Computers in Human Behavior 45 (2015) 69–76

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

The effect of music streaming services on music piracy among college students

Karla Borja [a,*], Suzanne Dieringer [b,1], Jesse Daw [b]

[a] The University of Tampa, Tampa, FL, USA
[b] The University of South Florida, St. Petersburg, FL, USA

ARTICLE INFO

Article history:
Available online 18 December 2014

Keywords:
Music industry
Digital music piracy
Music streaming
Attitudes and collective views
Logit model

ABSTRACT

Previous studies examining the intention and level of music piracy among young people have postulated that collective attitudes, optimistic biases toward risk, and beliefs about copyright laws are the key factors involved in their decisions. We extend the analysis by studying the impact of music streaming services. Music streaming is an alternative business model in which, for a small fee, the consumer has access to a large set of songs without downloading them onto their devices. Results from a Logit model show that college students who are frequent users of music streaming are also more likely to download music illegally. A plausible explanation is that those engaged in music streaming are also heavy users of computer technology, software downloading, and digital sharing – factors that facilitate the conditions for music piracy. Demographics, collective attitudes, and beliefs about risk and rewards continue to play a key role in explaining music piracy, but their relevance is slightly reduced once controlled for music streaming usage.

1. Introduction

Illegal downloading of digital files is a growing threat to the music industry. No longer limited to sharing physical copies, millions of virtual strangers can share music files via the Internet. The International Federation of the Photographic Industry estimates that over 40 billion songs were illegally downloaded in 2008 (IFPI, 2009). New technology, faster wireless connections, and a wider range of mobile devices have facilitated the venue's shift to a space for file sharing and music piracy. This digital embezzlement decreases profits and earnings, but most importantly, it distorts the dynamic market of digital music.

The music industry and the research community have made advances in investigating the effects of music piracy as well as the attributes of those engaging in this illegal act. However, with the emergence and popularity of digital streaming services, more research is needed to determine the relationship between music streaming and music piracy. It is estimated that more than 28 million paying subscribers and many more free-service music streamers had access to 37 billion digital songs in 2013 (IFPI, 2014). Since music streaming is a low-cost alternative to listening to music, it has the potential to reduce music piracy. At the same time, music streamers are young computer users who might feel at ease downloading music illegally.

To address this issue, we use a representative survey of 197 college students who were asked about their online shopping habits, the frequency of movie and music downloading, the usage of streaming services, and the reasons for avoiding music downloading fees. After controlling for variables often considered in the literature, we show that, on average, a music pirate is more likely to be young, with lower income, heavily influenced by peers, and overconfident about risks and rewards. Most importantly, those who actively use a streaming service are also more likely to engage in music piracy. Our results offer valuable insights regarding the impact of online music consumption on the revenue of the music industry.

The rest of the paper proceeds as follows. In section two, we review the existing literature on music piracy and music streaming services, and propose five hypotheses. In section three, we describe the empirical methodology and data. In section four, we present the results from a Logit model analysis and discuss the findings. Finally, in section five, we offer conclusions and recommendations.

2. Theoretical framework, literature review and hypotheses

Music piracy – or, the copying and downloading of music illegally – is considered a serious problem for the music industry

* Corresponding author at: 401 W. Kennedy Blvd., Box O, Tampa, FL 33606, USA. Tel.: +1 813 257 3588; fax: +1 813 258 7408.

E-mail addresses: kborja@ut.edu (K. Borja), sdiering@mail.usf.edu (S. Dieringer), jdaw@mail.usf.edu (J. Daw).

URL: http://www.ut.edu/KarlaBorja/?terms=karla%20borja (K. Borja).

1 Address: 140 7th Ave. South, St. Petersburg, FL 33701, USA.

http://dx.doi.org/10.1016/j.chb.2014.11.088
0747-5632/

and the economy of developed nations. Although it is difficult to accurately assess the losses, preliminary evidence indicates that music crime reduces annual U.S. GDP by $12.5 billion (Siwek, 2007). The problem of music piracy goes beyond the current dollar losses. It is also about the economic, legal, and social distortions, and the market inefficiencies embedded in the act of stealing copyrighted songs. If so, the research community is interested in recognizing music pirates and their motivations.

Following this line of investigation, our interest is to examine the determinants of the digital music piracy by developing a set of hypotheses supported by prominent theories in the field. For instance, age, gender, and income are predictors of music piracy. According to the purchasing behavior theory, digital music is a hedonic product from which the consumer attains an affective experience such as pleasure or joy (Moe & Fader, 2001). The degree of such stimulation in the willingness to purchase an item is not homogenous among consumer segments (Sinha & Mandel, 2008). Madden and Lenhart (2003) conducted a telephone interview of over 2700 adults asking about their illegal downloading habits and found that more than 50% of those admitting to do so were between 18 and 29 years of age. In contrast, adults over the age of 50 who illegally download music represented less than 15% of the respondents. Rochelandet and Le Guel (2005) also identified similar patterns among young adults.

Previous research also indicates that men are more prone to engage in software piracy than women because men are more familiar with peer-to-peer (P2P) networks and other digital sharing technologies. Furthermore, men are more focused on economic incentives and personal advancement than females (Chiang & Assane, 2008; Gopal, Bhattacharjee, and Sanders (2006); Sims, Cheng, & Teegen, 1996).

Gopal and Sanders (1997, 1998), Madden and Lenhart (2003), and Bhattacharjee, Gopal, and Sanders (2003) found that household income and education are linked with illegal downloading behavior. Coyle, Gould, Gupta, and Gupta (2009) concluded that "people intending to pirate were younger, likely to be male, and had lower household income" (pp. 1036). Supported by the research cited above, we propose the following hypothesis:

H1. Age, gender, and income affect the likelihood of engaging in music piracy.

Ajzen (1991) and Akers (1998) developed models in which human behavior is determined by the beliefs and perceptions about consequences, social pressure, and the control and rewards of the outcomes from an action. Supported by these theoretical models, recent empirical studies have focused their attention on the beliefs associated with music piracy (Coyle et al., 2009; Cronan & Al-Rafee, 2008; Phau & Ng, 2010; Taylor, Ishida, & Wallace, 2009).

In addition, herding behavior models diagnose that collective viewpoints and social relations are strong predictors of individual choices, particularly when the consumer has incomplete information about the product or it is costly to calculate risks and rewards (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Manski, 2000; Schiller, 1995). In the specific case of digital music, herding behavior is manifested when music pirates encourage others to download songs with little concern about the risks or illegality of the choice. Shanahan and Hyman (2010) found that attitudes such as "everyone else is doing it," "my friends are doing it," and "important online users want to swap digital files" were strong indicators of music piracy behavior. Rochelandet and Le Guel (2005), Levin, Conway, and Manolis (2007), Chen, Shang, and Lin (2008) and Altschuller and Benbunan-Fich (2009) also found similar results. From this information, we test a second hypothesis:

H2. Peer pressure and herding behavior affect the likelihood of engaging in music piracy.

Rational choice theory predicts that individuals weigh the rewards and risks of any action. In the case of the music piracy act, a consumer weighs the reward of owning a wide range of music without paying for it, against the probability to be arrested and the severity of the penalty. In a study interviewing 500 individuals, McCorkle et al. (2012) found that lower perception of penalties and computer virus risks is associated with illegal file downloading. Coyle et al. (2009) also found that most music downloaders do not fully recognize the risks of being caught, which partially explains the persistence of illegal downloading even when governments have established clear copyright laws and raised fines and jail time (Cheng, Sims, & Teegen, 1997; Chiou, Huang, & Lee, 2005; Li & Nergadze, 2009; Nandedkar & Midha, 2012; Shanahan & Hyman, 2010). Supported by this literature, we develop the following hypothesis:

H3. Perceived risks and penalties associated with music piracy affects the likelihood of engaging in music piracy.

In the field of social learning, Akers (1998) argues that individuals exposed to criminal models for a long period of time are likely to commit the criminal act. Music pirates tend to experience little or no concern regarding the economic struggles of the music industry or the artists (Freestone & Mitchell, 2004; Lysonski & Durvasula, 2008; Rochelandet & Le Guel, 2005). In fact, music pirates tend to hold negative views about the industry, arguing that music companies take advantage of consumers by forcing the purchase of an entire CD, the price of a CD is extremely high, or artists are not being paid fairly by the record labels (Bowie, 2005; Coyle et al., 2009; Levin, Dato-on, & Rhee, 2004; Wang & McClung, 2012; Wingrove, Korpas, & Weisz, 2011). Thus, we propose the following hypothesis:

H4. Individuals' opinions about the music industry or the artists affect the likelihood of engaging in music piracy.

The role of music streaming services in the context of illegal digital downloading also needs to be investigated. Music streaming services send files of songs or videos to a computer or mobile device without downloading the file into the device. Thus, consumers, at a low cost, have access to the digital content without actually owning it. Music streaming is thriving globally. In 2010, the industry recorded 8 million subscribers, and by 2013 there were more than 28 million paid subscribers and countless more free-service members considered active users of music streaming services (IFPI, 2014). This new model of music purchasing has gained popularity thanks to faster Internet speed and mobile technology.

Controversial notions have risen around the music streaming service. Models of consumer surplus predict that lower prices increase the net utility arising from a product, prompting higher demand. Music streaming is a less expensive alternative to other music purchases; it also promotes new and unfamiliar artists, propelling consumers to purchase music online (Gopal et al., 2006). Using a panel of 16,000 European consumers, Aguiar and Martens (2013) found a positive relationship between music streaming and online music purchases.

On the other hand, streaming services are also associated with tech savvy consumers who feel comfortable with software downloading, digital sharing practices, and music piracy. Coyle et al. (2009) found that individuals "who are heavy consumers of legally purchased online music will be more likely to pirate music in the future" (pp. 1034). Rob and Waldfogel (2006) concluded that file-sharing and file-downloading reduce music spending. Thus, we propose the following hypothesis:

Table 1
Hypotheses and source of the variables.

Variable/survey question
H1: Age, gender, and income affect the likelihood of engaging in music piracy
Age (Q1), gender (Q2), annual income (Q8)
I could not afford to purchase all of the music I would want to download (Q22a)
H2: Peer pressure and herding behavior affect the likelihood of engaging in music piracy
Why should I pay when everyone else gets it for free (Q22b)
H3: Perceived risks and penalties associated with music piracy affects the likelihood of engaging in music piracy
I do not believe there is a high risk of getting caught (Q22c)
I do not believe the consequences are very severe if I do get caught (Q22d)
I do not believe it is wrong to download it (Q22e)
I refuse to pay the price because it's not worth it to me (Q22f)
H4. Individuals' opinions about the music industry or artists affect the likelihood of engaging in music piracy
The artist is successful enough that it won't hurt him/her (Q22g)
I do not want to support the record company (Q22h)
H5: Music streaming affects the likelihood of engaging in music piracy
Do you use any music streaming service? (Q16)
If yes, how many times in the past 30 days? (Q17)

Note: The Q# in parenthesis is the question number as presented in the survey instrument. Details about the variables used to test these hypotheses are described in Section 3 and presented in Appendix A.

H5. Music streaming affects the likelihood of engaging in music piracy.

In summary, it is expected that the average music pirate is young, male, with low income, severely influenced by peers, overconfident about risks and rewards, and a heavy user of music streaming.

Much research has been completed on the negative impact that piracy has on the music industry as well as the characteristics of those who engage in music piracy. However, with the emergence of music streaming services, we contribute to the literature by examining the relationship between music streaming and music piracy among college students. Specifically we test the five hypotheses summarized in Table 1.

3. Experimental design and methodology

We collected a sample of 197 undergraduate student surveys at the University of South Florida, St. Petersburg campus. College students were chosen because file downloading and music sharing are observed more often among college students (Bhattacharjee et al., 2003; Coyle et al., 2009; Rob & Waldfogel, 2006; Shanahan & Hyman, 2010). The sample has a fair mix of 99 males and 98 females. Surveys were administered in several College of Business course classrooms. All participants received an informed consent form, which assured the surveys had no identifying information. Participation was voluntary, and the subjects were allowed to withdraw at any time during the completion of the survey.

The survey consisted of 26 semi-structured questions. The first section of the questionnaire identified demographic information of the participants. In the second section, respondents were asked about the frequency of online shopping, music downloading, and music streaming. Finally, those engaged in illegal downloading of music were asked to identify the reasons to do it from a list of nine factors. Afterward, these factors were converted into dichotomous indexes. For example, a participant who marked the box "I do not believe it is wrong to download it" (Q22e) is assigned with the value of one under Q22e, otherwise it is zero. A participant could mark more than one of the nine factors. Thus, each observation could have several 0/1 values. Appendix A provides detailed information on the questions and the codifications.

Participant ages range from 18 to 52 years old, with an average of 23 years of age. Table 2 illustrates the statistical differences between two groups: those who illegally downloaded music (Type-1), and those who did not download music at all or who paid for it during the last 30 days (Type-0). Age and income are statistically different between the two groups. On average, older students (24.3 years) did not download music illegally as much as younger ones did (21.5 years). Higher income students (Group 3: $15,000–20,000) illegally downloaded less music than lower income students (Group 2: $10,000–15,000).

Table 2 also shows that the usage of music streaming services is significantly different between the two groups: Type-1 subjects have used more music streaming services than Type-0 during the last month ($p = 0.002$). Similar to the findings in Robertson, McNeill, Green, and Roberts (2012), men and women were equally likely to illegally download music ($p = 0.142$). Type-1 students were also inclined to download more movies without paying for them ($p = 0.000$). The frequency of online shopping was not statistically different between the two groups ($p = 0.781$). In summary, the two groups show relevant differences in age, income, online shopping, the frequency of illegal downloading of movies, and the usage and frequency of streaming services.

Concerns regarding the dispersion of the participants' age persuaded us to replicate the results from Table 2 using a subsample of only young participants (age $\leqslant 27$, $n = 173$). These results are presented in Appendix B and do not differ from those in Table 2. Age is still statistically different between the two groups. On average, older students (21.6) did not download music illegally as much as younger ones did (20.7 years, $p = 0.017$). These two subgroups also show statistical differences in age, income, online shopping, the frequency of illegal downloading of movies, and the usage and frequency of streaming services.

We complement the preliminary statistical evaluation by completing a Logit model analysis. Doyle (1977) and Menard (2002) recommend that the most suitable estimation approach when the dependent variables are dichotomous or non-metric is a Probit or Logit model. Since the dependent variable of our study is a dichotomous index that takes the value of one if the student downloaded music without paying for it in the last 30 days and zero otherwise, we used a Logit model, or response probability function, of the form:[2]

$$P[Y_i = 1|X] = F(X'\beta) = F(\beta_0 + \beta_1 MS_i + \beta_2 Z_i + \beta_3 R_i + \varepsilon_i) \quad (1)$$

where $F(Z) = e^Z/(1 + e^Z)$, Y_i is the binary indicator that takes the value of one if the student i downloaded music illegally. MS takes the value of one if any music streaming service was used during the past 30 days; otherwise, it takes the value of zero. Z is a vector of control variables such as age, gender, income, major, and race. Finally, R represents a vector of the reasons for illegally downloading music.

The Logit regressions identify the factors that increase the likelihood of illegal downloading of music. We estimate the marginal effects of the probability that a student illegally downloaded music to provide meaningful interpretations of the results.

All regressions were completed using five control variables: age, gender, school year, major, race, and income. However, only age was statistically relevant in all regressions; thus, it is the only

[2] Prieto-Rodriguez and Fernandez-Blanco (2000), Rochelandet and Le Guel (2005) and Chiang and Assane (2007), Chiang and Assane (2008) also applied Logit/Probit models to investigate the factors affecting music piracy. Other empirical studies have applied Structural Equation Modeling and Principal Component Analysis to find the statistical relationship between latent and observable variables in the music field (Cockrill & Goode, 2012; Gopal, Sanders, Bhattacharjee, Agrawal, & Wagner, 2004; Morton & Koufteros, 2008; and Agrebi & Jallais, 2015). However, these models aim at reducing the dimension of the analysis by constructing factors or components stemming from the covariance matrix of the original set of observable variables. In most of these cases the observable data are metric or scores, providing more meaningful results than when using binary indexes.

Table 2
Descriptive statistics.

Control Variable	Download illegally (Type-1)	No download illegally (Type-0)	SE (*P*-value)
Observations	118	79	
Age (median)	21.5 (20)	24.2 (22)	0.734 (0.000)
Gender (1 = male, 0 = female)	0.534	0.456	0.073 (0.142)
School Year (1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior)	2.624	2.829	0.145 (0.158)
Major (1 = Business, 0 = Non-business)	0.771	0.823	0.059 (0.384)
Race (0 = White, 1 = Other)	0.275	0.310	0.069 (0.619)
Income (1 = <$10,000, 2 = $10,001–15,000, 3 = $15,001–20,000, 4 = $20,001–25,000, 5 = >$25,000)	2.052	2.712	0.233 (0.005)
Online music shopping	0.720	0.734	0.065 (0.416)
Music streaming services	0.924	0.772	0.049 (0.002)
Music streaming frequency	3.042	2.658	0.166 (0.021)
Online shopping	0.983	0.949	0.025 (0.089)
Online shopping frequency	1.923	1.949	0.092 (0.781)
Movie downloading	0.627	0.607	0.071 (0.783)
Movie download frequency	1.500	1.418	0.102 (0.423)
Illegal movie downloading frequency	2.821	1.721	0.268 (0.000)
Total observations = 197			

Note: Values in columns 2 and 3 are means of the sample. The last column shows the standard error of the difference between the two samples. It also shows the *p*-values from an equal-mean *t*-test between two groups: those who downloaded music without paying for it and those who did not download music at all or paid for it.

Table 3
The probability of illegal downloading of music.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Logit	MgE	Logit	MgE	Logit	MgE	Logit	MgE	Logit	MgE
Age	−0.10* (0.035)	−2.4%	−0.10* (0.035)	−2.3%	−0.09* (0.034)	−2.2%	−0.09* (0.034)	−2.0%	−0.11* (0.033)	−2.6%
H5-MS	0.98** (0.472)	23.5%								
H1-I can't afford it			2.61* (0.484)	57.8%						
H2-Everybody does it					1.48* (0.426)	34.7%				
H3-Low risk							1.51* (0.477)	35.3%		
H4-It won't hurt the artist									1.23** (0.620)	28.9%
Constant	1.84** (0.938)		2.13* (0.809)		2.19* (0.804)		2.11* (0.798)		2.80* (0.757)	
Pseudo-R2	0.07		0.22		0.11		0.10		0.07	
Walt-Test (Prob > χ^2)	0.000		0.000		0.000		0.000		0.001	
Goodness-of-fitness (P-χ^2)	0.557		0.369		0.508		0.612		0.628	
Correctly Classified	66.0%		70.1%		65.5%		66%		65.5%	

Note: The dependent variable takes the value of one if the respondent illegally downloaded music; zero otherwise. H*i* = hypothesis *i*. MgE = marginal effect. MgE is calculated at the mean. The Walt-Test verifies that all estimated coefficients are statistically significant predictors of the dependent variable. *P*-values lower than 0.05 corroborate the validity of the variables in the model. The goodness-of-fitness test is a Pearson-χ^2 test that validates how well the Logit model fits the data. *P*-values higher than 0.05 indicate that the Logit model fits reasonably well the data. Correctly classified is the overall rate of correct classification of the observations.
* Statistical significance at .01.
** Statistical significance at .05.
*** Statistical significance at .1.

variable included in all scenarios.[3] Similar to Gopal et al. (2006), absolute income has little or no significant effect in all specifications, which can be explained by the small cost of one song relative to the budget of a typical music consumer.

4. Results

Table 3 displays the parameters of the Logit model and the marginal values of five different scenarios. Model 1 corroborates hypothesis five (H5): music streaming is a strong predictor of music piracy. Streaming increases the probability that a student illegally downloads music by 23.5%. Age is statistically relevant in all model specifications; however, the marginal impact of the age parameter is relatively small, ranging between 2% (Model 4) and 2.6% (Model 5).

Models 2–5 yield results for the rest of the hypotheses described in Table 1. As mentioned above, absolute income is not statistically relevant, but answering "yes" to question Q22a, "I could not afford to purchase all of the music I want to download" increases the likelihood of music piracy by 57.8% (Model 2). Thus, relative income (cost per song-to-music budget), instead of absolute income, is a predictor of music piracy behavior (H1).

Peer pressure encourages music piracy (H2): the belief that "why pay if others don't do it" increases the probability of music piracy by 34.7% (Model 3). Perceptions of low risks associated with music piracy increase the likelihood of engaging in the illegal act of downloading copyrighted music by 35.3% (Model 4). Finally, individual opinions on the artist's success increase the likelihood of engaging in music piracy by 28.9% (Model 5).

The next step in our analysis is to determine the changes in the likelihood of music piracy once controlling for music streaming, *MS* (Table 4). It is evident that the hypotheses regarding peer-behavior, risk-reward overconfidence, and beliefs about the artist's success still hold true (all parameters of Hypotheses 1–4 are statistically relevant in Table 4). However, the parameter values and the corresponding likelihood rates are slightly smaller than those shown in Table 3. For instance, the belief about the artist's success increases the probability of music crime by 28.9% in the first analysis (Table 3, Model 5), but only by 25.9% when including

[3] Regression results using all control variables are available upon request.

Table 4
The probability of illegal downloading of music with MS.

	Model 2		Model 3		Model 4		Model 5	
	Logit	MgE	Logit	MgE	Logit	MgE	Logit	MgE
Age	−0.10* (0.036)	−2.2%	−0.08** (0.035)	−1.9%	−0.08** (0.035)	−1.8%	−0.10* (0.034)	−2.3%
H5-MS	0.58 (0.501)	12.9%	0.86*** (0.472)	20.2%	0.80*** (0.469)	18.8%	0.88*** (0.468)	20.8%
H1-I can't afford it	2.54* (0.486)	56.5%						
H2-Everybody does it			1.44* (0.429)	33.7%				
H3-Low risk					1.43* (0.481)	33.4%		
H4-It won't hurt the artist							1.10*** (0.618)	25.9%
Constant	1.52 (0.965)		1.21 (0.963)		1.21 (0.951)		1.82** (0.913)	
Pseudo-R2	0.23		0.12		0.11		0.08	
Walt-Test (Prob > χ^2)	0.000		0.000		0.000		0.001	
Goodness-of-fitness (P-χ^2)	0.485		0.615		0.732		0.564	
Correctly Classified	72%		67.5%		68%		66.5%	

Note: The dependent variable takes the value of one if the respondent illegally downloaded music; zero otherwise. H*i* = hypothesis *i*. MgE = marginal effect. MgE is calculated at the mean. The Walt-Test verifies that all estimated coefficients are statistically significant predictors of the dependent variable. *P*-values lower than 0.05 corroborate the validity of the variables in the model. The goodness-of-fitness test is a Pearson-χ^2 test that validates how well the Logit model fits the data. *P*-values higher than 0.05 indicate that the Logit model fits reasonably well the data. Correctly classified is the overall rate of correct classification of the observations.

* Indicate statistical significance at .01.
** Indicate statistical significance at .05.
*** Indicate statistical significance at .1.

Table 5
The probability of illegal downloading of music with MS (Part II).

	Model 6		Model 7		Model 8		Model 9	
	Logit	MgE	Logit	MgE	Logit	MgE	Logit	MgE
Age	−0.09* (0.035)	−2.1%	−0.08** (0.035)	−1.8%	−0.09* (0.036)	−2.2%	−0.10* (0.035)	−2.3%
H5-MS	0.91** (0.465)	21.6%	0.87*** (0.466)	20.4%	0.93** (0.474)	21.7%	0.92** (0.466)	21.7%
H3-No severe penalty	0.99*** (0.657)	23.5%						
H3-It is not wrong			1.53* (0.567)	35.8%				
H3-It is not worth it					1.53* (0.484)	35.8%		
H4-No support record co.							1.68 (1.068)	39.7%
Constant	1.61*** (0.939)		1.25 (0.942)		1.52 (0.967)		1.78*** (0.943)	
Pseudo-R2	0.08		0.11		0.11		0.08	
Walt-Test (Prob > χ^2)	0.001		0.000		0.000		0.001	
Goodness-of-fitness (P-χ^2)	0.734		0.669		0.653		0.713	
Correctly Classified	67%		67.5%		67%		66.5%	

Note: The dependent variable takes the value of one if the respondent downloaded music without paying; zero otherwise. H*i* = hypothesis *i*. MgE = marginal effect. MgE is calculated at the mean. The Walt-Test verifies that all estimated coefficients are statistically significant predictors of the dependent variable. *P*-values lower than 0.05 corroborate the validity of the variables in the model. The goodness-of-fitness test is a Pearson-χ^2 test that validates how well the Logit model fits the data (*P*-values > 0.05 indicate that the model fits reasonably well the data). Correctly classified is the overall rate of correct classification of the observations.

* Indicate statistical significance at .01.
** Indicate statistical significance at .05.
*** Indicate statistical significance at .1.

MS (Table 4, Model 5). Similarly, the perception of low risk increases the probability of engaging in music piracy by 35.3% (Table 3, Model 3), but only by 33.4% when *MS* is included in the model (Table 4, Model 3). The parameter *MS* is statistically relevant and fairly stable at around 20% in all specifications except one.

Table 5 reports the results from the rest of the questions in Table 1. For instance, Model 6 shows the parameter value for question Q22d "I do not believe the consequences are very severe if I do get caught" (H3). Models 7–9 are linked to questions Q22e (H3), Q22f (H3), and Q22h (H4), respectively. No statistical evidence was found on the relationship between music piracy and beliefs about the record companies (Table 5, Model 9). The *MS* value is statistically relevant in all but one specification (Table 4, Model 2). The *MS* marginal parameter ranges from 18.8% (Model 4) to 21.7% (Model 8).

As a robustness measure, Table 6 replicates the results from Table 4 using the subsample of only young participants (age $\leqslant$ 27, n = 173). The main results hold true and no significant differences are observed.[4]

[4] We completed Tables 3–5 using the subsample. Total regression results using this smaller sample are available upon request.

As expected, a more homogeneous sample produces a non-significant *Age* parameter; however, *MS* preserves its statistical value in all model specifications. For example, the *MS* of the full sample is 0.92 (Table 4, Model 5), and its value with the subsample is 1.07 (Table 6, Model 5), corroborating the hypothesis that the usage of music streaming increases the likelihood of music piracy among young college students.

Overall, students tend to engage in music piracy if they believe that "everybody else is doing it" or "there is nothing wrong with doing it." Also, the perception of low risk and limited punishment increases the digital music crime. Most notably, music streaming is a factor explaining music piracy. Finally, beliefs about the artist's achievements influence students to engage in music piracy as well.

This research provides evidence on the negative effect of music streaming services in the digital music piracy. However, we need to acknowledge some limitations and recommendations for future research. The sample size is fairly small and biased toward college students. We believe that a larger and more diverse sample might improve the accuracy of the statistical tests in the regression analysis. The next step in our research agenda is to replicate the experiment with a larger sample size and a more structured

Table 6
The probability of illegal downloading of music with MS (subsample).

	Model 2		Model 3		Model 4		Model 5	
	Logit	MgE	Logit	MgE	Logit	MgE	Logit	MgE
Age	−0.09 (0.073)	−1.8%	−0.11 (0.068)	−2.4%	−0.09 (0.069)	−2.0%	−0.12*** (0.067)	−2.8%
H5-MS	0.75 (0.555)	15.5%	0.97*** (0.533)	21.4%	0.96*** (0.529)	21.2%	1.07** (0.523)	24.1%
H1-I can't afford it	2.37* (0.509)	49.2%						
H2-Everybody does it			1.48* (0.454)	32.7%				
H3-Low risk					1.34* (0.487)	29.8%		
H4-It won't hurt the artist							1.07* (0.523)	23.4%
Constant	1.20 (1.624)		1.72 (1.535)		1.43 (1.544)		2.19 (1.487)	
Pseudo-R2	0.18		0.10		0.08		0.06	
Walt-Test (Prob > χ^2)	0.000		0.000		0.000		0.005	
Goodness-of-fitness (P-χ^2)	0.462		0.712		0.738		0.672	
Correctly Classified	79.4%		67.7%		67.7%		66.5%	

Note: The dependent variable takes the value of one if the respondent illegally downloaded music; zero otherwise. H*i* = hypothesis *i*. MgE = marginal effect. MgE is calculated at the mean. The Walt-Test verifies that all estimated coefficients are statistically significant predictors of the dependent variable. *P*-values lower than 0.05 corroborate the validity of the variables in the model. The goodness-of-fitness test is a Pearson-χ^2 test that validates how well the Logit model fits the data. *P*-values higher than 0.05 indicate that the Logit model fits reasonably well the data. Correctly classified is the overall rate of correct classification of the observations.
* Indicate statistical significance at .01.
** Indicate statistical significance at .05.
*** Indicate statistical significance at .1.

questionnaire; hence, the dependent and independent variables could be metric values instead of binary indexes.

5. Conclusions

Digital music crime reduces the profits and income of artists, record companies, workers, and nations. It is also a matter of interest among economists because it distorts the market of music by changing the incentives to supply and demand new products in the growing market of online music.

This paper provides evidence on the role of music streaming services in digital music piracy. It also shows that factors such as peer and social pressure, risk-reward overconfidence, and beliefs about the artist's success are relevant in explaining music crime. However, the weight of such factors is reduced once controlled for music streaming.

The results indicate that music streaming increases the likelihood of engaging in music piracy by about 20%. We also find that pirates are more concerned about the prices and cost of each song. They are influenced by their peers; thus, as a student observes that the crime is well accepted and executed among peers, he is more likely to practice it. Corroborated by previous studies, the belief that music piracy is a minor fault or that it implies low risk of apprehension and penalization, leads to an increased probability of illegal music downloading.

Demographic factors such as gender, race, major, school year, computer or Internet access, and absolute income are not helpful in differentiating pirates. These days, most college students of all characteristics could engage in the digital music crime. The key discriminating factors are related to values, beliefs, and new available technology, such as online file streaming.

The statistical relevance of music streaming is persistent among different scenarios and assumptions. In fact, music streaming is still a strong explanatory factor of music piracy even when controlling for attitudes regarding risk-reward beliefs, peer-pressure behavior, and concerns about the artist or the record companies.

Solutions to combat copyright piracy emphasize enforcement, legal and risk awareness, and economic incentives. Music streaming services are less expensive alternatives to buying and owning music and thus, are expected to act as an economic incentive to reduce music piracy. However, we still observe rampant illegal sharing and downloading of music. The findings from our study are in line with this reality: individuals who intensively use music streaming are also digital technology savvies who feel comfortable with music sharing and music piracy. Thus, we do not expect to see a reduction in music piracy rates as a consequence of the rising popularity of music streaming services.

In order to combat music piracy, governments and the music industry should target young consumers regarding law and risk awareness, recognition of artists' harms and losses, and strengthen law enforcement. The industry should plan new methods to substitute the means of listening to digital music without relying on streaming technology as a way to reduce online music crime.

Appendix A. Variables and descriptions

Variables	Description/survey question
Dependent variable	
Music piracy	= 1 if the student engaged in illegal downloading of music during the past 30 days; = 0 if otherwise
Independent variables	
Age	Age of student (in years) (Q1)
Gender	= 1 if male, = 0 if female (Q2)
Major	= 1 if Business/economics major, = 0 if other majors (Q3)
Race	= 1 if White/Caucasian, = 0 if any other race (Q4)
School year	= 1 if Freshman, = 2 if Sophmore, = 3 if Junior, = 4 if Senior (Q5)
Income	= 1 if income is less than $10,000 a year, = 2 if between $10,001 and $15,000, = 3 if between $15,001 and $20,000, = 4 if between $20,001 and $25,000, and = 5 if higher than $25,000 (Q8)
Music streaming services	= 1 if yes. Do you use any music streaming service? (Q16)
Music streaming frequency	If yes, how many times in the past 30 days? (Q17)
Online shopping	= 1 if yes. Have you ever made any kind of purchase online? (Q12)
Online shopping frequency	If yes, how many times in the past 30 days? (Q13)

Appendix A (*continued*)

Variables	Description/survey question
Movie downloading	= 1 if yes. Have you ever downloaded a movie off the internet? (Q14)
Movie download frequency	If yes, how many times in the past 30 days? (Q15a)
Illegal movie downloading frequency	What percentage of movies have you downloaded that you were supposed to pay for but didn't? (Q15b)
Factors/reasons	
I can't afford it	= 1 if marked. I could not afford to purchase all of the music I would want to download (Q22a)
Everybody does it	= 1 if marked. Why should I pay when everyone else gets it for free (Q22b)
Low risk	= 1 if marked. I do not believe there is a high risk of getting caught (Q22c)
No severe penalty	= 1 if marked. I do not believe the consequences are very severe if I do get caught (Q22d)
It is not wrong	= 1 if marked. I do not believe it is wrong to download it (Q22e)
It is not worth it	= 1 if marked. I refuse to pay the price because it's not worth it to me (Q22f)
It won't hurt the artist	= 1 if marked. The artist is successful enough that it won't hurt him/her (Q22g)
No support record co.	= 1 if marked. I do not want to support the record company (Q22h)

Appendix B. Descriptive statistics from a smaller sample size (subjects age $\leqslant 27$)

Control variable	Download illegally (Type-1)	No download illegally (Type-0)	SE (*P*-value)
Observations	110	63	
Age (median)	20.7 (20)	21.6 (21)	0.391 (0.017)
Gender (1 = male, 0 = female)	0.536	0.429	0.079 (0.087)
School year (1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior)	2.568	2.709	0.156 (0.184)
Major (1 = Business, 0 = Non-business)	0.782	0.793	0.065 (0.428)
Race (0 = White, 1 = Other)	0.277	0.298	0.075 (0.390)
Income (1 = <$10,000, 2 = $10,001–15,000, 3 = $15,00120,000, 4 = $20,00125,000, 5 = >$25,000)	1.953	2.281	0.239 (0.087)
Online music shopping	0.727	0.809	0.067 (0.227)
Music streaming services	0.936	0.809	0.048 (0.005)

Appendix B (*continued*)

Control variable	Download illegally (Type-1)	No download illegally (Type-0)	SE (*P*-value)
Music streaming frequency	3.063	2.761	0.176 (0.044)
Online shopping	0.982	0.936	0.028 (0.059)
Online shopping frequency	1.918	1.905	0.096 (0.889)
Movie downloading	0.600	0.651	0.077 (0.511)
Movie download frequency	1.509	1.444	0.114 (0.572)
Illegal movie downloading frequency	2.761	1.778	0.296 (0.001)
Total observations = 173 (86% of the total sample size)			

Note: This table replicates the results from Table 2, but with a subsample of only those participants with age 27 or less. Values in columns 2 and 3 are means of the sample. The last column shows the standard error of the difference between the two samples. It also shows the *p*-values from an equal-mean *t*-test between two groups: those who downloaded music without paying for it and those who did not download music at all or paid for it.

References

Agrebi, S., & Jallais, J. (2015). Explain the intention to use smartphones for mobile shopping. *Journal of Retailing and Consumer Services, 22*, 16–23.

Aguiar, L., & Martens, B. (2013). *Digital music consumption on the internet: Evidence from clickstream data*. Digital economy working paper 2013/04. Institute for Prospective Technological Studies, Joint Research Centre of the European Commission. <http://ftp.jrc.es/EURdoc/JRC79605.pdf> Retrieved 11.08.14.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179–211.

Akers, R. (1998). *Social learning and social structure: A general theory of crime and deviance*. Boston: Northeastern University Press.

Altschuller, S., & Benbunan-Fich, R. (2009). Is music downloading the new prohibition? What students reveal through an ethical dilemma. *Ethics Information Technology, 11*, 49–56.

Banerjee, A. (1992). A simple model of herd behavior. *Quarterly Journal of Economics, 107*, 797–817.

Bhattacharjee, S., Gopal, R., & Sanders, G. (2003). Digital music and online sharing: Software piracy 2.0? *Communications of the ACM, 46*, 107–111.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom and cultural change as information cascades. *Journal of Political Economy, 100*, 992–1026.

Bowie, N. (2005). Digital rights and wrongs: Intellectual property in the information age. *Business and Society Review, 110*, 77–96.

Chen, Y., Shang, R., & Lin, A. (2008). The intention to download music files in a P2P environment: Consumption value, fashion, and ethical decision perspectives. *Electronic Commerce Research and Applications, 7*, 411–422.

Cheng, H., Sims, R., & Teegen, H. (1997). To purchase or to pirate software: An empirical study. *Journal of Management Information System, 13*, 49–60.

Chiang, E., & Assane, D. (2007). Determinants of music copyright violations on the university campus. *Journal of Cultural Economics, 31*, 187–204.

Chiang, E., & Assane, D. (2008). Music piracy among students on the university campus: Do male and females react differently? *The Journal of Socio-Economics, 37*, 1371–1380.

Chiou, J., Huang, C., & Lee, H. (2005). The antecedents of music piracy attitude and intentions. *Journal of Business Ethics, 57*, 161–174.

Cockrill, A., & Goode, M. (2012). DVD pirating intentions: Angels, devils, chancers, and receivers. *Journal of Consumer Behavior, 11*, 1–10.

Coyle, J., Gould, S., Gupta, P., & Gupta, R. (2009). "To buy or pirate": The matrix of music consumers' acquisition-model decision-making. *Journal of Business Research, 62*, 1031–1037.

Cronan, T., & Al-Rafee, S. (2008). Factors that influence the intentions to pirate software and media. *Journal of Business Ethics, 78*, 527–545.

Doyle, P. (1977). The application of probit, logit and tobit in marketing: A review. *Journal of Business Research, 5*, 235–248.

Freestone, O., & Mitchell, V. (2004). Generation Y attitudes towards e-ethics and internet related misbehaviors. *Journal of Business Ethics, 54*, 121–128.

Gopal, R., Bhattacharjee, S., & Sanders, G. (2006). Do artists benefit from online music sharing? *The Journal of Business, 79*, 1503–1533.
Gopal, R., & Sanders, G. (1997). Preventive and deterrent controls for software piracy. *Journal of Management Information Systems, 13*, 29–48.
Gopal, R., & Sanders, G. (1998). International software piracy: Analysis of key issues and impacts. *Information Systems Research, 9*, 380–397.
Gopal, R., Sanders, G., Bhattacharjee, S., Agrawal, M., & Wagner, S. (2004). A behavioral model of digital music piracy. *Journal of Organizational Computing and Electronic Commerce, 14*, 89–105.
IFPI (2009). *New business models for a changing environment*. IFPI digital music report. International Federation of the Photographic Industry (IFPI), London, UK.
IFPI (2014). *Lighting up new markets*. IFPI digital music report. International Federation of the Photographic Industry (IFPI), London, UK.
Levin, A., Conway, M., & Manolis, C. (2007). Deterring illegal downloading: The effects of threat appeals, past behavior, subjective norms, and attributions of harm. *Journal of Consumer Behaviour, 6*, 111–122.
Levin, A., Dato-on, M., & Rhee, K. (2004). Money for nothing and hits for free: The ethics of downloading music from peer-to-peer web sites. *Journal of Marketing Theory and Practice, 12*, 48–60.
Li, X., & Nergadze, N. (2009). Deterrence effect of four legal and extralegal factors on online copyright infringement. *Journal of Computer-Mediated Communication, 14*, 307–327.
Lysonski, S., & Durvasula, S. (2008). Digital piracy of mp3s: Consumer and ethical predispositions. *Journal of Consumer Marketing, 25*, 167–178.
Madden, M., & Lenhart, A. (2003). *Music downloading, file-sharing and copyright*. Pew research internet project, report from July 31. Pew Research Center, Washington, DC.
Manski, C. (2000). Economic analysis of social interactions. *Journal of Economic Perspectives, 14*, 115–136.
McCorkle, D., Reardon, J., Dalenberg, D., Pryor, A., & Wicks, J. (2012). Purchase or pirate: A model of consumer intellectual property theft. *Journal of Marketing Theory and Practice, 20*, 73–86.
Menard, S. (2002). *Logistic regression* (2nd ed). Thousand Oaks, CA: Sage.
Moe, W., & Fader, P. (2001). Modeling hedonic portfolio products: A joint segmentation analysis of music compact disc. *Journal of Marketing Research, 38*, 376–385.
Morton, N., & Koufteros, X. (2008). Intention to commit online music piracy and its antecedents: An empirical investigation. *Structural Equation Modeling: A Multidisciplinary Journal, 15*, 491–512.
Nandedkar, A., & Midha, V. (2012). It won't happen to me: An assessment of optimism bias in music piracy. *Computers in Human Behavior, 28*, 41–48.
Phau, I., & Ng, J. (2010). Predictors of usage intentions of pirated software. *Journal of Business Ethics, 94*, 23–37.
Prieto-Rodriguez, J., & Fernandez-Blanco, V. (2000). Are popular and classical music listeners the same people? *Journal of Cultural Economics, 24*, 147–164.
Rob, R., & Waldfogel, J. (2006). Piracy on the high C's: Music downloading, sales displacement, and social welfare in a sample of college students. *Journal of Law and Economics, 49*, 29–62.
Robertson, K., McNeill, L., Green, J., & Roberts, C. (2012). Illegal downloading, ethical concern and illegal behavior. *Journal of Business Ethics, 108*, 215–227.
Rochelandet, F., & Le Guel, F. (2005). P2P music sharing networks: Why the legal fight against copiers may be inefficient. *Review of Economic Research on Copyright Issues, 2*, 69–82.
Schiller, R. (1995). Conversation, information, and herd behavior. *Rhetoric and Economic Behavior, 85*, 181–185.
Shanahan, K., & Hyman, M. (2010). Motivators and enablers of SCOURing: A study of online piracy in the US and UK. *Journal of Business Research, 63*, 1095–1102.
Sims, R., Cheng, H., & Teegen, H. (1996). Toward a profile of student software piraters. *Journal of Business Ethics, 15*, 839–849.
Sinha, R., & Mandel, N. (2008). Preventing digital music piracy: The carrot or the stick? *Journal of Marketing, 72*, 1–15.
Siwek, S. (2007). *The true cost of sound recording piracy to the US economy*. Policy report 188. Institute for Policy Innovation (IPI), Center for Technology Freedom, Lewisville, TX.
Taylor, S., Ishida, C., & Wallace, D. (2009). Intention to engage in digital piracy: A conceptual model and empirical test. *Journal of Service Research, 11*, 246–262.
Wang, X., & McClung, S. (2012). The immorality of illegal downloading: The role of anticipated guilt and general emotions. *Computers in Human Behavior, 28*, 153–159.
Wingrove, T., Korpas, A., & Weisz, V. (2011). Why are millions of people not obeying the law? Motivational influences on noncompliance with the law in the case of music piracy. *Psychology, Crime, & Law, 17*, 261–276.