



Music piracy: Bad for record sales but good for the iPod?



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ARTICLE INFO

Article history:

Received 11 June 2013

Received in revised form 16 March 2015

Accepted 15 April 2015

Available online 23 April 2015

Keywords:

Demand estimation

iPod

Music piracy

ABSTRACT

Music piracy is a double-edged sword for the music industry. On the one hand, it hurts record sales. On the other hand, it increases sales of its complements. To quantify the effect of music piracy, I construct a unique survey data set and use a Bayesian method to estimate the demand for music and iPods, and find three things. First, music piracy decreases music sales by 24% to 42%. Second, music piracy contributes 12% to iPod sales. Finally, counterfactual experiments show that, if music were free, the increase in Apple's profits from iPod can more than compensate the loss of musicians. The last result implies that a Pareto improving iPod tax is possible.

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1. Introduction

In 1999, record sales started to decline after more than a decade of steady growth. The very same year, Napster, the first peer-to-peer (P2P) software used for pirating music, began operations. While there are other factors that might lead to a decline in record sales,¹ there is almost a consensus in the economics literature that music piracy has led to the decline (see Blackburn (2004), Liebowitz (2006), Peitz and Waelbroeck (2004), Rob and Waldfogel (2006), Waldfogel (2010), and Zentner (2006). Smith and Telang (2012) provide a more recent review of the literature.)²

Although, as noted, many economists argue that music piracy hurts record sales, Oberholzer-Gee and Strumpf (2010) argue that it can increase revenue from music complements such as concerts. When music piracy drives the effective price of an album down to nearly zero, more

consumers become familiar with the artist's music, thus driving up demand for concerts. Mortimer et al. (2012) show empirically that music piracy has a significant effect on concert demand, particularly for small artists. Concerts are not the only music complements to benefit from music piracy. Fig. 1 shows that the revenue of iPod, the most popular MP3 player by far, has increased considerably when music piracy becomes more widespread. Although record sales have declined by more than 25% since Napster was launched, Apple has seen exponential growth in iPod sales since the device was introduced in 2001. Revenue from iPod sales grew from \$344 million in 2003 to \$7.6 billion in 2006.

Netanel (2003) and Fisher (2004) argue, if there is strong complementarity between music piracy and iPod sales, it might be welfare-improving to have a regime in which music piracy is legal and a government-financed fund (financed by a tax on music complements such as iPods) compensates music producers according to the download rates of their records. In fact a similar system, private copying levy, which is a surcharge on the price of media capable of making copies and is supposed to be redistributed to copyright holders, is enforced in many countries, including the U.S., Canada and many other European countries. The goal of such levies is to offset

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¹ For example, as a referee pointed out, the availability of internet radio might lead to a decrease in demand for music records.

² Oberholzer-Gee and Strumpf (2007) disagree, however, arguing that music piracy "allows users to learn about music they would not otherwise be exposed to" and thus may actually boost record sales.

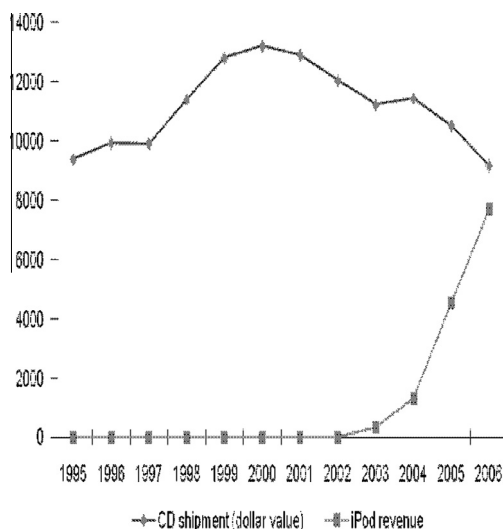


Fig. 1. RIAA and Apple: CDs revenue decreasing, iPods revenue growing in the U.S. (\$ millions).

the loss resulted from lawful copies made for private consumer use.³ While most countries' private copying levy is imposed on media such as blank CD-Rs, some European countries such as Belgium, Finland, and Switzerland have imposed private copying levy on MP3 players including iPods.

This paper attempts to answer two questions: (1) how much does music piracy hurt record sales; (2) how much does music piracy benefits iPod sales, and whether an iPod tax is welfare improving? To answer these two empirical questions, I constructed a unique conjoint data set derived from a survey of 884 University of Minnesota undergraduates. The students were first asked to report their demographic information and their recent consumption of both music and iPods. Then, in the conjoint survey, they were asked to make choices about music (from both legal and illegal sources) and iPods in 12 hypothetical situations.

My empirical analysis consists of three parts. First, I set up a demand system with three types of music: CDs, legally purchased songs from iTunes, and pirated songs from P2P websites. I estimate this system of three simultaneous equations using the three-stage least-squares method. My results corroborates with the majority of the literature that music piracy hurts record sales. Second, I use the estimates from the first part to establish a random-coefficient discrete-demand model for iPods. I follow Rossi et al. (2005) in setting up a hierarchical Bayesian discrete-demand model. These estimates indicate that music piracy boosts demand for and sales of iPods. Third, I use the estimates from the first and second parts of the analysis to conduct counterfactuals to predict the changes in demand for music and iPods in different regimes. The results show that approximately 12% of Apple's revenue comes from music

piracy, which translates into \$1.1 billion using 2008 revenue figures. Also a Pareto improving iPod tax is possible.

The remainder of the paper is organized as follows. Section 2 discusses the conjoint survey data set. Sections 3 and 4 describe the set-up of the demand estimates for music and iPods, respectively, and discuss the estimation results. Section 5 reports the results of counterfactual experiments using the results from Sections 3 and 4. Section 6 concludes the paper.

2. Data collection and description

There has been a consensus that music piracy hurts record sales. Fig. 1 in the Introduction shows that the decline of record sales started in 1999, the year in which the first P2P software, Napster, was introduced. At the same time, the sales of iPod, a complement of music, has seen exponential growth since it was introduced in 2001.

In order to jointly investigate the impact of music piracy on the both the music demand and iPod demand, I build a discrete choice demand model for iPod in which consumers consider their (continuous) music and (discrete) iPod consumption jointly in Sections 3 and 4. In the model, an agent can attain a higher utility by consuming both music and iPod than by consuming only one of them. Because a data set encompassing the consumption of illegal downloads, legal music, and iPods is hard to come by, I use a different approach from that of previous researches.

I collected conjoint survey data from college students, who generally have a lower income and greater exposure to the Internet than other age groups. As Table 1 shows, college students also tend to download or pirate more music than other age groups. There is concern that the sample is not representative of the U.S. market. However, according to AdMob, a Google subsidiary and one of the world's largest mobile advertising platform, 78% of iPod touch users were 24 years old or younger in 2010 (Admob (2010)).

2.1. Conjoint survey

I conducted the survey in Fall 2007 (September and October) and Spring 2008 (January and February) among seven undergraduate classes.⁴ Of the approximately 1800 students registered for these classes, approximately 900 attended class on the day of the survey and 884 turned in completed surveys.

Table 2 shows that Apple enjoys more than 70% share of the MP3 market. Sandisk, its closest competitor of Apple, sells only one-eighth of what Apple does.⁵ Therefore the survey focuses on one dominant brand of MP3 player, the Apple iPod.

The survey comprised of two parts. The first asked students to report demographic information and give details concerning their Internet access and music and iPod consumption preferences. The second was the conjoint survey.

³ Note that the private copying levy is different from the system proposed by Netanel (2003) and Fisher (2004) in the sense that the former system does not legalize music piracy.

⁴ All of them were Principles of Microeconomics.

⁵ The respondents also showed a distinct preference for iPods in a trial run of the survey that included other brands of MP3 players.

Table 1

Percentage of U.S. Adult Population Answering YES to “Do you ever download music files on your computer so you can play them at any time you want?”.

| | August–September 2001 | October 2002 | June 2003 | November 2003 | May–June 2004 | February 2005 |
|---------|--------------------------|-----------------|--------------|------------------|------------------|------------------|
| Overall | 15 | 19 | 19 | 9 | 13 | 13 |
| 18–29 | 36 | 41 | 43 | 23 | 31 | 32 |
| 30–49 | 16 | 21 | 20 | 9 | 11 | 13 |
| 50–64 | 6 | 8 | 8 | 4 | 6 | 7 |
| 65+ | 2 | 3 | 1 | 2 | 2 | 1 |
| Men | 19 | 22 | 23 | 12 | 17 | 14 |
| Women | 13 | 16 | 15 | 7 | 9 | 12 |

Source: Pew internet project.

Table 2

Apple dominates the MP3 market.

| Brand | Unit share (%) |
|---------------|----------------|
| Apple | 72.7 |
| Sandisk | 8.9 |
| Microsoft | 3.2 |
| Creative Labs | 2.9 |
| Samsung | 2.0 |

Source: NPD group.

Green and Rao (1971) were the first to introduce conjoint analysis to the marketing field. I followed the approach of Louviere and Woodworth (1983) in using choice-based conjoint analysis, which integrates conjoint analysis and discrete choice analysis. The questions in conjoint surveys are not descriptive such as “How much would you be willing to pay for an iPod?” Instead, they ask students to make concrete choices such as “Given brand A, B, and C with different attributes and prices, which one would you buy?” Conjoint survey data are a type of stated-preference data, as opposed to revealed-preference data, which are collected from real market transactions.

The conjoint survey used in this study included 12 hypothetical tasks. In each task, the respondents were given the option of listening to music on an iPod, a computer or a radio (which I treat as an outside choice). The choices differed in the level of each of the following six choice-specific covariates.

- Price of an iPod (varies from \$30 to \$650).
- Capacity of an iPod (varies from 1 gigabyte to 8 gigabytes).
- Probability of getting caught pirating music (varies from 0 to 1).
- Fine per song if caught pirating music (varies from \$0 to \$10,000).
- Price per song in iTunes (varies from \$0.1 to \$3).
- Price per CD (varies from \$1 to \$30).

There were five to ten levels for each covariate within the pre-specified range. The levels of most of the covariates were evenly distributed within the ranges specified above.⁶

⁶ Two exceptions were the probability of getting caught and the fine per song. The levels of the former were more evenly distributed between zero and 3.3%. The levels of the latter were more evenly distributed between zero and \$1000.

I followed the following three principles proposed by Sawtooth Software (2008) to draw the levels of each covariate.

1. **Minimal Overlap:** Each covariate level is shown as few times as possible in a single task.
2. **Level Balance:** Each covariate level is shown an approximately equal number of times.
3. **Orthogonality:** Covariate levels are chosen independently of other attribute levels, such that each level's effect on utility can be measured independently of all other effects.

The student were asked to complete two sub-tasks in each of the 12 tasks. In the first sub-task, they were asked to imagine that they did not have an iPod and then to rank the three choices in the task. Fig. 2 presents a sample of the first sub-task.

In the second sub-task, I randomly assigned the students one of two choices—iPod or computer. This assignment may or may not have been their first choice in the first sub-task. Given their assigned choice and associated music prices, students were then asked how they would change their music consumption from the previous month and estimate their consumption from three sources (CDs, iTunes and P2P websites). Fig. 3 shows a sample of the second sub-task, which was included in the conjoint survey administered to two of the seven classes, meaning that 270 students completed it.

Students were asked to evaluate the two sub-tasks jointly. In particular, when they ranked the three discrete choice of listening to music, they would have to estimate the amount of music that they would buy or pirate had they chose a particular option.

2.2. Conjoint survey data versus real market data

There are several advantages and disadvantages to using conjoint survey rather than real market transaction data to estimate the demand for music and iPods.

One of the disadvantages of doing so is that conjoint analysis requires attributes to be quantifiable, and some attributes, such as the quality of sound from an iPod and a computer, are difficult to quantify. However, because these attributes are unlikely to vary across the different copyright regimes I discuss in the counterfactuals section, omitting them is unlikely to affect the results.

When you listen to music,
Your first choice is: _____ Second choice is: _____




| Option 1 | Option 2 | Option 3 |
|--|--|--|
| <p>iPod nano</p>  <p>SUS200, 4GB</p> | <p>Your computer</p>  | <p>Radio</p>  |
| <p>Free P2P downloading illegal. Fine: SUS200/song downloaded that month</p> <p>Chance of getting caught per month: 1 in 2000 songs</p> | <p>Free P2P downloading illegal. Fine: SUS50/song downloaded that month</p> <p>Chance of getting caught per month: 1 in 100,000 songs</p> | |
| <p>iTunes: \$ US 0.3/song</p> <p>CD: \$5 each</p> | <p>iTunes: \$ US 3/song</p> <p>CD: \$10 each</p> | <p>Free music</p> |

Fig. 2. A sample of the first sub-task.

Some researchers have also expressed concerns about the validity of conjoint survey data. Some consider real market data to be more reliable because it is revealed-preference data. However, since [Green and Rao \(1971\)](#) introduced conjoint survey analysis to the marketing area, it has been widely adopted in the marketing literature to elicit demand estimates. An important factor for the conjoint survey to generate reliable demand estimates is that the survey can mimic the real market situation. In this study, I am able to include the main (and quantifiable) attributes without overwhelming the students with too many choices and irrelevant attributes. Several studies argue that conjoint survey data generate reliable demand estimates,⁷ and applications of conjoint survey analysis abound.⁸

Among the advantages of using conjoint survey data rather than real market data in this research were the following. First, conjoint survey was possibly the only way to create a panel data set encompassing the consumption of illegal downloads, legal music, and iPods.⁹ [Oberholzer-Gee and Strumpf \(2007\)](#) and [Blackburn \(2004\)](#) gather panel data sets on music piracy by tracking individual illegal downloading behavior on a P2P network. They then combine weekly album sales with their novel data on weekly

download volumes to estimate the effect of illegal downloads on album sales. [Rob and Waldfogel \(2006\)](#) carry out surveys among college students to create a panel data set incorporating legal music consumption and illegal downloading behavior, and then use their data set to estimate effect of piracy on record sales. However, as I argued before, it is important to ascertain the effect of any copyright regime changes in the music industry on other related products such as iPods. Doing so requires a clean panel data set on both the consumption of music (both legal and illegal) and iPods. To the best of my knowledge, this paper is the first to construct such a panel data set using a conjoint survey.

Second, conjoint survey analysis provides good instruments. Both [Oberholzer-Gee and Strumpf \(2007\)](#) and [Rob and Waldfogel \(2006\)](#) use an instrumental variable approach to deal with endogeneity. In this paper, I use the expected probability of getting caught and possible fines as instruments for illegal downloads. Although each affects illegal downloads, neither has a direct effect on legal music consumption.¹⁰ However, despite serving as instruments for my purposes here, they would not work in other cases for two reasons. First, there is greater variation in expected punishment in my conjoint survey than in the real world. In a conjoint survey, the designer can vary the prices of different choices within a pre-specified range. For instance, I vary the fine per song from \$0 to \$10,000, whereas the real fine is usually \$10 to \$50 per song. Basic econometrics tells us that a larger degree of variation in independent variables (the expected probability of getting caught and possible fines in our case) provides more information about their effect on the dependent variable (illegal downloads here). The second reason is that the levels of these two covariates are drawn exogenously and independently owing to the orthogonality principle described in

⁷ [Carlsson and Martinsson \(2001\)](#) and [Hensher et al. \(1999\)](#) collect both stated-preference and revealed-preference data on donation choice and freight shipper choice, respectively, and show that the hypothesis of parameter equality holds for most parameters across the two data sources.

⁸ [Hensher and Louviere \(1983\)](#) forecast the choice of attendance at various types of international expositions. [Hensher \(1994\)](#) reviews the development of conjoint analysis's use in estimating transportation choice. Many multinational corporations, including Marriott, Procter & Gamble (P&G), and General Motors, also use conjoint survey data to estimate the demand for new products (see [Green et al., 2004](#); [Orme, 2005](#)). [Leung \(2013\)](#) uses a similar methodology to study software piracy, and shows that the substitutability between street and Internet piracy of Microsoft Office in Hong Kong is high.

⁹ I call this a panel data in the sense that I observe twelve repeated consumption choice from the same individual.

¹⁰ I also used the price of an iTunes song, the price of a CD, and the price of an iPod as instruments for their corresponding demands.



Suppose you had an iPod last month and prices of music from different sources were as follows:

| | | | |
|-----------------|------------|------------------|---|
| P2P downloading | Illegal | Fine: \$200/song | Prob. Of getting caught: 1 in 2000 songs |
| iTunes | \$0.3/song | | |
| CDs | \$5/CD | | |

What would be your music consumption from the 3 sources?

P2P downloading : _____ songs
 iTunes : _____ songs
 CDs : _____ CDs

Fig. 3. A sample of the second sub-task.

Table 3
Summary statistics of the data.

| | Mean (s.d.) | Min | Max |
|-------------------------------------|--------------|-----|--------|
| Age | 18.94 (1.87) | 13 | 45 |
| Owens an MP3 player | 0.86 (0.35) | 0 | 1 |
| Owens an iPod | 0.72 (0.45) | 0 | 1 |
| Number of songs on computer | 2508 (4773) | 0 | 75,000 |
| Bought a CD in past month | 0.28 (0.45) | 0 | 1 |
| Bought songs from iTunes last month | 0.32 (0.47) | 0 | 1 |
| Downloaded free songs last month | 0.54 (0.50) | 0 | 1 |

N = 844.

the previous subsection. This provides clear identification for my empirical analysis.

2.3. Data description

Completed surveys were received from 884 students. Most were typical university students: They did not have a high income, with around 90% of them earning less than \$200 per week. In addition, they reported spending an average of three to four hours a day on the Internet.

Table 3 shows that the respondents expressed great interest in listening to music. They reported having an average of 2508 songs on their computers. They both bought music, and pirated it. Twenty-eight percent and 32% had bought a CD or a song from iTunes, respectively, in the previous month. In addition, more than half (54%) of them had downloaded songs illegally from the Internet in the previous month.

More than 70% of the students said they owned an iPod.¹¹ Unsurprisingly, the students who owned more music were more likely to own an iPod. If I define students who have more than 1000 songs on their computers as music lovers and others as non-music lovers, 80% of music lovers own an iPod, whereas only 60% of non-music lovers do.

¹¹ Among the students who owned an MP3 player, more than 80% owned an iPod, which justifies my focus on iPods specifically, instead of MP3 players generally, in this paper.

Table 4
Summary statistics of conjoint survey.

| Choice | First choice (%) | Second choice (%) |
|----------|------------------|-------------------|
| iPod | 46.11 | 28.50 |
| Computer | 36.63 | 37.23 |
| Radio | 17.27 | 34.28 |

N = 10,608.

Table 5
iPod as first choice under extreme attribute levels.

| Attribute | Lowest level (%) | Highest level (%) |
|-------------------------------|------------------|-------------------|
| iPod price | 56.75 | 42.21 |
| Price per song in iTunes | 74.22 | 42.37 |
| Price per CD | 66.88 | 39.66 |
| Probability of getting caught | 85 | 23.89 |
| Fine per song | 85 | 39.22 |
| GB | 53.04 | 53.51 |

N = 10,608.

Table 4 shows that in the first sub-task of the conjoint survey, iPod was the most popular of the three choices, with computer coming second.

An iPod was students' first choice almost half of the time. Not only did they show a preference for iPods, but they also preferred lower prices. Table 5 shows that when iPod or music prices decreased, iPods were the first choice more often.

Table 6

Indicated music consumption under extreme prices.

| | P2P Downloads | | iTunes | | CDs | |
|-------------------------------|---------------|---------------|--------------|---------------|--------------|---------------|
| | Lowest level | Highest level | Lowest level | Highest level | Lowest level | Highest level |
| Price per song in iTunes | 64.80 | 73.85 | 24.14 | 0.59 | 0.15 | 1.01 |
| Price per CD | 89.13 | 26.62 | 2.44 | 7.40 | 0.70 | 0.08 |
| Probability of getting caught | 198.10 | 0.05 | 6.77 | 4.97 | 0.45 | 0.39 |
| Fine per song | 198.10 | 11.97 | 6.77 | 1.08 | 0.45 | 1.17 |

N = 3240.

As noted, I included the second sub-task in the conjoint survey in two of the seven classes. Of the approximately 884 students surveyed, 270 completed surveys with the second sub-task. These 270 students have similar characteristics to the overall sample.

Table 6 shows that students responded reasonably to questions in the second sub-task. When the prices of CDs, iTunes songs, and P2P downloads (probability of getting caught and fine per song) increased from the lowest levels to the highest levels, the indicated consumption of music from the corresponding sources would decrease significantly.

3. Music demand

I used the data from the second sub-task in the conjoint survey to estimate music demand. The three dependent variables are CDs, iTunes songs, and pirated songs from P2P websites, and the independent variables are the prices of music from different sources and demographic variables.

As my first question in this study was whether music piracy hurts record sales, I needed to determine the effect of pirated songs on CD and iTunes song consumption. The problem can be expressed as a simultaneous equations problem. The simultaneous demands for music from agent i in task t are

$$\log Y_{itp}^* = \mathbf{z}_{itp}'\gamma_p + \log(Y_{its}^*)\phi_{ps} + \log(Y_{itc}^*)\phi_{pc} + u_{itg} \quad (1)$$

$$\log Y_{its}^* = \mathbf{z}_{its}'\gamma_s + \log(Y_{itp}^*)\phi_{sp} + \log(Y_{itc}^*)\phi_{sc} + u_{its} \quad (2)$$

$$\log Y_{itc}^* = \mathbf{z}_{itc}'\gamma_c + \log(Y_{its}^*)\phi_{cs} + \log(Y_{itp}^*)\phi_{cp} + u_{itc} \quad (3)$$

where subscripts p, s and c denote P2P (pirated songs), iTunes songs, and CDs. For $g \in \{p, s, c\}$ $Y_g^* = Y_g + 1$, Y_g is the consumption of g ; \mathbf{z}_g is a vector of exogenous regressors, including prices, that are uncorrelated with u_g ; and u_{itg} are i.i.d. over i and t and homoskedastic, but correlated across g . Table 7 presents all of the \mathbf{z} .

Each dependent variable has its own instruments. For instance, the probability of getting caught pirating music (π) instruments for the demand for pirated music from P2P websites, the price per song in iTunes instruments for the demand for iTunes songs; and the price per CD instruments for CD demand. Also, iPod ownership, which was exogenously varied in survey, instruments for the demand for pirated music and the demand for iTunes songs. I used the three-stage least-square method to estimate this simultaneous equations system, and the results are presented in Table 8.

Table 7

Exogenous regressors in music demand.

| | |
|-----------------------|---|
| $\pi^* = \pi + 0.001$ | Probability of getting caught |
| $f^* = f + 1$ | Fine per song if caught |
| P_s^* | Price per iTunes song |
| P_c^* | Price per CD |
| <i>iPod</i> | Indicator for iPod |
| $h^* = h + 1$ | Hours spent on Internet per day |
| <i>Antivirus</i> | Indicator for having antivirus software |
| <i>P2Pfd</i> | Indicator for having friend who engages in piracy |
| <i>Dorm</i> | Indicator for living in dorm |
| <i>Income</i> | Level of income |
| <i>Prob</i> | Perceived probability of getting caught in real world |
| <i>MusInt</i> | Level of music interest |
| <i>P2P*</i> | Illegal songs downloaded last month |
| <i>iTunes*</i> | iTunes songs purchased last month |
| <i>CD*</i> | CD purchased last month |

Table 8

Music demand/month (std. err.).

| | $\log(P2P + 1)$ demand/month | $\log(iTunes + 1)$ demand/month | $\log(CD + 1)$ demand/month |
|------------------|---------------------------------|------------------------------------|--------------------------------|
| Constant | 0.27 (0.19) | 2.21 (0.07) | 0.93 (0.04) |
| $\log Y_p^*$ | | -0.07 (0.01) | -0.04(0.01) |
| $\log Y_s^*$ | -0.33 (0.03) | | -0.09 (0.01) |
| $\log Y_c^*$ | -0.02 (0.10) | -0.09 (0.06) | |
| <i>iPod</i> | 0.37 (0.06) | 0.14 (0.03) | |
| $\log \pi^*$ | -0.32 (0.01) | | |
| $\log f^*$ | -0.21 (0.01) | | |
| $\log P_s^*$ | | -1.82 (0.04) | |
| $\log P_c^*$ | | | -0.28 (0.01) |
| <i>Antivirus</i> | 0.29 (0.12) | | |
| $\log h^*$ | -0.20 (0.07) | | |
| <i>P2Pfd</i> | 0.06 (0.03) | | |
| <i>Dorm</i> | 0.11 (0.06) | | |
| <i>Income</i> | 0.05 (0.03) | | |
| <i>Prob</i> | 0.05 (0.01) | | |
| <i>MusInt</i> | | 0.02 (0.02) | 0.02 (0.01) |
| <i>MusInstr</i> | | | -0.004 (0.015) |
| $\log P2P^*$ | 0.35 (0.01) | | |
| $\log iTunes^*$ | | 0.23 (0.01) | |
| $\log CD^*$ | | | 0.25 (0.01) |

N = 3240.

There are several things to note. First, the students would pirate more music when they owned an iPod. Second, the law of demand holds, that is, the demand for music would drop when prices increased. However, because I used a simultaneous equations system, the

Table 9
Percentage change in demand for music with price changes.

| | y_{P2P} (%) | y_{iTunes} (%) | y_{CD} (%) |
|----------------------------------|---------------|------------------|--------------|
| $\pi(0.0001 \rightarrow 0.0002)$ | -2.83 | 0.20 | 0.10 |
| $f(\$100 \rightarrow 200)$ | -13.76 | 1.03 | 0.54 |
| $P_s(0.99 \rightarrow 1.09)$ | 3.05 | -8.73 | 0.72 |
| $P_c(15 \rightarrow 16.5)$ | -0.01 | 0.22 | -2.51 |
| To a "no-iPod" world | -20.21 | -7.77 | 1.80 |

Table 10
Piracy elasticity of sales (%).

| | |
|----------------------------|----------|
| Oberholzer-Gee and Strumpf | -0.00001 |
| Rob and Waldfogel | -0.13 |
| Blackburn | -0.18 |
| This paper (CD sales) | -0.04 |
| This paper (iTunes sales) | -0.07 |

coefficients of price do not fully reflect the effect of price changes on all three demands equations.

Table 9 shows how the demand for music from different sources changed when music prices changed and when an iPod was not available. When students could not own an iPod, in contrast to the real world in which 72% owned an iPod, they would pirate 20.21% less music from P2P websites, and would consume 7.77% fewer songs from iTunes, but would consume 1.8% more CDs.

The probability of getting caught and the payment of a fine are significant components of the price of (or punishment for) pirating music. Students would pirate less music when the punishment was more severe. When the probability of getting caught increased 100% from 0.01% to 0.02%, students would pirate 2.83% less music from P2P websites, and would consume 0.20% more songs from iTunes and 0.10% more CDs. When the fine per song increased 100% from \$100 to \$200, students would pirate 13.76% less music from P2P websites, and would consume 1.03% more songs from iTunes and 0.54% more CDs.

Students would buy fewer iTunes songs when these were more expensive. When the price per song rose 10% from \$0.99 to \$1.09, they would buy 8.73% fewer songs from iTunes. They would also pirate 3.05% more music from P2P websites and would consume 0.72% more CDs.¹²

Similarly, student would buy fewer CDs when CDs were more expensive. When the price of a CD increased 10% from \$15 to \$16.5, they would buy 2.51% fewer CDs. At the same time, they also would pirate approximately the same amount of music, but would buy 0.22% more songs from iTunes.

Note that record sales from different sources are substitutes for one another. When students bought 10% more CDs, demand for iTunes songs would decrease by 0.9%. At the same time, demand for CDs would decrease by 0.9%

when consumption of iTunes songs increased by 10%. The emergence of online music stores such as iTunes plays a role in the decline of revenue from CD sales.

Finally, it is clear that music piracy does hurt record sales. Table 10 reports the piracy elasticity of sales.¹³ My results corroborates most studies in the literature.

4. Discrete-choice demand for iPods

The results in Section 3 suggest that music piracy does hurt record sales. Before quantifying the welfare implications of the three copyright regimes, I here build a discrete-choice demand model for iPods to quantify the complementary relationships between music and iPods.

In each of the 12 first sub-tasks in the conjoint survey, students were asked to rank three options for listening to music: an iPod, a computer, and the radio (which I treat as an outside good). These rankings served as the students' choices, and thus constitute the dependent variables in the demand estimation.

Students would generally be expected to have a rough estimate of their music consumption before they purchased an iPod. The average lifespan of an iPod battery is two years. But Apple introduces new models almost every year, and many buyers replace their old iPods with new ones in less than two years. Steve Jobs once said in an NBC interview that, "if you always want the latest and greatest, then you have to buy a new iPod at least once a year."¹⁴ Students would only buy one if they thought they would buy or pirate a considerable amount of music in a year. I thus entered the estimated demands for music from the previous section into the indirect utility of a choice to account for how music complements that choice.¹⁵ The indirect utility of choice j for student i in task t is

$$U_{ijt} = \beta_{ij} + \alpha_{i,price} P_{jt} + \alpha_{i,gb} GB_{jt} + \alpha_{i,p2p} P2P_{ijt} + \alpha_{i,itunes} iTunes_{ijt} + \alpha_{i,cd} CD_{ijt} + \epsilon_{ijt}, \quad (4)$$

where P_{jt} is the price of choice j in task t , GB_{jt} is the capacity (in gigabytes) of choice j in task t , and ϵ_{ijt} is the usual i.i.d. logit error. The estimated demands for illegal downloads, iTunes songs, and CDs are represented by $P2P_{ijt}$, $iTunes_{ijt}$, and CD_{ijt} respectively.

We can express the demand parameters of student i in Eq. (4) as

$$\Theta_i \equiv [\beta_{i1}; \beta_{i2}; \alpha_{i,price}; \alpha_{i,gb}; \alpha_{i,p2p}; \alpha_{i,itunes}; \alpha_{i,cd}],$$

where Θ_i is a 1×7 vector of individual parameters. Θ is a $n_i \times 7$ matrix whose i th row is Θ_i , and n_i is the number of students in the sample. Define X_{jt} as a 1×7 vector of

¹² Using my estimates, when the price of an iTunes song increased from \$0.99 to \$1.87, demand would drop 49%, which is reasonably close to the 42% decrease estimated in Shiller and Waldfogel (2011).

¹³ Oberholzer-Gee and Strumpf (2007) and Rob and Waldfogel (2006) report only estimates of the displacement effect of illegal downloads (P2P) on album sales. I combine those estimates with their sample statistics on album consumption and illegal downloads to calculate the elasticities.

¹⁴ See Williams (2006).

¹⁵ I did not correct the standard errors in the second-stage estimation of discrete demand. In other words, I treat the estimated demands for music as true demands.

covariates in Eq. (4), and we can then express the indirect utility as

$$U_{ijt} = \Theta_i X_{jt} + \epsilon_{ijt}. \quad (5)$$

The likelihood that student i will choose j in task t takes the following logit form.

$$\Pr_{ijt} = \frac{\exp(U_{ijt})}{\sum_k \exp(U_{ikt}) + 1}. \quad (6)$$

As [Berry et al. \(1995\)](#), [Nevo \(2000\)](#), [Petrin \(2002\)](#) and [Rossi et al. \(2005\)](#) argue, random coefficient models generate better estimates of consumer demands than do homogenous coefficient models. In this data set, it is natural to consider that the students have heterogeneous coefficients. For instance, an average student may be more responsive to iPod price changes than an iPod lover, which translates into a higher price coefficient (in absolute value) for the average student.

I follow [Rossi et al. \(2005\)](#) in using a hierarchical Bayesian model with a mixture of five components of normal priors to estimate the random coefficients. This approach is more flexible than the classical approach because it does not restrict the coefficients to coming from a normal distribution. Moreover, this approach allows for correlated coefficients without additional computation time.

Because the students provided demographic information in the survey, I include aspects of that information in the demand model to account for the observed heterogeneity across students. Define Z_i as a $1 \times n_z$ vector of the demographic characteristics of student i , where n_z is the number of such characteristics. Define Z as an $n_i \times n_z$ matrix. The demand model, in which the unobserved heterogeneity is distributed as a K mixture of normal, can be expressed as follows.

$$\begin{aligned} U_{ijt} &= \Theta_i X_{jt} + \epsilon_{ijt} \\ \Theta_i &= Z_i \Delta + u_i \\ u_i &\sim N(\mu_{ind_i}, \Sigma_{ind_i}) \\ ind_i &\sim \text{Multinomial}_K(\gamma) \end{aligned}$$

γ is a vector giving the mixture probabilities for each of the K components. The complete specification with priors over the mixture probabilities (α), mean ($\bar{\mu}$ and σ_μ^{-1}), and covariance matrices (v and V) is

$$\begin{aligned} \gamma &\sim \text{Dirichlet}(\alpha) \\ \mu_k | \Sigma_k &\sim N(\bar{\mu}, \Sigma_k \times \sigma_\mu^{-1}) \\ \Sigma_k &\sim \text{IW}(v, V) \\ \{\mu_k, \Sigma_k\} &\text{independent} \end{aligned}$$

4.1. Estimation

I follow [Rossi et al. \(2005\)](#) in using a hybrid of Gibbs sampling and the Metropolis-Hasting method to implement posterior inference for this model. I use a hybrid Metropolis method that employs customized Metropolis candidate density to draw Θ_i for each student. Conditional on Θ_i , I use an unconstrained Gibbs sampler

Table 11
Heterogeneity improves fit.

| | Log marginal density |
|------------------|----------------------|
| Homogenous Coef. | -15786.634 |
| 1 Component | -11870.235 |
| 5 Components | -10960.389 |

to draw δ , μ_k , and Σ_k .¹⁶ In particular, I alternately obtain draws between the individual-level parameters in (7) and hyperparameters in (8):¹⁷

$$\Theta_i | ind_i, Z_i \Delta, \mu_{ind_i}, \Sigma_{ind_i} \quad (7)$$

$$\gamma, ind, \Delta, \{\mu_k\}, \{\Sigma_k\} | \{\Theta\} \quad (8)$$

The conditional posterior in (7) is proportional to the product of the likelihood in (6) and the prior of the hyperparameters. I use the Random-Walk Metropolis to obtain the draws of Θ_i . The draws of the hyperparameters in (8) can be broken down into a succession of conditional draws as follows.

$$ind | \gamma, Z, \Delta, \{\mu_k, \Sigma_k\}, \{\Theta\} \quad (9)$$

$$\gamma | ind \quad (10)$$

$$\{\mu_k, \Sigma_k\} | ind, \Theta \quad (11)$$

$$\Delta | ind, Z, \{\mu_k, \Sigma_k\}, \Theta, \quad (12)$$

where the draw of the indicators in (9) is a multinomial draw based on the likelihood ratios with γ_k as the prior probability of membership in each component. The draw of γ given ind in (10) is a Dirichlet draw. The draw of each (μ_k, Σ_k) in (11) can be made using a standard algorithm to draw from a multivariate regression model. The draw of Δ in (12) requires that the pooling of data from all K components into one regression model.

4.2. Estimates

[Table 11](#) reports the log marginal density for alternative model specifications. The model's posterior probability is monotone in the log marginal density. Hence, a higher log marginal density means a better fit. Note also that log marginal density includes an automatic penalty for the addition of additional parameters ([Rossi et al. \(2005\)](#)). Heterogeneity leads to a substantial improvement in fit. In addition, a more flexible distribution of parameters fits the data better. The estimates from the five-component mixture model yield a higher log marginal density than those from the one-component model.

[Fig. 4](#) displays the density distribution of the coefficients, which indicates substantial heterogeneity among students' preferences. The five-component model is more

¹⁶ Constraints must be imposed on the Gibbs sampler to fix an identification problem called "label switching" if inference is desired for the mixture component parameters. This is not a problem here because I am interested in estimating individual student parameters and their distribution across students alone. An unconstrained Gibbs sampler is enough to ensure identification. See [Rossi et al. \(2005\)](#) for more details.

¹⁷ Interested readers can find the details of the implementation of the MCMC draws in Chapter 5 of [Rossi et al. \(2005\)](#).

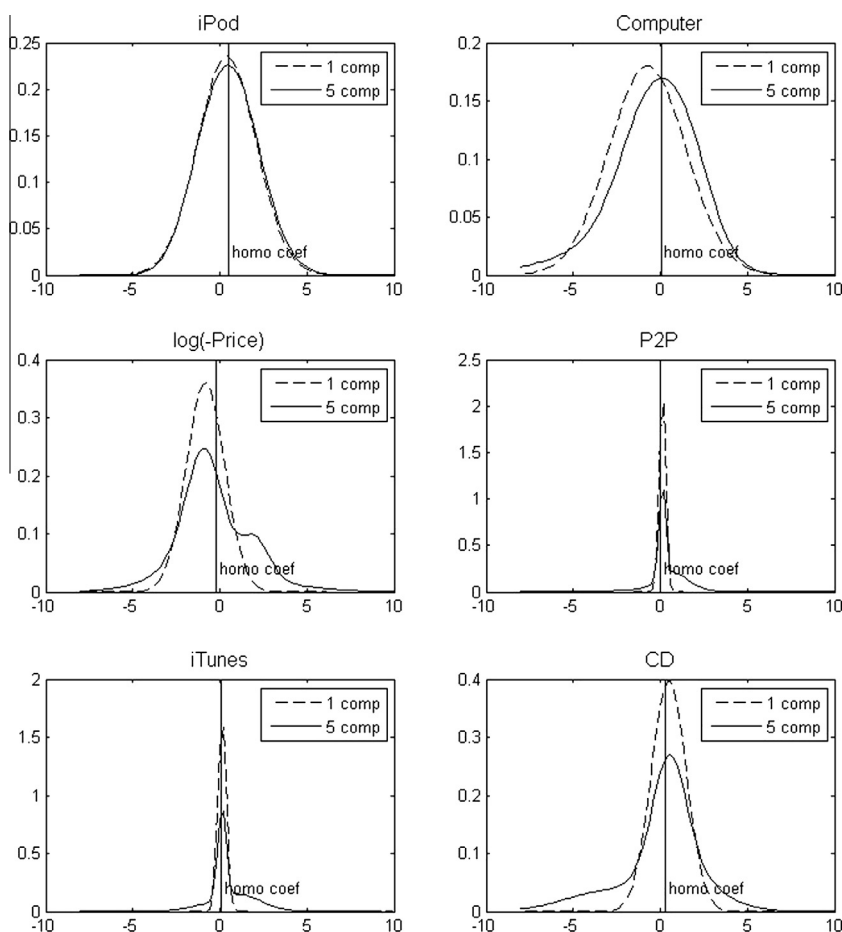


Fig. 4. Density of random coefficients.

Table 12
Elasticity of iPod demand.

| | 1 Component | 5 Components |
|--------------|------------------|------------------|
| P_{iPod} | -0.229 | -0.242 |
| | [-0.251, -0.208] | [-0.283, -0.203] |
| π | -0.017 | -0.017 |
| | [-0.018, -0.016] | [-0.020, -0.015] |
| f | -0.021 | -0.022 |
| | [-0.022, -0.019] | [-0.024, -0.019] |
| P_{iTunes} | 0.007 | 0.008 |
| | [-0.006, 0.008] | [-0.006, 0.009] |
| P_{cd} | -0.013 | -0.010 |
| | [-0.016, -0.009] | [-0.013, -0.007] |

The 5th and 95th percentiles of the estimates are reported in brackets.

flexible and is able to capture the fatter tail of the preference distribution of some of the coefficients.

Students' demand for iPod is not elastic. Table 12 shows that iPod's own price elasticity ranges between -0.229 and -0.242 under different specifications. Music consumption and the iPod are complements to each other: iPod demand decreases if music prices increase. The elasticities of iPod demand with respect to the prices of music from different sources are all below -0.01%.

5. Counterfactual experiments

The results in Section 3 suggest that music piracy hurts record sales, and those in Section 4 suggest that it increases demand for, and thus the revenue from, iPods. In this section, I discuss how demand for music and iPods would change in three different copyright regimes, which may shed light on the direction of future copyright policies.

The three copyright regimes are as follows.

5.1. Current Regime

In this regime, the RIAA uses the No Electronic Theft Act to occasionally file lawsuits against P2P software companies and individual music pirates. In the first decade of this century, two of the largest P2P software companies, Napster and Kazaa, were sued and later forced to shut down. Between September 2003 and June 2005, 11,700 music pirates were sued (Associated Press (2005)). This wave of lawsuits, however, turned out to have no lasting effect. After a slight decrease in music piracy immediately following the rulings, the number of music pirates began to grow again.

5.2. No Music Piracy Regime

In this regime, the government would increase the penalties for music piracy with the aim of eradicating it, which would provide music producers with sufficient income and incentive to create music. Eradicating music piracy would be difficult, but it would be possible if Internet service providers cooperated. Many countries in North America and in Europe have imposed or are in the process of imposing legislation to force Internet service providers to band together voluntarily to crack down on pirate subscribers.

5.3. Free Music Regime

In this regime, music piracy would be legal, and music from all sources would be free. The idea of legalizing music piracy is not new. Fisher (2004) and Netanel (2003) propose a copyright regime in which it is legal to share music files, but firms such as Apple, which would benefit from the boost in iPod sales, would have to pay royalties to the music industry. Such royalties are similar to the private copying levy, a government-mandated scheme in which a levy is charged on transactions involving recordable media. In the U.S., the levy applies to stand-alone CD recorders and portable satellite radio recording devices. Analyzing the demand for music and the demand for iPods can shed light on the range of possible royalties to be imposed on iPods and other MP3 players.

Table 13 gives the product attributes in the three regimes. The Current Regime describes the current music world. I mimic the current copyright system of the U.S. government and the RIAA's approach with a low probability of getting caught and a small fine for pirating music. At the time the survey was conducted, an 8-gigabyte iPod cost \$200, and iTunes songs and CDs cost \$0.99 and \$15, respectively.

The government and the RIAA would impose a more severe penalty on music piracy in the No Music Piracy Regime. Those engaging in it would be caught for sure, and they would have to pay \$10,000 for every song they illegally downloaded.

In the Free Music Regime, downloading music online would be free and legal and CDs would cost \$5 to cover the marginal cost of production (I varied this amount from \$1 to \$7, but my main conclusion remained unchanged).

5.4. Music consumption

Table 14 reports the changes in the consumption of music from the Current Regime to the two other regimes.

Table 13
Product attributes in all regimes.

| Product attributes | Current Regime | No Music Piracy Regime | Free Music-Royalty Regime |
|-----------------------|----------------|------------------------|---------------------------|
| Price per iPod | \$200 | \$200 | \$200 |
| Price per iTunes song | \$0.99 | \$0.99 | \$0 |
| Price per CD | \$15 | \$15 | \$5 |
| π (in %) | 0.01 | 100 | 0 |
| Fine per song | \$30 | \$10,000 | \$0 |

Table 14
Changes in monthly music consumption from Current Regime.

| To | Free Music Regime (%) | No Music Piracy Regime (%) |
|---------------|-----------------------|----------------------------|
| P2P | ↑690 | ↓100 |
| iTunes | ↑70 | ↑42 |
| CD | ↑29 | ↑24 |
| Overall Songs | ↑527 | ↓68 |

In calculating the changes in overall song consumption, I assumed each CD contained 10 songs.

Table 15
iPod purchase probability in different regimes (in %).

| | Current Regime | Free Music Regime | No Music Piracy Regime |
|------------------------|----------------|-------------------|------------------------|
| Predicted market share | 53.04 | 70.66 | 46.75 |
| | [51.58, 54.45] | [69.49, 71.78] | [45.15, 48.39] |

The 5th and 95th percentiles of the estimates are reported in brackets.

When online music becomes free and CDs are sold at a marginal cost in the Free Music Regime, the overall consumption of music would increase by more than 500%. When there is no music piracy, the consumption of legally purchased would increase, with demand for iTunes songs and CDs increasing by 42% and 24%, respectively. In other words, music piracy reduces record sales by 24% to 42%. However, because the average student would pirate more music than he would consume, the overall consumption of music would decrease by 68%.

Table 14 sheds light on how students' probability of purchasing an iPod varies across the regimes. In the Free Music Regime, in which the demand for music would be much higher than that in the Current Regime, we should see an increase in the demand for iPods. In the No Music Piracy Regime, in which overall music consumption would drop by 68%, we should see a drop in iPod demand.

5.5. iPod consumption

Table 15 shows students' iPod purchase probabilities are consistent with the changes in music consumption in the different regimes.¹⁸ On average, students would be approximately 18% more likely to buy an iPod in the Free Music Regime than in the Current Regime because of the increase in overall music consumption. That would translate into a \$36 increase in expected revenue from each student.

When the average student's overall music consumption would decrease in the No Music Piracy Regime, he would become approximately 6% less likely to buy an iPod. Put another way, in this scenario, approximately 12% of Apple's revenue from iPods would come from the additional music consumption realized by music piracy. Using Apple's iPod revenue in 2008 (\$9.2 billion) as a reference,

¹⁸ Note that the purchase probability in the Current Regime is lower than the actual share of students that owned iPod (72%). One of the potential reasons for the discrepancy is that some students obtained their iPods as a gift.

we can estimate that \$1.1 billion of the company's revenue that year came from music piracy.

5.6. Industry welfare analysis

What is a better copyright regime? This is an empirical question that is still up for debate. I calculate the profit of Apple and musicians in various copyright regimes.

In order to calculate profits of Apple and musicians, I make several assumptions about the profit margins of music producers and Apple. First, the marginal cost of each iTunes song is zero.

Second, because Apple is a supplier in both the MP3 player and the music content market, I need to make an assumption on the revenue sharing arrangement between Apple and musicians in the iTunes. While Apple does not publicize their cut from each song, industry expert estimated that Apple take 20% from a 99-cent song (see [Noguchi \(2006\)](#)). I therefore assume 80% of iTunes' revenue goes to the music producers as profit, and the rest goes to Apple.

Third, I make several assumptions about the profit margin of each CD according to usual practice in the music industry. Three main parties gain profit from selling a CD. First, a writer (and a publisher whom he works with to publish his song) receives mechanical royalties of \$0.09 for each song in a CD that is sold. They thus receive \$0.9 for each CD sold. Second, after deducting 25% of the retail price per CD as "packaging cost", a recording artist gets 8–25% of the deducted retail price per CD as her part of mechanical royalties. If the retail price of Britney Spears's latest CD is \$15, and her mechanical royalty rate is 15%, she would get $\$15 \times 0.75 \times 0.15 = \1.7 for each CD sold. Third, I assume record companies earn 7% off the retail price of each CD sold. Based on the information in [Connolly and Krueger \(2006\)](#), record companies can take a substantial portion of the CD revenues. The profit margin of selling a CD, however, can be much lower after deducting costs such as manufacturing costs and promotion costs. The assumption of 7% is higher than the operating margins at Warner, the only publicly traded record company, which is 5% in 2001.¹⁹ In [Table 16](#), I add up the profit margins of the three parties as the combined profit margin of music producers. Note that music producers do not earn anything directly from selling CDs in the Free Music-Royalty Regime as I assume they are selling at marginal cost.

Finally, I assume the marginal cost of producing an iPod to be \$100. According to iSuppli, a marketing company in the electronic and media market, estimated that the direct materials cost of an 8 GB-iPod Nano is approximately \$83.

[Table 17](#) reports the changes in profits for Apple and musicians from the Current Regime to the other two regimes.²⁰ In the No Music Piracy Regime, musicians would benefit from the absence of music piracy. However, Apple's

Table 16
Breakdowns of CD profit margins.

| | Current Regime ($P_{cd} = \$15$) | Free Music Regime ($P_{cd} = \0) | No Music Piracy Regime ($P_{cd} = \$15$) |
|-------------------|---------------------------------------|---|---|
| Writer/publisher | \$0.90 | \$0 | \$0.90 |
| Recording artist | \$1.70 | \$0 | \$1.70 |
| Recording company | \$1.05 | \$0 | \$1.05 |
| Total | \$4.05 | \$0 | \$4.05 |

Table 17
Changes of (per student) profit from the Current Regime.

| To | Free Music Regime | No Music Piracy Regime |
|---------------------|-------------------|------------------------|
| Δ Apple's Profit | ↑\$18.5 | ↓\$5.8 |
| Δ Musician's Profit | ↓\$13.0 | ↑\$4.0 |
| Total change | ↑\$5.5 | ↓\$1.8 |

profit from iPod would decrease more than the musicians' gain. In other words, the overall welfare would decrease if we switched to the No Music Piracy Regime.

In the Free Music Regime, musicians' profits would decrease by \$13 per student because music becomes free. Apple's profit from iPod, however, would increase by \$18.5 per student, which is more than the loss of musicians. Potentially, there can be arrangements such as the royalties mechanism suggested by [Fisher \(2004\)](#) and [Netanel \(2003\)](#) that can be Pareto improving. In particular, if supply is perfectly inelastic, then a tax of \$13 (6.5% of the retail price) per unit of iPod sale would be sufficient for such Pareto improvement.²¹ In this case, musicians' profit would not decrease even when music piracy became legal, which would not lead to a decrease in the supply of music content.²²

6. Conclusion

I answer two important empirical questions regarding music piracy in this paper. First, does music piracy hurt record sales, and, if so, by how much? Second, does music piracy benefit the sales of music complements, such as iPods and, if so, by how much? I answer these questions using a unique conjoint survey data set. Estimates from three-stage least-squares estimation indicate that music piracy does indeed hurt record sales, which corroborates the prevailing belief in the music industry. I also use a Bayesian approach to estimate the demand for iPods and find that music piracy benefits iPod sales. If there were no music piracy, Apple's revenue from iPod sales would decrease by 12%, which would have translated to \$1.1 billion in 2008. If music were free, however, then Apple's expected revenue would increase by \$36 per student.

²¹ I acknowledge that the iPods' supply is not perfectly inelastic. The full welfare analysis of this iPod tax with supply side response would require further analysis of Apple's profit maximization decision which is beyond the scope of this paper. I leave this important question to future studies.

²² In fact, it is unclear whether the supply of music content would drop even if musicians were slightly worse off. As [Handke \(2012\)](#) shows, the annual number of new titles released continued to expand despite a strong reduction in record sales in Germany.

¹⁹ See the 2011 annual report of Warner Music Group Corp.

²⁰ Consistent with the rest of the paper, I focus here on industry surplus. Note that while a higher iPod tax would be bad for consumers, it is clear that consumer surplus would still be higher in the Free Music Regime compared to the Current Regime. The consumer welfare in the No Music Piracy Regime, however, would be the lowest among the three regimes.

These results indicate that a copyright regime in which music piracy is legal and an iPod tax (which would be redistributed to musicians) could be welfare improving. Indeed, the counterfactual experiments in this paper show that, under some assumptions, an iPod tax of \$13 (or 6.5% of retail price) can be Pareto improving. This result can shed light on the current policy debate over the private copying levies in the U.S., Canada, and many European countries.

In addition to iPods, many other products are also music complements and thus would benefit from a Free Music Regime. Examples include other brands of MP3 players, Internet providers, and live music performances. Although I only focus on iPods in this paper, my approach could easily be extended to examine the complementary relationships between music and these other products. This extension would make possible the evaluation of the effects of different copyright regimes on different products.

Acknowledgments

I am indebted to my advisor Pat Bajari for his continuous encouragement and support. I have benefited from the suggestions of Tom Holmes, Kyoo il Kim, Om Narasimhan, Minjung Park, Amil Petrin, Hakki Yazici, an associate editor, two anonymous referees and seminar participants at Bates White, CUHK, Colby College, Columbia University, the Federal Reserve Bank in Kansas City, HKUST, and the University of Minnesota. I also thank Dulguun Batbold, Andrew Cassey, John Dalton, Tom Holmes, Nick Guo, Christos Ioannou, Ka Fai Li, Mallory Leung, Tina Marsh, Connan Snider, and Junichi Suzuki for their help in conducting the survey. Lastly I am grateful to the Economics Department of the University of Minnesota for financial support. The usual disclaimers apply.

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