it}) - \ln(\mathit{Price}_{it-1})$, so effectively a percentage change for small price changes. As before, the reported standard errors are heteroskedasticity robust, adjusted to account for non-independence across observations for the same firm. Besides the first two variables (constant and *Markup*), the coefficients for the remaining variables are scaled by 10^2 for legibility. The results are generally sensible and consistent with prior expectations. Notice that the R^2 in Table 5 is an order of magnitude higher than the pseudo R^2 from Table 4, implying that it is much easier to predict the size of price change than its exact timing at an hourly frequency.

We will focus on the more robust, substantial, and significant results, starting with the constant term. Comparing the constant term across clusters 1 and 3, we see that cluster-1 firms on average have larger reductions in price when they change it compared to cluster-3 firms. This is consistent with cluster 1 maintaining low prices. *Markup* is negative and significant across all columns. This implies that firms adjust prices to re-establish their ideal margins, increasing price when margins are negative and decreasing them when margins become too large. *SinceChange* is negative and significant for at least one specification for clusters 1 and 2, indicating that these firms tend to make larger price adjustments when they have not adjusted price for a while, since according to the constant these firms tend to make negative price adjustments when they make them. The positive coefficient for cluster 3 is evidence for a similar strategy, but since the constant for this cluster is positive, a larger positive adjustment is made when they change price. *SinceBump* is only significant for cluster 3, indicating that these firms tend to decrease price more when they have not attended to a worsening in their ranking for a while. The next rwo variables show a significant price response to establish desired rank positions. *Rank* is negative and significant in the parsimonious specification for clusters 1 and 3, indicating that the firms reduce price when they have a high rank. *NumBumps* is negative and significant overall and for clusters 1 and 3, indicating that a larger displacement in the rankings is met with a bigger price adjustment downward to establish the desired rank.

The local position variables, *Placement* and *Density*, do not show very significant effects on size of price change. *Placement* is positive and significant (though only at the 10% level) for cluster 1, consistent with these firms reducing price less when they are in a preferred position in local price space, just undercutting their higher-priced neighbor. The next four variables, capturing the global price distribution, do not show much significance except for *AvgMargin*, which is positive in all cases and significant for the combined and cluster-1 regressions. Higher average margins lead firms to increase price (or equivalently not decrease price as much as they would otherwise).

The last two variables, *CostTrend* and *CostVol*, are consistent with firms responding to recent and expected future cost changes. The positive coefficient on *CostTrend* suggests that firms tend to match price changes to recent trends in costs, although the result is not significant. Higher recent cost volatility leads to higher prices, significantly so in the combined and cluster-1 regressions, indicating that these firms, which are near zero margins, try to preserve an extra cushion when costs have been volatile.

7. Simulations

In addition to documenting the heterogeneity in firm strategy, classifying the firms into strategic clusters to reflect the salient features of that heterogeneity, and examining the pricing dynamics of the mix of firm types that exist in this market, we are also interested in examining some counterfactuals. In particular, we would like to know how pricing dynamics would change if the mix of firm types were to change.

In order to answer variants on this question, we perform a series of simulations. We create a set of twenty-four simulated firms and assign them starting markups by drawing randomly from the empirical markup distribution we observe. From those markups, we then can back out prices (given cost) and generate ranks. We then allow cost to move as it actually did and the simulated firms' prices to evolve as governed by the empirical models we developed and discussed in the previous section. We can alter the mix of firms competing at will, by simply having different proportions of them governed by the three cluster-level empirical models. For instance, to simulate the dynamics of price competition with a group of firms entirely composed of active, low-price firms, we just have all of our simulated firms' hour-by-hour decisions arising from cluster 1 empirical estimates.

This simulation exercise is in the spirit of the seminal work on repeated games by Axelrod (1984). Axelrod invited game theory colleagues to submit strategies for a simple two-person repeated game. He then pitted the strategies against one another in a tournament of simulations to see which strategies did best (in terms of maintaining prices closest to the monopoly price) against themselves, different stratgies, the entire field of strategies, and so forth. Since Axelrod's game was entirely an invention, he was able to control all aspects of it. In particular, he specified cost functions and profit functions for firms, assuring homogeneity in those dimensions. Since our simulations are based on actual firms operating in an actual market, we have no such control, but we can also structure our simulations based on quantities we can observe and estimate in our market, which Axelrod could not do.

Note that to ensure well-behaved simulations, we use the more parsimonious specifications for both the probability-of-change and size-of-change models. In particular, we allow the variables *Markup*, *SinceChange*, *SinceBump*, and *Rank* to drive the firms' decisions on timing and size of price change in the simulations.

Also, we allow for entry of new firms in the simulations. Firms enter at random times and random ranks on the list consistent with the frequency and location of firm entry in the actual market.[14] Note that firm entry has the effect of knocking the highest-priced firm off the list so that we always maintain twenty-four firms.

We performed four different simulations. Our first was simply a simulation where we reproduced the actual mix of the three strategic clusters we observe.[15] The second simulation imposed

[14]For class 1, firms entered with probability 8/720 each hour, which resulted in eight expected entrants per month. They entered uniformly over rank. For class 2, firms entered with the probability 12/720 each hour and were twice as likely to enter ranks 15-24 as ranks 1–14. For class 3, firms entered with probability 16/720 each hour and were twice as likely to enter ranks 15–20 and three times as likely to enter ranks 21–24 as ranks 1–14. These figures were chosen to approximate actual entry rates and locations of firms of different classes.

[15]The mix of firm types varies over the year, of course, so we used a mix based on the fraction of our 47 firms

the counterfactual that all firms are of cluster 1. The third simulation imposed the counterfactual that all firms are of cluster 2. Finally, the fourth simulation imposed the counterfactual that all firms are of cluster 3.

Table 6 contains the results from our simulations.[16] Note first that our simulations maintaining the actual mix produce smaller markups than the actual markups. For all firms, markups averaged 3.55%, but our simulation produced markups below 1%. The ordering of markups by class was maintained, though, with class 1 having the lowest markup and class 3 the highest. The last three columns in the table are the average markups from our counterfactual simulations. It is interesting to note how the average markups change when only one type of firm is present. For cluster 1, the markups edge down slightly, from –0.6% to –1.5%. Strikingly, the cluster 2 markups move down substantially further, going from –0.6% to almost –3% when only firms of that type are present. Finally, the cluster 3 markups actually edge up slightly but stay close to 3%. Recall that we characterized cluster 2 firms as mid-priced but least active, so it is surprising that the counterfactual with all firms of that less-active type would result in substantially lower markups than cluster 2 firms had in the actual-mix simulation. Note, though, that cluster 2 was the smallest cluster, so the counterfactual involving all firms being in that cluster is, in some sense, furthest from the mix we observe. Cluster 3, the moderately active and highest-priced firms have, not surprisingly, the highest average markups in the actual-mix simulation, and are not only able to maintain those in the cluster-3-only simulation, but actually are able to increase them slightly.

We view this set of simulations as only a first attempt at using our methodology to examine how the dynamics of firm interactions can change when various aspects of the setting, such as the mix of firm types, changes.

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that are assigned to each of the three strategic clusters. For 24 firms, that mix turns out to be eleven in cluster 1, three in cluster 2, and 10 in cluster 3.

[16]For each of the four scenarios we explored through simulations, we performed five simulated years. The range in average markups across the five years was quite small in each case, –0.0166 to –0.0131 for the cluster 1 simulations, for instance. We report here the average markups averaged across the five simulated years. Simulating a large number of years in each case would have been impossible given our current computing constraints, but even if it had been possible, we are quite confident that the results would be largely unchanged.

8. Conclusion

The empirical setting and particular data we have gathered lend themselves to the study of repeated-game strategies. The observed patterns in prices, price ranks, and markups have not been well documented to date, and part of our objective is their careful description. In addition to simply documenting these patterns, we develop empirical models of firms' price-changing behavior, and we construct a framework for simulating market outcomes when aspects of the empirical setting are altered. We view this framework as quite flexible, allowing many types of simulations beyond the preliminary ones we present here.

References

Aguirregabiria, Victor and Pedro Mira. (2007) "Sequential Estimation of Dynamic Discrete Games," *Econometrica* 75: 1-53.

Atkinson, Benjamin. (2009) "Retail Gasoline Price Cycles: Evidence from Guelph, Ontario Using Bi-Hourly, Station-Specific Retail Price Data," *Energy Journal* 30: 85–110.

Axelrod, Robert. (1984) *The Evolution of Cooperation*. New York: Basic Books.

Bajari, Patrick, C. Lanier Benkard, and Jonathan Levin. (2007) "Estimating Dynamic Models of Imperfect Competition," *Econometrica* 75: 1331-1370.

Barron, John M., Beck A. Taylor, and John R. Umbeck. (2004) "Number of Sellers, Average Prices, and Price Dispersion," *International Journal of Industrial Organization* 22: 1041–1066.

Baye, Michael R., John Morgan, and Patrick Scholten. (2004) "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site," *Journal of Industrial Economics* 52: 463–496.

Bhaskar, V., S. Machin, and G. Reid. (1991) "Testing a Model of the Kinked Demand Curve," *Journal of Industrial Economics* 39: 241–254.

Bhaskar, V. and Fernando Vega-Redondo. (2002) "Asynchronous Choice and Markov Equilibria," *Journal of Economic Theory* 103: 334–350.

Borenstein, Severin, A. Colin Cameron, and Richard Gilbert. (1997) "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* 112: 305–339.

Cahuc, Pierre and Hubert Kempf. (1999) "Asynchronized Multiperiod Commitments and Cycles," *Journal of Economic Behavior and Organization* 40: 387–407.

Castanias, Rick and Herb Johnson. (1993) "Gas Wars: Retail Gasoline Price Fluctuations," *Review of Economics and Statistics* 75: 171–174.

Chowdhury, Prabal Roy. (2008) "Bertrand-Edgeworth Equilibrium with a Large Number of Firms," *International Journal of Industrial Organization* 26: 746–761.

Davis, Douglas D. and Oleg Korenok. (2009) "Posted Offer Markets in Near-Continuous Time: An Experimental Investigation," *Economic Inquiry* 47: 449–466.

Davis, Michael C. and James D. Hamilton. (2004) "Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices," *Journal of Money, Credit and Banking* 36: 17–37.

Dixit, Avinish. (1991) "Analytical Approximations in Models of Hysteresis," *Review of Economic Studies* 58: 141–151.

Doyle, Joseph, Erich Muehlegger, and Krislert Samphantharak. (2010) "Edgeworth Cycles Revisited," *Energy Economics* 32: 651–660.

Eckert, Andrew. (2003) "Retail Price Cycles and the Presence of Small Firms," *International Journal of Industrial Organization* 21: 151–170.

Eckert, Andrew. (2004) "An Alternating-Move Price-Setting Duopoly Model with Stochastic Costs," *International Journal of Industrial Organization* 22: 997–1015.

Eckert, Andrew and Douglass West. (2004) "Retail Gasoline Price Cycles across Spatially Dispersed Gasoline Stations," *Journal of Law and Economics* 47: 245–271.

Edelman, Benjamin and Michael Ostrovsky. (2010) "Strategic Bidder Bahavior in Sponsored Search Auctions," *Decision Support Systems*, forthcoming.

Edgeworth, Francis. (1925) "The Pure Theory of Monopoly," in *Papers Relating to Political Economy*, vol. 1. London: MacMillan, 111–142.

Ellison, Glenn. (1994) "Theories of Cartel Stability and the Joint Executive Committee," *RAND Journal of Economics* 25: 37–57.

Ellison, Glenn and Sara Fisher Ellison. (2009a) "Search, Obfuscation, and Price Elasticities on the Internet," *Econometrica* 77: 427–452.

Ellison, Glenn and Sara Fisher Ellison. (2009b) "Tax Sensitivity and Home State Preferences in Internet Purchasing," *American Economic Journal: Economic Policy* 1: 53–71.

Fishman, Arthur. (1992) "Search Technology, Staggered Price-Setting, and Price Dispersion," *American Economic Review* 82: 287–298.

Fudenberg, Drew and Eric Maskin. (1986) "The Folk Theorem in Repeated Games with Discounting or with Incomplete Information," *Econometrica* 54: 533–554.

Genesove, David and Wallace P. Mullin. (2001) "Rules, Communication, and Collusion: Narrative Evidence from the Sugar Institute Case," *American Economic Review* 91: 379–398.

Green, Edward J. and Robert H. Porter. (1984) "Noncooperative Collusion under Imperfect Price Information," *Econometrica* 52: 87–100.

Hansen, Per Svejstrup, *et al.* (1996) "Asymmetric Adjustment in Symmetric Duopoly," *Economic Letters* 53: 183–188.

Hosken, Daniel S., Robert S. McMillan, and Christopher T. Taylor. (2008) "Retail Gasoline Pricing: What Do We Know?" *International Journal of Industrial Organization* 26: 1425–1436.

Klenow, Peter J. and Benjamin A. Malin. (forthcoming) "Microeconomic Evidence on Price-Setting," in Benjamin Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, vol. 3. Amsterdam: North-Holland.

Lach, Saul. (2002) "Existence and Persistence of Price Dispersion: An Empirical Analysis," *Review of Economics and Statistics* 84: 433–444.

Lal, Rajiv and Carmen Matutes. (1989) "Price Competition in Multimarket Duopolies," *Rand Journal of Economics* 20: 516–537.

Lau, Sau-Him Paul. (2001) "Aggregate Pattern of Time-dependent Adjustment Rules, II: Strategic Complementarity and Endogenous Nonsynchronization," *Journal of Economic Theory* 98: 199–231.

Leufkens, Kasper and Ronald Peeters. (2008) "Intertemporal Price Competition with Exogenous Demand Shocks," *Economic Letters* 99: 301–303.

Leufkens, Kasper and Ronald Peeters. (forthcoming) "Price Dynamics and Collusion under Short-Run Price Commitments," *International Journal of Industrial Organization*.

Lewis, Matthew. (2008) "Price Dispersion and Competition with Differentiated Sellers," *Journal of Industrial Economics* 56: 654–678.

Lewis, Matthew. (2009) "Temporary Wholesale Gasoline Price Spikes Have Long-Lasting Retail Effects: The Aftermath of Hurricane Rita," *Journal of Law and Economics* 52: 581–605.

Maskin, Eric and Jean Tirole. (1988) "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles," *Econometrica* 56: 571–599.

Millner, Edward L., Michael D. Pratt, and Robert J. Reilly. (1990) "Contestability in Real-Time Experimental Flow Markets," *Rand Journal of Economics* 21: 584–599.

Noel, Michael. (2007a) "Edgeworth Price Cycles, Cost-Based Pricing, and Sticky Pricing in Retail Gasoline Markets," *Review of Economics and Statistics* 89: 324–334.

Noel, Michael. (2007b) "Edgeworth Price Cycles: Evidence from the Toronto Retail Gasoline Market," *Journal of Industrial Economics* 55: 69–92.

Noel, Michael. (2008) "Edgeworth Price Cycles and Focal Prices: Computational Dynamic Markov Equilibria," *Journal of Economics and Management Strategy* 17: 345–377.

Porter, Robert. (1983) "A Study of Cartel Stability: The Joint Executive Committee, 1880-1886," *Bell Journal of Economics* 15: 301–314.

Romesburg, H. Charles. (2004) *Cluster Analysis for Researchers*. North Carolina: Lulu Press.

Rotemberg, Julio J. and Garth Saloner. (1986) "A Supergame-Theoretic Model of Price Wars During Booms," *American Economic Review* 76: 390–407.

Scott Morton, Fiona. (1997) "Entry and Predation: British Shipping Cartels 1879–1929," *Journal of Economics and Management Strategy* 6: 679–724.

Tirole, Jean. (1988) *The Theory of Industrial Organization*. Cambridge, Massachusettes: MIT Press.

Wallner, Klaus. (1999) "Sequential Moves and Tacit Collusion: Reaction-Function Cycles in a Finite Pricing Duopoly," *Journal of Economic Theory* 84: 251–267.

Wang, Zhongmin. (2009) "(Mixed) Strategy in Oligopoly Pricing: Evidence from Gasoline Price Cycles Before and Under a Timing Regulation," *Journal of Political Economy* 117: 987–1030.

Zhang, Xiaoquan. (2010) "Finding Edgeworth Cycles in Online Advertising Auctions," Sloan School of Management working paper.

Table 1: Definition of Variables

Variable	Indexes Varies Over	Definition
Price	i, t	Current listed price in dollars
Markup	i, t	Proportional markup of price over wholesale cost, $\frac{(P-C)}{P}$
SinceChange	i, t	Hours since firm last changed its price
SinceBump	i, t	Hours since firm involuntarily bumped in rank
Rank	i, t	Rank of listing in price-sorted order
NumBumps	i, t	Net number of ranks bumped since last price change
Placement	i, t	Placement between adjacent firms in price space
Density	i, t	Measure of density in price space of firms with nearby ranks
LowPrice	t	Lowest of currently posted prices
AvgPrice	t	Average across currently posted prices
HighPrice	t	Highest of currently posted prices
AvgMargin	t	Average across firms' price margins in levels
NewFirms	t	Number of new firms in current list
CostTrend	t	Wholesale cost trend over previous two weeks
CostVol	t	Wholesale cost volatility over previous two weeks

Notes: i indexes firms and t indexes hours.

Table 2: Descriptive Statistics

Variable	Mean	Std. dev.	Min.	Max.	Obs.
Price	68.80	34.73	21	131	171,888
Markup	0.04	0.10	−0.35	0.38	171,888
SinceChange	115.56	140.87	1	1113	171,888
SinceBump	23.01	25.56	0	256	171,888
Rank	11.81	6.74	1	24	171,888
NumBumps	1.36	3.74	−23	21	171,888
Placement	0.60	0.42	0	1	171,888
Density	0.56	0.39	0	3	171,888
LowPrice	62.63	32.90	21	122	8,218
AvgPrice	69.38	34.25	25.13	126.67	8,218
HighPrice	75.24	35.10	30	131	8,218
AvgMargin	1.73	3.84	−11.71	12	8,218
NewFirms	2.67	2.28	0	10	8,218
CostTrend	−0.18	0.70	−2.06	1.53	8,185
CostVol	1.62	1.06	0.00	4.36	8,185

Table 3: Selected Descriptive Statistics by Strategic Cluster

	Cluster 1 (22 firms)		Cluster 2 (6 firms)		Cluster 3 (19 firms)	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Markup	0.00	0.01	0.06	0.01	0.09	0.01
SinceChange	90.90	9.70	202.41	38.57	147.45	33.52
SinceBump	16.02	0.67	27.57	6.02	17.16	1.53
Rank	8.67	0.65	14.91	1.25	17.13	0.46
NumBumps	0.77	0.23	4.32	1.05	1.10	0.48

Table 4: Probit Model of Timing of Price Change

Variables	Firms Combined		Cluster 1		Cluster 2		Cluster 3	
Markup	−0.012***	−0.032***	−0.013***	−0.035***	−0.006*	−0.023***	−0.003	−0.025**
	(0.002)	(0.005)	(0.003)	(0.006)	(0.003)	(0.008)	(0.009)	(0.010)
Markup^2	0.037***	0.033***	0.047**	0.033**	0.006	0.025	0.000	0.051
	(0.012)	(0.012)	(0.018)	(0.015)	(0.029)	(0.025)	(0.041)	(0.028)
SinceChange	−0.014***	−0.011***	−0.017***	−0.013***	0.001	−0.001	−0.008*	−0.004
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)
SinceBump	−0.101***	−0.088***	−0.133***	−0.120***	0.022**	0.020*	−0.062**	−0.052*
	(0.014)	(0.015)	(0.016)	(0.018)	(0.008)	(0.012)	(0.033)	(0.031)
Rank	−0.193**	−0.042	−0.129	0.072	−0.062	0.164	0.172*	0.256*
	(0.082)	(0.088)	(0.123)	(0.131)	(0.122)	(0.107)	(0.103)	(0.157)
NumBumps		0.107		0.054		0.093		−0.082
		(0.111)		(0.192)		(0.060)		(0.142)
Placement		−0.112		−0.118		−1.894*		0.741
		(0.732)		(0.875)		(0.913)		(1.287)
Density		1.890***		2.823***		0.988		−0.447
		(0.740)		(0.951)		(0.769)		(1.595)
LowPrice		−0.539***		−0.520**		0.048		−0.557***
		(0.162)		(0.246)		(0.162)		(0.230)
AvgPrice		0.396		0.390		−0.015		0.134
		(0.299)		(0.475)		(0.331)		(0.314)
HighPrice		0.106		0.079		−0.049		0.395**
		(0.184)		(0.299)		(0.242)		(0.140)
AvgMargin		0.716***		0.812***		0.176		0.415**
		(0.132)		(0.175)		(0.191)		(0.208)
NewFirms		0.695***		0.670***		−0.184		0.584***
		(0.088)		(0.121)		(0.270)		(0.135)
CostTrend		1.628***		2.494***		−0.538		−0.051
		(0.532)		(0.639)		(0.835)		(0.917)
CostVol		0.150		0.028		−0.053		0.339
		(0.193)		(0.274)		(0.333)		(0.284)
Pseudo R^2	0.016	0.022	0.015	0.021	0.024	0.068	0.006	0.020
Observations	171,263	171,263	106,306	105,879	9,782	9,782	55,800	55,602

Notes: Dependent variable is a 0–1 indicator for price change by firm i at time t. Marginal effects reported. Heteroskedasticity-robust standard errors accounting for non-independence across observations for same firm reported in parentheses. Results for all but the first two variables (*Markup* and *Markup*^{2}) scaled up by 10^3 for display purposes. Statistically significant in a two-tailed test at the *10% level, **5% level, ***1% level.

Table 5: Ordinary Least Squares Model of Size of Price Change

Variables	Firms Combined		Cluster 1		Cluster 2	Cluster 3	
Constant	-0.033	-0.015^{**}	-0.000	-0.017^{**}	-0.028	0.048^{***}	0.044^{***}
	(0.005)	(0.007)	(0.006)	(0.007)	(0.021)	(0.013)	(0.014)
Markup	-0.211^{***}	-0.197^{***}	-0.203^{***}	-0.227^{***}	-0.374^{**}	-0.254^{***}	-0.215^{*}
	(0.029)	(0.045)	(0.034)	(0.060)	(0.105)	(0.045)	(0.083)
SinceChange	-0.005^{**}	0.000	-0.006^{**}	-0.001	-0.023^{*}	-0.000	0.005^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.003)	(0.002)
SinceBump	-0.001	-0.001	0.004	0.006	0.012	-0.025^{**}	-0.030^{***}
	(0.004)	(0.005)	(0.004)	(0.005)	(0.022)	(0.009)	(0.009)
Rank	-0.035	-0.009	-0.128^{**}	-0.062	0.019	-0.206^{***}	-0.123
	(0.036)	(0.041)	(0.050)	(0.055)	(0.382)	(0.072)	(0.074)
NumBumps		-0.512^{***}		-0.487^{***}			-0.430^{***}
		(0.064)		(0.085)			(0.103)
Placement		0.560		0.793^{*}			-0.080
		(0.359)		(0.443)			(0.541)
Density		0.147		0.133			0.253
		(0.412)		(0.480)			(0.794)
LowPrice		0.090		0.070			0.140
		(0.077)		(0.103)			(0.138)
AvgPrice		-0.052		0.035			-0.073
		(0.151)		(0.193)			(0.246)
HighPrice		-0.037		-0.098			-0.077
		(0.093)		(0.113)			(0.198)
AvgMargin		0.140^{*}		0.222^{*}			0.033
		(0.083)		(0.111)			(0.145)
NewFirms		0.153^{**}		0.123			0.109
		(0.060)		(0.074)			(0.088)
CostTrend		0.246		0.416			0.179
		(0.279)		(0.323)			(0.680)
CostVol		0.366^{***}		0.294^{*}			0.255
		(0.131)		(0.146)			(0.274)
R^2	0.186	0.308	0.204	0.313	0.656	0.306	0.406
Observations	1,605	1,599	1,210	1,204	19	376	376

Notes: Dependent variable is $\ln(Price_{it}) - \ln(Price_{it-1})$ for only those observations it with a non-zero price change between $t-1$ and t. Heteroskedasticity-robust standard errors accounting for non-independence across observations for same firm reported in parentheses. Results for all but the first two variables (constant and *Markup*) scaled up by 10^2 for display purposes. Full regression for cluster-2 firms not reported because of lack of degrees of freedom. Statistically significant in a two-tailed test at the *10% level, **5% level, ***1% level.

Table 6: Actual Versus Simulated Values of Average Markups

Subgroup of firms	Actual markups	Simulated markups in listed scenario: Maintaining actual mix	Assuming all firms in cluster 1	Assuming all firms in cluster 2	Assuming all firms in cluster 3
All firms	0.0355	0.0076			
Cluster 1 firms	0.0050	−0.0060	−0.0150		
Cluster 2 firms	0.0633	−0.0056		−0.0292	
Cluster 3 firms	0.0886	0.0289			0.0313

Figure 1: Example of a Pricewatch webpage

PRICE WATCH® Query = System Memory PC100 128MB

Back To - New Components Home

Back To - "Not Exactly New" Home

BRAND	PRODUCT	DESCRIPTION	PRICE	SHIP	DATE/HR	DEALER/PHONE	ST	PART#
Generic	PRICE FOR ONLINE ORDERS ONLY - 128MB PC100 SDRAM DIMM - 8ns Gold leads	.- * LIMIT ONE - Easy installation - in stock	$ 68	9.69 INSURED	10/12/00 12:40:05 AM CST	Computer Craft Inc. 800-487-4910 727-327-7559 Online Ordering	FL	MEM-128-100PCT
Generic	ONLINE ORDERS ONLY - 128MB SDRAM PC100 16x64 168pin	- * LIMIT ONE	$ 69	INSURED$9.95	10/11/00 10:59:56 PM CST	Connect Computers 888-277-6287 949-367-0703 Online Ordering	CA	-
Generic	PRICE FOR ONLINE ORDER - 128MB PC100 SDRAM DIMM	- * LIMIT ONE - - InStock, 16x64-Gold Leads	$ 70	10.75	10/11/00 2:11:00 PM CST	1st Choice Memory 949-888-3810 -- P.O.'s accepted Online Ordering	CA	-
Generic	PRICE FOR ONLINE ORDER - 128mb True PC100 SDRAM EEPROM DIMM16x64 168pin 6ns/7ns/8ns Gold Leads	- * LIMIT ONE - in stock - with Lifetime Warranty	$ 72	9.85	10/10/00 11:30:39 AM CST	pcboost.com 800-382-6678 -- P.O.'s accepted Online Ordering	CA	-
Generic	IN STOCK, 128MB PC100 3.3volt unbuffered SDRAM Gold Lead 168 Pin, 7/8ns - with Lifetime warranty	- * LIMIT ONE Not compatible with E Machine	$ 74	10.95- UPS INSURED	10/11/00 12:44:00 PM CST	Memplus.com 877-918-6767 626-918-6767	CA	- 880060
Generic	PRICE FOR ONLINE ORDERS ONLY - 128MB True PC100 SDRAM DIMM - 8ns Gold - warranty	- * LIMIT ONE	$ 74	10.25	10/9/00 6:53:25 PM CST	Portatech 800-487-1327 .	CA	-
House Brand	128MB PC100 3.3volt SDRAM 168 Pin, 7/8ns - with LIFITIME WARRANTY	- * LIMIT ONE	$ 74	10.50 FedEx	10/11/00 10:20:23 AM CST	1st Compu Choice 800-345-8880 800-345-8880	OH	-
Generic	128MB 168Pin TRUE PC100 SDRAM - OEM 16X64	DIMM16x64 168pin 6ns/7ns/8ns Gold Leads	$ 75	$10	10/11/00 2:37:00 PM CST	Sunset Marketing, Inc. 800-397-5050 410-626-0211 -- P.O.'s accepted	MD	-
Generic	128MB 16x64 PC100 8ns SDRAM.	- * LIMIT ONE	$ 77	10.90	10/12/00 9:37:45 AM CST	PC COST 800-877-9442 847-690-0103 Online Ordering	IL	-
Generic	IN STOCK, PC100, 128MB, 168pins DIMM NonECC, - with Lifetime warranty	- * LIMIT 5	$ 77	$10.95 & UP For UPS Ground	10/9/00 5:11:10 PM CST	Augustus Technology, Inc 877-468-5181 909-468-1883 Online Ordering	CA	-
Generic	128MB PC100 8NS 16x64 SDRAM - one year warranty	- * LIMIT ONE	$ 78	Ups Ground $10.62	10/11/00 5:16:36 PM CST	Computer Super Sale 800-305-4930 847-640-9710 Online Ordering	IL	-
Generic	PRICE FOR ONLINE ORDERS ONLY - PC100 128MB NonBuffered, NonECC 16x64 SDRAM DIMM 3.3V 8ns mem module	- * LIMIT ONE - with lifetime warranty	$ 78	10.95	10/5/00 6:29:59 PM CST	Jazz Technology USA, LLC 888-485-8872 909-869-8859	CA	ME-GBP100128

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1 5 10 15 20 25 30 Next

Figure 2: Price series (rank and level) for representative month and representative firm from each strategic cluster

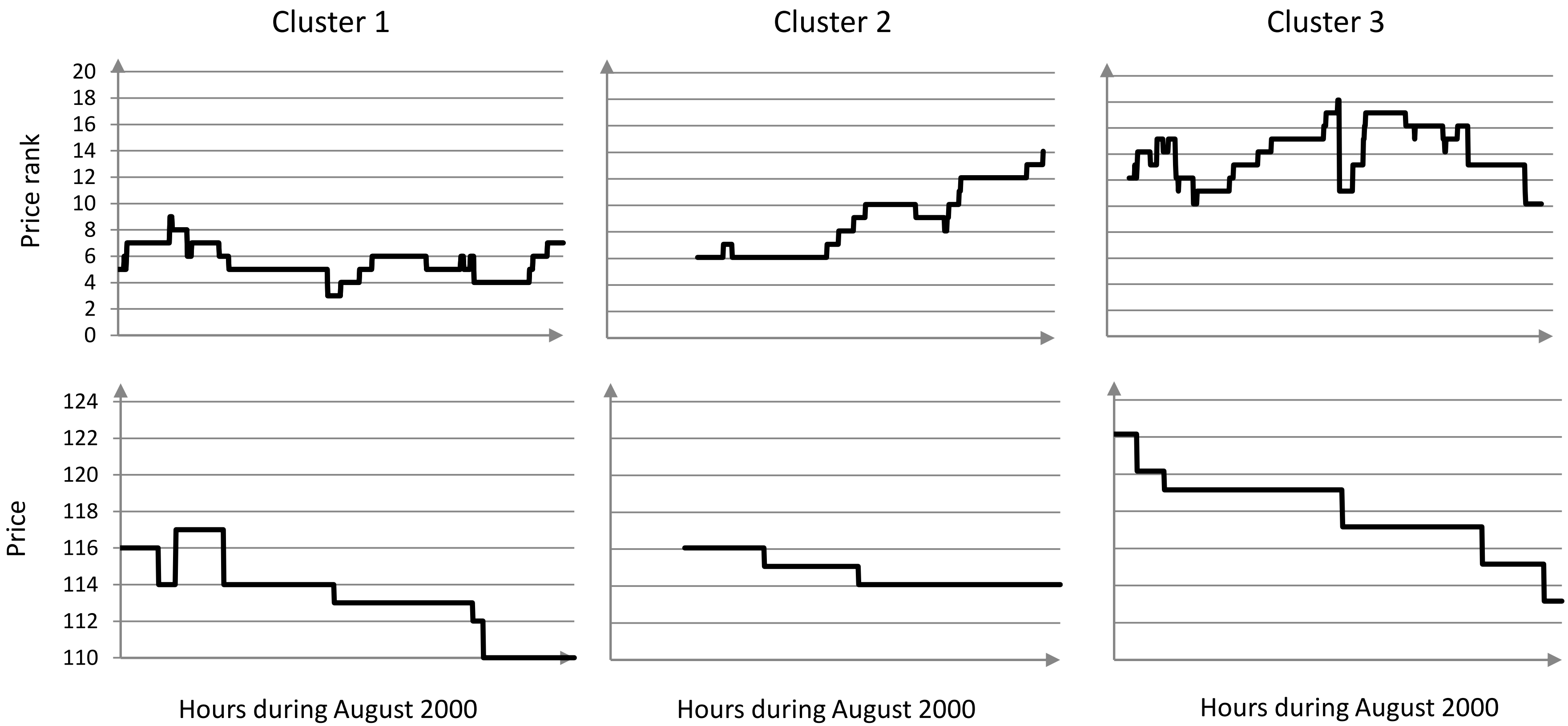
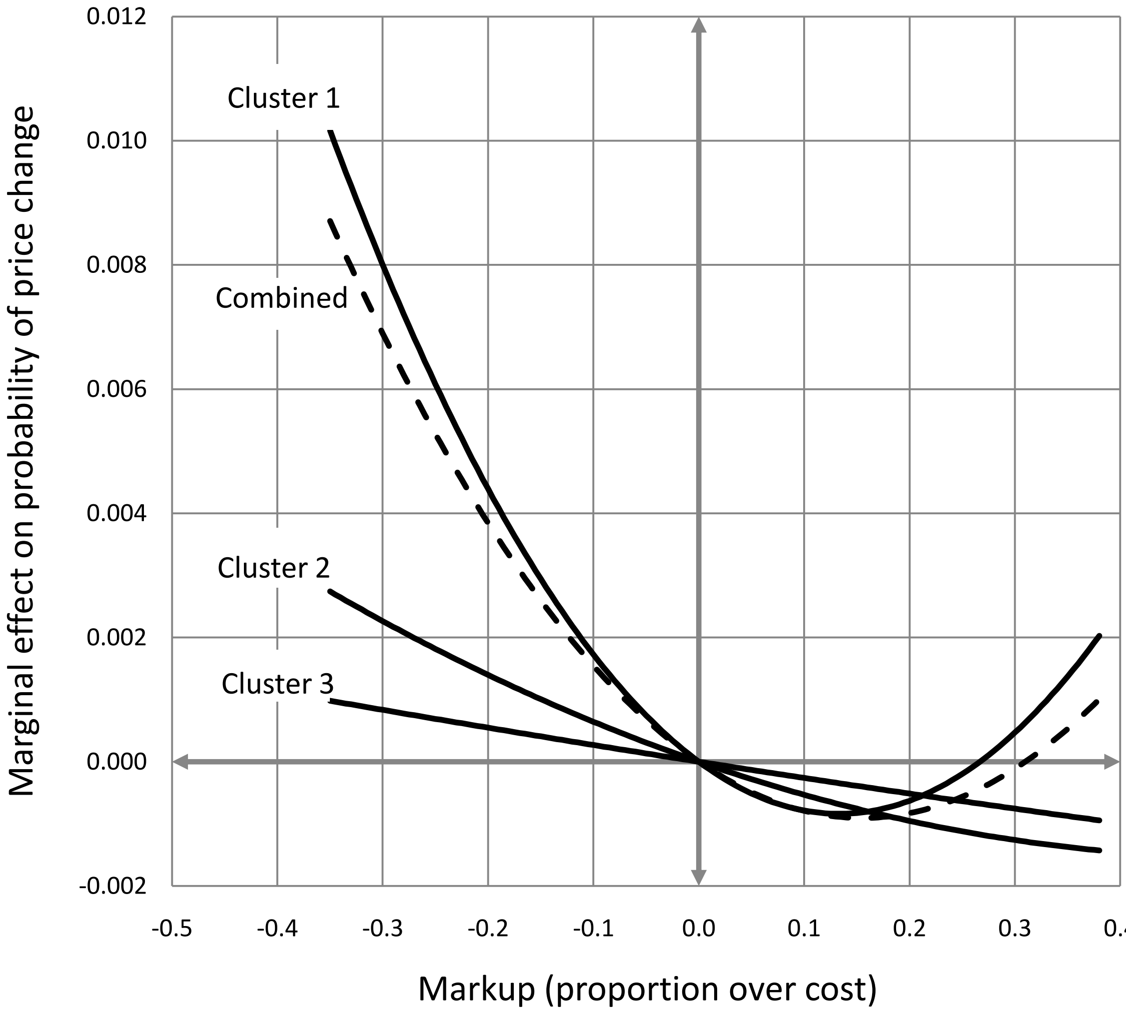


Figure 3: Quadratic marginal effect of markup on probability of price change



Note: Based on linear and squared markup coefficients from parsimonious models in Table 4 probits.