Retail Strategies in the Presence of Online Music Sharing

by

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Abstract

Advances in online technologies and bandwidth availability have opened new vistas for online distribution of digital goods. But potential benefits for consumers are juxtaposed against challenges for retailers of such goods. Here we investigate one type of digital good - music - whose market faces the very real presence of online piracy options. While arguments abound for and against online distribution of such digital goods, little research exists in this area. We model five different market environments for retailers, from a traditional brick and mortar retailer not facing a piracy option to an online retailer offering multiple pricing options to consumers who have opportunities for unauthorized sharing. Retailer cost to music publishers is modeled using a variety of licensing schema. Results from survey together with data from music sharing sites are utilized to investigate the validity of a key assumption. Finally, extensive simulation analysis is used to develop insights related to conditions that cannot be solved for analytically. We find that online selling strategies for a traditional retailer can provide additional profits even in the face of existing piracy options. Our results clearly indicate that decreasing piracy is not necessarily equivalent to increasing profit. In addition, leading strategies for such business should include the use of pricing options, provision of efficient search tools to consumers and new approaches to licensing structures with music publishers.

Keywords: Sampling, Piracy, Online Channels, Digital Experience Goods, License, Music
1. Introduction

Emerging technologies often result in new opportunities, choices and possibilities. Advances in Internet technologies have opened new channels for online retailing of digital goods. But the same technology can be utilized for unauthorized copying and dissemination of such goods. The retailer of a digital good thus faces two challenges: 1) determining a business model along with a pricing strategy in a new environment, and 2) analyzing the impact of piracy options and different license contract structures with the wholesaler.

Here we present a formal analysis for retailers of one particular digital product, music. Music is an experience good, a type of hedonic product whose valuation is based on the experience it provides to a consumer (Dhar and Wertenbroch, 2000). A music item must be experienced (heard) to be accurately valued by a consumer. The digital nature of today’s music offers convenience and portability, as predicted by Alexander (1994b), but also raises the specter of piracy and lost sales. In fact, the economics of music, the market structure and the impact of piracy has been the subject of current studies (Alexander 1994a, 1997, 2002, Crain and Tollison 2002, Cunningham, et. al. 2003, Gopal, Bhattacharjee and Sanders 2004, Gopal, et. al 2004, Ravid 1999).

Retailer business models and pricing options in such online digital experience good markets have not been widely studied. While physical piracy of digital music (through CDs) is rampant in certain markets, our focus is on those markets where increasing broadband connections render online sharing and piracy a bigger threat. The work reported on here is not intended to address legal issues or viewpoints regarding the efficacy of piracy. Our goal is to contribute to the debate on electronic markets and piracy; it is not to take sides or argue a particular viewpoint. We
ask whether there are conditions such that the existence of online piracy might actually benefit retailers. Might it be the case that electronic music sharing/piracy options actually foster increased searching by consumers seeking to experience the product prior to making the purchase decision? Is it possible that increased searching is linked to increased sales and thus benefits retailers? In fact, there is anecdotal evidence pointing toward online sampling as increasing sales (Kot 2002, Matthews 2000, CNET 2003). In addition, there is some indication that the music industry is realizing that illegal networks cannot be closed down by legal means alone. In short, the industry needs to develop new business models, pricing strategies, and licensing schema (BBC News Online 2001, Weber 2002, Healey 2003).

In this paper, we present and analyze a series of models for retailers of such digital goods. These represent differing market environments, pricing options, and licensing arrangements. Our models of pertinent markets include the traditional retailer, an online retailer offering per unit pricing, an online retailer offering subscription pricing, and an online retailer offering both types of pricing options. Our theoretical results suggest that, under certain conditions, retailers may actually do better in an environment with piracy, largely due to the use of downloads as a means of pre-purchase sampling. We provide analysis of a key assumption in our modeling using: a) data from sharing activity on a major peer-to-peer network, and b) results of a survey. Extensive simulation experiments are used to gain additional insights into emerging online market scenarios that are not yet offered by sellers. Key results from these experiments are: i) online selling strategies for a traditional retailer can provide additional profits even under piracy environments; ii) efficient search techniques are essential to attract consumers to legal online markets; iii) maximum profit solutions do not occur in the absence of piracy; and iv) licensing cost structures of online retailers with music publishers have a significant impact on pricing and profits.
We begin with a brief literature review in §2. §3 presents a consumer search model, followed by profit implications under various market scenarios. §4 offers validation of a key modeling assumption. §5 discusses results and insights from a detailed set of simulation experiments on emerging online markets that are not yet available to consumers. §6 reviews key results and provides future research directions.

2. Literature Review

Previous research on experience goods, shared goods, software piracy, and consumer search processes all helped to shape our modeling and analysis, but there are critical differences that set our work apart. In the following, we note limited similarities with these bodies of work while emphasizing critical differences that necessitate our development of new models for studying digital music markets.

**Experience Goods and Assumption of Restrictions on Sharing:** Existing research on experience goods primarily models market issues for physical goods at a given location such that sharing or redistribution is not easy. Restrictions on sharing are not characteristic of current or emerging digital music markets. Oi (1971) implicitly assumed that sharing or redistribution of the good across different locations is difficult in a monopolistic market of entertainment experience goods. Shapiro (1983) assumed that there is only one source of product information, personal experience, but dealt with a scenario with impediments to the resale and redistribution of products. Additional related studies include Gale and Rosenthal (1994), Liebeskind and Rumelt (1989), and Riordan (1986). The digital music markets we study involve experience goods, but the possibility of broad sharing and redistribution makes these markets quite different from those in previous studies.
**Economic Models with Subscription Pricing:** Models on economics of subscription pricing and shared goods has usually focused on products where private sharing occurs among only a small group of consumers. Ordover and Willig (1978) and Glazer and Hassin (1982) assumed that individual customers do not share subscribed journals among themselves. Coyte and Ryan (1991) extended the subscription model and examined a consumer's decision to purchase or renew a subscription of an *information* good, a book. Borrowing a library book has low cost, but can only be borrowed for a limited time and only shared in a limited way. On the other hand, a downloaded digital music file from a subscription service potentially can be owned permanently and shared very widely.

**Software Piracy - Issues of Quality and Ease of Dissemination:** While several studies on software piracy have examined consumer decisions to purchase or pirate the product (Conner and Rummelt 1991, Gopal and Sanders 1997, 1998, 2000, and Givon, Mahajan, and Muller 1995), several key parameters distinguish music from software. Unlike computer software, digitized music is much easier to copy and disseminate due to typically smaller size. In addition, “consuming” music requires much less skill, hardware and supporting software. A critical difference, important in our study, is that the audio quality of music is better in original format (high quality recording media) than in a compressed digital file, the format typical for music items pirated online. On the other hand, a pirated software application requires lossless compression for proper functioning (Bhattacharjee, Gopal and Sanders 2003). Further, due to a large volume of online music, a search process should be an integral part of market analysis and research in this arena. As the literature indicates, this does not appear to be the case for analyses focusing on software piracy.
Search Process and Costs - Why is Digital Music Different? The large volume of available music poses dual search costs for consumers who must identify music items and partially review or “experience” the item in order to decide whether or not to subsequently acquire the item. This search process and cost is different from those studied in existing literature (Gastwirth 1976, Stigler 1961, Telser 1979). Nelson (1970) modeled a consumer who searches through different brands of canned tuna fish (a prototypic experience good) to find her favorite brand. Once the consumer finds the brand she likes, she no longer needs to search further for her next purchase since the same brand would be expected to have the same taste over time. Given increasing interest in marketing hedonic products (Krider and Weinberg 1998, Radas and Shugan 1998, Sawhney and Eliashberg 1996), we observe that the search process for digital music is significantly different from a prototypical search process. For a consumer, searching and finding a music item by a particular artist that the consumer likes is no guarantee that the next music item by the same artist (read brand) would be similarly liked by the consumer (have the same “value”). Each piece of musical performance contains its own unique characteristics. This variability together with a large volume of music items available leads to consumers performing additional searches for additional products, a process quite different from that modeled in earlier studies.

In sum, we view the evolving music market as sufficiently different to necessitate new models. Next, we present models of music markets, ranging from a base case with no-piracy to cases with the possibility of piracy together with delivery channel options.

3. Modeling Music Market Environments

Music retailers face consumers who search to evaluate and obtain music. The search process involves a consumer who may decide to purchase or pirate a number of music items,
which directly affects the profit-maximizing choices of the retailer. We first focus on consumer search process, including availability of various channels to experience and evaluate the music, related search costs on these channels, and potential channel switching options. We then detail the revenue implications of consumer actions on retailers, followed by profit implications of various licensing structures that retailers may choose.

3.1 Models of Consumer Search Process

Consumers search to evaluate and obtain music. Completion of each search indicates that a consumer searched for, identified, and experienced a new music item. Our consumer is not pursuing a directed search, but may start the search process with recommendations by friends or music reviewers about music items that she should consider. In our representation, if a consumer completes $n$ searches, she would have experienced $n$ different music items. This differs from typical best option, single item purchase represented in the literature using concepts of a consideration set, reservation utilities, and an ordered search (Moorthy, et. al. 1997). Following basic economic theory (e.g. Lloyd 1967), we assume that the consumer is seeking to maximize utility by choosing a set of music items, while remaining within a budget constraint specific to that type of good.

In each model we study there are: i) non-trivial costs to search, evaluate and obtain music; and ii) opportunities for consumers to pirate music (except in the base case model). We assume that each consumer, $i$, has a range of values that they would place on the music items under consideration. Notationally, $v_{ij} = \text{value that consumer } i \text{ places on music item } j \text{ after experiencing}$, where $v_{ij} \in [0, V_{i}^{\text{max}}]$ and takes on a discrete set of values in the set $[0, V_{i}^{\text{max}}]$. $V_{i}^{\text{max}}$ is the individual $i$'s maximum value for any music item offered by the seller.
We assume that the music retailer offers CD quality music, either electronically or on a physical CD. We also allow differential utility of a music item if it is obtained legally versus illegally based on a “quality of experience” factor. Notationally, we use $\delta$ as a multiplier if the music item is procured illegally. For example, consumer $i$ who downloaded song $j$ from an online illegal channel would receive a utility value of $\delta v_{ij}$. The factor $\delta$ can be viewed as capturing: i) lower acoustic quality of music at illegal sites due to compression technologies; ii) value-added services that a retailer might offer that are not offered at illegal sites; iii) the fact that a user is undertaking an illegal activity; and iv) restrictions on usage of legal copies (e.g., iTunes portability to only Apple’s iPod players) that can make illegal copies more flexible and attractive. Factors (i), (ii), and (iii) serve to lower the value of $\delta$, while (iv) pushes $\delta$ upward. For ease and brevity of presentation, we use $0 < \delta < 1$ in our analytic presentation in §3. In fact, all the four results derived in §3 continue to hold for $\delta \geq 1$. In §5, we do include simulations that involve values of $\delta$ greater than 1.

Searches are, by their nature, uncertain activities. Because the goods on which we focus are experience goods, a consumer can attach individual value only after listening to an item. In addition, the volume of commercially available music is vast. The major labels by themselves release over 27,000 new albums every year (Goodley 2003). Hence we assume that no consumer is aware of all music items available. The limiting case is where an individual somehow knows (has identified) a set of music items and has sufficient knowledge (i.e., consumer already knows the song, and just wants to obtain it) so that uncertainty is zero.

Each search involves processing consumer queries with a search tool. Potentially, a consumer may use three different channels to conduct a search, each channel having a different search cost. We consider each in turn:
Traditional: The consumer performs the search in a typical brick-and-mortar setting (referred to as BM hereafter). Consumers search in a traditional channel and either purchase or do nothing. Let the search cost for this traditional channel be $\psi^{BM}$.

Illegal: The consumer performs the search online at an illegal source, where consumers can download a copy of the music item for free, without authorization from the seller. A consumer can search in an illegal channel and download and keep the illegal version or do nothing. We hereafter refer to this online illegal channel as ONI and the search cost as $\psi^{ONI}$.

Legal: This online channel is set up by a legitimate seller (referred to as ONLG hereafter). The seller allows consumers to sample, evaluate, and purchase music legally. Of course, a consumer cannot download and obtain a music item illegally from this channel. A consumer can search in a legal channel and either purchase or do nothing. Let the search cost be $\psi^{ONLG}$.

Notice that a consumer can pirate music only from ONI, but can purchase music legitimately from either BM or ONLG channels. Given the limited time available at a brick-and-mortar store and the effort required to access it, compared to illegal online channels, we assume $\psi^{BM} > \psi^{ONI}$. Also, given a greater incentive from legal online sellers to provide better search tools, we assume $\psi^{ONLG} < \psi^{ONI}$. Hence $\psi^{BM} > \psi^{ONI} > \psi^{ONLG}$. Violations of this assumption are investigated later through simulation analyses.

Of course, a consumer can perform a search on one channel and then switch to another channel to procure the music item. We summarize our representation of such two-stage searches in Figure 1. For instance, starting at the BM channel, a consumer performs the $n^{th}$ search and evaluates the music, incurring a cost of $\psi^{BM}$. She then goes to ONI, and performs a directed search and downloads an illegal version of the same song, incurring a cost of $\psi^{BM\rightarrow ONI}$. The cost for this two-stage search would be $\psi^{BM} + \psi^{BM\rightarrow ONI}$. Similarly, starting at ONI, the consumer searches and incurs a cost of $\psi^{ONI}$. Given her consumer surplus, she might choose to terminate the search here, or switch to BM and buy the item, incurring an additional cost of $\psi^{ONI\rightarrow BM}$. The other
options and related costs are depicted in Figure 1. Note that a consumer who switches channels is assumed to do so after gathering the information necessary to make a specific \( n^{th} \) item procurement (legal or illegal). When moving to the new channel, the consumer has the information necessary to move as directly as possible to finalize a transaction. More formally, we make the following assumptions about search costs:

1. \( \psi_{ONI\rightarrow BM} = 0 \) and \( \psi_{ONI\rightarrow ONLG} = 0 \); i.e. once a consumer has identified a piece of music using the illegal channel, a directed search is performed when switching to and using \( BM \) and \( ONLG \). We assume better cataloging features of legal channels drastically reduce directed search costs;

2. \( 0 < \psi_{BM\rightarrow ONI} \leq \psi_{ONI} \); i.e. a customer having the information gathered in the \( n^{th} \) search at \( BM \) is more efficient when switching to \( ONI \) than when making the \( n^{th} \) search initially at \( ONI \); and

3. \( 0 < \psi_{ONLG\rightarrow ONI} \leq \psi_{ONI} \); i.e. a customer having the information gathered in the \( n^{th} \) search at \( ONLG \) is more efficient when switching to \( ONI \) than when making the \( n^{th} \) search initially at \( ONI \).

Figure 1: Consumer Search Process: Possible Channel Switching Options

A search is designed as a draw over a set of finite music items. The quality of a search tool (e.g. a music recommender system) will impact the probability of identifying a high or low value music item for a given consumer. If there are \( N \) music items available to search, then a "random

\[ \text{(10)} \]

We show later that \( BM \rightarrow ONLG \) and \( ONLG \rightarrow BM \) options would not be feasible given the search cost structure.
"A "better" search tool will make it more likely that a high value music item is identified by the search\textsuperscript{2}. We argue that, for legal online channels, retailers have a monetary incentive to provide customer support (i.e., provide a more “helpful” search tool) while the piracy channel has no comparable incentives. Searches in each of our channels are more efficient than a random search and there is an ordering on their efficiency. For the \(n\textsuperscript{th}\) search, there is a true probability distribution across consumer \(i\)'s value assignments to each of the finite set of songs to be searched. We assume that consumer \(i\) is able to place a value on a music item after experiencing it. This probability distribution of values, not known a priori (before experiencing items) by the consumer, is denoted \(\sum_{v_y \in [0, V_{\text{max}}]} \phi_{y}^{i,A}(v_y) = 1\), for each \(A\), where \(A\) denotes the channel (\(BM\), \(ONLG\), or \(ONI\)) in which the \(n\textsuperscript{th}\) search is being conducted. Within a given channel, searches have decreasing expected values as \(n\) increases, or \(\sum_{v_y \in [0, V_{\text{max}}]} V_{y} \phi_{y}^{i,A}(v_y) > \sum_{v_y \in [0, V_{\text{max}}]} V_{y} \phi_{y}^{i,A+1}(v_y)\). Search repetitions occur without replacement. Thus, if a search identifies a music item with value to the consumer above the mean value for all music items in the search space, then removal of that item will result in a lower expected value for the subsequent search. We argue that electronic searches tend to be more efficient than manual/physical searches. In addition, legal online sellers have incentives to develop and enhance customer service while illegal online sites have no such incentives. With this in mind, we posit the following final assumption for early searches (low values of \(n\)):

\[
\sum_{v_y \in [0, V_{\text{max}}]} V_{y} \phi_{y}^{ONLG,n}(v_y) > \sum_{v_y \in [0, V_{\text{max}}]} V_{y} \phi_{y}^{ONI,n}(v_y) > \sum_{v_y \in [0, V_{\text{max}}]} V_{y} \phi_{y}^{BM,n}(v_y)
\]

\textsuperscript{2} We assume the search tool incorporates an individual’s taste and delivers a high value item to a consumer. Designing such tools are a fruitful area of research.
After some number of searches, the efficiency of the legal online search channel can be expected to lead to the identification of mostly high value music items. The same number of searches in the other channels would be expected to lead to identification and removal of relatively lower valued music items. At some point, the set of music items remaining to be searched in the legal online channel will consist of mostly low valued items. Our assumption is that the consumer will stop searching before violations of (1) occur.

![Diagram: Consumer Choices under Different Retail Models](image)

**Figure 2: Consumer Choices under Different Retail Models**

- **Base Model**: Consumer Choices
  - Take no action
  - Traditional brick and mortar Store

- **Brick-and-Mortar Model**: Consumer Choices
  - Take no action
  - Illegal online networks
  - Traditional brick and mortar Store

- **Per-Unit Price Model**: Consumer Choices
  - Take no action
  - Illegal online networks
  - Online store with per-unit price

- **Subscription Model**: Consumer Choices
  - Take no action
  - Illegal online networks
  - Online store with subscription

- **Mixed Model**: Consumer Choices
  - Take no action
  - Illegal online networks
  - Per-unit Price
  - Subscription

**Case 1: Consumer Choices in Base Model (Base)**
**Case 2: Consumer Choices in Brick-and-Mortar Model (BM)**
**Case 3: Consumer Choices in Online Per-Unit Price Model (Unit)**
**Case 4: Consumer Choices in Online Subscription Model (Subs)**
**Case 5: Consumer choices in Online Mixed Pricing Model (Mixed)**

Our analysis focuses on retailers facing a set of consumers who differ in their $V_{i}^{max}$ values.

Each of the steps that follow can be generalized where a retailer faces a distribution of consumers
with varying $\phi_{ij}^{-\Lambda}(v_{ij})$ forms. Notationally, we center on a representative consumer $i$, utilizing $v_{ij}$ to indicate the value consumer $i$ assigns to the music item $j$ resulting from a given search in channel $BM$, $ONLG$ or $ONI$.

Figure 2 illustrates five possible cases that a seller of digital music may face: 1) a base case with brick-and-mortar retailer ($BM$) operating in a "world without piracy", 2) $BM$ operating where consumers have a piracy option, and may switch between channels, 3) an online retailer ($ONLG$) offering a per unit pricing and where consumers have a piracy option, and may switch between channels, 4) same as (3) except the retailer offers only subscription pricing, where consumers would not switch channels (explained in Case 4 discussion below), and 5) same as (3) but retailer offers both per unit pricing and subscription pricing (a mixed pricing model), which also permits the switching option between per-unit offering and $ONI$. The last three involve differing pricing options for emerging online market settings.

### 3.1.1 Case 1: Base model - Consumers have no piracy option

Here we consider a $BM$ who operates in a world without a piracy option for consumers (Figure 2: Case 1). Pricing is per unit with each music item available at a price of $p_u$, and each consumer has a budget constraint specific to this type of good (as indicated earlier). In this situation, consumer $i$ would initiate a first search only if $\sum_{v_y \in [p_u, V_i^{max}]}^{BM} \phi_{ij}^{-\Lambda}(v_{ij})(v_{ij} - p_u) > \psi^{BM}$. Let $N^{base}(V_i^{max})$ denote the number of searches conducted by consumer $i$ in this base case. It follows that $\sum_{v_y \in [p_u, V_i^{max}]}^{BM} \phi_{ij}^{-\Lambda}(v_{ij})(v_{ij} - p_u) > \psi^{BM}$ and $\sum_{v_y \in [p_u, V_i^{max}]}^{BM} \phi_{ij}^{-\Lambda}(v_{ij})(v_{ij} - p_u) < \psi^{BM}$. Note that the number of searches is monotonically non-decreasing in the value of $V_i^{max}$ so that consumers with higher $V_i^{max}$ values are expected to conduct more searches.
3.1.2 Case 2: BM Model where consumers have piracy option

Our second case still involves a BM and introduces an online illegal channel. The consumer who wishes to search music items can start the search process from either BM or ONI. Again, if the search costs exceed the expected value of searching, no search would occur (Fig. 2: Case 2).

Consider first a consumer whose $V_{i}^{max}$ is sufficient to justify at least one search. Suppose that she is at the starting point of the $n^{th}$ search and starts this search process at the illegal channel, incurring a search cost of $\psi_{ONI}$. Her subsequent behavior depends on the value, $v_{ij}$, of the music item experienced at the end of the $n^{th}$ search. The three consumer choices and the net benefits are:

i) switch to BM and buy: $v_{ij} - p_u - \psi_{ONI \rightarrow BM} = v_{ij} - p_u$; ii) pirate: $\delta v_{ij}$; iii) do nothing: 0.

If $v_{ij} - p_u > \delta v_{ij}$, the consumer would switch to BM. If not, would pirate the music item. Thus, the consumer’s net a priori expected benefit from an $n^{th}$ search that starts with the illegal channel is

$$\sum_{v_{ij} \in [0, \frac{p_u}{1-\delta}]} \phi_{ij}^{ONI, a}(v_{ij}) + \sum_{v_{ij} \in [\frac{p_u}{1-\delta}, V_{ij}^{max}]} \phi_{ij}^{ONI, a}(v_{ij})(v_{ij} - p_u) - \psi_{ONI}$$  \hspace{1cm} (2)

Now consider a consumer who starts the $n^{th}$ search at BM and incurs a search cost of $\psi_{BM}$. The subsequent behavior depends on the value, $v_{ij}$, of the music item she experienced at the end of the $n^{th}$ search. The consumer choices and the net benefits are: i) buy from BM: $v_{ij} - p_u$; ii) pirate: $\delta v_{ij} - \psi_{BM \rightarrow ONI}$ or iii) do nothing: 0.

The consumer will buy from BM if $v_{ij} - p_u > \delta v_{ij} - \psi_{BM \rightarrow ONI}$. Thus, her a priori expected benefit from an $n^{th}$ search that starts with BM is
\[
\sum_{v_y \in \{a,b\}} \delta_{ij} \phi_{ij}^{BM,n}(v_{ij}) + \sum_{v_y \in [b,v_y^{max}]} \phi_{ij}^{BM,n}(v_{ij})(v_{ij} - p_u) - \psi^{BM} - \psi^{BM\rightarrow ONI} \left( \sum_{v_y \in \{a,b\}} \phi_{ij}^{BM,n}(v_{ij}) \right)
\]

(3)

where \( a = \frac{\psi^{BM\rightarrow ONI}}{\delta} \) and \( b = \frac{p_u - \psi^{BM\rightarrow ONI}}{(1 - \delta)} \). The first term above is the expected value over the range where pirating the music item is optimal. The second term is the expected value over the range where buying the music item from BM is optimal. The third term is the search cost in BM. Finally the fourth term is the switching cost (BM to ONI) times the probability of the consumer switching from BM to ONI to obtain the music item identified in the \( n^{th} \) search at BM. Table 1 summarizes the costs and the expected benefits. For brevity, we denote \( c = \frac{p_u}{(1 - \delta)} \), in addition to \( a \) and \( b \) denoted earlier.

**Table 1: Brick-and-Mortar (BM) Model Expected Benefits and Search Costs**

<table>
<thead>
<tr>
<th>Starting Channel</th>
<th>Expected Benefit from ( n^{th} ) search</th>
<th>Search Cost for the ( n^{th} ) search</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Traditional Brick-and-Mortar (BM)</strong></td>
<td>( \sum_{v_y \in {a,b}} \delta_{ij} \phi_{ij}^{BM,n}(v_{ij}) + \sum_{v_y \in [b,v_y^{max}]} \phi_{ij}^{BM,n}(v_{ij})(v_{ij} - p_u) )</td>
<td>( \psi^{BM} + \psi^{BM\rightarrow ONI} \left( \sum_{v_y \in {a,b}} \phi_{ij}^{BM,n}(v_{ij}) \right) )</td>
</tr>
<tr>
<td>I</td>
<td></td>
<td>III VI</td>
</tr>
<tr>
<td><strong>Online Illegal (ONI)</strong></td>
<td>( \sum_{v_y \in {a,b}} \delta_{ij} \phi_{ij}^{ONI,n}(v_{ij}) + \sum_{v_y \in [c,v_y^{max}]} \phi_{ij}^{ONI,n}(v_{ij})(v_{ij} - p_u) )</td>
<td>( \psi^{ONI} )</td>
</tr>
<tr>
<td>V</td>
<td></td>
<td>VII</td>
</tr>
</tbody>
</table>

Let the number of searches in Case 2 be \( N^{BM}(v_i^{max}) \). Using the Roman numerals in Table 1 to correspond to the terms directly above them in the table, we can specify \( N^{BM}(v_i^{max}) \):

For \( n = N^{BM}(v_i^{max}) \), \((I + II) > (III + IV)\) or \((V + VI) > VII\),  

(4)

**and** For \( n = N^{BM}(v_i^{max}) + 1 \), \((I + II) < (III + IV)\) and \((V + VI) < VII\)  

(5)
The expected benefit of beginning the search at the illegal channel is higher than at the traditional channel. Therefore, a rational consumer starts at the illegal network, and if the value of the music is high enough will subsequently buy the music legally. This leads to the following observation:

1) **Rational consumers perform more number of searches for music in the BM model with piracy than in the base model (without piracy).** (proof in Appendix I)

A direct implication is that the existence of an illegal online channel leads to consumers searching for and experiencing more music items.

### 3.1.3 Unit, Subs and Mixed models where consumers have piracy option

In these three cases, we consider an online music retailer who offers one of three types of pricing strategies: per unit pricing with price $p_u$ (unit model) (Figure 2: Case 3), subscription pricing with an upfront price $p_s$ (subs model) (Figure 2: Case 4), or a mix with both per unit and subscription pricing offered (mixed model) (Figure 2: Case 5). Modeling of cases 3, 4, and 5 follows the same steps utilized in cases 1 and 2 above. For brevity, we do not repeat details, choosing instead to summarize in Table 2. We denote $d = \frac{\psi_{ONL\rightarrow ONI}}{\delta}$ and $e = \frac{p_u - \psi_{ONL\rightarrow ONI}}{(1 - \delta)}$.

**Table 2: Unit and Subs Models: Net Benefits and Search Costs**

<table>
<thead>
<tr>
<th>Consumer's net benefit from starting $n^{\text{th}}$ search in $ONI$ channel</th>
<th>Unit Model</th>
<th>Subs Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{v_j \in [0, c)} \psi_{ij}^{ONL, n} (v_j) + \psi_{ij}^{ONL, n} (v_j) (v_j - p_u) - \psi_{ONI}$</td>
<td></td>
<td>$\sum_{v_j \in [0, V_i^{\text{max}}]} \psi_{ij}^{ONL, n} (v_j) - \psi_{ONI}$</td>
</tr>
</tbody>
</table>

| Consumer's net benefit from starting $n^{\text{th}}$ search in $ONLG$ channel | | |
| --- | | |
| $\sum_{v_j \in [d, c)} \psi_{ij}^{ONL, n} (v_j) + \psi_{ij}^{ONL, n} (v_j) (v_j - p_u) - \psi_{ONLG} - \psi_{ONL\rightarrow ONI} \left( \sum_{v_j \in [d, c)} \psi_{ij}^{ONL, n} (v_j) \right)$ | | $\sum_{v_j \in [0, V_i^{\text{max}}]} \psi_{ij}^{ONL, n} (v_j) - \psi_{ONLG}$ |

| Initial lump sum payment to music seller | 0 | $p_s$ |
3.2 Retailer Revenue Implications under Proposed Models

Observation (2) from the BM model with piracy (Case 2) suggests that, since consumers search for and experience more music items compared to a no-piracy scenario (Case 1), it is arguable that consumers may purchase more under Case 2 if they find music of sufficient value. More interestingly, a unit model (Case 3) provides at least as much revenue as Case 2, leading to Result 1 (proof in Appendix I):

Result 1: Retailer revenues with the unit model weakly dominate the BM model with piracy.

In the mixed model, the retailer offers both a subscription service and an á la carte purchase option. A consumer who opts to subscribe obtains all her music via the retailer, while one who does not subscribe resorts to some combination of purchase á la carte and pirate. The following results formalizes the impact on retailer revenues (proof in Appendix I):

Result 2: Retailer revenues with the mixed model weakly dominate the unit and subs models.

3.3 Licensing Cost Structures and Retailer Profits

The marginal cost of physical reproduction of digital music is near zero. But there are licensing costs incurred by the retailer that may significantly affect overall profit. Wingfield and Smith (2003) reported that Apple pays 65 to 79 cents licensing fees for each 99 cents download it sells. In addition, in online music retailing, license contract structures have become quite flexible (Mitchener 2003, Wingfield and Smith 2003). With this in mind, our analysis considers three distinct cost structures: a) a lump sum payment ($c_{\text{lump-sum}}$) by retailer to music publisher based on the number of songs offered (N), b) a payment set as a percentage ($c_{\text{percent}}$) of overall retailer revenue (R), and c) a per-download fee ($c_{\text{per-download}}$) for a music item.
The retailer incurs the following costs: $N_{\text{lump-sum}}$ with (a) above; $R_{\text{percent}}$ with (b); and a fixed marginal cost per _download_ of $c_{\text{per-download}}$ with (c) every time a consumer downloads a music item (in _unit_, _subs_ or _mixed_ model). However, with (b), if a music item is sold on a per-unit basis, the retailer faces a fixed marginal cost per _download_ of $p_u c_{\text{percent}}$. If a subscription service is offered with (b), the retailer incurs a fixed marginal cost per _subscriber_ of $p_s c_{\text{percent}}$ per subscriber. Note that the license fees with (b) are independent of the number of downloads by a subscriber.

The following results highlight the profit implications of license structures (proofs in Appendix I):

**Result 3:** Retailer profits with the _mixed_ model weakly dominate the _unit_ and _subs_ models when the license structure is based on either (a) lump-sum payment or (b) percentage of retailer revenue.

**Result 4:** Retailer profits with the _mixed_ model weakly dominate the _subs_ models when the license structure is based on a per-download fee per music item.

Note that Result 3 continues to hold if the license structure to the music publisher is based on some combination of a lump-sum payment and a percentage of retailer proceeds. The above results indicate the importance of contract structures on the retailer pricing strategies. In particular, when the fees are based on the per-download structure, the pure subscription option becomes less viable. The retailer would only offer a per-unit option with the per-download licensing fee structure. This is because under a subscription option with a per-download licensing fee structure, a disgruntled or malevolent consumer could bankrupt the retailer by repeated downloads.

\footnote{An initial sample of 76 graduate students from three university classes was used to pilot and critique the survey form and scale items. Following feedback and survey revision, the survey was distributed to a new sample of 200 undergraduate and graduate students of a business school. We chose this group since young adults represent a considerable proportion of music listeners (Holbrook and Schindler, 2001) and comprise one of the key consumer groups where online music sharing appears to be prevalent. All respondents submitted completed surveys. Among the respondents, 61% were male, 15% were employed full-time and 54% part-time. The ages range from 19 to 54, averaging 23.}
3.4 Limiting the usability of legal downloads

Finally, we investigate retailer strategies of restricting the usability of legal downloads. This scenario currently plays out in the online music market. Retailers often place restrictions on the usage of legally downloaded music. For example, downloads from Apple’s iTunes service are only portable to Apple’s iPod player (Wingfield and Smith 2003). Various services place restrictions on the number of portable devices and copies allowed (Graham 2003). The underlying rationale appears to be that even if such restrictions cause inconvenience to paying consumers, they help in tackling the piracy problem. Because these restrictions make it more difficult for individuals to share music, the resulting lowered availability tends to increase search efforts necessary to find the music items on an illegal channel. In our modeling context, such restrictions have the following impacts: i) increase in value of $\delta$, and ii) increase in values of $\psi^{\text{ONI}}$ and $\psi^{\text{ONLG} \rightarrow \text{ONI}}$. We are motivated to ask whether a retailer’s strategy that increases the values $\psi^{\text{ONI}}$ and $\psi^{\text{ONLG} \rightarrow \text{ONI}}$ is beneficial even if it results in increasing the value of $\delta$.

Consider the unit model. The probability that a consumer purchases the music is dependent on the value of $e = \frac{p_a - \psi^{\text{ONLG} \rightarrow \text{ONI}}}{(1 - \delta)}$ (see §3.1.3). The lower the value of $e$, the higher the probability the consumer will purchase the music item (see Table 2). If the retailer places additional restrictions (i.e., increases the value of $\delta$ and $\psi^{\text{ONLG} \rightarrow \text{ONI}}$), there are positive profit implications as long as this results in a lower value of $e$ and consumers continue to search for the same or greater number of music items. In cases where both conditions hold, strategies such as placing restrictions on usage of legal music pay off even when they make pirated music more attractive. We provide further insights in §5.
In our analytical model (§3.1), one factor reflected in δ is the lower acoustic quality of music at illegal sites due to losses from compression technologies. In addition, we suggested that there is a perception by consumers that music items obtained from an illegal site are of lower quality. Here we provide validation for our use of δ.

A number of factors influence the acoustic quality of compressed music, including bitrate of the compressed file, compression algorithms, equipment utilized for compression and listening, and the user’s ability to discern various audio outputs. Amongst these, bitrate, which indicates how many bits are used to capture one second of music, is a widely utilized proxy for acoustic quality.

According to www.slyck.com, following is the mapping between bitrate and acoustic quality:

<table>
<thead>
<tr>
<th>Bitrate (kbps)</th>
<th>File Size (MB)</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>48</td>
<td>1.2</td>
<td>Poor</td>
</tr>
<tr>
<td>96</td>
<td>2.3</td>
<td>Tolerable</td>
</tr>
<tr>
<td>128</td>
<td>3.1</td>
<td>Good</td>
</tr>
<tr>
<td>160</td>
<td>3.9</td>
<td>Good</td>
</tr>
<tr>
<td>192</td>
<td>4.7</td>
<td>Very good</td>
</tr>
<tr>
<td>256</td>
<td>6.2</td>
<td>High</td>
</tr>
<tr>
<td>320</td>
<td>7.8</td>
<td>Near CD</td>
</tr>
<tr>
<td>Variable</td>
<td>4.8</td>
<td>Varies</td>
</tr>
</tbody>
</table>

Most common peer-to-peer networks report the bitrate of music files that are available for downloading. We monitored music files available on WinMX, a popular peer-to-peer network for 17 weeks, from October 28, 2002 to February 20, 2003, without exchanging any copyrighted materials. This included daily searches for songs that were in the top 100 albums on the weekly Billboard 200 chart. From 4.3 million music files observed, we found less than 10% were of the level considered “High” or “Near CD” in the www.slyck.com ratings (Table 3). The remaining (over 90%) had bitrates ranging from 96 kbps (tolerable) to 192 kbps (very good). These findings provide empirical support for our assumption relating to δ in an illegal network and its range.
To analyze consumer perceptions of quality at illegal sites, we conducted a survey study comparing the current sales environment (BM with piracy option). This setting represents the predominant existing model that majority of retailers use and is the one with which consumers are most familiar. While we took the opportunity to seek additional information not relevant to the present analysis, one specific question focused on respondent perceptions of comparative quality. The question of interest asked respondents for their perception, for the same music item, of the quality of an MP3 file (the typical online sharing format) relative to that of an original CD. The five choices available to the respondents and the corresponding responses are shown in Table 4.

Thus, both the observed quality at a major sharing site and the survey responses offer support for our assumption regarding $\delta$. Next, we report on a detailed set of experiments used to gain insights into emerging online music markets.

### 5. Simulation Analysis of Online Models

Here we investigate pricing and profit implications for consumers, music retailers and publishers, all of whom operate in a market that has piracy options. To gain additional insight into the three emerging online market models (unit, subs, and mixed) that are not yet widely available to consumers, we developed a series of simulation experiments to address each of the following questions: i) How do retailer pricing strategies differ under each of the three models? ii) How do

<table>
<thead>
<tr>
<th>Bit rate distribution (in bit-per-second, bps)</th>
<th>Percentage</th>
<th>Quality (from <a href="http://www.slyck.com">www.slyck.com</a>)</th>
</tr>
</thead>
<tbody>
<tr>
<td>96 bps</td>
<td>0.85%</td>
<td>Tolerable</td>
</tr>
<tr>
<td>128 bps</td>
<td>20.61%</td>
<td>Good</td>
</tr>
<tr>
<td>160 bps</td>
<td>5.66%</td>
<td>Good</td>
</tr>
<tr>
<td>192 bps</td>
<td>62.60%</td>
<td>Very good</td>
</tr>
<tr>
<td>256 bps</td>
<td>2.62%</td>
<td>High</td>
</tr>
<tr>
<td>320 bps</td>
<td>7.65%</td>
<td>Near CD</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Choices available</th>
<th>Response Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Almost the same</td>
<td>42.5%</td>
</tr>
<tr>
<td>Very good, but not the same</td>
<td>37.3%</td>
</tr>
<tr>
<td>Half as good</td>
<td>7.5%</td>
</tr>
<tr>
<td>Does not even compare</td>
<td>0.7%</td>
</tr>
<tr>
<td>Do not know</td>
<td>11.9%</td>
</tr>
</tbody>
</table>
licensing structures affect pricing and profits? ii) What is the piracy activity associated with maximum profit solutions? iii) What are the impacts of usage restrictions of legal downloads?

We simulated 100 consumers with $V_i^{\text{max}}$ randomly drawn over $U[1,100]$. The retailer offers 250 songs and an online piracy network exists and offers "pirated" copies of the same songs. Differing search cost ($\psi^{\text{ONLG}}$ and $\psi^{\text{ONI}}$) and quality of experience ($\delta$) values are as given in Table 5. As indicated in the table, we also simulated two scenarios where our assumption on search cost ordering was violated (i.e., $\psi^{\text{ONLG}} \geq \psi^{\text{ONI}}$). Each experimental design point required approximately 3 days to complete on dedicated racks of Intel Pentium III servers, for a total of 61,820,000 observations per experiment. We perform brute force solutions for the following information: i) maximum profit for each of the three models; ii) $p_u, p_s$, and $p_u$ and $p_s$ (as appropriate) for each profit maximizing solution; and, iii) piracy activity associated with each profit maximizing solution.

### Table 5: Simulation Parameter Settings

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Notation</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of search costs ($\psi^{\text{ONI}} = 1$)</td>
<td>$\psi^{\text{ONLG}} / \psi^{\text{ONI}}$</td>
<td>0.1, 0.2, ..., 1.0, and 1.2</td>
</tr>
<tr>
<td>Cost of switching channel</td>
<td>$\psi^{\text{ONLG} \rightarrow \text{ONI}}$</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>$\psi^{\text{ONI} \rightarrow \text{ONLG}}$</td>
<td>0</td>
</tr>
<tr>
<td>Quality of experience measure of pirated music</td>
<td>$\delta$</td>
<td>0.1, 0.2, ..., 0.9, and 0.95</td>
</tr>
<tr>
<td>Per-unit price</td>
<td>$p_u$</td>
<td>1, 2, ..., 20</td>
</tr>
<tr>
<td>Subscription price</td>
<td>$p_s$</td>
<td>100, 105, 110, ..., 1,500</td>
</tr>
</tbody>
</table>

As explained in §3, consumers are assumed to know that the online legal search channel is more efficient than the online illegal search channel (the former has incentives to compete on service, the latter does not). In our simulation, using the legal search service, the consumer would obtain a song randomly drawn from the top half of available songs, while the illegal search would yield a song from the top two-third of available songs. Once a song is chosen, that particular song is removed from consideration in subsequent searches, resulting in a diminishing expected return from both types of search as the number of searches increases.
For the \textit{unit} model, each consumer can start a search either through a legal or illegal channel or choose not to initiate a search. If the consumer eventually chooses to acquire the song from the legal channel, the revenue to the retailer would be $p_u$. For the \textit{subs} model, we calculate each consumer’s net benefit from subscription and piracy (according to Table 2), to determine which consumers would become subscribers. The consumer would subscribe if the expected benefit from subscription exceeds that from pirating, otherwise she would pirate. If she subscribes, the revenue to the retailer would be $p_s$. For the \textit{mixed} model, we compare each consumer’s benefits from subscription and from purchasing individual songs that would be acquired by the consumer. The consumer would choose to subscribe if the benefit from subscribing is positive and exceeds that from purchasing individual songs. If she chooses not to subscribe, she can either purchase or pirate individual songs. In this case, her decision becomes similar to that in the \textit{unit} model. She can also choose not to acquire any song at all if the expected benefits in all cases are negative. In subsequent discussion, we will only refer to the percent cost structure, since results will hold equally for the lump-sum cost structure. We will mainly contrast these with the per download fee cost structure.

Next, we discuss the main results and their implications for retailers. The complete set of results for each design point, and additional charts highlighting the results, are available at Bhattacharjee, et al (2003).

\section{Profit Implications}

Result 3 (§3.3) shows the \textit{mixed} model yields higher profit than \textit{unit} and \textit{subs} in most cases (under percent and lump-sum cost structures), and simulation results suggest that this is considerably impacted by the quality of experience ($\delta$). As $\delta \to 1$, the difference between the maximum profit from \textit{mixed} and \textit{subs} models decreases and the two converge, as consumers no
longer find it beneficial to purchase individual songs and those who can still benefit from making the purchase would only do so through subscription. Similar trends are observed for profits from mixed and unit models with respect to $\delta$, however the profits from the two models converge only at a high value of legal search cost ($\psi^{ONLG}$) (please see complete results in Bhattacharjee, et al, 2003).

The profit increase from the mixed model is derived from the retailer’s ability to fine tune the value of the per-unit ($p_u$) and subscription ($p_s$) prices. In many cases, the retailer can increase $p_s$ to extract additional revenue from subscribers while lowering $p_u$ to encourage non-subscribers to purchase individual songs (Figures 3 and 4). This non-intuitive mixed pricing policy shows significant difference from unit and subs pricing, especially at lower values of $\delta$. As before, a complete enumeration on price comparison can be found in Bhattacharjee, et al (2003).

5.2 Implications of License Structures

The licensing structure of an online music retailer with a publisher has a significant effect on the viability of different online models, in terms of prices charged to consumers and overall
profits generated. As Figure 5 illustrates, the ratio of $p_u$ for the unit model, with percent and per-
download cost structures, is always less than 1. This demonstrates that for the same net license
fees offered to the music publisher (cost to retailer), the optimal price under percent is lower than
the per download fee structure, with the difference increasing as $\delta$ increases. This implies that the
net benefit to the consumer is higher under the percent structure (for the same music item),
especially at high $\delta$ values. We also note that at high values of $\delta$ and $C_{\text{per-download}}$, the maximum
profit achievable by the retailer under per-download structure is 0. This leads to the truncated
graph at high values of $\delta$ and $C_{\text{per-download}}$. This implies that consumers are better off under percent
than per-download fee structures.

Turning towards retailer profits, we find profit under the percent structure weakly
dominates the per-download cost structure. Figure 6 depicts results for the unit model. Further,
we note that as $C_{\text{per-download}}$ increases, percent strictly dominates per-download. As $\delta$ approaches 1,
the difference in the maximum profit in the two cost environments becomes considerably more
distinct.

Hence profits are higher with a percent license structure than with a per-download
structure. This suggests that a bounded cost structure (lump-sum or percentage of revenue) is a
more viable option for consumers as well as retailers and music publishers, compared to an unbounded per-download fee structure. Also, given higher profit under percent, it is possible for a retailer to share the growing pie with a music publisher, with a win-win situation for all.

Retailer profits can be increased further by introducing the mixed model (per-unit as well as subscriptions). Figure 7 compares profits in the mixed model under percent with unit model under per-download structure. Comparing with Fig. 6, we note the significant difference in the profit ratios between the two environments. The result shows that with the same net payment to the publisher, the retailer can generate higher profit by using a percent cost structure while offering both subscription and per-unit pricing options.

5.3 Piracy Implications

We find that at the maximum profit prices, piracy levels are lower or similar with a percent structure than per-download fee, for the unit model (Figure 8). The piracy ratio shows similar patterns for different $C_{\text{per-download}}$ values, and the lower piracy benefit decreases with $\delta$. This directly flows from the previous discussion of prices charged to consumers. Lower prices lead more consumers to purchase than to pirate under the percent structure.
Further, the retailer’s profit maximizing position occurs in an environment with piracy activity above minimum levels (Table 6). In general, the retailer obtains higher profit under the mixed model than other models. However, the piracy level in the mixed model is higher than in the subs model in most cases (except those where when $\delta = 0.8$ and 0.95), while the piracy level in the mixed model ranges from 8% to 45% of the piracy level under the unit pricing model (except when $\delta = 0.95$). This demonstrates that retailer strategies that lower piracy do not necessarily increase profits.

**Table 6: Piracy Levels at Maximum Profit ($\psi^{ONLG} = 0.5$)**

<table>
<thead>
<tr>
<th>$\delta$</th>
<th>$PU$</th>
<th>Songs Bought</th>
<th>Songs Pirated</th>
<th>Profit</th>
<th>$PS$</th>
<th>Songs Pirated</th>
<th>Profit</th>
<th>$PS$</th>
<th>Profit</th>
<th>Subscribers</th>
<th>Songs Pirated</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>7</td>
<td>6,655</td>
<td>6,587</td>
<td>46,585</td>
<td>1,220</td>
<td>79,300</td>
<td>0</td>
<td>1,495</td>
<td>5</td>
<td>83,970</td>
<td>50</td>
</tr>
<tr>
<td>0.2</td>
<td>6</td>
<td>6,951</td>
<td>6,364</td>
<td>41,706</td>
<td>1,190</td>
<td>71,400</td>
<td>89</td>
<td>1,500</td>
<td>5</td>
<td>78,145</td>
<td>45</td>
</tr>
<tr>
<td>0.3</td>
<td>6</td>
<td>6,136</td>
<td>7,264</td>
<td>36,816</td>
<td>975</td>
<td>63,375</td>
<td>0</td>
<td>1,285</td>
<td>4</td>
<td>68,999</td>
<td>47</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>6,351</td>
<td>7,066</td>
<td>31,755</td>
<td>845</td>
<td>54,925</td>
<td>172</td>
<td>1,170</td>
<td>3</td>
<td>60,078</td>
<td>44</td>
</tr>
<tr>
<td>0.5</td>
<td>4</td>
<td>6,664</td>
<td>6,779</td>
<td>26,656</td>
<td>725</td>
<td>47,125</td>
<td>678</td>
<td>1,005</td>
<td>3</td>
<td>50,823</td>
<td>43</td>
</tr>
<tr>
<td>0.6</td>
<td>3</td>
<td>7,215</td>
<td>6,237</td>
<td>21,645</td>
<td>605</td>
<td>39,325</td>
<td>0</td>
<td>785</td>
<td>2</td>
<td>42,037</td>
<td>47</td>
</tr>
<tr>
<td>0.7</td>
<td>2</td>
<td>8,155</td>
<td>5,318</td>
<td>16,310</td>
<td>480</td>
<td>31,200</td>
<td>503</td>
<td>645</td>
<td>2</td>
<td>32,900</td>
<td>44</td>
</tr>
<tr>
<td>0.8</td>
<td>2</td>
<td>5,630</td>
<td>7,875</td>
<td>11,260</td>
<td>360</td>
<td>23,400</td>
<td>829</td>
<td>390</td>
<td>1</td>
<td>24,252</td>
<td>59</td>
</tr>
<tr>
<td>0.9</td>
<td>2</td>
<td>3,178</td>
<td>7,168</td>
<td>6,356</td>
<td>240</td>
<td>15,600</td>
<td>0</td>
<td>240</td>
<td>1</td>
<td>15,820</td>
<td>65</td>
</tr>
<tr>
<td>0.95</td>
<td>1</td>
<td>2,472</td>
<td>11,032</td>
<td>2,472</td>
<td>170</td>
<td>11,730</td>
<td>0</td>
<td>170</td>
<td>1</td>
<td>11,730</td>
<td>69</td>
</tr>
</tbody>
</table>

Further, the retailer’s profit maximizing position occurs in an environment with piracy activity above minimum levels (Table 6). In general, the retailer obtains higher profit under the mixed model than other models. However, the piracy level in the mixed model is higher than in the subs model in most cases (except those where when $\delta = 0.8$ and 0.95), while the piracy level in the mixed model ranges from 8% to 45% of the piracy level under the unit pricing model (except when $\delta = 0.95$). This demonstrates that retailer strategies that lower piracy do not necessarily increase profits.
To evaluate whether there exist conditions under which the retailer reaps higher profit in the complete absence of piracy, we considered the base case scenario (Case 1) where the music retailer operates in a world without a music piracy option for consumers. Here, the brick-and-mortar retailer is assumed to offer a search channel whose efficiency is identical to the online legal music channel, and $\psi^{BM}$ ranges from 0.1 to 1.2, in increments of 0.1. At the completion of each search in the no-piracy scenario, the consumer either purchases the music item at a price of $p_u$ or decides to not purchase the item. Figure 9 presents a comparison of profits in the no-piracy base case with the mixed model with piracy option. For lower values of $\delta$, presence of piracy yields higher profits, even when search efficiency and search costs are identical. Interestingly the cutoff point for $\delta$ below which the piracy option dominates increases as the search cost decreases.

### 5.4 Limiting Usability of Legal Downloads

As discussed in §3.4, retailer strategies that limit usability of legal downloads lower the likelihood of piracy and increase search cost on illegal channels. It might also increase value of illegal downloads ($\delta$) due to their portability and absence of restrictions. The tradeoff between $\delta$ and $\psi^{legal}/\psi^{illegal}$ for various retailer revenues is shown in Figure 10. If $\delta$ increases, in order for the retailer to maintain the same level of profit, the ratio of legal channel to illegal channel search costs must decrease. At a low value of $\delta$ ($\delta<0.4$), the search cost ratio must decrease at approximately a rate of 10 times the change in $\delta$ for the retailer to realize the same profit level. As $\delta$ becomes greater than 1, the search cost ratio must decrease at a rate of about 2 times the increase in $\delta$ to remain on the same iso-profit curve. Figure 10 shows that each iso-profit curve spans a limited range of $\delta$. Thus, restriction strategies that increase $\delta$ by any significant amount may push the retailer to a lower iso-profit curve, since even a major decrease in the search cost ratio cannot
compensate sufficiently.

In summary, we show:

i) the mixed online distribution model for digital music generally dominates the unit and subs models,

ii) retailer profits are significantly affected by quality of experience, search costs and license structures,

iii) lower piracy levels do not necessarily translate into higher profits for retailers for various traditional and online models, and

iv) restrictions on the usability of legal downloads is likely to result in lower profits.

6. Concluding Remarks

New opportunities and potential benefits of advances in Internet connectivity are juxtaposed against challenges for retailers of digital goods. Here we modeled and analyzed alternative market channels for one type of digital experience good, music. We offered models for five different market environments that a retailer may choose to operate in. We developed a search model for consumers seeking music items digitally in different channels, which incorporates channel switching strategies. We derived a variety of implications for the differing
environments, and provided validation for “quality of experience” ($\delta$), a key modeling construct for pirated music items. Finally, results from extensive simulations are presented to offer insights for emerging music markets.

Our results indicate that decreasing piracy does not necessarily imply increasing profits. Rather, maximum profit outcomes occur in the presence of piracy. Seeking regulatory means to stop piracy is likely to be a self-harming strategy. Part of access to unauthorized networks enabling music sharing may well be pre-purchase sampling, an activity aiding consumers to make better purchases. Our analysis also suggests that online music sales is a dominant strategy for retailers. Restrictions on copying and sharing of legally downloaded music items may deter piracy and increase search and sampling cost, but will also increase the value of unrestricted downloads from illegal networks. The tradeoff suggest that such restrictive policies do not increase profits in the long run.

Our results also indicated that the **mixed** model, where a consumer can either subscribe or purchase music *ala carte* is the dominant strategy for the retailer. The dominance of the **mixed** strategy continues to hold even when the search cost in the legal channel exceeds that in the illegal channel. License fee structures with music publishers is a significant factor affecting pricing and overall profits. We show that a lump-sum or percent of revenue payment model dominates a per-download cost structure, suggesting a need for new licensing models for online music sales.

Various companies, including Apple, Roxio, Musicmatch, Wal-Mart, SONY and Microsoft, have or are planning online music services. Our analysis suggests that some of them may be missing a dominant strategy - the **mixed** strategy. As we continue to study online digital markets and the impact of piracy, the long-term viability and popularity of such market offerings will always be of great interest as a complement of our theoretical results. Online music retailing
is a challenging enterprise. Our goal here has been to initiate a formal analysis of alternative pricing and licensing structures. Technology has forever changed the way consumers sample and procure music items. Competitive advantage is the golden ring awaiting retailers who can understand the new landscape and adapt appropriately.

Appendix: Proofs

**Proof of observation 1**: Note that the cost incurred for performing a search in the $BM$ model with piracy is lower than in the *base* model. This follows from the inequality below. Considering the expected benefit from the $n^{th}$ search at $BM$, we have:

$$\sum_{v_y \in [a,b]} \delta_{v_y} \phi^{BM,n}_{v_y}(v_y) + \sum_{v_y \in [b,V^\text{max}_y]} \phi^{BM,n}_{v_y}(v_y)(v_y - p_u)$$

$$= \sum_{v_y \in [a,b]} \delta_{v_y} \phi^{BM,n}_{v_y}(v_y) + \sum_{v_y \in [b,c)} \phi^{BM,n}_{v_y}(v_y)(v_y - p_u) + \sum_{v_y \in [c,V^\text{max}_y]} \phi^{BM,n}_{v_y}(v_y)(v_y - p_u)$$

When $b \leq v_y \leq c$, then $\delta_{v_y} \leq v_y - p_u$. Therefore,

$$\sum_{v_y \in [0,V^\text{max}_y]} \phi^{BM,n}_{v_y}(v_y) \text{Max}\{\delta_{v_y}, v_y - p_u\} \leq \sum_{v_y \in [0,V^\text{max}_y]} \phi^{ON,\text{int},n}_{v_y}(v_y) \text{Max}\{\delta_{v_y}, v_y - p_u\}$$

Further the expected benefit from each search outcome is higher in $BM$ with piracy compared to *base* (without piracy) as

$$\sum_{v_y \in [0,V^\text{max}_y]} \phi^{BM,n}_{v_y}(v_y)(v_y - p_u) < \sum_{v_y \in [0,V^\text{max}_y]} \phi^{BM,n}_{v_y}(v_y) \text{Max}\{\delta_{v_y}, v_y - p_u\}$$

**Proof of Result 1**: Note that in the $BM$ model with piracy (Case 2), consumers initiate each search at the illegal channel. Consider the *unit* model. If all consumers initiate each search at the illegal channel, then the expected benefits and search costs are identical to $BM$ (Tables 1 and 2). Thus, the seller’s expected revenues are identical in this case. Now consider the conditions under which a consumer initiates a search at the legal channel. This occurs when
\[
\sum_{v_y \in \{d, u\}} \delta_{v_y}^{\text{ONLG}} (v_y) + \sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONLG}} (v_y) (v_y - p_u) - \psi^{\text{ONLG}}(\sum_{v_y \in \{d, u\}} \delta_{v_y}^{\text{ONLG}} (v_y)) > \\
\sum_{v_y \in \{d, u\}} \delta_{v_y}^{\text{ONI}} (v_y) + \sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONI}} (v_y) (v_y - p_u) - \psi^{\text{ONI}}
\]

The above can be recast as follows.

\[
\sum_{v_y \in \{d, u\}} \phi_{v_y}^{\text{ONLG}} (v_y) \max \{\delta_{v_y}, v_y - p_u\} - \sum_{v_y \in \{d, u\}} \delta_{v_y}^{\text{ONLG}} (v_y) - \sum_{v_y \in \{e, c\}} \delta_{v_y}^{\text{ONLG}} (v_y) + \\
\sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONLG}} (v_y) (v_y - p_u) - \psi^{\text{ONLG}}(\sum_{v_y \in \{d, u\}} \delta_{v_y}^{\text{ONLG}} (v_y)) > \\
\sum_{v_y \in \{d, u\}} \phi_{v_y}^{\text{ONI}} (v_y) \max \{\delta_{v_y}, v_y - p_u\} - \psi^{\text{ONI}}
\]

Rearranging, we have

\[
\sum_{v_y \in \{0, c\}} \phi_{v_y}^{\text{ONLG}} (v_y) \max \{\delta_{v_y}, v_y - p_u\} - \sum_{v_y \in \{0, c\}} \phi_{v_y}^{\text{ONI}} (v_y) \max \{\delta_{v_y}, v_y - p_u\} + \\
\sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONLG}} (v_y) (v_y - p_u) + \psi^{\text{ONI}} - \psi^{\text{ONLG}} > \\
\sum_{v_y \in \{0, d\}} \delta_{v_y}^{\text{ONLG}} (v_y) + \sum_{v_y \in \{e, c\}} \delta_{v_y}^{\text{ONLG}} (v_y) + \psi^{\text{ONLG}} - \psi^{\text{ONI}}(\sum_{v_y \in \{d, u\}} \phi_{v_y}^{\text{ONLG}} (v_y))
\]

The LHS in the above inequality is strictly positive. The RHS is monotonically decreasing in \(V_i^{\max}\).

Thus, there exists a \(V^*\) such that a consumer with \(V_i^{\max} \geq V^*\) will initiate at least one search on the legal channel. The probability that a consumer who initiates the search on the legal channel would subsequently purchase \(\sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONLG}} (v_y)\) is higher than when the consumer initiates the search at the illegal channel \(\sum_{v_y \in \{e, c\}} \phi_{v_y}^{\text{ONI}} (v_y)\). QED.

**Proof of Result 2:**

Proof that seller revenues with mixed model weakly dominate the subs model: Consider a seller who offers a subscription service at a price of \(p_s\). In this case, consumers either subscribe and procure all the music items legally, or obtain all the music items illegally. Now suppose that the
seller offers music on a per unit basis and sets \( p_u = p_s \). Clearly, no rational consumer will purchase on a per unit basis at this price. The number of subscribers and the seller revenues will be identical to the case of the \textit{subs} model. As \( p_u \) is lowered below \( p_s \), the incentive for subscribers to switch to purchasing on a per-unit basis increases. Let \([\bar{\sigma}, p_s]\) denote the price range for \( p_u \) in which all current subscribers continue to subscribe. If some of the individuals who only pirate music in the \textit{subs} model purchase some music from the legal seller when \( p_u = \bar{\sigma} \), then the seller is strictly better off by setting the per unit price at \( \bar{\sigma} \). Otherwise, she is no worse than in the \textit{subs} model. \textbf{QED.}

Proof that seller revenues with \textit{mixed} model weakly dominate the \textit{unit} model: Consider a seller who offers music at a per unit basis with a price of \( p_u \). Let \( V^* = \text{Max}\{V_i, \forall i\} \). It follows that \( (p_u N^{\text{unit}}(V^*)) \) is the maximum per-customer expected revenue to the seller. Now suppose that the seller also offers a subscription option and sets a value of \( p_s \) such that \( p_s > p_u N^{\text{unit}}(V^*) \). If none of the customers opt for the subscription service, the seller is no worse off. The seller revenues from each customer who subscribes are strictly higher than in the unit model. \textbf{QED.}

\textbf{Proof of Result 3:} Let \( R \) and \( \Pi \) denote the retailer’s revenues and profit, respectively. In the lump sum payment structure, we have \( \Pi = R - Nc_{\text{lump-sum}} \). In the percentage payment structure, \( \Pi = R(1-c_{\text{percent}}) \). For given values of \( N, c_{\text{lump-sum}} \) and \( c_{\text{percent}} \), strategy that maximizes revenues also maximizes profits. Result 2 shows that the mixed model weakly dominates the unit and subs model for seller revenues. \textbf{QED.}

\textbf{Proof of Result 4:} Consider the analysis of Result 2 when the retailer offers a subscription service at a price of \( p_s \). If the retailer offers a \textit{per-unit} option, let \([\bar{\sigma}, p_s]\) denote the price range for \( p_u \) in
which all current subscribers continue to subscribe. If there exists a value of $p_u$ such that

$$p_u > c_{\text{fixed}} \quad \text{and} \quad \bar{p} \leq p_u \leq p,$$

and if at least one individual who only pirates music in the \textit{subs} model now purchases some music legally at $p_u$, the retailer profits are strictly higher. Otherwise, the retailer is no worse off. \textbf{QED.}

\section*{References}


