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Abstract

In this paper we propose a model which shows that the impact of copyright infringement on music artists depends on the type of revenue that they receive (royalties from record companies, profits for self-released artists, revenues from live concerts). We then test the hypotheses derived from the model on a dataset consisting of a survey of 710 artists representative of the whole population of French professional musicians. The results are consistent with our model in so far as: (i) those artists with a recording contract who do more live performances are more tolerant of piracy; and (ii) self-released artists are less tolerant of piracy, and that their attitude is therefore closer to that of record companies.

Keywords: Copyright; Piracy; Music industry; Artists.

JEL Codes: K42; L82; O34.

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1 Introduction

In some industrialized countries, such as South Korea, Taiwan (2009), France and the United Kingdom (2010), new legislation has recently been adopted to fight against piracy on Peer-to-Peer (P2P) networks. According to the International Federation of the Phonographic Industry (2010, p. 3), "these countries established in law that it is appropriate for those who persistently violate copyright, despite repeated warnings, to face a proportionate and effective sanction."

Such legislation is widely supported by record companies, who consider it self-evident that their own interests and those of their artists are perfectly aligned. However, the artists' positions are mixed. For example, in France, Adami, the organization that collects royalties for musicians and therefore represents their interests (at least partially), has declared that it is neutral towards the new anti-piracy legislation (the "Hadopi" law), arguing that many artists are just not willing to sue their fans.[1] Moreover, while some artists have been critical of piracy, there are also examples of artists who encourage consumers to pirate their music.[2]

Rodrik (1996, p. 33) argues that a reform "should strive for a consensus with affected groups." Why is that not the case with anti-piracy laws? Why are there conflicting opinions within the artistic community on the impact of file-sharing? Do these conflicting opinions reflect heterogeneous economic interests, heterogeneous individual moral values, or irrationality?[3]

The aim of this paper is to understand an artist's attitude towards piracy. We start by building up a model to determine these attitudes in relation to an artist's sources of revenue: (i) royalties from record companies, (ii) profits from self-released albums, (iii) revenues from live concerts. We then test the predictions of the model on a survey of 710 French musicians representative of the population of professional musicians in France. Our estimation results are consistent with our theoretical conclusions. For artists under contract with a record label, those with a high frequency of live performances are more tolerant of piracy. Furthermore, we find that self-released artists are less tolerant of piracy. Their attitude is therefore close to that of the record companies.

This paper is related to the economic literature on copyright infringement in the recorded music industry,[4] which focuses strongly on the impact of file-sharing on music sales. Some authors hold

[1] Cf. http://www.adami.fr/defendre-les-droits-des-artistes.html.

[2] Artists like Skrillex, Franz Ferdinand and Trent Reznor have even encouraged their fans to pirate their music. Others, like Lily Allen or James Blunt, campaign against file-sharing.

[3] For example, Throsby (2001) argues that, for some artists at least, creativity sometimes appears as an irrational process.

[4] See Belleflamme and Peitz (2010) for a recent survey of the theoretical literature on online piracy.

piracy entirely responsible for the decline in record sales (Liebowitz, 2008), while others completely exempt it from blame (Oberholzer-Gee and Strumpf, 2007), but most of the literature derives more nuanced conclusions. Some authors have looked at the effectiveness of measures to reduce piracy, through legal means (Bhattacharjee et al., 2006; Maffioletti and Ramello, 2004) or technological solutions, such as digital rights management (DRM) systems that prevent the copy of legally purchased music (Liebowitz and Watt, 2006). However, as these papers estimate the impact of piracy at the industry level, they cannot assess its impact on creators (artists), which is the focus of our paper.

Closer to our paper, Duchêne and Waelbroeck (2006) show that increasing legal protection benefits artists who use information-push technologies (i.e., marketing and promotion) and whose music is well-known to consumers. But increasing legal protection can hurt small-audience artists who benefit most from information-pull technologies (e.g., P2P networks), since digital copies allow consumers to discover their music. In the same vein, Gopal et al. (2006) show that file-sharing on P2P networks may encourage some consumers to pirate music, but it also enhances the legitimate customer base by reducing the total cost of music acquisition. They conclude that file-sharing technologies erode the superstar phenomenon widely prevalent in the music business. Finally, Walfogel (2011) finds no evidence that the development of file-sharing has undermined the creation of new works.

The closest papers to ours are Gayer and Shy (2006) and Curien and Moreau (2009a and 2009b), who show that, faced with piracy, the interests of artists and record labels are not necessarily aligned. In these papers, it is assumed that the consumption of recorded music (through legal purchases or piracy) increases the live audience of an artist.[5] Hence, if the positive impact of piracy on the live market is high enough, artists can benefit from a limited amount of piracy, provided that their revenues from royalties are low (Gayer and Shy, 2006) or that they do not face the risk of having their contracts terminated (Curien and Moreau, 2009a). However, these papers are theory-focused and provide no empirical evidence of their findings. Our contribution is to provide empirical evidence that an artist's attitude towards piracy depends on her sources of revenues.

On the empirical side, Mortimer et al. (2010) compare the live music revenues of artists before

[5] Dewenter et al. (2011) take into account the reverse positive externality, according to which live music attendance boosts recorded music sales. El Harbi et al. (2011) introduce a third option for consumers besides paying the listed price or using file sharing: the pay-what-you-want option. Using a theoretical model, they show that offering such an option to consumers increases the demand for live performances.

and after the creation of Napster (1995-1999 vs. 2000-2002). They show that for small artists, file-sharing on Napster reduced album sales, while it increased their revenues from live performances (for large artists the impact is negligible). However, their analysis focuses on a very early stage of digitization and furthermore, and they only consider cohorts of fifty artists ranked by the level of success. In contrast we focus on a more mature stage of file-sharing (our data pertain to year 2008) and we propose an analysis at the artist (individual) level. This allows us to take into account the composition of revenues for each artist (i.e., revenues from recorded music vs. revenues from live concerts), as well as the artist's specific contractual situation (under contract with a record company or self-released).

The remainder of the paper is organized as follows. In Section 2 we build up a model to analyze the effect of piracy on artists' revenues, and we derive two hypothesis. In Section 3 we describe the data, and in Section 4 the econometric method. The estimation results are discussed in Section 5. Finally, in Section 6 we conclude.

2 The Model

In this section we build a simple model to study the impact of piracy on musicians' revenues. We consider an artist with a given popularity, and determine how piracy affects her revenues, depending on whether she has a contract with a record company or is a self-released artist.

The artist. The artist has a popularity $a > 0$, and obtains revenues from two different sources: live concerts and recorded music sales.

Consumers. Each consumer is characterized by his taste for the music of the artist, x, which is uniformly distributed over $[0, \infty)$. A lower x represents a greater taste for the artist's music. An exogenous proportion of consumers, $\tau \in (0, 1)$, are pirates, and have to choose between pirating (and listening to) the artist's music and not pirating (and not listening to) it.[6] The utility of a consumer with taste x who pirates the artist's music is $u^P(x) = a - x$ (where the superscript "P" stands for Pirate), and therefore the number of consumers who listen to the music by pirating it is $D^P = \tau a$.

[6] To simplify the analysis, we do not model the consumer choice between purchasing music and pirating it. For a model setup which incorporates this choice, see, for instance, Gayer and Shy (2006).

The rest of the consumers, in the proportion $1-\tau$, are legal consumers. They have to choose between purchasing the music and not purchasing it. The utility of a legal consumer of type x is $u^L(x,p) = a - x - p$, where the superscript "L" stands for Legal, and p denotes the price of the recorded music. Therefore, the demand from legal consumers is given by $D^L(p) = (1-\tau)(a-p)$.

The total number of consumers who listen to the music (either by pirating or by purchasing it) is then $D^P + D^L(p) \equiv D(p)$.

Live concerts. The demand for live concerts depends on how many consumers have listened to the music.[7] It is given by

$$D^c(p^c, p) = \gamma D(p) - p^c,$$

where p^c is the price of live concerts, and $\gamma \geq 0$ captures the externality between recorded music and live concerts. We assume that $\gamma < 2/\sqrt{1-\tau}$, which ensures that the second-order conditions are satisfied. Finally, we normalize the cost of live concerts to zero.

We assume that the artist sets the price of concerts, p^c, so as to maximize her profit from them, $\pi^c(p, p^c) = p^c(\gamma D(p) - p^c)$.[8] Solving for the first-order condition[9] gives the optimal price of concerts as a function of the price of recorded music,

$$(p^c)^*(p) = \frac{\gamma D(p)}{2},$$

and the associated artist's profit from live concerts,

$$(\pi^c)^*(p) = \left(\frac{\gamma D(p)}{2}\right)^2.$$

Record sales. We now determine the artist's revenues from record sales. We distinguish two cases, depending on whether the artist has a contract with a record company or self-releases her music. The costs of recorded music are normalized to zero.

If the artist has a contract with a record company, she receives an exogenous share $s \in (0,1)$

[7] The idea is that only the consumers who have listened to the artist's music are aware of the existence of the artist, and could therefore consider attending a live concert. The existence of such a positive externality from the recorded music market towards the live music market is empirically confirmed by Montoro-Pons and Cuadrado-Garcia (2011).

[8] Despite the attempt of record companies to propose contracts where all the music revenues (from CD sales, live performances, merchandising, etc.) are shared between an artist and the label (the so-called "360-degree deals"), full control of live performances by the artist is still the dominant model.

[9] The second-order condition is always satisfied.

of profits made on the sales of music.[10] The record company then chooses the price of recorded music, p, to maximize its profit,

$$\pi^R(p) = (1-s)\, pD^L(p).$$

Solving for the first-order condition,[11] we find that $p^* = a/2$ and $\left(\pi^R\right)^* = (1-s)(1-\tau)(a/2)^2$. Provided that the artist has a contract with a record company, her total revenue is

$$R_A^{\text{contract}} = \underbrace{s(1-\tau)(a/2)^2}_{\text{revenues from record sales}} + \underbrace{\frac{\gamma^2}{4}(\tau a + (1-\tau)(a/2))^2}_{\text{revenues from live concerts}}.$$

The variation of the artist's revenues with respect to the proportion of pirates is given by

$$\frac{dR_A^{\text{contract}}}{d\tau} = \frac{a^2}{8}\left[-2s + \gamma^2(1+\tau)\right]. \tag{1}$$

The following proposition characterizes the effect of piracy on the artist's revenues when she has a contract with a record company.

Proposition 1 *When the artist has a contract with a record company, her revenues decrease with the proportion of pirates if her demand for live concerts is low enough and/or her share of recorded music sales is high enough.*

Proof. From equation (1), the artist's revenues decrease with the proportion of pirates τ if and only if $\gamma \leq \sqrt{2s/(1+\tau)}$, that is, if the demand for live concerts γ is low enough, and/or the share of recorded music sales s is high enough. ■

If the artist self-releases her music, she sets the price of recorded music p to maximize her total revenue,

$$R_A^{\text{sr}}(p) = \underbrace{pD^L(p)}_{\text{record sales}} + \underbrace{\left(\frac{\gamma D(p)}{2}\right)^2}_{\text{live concerts}}.$$

Note that, in contrast to the previous case, the externality between record sales and live concerts is now internalized by the artist. Solving for the first-order condition, we find that

$$p^* = \frac{a\left(2-\gamma^2\right)}{4-(1-\tau)\gamma^2}.$$

[10] This corresponds to the "royalty rate."

[11] The second-order condition is always satisfied.

The second-order condition is satisfied if $4-(1-\tau)^2\gamma^2-4\tau>0$, which is true with our assumption on γ. Substituting for p^* in $R_A^{\text{sr}}(p)$, we find the artist's total equilibrium revenue,

$$R_A^{\text{sr}}=\frac{a^2\left[1-\left(1-\gamma^2\right)\tau\right]}{4-(1-\tau)\gamma^2}.$$

Note that our assumption, $\gamma<2/\sqrt{1-\tau}$, implies that $4-(1-\tau)\gamma^2>0$. We find that

$$\frac{dR_A^{\text{sr}}}{d\tau}=-\frac{a^2\left(2-\gamma^2\right)^2}{\left[4-(1-\tau)\gamma^2\right]^2}<0,$$

and can therefore state our second proposition.

Proposition 2 *When the artist is self-released, her revenues always decrease with the proportion of pirates.*

In the rest of the paper, we will consider that a "rational" artist should have a negative attitude towards piracy if it reduces her revenues, and a positive attitude otherwise (everything else equal). We can now state the two hypotheses that we wish to test in the empirical part:

H1: For artists under contract, the tolerance for piracy increases with the intensity of live performances.

H2: Self-released artists are opposed to piracy.

3 The data

We use a dataset built from a postal survey[12] conducted during fall 2008, of French musicians who are members of Adami, the French organization for the collective administration of performers' rights. Adami, which collects the sums paid for the use of artists' recorded works, had over 23,000 members in 2008, including 9,000 musicians.[13] Only musicians who have already participated in an album commercialized by main retailers can join Adami. There are also strong incentives for professional musicians to join, because Adami guarantees the collection of royalties on their music, especially from radio airplays and TV broadcasts.

[12] The survey was conducted with a specialized survey company, ISL.
[13] The remaining 14,000 members are actors.

We conducted a questionnaire survey on approximately 4,000 musicians, randomly drawn from the 9,000 members of Adami. With a response rate of about 20%, we finally have 710 artists in our data base.

Our dependent variable (*PIRACY*) is binary and takes the value 1 if the artist answered the following question in the affirmative: "Are you bothered by the fact that your music is shared on P2P networks?"[14] It takes the value 0 if the artist answered that she was either not bothered or actually pleased. We exclude from the analysis 146 artists who stated that their music was not available on P2P networks (21.6% of the whole population) and 33 artists who did not answer this question. We finally have 531 respondents who were more or less concerned by the availability of their music on P2P networks.[15]

We distinguish artists who were under contract with a record company at the time they answered the survey and those who were not. The variable *CONTRACT* gives the contractual situation of the artist; it equals 1 if the artist has a contract and 0 otherwise. We also introduce the complementary dummy *NOCONTRACT* that equals 1 if the artists does not have a contract. We furthermore sort artists according to the intensity of their live music activity. The dummy variable *LIVE* distinguishes artists who performed more than 10 times on stage in 2007 from those who performed less often. *LIVE* is used as a proxy for the demand for the live music of a given artist (which corresponds to the parameter γ in our model).

The results of our model suggest that the intensity of an artist's live activity matters when she has a contract with a record company. We therefore introduce a dummy variable, which distinguishes between artists under contract, who an intense live activity, and those under contract who have a low-intensity live activity (*CONTRACT_LIVE*).

Finally, we consider the self-release experience of the artist. The dummy variable *SELFRELEASE* takes the value 1 if the artist had self-released an album during the three years preceding the survey, and the value 0 otherwise.

We also control for several characteristics of artists that could affect their attitude towards piracy: their level of education (*HIGHEDUCATION*), whether they live outside the Paris area or not (*NONPARIS*), their income (*INCOME1* to *INCOME5*), their age (*AGE*), and their gender (*GENDER*). We moreover include a dummy variable to identify classical artists (*CLASSICAL*).

[14] Here, we aggregate two positive answers: "very bothered" and "a little bothered". We discuss this aggregation in the robustness section.

[15] Artists who declared that their music is not shared on P2P networks will be included in the analysis in Section 5.3 as a robustness check.

Finally, we take into account the artist's familiarity with digital technologies. It is possible that those artists who are more familiar with digital technologies are also more tolerant of piracy (possibly because they are themselves more prone to downloading music files on P2P networks). To measure this degree of digitization, we introduce the variable *INTERNET*, which measures the frequency with which an artist used the Internet during the year preceding the survey (never/several times a month/several times a week/every day).

In the appendix, Table 1 describes our variables and Table 2 provides some summary statistics. Table 2 reveals that out of the 531 artists concerned by the issue of music file sharing, 28.6% claim to be indifferent or pleased that their music is shared on P2P networks.

4 Econometric method

To study how the characteristics of an artist affect her attitude towards piracy, we estimate a probit model. The dependent variable, *PIRACY*, takes the value 1 if the artist is bothered by the availability of her music on P2P networks, and the value 0 otherwise. Since the dependent variable is binary, we estimate the following Probit model:

$$P_t = \Pr(PIRACY = 1) = \Phi(\beta_0 + \beta X_t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\beta_0+\beta X_t} e^{-\frac{z^2}{2}} dz,$$

where $z = \beta_0 + \beta X_t$, P_t is the probability that $PIRACY = 1$ for observation t, X_t is a vector of explanatory variables (including control variables), and β is the parameter vector to be estimated.

Following the results of the theoretical model, the main model we wish to test is:

$$\begin{aligned} P_t &= \Phi(\beta_0 + \beta_1 NOCONTRACT + \beta_2 CONTRACT\_LIVE \\ &\quad + \beta_3 SELFRELEASE + \beta' Y_t). \end{aligned}$$

Our two propositions lead to the following research hypotheses:

H1: $\beta_2 = 0$ (null hypothesis) against $\beta_2 < 0$ (alternative hypothesis).
H2: $\beta_3 = 0$ (null hypothesis) against $\beta_3 > 0$ (alternative hypothesis).

Hypothesis H1 states that artists under contract with a high level of live activity are more tolerant of piracy than artists under contract who perform little on stage. Hypothesis H2 states

that self-released artists are less tolerant of piracy.

5 The results

In this section we begin by discussing our main results and then perform various robustness checks.

5.1 Main results

The estimation results of the probit model are reported in the first column of Table 3. The results are consistent with our theoretical hypotheses. The coefficients of *CONTRACT_LIVE* and *SELFRELEASE* have the expected signs and are both statistically significant. Hypothesis 1 and 2 are thus validated.

Compared with artists who have a contract but perform little on stage (the reference category), artists with a contract and an intense live activity (*CONTRACT_LIVE*) are significantly more tolerant of piracy. Similarly, self-released artists (*SELFRELEASE*) are significantly less tolerant of piracy than artists who have not self-released an album. The marginal effects[16] are also significant since, compared with artists under contract but with little live activity, the probability of artists under contract and with a high level of live activity claiming to be bothered by piracy decreases by 0.36 point. For self-released artists, the increase in this probability is of a lower magnitude, 0.10 point (see Table 4).

Note that artists who do not have a contract (*NOCONTRACT*) are also more tolerant of piracy. This might reflect the fact that those artists, who mostly have a small audience, consider file-sharing as a way to increase their audience and thus their ancillary revenues.

As far as control variables are concerned, few of them play an important role in explaining artists' attitudes towards piracy. Surprisingly, younger artists are not significantly more tolerant of piracy. Gender does not either play any significant role in explaining artists' attitudes towards piracy. However, artists who do not live in the Paris region (*NOPARIS*) tend to be less tolerant of piracy, as do the wealthier artists (*INCOME5*). We find, finally, that the more an artist uses the Internet (*INTERNET*), the more tolerant of piracy she is. This could be because heavy Internet users are also more prone to be P2P file-sharing users.

[16] Marginal effects have been calculated at sample means. Note that for the dummy variable the marginal effect reports a change from 0 to 1.

5.2 Endogeneity issues

The main pitfall with our empirical estimation is the possible endogeneity of the *NOCONTRACT* variable. We cannot exclude a priori the possibility that an unobserved variable may simultaneously affect both the contractual situation of an artist and that artist's attitude towards piracy. The celebrity and/or success of an artist could play such a role.[17]

To test the robustness of our results, we first include in our main regression two proxy dummy variables reflecting the celebrity of an artist, *NONMUSIC* and *GOLD*. *NONMUSIC* identifies the less well-known artists as those who earned revenues from other activities (such as sound technician, management of a band or a Non-Profit Organization, etc.).[18] At the other end of the spectrum of success, some artists in our sample have already won music awards and/or gold records (*GOLD*). The coefficients of both variables are not significant at the 10% level. Above all, our other explanatory variables remain significant.

To test for the exogeneity of *NOCONTRACT,* we use an instrumental variable. Finding an instrumental variable is usually challenging. The variable *MANAGER* appears to be the best candidate. *MANAGER* is a dummy variable that takes the value 1 if the artist stated that she has a manager, and the value 0 otherwise. We argue that the *MANAGER* variable satisfies exclusion and inclusion restrictions. First, there is no reason to believe that having a manager could have a direct effect on the dependent variable (the opinion on piracy). Second, *MANAGER* is correlated with *NOCONTRACT.* A simple probit model with *NOCONTRACT* as the dependent variable and *MANAGER* as the independent variable shows that this is the case at the 5% significance level. The inclusion restriction of our IV is thus also satisfied.[19]

Since our potentially endogenous variable (*NOCONTRACT)* is binary, we cannot use an IV procedure to test for the exogeneity of *NOCONTRACT* using *MANAGER* as an instrumental variable. As suggested by Wooldridge (2002), we run a bivariate probit with our structural probit, and a second probit using *NOCONTRACT* as the dependent variable and including our IV in the covariates. A bivariate probit approach provides a test of exogeneity. Under the exogeneity

[17] The suspicion of an endogenity problem does not arise for the *SELFRELEASE* variable. Indeed, self-releasing is a common practice for all types of artists, regardless of how well-known they are. The stars, whose projects often carry little risk, can self-release their music to capture the profits otherwise left to their record company. Conversely, small-audience artists self-release their albums mainly because record companies refuse to fund their musical projects.

[18] Our implicit assumption is that these artists are less well-known than those whose revenues come exclusively from music activities.

[19] We also performed the same analysis by considering as an IV candidate a dummy reflecting the possession of a homestudio (*HOMESTUDIO*). A homestudio is composed of a computer, some relevant software and additional devices, which allow an artist to record her music with an almost professional quality. Our results remain unchanged.

assumption, the error terms of both corresponding underlying equations included in the bivariate probit are not correlated, that is, the null hypothesis of exogeneity can be stated as $\rho = 0$. A likelihood ratio test of the significance of ρ is thus a direct test of the exogeneity of *NOCONTRACT*. If $\rho \neq 0$, only the results of the bivariate probit have to be considered. But if $\rho = 0$, it is appropriate to use the univariate probit model.

In Table 3, columns 2 and 3 display the results of the bivariate probit. The second column corresponds to the regression with *NOCONTRACT* as the dependent variable, and includes the IV. It confirms that the instrumental variable *MANAGER* is correlated with *NOCONTRACT*. Table 3 also reports that the estimated value for the parameter ρ is not significantly different from zero. These results suggest that we cannot reject the exogeneity of *NOCONTRACT*, using *MANAGER* as an instrumental variable, since we cannot reject the hypothesis that $\rho = 0$.

One might also suspect the endogeneity of the *CONTRACT_LIVE* variable. We applied the same method of estimation by using *AGENT* as a candidate instrumental variable. *AGENT* is a dummy that equals 1 if the artist has an agent to take care of her stage performances. As we cannot reject the hypothesis that the error terms of both regressions of the bivariate probit are not correlated, it is appropriate to use the univariate probit model.[20]

5.3 Other robustness checks

The question that we used to define our dependent variable,[21] "Are you bothered by the fact that your music is shared on P2P networks?", had four possible answers (for artists whose music is shared): "very bothered", "a little bothered", "indifferent" and "pleased". Our binary variable *PIRACY* was constructed by grouping together the first two and the last two modalities. Though this binary variable best fits our data, we also ran estimations with three ordered probit models: one with all four of the above modalities and the other two with only three modalities, grouping together either the last two or the first two of them. Our main results are preserved in these alternative models.

Since our database contains a few inactive artists, who could have a biased opinion on piracy, we ran our estimations on the subsample of "active" artists, that is, artists who had either worked in recording sessions or performed live at least once within the last twelve months. The estimations for the subsample of active artists yield the same results. We also tested our model on the subsample

[20] The results are available upon request from the authors.

[21] We also checked that the use of a logit model instead of a probit model does not change our results.

of artists who either had a contract or had self-released an album within the last three years. Our results remained unchanged. Finally, we considered a model in which we grouped together artists who were "pleased" or "indifferent" and artists whose music was not shared on P2P networks. Once again, our results are unchanged.[22]

Another potential problem is that, in our main regression, we are not observing the equation for the population as a whole. Since our sample of artists who answered the question about piracy feel concerned by file-sharing, our results might suffer from a selection bias. In particular, it might be possible that, the more an artist is exposed to piracy, the less she is tolerant of it. The Heckman selection estimation can solve this selection bias problem, since we can estimate the probability of being tolerant of piracy, conditional on whether the artist's music is available on the Internet or not. We ran such a Heckman selection estimation. The first equation is a Probit on a dummy variable that equals one if the artist answered that she was concerned by file-sharing. The second equation is our previous Probit equation. The exogenous variables are the same as before, except that we add a dummy variable that equals 1 if the artist has a webpage ($WEBPAGE$). This exogenous variable is expected to affect the artist's opinion on file-sharing, since music can be available on the artist's webpage. Our results are qualitatively the same with this alternative model (see Table 5 in appendix).

6 Conclusion

In this paper, we have proposed a simple model to determine the impact of piracy on musicians' revenues from two related markets: (i) the recorded music market, and (ii) the live concerts market. Our model predicts that, for the artists who have a contract with a record label, piracy has a negative effect on revenues if they perform little on stage, and a positive effect otherwise. In contrast, piracy always hurts self-released musicians. Using data from a survey of 710 French professional musicians, we show that the attitudes of artists towards piracy are consistent with our model predictions.

Our estimation results highlight the fact that the attitudes of artists under contract with a record company are not uniform. Those artists who perform frequently on stage are more tolerant of piracy than those with little live activity. It also appears that the artists who self-release their albums have an attitude towards piracy which is very close to that of record labels. Self-releasing an

[22] All the regressions concerning these robustness checks are available upon request from the authors.

album makes artists significantly less tolerant of piracy, probably because, like record labels, they have an investment to recoup. Furthermore, we find that the artists who have no record contract are more tolerant of piracy. This suggests that they may see P2P networks as a way to increase their audience, which is consistent with Duchêne and Waelbroeck (2006)'s theoretical insight that small-audience artists benefit from information-pull technologies (e.g., P2P networks).

To sum up, artists seem rational in their attitudes towards piracy. The heterogeneity that we observe in their opinions stems from the heterogeneity of the impact of piracy on their revenues, according to their contractual situation, the intensity of their live activity, and their entrepreneurial behavior (self-releasing).

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Variables	Description
PIRACY	takes the value 1 if the artist is bothered by the fact that her music is shared on P2P networks, and 0 otherwise.
NOCONTRACT	takes the value 1 if the artist is not under contract, and 0 otherwise.
SELFRELEASE	takes the value 1 if the artist has self-released an album within the last three years, and 0 otherwise.
LIVE	takes the value 1 if the artist performed more than 10 times on stage in 2007, and 0 otherwise.
CONTRACT_LIVE	takes the value 1 if both CONTRACT and LIVE take the value 1, and 0 otherwise.
HIGHEDUCATION	takes the value 1 if the artist holds a master degree (at least), and 0 otherwise.
CLASSICAL	takes the value 1 if the artist declares that her main musical genre is classical music, and 0 otherwise.
NONPARIS	takes the value 1 if the artist does not live in Paris or in the "Ile de France" region (i.e., in the Paris area), and 0 otherwise.
AGE	age of the artist (continuous variable).
GENDER	takes the value 1 if the artist is a woman, and 0 otherwise.
INTERNET	takes the value 0 if the artist never uses Internet, 1 if she uses Internet several times a month, 2 several times a week and 3 everyday
INCOME1	takes the value 1 if the artist earned less than €9,000 euros in 2007, and 0 otherwise.
INCOME2	takes the value 1 if the artist earned between €9,000 and €15,000 in 2007, and 0 otherwise.
INCOME3	takes the value 1 if the artist earned between €15,000 and €30,000 in 2007, and 0 otherwise.
INCOME4	takes the value 1 if the artist earned between €30,000 and €60,000 in 2007, and 0 otherwise.
INCOME5	takes the value 1 if the artist earned more than €60,000 in 2007, and 0 otherwise.
MANAGER	takes the value 1 if the artist has a manager, and 0 otherwise.
AGENT	takes the value 1 if the artist has an agent for her live career, and 0 otherwise.
HOMESTUDIO	takes the value 1 if the artist has a homestudio, and 0 otherwise.
NONMUSIC	takes the value 1 if the artist earned revenues from other activities, and 0 otherwise.
GOLD	takes the value 1 if the artist has already won a music award and/or a gold record, and 0 otherwise.
WEBPAGE	takes the value 1 if the artist has a Web site devoted to her musical activity, and 0 otherwise.

Table 1: Description of the variables

	N	Min	Max	Mean	St. dev.
PIRACY	531	0	1	0.714	0.452
NOCONTRACT	708	0	1	0.799	0.401
CONTRACT_LIVE	691	0	1	0.140	0.348
LIVE	693	0	1	0.514	0.500
SELFRELEASE	689	0	1	0.496	0.500
HIGHEDUCATION	692	0	1	0.366	0.482
CLASSICAL	708	0	1	0.189	0.392
NONPARIS	710	0	1	0.521	0.500
INCOME1	659	0	1	0.249	0.433
INCOME2	659	0	1	0.226	0.419
INCOME3	659	0	1	0.319	0.466
INCOME4	659	0	1	0.168	0.375
INCOME5	659	0	1	0.038	0.191
AGE	698	18	83	47.742	12.305
GENDER	708	0	1	0.445	0.497
INTERNET	691	0	3	2.606	0.801
MANAGER	702	0	1	0.171	0.377
AGENT	689	0	1	0.309	0.462
HOMESTUDIO	693	0	1	0.633	0.482
NONMUSIC	606	0	1	0.304	0.460
GOLD	710	0	1	0.194	0.396
WEBPAGE	703	0	0	10.644	0.479
Note: due to unanswered questions by some artists, N varies among variables.					

Table 2: Summary statistics

	PROBIT	BIPROBIT	BIPROBIT
	PIRACY	PIRACY	NOCONTRACT
CONTRACT_LIVE	-0.965^{***}	-1.02^{***}	
	(-2.65)	(-2.81)	
NOCONTRACT	-0.759^{**}	-1.14^{**}	
	(-2.26)	(-1.93)	
SELFRELEASE	0.288^{**}	0.241^{*}	-0.343^{**}
	(2.09)	$(1,61)$	(-2.22)
CLASSICAL	0.198	0.163	-0.18
	(1.06)	(0.86)	(-0.89)
NONPARIS	0.283^{**}	0.268^{***}	0.049
	(2.19)	(2.07)	(0.34)
GENDER	0.226	0.237^{*}	0.12
	(1.60)	(1.68)	(0.80)
HIGHEDUCATION	-0.134	-0.131	-0.061
	(-0.98)	(-0.97)	(-0.42)
AGE	0.0000945	0.0026	0.0013
	(0.02)	(0.41)	(0.19)
INCOME2	-0.146	-0.166	-0.215
	(-0.77)	(-0.86)	(-0.96)
INCOME3	0.0584	-0.049	-0.344
	(0.32)	(0.26)	(-1.59)
INCOME4	0.161	0.11	-0.372
	(0.76)	(0.50)	(-1.50)
INCOME5	0.673^{*}	0.557	-0.823^{**}
	(1.80)	(1.35)	(-2.26)
INTERNET	-0.267^{**}	-0.299^{**}	-0.0389
	(-2.38)	(-2.55)	(-0.34)
CONSTANT	1.604^{***}	1.94^{***}	1.636^{***}
	(2.78)	(2.85)	(3.27)
MANAGER			-0.90^{***}
			(-5.51)
LIVE			-0.275^{*}
			(-1.79)
N	459	456	456
	Log likelihood = -265.7861	LR $\chi^2(13) = 29.71$	Log likelihood = -478.53
	Prob $> \chi^2 = 0.0052$	ρ=0.221	$\chi^2(1) = .54$
	Pseudo $R^2 = 0.0529$		Prob $> \chi^2 = 0.46$
	Correctly classified 70.15%		
t statistics in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.			

Table 3: Main regressions

Variables	Change in probability
CONTRACT_LIVE	-.361
NOCONTRACT	-.224
SELFRELEASE	.099

Table 4: Marginal effects (calculated at sample means)

	SELECTION (dummy=1 if concerned)	PIRACY
CONTRACT_LIVE	0.298	-0.934^{***}
	(1.00)	(-2.72)
NOCONTRACT	0.0458	-0.699^{**}
	(0.19)	(-2.21)
SELFRELEASE	0.0728	0.224^{*}
	(0.53)	(1.73)
CLASSICAL	-0.0615	0.249
	(-0.35)	(1.45)
NONPARIS	0.0540	0.245^{**}
	(0.42)	(2.03)
GENDER	-0.392^{***}	0.310^{**}
	(-3.01)	(2.35)
HIGHEDUCATION	0.276^{**}	-0.202
	(2.01)	(-1.58)
AGE	-0.0112^{*}	0.00311
	(-1.80)	(0.53)
INCOME2	-0.118	-0.0993
	(-0.64)	(-0.56)
INCOME3	-0.322^{*}	0.135
	(-1.89)	(0.80)
INCOME4	0.107	0.110
	(0.49)	(0.55)
INCOME5	0.190	0.579
	(0.52)	(1.60)
INTERNET	0.121	-0.269^{***}
	(1.42)	(-2.59)
CONSTANT	$.907^{*}$	1.619^{***}
	(1.85)	(3.01)
WEBPAGE	0.271^{**}	
	(1.94)	
N		677
Log likelihood = -545.9298		
ρ =-.902 $\chi^2(1) = 0.52$ Prob > $\chi^2 = 0.469$		
t statistics in parentheses *p < 0.1, **p < 0.05, ***p < 0.01.		

Table 5: Heckman Probit Selection Model