ANALYZING COMPETITIVE AND TACITLY COLLUSIVE STRATEGIES IN ELECTRONIC MARKETPLACES

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ABSTRACT

Electronic commerce researchers are divided between those who show how e-commerce can cause intense competition and those who show an absence of this competition. This research takes a more central stance to show when intense competition occurs and when tacit collusion occurs in e-commerce. We present a multi-industry investigation of competition and tacit collusion related to firm pricing behavior with data collected via a customized data-collecting Internet agent. We apply economic theory to show how Internet technology increases the ability of firms to tacitly collude to keep prices higher than expected, even amid intense competition. We then develop a multinomial logit (MNL) regression model to test the predictions of our theory. The results show that Internet technology enhances both intense competition and tacit collusion, and that e-commerce vendors tend to choose one or the other based on industry and firm attributes. Our results indicate that market power, ability to respond quickly, and previous interactions with competitors all affect whether a firm will attempt to beat competitor prices in a competitive move or match competitor prices in a tacitly collusive move.

KEYWORDS: Econometric analysis, economic theory, electronic commerce, empirical research, information asymmetry, market power, multinomial logit, pricing, tacit collusion.

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1. INTRODUCTION

Some researchers have predicted intense competition among Internet-based sellers (e.g., Bakos 1997). Others argue that Internet technology will lead to a non-competitive environment, where prices are sustained above marginal costs (e.g., Harrington, 2001). In certain industries, like the airline parts industry (Choudhury, Hartzel and Konsynski, 1998), intense competition seems to be occurring. Yet in other contexts, like the book industry, intense competition appears to be less common (Dillard, 1999; Varian, 2000). Thus, it has become important that competitive reactions and pricing strategies in e-markets be more thoroughly examined.

Until now, the many research and trade journals have pointed out how the Internet can increase competition. But there are anecdotes that something different may be occurring, instead of the intense competition that low friction search might predict (e.g., Varian, 2000; Dillard, 1999). We will examine some new dimensions of price competition on the Internet that involve organizational strategies not previously considered. Carvajal (1999), for instance, reports that when Amazon.com has reduced its prices, other top booksellers have exactly matched those reductions. Bailey (1998), Dillard (1999), Kauffman and Wood (2000), and Varian (2000) all show evidence of how booksellers and music CD vendors tacitly collude and exactly match each other in both price increases and decreases. We define **collusion** as a formal agreement whereby competitors agree to match each other prices at a point above marginal costs. We define **tacit collusion** as matching prices at a point above marginal costs in the absence of formal agreement.

When purchasing goods that are highly substitutable (e.g., commodity products, information goods, items with low complexity specifications, etc.), sellers are often interested in matching rather than beating competitor prices. Varian (2000) comments on how e-commerce vendors can use shopbots to tacitly collude with each other as easily as customers use shopbots to compare
prices. Thus, Internet technology can promote a *decrease in information asymmetry with respect to price among sellers*, allowing sellers to match prices (either by raising or lowering them) almost instantaneously. This allows pricing strategies that are not feasible in traditional markets.

It is imperative that we understand how Internet technology impacts pricing strategy, since it is among the foundational elements of how IT can be used in the pursuit of winning corporate strategy. Evidence gathered in the e-commerce environment can help to shed light on the choice that Internet sellers make between tacit collusion and intense competition. When enough market friction exists, e-commerce consumers still must rely on reputation and brand awareness, even when choosing between firms selling identical products. This market friction forces consumers to rely on trust and vendor reputation, and may give rise to different seller pricing strategies.

In this research, we address the following research questions:

- Can we empirically evaluate competition or tacit collusion in e-commerce marketplaces?
- How does reduced information asymmetry drive Internet sellers pricing strategies?
- What factors lead to tacit collusion or intense competition in the marketplace?

A variety of things determine firm pricing strategy, including industry, product, and firm-specific factors. We explore the economic, marketing and IS perspectives on pricing, tacit collusion, and competitive approaches that reflect the factors that influence strategy-making. We use these perspectives to create a case for why Internet technology enhances the feasibility of tacit collusion. We collect pricing data for best-selling items in multiple industries sold by multiple vendors. We extract price changes, and develop and test a limited-dependent variable econometric model that describes the motivation for the price changes. We are able to empirically demonstrate that pricing strategy depends on the relative market power between a firm and its competitor, and the previous actions of that competitor.
We show that Internet sellers respond either competitively or in a manner that is suggestive of tacit collusion, based on a strategy that mirrors the established strategy of competitors with more market power. We also show that a single market leader that refuses to tacitly collude will create intense industry-wide competition. But if the leaders tacitly collude, the industry will follow their lead and tacitly collude too. Finally, we show how technologies within a firm that support discovery of competitors’ prices allow for quick responses to competitive actions and why they can cause competitors to reduce the intensity of price competition with that firm.

2. LITERATURE REVIEW

Marketing research tells us that firms compete asymmetrically where firms with greater market power, such as e-commerce firms Amazon.com, Barnes and Noble (hereafter referred to as BN.com), and CDNow are not affected by promotions from smaller firms, such as Books-a-Million or Rock.com (e.g., Carpenter et al., 1989; Blattberg and Wisniewski, 1989). Asymmetric competition suggests that firms with a large market share and significant brand recognition compete differently than smaller firms. By contrast, IS research has concentrated on how the Internet increases the tendency toward intense Bertrand competition (e.g., Bakos 1997; Choudhury, et al., 1998; Bailey, 1998). Bertrand competition occurs when two or more firms sell identical products (e.g., books or music CDs), and compete so fiercely that price is driven down to marginal costs. We seek to integrate these two research streams by drawing upon the discussion of tacit collusion in the economics literature (e.g., Chamberlin, 1929). This will enable us to more fully understand the role of pricing in the IT-intensive e-commerce environment. Tirole (1988) describes how tacit collusion is difficult to implement in non-technological selling settings. This is because “cheating” can occur, where one party secretly lowers its price, stealing market share from the other firms. We will show how Internet
technology decreases the likelihood of cheating by decreasing the information asymmetry with respect to price among Internet sellers, and thus makes tacit collusion a more viable strategy.

2.1. Why Might Product Pricing on the Internet Be Different?

Bakos (1997) associates Bertrand competition with the sale of products in e-markets. He predicted that Internet technology would decrease customer search costs and, therefore, would allow customers to easily compare prices, leading to a reduction of switching costs between vendors. The result will be intense Bertrand price competition between identical products. Choudhury, et al. (1998) show this to be at least partially true in the online airline parts industry. Alba et al. (1997) describe how vendors avoided embracing the Web because of fears of intense Bertrand competition. Reluctance to transact through the Internet allowed entry of new players (e.g., Amazon.com in bookselling and e*Trade in brokerage). In addition, Lynch and Ariely (2000) have shown how consumers are more price-sensitive when they purchase wine online.

However, there have been numerous observations of pricing behavior that argue otherwise. Harrington (2001) challenges Bakos’ (1997) findings and argues that prices in e-markets will be above marginal costs. Bertrand competition theory argues that prices will converge to a single price, where demand intersects marginal costs (Tirole, 1988), resulting in what economists term Bertrand’s one-price rule. IS research has shown how the one-price rule does not seem to apply on the Internet. For example, Bakos et al. (1999), in an innovative experimental study, suggest that the one price rule does not apply to online stockbrokers. Clemons, Hann, and Hitt (2002) describe how online travel agents charge different prices when given the same customer request. Brynjolfsson and Smith (2000) review customer actions when using a shopbot and demonstrate how friction still exists in online markets, and why consumers do not always purchase the cheapest item, but gravitate toward brand name retailers. Lal and Sarvary (1999) also cite vendor
preferences on the Web, especially if the product has digital attributes. We attribute this to an increase in information asymmetry (with respect to products and sellers) between e-commerce sellers and buyers. Buyers can search for the lowest costs, but they do not actually know if or when they will get a product, and whether the vendor is reputable. Exacerbating this problem, e-commerce sellers can remain anonymous and may resist detection and punishment of opportunistic behavior. This increase in information asymmetry with respect to sellers and products can reverse the effects of the decrease in information asymmetry with respect to price brought about by reduced search costs, and actually add to switching costs when an e-commerce buyer switches from a known and trusted seller to an unknown seller.

Economists call Bertrand’s one price rule the Bertrand Paradox because vendors of identical products often still manage to sell their commodities at a higher price (Tirole, 1988). Bertrand’s intense competition works well in a single-period game where every player is trying to clear all inventory. However, in a multi-period game, sellers know that they may be hurting long-run profit by making drastic price cuts. So, they choose to avoid this intense Bertrand competition, and concentrate on reputation and service, not prices, to gain market share.

2.2. How Does Asymmetric Competition Develop?

Carpenter et al. (1989) show how market leaders compete asymmetrically. Price promotions of the market leaders can steal customers from market followers, but smaller firms’ price promotions have little effect on the leaders. Blattberg and Wisniewski (1989) show how industries form price tiers: leaders compete with each other at a higher price level, and market followers compete with each other at a lower level. Information asymmetries for products and sellers appear to be at the heart of asymmetric competition. A consumer may prefer one Internet
seller over another for an identical product because of information asymmetries such as reliability to ship the product in a timely fashion or confidentiality with personal information.

Such information asymmetry for sellers encourages a consumer to include trust in addition to price when considering a vendor. An empirical study of pricing on the Internet should consider the effects of asymmetric competition among firms. Bigger firms may tend to ignore the actions of smaller firms. This may be explained by comparing their relative market power. They may be more willing to collude. Smaller firms, however, may be more willing to compete. They may be ignored by the larger firms, yet still want to capture some of the larger firms’ market share. Thus, we see the possibility of a competitive asymmetry effect being relevant in e-commerce.

2.3. The Role of Tacit Collusion in Price Competition

Chamberlin (1929) introduced tacit collusion and showed how competitors will tacitly cooperate with each other to avoid intense competition. Rather than the marginal cost-driven prices of Bertrand competition, tacit collusion brings the market price closer to the monopoly price. One limitation of tacit collusion is that colluding players will cheat, and charge a little less to capture a larger market share and profit (Tirole, 1988). Varian (2000) and Dillard (1999) provide evidence by tracking a single book price and show how collusion appears to be occurring in bookselling. Campbell, et al. (2001) develop a model that shows that the fast response times allowed by the Internet can cause price increases by facilitating tacit collusion.

Tacit collusion can result from a commitment to raise prices. Many researchers discuss how firms that promise to match the prices of their competitors result in higher customer prices. Dixit and Nalebuff (1991) discuss an example of stereo price wars in New York. Crazy Eddie and Newmark & Lewis had price guarantees on consumer electronics products that guaranteed the lowest price, and refunded the difference of the prices plus a percentage. The result: any price
promotion from one vendor would actually make customers buy from the other! Thus, by guaranteeing the lowest prices, vendors were tacitly colluding by punishing the price promotions of their competitors. Internet technology appears to allow the same dynamics. Researchers have documented how Internet technology allows firms to monitor and commit to matching competitor prices, thus allowing firms to minimize any competitor benefit from a price promotion. For example, Smith, Bailey, and Brynjolfsson (2000) describe how Buy.com has a basement full of computers used to monitor and match the lowest competitor price. Gately (1999) reports that when Amazon.com reduced its standard discount for books on the New York Times best-seller list from 40% to 50%, BN.com and Borders.com responded within hours to offer the same price to their customers. It follows from these observations that competitors will not be able to increase market share by price promotions and may be forced into tacit collusion, and that Internet technology will allow a commitment to tacit collusion by punishing any price promotion in the form of reduced competitor revenues and limited benefits.

3. PROPOSITIONS AND THEORETICAL MODEL

We next present several propositions drawn from the theory we have discussed.

3.1. Propositions About Why Collusion Might Be Observed

Tacit collusion theory indicates that any form of collusion is unlikely without some cooperation from every market leader in an industry. Without this collusion, as search costs decrease, e-commerce firms are forced to compete at an extreme level, resulting in few, if any profits, as prices dive toward marginal costs (Bakos, 1997). The first two propositions deal with the extent to collusive pricing behavior in Internet-based selling might be observed. The Reaction Proposition (P1a) argues that tacit collusion occurs only in the presence of cooperating competitors. "Tit-for-tat" refers to the act of mirroring your competitor's actions. Thus, if a
competitor shows a strong will to compete with you, you will respond with strong competition yourself. Dixit and Nalebuff (1991) describe a modified tit-for-tat strategy that involves reviewing the past recent actions of a competitor in aggregate, and responding with a similar strategy. For example, if a competitor of a firm acts competitively on one product, but colludes with all others, the firm will also be, for the most part, collusive toward that competitor. On the other hand, if a competitor has shown a reluctance to collude overall in past periods, there is no reason to believe that competitor will collude in current periods.

PROPOSITION 1A (THE REACTION PROPOSITION). Internet-based sellers will tend to react collusively if the competitors that they are responding to tend to act collusively. Conversely, Internet-based sellers will tend to act competitively (i.e., non-collusively) if competing Internet-based sellers that they are responding to refuse to tacitly collude.

PROPOSITION 1B (THE INDUSTRY EFFECTS PROPOSITION): Levels of collusion and competition will vary among different industries for which Internet-based selling is observed.

PROPOSITION 2 (THE TACITLY COLLUDING MARKET LEADERS PROPOSITION): The more market power an Internet-based seller has in relation to a competitor, the more likely the firm will tacitly collude with that competitor.

PROPOSITION 3A (THE COMPETITOR RESPONSE TIME PROPOSITION): The less time, on average, that a firm takes to respond to its competitors, the more likely its competitors will tend to act collusively toward that firm. Conversely, the more time, on average, that a competitor takes to respond to its competitors, the more likely its competitors will tend to act competitively (i.e., non-collusively) toward that firm.

PROPOSITION 3B (THE FIRM RESPONSE TIME PROPOSITION): The more quickly a firm responds to its competitors, the more likely that firm will tend to act competitively (i.e., non-collusively).

Since collusion requires cooperation, if a firm responds competitively to a price offered by a competitor, then that action is likely to cause the competitor to respond competitively. This is particularly true of market leaders. Asymmetric competition theory suggests that all competitors watch the market leaders, but that the market leaders often ignore smaller competitors (Carpenter et al., 1989). If a market leader firm refuses to cooperate and does not collude, the entire industry
will be forced into intense competition—at least with that market leader, and at worst with every competitor. Why? With an intensely competitive market leader, there is no benefit in colluding with other competitors at a higher price. The market leader will command a larger market share not only because of price but also because of brand recognition. Since market leaders differ across industries, companies will compete differently. The *Industry Effects Proposition* (\(P_{1b}\)) proposes how competitive and collusive decisions are likely to vary between different firms in each industry, and therefore affect competition at the industry level.

Market leaders have the greatest impact on smaller firms because price promotions of market leaders can affect smaller firms’ profits, while price promotions of smaller firms tend to not affect the market leaders’ profits (Carpenter, et. al., 1989). Brynjolfsson and Smith (2000) document how smaller firms need to price themselves lower than the market leaders because the brand recognition of the market leaders allows them to charge more than the smaller firms. Amazon, BN.com, and Borders.com can charge around 8% higher prices than other firms because of their reputations. The *Tacitly Colluding Market Leaders Proposition* (\(P_{2}\)) describes how market leaders may ignore smaller firms. Smaller firms will try to capture larger market shares through competitive actions directed at the larger firms, while larger firms will tend to collude to use their market dominance to command higher marginal profits.

Our final two propositions deal with response times and the extent to which they predict competitive or collusive pricing behavior. The *Competitor Response Time Proposition* (\(P_{3A}\)) describes how firms will find no profit in competing with a competitor that will respond immediately to a price promotion. If a competitor responds immediately to a price promotion, then the firm that makes the price promotion will not benefit from any increased market share. Conversely, a firm may be more likely to respond competitively if its actions typically do not
result in an immediate response, allowing the firm's competitive behavior to be rewarded by market demand at the lower price. The Firm Response Time Proposition (P3b) describes how competitive behavior is more likely to be observed for a firm with immediate response time. This competitor will be more likely to exhibit competitive behavior to take advantage of its quick response capabilities by reducing prices just below those of the competition increase share.

3.2. Theoretical Model

Our propositions can be used to develop a theoretical model that can then be operationalized and tested. Equation 1 and Table 1 show the form of the theoretical model that we have developed from our propositions:

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Tacitly Collusive Behavior = f (Competitor Propensity for Collusion, Competitor Relative Market Power, Competitor Response Time, Firm Response Time, Industry Effects)
\] (1)

Table 1. Variables in the Proposed Theoretical Model

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tacitly Collusive Behavior</td>
<td>Indicates whether the firm price changes match a competitor price above marginal costs. The opposite would be competitive behavior, where firm would beat each competitor prices until that price reached marginal cost.</td>
</tr>
<tr>
<td>Competitor Propensity for Collusion</td>
<td>Indicates whether typical competitor price changes are matching responses or are beating responses.</td>
</tr>
<tr>
<td>Competitor Relative Market Power</td>
<td>The market power for the firm relative to its competitors.</td>
</tr>
<tr>
<td>Competitor Response Time</td>
<td>The length of time, on average, it takes for a competitor to respond to other competitor price changes.</td>
</tr>
<tr>
<td>Firm Response Time</td>
<td>The length of time, on average, it takes for a firm to respond to a specific price change of a competitor.</td>
</tr>
<tr>
<td>Industry Effects</td>
<td>Controls for industry-specific aspects of price competition in Internet selling (e.g., for the music CD and bookselling industries).</td>
</tr>
</tbody>
</table>
4. PRELIMINARY MODELING ISSUES AND ANALYSIS

We next discuss the data, empirical model and some empirical regularities that we obtained, to show why price matching suggests tacit collusion and price beating suggests competition.

4.1. Data Collection

We collected Internet data from the bookselling and music CD industries with the assistance of a data collection software agent. We retrieved vendor-neutral lists of the top-selling items from the *USA Today* Web site for books and the *Billboard Magazine* site for the top-selling CDs. The agent ran at 4:00 a.m. every day from February 21 to March 29, 2000. The resulting dataset contains 70,552 daily prices, including 1,793 price changes from 169 products and 53 firms. The time frame is indicative of a vibrant e-marketplace, immediately before the DotCom bubble burst in mid-to-late 2000. This gives a picture of an expanding market, where firms are motivated to acquire market share (as opposed to being concerned with survival). Thus, our data are appropriate to support an investigation of competitive interaction.\(^1\) In this vein, we also affirm that this dataset is not designed to be reflective of all of electronic commerce, but rather is an examination of items where vendors are likely to react to their competitors. We assume (but do not show) that there is less pressure to react to competitors with low-selling items.

4.2. Empirical Analysis Techniques

In the data set that we will use in our empirical analysis, there were 871 price increases and 922 price decreases. The Bertrand competition literature disallows price increases unless there is an aggregate change in marginal costs across competitors in an industry. Since there are almost as many price increases as price decreases, and it is unlikely that marginal costs changed this

\(^1\) We only consider best-selling items, which are most visible to the consumer and should draw the most competitive interaction. Clay, et al. (2002) find no competitive interaction among non-best-sellers in e-markets, possibly indicating that vendors react selectively to others—those with high-visibility items.
drastically during this study, it intuitively follows that intense Bertrand competition is not the sole explanation for competitive pricing strategy on the Internet, although it may possibly be used to explain a portion of some firms’ pricing strategies. In this research, we examine motivations for price matching and price beating behavior. We define **price matching** as matching a price of any competitor. We define **price beating** as beating the price of any competitor while not matching any competitor. We recognize that it is also possible that a price change is neither competitive nor collusive, when a firm raises its prices above its competitors. We will include this possibility in our empirical analysis. We argue that when the price charged is above marginal costs, price-beating is competitive and price-matching is tacitly collusive.

### 4.3. Preliminary Evidence of Collusion and Competition

To illustrate the appropriateness of the proxy of price beating for competition and price matching for collusion in this research, we introduce specific products representing our empirical data. We illustrate the price trajectories during February and March 2000 for Michael Cunningham’s book, *The Hours*, and Mary J. Blige’s music CD, *Mary*.

**Evidence of Tacit Collusion Around Book Prices.** In Figure 2, prices for *The Hours* book appear to show a great deal of price matching. At first, all vendors charged $6.50 for the book. Then, when Amazon raised its price to $10.40, BN.com and Borders.com eventually raised theirs to the same amount. Amazon did not beat or match any competitor. Books-a-Million matched this price increase, however. Thereafter, Amazon lowered the price to $6.50, matching Books-a-Million. BN.com and Borders followed with identical price reductions. Finally, Books-a-Million raised its price to $10.40 (‘high-pricing’ the competition). The other vendors then followed suit.
with identical changes. So by the end of the study, all were charging $10.40.  

The booksellers’ actions are easily interpreted once the business rules used by these companies are noted. They all have a business rule that books on the New York Times best-seller list sell for 50% off cover price, and 20% off books that are selling well, but are not on this list. Thus, the price changes of The Hours are due to movement on and off the best-seller list. Based on conversations with publishers, we know that books bought directly from publishers are sold to the bookstore or distributor for 50% off list price or lower, depending on volume purchased.

Figure 2. Examples of Competition and Tacit Collusion

The book The Hours listed for $13.00 during this time. Thus, these competitors alternated between 50% off the cover price (e.g., $6.50) and 20% off the cover price (e.g., $10.40).
Note that all four booksellers adopt the *exact same business rule*, differing only in the day of week when the rule is implemented. Thus, even when the margins are greater (e.g., a book priced at 20% off the cover price), booksellers still charge the *exact same amount*, even to the exact cent! Second, the business rule adopted by these four booksellers *does not consider increases or decreases in costs*, evidence of some underlying strategic price rigidity. With pure competition, prices should be set at marginal cost and only change when marginal costs change. Exact price matching in this fashion suggests tacit collusion rather than Bertrand competition. All firms tacitly agree to employ the same business rules and end up charging the same price.

**Evidence of Collusion and Competition Around CD Prices.** Let us return to Figure 2 again for some additional inspection. *Mary*, a music CD, showed a wide variety of prices during the study period. Amazon charged $13.99 and made no price changes, and therefore made no matching, beating, or high-pricing moves. BN.com first charged $12.99, and raised its price to $14.98 for just two days, high-pricing the competition. No firm matched BN.com’s increase. Two days later, its price fell to $12.99, not matching any firm yet beating Amazon.

Meanwhile, Borders was charging $13.59 for *Mary* at the start. When BN.com raised its price to $14.98, Borders responded by raising its price to $14.39, matching no one and undercutting BN.com. But then, when BN.com moved its price back to $12.99, Borders reduced its price to $13.59, matching no one but undercutting Amazon.com by 40 cents. CDNow started with a $12.99 price just like BN.com. When BN.com increased its price to $14.98, CDNow decreased its price to $12.58, undercutting everyone else. And, when BN.com decreased its price to $12.99, CDNow raised its own price to $12.99 (matching BN.com). Later in the study, CDNow decreased its price to $12.49, beating all of the competition, and ended by raising its price again to match BN.Com at $12.99. To make a long story short, we see a more competitive
environment with the *Mary* CD than with *The Hours* book, although many of the same vendors are present. The difference, we argue, is whether a firm chooses to compete or to collude.

We further note that the lowest price charged for this CD during this study is CDNow’s $12.49. In a Bertrand model, this would be viewed as the “one low price” that all vendors eventually need to charge in perfect competition and where price meets marginal costs. Indeed, we view the CDNow price change to a point below its competitors as a clearly competitive move. However, other vendors never seem to have competed at the CDNow level during the study period. CDNow eventually raised its price to $12.99, matching BN.com at a point that is probably above the Bertrand one low price. Since CDNow matched a top-tier competitor at a point above the lowest price observed, we are justified in viewing such price-matching as an instance of tacit collusion. This prompts investigating what factors lead to price-beating (i.e., competitive moves) and what factors lead to price matching (i.e., tacitly collusive moves).

5. A MODEL FOR EXPLAINING INTERNET-BASED PRICE TACIT COLLUSION

We compare an Internet seller’s propensity to match prices, its propensity to beat prices, and its propensity to do neither. Our econometric analysis will use the behavior of competitors with large market power to predict the level of price matching in Internet selling.

5.1. Operationalization of Theoretical Model Variables and Hypotheses

We operationalize each of the variables discussed in our theoretical model and the propositions, and develop hypotheses to predict the price strategy-related behaviors.

**Competitor Behavior.** Our *Reaction Proposition* (P1A) states that firms will respond in a like manner to the competitive actions of their competitors. This is more than a tit-for-tat strategy; it indicates a larger issue. When a competitor tries to use price competition to drive a firm out of business rather than collude, a viable response is to compete fiercely, especially if
there is a good chance of a loss of market share. Hence, collusion will only tend to take place when all competitors collude. If a single strong competitor decides not to collude, there may be a change from one of general collusion to intense competition. However, this may be affected by the larger environment of an industry. So we hypothesize that:

| HYPOTHESIS 1A (THE PRICE CHANGE REACTION HYPOTHESIS). Whether a firm matches a competitor price will be positively affected by the ratio of the count of that competitor’s matching of competitor prices to the count of that competitor’s beating of competitor prices. |
| HYPOTHESIS 1B (THE INDUSTRY EFFECTS HYPOTHESIS). The observed level of price matching by firms will differ by industry. |

**Competitor Market Power.** Our model uses number of unique Web site users as a proxy for firm market power. We use a ratio for *Competitor Relative Market Power*: competitor market power divided by the market power of the firm, for unique users. A logarithmic transformation ensures that this measure is not infinite, by generating a sign for the ratio describing if the competitor has more (+) or less (-) market power. This preserves the magnitude of difference between firms and reduces the corrupting effects of outliers.  

| HYPOTHESIS 2 (THE PRICE-MATCHING MARKET LEADERS HYPOTHESIS): There will be a positive relationship between the natural log of the competitor market power ratio and the probability of price-matching. |

**Response Time.** We include two variables to examine price-time dynamics. *Competitor Response Time* measures the average time it takes a competitor to respond to price changes. The *Competitor Response Time Hypothesis (H3A)* suggests that firms will not want to intensely compete with a competitor that has the capability to respond quickly to price promotions. The

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3 For example, *PC Data Online* reported that eCampus had 110 unique users during the study month. Amazon had 14,812 unique users. If eCampus responds to the Amazon price, the untransformed market power ratio would be 14,812/110 = 134.65. But if Amazon responds to eCampus, the market power ratio would be 110/14,812 = .0074. Taking the natural logarithm of these numbers, eCampus’ response to Amazon is \( \ln(14,812 /110) = 4.90 \), and Amazon’s response to eCampus is \( \ln(110/14,812) = -4.90 \).
result will be reduced revenue for both firms. Profit-maximizing firms will realize that tangling with a competitor who responds quickly will result in reduced profits with no increase in market share. The firm may prefer to act collusively with that competitor.

Our **Firm Response Time Hypothesis** states that if a firm can respond quickly, it may prefer competitive behavior. Able quickly respond, a firm may feel that it can profit from competitive behavior more than a firm that responds more slowly. Hence, we think we will see more collusive behavior when firms are able to respond quickly to competitors’ price changes, and more competitive behavior from firms that are not able or willing to respond quickly. The **Firm Response Time** variable measures how quickly that particular response is to a competitor price change. To determine response time when collusion occurs, we assume that the firm is responding to the competitor who last made a price change. For competition, we assume the firm was responding to the competitor with the lowest price listed for the same product. For a tie with either the competitive or collusive responses, we assume the firm was responding to the competitor with the largest market power.

- **COMPETITOR RESPONSE TIME HYPOTHESIS (H3A):** The average response time for a given competitor to respond to the price changes of other market competitors positively influences whether a firm will match the prices of that competitor.
- **FIRM RESPONSE TIME HYPOTHESIS (H3B):** The average response time within which a firm reacts to a given competitor price changes negatively influences whether the firm matches the prices of that competitor.

### 5.2. Empirical Modeling Issues

We use the **multinomial logit (MNL) model** (Greene 1999). This enables a polychotomous dependent variable to be a qualitative or categorical choice, not a continuous value, as required by ordinary least squares (OLS) regression. We next discuss issues that arise in this context.

**Form of the Dependent Variable and Independence of Irrelevant Alternatives.** Because
of the polychotomous dependent variable (e.g., a price change either matches, beats or falls below competitor prices), a linear model is inappropriate. This would make estimates of the categorical dependent variable fall outside the appropriate range. The response probability cannot exceed 1 or be less than 0. OLS regression can lead to estimated values for the dependent variable that exceed the maximum and minimum values for a probability. Model transformations resolve this problem by forcing predictions about the dependent value to lie within the [0, 1] interval, as is appropriate with probabilities.

MNL transformations assume independence of irrelevant alternatives. This is appropriate when the alternatives are not readily substitutable (Greene, 1999; Kennedy, 1998). In our case, we exhaust all possible pricing choices with mutually exclusive choices that, by definition, are not substitutes for one another. We examine firms that price higher than the competition, firms that match the price of the competition, and firms that price lower than the competition. See Kennedy (1998) or Greene (1999) for a more in depth discussion.

**Endogeneity.** One of the major potential pitfalls encountered with this data set is endogeneity. Kennedy (1998, p. 157) reports how endogenous variables are problematic because endogenous coefficients are partially determined through their joint interaction with other variables in a system. Examples in the economics literature include firm choices about prices reflecting endogeneity due to demand and supply, economic growth and government regulations.

Considering how this applies in our context. Suppose Amazon.com reacts to the BN.com’s price changes, and BN.com reacts to Amazon’s. If the reactions occur in a time frame that is shorter than the data collection intervals that we employ, then model-induced endogeneity will result. However, we will not be able to distinguish its impact, i.e., if BN.com and Amazon both change prices on a book on the same day, we will not know if BN.com responded to Amazon, or
if Amazon responded to BN.com. Since our data were collected once per day, same-day reactions to price will result in endogeneity that reduces the predictive power of our model estimates, since simultaneous predictors will be omitted. Thus, if we interpret the endogenous reactions incorrectly, we can corrupt the parameter estimates produced by our model. 4

We resolved model-induced same-day pricing action endogeneity by eliminating 32 same-day reactions from our data, just 1.9% of our total price changes. These included 15 price changes that beat competitor prices and 17 price changes that matched competitor prices. Because of the relatively small number of observations, and the balance of price-matching and price-beating changes, there are no significant biases in the results we report. By removing concurrent responses and only considering reactions to previous period competitors, we have safely removed the possibility of endogeneity. Endogenous reactions are only possible in concurrent situations where joint determination of outcomes becomes possible.

**Product Descriptors.** Two additional product control variables help explain variance at the product level. *Product Rank* is the rank shown by the listing agent, and varies continuously from 1 to 100. Our data collection methodology involved downloading data from best-selling music CD and book lists from *Billboard Magazine* and *USA Today*. We include *Product Rank* to absorb information about how item popularity affects competitive actions. It may intensify a firm’s propensity to match or beat a competitor price. We also include *List Price*. Higher-priced items tend to generate larger returns, and may affect a company’s decision to match or beat a competitor price. Since collusion is typically more profitable and intense competition is typically more risky, high-priced items should show a tendency toward matching, not beating.

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4 For instance, if we say that BN.com responded to Amazon when, in fact, Amazon responded to BN.Com, then our estimates of the *Competitor Relative Market Power* and *Competitor Behavior* coefficients will be biased.
**Collinearity and Multicollinearity.** Strong *pairwise correlation* between independent variables can lead to estimation problems, as can *perfect collinearity* (or *multicollinearity*) among multiple variables (Kennedy, 1998). We found no unacceptable pairwise correlations; the highest pairwise correlation was 49%. Multicollinearity can still exist even though the correlation matrix shows no high correlations. To test for close-to-perfect collinearity, we used a *condition number test.* Greene (1999) describes the condition number of a square matrix as the square root of the largest and smallest matrix roots of the normalized $X'X$ matrix that is formed in regression analysis. A condition number of 20 or greater may indicate the presence of multicollinearity. We performed this test with our data, and derived a condition number of 15.6, less than the criterion value, so we are assured that multicollinearity does not exist in our data.

### 5.3. Estimation Form of the MNL Model

We next describe how and why we use a MNL model to analyze competitive pricing.

**Preliminaries: Binary Choices.** Kennedy (1998) describes how the MNL transformation uses a logistic function that resembles a cumulative normal distribution. Using logit, the probability of a choice (e.g., *Choice A*) can be closely estimated as the chance for selecting the choice weighed against all other choices, 

$$
Pr(A) = \frac{e^{\beta X}}{1 + \sum_{j=1}^{J} e^{\beta_j X}}.
$$

$\beta$ is set of coefficients, and $X$ is a matrix of observed independent variables. The probability that *Choice A* does not occur is 

$$
Pr(\text{not } A) = 1 - Pr(A) = 1 / (1 + e^{\beta X}).
$$

Combining these two equations allows selection between choices: 

$$
Pr(A) / Pr(\text{not } A) = e^{\beta X}.
$$

The *log-odds ratio* is the log of the ratio of the probability between each of the two choices: 

$$
\ln (e^{\beta X}) = \beta X.
$$

**Extension: MNL Choices.** Jain and Kini (1999) show how MNL allows for different choices. The probability of choosing among *Choice A, Choice B,* and *Choice C* is broken down
into log-odds ratio formulas describing Choice A over Choice C and Choice B over Choice C:
\[ \ln(A / C) = \beta_A X \] and \[ \ln(B / C) = \beta_B X. \] To derive the selection of Choice A over Choice B, a logarithmic operation is used: \[ \ln( A / B ) = \ln(A / C) – \ln( B / C) = (\beta_A – \beta_B) X. \] The full form of the MNL model for the empirical analysis is shown in Equations 2 and 3 and Table 1.

Table 1. Variables in the MNL Model

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>Intercept</td>
</tr>
<tr>
<td>(P_{HIGH})</td>
<td>An ordinal variable coded to indicate a firm’s pricing choice in relation to its competitors. (P_{HIGH}) describes when a firm employs high-pricing in that its price change results in a price charged for an item that is above all competitors for the same item; (P_{MATCH}) describes when a competitor employs price-matching and thus changes price to exactly match a competitor price; (P_{BEAT}) describes when a firm employs price-beating and thus beats a competitor price while not matching any other competitor.</td>
</tr>
<tr>
<td>(\beta_{11}, \ldots, \beta_{17} \ldots \beta_{21}, \ldots, \beta_{27})</td>
<td>Model coefficients. (\beta_{1x}) coefficients describe the effect of variables where price-beating is chosen over high-pricing. (\beta_{2x}) coefficients describe the effect of variables where price-matching is chosen over high-pricing.</td>
</tr>
<tr>
<td>(CompetitorBehavior)</td>
<td>Competitive pricing is a percent of pricing changes made by a competitor.</td>
</tr>
<tr>
<td>(CompetitorMarket PowerRatio)</td>
<td>Ratio of the number of unique visitors to competitors’ Web sites to the number of unique visitors to the firm’s Web site.</td>
</tr>
<tr>
<td>(FirmResponseTime)</td>
<td>The number of days since last competitor price change that was: [\checkmark] the exact same price, if price-matching is occurring; or, [\checkmark] the closest higher price, if price-beating is occurring; or, [\checkmark] the closest price change, if high-pricing is occurring.</td>
</tr>
<tr>
<td>(CompetitorResponse Time)</td>
<td>Number days on average it takes for competitor to respond to price changes.</td>
</tr>
<tr>
<td>(IndustryEffects)</td>
<td>A binary variable that captures industry effects, with bookselling industry = 0 (the base case), and the music CD industry = 1.</td>
</tr>
<tr>
<td>(ListPrice)</td>
<td>The list price of the product.</td>
</tr>
<tr>
<td>(ProductRank)</td>
<td>The current rank of the product among the best-selling 100 items ranked by \textit{USA Today} (for books) or by \textit{Billboard Magazine} (for music CDs).</td>
</tr>
</tbody>
</table>

**Estimation Models.** We will use three different estimation models. Equation 2 shows the probability of a firm’s choice of a price-beating strategy (coded by \(P_{BEAT}\), i.e., charging less than a competitor) compared to the probability of a firm choice of the high-pricing strategy (coded by
Equation 3 models the probability of a firm choice of a price-matching strategy (coded by \( P_{MATCH} \), i.e., charging the same as a competitor) compared to the probability of firm choice of the high-pricing strategy (coded by \( P_{HIGH} \), i.e., charging more than all competitors).

Applying algebraic rules for the logarithms of the probabilities of the first two outcomes, we can write the solution for the third to characterize the missing comparison, to yield Equation 4. This represents a model for when price-matching is chosen over price-beating.

- **Price-Beating Compared to High-Pricing:**

  \[
  \ln(P_{BEAT} / P_{HIGH}) = \alpha_{11} + \beta_{11} \text{CompetitorBehavior} \\
  + \beta_{12} \ln (\text{CompetitorMarketPowerRatio}) + \beta_{13} \text{FirmResponseTime} \\
  + \beta_{14} \text{CompetitorResponseTime} + \beta_{15} \text{IndustryEffects} + \beta_{16} \text{ListPrice} \\
  + \beta_{17} \text{ProductRank}
  \]  

- **Price-Matching Compared to High-Pricing:**

  \[
  \ln(P_{MATCH} / P_{HIGH}) = \alpha_{21} + \beta_{21} \text{CompetitorBehavior} \\
  + \beta_{22} \ln (\text{CompetitorMarketPowerRatio}) + \beta_{23} \text{FirmResponseTime} \\
  + \beta_{24} \text{CompetitorResponseTime} + \beta_{25} \text{IndustryEffects} + \beta_{26} \text{ListPrice} \\
  + \beta_{27} \text{ProductRank}
  \]  

- **Price-Matching Compared to Price-Beating:**

  \[
  \ln(P_{MATCH} / P_{BEAT}) = \ln (\frac{P_{MATCH}}{P_{HIGH}}) - \ln (\frac{P_{BEAT}}{P_{HIGH}}) \\
  = (\alpha_{21} - \alpha_{11}) + (\beta_{21} - \beta_{11}) \text{CompetitorBehavior} \\
  + (\beta_{22} - \beta_{12}) \ln (\text{CompetitorMarketPowerRatio}) \\
  + (\beta_{23} - \beta_{13}) \text{FirmResponseTime} \\
  + (\beta_{24} - \beta_{14}) \text{CompetitorResponseTime} \\
  + (\beta_{25} - \beta_{15}) \text{IndustryEffects} \\
  + (\beta_{26} - \beta_{16}) \text{ListPrice} + (\beta_{27} - \beta_{17}) \text{ProductRank}
  \]

Through our application of the MLN model, we are able to examine pricing strategy in its entirety to get a picture of when firms match and when they beat competitor prices.

6. RESULTS AND DISCUSSION

We next discuss some data elimination procedures and the estimation results.
6.1. Data Elimination Procedures and Estimation Technique

Of the 1793 price changes, we eliminated 26 because the vendor was selling an item at a time when no other competitor was also selling the item. We eliminated 82 price changes because the firm making the price change had always priced above the market for this time frame. These “high-pricers” are not included because our technique could not determine their competitive behavior. We also removed 32 price changes because of possible endogeneity due to simultaneous price changes. This data elimination procedure resulted in 1653 observations available for analysis. We estimated the MNL model in Equations 2-4 with 1653 observations, using LIMDEP 7.0, as described in Greene (1995). The results converged in five iterations to yield parameter estimates.

6.2. Results of Hypothesis Tests

We purposely included pricing data that was indicative of pricing strategies that were neither collusive nor competitive. This allowed us to analyze the entire data set of price changes, and to obtain a picture of the range of pricing strategies in our two industries. Our MLN approach is a means to estimate Equation 4, in which price-matching and price-beating firm strategies are compared. Equations 2 and 3 lay a foundation for the empirical analysis of Equation 4, but their results are also interesting for the insights they offer into the competitive pricing strategies of online industries. Table 2 shows our parameter estimates for each variable in the MNL model.
Table 2. Parameter Estimates for the MNL Model

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>PRICE - BEATING VS. HIGH-PRICING (EQUATION 2)</th>
<th>PRICE-MATCHING VS. HIGH-PRICING (EQUATION 3)</th>
<th>PRICE-MATCHING VS. PRICE-BEATING (EQUATION 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>t-Stat</td>
<td>Coeff.</td>
</tr>
<tr>
<td>$\alpha$ (Intercept)</td>
<td>-0.156</td>
<td>-0.3</td>
<td>3.030</td>
</tr>
<tr>
<td>CompetitorBehavior ($H1a$)</td>
<td>1.784</td>
<td>4.0***</td>
<td>-1.062</td>
</tr>
<tr>
<td>IndustryEffects ($H1b$)</td>
<td>0.553</td>
<td>2.0**</td>
<td>-1.369</td>
</tr>
<tr>
<td>Ln(CompMarketPowerRatio) ($H2$)</td>
<td>0.170</td>
<td>5.6***</td>
<td>0.316</td>
</tr>
<tr>
<td>CompetitorResponseTime ($H3a$)</td>
<td>0.018</td>
<td>1.9*</td>
<td>-0.024</td>
</tr>
<tr>
<td>FirmResponseTime ($H3b$)</td>
<td>-0.018</td>
<td>-4.9***</td>
<td>-0.029</td>
</tr>
<tr>
<td>ListPrice</td>
<td>-0.004</td>
<td>-0.2</td>
<td>-0.022</td>
</tr>
<tr>
<td>ProductRank</td>
<td>-0.002</td>
<td>-0.9</td>
<td>0.002</td>
</tr>
</tbody>
</table>

*Note:* *=significant at $p < 0.10$; **=significant at $p < 0.05$; ***=significant at $p < 0.01$

The results of our MNL model test include three comparisons of the pairs of three different pricing strategies available. We used an ordinal variable that is coded in the dependent variables of the models for price-matching, price-beating or high-pricing. Positive coefficients in Table 2 indicate that a unit increase in an independent variable causes the firm to exhibit a tendency toward the pricing strategy listed first (i.e., price-beating, price-matching, and price-matching). Negative coefficients indicate that a unit increase in an independent variable leads the firm to tend to exhibit the pricing strategy that is listed second.

Recall that although we present the total results of our empirical analysis of pricing strategies for Internet-based sellers of books and music CDs, the parameter estimates associated with Equation 4 (the right-hand column in Table 2) are most consistent with showing what factors cause the price-matching strategy to be selected by firms over the price-beating strategy, and vice-versa. By focusing on the estimation results of Equation 4, we can test our hypotheses, and interpret the drivers of tacit collusion and competitive pricing strategies.

The empirical analysis supports four of five hypotheses and reveals some interesting
relationships. Product popularity, proxied by ProductRank, was not significant. So product popularity does not appear to have an impact on the decision to match or beat competitor prices. Similarly, ListPrice appears to have no effect. However, the lack of a statistically significant coefficient does not lead us directly to a conclusion that the related variable is unimportant as an explanatory factor. We only considered the top 100 products in both industries. There are many more products that firms are selling via the Internet. We feel more comfortable suggesting (though not confirming) that firms do not distinguish among the relative popularity of individual top-100 best-sellers, and that the similarity in list price may not lend itself to easy comparison.

**The Price Change Reaction Hypothesis (H1A).** We tested this hypothesis by examining the CompetitiveBehavior variable. The coefficient estimate for this variable in Equation 4 shown in Table 3 is negative and significant (-2.846, \( p < .01 \)), indicating that an increase in a competitor’s competitive responses causes a firm to act more competitively and less collusively. Thus, we show that firms echo their competitors’ typical behavior. Firms tend to match prices with firms that also match price and compete with firms that also compete on price. This makes sense based on our theory. If price-matching is indicative of collusion, then our results show that a firm is more willing to collude with a competitor if it has shown a general willingness to collude.

As expected, the positive parameter estimate for the CompetitiveBehavior variable in Equation 2 (1.784, \( p < .01 \)) indicates that firms that engage in fierce competition in the past will avoid selecting a high pricing strategy. They will continue to compete fiercely on price when given a choice between the two strategies. The negative coefficient of CompetitiveBehavior in Equation 3 (-1.062, \( p < .10 \)) is not highly significant, but the sign suggests that companies will not choose to collude with a highly price-competitive firm. Instead, its competitors will be more likely to ignore fierce competitors. Thus, more competitive pricing by a firm results in
reciprocated competitive behavior from competitors, while price-matching behavior results in similarly reciprocated price-matching behavior from the competitor. This matches our theory.

**Industry Effects Hypothesis (H1B).** Do different industries exhibit different price-matching and price-beating responses, even when some of the same firms occupy both industries? Our results in Table 2 also show that industry is likely to affect the pricing strategies that firms apply. We see this from the significant coefficient for the IndustryEffects variable (-1.922, \( p = .01 \)) in Equation 4. The negative sign suggests that music CD firms, in comparison to booksellers, tend to exhibit a lower propensity to engage in price-matching relative to price-beating. Instead, music CD firms are more prone to price-beating than booksellers.

This result is further supported by the analysis of Equations 2 and 3. In Equation 2, a positive and significant parameter estimate for IndustryEffects (0.533, \( p < .05 \)) indicates that the music CD industry is more likely to exhibit price-beating behavior rather than high-pricing behavior, as expected in a competitive industry. A negative value for the IndustryEffects variable in Equation 3 (-1.369, \( p < .01 \)) indicates that the music CD industry is more likely to exhibit high-pricing behavior. So Internet sellers in the music CD industry are most likely to compete intensely, but are also likely to ignore the competition than they are to tacitly collude.

**Price-Matching Market Leaders Hypothesis (H2).** We tested this hypothesis by examining the \( \ln \ (\text{CompetitorMarketPowerRatio}) \) variable. Analysis of Equation 4 in Table 2 shows that the parameter estimate of \( \ln \ (\text{CompetitorMarketPowerRatio}) \) is significant and has a positive coefficient (0.146, \( p < .01 \)). This indicates that the more market power a firm had when compared to its competitors, the more likely it would be to match competitor prices. Carpenter, et al. (1989) note that the actions of the lower-pricing, smaller firms have little impact on the sales and revenues of market leaders. Our results appear to show the existence of asymmetric
competition within e-commerce sectors. The intense competition predicted by Bertrand (1883) for identical items, where prices approach a single low price, does not appear to be occurring. Rather, our data suggest that firms set prices while considering the actions, size and strength of the market leaders. They probably do not set prices based on marginal costs.

However, market leaders do not appear to be more likely to ignore their competitors. Table 2 shows significant positive coefficient estimates for the $\ln(\text{CompetitorMarketPowerRatio})$ variable in Equation 2 ($0.170, p < .01$) and Equation 3 ($0.316, p < .01$). These indicate that those with market power are more likely to compete or collude than they are to ignore the competition than those with less market power—at least in the industries our data set covers.

**Competitor Response Time Hypothesis (H3A).** Does the average response time for a given competitor to respond to the price changes of other market competitors positively influence whether a firm will match the prices of that competitor? In Equation 4 in Table 2, we observe a negative and significant coefficient parameter estimate for $\text{CompetitorResponseTime}$ (-0.042, $p < .01$). Two assumptions are implicit: (1) if a firm possesses the ability to respond more quickly to competitor price changes, then it will do so; and, (2) there are no other factors that would cause competitors to delay this response. Our results lead us to accept the hypothesis that firms able to respond quickly can *coerce* competitors into applying less competitive pricing.

Equations 2 and 3 show little evidence for the $\text{CompetitorResponseTime}$ effect. In Equation 2, the parameter estimate is positive and weakly significant ($0.018, p < .10$), indicating that fast price change responses may be associated with competitive pricing. In Equation 3, we saw a negative insignificant parameter for $\text{CompetitorResponseTime}$ (-0.024, not significant). If this had been significant, a fast response time would be associated with observations in the market of high-price pricing strategy. However, with weak significance, we cannot conclude this.
**Firm Response Time Hypothesis (H3B).** Does the average response time with which a firm reacts to a given competitor’s price changes negatively influence whether it will match the competitor’s prices. This hypothesis tests if longer average times to respond to a competitor price change leads to a greater propensity for the firm to implement a competitive, price-beating pricing strategy, via the parameter estimate for the *FirmResponseTime* variable. The implicit assumptions mentioned above also hold here. In the estimate results for Equation 4 shown in Table 2, the negative and barely significant parameter estimate (-0.011, $p < .10$) is consistent with the interpretation that a firm’s quick responses to competitor price changes may allow for more implementation of competitive pricing. Our analysis suggests that firms do not consider their own response time, but only their competitors’ response time, when making price strategy decisions. The negative and significant coefficient estimates for *FirmResponseTime* in Equation 2 (-0.018, $p < .01$) and Equation 3 (-0.029, $p < .01$) indicate that fast response allows a firm to ignore the actions of its competitors and price higher than the competition to a greater extent.

We caution the reader when interpreting these results. There may be endogeneities beyond the scope of our modeling approach. Firms that are the most successful have developed the best resources for making competitive responses in their approaches to product pricing. They may set higher prices than the competition, and rely on brand recognition to create sufficient willingness-to-pay on the part of the consumer to be able to take advantage of demand (Brynjolfsson and Smith, 2000.) We refrain from asserting that the findings for response time are strong.

**6.3. Goodness of Fit and Predicted Outcome Issues**

Kennedy (1998) notes that there is no universally-accepted *goodness of fit measure*, such as $R^2$ for linear regression, for binary choice models. However, the $\chi^2$ test shows significance within $p < 0.0001$ at $\chi^2 = 651$, thus indicating our models Equations 2-4 have predictive power.
Kennedy (1998) tells us that it is considered naive to take a measure of the percentage of correctly predicted observations, because in a qualitative choice model, a model may predict well because it has strong predictors of one choice but weak predictors of other choices. With our data, if we predict that price-beating always occurs, we would be right about 63% of the time (1,039 / 1,653). However, we would never successfully predict a price-matching or high-pricing outcome. This would mislead us into thinking that price-beating responses are natural. Table 3 shows the actual versus predicted values of price-beating and price-matching price changes from the online music CD and book industries. (See Table 3.)

**Table 4. Frequencies of Actual and Predicted Outcomes for the MNL Model**

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>High-Priming</th>
<th>Price-Beating</th>
<th>Price-Matching</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-Priming</td>
<td>67*</td>
<td>304~</td>
<td>24~</td>
<td></td>
<td>395</td>
</tr>
<tr>
<td>Price-Beating</td>
<td>31~</td>
<td>959*</td>
<td>49~</td>
<td></td>
<td>1,039</td>
</tr>
<tr>
<td>Price-Matching</td>
<td>17~</td>
<td>74~</td>
<td>128*</td>
<td></td>
<td>219</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>115</td>
<td>1,337</td>
<td>201</td>
<td></td>
<td>1,653</td>
</tr>
</tbody>
</table>

* = Correct prediction; ~ = Incorrect prediction

To substantiate model fit, McIntosh and Dorfman (1992) suggest determining the fit of a logit model by the standard that the sum of the percentage of correct predictions of 1 and correct predictions of 0 in each category be greater than 100%. Our model correctly predicts when there is **price-matching** 58% of the time (128 / 219) and **no price-matching** 95% of the time (1 – [24+49] / [395+1039]). Thus, we achieve a score of 153% (58% + 95%) for **price-matching**, indicating the model predicts **price-matching** well. Our model correctly predicts **price-beating** 92% of the time (959 / 1039) and **no price-beating** 38% of the time (1 – [304+74] / [395+219]). The score is 130% (92% + 38%) for **price-beating**, which also shows good predictive power. Our model correctly predicts **high-pricing** 17% of the time (67 / 395) and **no high-pricing** 96% of
the time \((1 - [31+17] / [1039+219])\). The model scores 113\% (17\% + 96\%) for high-pricing, also indicating adequate predictive power.

Table 3 shows that, while our predictions of high-pricing strategies are adequate according the McIntosh and Dorfman methodology, our modeling approach does not predict high-pricing strategy selection as well as it predicts the other two. This is expected. The theory that drives our analysis is focused on the choice between collusive and competitive behavior. Thus, our model should not be viewed as optimal for examining choices among all types of pricing strategy. Instead, our approach offers a means to examine how firms choose between collusion and competition, as our theory and the empirical model suggest.

7. DISCUSSION

In this section, we will examine the industry-wide effects of competition and collusion as predicted by our models. We discuss CDNow's competitive behavior, and then compare some of the related dynamics of the music CD and bookselling sectors on the Internet. We end by discussing some broader implications for other industries that are brought to light by this study.

7.1. Evidence of Collusion and Competition at the Aggregate Industry Level

Figure 3 shows the price change strategies of the top three firms (i.e., the market leaders) in each industry we examined. In the bookselling industry, we analyze the actions of Amazon, BN.Com, and Borders.com, which sold 95\% of the books that are sold on the Internet, based on data we obtained from PC Data Online for 2000 (www.pcdataonline.com). Brynjolfsson and Smith (2000) indicated that the “Big Three” online bookstores represented an estimated 88\% of the total market share in 1998. There were 58 price-matching responses (73\%) and only 20 price-beating responses (25\%) among the market leaders, with 1 high-pricing response (1\%).
The situation is reversed for music CDs. The top three music Internet sellers on the Internet during the time of our study were CDNow, Amazon, and BN.Com with 83% of the unique hits in the music CD sector. These leaders had only 21 (19%) price-matching responses and 60 (55%) price-beating responses, with 28 (26%) high-pricing responses. The music CD sector seems more competitive, with 55% price-beating responses compared with 25% price-beating responses in the bookselling sector. Pricing strategy in bookselling also seems more collusive among the market leaders, with 73% price-matching responses, compared to only 19% price-matching responses in the music CD market. Competitors also tend to price higher than the competition in the music CD market (26%) when compared with the book market (1%). Apparently many vendors cannot afford to be fiercely competitive, and so are more prone to charge a higher price rather than simply recoup costs or even lose money in the music CD market.

We also examine the aggregate of competitive or collusive responses of all the Internet sellers, not just the market leaders. Figure 4 shows the price-beating or price-matching price changes from all competitors. The low number of 67 price-beating responses (23%) and the high number of 151 price-matching responses (51%) indicate that bookselling competitors may tacitly collude with each other. Conversely, the music CD firm have 68 price-matching responses (5%) and 962 competitive responses (71%) overall. This suggests they are more competitive.
Figure 4. Industry-Wide Responses to Competitor Prices

![Figure 4](image-url)

Much of the high-pricing behavior occurs among firms with smaller market shares in the lower tier markets. (Refer to Figures 3 and 4.) Small firms cannot compete with the economies of scale of larger firms, and must price higher on certain items while being competitive on others. Smaller firms also may go after niche markets (e.g., Christian books, rare CDs).

7.2. Industry Analysis

For bookselling, Amazon.com has adopted a formula for setting the price of books based on a book’s appearance on and off of the *New York Times* best-seller list. This practice has been copied by many of its competitors, differing only on the day the price change occurs. Such identical policies lead to tacitly collusive situations where identical price increases and decreases occur based on non-cost factors, leading to price-matching behavior.

One expects music CD and bookselling firms to be similar in the exhibition of collusive and competitive pricing on the Internet. They sell identical commodity-like products to end users through similar Internet-based interfaces. Both industries have Amazon.com and BN.com as two of their top three competitors. However, the largest competitor in music CDs was CDNow (Brady, 2000). As the market leader of the time, it may be the reason for the change in marketplace dynamics. Taylor and Jerome (1999) documented intense price competition between CDNow and N2K's Music Boulevard, and also noted how music CD companies were forced at this time to compete against free MP3 music downloads from Web sites such as
Napster. Hill and O'Brien (1999) describe how Amazon's entry into CD music sales forced CDNow to compete on price because of worries that Amazon's large Web presence would erode CDNow's customer base. English (1999) echoes this sentiment: CDNow may have lowered prices because a large customer base is initially considered more valuable than current period profits. Thus, CDNow competed fiercely with its competitors despite the benefits of collusion.

When we examined the high level of competition for music CDs, we found that CDNow made price-beating responses about 67% of the time and price-matching responses only 33% of the time. Compare this with Amazon.com, a market leader in both industries. Amazon made competitive responses to other market leaders only 27% of the time and apparently collusive responses 73% of the time. If our interpretation is correct, Amazon was tacitly cooperating with other Internet-based booksellers. Booksellers appear to have been willing (or perhaps were forced) to allow such collusion to occur. Conversely, CDNow did not appear to be cooperating with the other firms, thus making the music CD marketplace extremely competitive, new entry difficult, and probably hurting all competitors, especially smaller firms.

Our evidence points to CDNow’s propensity to use price competition to capture market share while driving competitors out of business and discouraging new entrants. CDNow’s competitive actions would result in less competition because of brand-name preferences. But without tacit cooperation, tacit collusion is impossible. CDNow's strategy did not drive out new sellers, however, as Amazon, BN, and Borders all began selling music CDs within the last three years.5

Although we did not examine other industries, our model shows how companies why tacitly collude, unless there is a chance for market dominance by driving out less-efficient competitors,

5 CDNow’s strategy led to a forced friendly buyout by German media conglomerate, Bertelsmann, for a mere $117 million, despite having the largest at home purchasing market of any Internet-based CD seller (Farmer, 2000). CDNow had purchased competitor N2K for $522 million a year earlier (Peterson, 1999).
or by erecting barriers to entry to prevent future competitors, thus increasing profits from competitive pricing. Pricing strategy is vital for success, and a market leader can create a competitive environment that reduces profits to minimal levels and makes survival difficult.

E-commerce firms of all types can apply our findings to their own situations. By examining competitive actions of the market leaders, new entrants will understand the competitive demands of the industry they are entering. Existing companies can clarify their existing strategy, and decide the best way to compete in the future. Finally, as this research shows, a firm’s ability to effectively respond reduces competitive behavior from other firms in an industry. Firm revenue and survivability can be enhanced by employing technology to rapidly respond to competitors.

8. CONCLUSION

We still know relatively little about whether Internet-based sellers intensely compete or tacitly collude. We have made the case that tacit collusion is a part of their strategy repertoire. Our model suggests how Internet technology enables firms to be responsive to market price changes. It enables them to tacitly collude to ensure higher profits for all. Our perspective differs from the primary findings of existing research, which maintains that IT will force Internet-based sellers to compete in a manner associated with intense Bertrand competition.

The results of our study of the online bookselling and music CD industries initially surprised us. We guessed they would be similar. They have similar competitors, especially in the top tier, and the products that they sell are similar. They sell products that are developed by an author or artist, produced by a publisher or label, and sold to a distributor. However, we learned that firms within these industries act quite differently. We attribute this to the intensely competitive actions of CDNow, a market leader in the music CD industry that does not compete in the bookselling industry. We conclude that an “unfriendly competitor” who chooses not to tacitly collude will
cause other firms to compete more intensely, especially with that unfriendly competitor.

We also show that the same firms can act differently in different environments, and that the competitive choices of the market leaders in an industry can determine the nature of competitive interactions. Such interaction can lead to an environment that is either collusive or highly competitive. Our econometric estimates of price-matching and price-beating (i.e., as instances of collusive and competitive pricing strategies) confirm our hypotheses describing how a firm’s choice of pricing strategy is influenced. Our results suggest that they are influenced by the actions of the competitor to whom the firm is responding, by the market power of that firm relative to the market power of the competitor, and by competitors’ ability to immediately respond. We also show that a firm may choose to intensely compete to drive current and future competitors from the market, but we point out that this strategy is risky. The example we offer is CDNow’s failure, which occurred in the competitive environment created by its pricing strategy.

This research makes several contributions. First, it is one of the first multi-industry empirical studies of Internet sellers’ competitive pricing behavior. We offer new insights into the effects that technology has on Internet seller pricing strategy, especially in the bookselling and CD industries. The results are surprising, and our econometric model should be useful for IS and e-commerce researchers who wish to study other contexts. Second, this study incorporates tacit collusion theory and demonstrates a viable alternative to predictions of intense competition in Internet-based selling. This is interesting since the inclusion of tacit collusion theory gives Internet-based sellers the opportunity to make larger profits. This is in sharp contrast to Bertrand competition, which is typically used to describe competitive interaction between Internet-based sellers. Third, this study makes a contribution by showing how large firms on the Internet set the tone for actions in the entire industry. This observation prompts more in-depth study of the
competitive interactions within industries. *Fourth*, we show the strategic importance of developing Internet technology so a firm can respond to a competitor’s price promotion. By matching competitor prices and showing an ability to quickly respond, Internet sellers can reduce competition in their industry. Web technology investments to monitor and allow quick responses to competitor actions may help the firm to charge higher prices for what they sell. By evaluating the actions of the market leaders, managers can develop strategies that fit better with their industry. By understanding the impact of their own actions, including increasing their response time, Internet sellers can help define the very environment in which they compete.

This work has some limitations. We assumed that undetected price changes were zero. Several times, especially with small companies, Web sites were unreachable or the required price information was not available when our software agent was polling for information. But, assuming price stability, in our view, is valid and conservative. We also excluded some price changes where competitive price-beating information was not available. These exclusions were slight and do not bias our results, in our view. Furthermore, we freely acknowledge that the price changes described in this paper are not necessarily due to competitor monitoring. For example, during the period of this study, movement on and off the New York Times bestseller list often triggered identical book price changes among competitors. Finally, this study is not intended to causally show the effect that technology or reduced search costs have upon competition, but rather to illustrate the dynamics of competitive behavior within an electronic market, the factors that can affect this competitive behavior, and how this competitive behavior matches with existing theory on electronic market competition.

9. REFERENCES


