Economic of Online Music

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ABSTRACT
Novel online file sharing technologies have created new market dynamics for the online distribution of *digital goods*. But the new potential benefits for consumers are juxtaposed against challenges and opportunities for sellers of such goods. Here we investigate one type of digital experience good, music, whose markets include the presence of piracy options. We present five different pricing models running from a base case of a traditional brick and mortar retailer not facing a piracy option to an online retailer offering per unit and subscription pricing but facing piracy alternatives. In addition, simulation results are presented as a vehicle to develop insights related to the model implications on revenue-maximization and piracy conditions.

Keywords
Online Consumer Behavior, Piracy, Retail Channels, Experience Goods, Digital Goods, Emerging Technologies

I. INTRODUCTION
Emerging technologies of online distribution of digitized goods have created opportunities and potential benefits for consumers to share the products they own with others. Consumers can take advantage of online technology to share or download documents, including digitized images, magazine articles, software, and music. However, it has become much more difficult for producers and sellers of such goods to track and control their distribution. The music industry is one such business sector that has been dramatically affected by the online sharing phenomenon.

Music is a pure *information* good, and specifically an *experience* good (Nelson 1970) whose true value is realized only after its consumption. For a typical *experience* good, a consumer makes a purchase decision with imperfect information about the true value of the product. Emerging online technologies like computer networks and digital compression technology are creating challenges for the traditional music business, where consumers have typically experienced music after its purchase. Now, music listeners can sample music online before making a purchase decision. This wide availability of music online has reportedly led to piracy and reduced sales. The music industry has attempted to counter this online piracy phenomenon (Clark 2000). However, the fast-paced evolution of the file sharing technology makes this a difficult challenge (Chmielewski 2001).

Supporters of online music sharing consider it a novel marketing and distribution tool. According to one study, a significant 59% of consumers who listened to music from illegal online sources subsequently made a purchase (Matthews 2000). Additionally, some music enthusiasts claim that file sharing can help facilitate an efficient market by enabling "new" artists to market and distribute their products to music fans at a modest cost. This would potentially help propel competition among musicians, which in turn would benefit the consumers and the market as a whole.

Studies have suggested that online delivery of legal music items is a viable alternative (Bhattacharjee, et al.). Trends in the music business have incorporated online music stores and are continuing to include subscription services. Most online music services mirror almost the same pricing structures as traditional brick-and-mortar stores. Consumers select and then pay a per-unit price for a music item. It is not clear whether such pricing and services provide an optimal return for both buyers and sellers.

The focus of this research is on analyzing the revenue and piracy implications of legal online music offerings. We consider the following online models: i) per unit sales of digital music items, ii) subscription service, and iii) a mixed service incorporating both per unit and subscription choices, and study consumer purchasing and pirating behavior under these selling strategies. We employ analytical modeling and simulation analysis to evaluate different scenarios. Important propositions derived from the analysis are:

i) offering music online is always beneficial to a legal seller, as it enables them to compete more effectively with illegal networks,

ii) as the quality of illegal online music approaches that of the legal service, revenues from the per unit service becomes less than that from subscription as well as mixed service, and

iii) on a legal online music service, as the search cost to find unheard music decreases substantially, a subscription service provides the highest overall social welfare among all the strategies.

The remainder of the paper is organized as follows. Section II gives an overview of related research. In Section III, we present five different pricing and service strategies. Section IV includes empirical results from computer simulations that provide further insights. Conclusions from the study form the subject of Section V.

II. LITERATURE REVIEW

Existing studies on experience goods, shared goods, price discrimination and consumer search process form the basis of our modeling and analysis. However, existing theories underlying these research streams chiefly assume physical goods or locations such that sharing or redistribution is not easy, unlike in online digital music sharing. We provide a review of the related research and highlight similarities and differences with our online market model.

Studies have been conducted on experience goods in a traditional market setting [see for example Gale 1994, Liebeskind 1989, Oi 1971, Riordan 1986, Chapiro 1983]. These studies, however, do not address the issue of considerable redistribution of products among consumers, a situation quite unique in our research setting.

Research on the economics of shared goods usually focuses on products where piracy or private sharing is among a small group of consumers. Ordover (1978) proposes a framework for pricing strategies of technical journals. The framework is based on separated but linked markets, such that institutional customers, such as public libraries, act as intermediate purveyors and share the products with individual readers. However, the study does not address the concept of sharing among individual readers. Glazer and Hassin (1982) show that subscription mechanism can be used to price discriminate and increase a firm's profits, and that the firm would obtain larger profits if consumers were imperfectly informed. The assumption again was that consumers do not share a copy of their journal among themselves.

Another important aspect of our research deals with the prevalence of music piracy. Unlike computer software, music is much easier to copy and disseminate. A digital music file is much smaller than computer software and requires much less resources. While many studies in software piracy have examined consumer decisions to purchase or pirate the product [Conner and Rummelt 1991, Gopal and Sanders 1997, 1998, 2000], several key parameters distinguish music from software. The quality of music is better in an original CD than in a compressed file. Thus, the utility level of pirated online music can be reduced, whereas a pirated software application, once properly installed, would be as functional as its original copy. Also, the average price of music is much lower than that of commercial software, which may decrease the consumer perception that music piracy is an illegal activity (Gopal, et al 2002).

The large volume of music introduces another unique aspect in that consumers may need to conduct searches for the music items they wish to obtain. This search process and cost is different from the typical search in existing literature. The classic reference on traditional search cost (Stigler 1961) defined the term "search" as an attempt by consumers to "ascertain the most favorable price", a definition extensively adopted. A volume of literature exists on studying the problem of consumer search for lower prices (Gastwirth 1976). Nelson (1970) extended the concept to include consumer searches for information about the quality of products. Here, two special types of products, *experience* and *search* goods, were studied. Telser (1979) studied a search process by imperfectly informed consumers in a market offering "various combinations of price and quality". However, the search cost in our problem is significantly different. For a music consumer, searching and finding a particular artist or album that he likes is no guarantee that the next album by the same artist would be likeable to him. Each piece of music contains its own unique characteristics, and this variability forces the consumer to perform additional searches for additional products.

In the next section, we investigate different scenarios to extend existing theory on digital experience goods in an online environment.

III. ANALYTICAL MODEL OF MUSIC MARKET ENVIRONMENT

Recorded music can be accessed and stored digitally and must be heard to be valued. We first model the consumer behavior in the music market. We set forth our assumptions about the consumers and the process they follow to identify music items to purchase or to pirate. Each of our models assume the following:
i) there are non-trivial costs to search, evaluate and obtain music; and
ii) there are opportunities for consumers to pirate music from online sources.

We define each search as a process that yields a new and a unique music item that is experienced. Our search process involves a consumer that may decide to purchase or pirate a number of music items. Each search involves a consumer searching for, identifying, and experience one 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.

In our setting, searches are uncertain activities. Because the product on which we focus, music items, are experience goods, a consumer can attach individual consumer value only after listening to an item. In addition, the volume of commercially available music is vast (over 27,000 new albums are released every year (Goodley, 2003)). We assume that the set is sufficiently large that no consumer can be aware of all music items available. The limiting case for a consumer is where that individual consumer somehow knows a set of music items and has sufficient knowledge so that uncertainty is zero.

Each search involves processing against 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 on a *traditional* channel and either purchase or do nothing. Let the search cost for this traditional channel be ψ^{BM}.

Illegal: The consumer performs the search online at a site that is considered by the legitimate seller to be an illegal source. They are illegal because consumers can download a copy of the music item for free, without authorization from the seller. A consumer can search on an *illegal* channel and download and keep the illegal version. We hereafter refer to this online illegal channel as *ONI* and the search cost as ψ^{ONI}.

Legal: This online channel is setup by a legitimate seller (referred to as *ONLG* hereafter). The seller allows consumers to sample, evaluate and purchase music legally. A consumer can search on a *legal* channel and either purchase or do nothing. Let the search cost be ψ^{ONLG}.

Notice that a consumer can pirate music only from the illegal channel but can purchase music from either the traditional (*BM*) or the legal online (*ONLG*) channels. Based on experience and the nature of the channels, we make the following assumptions on the search costs for a search on each of the three available channels:

$$\psi^{BM} > \psi^{ONI} > \psi^{ONLG}$$

Of course, a consumer can perform a search on one channel and then move to another channel to procure the music item. We summarize our representation of such two-stage searches as follows:

1. The consumer first performs a search and evaluates the music on a traditional channel incurring a cost of ψ^{BM}. The consumer then goes to the illegal channel, searches and downloads an illegal version of the same song, incurring a cost of $\psi^{BM\to ONI}$. The cost for this two-stage search would be $\psi^{BM} + \psi^{BM\to ONI}$;
2. The consumer first searches and downloads an item of music on an illegal channel, incurring a cost of ψ^{ONI}. The consumer then goes to a traditional channel, searches for, and purchases a legal copy of the same music item, incurring a cost of $\psi^{ONI\to BM}$. The cost for the two-stage search would be $\psi^{ONI} + \psi^{ONI\to BM}$;
3. The consumer first searches and downloads a music item on an illegal channel. The consumer then goes to a legal online channel, searches for, and purchases a legal copy of the music item, incurring a cost of $\psi^{ONI\to ONLG}$. The cost for the two-stage search would be $\psi^{ONI} + \psi^{ONI\to ONLG}$; and,
4. The consumer first searches a music item on a legal channel and then goes to the illegal channel to download an illegal version of the same music item. The cost for the two-stage process is $\psi^{ONLG} + \psi^{ONLG\to ONI}$.

Moreover, we make the following assumptions about search costs:

1. $\psi^{ONI\to BM} = 0$ and $\psi^{ONI\to ONLG} = 0$; that is, once a consumer has identified a piece of music using the illegal channel, no meaningful search is required when switching to and using the traditional or legal online channels;
2. $0 < \psi^{BM\to ONI} \leq \psi^{ONI}$; that is, a customer having the information gathered in a given search at the traditional channel is more efficient when switching to the illegal channel than she would be if making the same search at the illegal site without benefit of the search at the traditional channel; and,
3. $0 < \psi^{ONLG\to ONI} \leq \psi^{ONI}$; that is, a customer having the information gathered in a given search at the legal online channel is more efficient when switching to the illegal channel than she would be if making the same search at the illegal site without benefit of the search at the legal online channel.

Our rationale for these three assumptions is that services offered by the traditional and online channels (legal sellers) are not available at illegal networks that are based on a peer-to-peer concept. The effort required to locate the song in illegal networks are borne completely by the user. There is little incentive on such networks to expend funds developing and implementing efficient search procedures to enhance customer service. Once a user has learned about a music offering (from either channel), it is easier to procure that song legally than illegally.

We assume that each consumer, *i*, has a range of values that they would place on the music items under consideration. The range runs from a minimum of zero to the individual *i*'s maximum value, V_i^{max}, for any music item offered by the seller. In the models that follow, V_i^{max}, is utilized in modeling consumer choices and subsequent actions (search and/or purchase in multiple channels). We use the following notation:

v_{ij} = value that consumer *i* places on music item *j* (after experiencing) where $0 \le v_{ij} \le V_i^{max}$

Thus v_{i1} is the lowest value that consumer *i* would assign to a music item (typically, but not necessarily, 0). This probability distribution of values, not known a priori (before experiencing items) by the consumer, is denoted:

I. $$\sum_{v_{ij}=0}^{V_i^{\max}} \phi_{ij}^{\wedge,n}(v_{ij}) = 1,$$ where Λ denotes the channel (*BM*, *ONLG*, or *ONI*) in which the n^{th} search is being conducted.

We also assume that within a given channel, searches have decreasing expected values as *n* increases.

We also allow differential utility of a music item if it is obtained legally versus illegally based on a lower "quality of experience". To represent this in our model, we use the symbol δ as a multiplier ($0 \le \delta \le 1$) if the music item is procured illegally. That is, we assume that, in comparison to a legally purchased copy of a music item, an illegally downloaded version provides diminished value. The factor δ can be viewed as capturing:

a) lower quality of music at illegal sites due to compression technologies;

b) value-added services that a legal seller might offer that are not offered at illegal sites; and

c) the fact that a user is undertaking an illegal activity.

Our search process can be summarized as follows: At any point in time, there are a finite number of music items to be searched. Each consumer is able to place a value (a utility value) on an item of music after experiencing (listening to) it. For any search, these values can be ordered and would lie in the range from zero to the maximum value the individual is willing to assign to any music item in the set searched. Searches can range in effectiveness from pure random draws to outcomes weighted heavily toward music items with high values. Search repetitions occur without replacement. 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:

II.. for early searches (low values of *n*):

$$\sum_{v_{ij}=0}^{V_i^{\max}} v_{ij}\phi_{ij}^{ONLG,n}(v_{ij}) > \sum_{v_{ij}=0}^{V_i^{\max}} v_{ij}\phi_{ij}^{ONI,n}(v_{ij}) > \sum_{v_{ij}=0}^{V_i^{\max}} v_{ij}\phi_{ij}^{BM,n}(v_{ij})$$

However, 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 II occur. The rest of this section discusses five alternative cases as illustrated in Figure 1.

Case 1: Base model with brick-and-mortar retailer and no online piracy

In this setting, consumers may obtain music items only from the retailer who offer a per-unit pricing, p_u, for each item of music (Figure 1: Case 1). Obviously, in this situation, the consumer would initiate a search only if the expected benefit from the first search exceeds the cost of search, ψ^{BM}. In addition, the consumer would continue the search process as long as the expected benefit from the next search remains higher than the search cost.

Case 2: "BM" model with brick-and-mortar retailer and online piracy option

Our second case still involves a traditional brick-and-mortar retailer but includes an online illegal channel network. The consumer who wishes to search music items can start the search process from either the *BM* channel or the *ONI* channel. Again, if the search costs exceed the expected value of searching, no search would occur (Figure 1: Case 2).

Consider first a consumer whose V_i^{max} is sufficient to justify at least one search. Suppose that this consumer is at the starting point of an arbitrarily numbered n^{th} search and the consumer starts this search process at the illegal channel, incurring a search cost of ψ^{ONI}.

The subsequent behavior of the consumer depends on the value, v_{ij}, to the consumer of the music item experienced at the end of the n^{th} search. The three consumer choices and the net benefits are as follows: 1) switch to traditional channel and buy: $v_{ij} - p_u - \psi^{ONI \to BM} = v_{ij} - p_u$; 2) pirate: δv_{ij} ***<u>or</u>*** 3) do nothing: 0

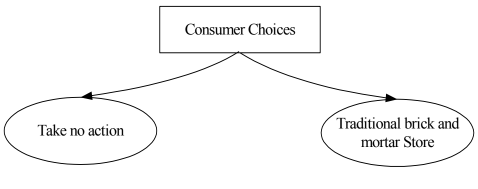
If a consumer starts a search at the traditional channel, the consumer incurs a search cost of ψ^{BM}. The subsequent behavior of the consumer depends on the value, v_{ij}, of the music item the consumer experienced at the end of the n^{th} search. The consumer choices and the net benefits are as below:

1) buy from traditional channel: $v_{ij} - p_u$; 2) pirate: $\delta v_{ij} - \psi^{BM \to ONI}$ ***<u>or</u>*** 3) do nothing: 0

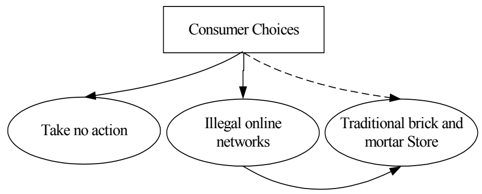
Cases 3, 4, and 5 -- Online Retailer facing piracy option and offering per unit pricing (Case 3), subscription pricing (Case 4), or both (Case 5)

In these three cases, we consider an online music seller who can choose one of three types of pricing strategy: per unit pricing with price denoted as p_u (***unit*** model), subscription pricing with price denoted as p_s (***subs*** model), or a mix with both per unit and subscription pricing offered (***mixed*** model). Modeling

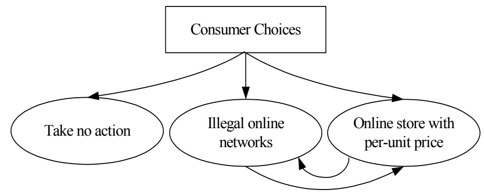
Figure 1: Consumer Choices under Different Selling Strategies



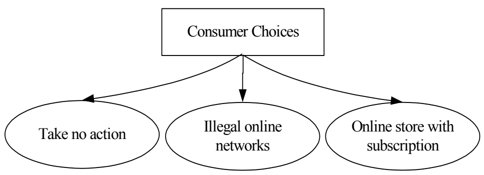
Case 1: Consumer Choices in Base Model (*Base*)



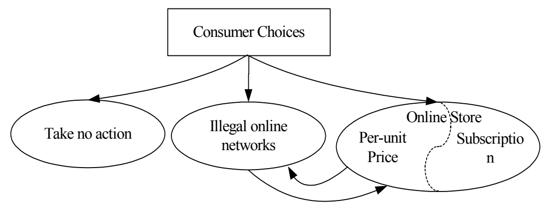
Case 2: Consumer Choices in Brick-and-Mortar Model (*BM*)



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*)

of cases 3, 4, and 5 follows the same steps utilized in cases 1 and 2 above.

In the case of the ***mixed*** model, the seller offers both a subscription service and an option to purchase music items individually. A consumer who opts to subscribe obtains all her music via the music seller. A consumer who does not subscribe, resorts to some combination of *purchase á la carte* and pirate options.

IV. SIMULATION

To gain additional insight into the three emerging online pricing models (***unit***, ***subs***, and ***mixed*** models) presented in Section III above, we completed a series of simulation experiments structured to address the impacts of quality of experience and search costs and pricing options on revenues and piracy activity

Our design is as follows. We generated 100 simulated consumers with different values of V_i^{max} randomly drawn from a uniform distribution over the interval [1,100]. Our music seller offers 250 songs and an online piracy network exists and offers "pirated" copies of the same songs. Differing search cost values (ψ^{ONLG} and ψ^{ONI}) and quality of experience values (δ) are shown in Table 1. In each experiment, we perform three brute force solutions for revenue maximization under the *unit*, *subs*, and *mixed* pricing models to determine the revenue maximizing pricing values (p_u, p_s, and combination of p_u and p_s) and the piracy level or activity associated with each solution of the three pricing option alternatives.

Each brute force solution required approximately 3 machine days to complete with each experiment (design point) yielding a total of 61,820,000 observations per experiment, taking up approximately 20 gigabytes of hard drive space.

Table 1: Simulation Parameter Settings

Parameter	Notation	Values
Illegal search cost	ψ^{ONI}	*1*
Ratio of search costs	ψ^{ONLG} / ψ^{ONI}	*0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, and 1.2*
Cost of switching channel	$\psi^{ONLG \rightarrow ONI}$	*0.2*
	$\psi^{ONI \rightarrow ONLG}$	*0*
Quality of experience measure of pirated music	δ	*0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 0.95*
Per-unit price	p_u	*1 to 20 with 1 unit increment*
Subscription price	p_s	*100 to 1,500 with 5 unit increment*

IV.1 Simulation Results

The simulation results show that the *mixed* pricing model yields higher revenue than *unit* and *subs* in most cases and that this benefit from the *mixed* pricing model is considerably impacted by the quality of experience (δ). We found that as δ increases, the revenue benefit from employing the mixed pricing model diminishes. Figure 2 is a result where $\psi^{ONI} = 1$, $\psi^{ONLG} = 0.5$, and $\psi^{ONLG \rightarrow ONI} = 0.2$ with varying values of δ. As shown on the chart, the difference between the maximum revenues from the mixed and subs pricing models decreases and the two converge as the $\delta \rightarrow 1$. We also observe that as $\delta \rightarrow 1$, the results from the *mixed* pricing model become similar to those from the *subs* pricing model as the 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.

When comparing the difference between the revenues from the *mixed* and *unit* pricing models, we observe similar trends with respect to the differing values of δ. However, the revenues from the two pricing models converge only at a high value of ψ^{ONLG}. In Figure 3, we also see that, as the value of δ increases, the *subs* pricing model becomes the least profitable strategy for the seller who is unable to provide efficient search services (as reflected in a high value of $\psi^{ONLG} = 1.2$).

Further, the results show that under the *mixed* pricing model, the seller can adjust the value of the per-unit (p_u) and subscription (p_s) prices to increase revenue. In many cases, the seller can increase p_s to extract additional revenue from subscribers while lowering p_u to encourage non-subscribers to purchase individual songs. Figures 4 and 5 highlight this pricing policy difference in the *mixed* pricing model with varying values of δ. We also observe that this pricing policy difference is more significant at lower values of δ. Among the results, we find only one exception to this price discrimination effect where p_u in the *unit* pricing model is lower than that in the *mixed* pricing model.

Finally, the results also show that, under certain conditions, the seller's revenue maximizing position occurs in an environment with piracy activity above minimum levels. In general, the seller obtains higher revenue under the *mixed* pricing model than other pricing models. However, the piracy level in the *mixed* pricing model is higher than in the *subs* pricing model in most cases, while the piracy level in the *mixed* pricing model ranges from 8% to 45% of the piracy level under the *unit* pricing model (except when $\delta = 0.95$).

IV.2 Comparison with no-piracy scenario

To evaluate whether there exist conditions under which the seller reaps higher revenues in the presence of piracy, we considered the base case scenario where the music retailer operates in a world without a music piracy option for the consumers. In this set of simulation experiments, the retailer is assumed to offer a search channel whose efficiency is identical to the online legal music channel. The values of ψ^{ONI} considered range from 0.1 to 0.7, in increments of 0.1.

In the no-piracy scenario, each consumer either chooses to start a search at the retailer's search channel or chooses not to initiate a search. At the completion of each search, the consumer either purchases the music item at a price of p_u or decides to not purchase the item. A consumer continues the search process until the search cost exceeds the net expected return from additional searches. As before we employ a brute force technique to identify the revenue maximizing value of p_u.

Figure 6 presents a comparison of the music seller revenues in the no-piracy base case with the *mixed* model with the piracy option. For lower values of the δ, presence of piracy yields higher revenues to the seller, even when the search efficiency and the search costs are identical. Interestingly the cutoff point for δ below which the piracy option dominates increases as the search costs at the seller's channel decreases.

V. CONCLUSION

The focus of this paper was the analysis of models to enhance revenues from digital music sales in the presence of online music piracy. We presented analytical models of different selling strategies that incorporate consumer valuation for music, search cost of music, consumer surplus and the economics of seller revenue. We demonstrate possible selling strategies that music seller can use in the face of online piracy.

We find that revenue-maximization strategies for the seller do not necessarily involve efforts to eliminate online music piracy. In fact, piracy reduction strategy is found to be different from revenue-maximizing strategy, especially when illegal online music is perceived to be of high quality.

Further research needs to be conducted to investigate the relationship between consumers purchasing behaviors. In online storefronts, product recommendations to consumers are based mostly on past purchases and from purchasing patterns of other consumers. Obviously this is not an optimal recommendation procedure. To enhance online services, future research is required to involve marketing mechanisms such as personalized recommendation and improved search mechanisms. Studies also need to be conducted on unique characteristics of music products, such as the temporal nature of music popularity and related consumer taste.

Figure 2: Comparison of Maximum Achievable Revenue
ψ_{ONI} = 1.0, $\psi_{ONLG\text{-->}ONI}$ = 0.2, ψ_{ONLG} = 0.5

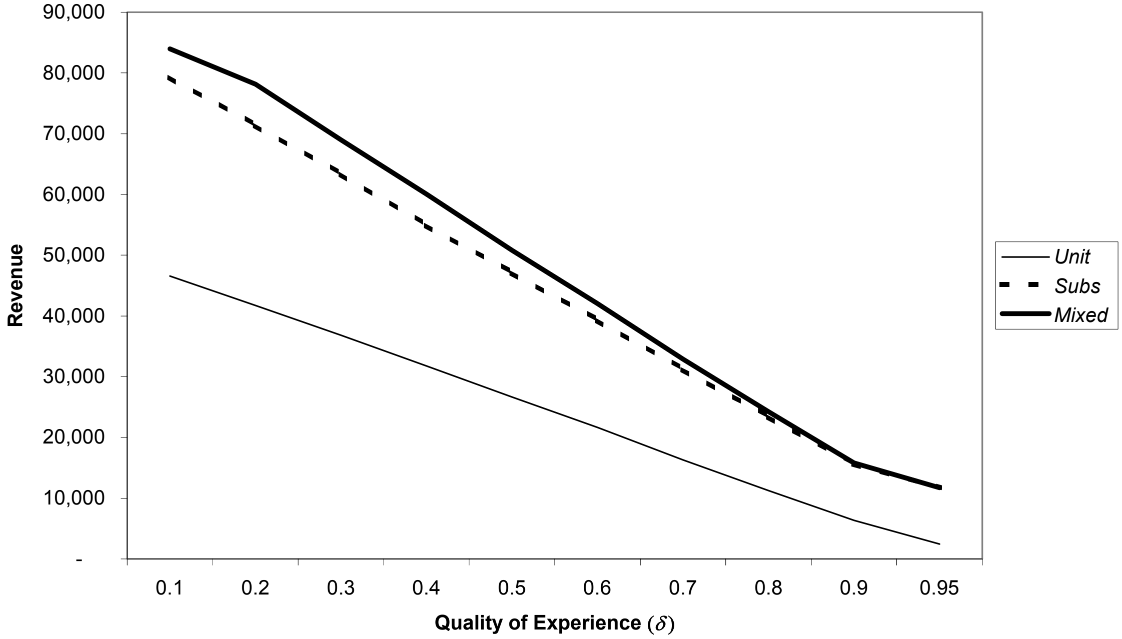


Figure 3: Comparison of Maximum Achievable Revenue
ψ_{ONI} = 1.0, $\psi_{ONLG\text{-->}ONI}$ = 0.2, ψ_{ONLG} = 1.2

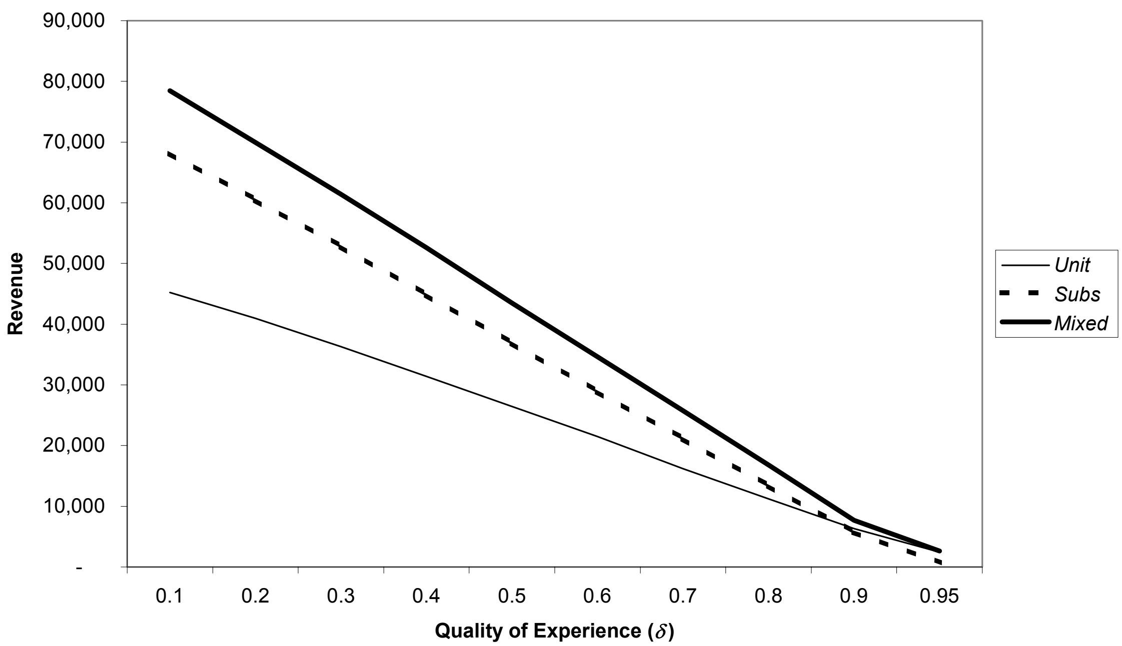


Figure 4: Comparison of Revenue-Maximizing Per-Unit Price (p_u)
ψ_{ONI} = 1.0, $\psi_{ONLG\text{-->}ONI}$ = 0.2, and ψ_{ONLG} = 0.5

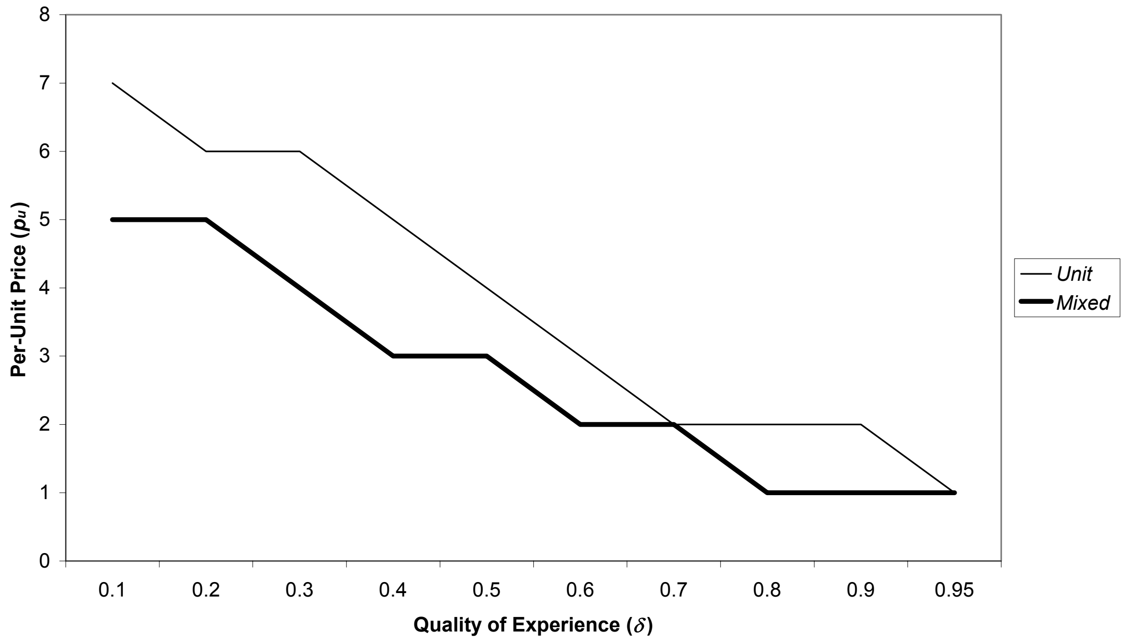


Figure 5: Comparison of Revenue-Maximizing Subscription Price (p_s)
ψ_{ONI} = 1.0, $\psi_{ONLG\text{-->}ONI}$ = 0.2, and ψ_{ONLG} = 0.5

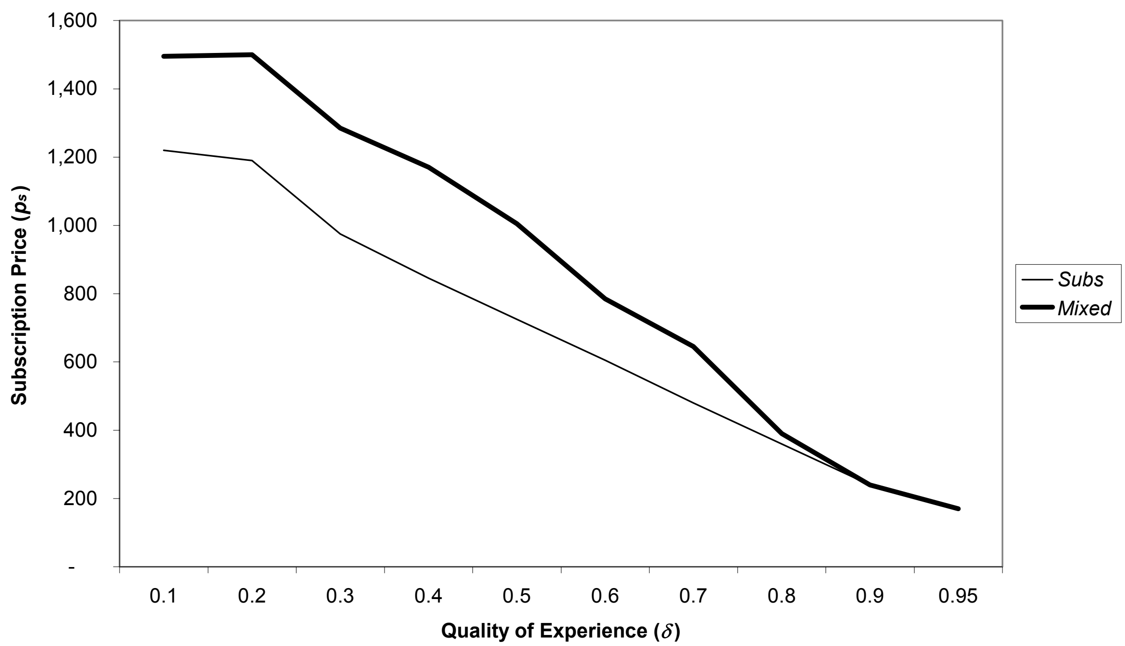


Figure 6: Comparison of Maximum Achievable Revenue Between Base and Mixed Models

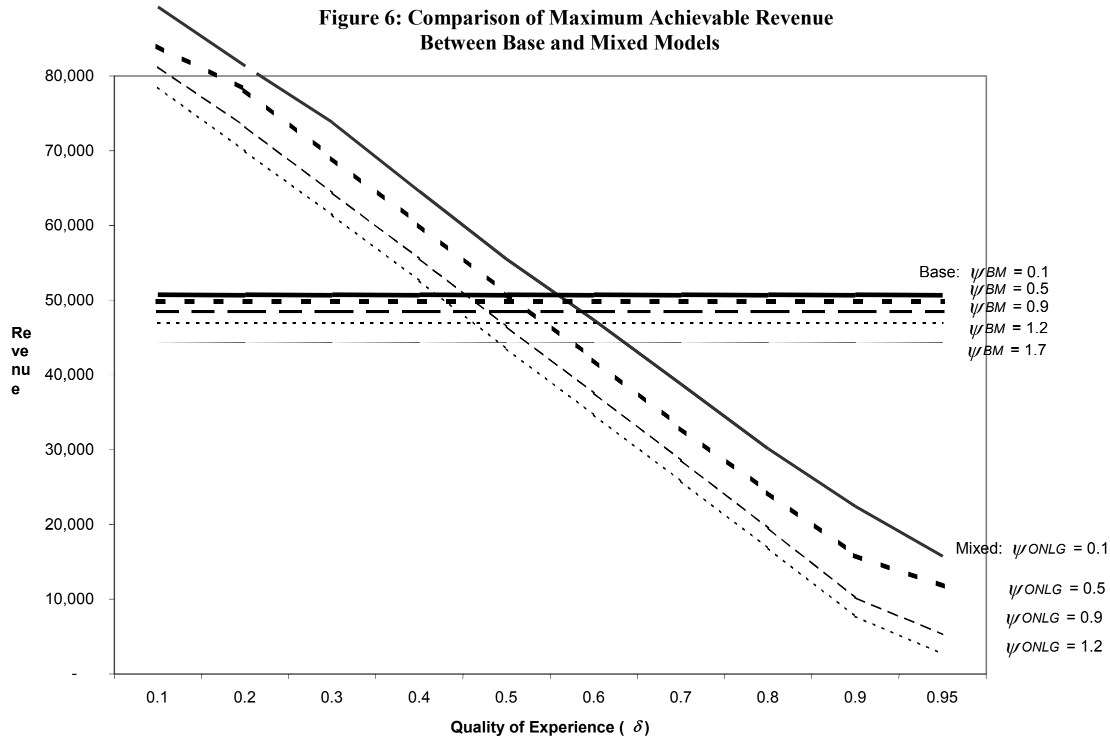


Table 2: An Excerpt from Simulation Results ($\psi^{ONLG} = 0.5$)

	Unit Model				*Subs* Model			*Mixed* Model				
δ	*Pu*	Number of Songs Bought	Number of Songs Pirated	Revenue	*Ps*	Revenue	Number of Songs Pirated	*Ps*	*Pu*	Revenue	Number of Subscribers	Number of Songs Pirated
0.1	7	6,655	6,587	46,585	1,220	79,300	0	1,495	5	83,970	50	1,557
0.2	6	6,951	6,364	41,706	1,190	71,400	89	1,500	5	78,145	45	2,235
0.3	6	6,136	7,264	36,816	975	63,375	0	1,285	4	68,999	47	1,861
0.4	5	6,351	7,066	31,755	845	54,925	172	1,170	3	60,078	44	1,752
0.5	4	6,664	6,779	26,656	725	47,125	678	1,005	3	50,823	43	2,256
0.6	3	7,215	6,237	21,645	605	39,325	0	785	2	42,037	47	1,481
0.7	2	8,155	5,318	16,310	480	31,200	503	645	2	32,900	44	2,371
0.8	2	5,630	7,875	11,260	360	23,400	829	390	1	24,252	59	642
0.9	2	3,178	7,168	6,356	240	15,600	0	240	1	15,820	65	627
0.95	1	2,472	11,032	2,472	170	11,730	0	170	1	11,730	69	0

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