Graduated Response Policy and the Behavior of Digital Pirates: Evidence from the French Three-strike (Hadopi) Law*

Michael Arnold†, Eric Darmon‡, Sylvain Dejean§ and Thierry Penard¶

January 16, 2014

Abstract

Most developed countries have tried to restrain digital piracy by strengthening laws against copyright infringement. In 2009, France implemented the Hadopi law. Under this law individuals receive a warning the first two times they are detected illegally sharing content through peer to peer (P2P) networks. Legal action is only taken when a third violation is detected. We analyze the impact of this law on individual behavior. Our theoretical model of illegal behavior under a graduated response law predicts that the perceived probability of detection has no impact on the decision to initially engage in digital piracy, but may reduce the intensity of illegal file sharing by those who do pirate. We test the theory using survey data from French Internet users. Our econometric results indicate that the law has no substantial deterrent effect. In addition, we find evidence that individuals who are better informed about the law and piracy alternatives substitute away from monitored P2P networks and illegally access content through unmonitored channels.

*We thank Brett Danaher, Bob Hammond and participants at the workshops on Digital Piracy at the University of Delaware Alfred Lerner College of Business and Economics, and at the University of Rennes 1. This research was supported by Conseil RÃ©gional de Bretagne and Marsouin.

†Department of Economics, University of Delaware, marnold@udel.edu

‡CREM, University of Rennes 1, eric.darmon@univ-rennes1.fr.

§CREM, LR-MOS, University of La Rochelle sylvain.dejean@univ-lr.fr

¶CREM, University of Rennes 1 & University of Delaware. thierry.penard@univ-rennes1.fr.

1 Introduction

Digital piracy is a major concern for the music and movie industries. According to the RIAA, two-thirds of music changes hands without payment, through digital lockers, hard drives, burned and ripped CDs, and peer-to-peer networks. Forty-six percent of American adults have consumed pirated content (*e.g.*, pirated DVD's, copied files or discs, downloaded files).[1] Similary, the IFPI *Digital Music Report 2012* cites evidence that 27% of Internet users in Europe access at least one unlicensed digital content site per month. A growing body of empirical research finds that digital piracy is a significant cause of reduced sales (Danaher *et. al.* (2010), Danaher, Smith and Telang (2013), Liebowitz (2008), Smith and Telang (2010, 2012), Rob and Waldfogel (2006, 2007), Waldfogel (2010), Zentner (2006, 2008)),[2] although Hammond (2014) shows that some individual artists may benefit from piracy.

Most developed countries have responded to the increasing incidence of digital piracy by strengthening laws against copyright infringement (Klump 2012). As noted by Danaher and Smith (2013), these responses can generally be characterized as either supply side or demand side interventions. Supply-side interventions include legal action against sites or servers that illegally host and share content such as Napster, MegaUpload, and PirateBay.[3] Demand-side interventions target consumers with the threat of legal action in order to deter them from downloading or sharing content.[4]

In 2009 France undertook a novel demand side policy referred to as the three-strike law (more formally known as the Hadopi Law). This graduated response approach entails formal warnings issued to individuals for the first two illegal file sharing in-

[1]But large scale digital piracy is rare. Two percent of Americans are heavy music pirates (more than 1000 pirated files).

[2]Oberholzer-Gee and Strumpf (2007) find a positive impact of piracy on sales, and Peitz and Waelbroeck (2004) find conflicting evidence about the the magnitude of the causal effect

[3]Megaupload was sued and shut down. YouTube was also sued for facilitating copyright violations, but now implemented tools to identity unauthorized content and block or monetize it with consent of copyright holders. New challenges for antipiracy efforts include streaming, seedboxes and cloud computing.

[4]The RIAA began initiating lawsuits against individuals in 2003 (Bhattacharjee et al., (2006)).

fringements and legal action only when a third violation is detected. The Hadopi Law only applies to peer-to-peer (P2P) file sharing.[5] Since October 2010, the Hadopi agency has issued 2.4 million first warnings, 250,000 second warnings, and less than one thousand third warnings.[6] In March of 2013 a similar antipiracy effort was implemented in the US by five large ISPs in partnership with the movie and music industries. The so-called US Copyright Alert System is a six-strike rule which entails progressively more informative and threatening alerts for each detected infringement. After six alerts, a customer faces the possibility of reduced (slower) service or a persistent in-browser alert.[7]

This paper focuses on how antipiracy interventions influence individual decisions to engage in illegal consumption of content. In particular, we consider the effectiveness of a graduated response policy in reducing digital piracy and in converting pirates into legal consumers of digital content. We begin by extending the work of Davis (1988) to incorporate a graduated response in a model of intertemporal criminal choice. Becker's (1968) classic model of crime considers the static trade-off between the marginal benefit of committing a crime and the marginal cost of being caught. In this setting individuals respond equivalently to an increase in the probability of being caught and an increase in the penalty. Davis (1988) demonstrates that a dynamic setting alters this trade-off because the benefits of criminal activity are enjoyed immediately, but the punishment is imposed, with uncertainty, at some future time. Thus, increased illegal activity involves a trade-off between increased benefits from that activity today and the associated increased probability of future detection which shortens the period during which gains from illegal activity are enjoyed.

A graduated response policy like the Hadopi law alters the timing of detection and punishment (by delaying punishment until a third warning is received). Our

[5] Under the law ISPs must provide customer names to the Hadopi agency which then sends warnings to any customer who is detected engaging in illegal file sharing.

[6] As of December 2013, only 54 third warnings have resulted in legal actions.

[7] In contrast to the French Hadopi law, the Copyright Alert System is a private effort which does not include automatic legal action.

model predicts that under a graduated response policy an increase in the probability of detection has no impact on the decision of whether or not to engage in piracy. However, conditional on one's decision to pirate, an increase in the probability of detection reduces the level of illegal activity. The extent of this deterrent effect also depends upon the individual's utility from obtaining content through other channels. An implication of the model is that an increase in the utility from legal channels (which might be achieved by lower prices or more user-friendly outlets like iTunes) actually creates an incentive to increase illegal content acquisition prior to receiving a warning.

We test the theory using survey data from French Internet users. In contrast to previous studies which focus on the impact of antipiracy efforts on digital content sales, our data provide insights into individual piracy behavior. Individuals were surveyed about their understanding of the French Hadopi law, their perceived probability of detection under the law, whether they engaged in illegal downloading, and their level of illegal content acquisition. The data also include socioeconomic information, measures of each respondent's taste for digital music and movie content, and information about the proportion of pirates in an individual's social network.

Consistent with theoretical predictions, our econometric results indicate that the Hadopi law has not deterred individuals from engaging in digital piracy and that it did not reduce the intensity of illegal activity of those who did engage in piracy. In particular, while several factors affect the perceived probability of detection under the law, our results show that the propensity to engage in illegal file-sharing is independent of these beliefs. Moreover, better information about digital piracy alternatives, as measured by the proportion of digital pirates in one's social network increases one's propensity to violate copyright law. Our empirical results also provide evidence of substitution effects between monitored P2P channels and unmonitored channels (*e.g.,* direct downloads or newsgroups) by individuals who have a large number of pirates in their social network.

Our results contribute to the growing literature on digital piracy and content management. Battacharjee et al. (2006) explore how significant penalties targeting individuals through RIAA lawsuits initiated in 2003 and 2004 impact individual behavior. They find that such legal actions had a substantially greater impact on individuals who share a large number of files than those who share a small number. Our results expand understanding of the effectiveness of recent graduated response policies to deter piracy. By focusing on individual response to a specific law, our results also enhance understanding gained through other research based on the value of digital content sales (Adermon and Liang (2010), Danaher and Smith (2013)). For example, Danaher et al. (2014) analyze the impact of the Hadopi law on French music sales through iTunes. They find that the publicity surrounding the Hadopi law caused a 20-25% increase in French music sales relative to control countries prior to implementation of the law. Our results suggest that the increase in French iTunes sales cannot be attributed to a direct deterrent effect from the law. Rather, the increased sales are likely to have been caused by public educational efforts that coincided with the introduction of the Hadopi law.

In section 2 below we develop an intertemporal model of piracy which generates hypotheses about how a graduated response impacts individual piracy behavior. These hypotheses are then tested using survey data on French internet users. The data and empirical methodology are presented in section 3, and empirical results are presented in section 4. Section 5 offers concluding remarks.

2 An intertemporal model of digital piracy

2.1 Utility of legal and illegal consumption

We consider an individual that can access and consume digital goods (music or movies) either legally or illegally. Suppose that an anti-piracy agency is established to enforce copyright law. This agency monitors only some illegal channels and implements a graduated response policy with two strikes.[8] When an individual is detected for the first time, he receives a simple warning. If that individual is detected a second time, then the agency undertakes legal action which imposes a cost (or fine) of F on the individual at the time of detection.

The individual can avoid legal action by consuming legal content and/or by using illegal channels that are not monitored by the anti-piracy agency. Let c, $(0 \leq c \leq 1)$, denote the proportion of consumption through the monitored illegal channel. Thus, $(1 - c)$ is the proportion of content consumed through legal channels and unmonitored illegal channels. Let $u(c)$ denote the utility derived from this pattern of consumption. We assume the utility function is concave, so $u''(c) < 0$. As discussed in section 2.3 below, if $u'(0) < 0$, the individual will never use the monitored channel. Therefore, our analysis focuses on the case of $u'(0) > 0$. In this case, there is an optimal level $\hat{c}$ of consumption through the monitored illegal channel (with $u'(\hat{c}) = 0$) that would occur if the fine $F = 0$. Finally, we assume that an individual who is detected engaging in illegal consumption a second time is convicted and ceases use of the monitored illegal channel. Let $u(0) \equiv u^N$ denote the utility when $c = 0$. If $u'(0) > 0$, then $u^N < u(\hat{c})$ so that in the absence of antipiracy law, an individual would always engage in some illegal consumption through the monitored channel.

2.2 Graduated response

Under the graduated response policy, an infringing individual doesn't know exactly when he will be detected by the antipiracy agency. Let $P(c, t)$ be the objective probability that an individual engaged in monitored illegal activity will be detected at any time t. This probability depends positively on the level c of monitored piracy activity, with a maximum probability $\overline{P} < 1$ (technical and budget constraints prevent the agency from detecting every pirate with certainty). Moreover we suppose that each individual has perceived probability of detection, which may differ from $P(c, t)$.

[8] The results do not change in any substantive way if the model is extended to allow for additional warnings prior to legal or other punitive action as called for by the French Hadopi law or by the US Content Alert System.

(This perception plays an important role in our empirical analysis). Therefore, let k_i denote an individual specific parameter that determines individual i's perceived probability of detection $k_i P(\cdot)$ where $k_i \in \left[0, 1/\bar{P}\right]$. An individual with k_i close to zero underestimates the threat of detection by the anti-piracy agency whereas an individual with k_i close to $1/\overline{P}$ overestimates this threat. Individuals with $k_i = 1$ have an accurate perception of the detection probability. The perceived probability of detection at any time t, given the individual has not yet been detected, is simply a hazard rate. Letting $G_i(c,t)$ denote individual i's perceived probability of not being detected by time t given c, so $G_i(c,t)$ is a cumulative distribution function, and letting $g_i(c,t)$ be the corresponding density function,

$$k_i P(c,t) = \frac{g_i(c,t)}{1 - G_i(c,t)}. \tag{1}$$

Consistent with the Hadopi law, we assume that the antipiracy agency randomly monitors consumers which implies that $P(c,t)$ is invariant over time, so we denote it by $P(c)$ going forward.[9]. Finally, we assume the probability of detection is increasing in c and the marginal probability is non-decreasing, so $P'(c) > 0$ and $P''(c) \geq 0$.

We are now able to analyze the optimal intertemporal consumption pattern under a graduated response by considering the individual's choice both prior to receiving a warning (Stage 0) and after receiving a warning (Stage 1). We begin our analysis with the individual's optimal choice after receiving a warning. Let r be the discount rate used by each individual to calculate the present value from consuming digital content.

2.2.1 Stage 1 (after a first warning)

An individual who has received an initial warning can choose to cease illegal activity through the monitored channel which would generate a utility of $\int u^N e^{-rt} dt = u^N/r$. Alternatively, the utility from continuing the monitored illegal activity following the

[9]Random monitoring is required by the Hadopi law. Targeting individuals with prior warnings is not allowed.

warning is (for convenience we now drop the i subscript)

$$V_1 = \max_c \int \left((1 - G(c,t))\, u(c) + G(c,t)\, u^N - g(c,t)\, F \right) e^{-rt} dt. \tag{2}$$

Noting that equation (1) is a linear differential equation,[10] we can restate equation (2) as

$$V_1 = \max_c \left(\frac{u(c) - u^N - kP(c)\, F}{r + kP(c)} + \frac{u^N}{r} \right), \tag{3}$$

The first term on the right-hand side is the net expected utility from the consumption pattern c discounted by the individual opportunity cost of time r plus the perceived probability $kP(c)$ of being detected. The perceived probability of being detected affects not only the expected utility $u(c) - u^N - kP(c)\, F$ per unit time, but also the effective discount rate $r + kP(c)$.

Maximizing V_1 with respect to c yields the first-order condition

$$\left(u'(c) - kP'(c)\, F \right) (r + kP(c)) = kP'(c) \left(u(c) - u^N - kP(c)\, F \right)$$

or

$$u'(c) = \frac{kP'(c) \left(u(c) - u^N + rF \right)}{(r + kP(c))}. \tag{4}$$

Let c_1^* denote the solution to (4). Note because u is concave, $P' > 0$, and $P'' \geq 0$, the individual consumes less through the monitored channel following a warning than he would if no enforcement policy was in place (i.e. $c_1^* < \hat{c}$). [11]

[10] As the probability of being detected is independent of time, the optimal level of illegal activity is constant over time. Thus, equation (1) becomes a linear differential equation

$$\frac{dG_i(t)}{dt} + k_i P G_i(t) = k_i P$$

As $G(0) = 0$, the solution to this equation is $G(t) = 1 - e^{-k_i P t}$.

[11] We can show that the solution c_1^* to (4), if it exists, is unique. Because $u''(c) < 0$, the left-hand side of (4) is strictly decreasing and equals 0 at $\hat{c}$. The sign of the derivative of the right-hand side equals

$$\text{sign}\left(P''(c) \left(u(c) - u^N + rF \right) (r + kP(c)) + P'(c) \left(u'(c) (r + kP(c)) - kP'(c) \left(u(c) - u^N + rF \right) \right) \right).$$

Note that (4) implies $u'(c)(r + kP(c)) - kP'(c) \left(u(c) - u^N + rF \right) = 0$ at c_1^*. In addition, given $u'(0) > 0$ it follows that $u(c_1^*) - u^N + rF > 0$ must hold. Thus, because $P'(c) > 0$ and $P''(c) \geq 0$, the *rhs* must be non-decreasing and strictly positive at any solution to (4), which implies $c_1^* < \hat{c}$. Because the *lhs* is strictly decreasing, it follows that the solution to (4), if it exists, must be unique. A solution to (4) does not exist if F is sufficiently large so that $P''(0)\, rF > u'(0)$ (recall that $u(0) = u^N$, so $u(0) - u^N = 0$). In this case, the consumer ceases illegal activity after receiving a warning.

The individual will choose to stop using the monitored channel following a warning if

$$\frac{u^N}{r} \geq V_1 = \frac{u(c_1^*) - u^N - kP(c_1^*)F}{r + kP(c_1^*)} + \frac{u^N}{r}. \tag{5}$$

The left-hand side of condition (5) is the discounted present value from ceasing the monitored activity, and the right-hand side is the expected return from continuing to access content through the monitored channel.

Condition (5) can be restated as

$$u(c_1^*) - u^N \leq kP(c_1^*)F \tag{6}$$

which implies that individuals are more likely to cease illegal consumption through the monitored channel following a warning for larger values of the fine F and of the utility u^N from accessing content through alternative channels.

2.2.2 Stage 0 (before receiving a warning)

Illegal activity in the early stage (prior to receiving a warning) will depend on whether the individual will continue or cease using the monitored channel after receiving a warning. Following Condition (5), if $V_1 \leq u^N/r$, then it is optimal for an individual who has received a first warning to cease the monitored activity. Alternatively if $V_1 > u^N/r$, then the individual will continue to acquire illegal content through the monitored channel until he is detected a second time.

If the individual stops the monitored illegal activity after receiving a warning (*i.e.,* if $V_1 \leq \frac{u^N}{r}$), then the expected return from engaging in the monitored activity prior to a warning is

$$V_0 = \max_c \left(\frac{u(c) - u^N}{r + kP(c)} + \frac{u^N}{r} \right).$$

Clearly $V_0 > u^N/r$ if and only if there is some value of $c > 0$ such that $u(c) > u^N$. Let c_0^* be the utility-maximizing consumption pattern at this stage. Then c_0^* solves the first-order condition[12]

$$u'\left(\tilde{c}_0^*\right) = \frac{kP'\left(c\right)\left(u\left(c\right) - u^N\right)}{\left(r + kP\left(c\right)\right)}. \tag{7}$$

As $u^N < u(\hat{c})$, there is always an optimal level of illegal consumption c_0^* that yields more utility than u^N, and conditions (4) and (7) imply $c_0^* < \hat{c}$. Moreover, an increase in the utility u^N derived from alternative channels (*i.e.,* legal and unmonitored illegal channels) will actually increase the share c of content acquired through the monitored channel (because the right-hand side of (7) decreases with u^N).

Given the first-order condition (7) , the expected benefit from using the monitored channel prior to receiving a warning can be restated as

$$V_0 = \frac{u'\left(c_0^*\right)}{kP'\left(c_0^*\right)} + \frac{u^N}{r}.$$

Note that V_0 is always greater than $\frac{u^N}{r}$. This implies that prior to receiving a first warning, the propensity to initially engage in monitored illegal consumption is independent of the perceived probability of detection as well as the potential fine.

Now consider an individual who continues to download illegal content through the monitored channel after receiving a warning (*i.e.,* with $V_1 > \frac{u^N}{r}$). The expected return for such an individual from engaging in monitored illegal activity prior to a warning is

$$V_0 = \max_c \left(\frac{u\left(c\right) - rV_1}{r + kP\left(c\right)} + V_1\right).$$

The first-order-condition is

$$u'\left(c\right) = \frac{kP'\left(c\right)\left(u\left(c\right) - rV_1\right)}{\left(r + kP\left(c\right)\right)}. \tag{8}$$

Let $\tilde{c}_0^*$ denote the solution to (8) [13] and note that $u\left(\tilde{c}_0^*\right) > rV_1$ and $\tilde{c}_0^* < \hat{c}$. The implementation of a graduated response policy will reduce the level of illegal monitored

[12] Arguments similar to those in footnote 11 combined with the fact that $u\left(0\right) - u^N = 0$ imply that a unique solution c_0^* always exists if $u'\left(0\right) > 0$.

[13] Again, arguments similar to those in footnote 11 combined with the fact that $u\left(0\right) - rV_1 < 0$ imply that a unique solution $\tilde{c}_0^*$ always exists if $u'\left(0\right) > 0$.

activity (relative to $\hat{c}$) in stage 0 (even though a first warning imposes no fine). In addition, $c_1^* < \tilde{c}_0^*$ and

$$V_0 = \frac{u'\left(\tilde{c}_0^*\right)}{kP'\left(\tilde{c}_0^*\right)} + V_1.$$

As $V_1 > \frac{u^N}{r}$, it follows that $V_0 > \frac{u^N}{r}$ for any value of k. This implies that provided $u'(0) > 0$ an individual should always consume monitored illegal content in the early stage regardless of the probability of detection.

2.3 The impact of the perception parameter k

An increase in k has ambiguous effects on c. Similar to Davis (1988), the probability of detection has two opposite effects. Increasing k increases the expected fine which makes the monitored channel less attractive than the alternative (unmonitored or legal) channels, but increasing k also increases the discount factor which lowers the present value of any future punishment. This second effect may encourage the individual to increase near term gains from digital piracy by increasing c. We now show that the first effect dominates regardless of whether the individual ceases or continues to acquire content through the monitored channel after receiving a warning.

First, consider the case in which the individual stops the monitored illegal activity after receiving a warning (*i.e.*, $V_1 \leq u^N/r$). Because the right-hand side of (7) increases with k, a higher perceived probability of detection reduces illegal acquisition of content through the monitored channel. In the alternate case of $V_1 > u^N/r$, substituting for V_1 we can also verify that the right-hand side of (8) is increasing in k.[14] This outcome contrasts with the result from section 2.2.2 showing that if $u'(0) > 0$, then k doesn't impact the initial decision about whether or not to engage in consumption through the monitored channel – the individual should always set $c > 0$.

[14] Using the first-order condition (4) and equation (3) we can restate V_1 as

$$V_1 = \left(\frac{u'(c)\left(u(c) - u^N - kP(c)F\right)}{kP'(c)\left(u(c) - u^N + rF\right)} + \frac{u^N}{r}\right).$$

Substituting this expression for V_1 into equation (8) yields the result.

To this point our analysis has focused on the case of $u'(0) > 0$. It is easily seen that if $u'(0) < 0$, then V_0 is maximized at $c = 0$ for any $k > 0$, so the individual will never access content through the monitored channel. More specifically, as was the case with $u'(0) > 0$, the perceived probability of detection k has no impact on the individual's decision to access content through the monitored channel. Our main results are summarized in the following propositions.

Proposition 1 *The decision of whether or not to initially engage in illegal consumption through the monitored channel is independent of the perceived probability of detection.*

Proposition 2 *An increase in the perceived probability of detection will decrease the share of illegal consumption through the monitored channel prior to receiving a warning.*

Proposition 3 *An increase in u^N (i.e. the utility of alternative channels to access content) increases the share of content consumed through the monitored channel prior to receiving a first warning.*

Proposition 3 implies that making content more readily accessible through legal channels or lowering the cost of legally acquiring content would actually increase the intensity of illegal consumption during the early stage (prior to receiving a warning). This occurs because as u^N increases, the value V_1 realized by the consumer after receiving a warning also increases. Thus, there is less of an incentive to reduce c_0 in order to delay the (expected) time at which a warning will be received. In short, in our dynamic framework, an increase in future utility (achieved after receiving a warning) creates an incentive to increase illegal consumption in the present period.

In summary, the propensity to engage in digital piracy through the monitored channel under a graduated response law is independent of k and u^N, but the intensity of content consumed is influenced by k and u^N. These parameters can vary across individuals. For instance, the perceived probability of detection can depend on the technological skills of consumers and their awareness of antipiracy law. Similarly, u^N could increase with income and decrease with the preference for niche products (that are less readily available for purchase through legal channels). In the next section, we will present our empirical strategy for testing hypotheses generated by the theoretical analysis.

3 Data and Methodology

Data for the empirical analysis were collected from a representative sample of French Internet users in May 2012.[15] Quota sampling based on age, gender, location and occupational status was used to select the respondents. Two thousand individuals were surveyed about their legal and illegal consumption of music, movies and series, as well as their knowledge and perception of the Hadopi law.

Table 1 presents the variables used in the econometric analysis and Table 2 displays descriptive statistics. We distinguish between two categories of illegal downloading; peer-to-peer (P2P) downloading (monitored by Hadopi), and downloading using alternative illegal platforms including direct downloading sites (such as upload.to, DepositFiles.com) and newsgroups (e.g. Giganews, newshosting) that are not monitored by Hadopi. Of the total respondents, 37.6% are engaged in illegal downloading activity either through P2P networks (22%) or alternative channels (30%), and 3.6% have received a warning from the Hadopi (i.e. 16.4% of those engaged in the monitored activity).

[Insert Table 1 and Table 2 Here]

Respondents were asked to report an estimate of the probability of being detected and warned (DETECTION) by Hadopi if they engaged in illegal downloading.[16] The distribution of the perceived detection probability is displayed in Figure 1. The

[15] The survey was administered by the poll institute Harris Interactive.

[16] The precise question was: "Can you estimate the probability of being caught by the Hadopi for someone who illegally downloads music, movies or series?"

distribution is bimodal with a mass point at 50% and a high frequency of answers between 0% and 10%. Of the total respondents 32% reported a detection probability lower than 10%, and 19% estimated this probability at 50%. The average reported detection probability is 36%.

[Insert Figure 1 Here]

To incorporate consumer preferences, the survey collected information about individual "taste" (TASTE) for music and video, distinguishing between four levels (very strong, strong, moderate and low). Taste for cultural goods should positively impact the intensity of P2P downloading as it directly increases the utility from using this channel. It also increases the utility u_N from alternative channels which indirectly increases the share of content consumed through the monitored channel (see Proposition 3).

Respondents were also asked about illegal behavior of other individuals in their social network (PEERPIRACY). 41% reported that they have many friends or relatives who download and share illegal content and 18% reported knowing someone who had received a warning from the Hadopi agency. The economic literature on crime shows that the likelihood someone commits an illicit act increases if these acts are commonly observed in one's social network (friends, family, acquaintances, neighbors) (Lochner 2007). So we expect that a large proportion of pirates among friends and relatives will decrease the perceived probability of being detected and increase both the propensity to engage in piracy and the level of filesharing. PEERPIRACY is a measure of the individual's awareness of digital piracy. A large number of pirates in one's network provides substantial information about how to access P2P networks and the content available on these sites. An individual interacting with a small number of pirates, on the other hand, is less likely to be aware of the P2P channel and to use P2P networks.

The survey also included questions to measure consumer understanding of the Hadopi law. Because the law is somewhat complex, individuals might have misconceptions about practices that are monitored and exactly how the law is implemented. Figure 2 shows that 75% of respondents understood that P2P networks are monitored, but 68% incorrectly reported that direct downloading is monitored. Similarly, 37% and 12%, respectively, reported that illegal streaming and offline sharing are monitored. As presented in Figure 3, 66% of respondents overestimated the reach of the Hadopi law by including at least two illegal channels that are not monitored by Hadopi on their list of activities that would trigger a warning. Finally, to incorporate how individual ethics considerations might impact response to the law, we include a measure of the psychological cost or disutility from digital piracy (FRAUD). The survey asked whether "tax cheating can be justified" on a scale from 1 (tax fraud is never justifiable), to 10 (tax fraud is always justifiable). The average reported value is 2.6. We expect that an individual will be more likely to engage in digital piracy if he has a favorable attitude toward fraud.

[Insert Figures 2 and 3 Here]

Our econometric estimations test the impact of possible detection and punishment under the Hadopi law on an individual's decision to engage in illegal downloading and on the intensity of illegal downloading for those who do engage. Our theoretical results predict that the graduated response policy should have no impact on the decision to acquire content using monitored channels (P2P file sharing) as long as the individual has received less than two warnings (which is the case for nearly all of our respondents). However, the policy should reduce the level of content consumed through P2P networks by those who do choose to engage in illegal downloading.

We estimate a two stage model in which individual first decide whether or not to engage in illegal monitored P2P file sharing and then, conditional on the first stage decision, those who engage in illegal file sharing make a decision about the intensity or frequency of this behavior (at least once a month versus less than once a month).[17]

[17]We also conducted the analysis using a three-level measure of the intensity of P2P filesharing (daily, less than daily but more than once per month, less than once per month). Results were

Both the decision to illegally obtain content through P2P networks (P2PCHOICE) and the intensity of file sharing (P2PINTENSITY) are binary variables. Therefore, the model can be estimated using a bivariate probit specification with sample selection as follows:

$$\text{P2PCHOICE} = \alpha_1 + \beta_1 \mathbf{X}_1 + \gamma_1 \text{DETECTION} + \varepsilon_1 \quad (9)$$

$$\text{P2PINTENSITY} = \alpha_2 + \beta_2 \mathbf{X}_2 + \gamma_2 \text{DETECTION} + \varepsilon_2 \text{ if P2PCHOICE} = 1 \quad (10)$$

The variable of interest is the perceived probability of detection (DETECTION). Both $\mathbf{X}_1$ and $\mathbf{X}_2$ include socioeconomic measures (age, education, gender, and income), indicators of the respondent's understanding of the law, and measures of utility from consuming pirated content including the respondent's taste for digital music and movies (TASTE), the proportion of pirates among the respondent's friends and relatives (PEERPIRACY), and the respondent's attitude toward fraudulent behavior (FRAUD).

The identification condition in the bivariate probit model with selection requires that $\mathbf{X}_1$ include at least one variable which is excluded from $\mathbf{X}_2$ and this variable must affect P2PCHOICE, but not P2PINTENSITY. The individual attitude toward fraud (FRAUD) fulfills this condition. This variable reflects the individual's willingness to engage in illegal activity, which directly impacts whether or not he will consume copyrighted content through P2P networks. However conditional on the decision to use P2P networks, the intensity of P2P activity is driven by the individual's preference for digital content (captured by other variables in our estimation), not by FRAUD.

This initial model is subject to potential endogeneity of the perceived probability of detection. Past and current experience of file sharing can influence beliefs about the probability of being caught and fined by the Hadopi agency which, in turn, affect the decision to engage in illegal activity as well as the intensity of that activity if a decision to pirate is made. To address this endogeneity problem we use an

not significantly different from the estimates obtained with the two-level measure. Because the interpretation of the coefficients is more direct with the binary measure of P2P intensity, we only present the results using this measure.

instrumental variable (IV) approach which first estimates a perceived probability of detection equation

$$\text{DETECTION} = \alpha_3 + \beta_3 \mathbf{X}_3 + \varepsilon_3 \tag{11}$$

and then estimates equation (9) above using the estimated values of DETECTION from equation (11).

Identification conditions require that $\mathbf{X}_3$ contain all the variables in $\mathbf{X}_1$ plus the instruments which are correlated with DETECTION (relevance condition) but are not correlated with the error term ε_1 (exogeneity condition). We use the variable OFF-MONITORED as an instrument. This binary variable equals 1 when the respondent believes offline sharing or swapping of music and movies (using a hard drive, USB disk or other storage device) is monitored by the Hadopi. As suggested by Wooldridge (2009), simple OLS estimates can be used to test the relevance of our instrument. These estimates show a positive and significant correlation between our instrument and DETECTION. Several arguments also suggest that OFFMONITORED satisfies the exogeneity condition. OFFMONITORED is a measure of an individual's awareness or understanding of the Hadopi law. Individuals who answer that offline sharing of content is monitored lack a clear understanding of the law. In addition, they tend to overestimate the reach of the Hadopi Law while also understanding that P2P networks are monitored (92% of them declare that P2P networks are monitored). Because these individuals' misconceptions of how the Hadopi law is implemented includes both online and offline channels, they are unlikely to substitute offline channels for online channels in any systematic way. Therefore, OFFMONITORED should only influence the propensity to engage in illegal P2P content acquisition through its impact on the perceived probability of detection. In addition, the fact that individuals in our sample are all regular Internet users indicates that OFFMONITORED is not simply a proxy for a basic inability to access content online. This is further supported by chi-squared test results that show no statistical difference between an individual's propensity to engage in P2P file sharing and the belief that offline file sharing is monitored.

Finally, we estimate a model that is a mix of the two previous models. This model, which controls for both endogeneity and sample selection, estimates equations (9), (10) and (11) using full information maximum likelihood assuming multivariate normality of the error terms. This system of three equations has both binary and continuous explained variables and the maximum likelihood estimation is highly computationally demanding. Roodman (2009) provides a method to simulate maximum likelihood estimation in the context of a conditional mixed process regression which is a generalization of the seemingly unrelated regression when independent variables are not continuous. This method uses the Geweke–Hajivassiliou–Keane (GHK) algorithm to simulate the maximum likelihood method.

4 Empirical Results

4.1 P2P File sharing, Hadopi effects and peer effects

Table 3 displays results of the three econometric models presented in the previous section (and a simple probit model of P2P choice in column 1). The likelihood ratio test for the bivariate model (columns 2 and 3) doesn't reject the null hypothesis of the independence of the two equations. It suggests that selection bias is not a major concern. In this model, which does not account for the potential endogeneity issue, the estimated probability of detection has a negative impact on both the propensity to engage in and the level of P2P file-sharing. This result is consistent with a "Beckerian" static framework in which an increased probability of detection reduces criminal activity.

[Insert Table 3 Here]

However, the results support predictions of our dynamic model when an instrumental variables approach is used to control for endogeneity (columns 4 and 5). Consistent with Proposition 1, the perceived probability of detection under the Hadopi law has no impact on the decision to engage in monitored illegal P2P activity. Our regression results also show that OFFMONITORED is a strong instrument. The magnitude of the coefficient estimate for OFFMONITORED indicates that this instrument has a significant impact on the endogenous variable DETECTION. In addition, a strong correlation between our instrument and the other covariates in (11) can decrease the ability of our instrument to control for the endogeneity bias. Using a probit model we regress OFFMONITORED on the other covariates in equation (11). Table 5 (in the appendix) shows that our instrument is independent from the other covariates. Finally the Wald test of exogeneity[18] is not rejected, suggesting that any remaining potential biases due to endogeneity are small.

The third model analyses the two-stage decision of filesharing and controls for potential endogeneity (column 6, 7 and 8). Again, we find that the threat of detection under the Hadopi law does not deter digital piracy. Neither the decision to engage in P2P nor the intensity of filesharing are influenced by the perceived probability of detection. The former result is directly predicted by the theoretical model. The theoretical model also predicts a negative relation between the perceived probability of detection and the level of filesharing. Our empirical results produce a slightly weaker result indicating a negative but insignificant effect. This could be due to the facts that P2PINTENSITY is a binary variable that roughly measures the frequency of filesharing, not the share of content consumed through the P2P channel and that among the individuals who access content through P2P communities more than once per month there is considerable variance in the quantity of illegal content that is shared and consumed.[19]

The econometric estimates indicate that accounting for endogeneity in perceived detection is important – after correcting for endogeneity, DETECTION has an in-

[18] The Wald test for exogeneity tests whether the residuals from the first equation (DETECTION) are correlated with those from the second equation (P2PCHOICE). The correlation is zero if the two equations are independant.

[19] Note that potential correlation between error terms for the three equations in the third model is not a concern as indicated by the "athrho" statistic. The "athro" statistic is the Fisher Z transformation of the correlation.

significant effect on piracy choice and intensity prior to receiving a warning. It is also useful to consider the average marginal effects of the DETECTION coefficient on P2PCHOICE in each model. Table 6 presents these marginal effects. Although the marginal effect in the bivariate probit model is negative and significant, the magnitude of the effect is small. This model predicts that raising the perceived probability of detection by ten percentage points would only reduce the probability that an individual uses an illegal P2P network by 1 percentage point.

The coefficients for the other explanatory variables are quite consistent with expectations. The level of preference for audio/video content is positively associated with the decision to engage in file-sharing. Younger and lower-income internet users are also more likely to illegally download content through P2P networks.

Similar effects are evident in the equation estimating the intensity of filesharing. Taste for audio and video content is the main variable that drives the usage of P2P networks. Additionally, females and people over age 35 utilize P2P networks less frequently.

The reduced form equation estimating the probability of detection also provides interesting insights into the causes of digital piracy. Sociodemographic results are consistent with traditional findings in risk behavior. Males, younger internet users, and those with higher incomes all place a lower assessment on the probability of detection. Additionally those who find that tax fraud is more acceptable expect that the Hadopi agency will be less effective in detecting piracy.

The Hadopi law aims to educate internet users through a series of warnings and to punish sustained piracy of digital content. The limited scope of Hadopi monitoring and the low number of warnings issued at the time our survey was administered make it impossible to estimate the direct impact of warnings or criminal prosecution under the law on piracy behavior. However, the three strikes process and final legal sanctions have been highly publicized and are frequent topics of public debate. As presented in Figures 2 and 3, one clear impact of this process is that internet users tend to overestimate the Hadopi monitoring ability. Misconceptions of the law, as measured by OFFMONITORED increase the perceived probability of detection.

Peer effects are another potentially interesting avenue through which graduated response efforts might impact the level of digital piracy. We can explore these effects by controlling for the proportion of digital pirates in one's social network. On the one hand, peers with experience in digital piracy can share knowledge of tactics for using P2P networks without being detected by the Hadopi agency. For example, tunnel networks and services which enable users to conceal IP addresses have become increasingly popular since Hadopi was introduced. Use of these techniques requires a degree of knowledge and experience with computers that is more likely to be shared by a social network which includes individuals with experience in digital piracy. These peer effects can increase the use of P2P networks. Peer effects also can influence awareness of the law and the perceived probability of being caught. Our econometric results indicate that having many digital pirates in one's social network decreases the perceived probability of detection and increases both the propensity to engage in and the level of P2P filesharing

4.2 Interdependance between monitored and non monitored digital piracy channels

One recurrent criticism of the Hadopi law questions its focus on P2P file sharing. Because Hadopi only monitors P2P networks it may simply lead P2P users to obtain content from alternative illegal channels. Direct downloading and newsgroups are a potential substitute for P2P file sharing. It would be interesting to know whether these alternative digital piracy channels are indirectly promoted by the Hadopi law.

Our data allow us to test the existence of substitution effects between monitored P2P piracy and unmonitored illegal channels by introducing unmonitored illegal channels as an explanatory variable in the P2PCHOICE equation. To estimate the impact of direct downloading on P2P activity we consider the following three equation model with two instrumental variables DETECTION and DDCHOICE (which equals 1 if

Internet users are engaged in direct downloading or newsgroup activities).

$$\text{P2PCHOICE} = \alpha_1 + \beta_1\mathbf{X}_1 + \gamma_1\text{DETECTION} + \mu_1\text{DDCHOICE} + \varepsilon_1 \quad (12)$$

$$\text{DETECTION} = \alpha_2 + \beta_2\mathbf{X}_2 + \varepsilon_2 \quad (13)$$

$$\text{DDCHOICE} = \alpha_3 + \beta_3\mathbf{X}_3 + \varepsilon_3 \quad (14)$$

As in the previous section OFFMONITORED is used as an instrumental variable in the DETECTION equation. We also need a valid instrument to control for potential endogeneity of DDCHOICE. The variable DDMONITORED, which is equal to 1 if the individual (incorrectly) believes that direct downloading is monitored under Hadopi law, plausibly satisfies both the relevance and endogeneity conditions. The negative and significant coefficient for DDMONITORED in the DDCHOICE equations (columns 3 and 6 of table 4) confirms that DDMONITORED is highly relevant to DDCHOICE – Internet users who believe that Hadopi monitors direct downloading activity are less willing to engage in direct downloading. The engodeneity condition requires that DDMONITORED only influences the decision to engage in P2P filesharing indirectly through its impact on the decision to engage in illegal direct downloading measured by DDCHOICE. Clearly, for an individual who chooses not to directly download copyrighted files, P2P networks are another option for illegally accessing content. However, the decision to engage in P2P filesharing is driven by the fact that the direct downloading alternative is not being used, and not by the belief that direct downloading is monitored.

[Insert Table 4 Here]

The maximum likelihood estimates of this model are displayed in columns 1 through 3 of Table 4. The main results of the previous section still hold – the perceived probability of detection does not impact the decision to use P2P networks or the intensity of filesharing. The coefficient for our main variable of interest DDCHOICE is not significant. Although P2P networks and direct downloading are alternative channels for accessing content illegally, our estimates suggest that individuals do not substitute between these channels. The determinants of direct download activity are quite similar to those of P2P activity. Being male and young as well as having strong preferences for audio and video content all increase one's propensity to use alternative piracy channels. Internet users who report being more comfortable with tax cheating also are more willing to use direct download platforms. Finally, the presence of pirates in the close social network is also positive and significant both for the use of P2P and direct downloading. We now explore this peer effect in greater detail.

While our estimates find no substitution between monitored and unmonitored illegal channels for the sample as a whole, it is possible that such substitution may be limited to users who are better informed about alternative piracy channels. One's social network can provide this information and facilitate use of other piracy options. To test this idea, we create an interaction variable PEERPIRACY x DDCHOICE. This variable takes the value of 1 if users are involved in direct download or newsgroup activities and have many pirates in their social networks. Estimates are presented in columns 4 through 6 of table 4. The interaction term is negative and significant. In addition, the total effect of DDMONITORED (-0.628+0.433= -0.195) is also negative. This suggests a significant substitution effect between monitored and unmonitored illegal channels for those whose social network includes a relatively large number of pirates. The Hadopi law may highlight a strong inequality between those who understand the law and alternatives to P2P piracy and those who are less informed about unmonitored channels through which digital content can be accessed illegally. Once we control for the perceived detection probability, results in Table 4 show that those who are better informed are more likely to substitute between monitored and unmonitored channels. Those who are less informed are less strategic in their piracy behavior.

5 Discussion and Conclusion

This paper explores the impact of recent efforts to protect intellectual property rights to digital content. We construct a dynamic model of criminal behavior under a graduated response enforcement policy like those recently implemented in France (the Hadopi Law) and the United States (the U.S. Copyright Alert System). The model captures key attributes of the trade-off between obtaining digital content through illegal channels actively monitored under current programs (*e.g.,* P2P networks under the Hadopi law) and obtaining this content through other channels. The model reveals that the perceived detection probability $k_i P(c)$ has no impact on an individual's decision to initially engage in digital piracy. Furthermore, conditional on the decision to pirate content, the model implies that increasing the perceived detection probability will have two opposing effects on an individual's level (or intensity) of piracy prior to receiving a warning. Because raising the probability of detection increases the probability of future punishment, an increase in k_i directly reduces the incentive to pirate. However, as k_i increases, the discount rate $r + k_i P(c)$ applied to benefits from future illegal activity also increases. This leaves the individual less willing to wait for utility from consumption of pirated content in the future and increases the incentive to pirate content in the current period. Our model predicts that the negative effect dominates but also raises the empirical question of whether or not this deterrent effect is significant.

A further implication of the theoretical model is that efforts to reduce the cost of obtaining content through legal channels (by making legal distribution channels like iTunes more user-friendly or by simply reducing the price of legal downloads) also will increase the intensity of illegal content acquisition by individuals who choose to pirate. As the utility u^N from obtaining content legally increases, the continuation utility V_1 realized after receiving a warning also increases. This reduces the incentive to limit piracy in the first stage (prior to receiving a warning) in order to delay the expected time at which a first warning is received. As a result, the intensity of illegal content acquisition prior to receiving a warning increases. Although we are unable to test this prediction empirically, it does raise interesting questions about whether combining a graduated response policy to deter piracy with cost reductions to increase legal acquisition of content can generate unintended outcomes.

We empirically analyze predictions from the theoretical model regarding the impact of the Hadopi law on both the individual's decision to engage in digital piracy and, conditional on choosing to pirate, the intensity of this piracy. These predictions are tested using data from a survey of French Internet users. At the time of the survey very few individuals in our sample had received a warning, so our empirical analysis is limited to the behavior of individuals who had not yet received a warning from Hadopi (Stage 0 in our theoretical model). Because the perceived detection probability is likely to be endogenous, we employ both an instrumental variables approach and a conditional mixed process regression to control for potential endogeneity. The empirical results support the prediction that a graduated response policy fails to deter individuals from engaging in digital piracy and also find no significant deterrent effect on the level of illegal activity by those who do pirate; in both models neither the decision to engage in illegal P2P file sharing monitored under the law nor the intensity of filesharing by those who do engage is significantly impacted by the perceived detection probability.

In addition to testing predictions of the theoretical model, our data enable us to explore whether the Hadopi law encouraged substitution away from illegal P2P file sharing monitored under the law to other illegal content acquisition methods. The results provide no evidence that such substitution occurs in the aggregate, possibly because there is confusion in the general public about exactly which illegal behavior is monitored. However, there is evidence that the law encourages Internet users who better understand the law and alternative piracy channels (those with many digital pirates in their social network) to substitute away from the monitored P2P channel and to obtain content through unmonitored illegal channels. Thus, the deterrent effect of the Hadopi law is further weakened by the fact that it applies to only one of several popular alternatives for illegally acquiring digital content.

In conclusion, this paper focuses on the impact of recently implemented graduated response policies to deter digital piracy on the piracy behavior of individual consumers. Both our theoretical and empirical results indicate that these policies are not effective in deterring piracy activity, at least until a significant portion of the population has received initial warnings and faces punishment upon receiving a subsequent warning. In conjunction with evidence from Danaher et. al. (2013) suggesting that the Hadopi law increased legal purchases of content shortly before its implementation, our results indicate that these gains in legal purchases are likely the result of positive educational externalities generated by publicity surrounding the law, and that they are not attributable to a deterrent effect that reduced digital piracy.

6 References

Adermon, A. and C.-Y. Liang (2010) "Piracy, Music, and Movies: A Natural Experiment" Working Paper Series 2010:18, Department of Economics, Uppsala University.

Becker, G.S., (1968). "Crime and Punishment: An Economic Approach," Journal of Political Economy, 76 (2), 169-217.

Bhattacharjee, S., R.D. Gopal, K. Lertwachara, and J.R. Marsden (2006) "Impact of Legal Threats on Online Music Sharing Activity: An Analysis of Music Industry Legal Actions." Journal of Law and Economics, Vol. XLIX, 91-114.

Danaher, B. and Smith, M. D., (2013) "Gone in 60 Seconds: The Impact of the Megaupload Shutdown on Movie Sales". Available at SSRN: http://ssrn.com/abstract=2229349

Danaher, B., Smith, M. D., and R. Telang (2013) "Piracy and Copyright Enforcement Mechanisms," NBER Working Paper 19150, http://www.nber.org/papers/w19150

Danaher, B., Smith, M. D., Telang R. and S. Chen (2014) "The Effect of Graduated Response Anti-Piracy Laws on Music Sales: Evidence from an Event Study in France," Journal of Industrial Economics, forthcoming.

Danaher B., Dhanasobhon S., Smith M.D., and Telang R. (2010) "Converting Pirates Without Cannibalizing Purchasers: The Impact of Digital Distribution on Physical Sales and Internet Piracy" Marketing Science, Volume 29 Number 6. pp. 1138-1151.

Davis M. L. (1988) "Time and Punishment: An Intertemporal Model of Crime", Journal of Political Economy, vol. 96, n°21, 383-390.

Hammond, R.G. (2014). "Profit Leak? Pre-release File Sharing and the Music Industry," Southern Economic Journal, forthcoming.

Klump, T. (2012) "File Sharing, Network Architecture, and Copyright Enforcement: An Overview", Working Paper; Available at SSRN.

Liebowitz, S.L. (2008), "Testing File-Sharing's Impact by Examining Record Sales in Cities", Management Science, 54, 4, 852-859.

Lochner, L. (2007). "Individual Perceptions of the Criminal Justice System," American Economic Review, American Economic Association, vol. 97(1), pages 444-460.

Oberholzer, F., and K. Strumpf, (2007), "The Effect of File Sharing on Record Sales. An Empirical analysis", Journal of Political Economy, 115, 1, 1-42.

Peitz, M, and Waelbroeck, P, (2004), "The Effect of Internet Piracy on Music Sales: Cross-Section Evidence", Review of Economic Research on Copyright Issues, 1, 2, 71-79.

Rob, R. and Waldfogel J., (2007), "Piracy on the Silver Screen", Journal of Industrial Economics, 55, 3, 379-393.

Rob, R. and 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, 1, 29-62.

Roodman, D. (2009), "Estimating Fully Observed Recursive Mixed-Process Models with cmp," Working Papers 168, Center for Global Development.

Smith, M. and R. Telang (2010), "Piracy or promotion? The impact of broadband

Internet penetration on DVD sales," Information Economics and Policy, Volume 22, Issue 4, Special Issue: Digital Piracy, 289-298.

Smith, M.D. and R. Telang (2012) Assessing the Academic Literature Regarding the Impact of Media Piracy on Sales, Working Paper, Carnegie Mellon University, Pittsburgh. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2132153

Waldfogel, J. (2010), "Music file sharing and sales displacement in the iTunes era", Information Economics and Policy, 22, 306-314.

Wooldridge, J. M. (2009) Introductory econometrics: a modern approach. South-Western Pub.

Zentner A. (2006), "Measuring the Effect of File Sharing on Music Purchases," Journal of Law and Economics, April 2006, p. 63-90

Zentner, A. (2008) "Online Sales, Internet Use, Music Downloads, and the Decline of Retail Music Specialty Stores," Information Economics and Policy, Volume 20, Issue 3, September, Pages 288-300.

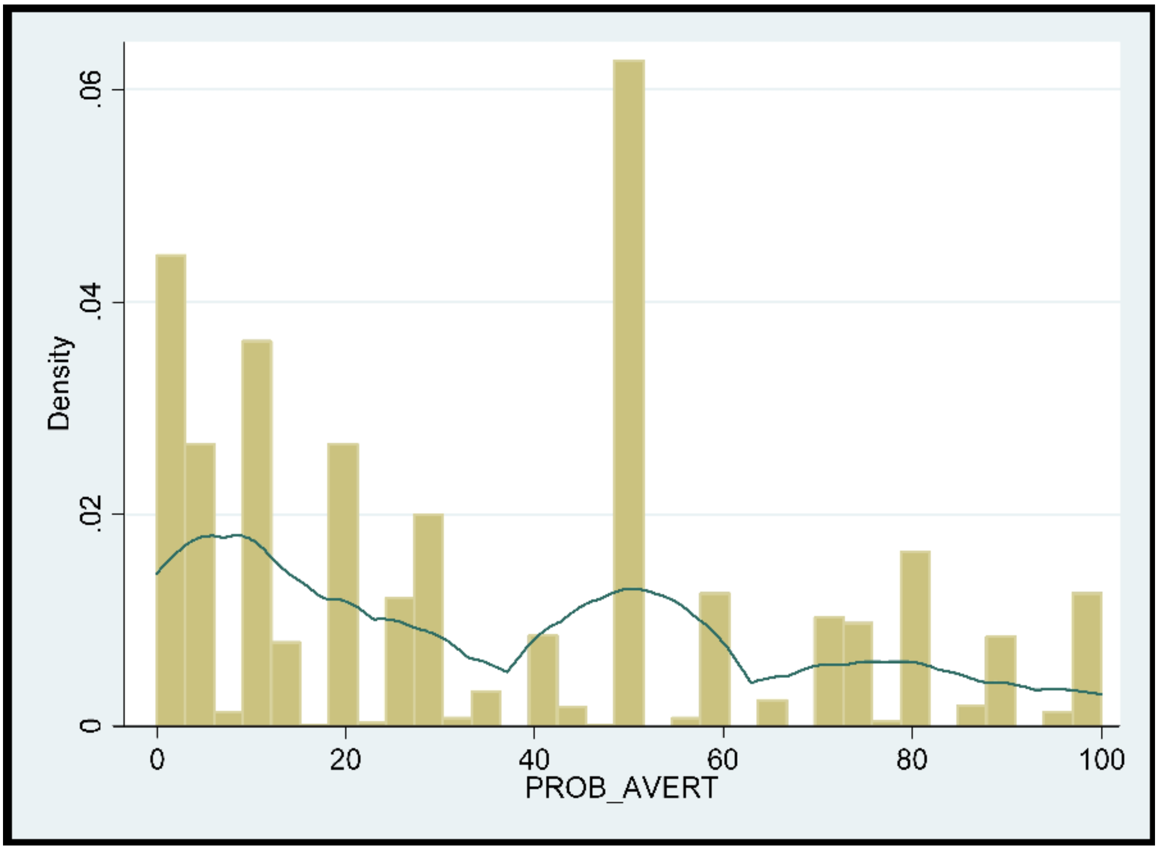

Figure 1: Distribution of the perceived probability to be detected by Hadopi in case of illegal downloading

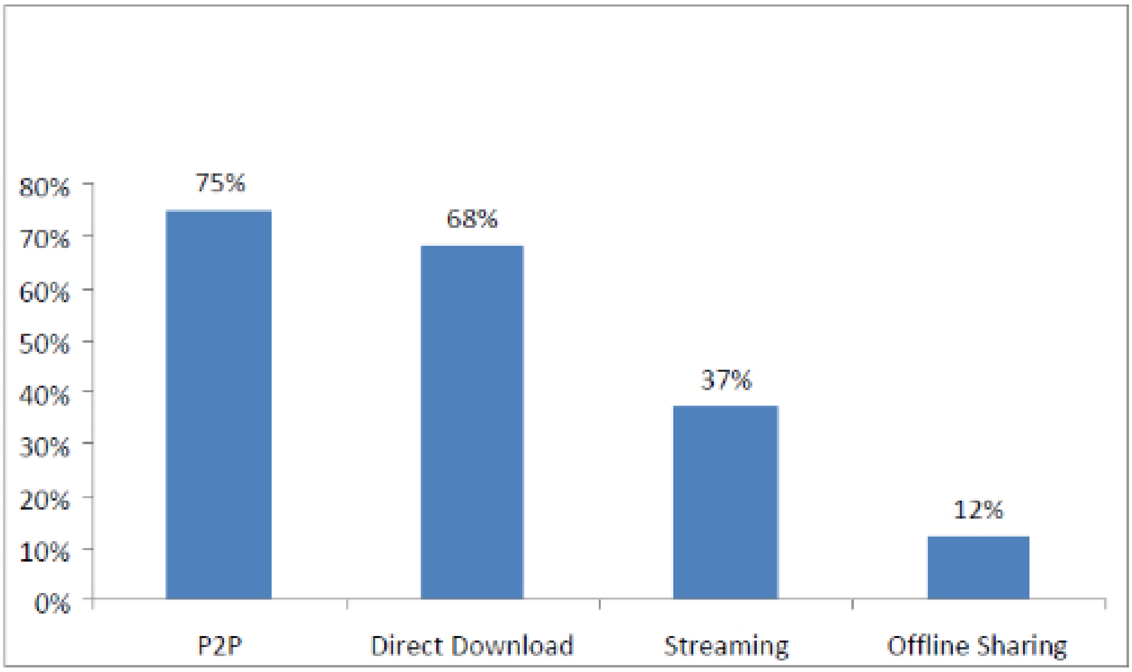

Figure 2: Awareness of the Hadopi Law: channels or techniques that are monitored by Hadopi

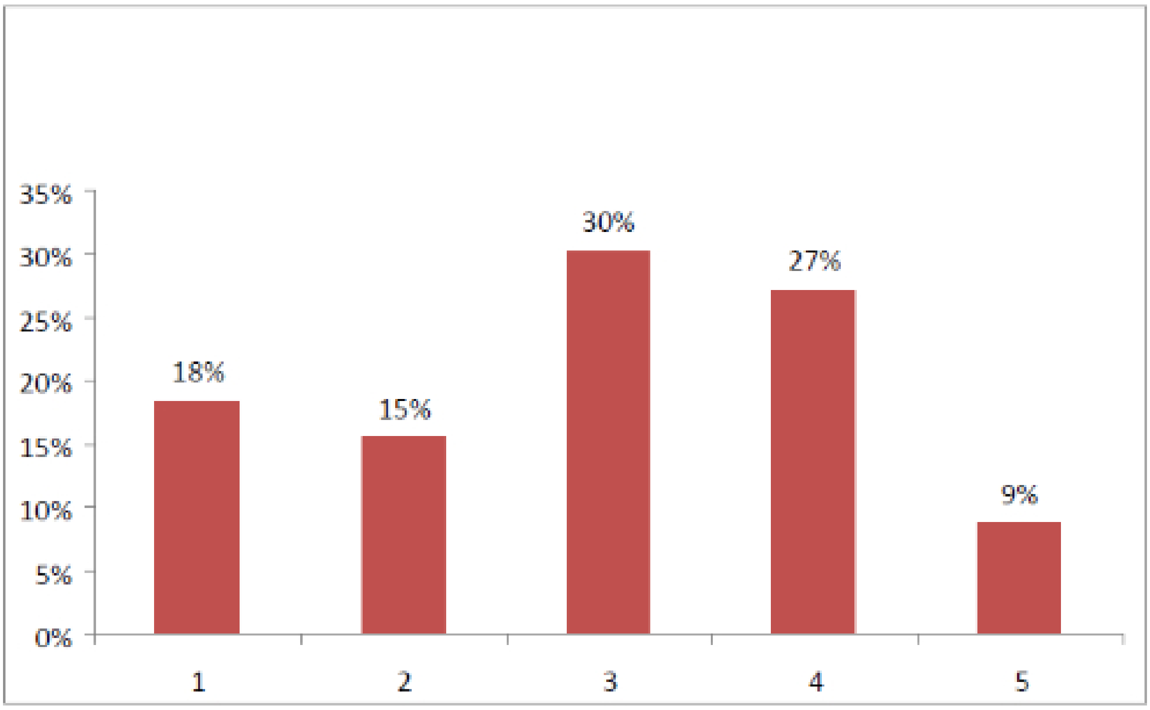

Figure 3: Awareness of the Hadopi Law: number of channels or techniques that are monitored by Hadopi

Table 1. Variable description

VARIABLES	Description
P2PCHOICE	1 if the individual is engaged in P2P filesharing.
P2PINTENSITY	1 if using P2P more than once a month (regular), 0 if less than once a month.
DDCHOICE	1 if the individual is engaged in direct download.
DETECTION	Perceived probability of being detected and notified by Hadopi.
FRAUD	Attitude toward fiscal fraud. Ten-point scale from 1 if tax cheating is never justifiable to 10 if tax cheating can always be justifiable.
PEERPIRACY	1 if many friends and relatives are sharing music or movies.
DDMONITORED	1 if the respondent thinks that HADOPI monitors direct download platforms or newsgroups.
OFFMONITORED	1 if the respondent thinks that HADOPI monitors offline sharing or swapping of digital content.
GENDER	1 if male.
AGE15-24	1 if age $[15 - 24]$
AGE25-34	1 if age $[25 - 34]$
AGE35-49	1 if age $[35 - 49]$
AGE50+	1 if more than 50 years old.
INCOME1	1 if income makes living conditions difficult.
INCOME2	1 if income meets the needs.
INCOME3	1 if income makes living conditions comfortable.
EDUCATION1	1 if primary or secondary education.
EDUCATION2	1 if first level of tertiary education (bachelor's degree).
EDUCATION3	1 if second level of tertiary education (post-graduate degree).
TASTE1	1 if very strong taste for music or video.
TASTE2	1 if strong taste for music or video.
TASTE3	1 if moderate taste for music or video.
TASTE4	1 if no or limited taste for music or video.

Table 2. Descriptive Statistics

	Mean	Std Dev	Min	Max
P2PCHOICE	0.22	0.41	0	1
P2PINTENSITY	0.45	0.49	0	1
DDCHOICE	0.3	0.45	0	1
DETECTION	36	29.3	0	100
FRAUD	2.59	2.17	1	10
PEERPIRACY	0.41	0.49	0	1
DDMONITORED	0.68	0.46	0	1
OFFMONITORED	0.12	0.32	0	1
GENDER	0.5	0.5	0	1
AGE15-24	0.25	0.42	0	1
AGE25-34	0.2	0.4	0	1
AGE35-49	0.32	0.46	0	1
AGE50+	0.23	0.42	0	1
INCOME1	0.33	0.47	0	1
INCOME2	0.44	0.49	0	1
INCOME3	0.23	0.41	0	1
EDUCATION1	0.2	0.4	0	1
EDUCATION2	0.43	0.49	0	1
EDUCATION3	0.37	0.48	0	1
TASTE1	0.17	0.37	0	1
TASTE2	0.33	0.33	0	1
TASTE3	0.31	0.46	0	1
TASTE4	0.18	0.38	0	1

Table 3. Determinants of P2P Filesharing (Propensity and Intensity)

	Probit model	Bivariate probit with sample selection		Probit with instrumental variable		Conditional mixed process regression		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	P2PCHOICE	P2PCHOICE	P2PINTENSITY	P2PCHOICE	DETECTION	P2PCHOICE	P2PINTENSITY	DETECTION
DETECTION	-0.00400***	-0.00403***	-0.00385*	-0.0194		-0.0176	-0.00381	
	(0.00127)	(0.00128)	(0.00221)	(0.0119)		(0.0125)	(0.0192)	
GENDER	0.356***	0.361***	0.424***	0.161	-10.24***	0.193	0.420**	-10.24***
	(0.0703)	(0.0712)	(0.115)	(0.199)	(1.281)	(0.199)	(0.197)	(1.281)
AGE15-24	0.633***	0.633***	0.890***	0.522***	-2.878	0.544***	0.886***	-2.876
	(0.111)	(0.110)	(0.201)	(0.177)	(2.024)	(0.170)	(0.206)	(2.025)
AGE25-34	0.488***	0.492***	0.547**	0.405***	-2.334	0.425***	0.543**	-2.330
	(0.113)	(0.114)	(0.217)	(0.153)	(1.996)	(0.149)	(0.223)	(1.996)
AGE35-49	0.146	0.146	0.353*	0.166*	1.975	0.166*	0.356	1.980
	(0.104)	(0.105)	(0.214)	(0.0984)	(1.721)	(0.100)	(0.219)	(1.721)
AGE50+	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
INCOME1	0.176*	0.176*	0.112	0.245**	5.540***	0.239**	0.110	5.549***
	(0.0967)	(0.0964)	(0.147)	(0.0992)	(1.785)	(0.103)	(0.203)	(1.785)
INCOME2	0.106	0.104	0.00316	0.144*	3.229**	0.139	0.000239	3.234**
	(0.0883)	(0.0877)	(0.138)	(0.0856)	(1.631)	(0.0877)	(0.168)	(1.631)
INCOME3	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
EDUCATION1	0.0103	0.0104	-0.0445	0.0583	3.264*	0.0528	-0.0459	3.267*
	(0.106)	(0.104)	(0.171)	(0.105)	(1.862)	(0.107)	(0.183)	(1.862)
EDUCATION2	0.0853	0.0850	0.0715	0.143*	4.217***	0.137	0.0705	4.220***
	(0.0779)	(0.0775)	(0.118)	(0.0828)	(1.447)	(0.0855)	(0.147)	(1.447)
EDUCATION3	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
TASTE1	0.393***	0.395***	1.055***	0.354***	-0.0198	0.365***	1.066***	-0.0131
	(0.122)	(0.124)	(0.252)	(0.134)	(2.177)	(0.133)	(0.262)	(2.177)
TASTE2	0.379***	0.380***	0.952***	0.392***	3.366*	0.396***	0.961***	3.372*
	(0.108)	(0.112)	(0.239)	(0.107)	(1.852)	(0.107)	(0.240)	(1.852)
TASTE3	0.280**	0.280**	0.489**	0.298***	2.978	0.298***	0.492**	2.985
	(0.110)	(0.114)	(0.237)	(0.107)	(1.842)	(0.108)	(0.245)	(1.842)
TASTE4	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
FRAUD	0.0453***	0.0458***		0.0162	-1.544***	0.0210		-1.544***
	(0.0152)	(0.0151)		(0.0307)	(0.289)	(0.0306)		(0.290)
PEERPIRACY	0.641***	0.641***	0.989***	0.414*	-10.20***	0.449*	0.988***	-10.20***
	(0.0752)	(0.0741)	(0.130)	(0.247)	(1.408)	(0.241)	(0.225)	(1.408)
OFFMONITORED					6.473***			6.480***
					(1.893)			(1.912)
Constant	-2.030***	-2.034***		-1.160	41.21***	-1.294		41.19***
	(0.161)	(0.164)		(0.883)	(2.554)	(0.867)		(2.556)
Observations	2000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Log likelihood	-906	-1167		-10379		-10769		
		LR test: 0.33 (Prob > chi2 = 0.56)		Wald test: 1.20 (Prob > chi2 = 0.2738)		athrho (6)_(7): 0.606 (0.861) ; athrho (6)_(8): 0.407 (0.425)		
						athrho (7)_(8): 0.000615 (0.515)		

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Impact of alternative digital piracy channels on the use of P2P filesharing

VARIABLES	(1) P2PCHOICE	(2) DETECTION	(3) DDCHOICE	(4) P2PCHOICE	(5) DETECTION	(6) DDCHOICE
DETECTION	-0.0140			-0.0132		
	(0.0140)			(0.0147)		
DDCHOICE*PEERPIRACY				-0.628***		
				(0.171)		
DDCHOICE	-0.0289			0.433		
	(0.374)			(0.536)		
PEERPIRACY	0.529**	-10.20***	0.625***	0.803***	-10.20***	0.616***
	(0.238)	(1.408)	(0.0705)	(0.276)	(1.408)	(0.0706)
GENDER	0.245	-10.24***	0.397***	0.258	-10.24***	0.398***
	(0.202)	(1.281)	(0.0675)	(0.208)	(1.281)	(0.0675)
AGE15-24	0.606***	-2.881	0.965***	0.590***	-2.881	0.968***
	(0.189)	(2.024)	(0.105)	(0.206)	(2.024)	(0.105)
AGE25-34	0.469***	-2.331	0.426***	0.458***	-2.331	0.425***
	(0.145)	(1.996)	(0.107)	(0.148)	(1.996)	(0.107)
AGE35-49	0.174*	1.978	0.0965	0.165	1.979	0.0947
	(0.104)	(1.721)	(0.0985)	(0.108)	(1.721)	(0.0981)
AGE50+	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
INCOME1	0.218*	5.541***	0.144	0.214*	5.541***	0.145
	(0.111)	(1.785)	(0.0930)	(0.116)	(1.785)	(0.0931)
INCOME2	0.124	3.228**	0.0426	0.117	3.228**	0.0431
	(0.0912)	(1.631)	(0.0843)	(0.0939)	(1.631)	(0.0843)
INCOME3	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
EDUCATION1	0.0417	3.261*	-0.160	0.0671	3.261*	-0.160
	(0.112)	(1.862)	(0.101)	(0.116)	(1.862)	(0.101)
EDUCATION2	0.120	4.218***	0.0458	0.120	4.218***	0.0457
	(0.0911)	(1.447)	(0.0746)	(0.0943)	(1.447)	(0.0747)
EDUCATION3	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
TASTE1	0.390***	-0.0167	0.487***	0.405***	-0.0167	0.490***
	(0.136)	(2.177)	(0.116)	(0.142)	(2.177)	(0.116)
TASTE2	0.401***	3.367*	0.376***	0.415***	3.367*	0.377***
	(0.113)	(1.852)	(0.103)	(0.119)	(1.852)	(0.103)
TASTE3	0.313***	2.978	0.0650	0.311***	2.978	0.0678
	(0.112)	(1.842)	(0.106)	(0.116)	(1.842)	(0.105)
TASTE4	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
FRAUD	0.0281	-1.544***	0.0351**	0.0330	-1.544***	0.0351**
	(0.0315)	(0.289)	(0.0151)	(0.0328)	(0.289)	(0.0151)
OFFMONITORED		6.350***			6.349***	
		(1.891)			(1.891)	
DD_MONITORED			-0.310***			-0.311***
			(0.0686)			(0.0694)
Constant	-1.544*	41.22***	-1.605***	-1.772*	41.22***	-1.597***
	(0.872)	(2.554)	(0.151)	(0.920)	(2.554)	(0.151)
Observations	2,000	2,000	2,000	2,000	2,000	2,000
Log Likelihood		-11268.834			-11257.484	
athrho (P2P)_(DETECT)		0.29 (0.43)			0.26 (0.45)	
athrho (P2P)_(DD)		0.54 (0.28)*			0.48 (0.32)	
athrho (DETECT)_(DD)		-0.08 (0.03)**			-0.08 (0.03)**	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Regression of the instrument on the covariates (Probit estimates)

VARIABLES	OFFMONITORED
GENDER	0.0726
	(0.0760)
AGE15-24	-0.158
	(0.119)
AGE25-34	0.102
	(0.115)
AGE35-49	0.131
	(0.0997)
AGE50+	Ref.
INCOME1	0.0101
	(0.106)
INCOME2	-0.0428
	(0.0966)
INCOME3	Ref.
EDUCATION1	-0.139
	(0.113)
EDUCATION2	0.0398
	(0.0847)
EDUCATION3	Ref.
TASTE1	0.108
	(0.127)
TASTE2	0.0228
	(0.111)
TASTE3	0.00330
	(0.110)
TASTE4	Ref.
PEERPIRACY	-0.0155
	(0.0798)
FRAUD	-0.00993
	(0.0173)
Constant	-1.205***
	(0.147)
Observations	2,000

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Marginal effect of DETECTION

	Model 1	Model 2	Model 3
VARIABLES	P2PCHOICE	P2PCHOICE	P2PCHOICE
DETECTION	-0.001***	-0.005	-0.0045
	(0.0003)	(0.003)	(0.0043)