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

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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.

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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 the consent of copyright holders, 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] Similarly, 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

[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).

entails formal warnings issued to individuals for the first two illegal file sharing infringements 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. 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 impacts the timing of detection (by increasing the probability of being caught) and punishment (by delaying the

[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. Serbin (2012) refers to this program as a "six strikes and you're maybe out" system.

sanction until a third warning is received). Our model predicts that under a graduated response policy the decision of whether or not to engage in the monitored illegal activity is independent of the probability of detection as long as the individual has not received a warning. However, an increase in the probability of detection will reduce the consumption of content through the monitored channel.

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.

The econometric results partially support the theoretical predictions. Several factors affect the perceived probability of detection under the law, and our results show that the propensity to engage in illegal file-sharing is independent of these beliefs as predicted by the theoretical model. However, the perceived probability of detection has no impact on the intensity of P2P filesharing. In addition, 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 suggest substitution effects between monitored P2P channels and unmonitored channels (e.g., direct downloads or newsgroups) for individuals who have a large number of pirates in their social network. Collectively our findings indicate that the Hadopi law has not deterred individuals from engaging in digital piracy, but has altered the way they access content legally and illegally.

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 affected individual behavior. They find that such legal action 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 contribute to related research based on the value of digital content sales (Adermon and Liang 2014, Danaher et al. 2014). For example, Danaher et al. (2014) analyze the impact of the Hadopi law on French music sales through iTunes. They find that 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 and increased information about legal channels 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) through both legal and illegal channels. 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 obtaining content through the monitored illegal channel, which we refer to

[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.

as simply the "monitored channel," for the first time, he receives a 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 content through legal channels and/or through illegal channels that are not monitored by the anti-piracy agency. We refer to these channels as "alternative channels." Let c_m denote consumption through the monitored channel and c_n denote consumption through alternative channels. An individual receives total utility $u(c_m, c_n)$ from consumption of content. We assume the utility function is concave (with second derivatives $u_{mm} < 0$ and $u_{nn} < 0$), and that a unique solution to the utility maximization problem ($c_m \geq 0$ and $c_n \geq 0$) exists (both with and without monitoring). Finally, we assume that an individual who is detected engaging in illegal monitored consumption a second time is prosecuted and ceases use of this 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 $P(c_m, t)$ be the objective probability that an individual consuming content through the monitored channel will be detected at any time t. This probability depends positively on the level c_m 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 a perceived probability of detection which may differ from $P(c_m, t)$. (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 a hazard rate. Letting $G_i(c_m, t)$ denote individual i's perceived probability of not being detected by time t given c_m, so $G_i(c_m, t)$ is a cumulative distribution function, and letting $g_i(c_m, t)$ be the corresponding density function,

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

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

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 a warning can choose to cease consuming through the monitored channel which would generate a utility of $\int u^N e^{-rt} dt = u^N / r$, where u^N is the utility achieved by only consuming content through alternative channels (setting $c_m = 0$ and then optimally choosing c_n).[10] Alternatively, the utility from continuing to access content through the monitored channel after receiving a warning is (for convenience we now drop the i subscript)

$$V_1 = \max_{c_m, c_n} \int \big((1 - G(c_m, t))\, u(c_m, c_n) + G(c_m, t)\, u^N - g(c_m, t)\, F \big) e^{-rt} dt. \tag{2}$$

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

[10] We assume a unique solution to this problem exists with $c_n > 0$.

Noting that equation (1) is a linear differential equation,[11] we can restate equation (2) as

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

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

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

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

or

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

Because c_n does not impact P, the first-order condition with respect to c_n yields

$$u_n(c_m, c_n) = 0. \tag{5}$$

Let (c^*_{m1}, c^*_{n1}) denote the solution to equations (4) and (5).

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

$$\frac{u^N}{r} \geq V_1 = \frac{u(c^*_{m1}, c^*_{n1}) - u^N - kP(c^*_{m1})F}{r + kP(c^*_{m1})} + \frac{u^N}{r}. \tag{6}$$

The left-hand side of condition (6) 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 (6) can be restated as

[11] 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

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

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

$$u(c^*_{m1}, c^*_{n1}) - u^N \leq kP(c^*_{m1})F \tag{7}$$

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 only through alternative channels.

2.2.2 Stage 0 (before receiving a warning)

Consumption through the monitored channel 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 (6), if $V_1 \leq u^N/r$, then it is optimal for an individual who has received a first warning to cease use of the monitored channel after receiving a warning. 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 using the monitored channel after receiving a warning, then the expected return from engaging in the monitored activity prior to a warning is

$$V_0 = \max_{c_m, c_n} \left(\frac{u\left(c_m, c_n\right) - u^N}{r + kP\left(c_m\right)} + \frac{u^N}{r} \right).$$

Let (c^*_{m0}, c^*_{n0}) be the utility-maximizing consumption at this stage. Then (c^*_{m0}, c^*_{n0}) solves the first-order conditions

$$u_m\left(c_m, c_n\right) = \frac{kP'\left(c_m\right)\left(u\left(c_m, c_n\right) - u^N\right)}{\left(r + kP\left(c_m\right)\right)} \tag{8}$$

and

$$u_n\left(c_m, c_n\right) = 0 \tag{9}$$

Note that an increase in u^N will actually increase content c^*_{m0} acquired through the monitored channel prior to receiving a warning (because the right-hand side of (8) decreases with u^N).

Given the first-order condition (8) , the expected benefit from using the monitored channel prior to receiving a warning can be restated as

$$V_0 = \frac{u_m\left(c^*_{m0}, c^*_{n0}\right)}{kP'\left(c^*_{m0}\right)} + \frac{u^N}{r}.$$

Note that V_0 is always greater than $\frac{u^N}{r}$. This implies that prior to receiving a first warning, one's propensity to initially consume content through the monitored channel is independent of both the perceived probability of detection and the potential fine.

Now consider an individual who continues to access 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 activity prior to a warning is

$$V_0 = \max_{c_m, c_n} \left(\frac{u\left(c_m, c_n\right) - rV_1}{r + kP\left(c_m\right)} + V_1 \right).$$

The first-order-conditions are

$$u_m\left(c_m, c_n\right) = \frac{kP'\left(c_m\right)\left(u\left(c_m, c_n\right) - rV_1\right)}{\left(r + kP\left(c_m\right)\right)} \tag{10}$$

and

$$u_n\left(c_m, c_n\right) = 0. \tag{11}$$

Let $\left(\tilde{c}^*_{m0}, \tilde{c}^*_{n0}\right)$ denote the solution to equations (10) and (11) and note that $u\left(\tilde{c}^*_{m0}, \tilde{c}^*_{n0}\right) > rV_1$. In addition, $c^*_{m1} < \tilde{c}^*_{m0}$ and

$$V_0 = \frac{u_m\left(\tilde{c}^*_{m0}, \tilde{c}^*_{n0}\right)}{kP'\left(\tilde{c}^*_0\right)} + V_1.$$

As $V_1 > \frac{u^N}{r}$, it follows that $V_0 > \frac{u^N}{r}$ for any value of k, so again the perceived probability of detection has no impact on the individual's decision to initially engage in (monitored) piracy.

To this point, we have limited our analysis to individuals who access at least some content through the monitored channel. Implicitly, we have assumed that $u_m\left(0, c^*_n\right) > 0$, where c^*_n is the optimal level of consumption through alternative channels when c_m is constrained to $c_m = 0$. It is also possible that $u_m\left(0, c^*_n\right) \leq 0$. In this case, the individual prefers not to engage in consumption through the monitored channel even if $k = 0$. Obviously, for such an individual, the decision of whether or not to access content through the monitored channel does not depend on k.

2.3 The impact of the perception parameter k on the individual's behavior

Subsection 2.2.2 analyzed the impact of the probability k on the initial decision to access content through the monitored channel. In this subsection, we consider how changes in k impact the magnitude of c_{m0} for consumers who do utilize the monitored channel. We then present two propositions that summarize these results.

An increase in k has ambiguous effects on the quantity c_{m0} of content accessed through the monitored channel prior to receiving a warning. 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 channels. However, increasing k also increases the discount rate which makes individuals more impatient, thereby reducing 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_{m0}. 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 activity after receiving a warning (*i.e.,* $V_1 \leq u^N/r$). Because the right-hand side of (8) increases with k, a higher perceived probability of detection reduces 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 (10) is increasing in k.[12] Thus,

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

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

Substituting this expression for V_1 into equation (10) yields the result.

whether the individual continues or ceases use of the monitored channel following a warning, an increase in k reduces consumption through the monitored channel prior to receiving a warning.

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 k.*

Proposition 2 *An increase in the perceived probability of detection will decrease the level c_{m0} of consumption through the monitored channel prior to receiving a warning.*

Another implication of our model is that an increase in u^N (i.e. the utility from only consuming content through alternative channels) increases the quantity c_{m0} of content consumed through the monitored channel prior to receiving a first 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_{m0} 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. This 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). Similarly, exogenous changes in access to illegal unmonitored channels may have counter-intuitive effects. For instance, supply-side interventions targeting unmonitored illegal channels (*e.g.*, the shutdown of Megaupload) may reduce u^N. Our model predicts that such supply side interventions will decrease the quantity of content accessed through monitored channels.

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 vary with income and other sociodemographics. In the next section, we present our empirical strategy for testing hypotheses generated by the theoretical analysis.

3 Data and Methodology

Our empirical analysis utilizes individual survey response data to test the predictions of the theoretical model. The survey was conducted on a representative sample of French Internet users to ensure relevance of the data. Although survey data are subject to limitations (due to the subjective nature of individual responses), surveys are commonly used to analyze digital piracy (Rob and Waldfogel, 2006, 2007).

The survey was administered by the poll institute Harris Interactive, in May 2012. 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 percent engaged in illegal downloading activity either through P2P networks (22 percent) or alternative channels (30 percent). Moreover, 3.6 percent had received a warning from the Hadopi agency (i.e. 16.4 percent of those engaged in the monitored activity) and 18 percent reported knowing someone who had received a warning from the Hadopi agency.

[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.[13] The distribution of the perceived detection probability is displayed in Figure 1. The distribution is bimodal with a mass point at 50 percent and a high frequency of answers between 0 and 10 percent. Of the total respondents 32 percent reported a detection probability lower than 10 percent, and 19 percent estimated this probability at 50 percent. 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). Stronger taste for cultural goods should increase the P2P downloading activity as it directly increases the utility from using this channel (e.g. to discover new artists or search niche content). It also increases the utility u_N from alternative channels which indirectly increases the quantity of content consumed through the monitored channel. Thus we expect TASTE to positively impact both the propensity to engage in and the intensity of P2P filesharing.

Respondents were also asked about illegal behavior of other individuals in their social network (PEERPIRACY). Forty-one percent reported that they have many friends or relatives who download and share illegal content. 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, Sah 1991). 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 also a measure of the individual's awareness of digital piracy. A large number of pirates in one's network provides substantial information about how

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

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 percent of respondents understood that P2P networks are monitored, but 68 percent incorrectly reported that direct downloading is monitored. Similarly, 37 percent and 12 percent, respectively, reported that illegal streaming and offline sharing are monitored. As presented in Figure 3, 66 percent 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. 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 recode this variable as a binary measure with FRAUD equal to 0 if the individual responds that tax fraud is never justifiable and equal to 1 otherwise (for individuals that declare tax fraud is more or less justifiable). We expect that an individual will be less likely to engage in digital piracy if he reports that tax fraud is not justified.

[Insert Figures 2 and 3 Here]

Our econometric specifications 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 from Proposition 1 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, as stated in Proposition 2, 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 individuals 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. The decision to illegally obtain content through P2P networks (P2PCHOICE) is a binary variable and the intensity of filesharing (P2PINTENSITY) is measured on a three-level scale (at least once a week, less than once a week but more than once a month, less than once a month).[14] Therefore, the model can be estimated using an ordered probit specification with sample selection as follows:

$$\text{P2PCHOICE} = \alpha_1 + \beta_1 X_1 + \gamma_1 \text{DETECTION} + \varepsilon_1 \tag{12}$$

$$\text{P2PINTENSITY} = \alpha_2 + \beta_2 X_2 + \gamma_2 \text{DETECTION} + \varepsilon_2 \quad \text{if P2PCHOICE} = 1 \tag{13}$$

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), and the proportion of pirates among the respondent's friends and relatives (PEERPIRACY).

The identification condition in the ordered 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) plausibly fulfills this condition. This binary variable allows us to

[14]We also conducted the analysis using a binary measure of the intensity of P2P filesharing (more than once per month versus less than once per month). Results were not significantly different from the estimates obtained with the three-level measure.

identify individuals who presumably oppose illegal activity, which directly impacts the decision to consume copyrighted content through P2P networks. However, conditional on the decision to use P2P networks, the intensity of P2P activity is mainly driven by the individual's preference for digital content (captured by other variables in our estimation).

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 monitored activity as well as the intensity of that activity if a decision to pirate is made. To address this endogeneity problem we use an instrumental variable (IV) approach which first estimates a perceived probability of detection equation

$$\text{DETECTION} = \alpha_3 + \beta_3 \mathbf{X}_3 + \varepsilon_3 \tag{14}$$

and then estimates equation (12) above using the estimated values of DETECTION from equation (14). $\mathbf{X}_3$ 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 OFFMONITORED 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 percent of them responded that P2P networks are monitored).

Because these individuals' misconceptions of how the Hadopi law is implemented include 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 correlation between an individual's propensity to engage in P2P file sharing and the belief that offline file sharing is monitored.[15]

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 (12), (13) and (14) using full information maximum likelihood assuming multivariate normality of the error terms. This system of three equations has binary, ordered 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 ordered 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 con-

[15]The Chi-Square is equal to 2.06 with a p value of 0.15.

cern. In this model, which does not control for potential endogeneity, 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 change 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. The robustness of this result depends on the quality of our instrument. The F-statistic value (11.6) suggests that OFF-MONITORED is a relevant instrument.[16] The magnitude of the coefficient estimate for OFFMONITORED indicates that this instrument has a significant impact on the endogenous variable DETECTION. In addition, using a probit model, we regress OFFMONITORED on the other covariates in equation (14) to test for correlation between our instrument and these covariates. The results, presented in Table 6 in the appendix, show that OFFMONITORED is independent from the other covariates, further supporting its use as an instrument. In particular, the belief that offline sharing is monitored is not influenced by factors like age or education that are known to be correlated with information technology skills. This strengthens the argument that our instrument is exogenous with regard to the choice of engaging in P2P filesharing. Finally the Wald test of exogeneity[17] is not rejected, suggesting that any remaining potential biases due to endogeneity are small.

The third model analyses the two-stage filesharing decision and also controls for potential endogeneity (columns 6, 7 and 8).[18] Again, we find that the threat of de-

[16]The rule-of-thumb for a strong instrument is a F-test above 10.

[17]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.

[18]Note that potential correlation between error terms for the three equations in this model is not a concern as indicated by the “athrho” statistic. The “athrho” statistic is the Fisher Z transformation of the correlation.

tection 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. Recall that the theoretical model 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 variable that roughly measures the frequency of filesharing, not the quantity 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.

To sum up, the estimates indicate that accounting for endogeneity in perceived detection is important – after correcting for endogeneity, DETECTION has an insignificant effect on piracy choice and intensity prior to receiving a warning. However, one could be concerned by the larger standard errors in the two specifications utilizing an instrumental variable. To address this potential concern, we have calculated the marginal effects of the DETECTION coefficient on P2PCHOICE in the models with and without the instrument. Table 4 presents these marginal effects. Although the marginal effect in the ordered probit model without instrumental variable is negative and significant, the magnitude of the effect is very small. The 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. In each of our estimated models, the perceived probability of detection clearly has no real deterrent effect.

[Insert Table 4 Here]

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 P2P filesharing. Taste for audio and video content is the main variable that drives the usage of P2P networks. Additionally, younger pirates 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. Male 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 strike 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 Interdependence between monitored and non-monitored digital piracy channels

One recurrent criticism of the Hadopi law questions is 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 activity 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).

$$\text{P2PCHOICE} = \alpha_1 + \beta_1 \mathbf{X}_1 + \gamma_1 \text{DETECTION} + \mu_1 \text{DDCHOICE} + \varepsilon_1 \quad (15)$$

$$\text{DETECTION} = \alpha_2 + \beta_2 \mathbf{X}_2 + \varepsilon_2 \quad (16)$$

$$\text{DDCHOICE} = \alpha_3 + \beta_3 \mathbf{X}_3 + \varepsilon_3 \quad (17)$$

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 5) 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 endogeneity 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 should not be directly driven by the belief that direct downloading is monitored. This argument is supported by a chi-squared test which shows no significant correlation between the propensity to engage in file-sharing and the belief that direct downloading is monitored under the Hadopi law.[19]

[Insert Table 5 Here]

The maximum likelihood estimates of this model are displayed in columns 1 through 3 of Table 5. 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 (FRAUD) also are more willing to use direct download platforms. Finally, the presence of pirates in the individual's close social network has a positive and significant impact on both the use of P2P networks and direct downloading. We now explore this peer effect in greater detail.

[19] The Chi-Square is equal to 0.0059 with a *p-value* of 0.939.

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 5. The interaction term coefficient is negative and significant. Among the respondents for which PEERPIRACY is equal to 1, the effect of DDCHOICE (-0.631+0.440 = -0.191) is negative. This suggests a substitution effect between monitored and unmonitored illegal channels for those whose social network includes a relatively large number of pirates. The Hadopi law may reinforce differences between those who understand the law and alternatives to monitored P2P piracy and those who are less informed about alternative (unmonitored) illegal channels. Results in Table 5 suggest that once we control for the perceived detection probability, those who are better informed (through their social network) are more likely to substitute between monitored and unmonitored illegal channels.

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 has no impact on an individual's decision to initially engage in monitored piracy. Furthermore, conditional on the decision to access content through the monitored channel, the model implies that increasing the perceived detection probability will have two opposing effects on an individual's level (or intensity) of monitored piracy prior to receiving a warning. Because raising the probability of detection increases the probability of future punishment, it directly reduces the incentive to pirate. However, it also increases the discount rate applied to benefits from future illegal activity on the monitored channel. 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 through the monitored channel. As the utility from obtaining content legally increases, the continuation utility realized after receiving a warning also increases. This reduces the incentive to limit monitored 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. Relatedly, the fact that the model predicts that reducing future utility by limiting access to content through unmonitored illegal channels (*e.g.,* the shutdown of Megaupload) will reduce content acquisition through monitored channels, suggests that broader antipiracy inerventions might be effective.

We empirically analyze predictions from the theoretical model regarding the impact of the Hadopi law on both the individual's decision to engage in monitored 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 (the early stage in our theoretical model). Because the perceived detection probability is likely to be endogenous, we employ an instrumental variables approach 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. We also find no significant deterrent effect on the level of illegal activity by those who do pirate which contradicts the theoretical prediction. 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. (2014) 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 to be 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.

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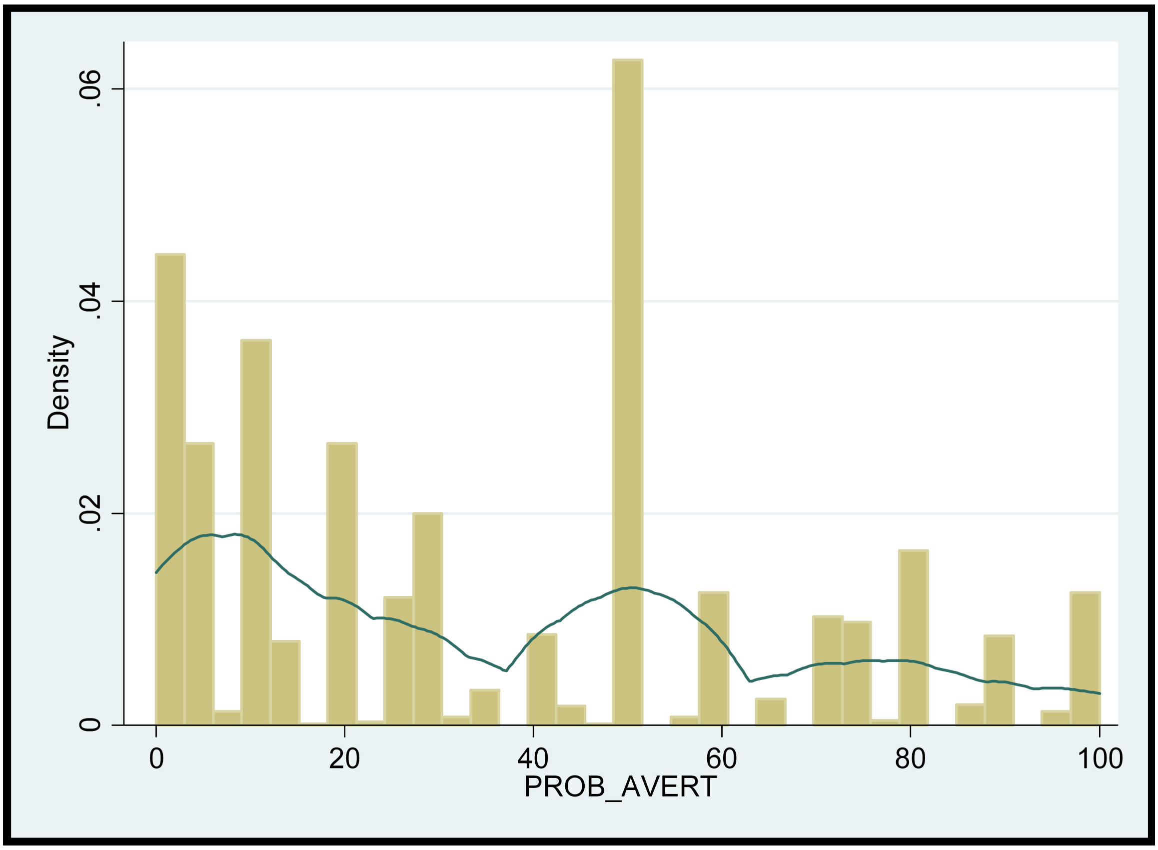

Figure 1: Distribution of the perceived probability to be detected by Hadopi in case of illegal downloading

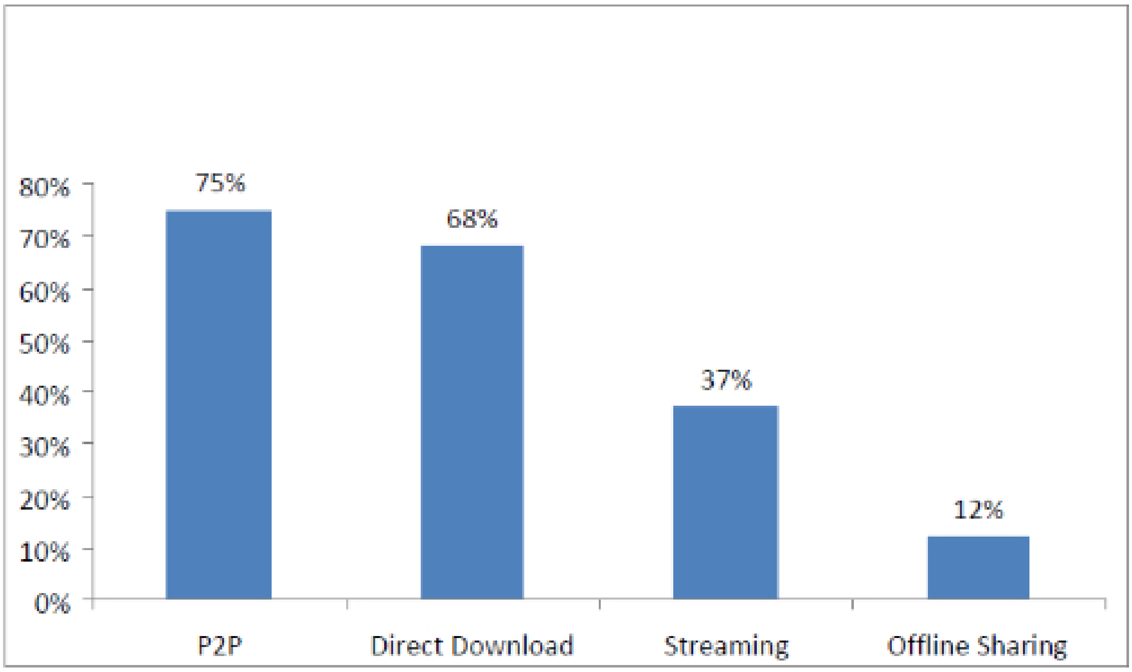

Figure 2: Awareness of the Hadopi Law: % of respondents that declare that these channels or techniques are monitored by Hadopi

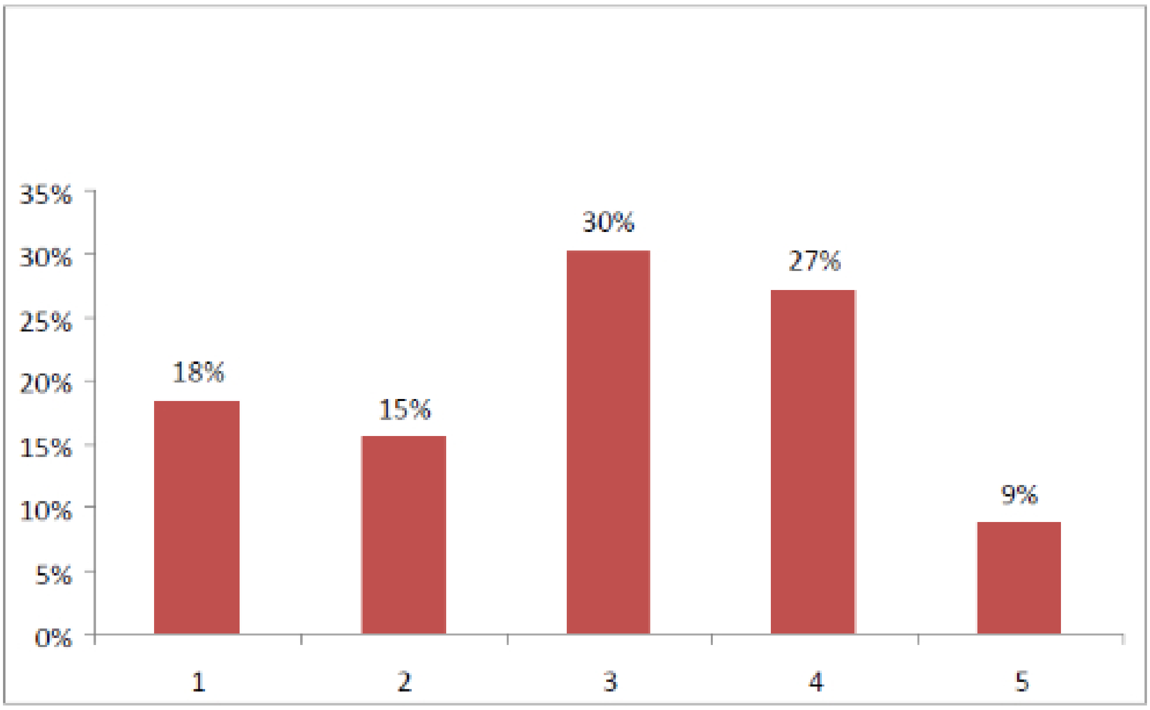

Figure 3: Awareness of the Hadopi Law: number of channels or techniques that are declared to be monitored by Hadopi

Table 1. Variable description

VARIABLES	Description
P2PCHOICE	1 if the individual is engaged in P2P filesharing.
P2PINTENSITY	3 if using P2P at least once a week, 2 if using less than once a week but more than once per month and 1 if less than once per 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, 1 if tax cheating may be justifiable and 0 if it is never 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	0.65	0.79	0	2
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)

		Model 1		Model 2		Model 3		
	Probit model	Ordered probit with sample selection		Probit with instrumental variable		Conditional mixed process regression		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	P2PCHOICE	P2PINTENSITY	P2PCHOICE	P2PCHOICE	DETECTION	P2PINTENSITY	P2PCHOICE	DETECTION
DETECTION	-0.00412***	-0.00351	-0.00413***	-0.0192		-0.0109	-0.0184	
	(0.00126)	(0.00252)	(0.00127)	(0.0120)		(0.0211)	(0.0121)	
GENDER	0.359***	0.404***	0.362***	0.167	-10.32***	0.329	0.183	-10.32***
	(0.0703)	(0.138)	(0.0713)	(0.201)	(1.287)	(0.256)	(0.198)	(1.287)
AGE15-24	0.625***	0.867***	0.625***	0.521***	-2.741	0.843***	0.531***	-2.740
	(0.112)	(0.235)	(0.110)	(0.175)	(2.032)	(0.242)	(0.169)	(2.032)
AGE25-34	0.481***	0.519**	0.484***	0.404***	-2.197	0.508**	0.415***	-2.197
	(0.113)	(0.249)	(0.114)	(0.151)	(2.003)	(0.238)	(0.148)	(2.003)
AGE35-49	0.147	0.362	0.147	0.166*	1.948	0.370*	0.167*	1.947
	(0.104)	(0.231)	(0.105)	(0.0986)	(1.727)	(0.222)	(0.0995)	(1.727)
AGE50+	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
INCOME1	0.171*	0.0938	0.170*	0.242**	5.752***	0.143	0.239**	5.752***
	(0.0968)	(0.160)	(0.0963)	(0.101)	(1.791)	(0.207)	(0.103)	(1.791)
INCOME2	0.0960	-0.0147	0.0955	0.139	3.491**	0.0155	0.136	3.491**
	(0.0883)	(0.148)	(0.0877)	(0.0872)	(1.637)	(0.172)	(0.0881)	(1.637)
INCOME3	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
EDUCATION1	0.0239	-0.0513	0.0256	0.0584	2.535	-0.0331	0.0577	2.530
	(0.105)	(0.183)	(0.104)	(0.101)	(1.860)	(0.186)	(0.102)	(1.860)
EDUCATION2	0.0895	0.0598	0.0903	0.142*	3.977***	0.0892	0.140*	3.974***
	(0.0778)	(0.127)	(0.0774)	(0.0814)	(1.451)	(0.149)	(0.0822)	(1.451)
EDUCATION3	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
TASTE1	0.401***	1.089***	0.401***	0.362***	0.00780	1.064***	0.368***	0.0181
	(0.122)	(0.254)	(0.124)	(0.135)	(2.187)	(0.297)	(0.133)	(2.187)
TASTE2	0.383***	0.976***	0.383***	0.397***	3.419*	0.978***	0.399***	3.428*
	(0.107)	(0.244)	(0.112)	(0.107)	(1.859)	(0.249)	(0.107)	(1.859)
TASTE3	0.287***	0.489*	0.287**	0.302***	2.802	0.504**	0.302***	2.808
	(0.110)	(0.256)	(0.113)	(0.107)	(1.848)	(0.245)	(0.108)	(1.848)
TASTE4	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
FRAUD	0.191***		0.189***	0.0976	-4.790***		0.105	-4.750***
	(0.0705)		(0.0700)	(0.114)	(1.306)		(0.111)	(1.314)
PEERPIRACY	0.639***	0.959***	0.639***	0.416*	-10.29***	0.873***	0.433*	-10.29***
	(0.0753)	(0.170)	(0.0741)	(0.248)	(1.415)	(0.330)	(0.242)	(1.415)
OFFMONITORED					6.481***			6.539***
					(1.900)			(1.895)
Constant	-1.978***		-1.979***	-1.167	39.05***		-1.230	39.03***
	(0.156)		(0.160)	(0.850)	(2.504)		(0.827)	(2.505)
Observations	2000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Log likelihood	-906	-1297		-10387		-10778		
		LR test: 0.33 (Prob > chi2 = 0.56)		Wald test: 1.14 (Prob > chi2 = 0.2750)		athrho (6)_(7): 0.57 (0.83) ; athrho (6)_(8): 0.21 (0.60)		
						athrho (7)_(8): 0.43 (0.42)		

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

Table 4. 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)

Table 5. 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	-0.0138			-0.0129		
	(0.0140)			(0.0148)		
DDCHOICE*PEERPIRACY				-0.631***		
				(0.171)		
DDCHOICE	-0.0273			0.440		
	(0.380)			(0.549)		
PEERPIRACY	0.530**	-10.29***	0.624***	0.805***	-10.29***	0.615***
	(0.237)	(1.415)	(0.0705)	(0.274)	(1.415)	(0.0706)
GENDER	0.251	-10.32***	0.400***	0.265	-10.32***	0.401***
	(0.202)	(1.287)	(0.0675)	(0.209)	(1.287)	(0.0675)
AGE15-24	0.602***	-2.746	0.960***	0.584***	-2.746	0.963***
	(0.187)	(2.032)	(0.105)	(0.205)	(2.032)	(0.105)
AGE25-34	0.467***	-2.196	0.422***	0.454***	-2.195	0.422***
	(0.142)	(2.003)	(0.107)	(0.145)	(2.003)	(0.107)
AGE35-49	0.174*	1.950	0.0968	0.165	1.950	0.0950
	(0.104)	(1.727)	(0.0984)	(0.109)	(1.727)	(0.0980)
AGE50+	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
INCOME1	0.213*	5.750***	0.140	0.209*	5.750***	0.140
	(0.114)	(1.791)	(0.0929)	(0.119)	(1.791)	(0.0930)
INCOME2	0.117	3.488**	0.0363	0.108	3.488**	0.0368
	(0.0934)	(1.637)	(0.0843)	(0.0963)	(1.637)	(0.0843)
INCOME3	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
EDUCATION1	0.0464	2.529	-0.150	0.0729	2.529	-0.150
	(0.108)	(1.860)	(0.101)	(0.112)	(1.860)	(0.101)
EDUCATION2	0.120	3.977***	0.0487	0.121	3.977***	0.0485
	(0.0892)	(1.451)	(0.0746)	(0.0924)	(1.451)	(0.0746)
EDUCATION3	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
TASTE1	0.395***	0.0114	0.489***	0.411***	0.0116	0.492***
	(0.136)	(2.187)	(0.116)	(0.143)	(2.187)	(0.116)
TASTE2	0.403***	3.420*	0.376***	0.417***	3.420*	0.378***
	(0.113)	(1.859)	(0.103)	(0.119)	(1.859)	(0.103)
TASTE3	0.316***	2.802	0.0689	0.315***	2.802	0.0718
	(0.112)	(1.848)	(0.106)	(0.116)	(1.848)	(0.105)
TASTE4	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]	[Ref.]
FRAUD	0.134	-4.792***	0.138**	0.156	-4.792***	0.139**
	(0.114)	(1.306)	(0.0683)	(0.119)	(1.306)	(0.0683)
OFFMONITORED		6.353***			6.351***	
		(1.898)			(1.898)	
DD_MONITORED			-0.311***			-0.311***
			(0.0686)			(0.0694)
Constant	-1.532*	39.07***	-1.563***	-1.758**	39.07***	-1.555***
	(0.830)	(2.504)	(0.148)	(0.876)	(2.504)	(0.147)
Observations	2000	2,000	2,000	2000	2,000	2000
Log Likelihood		-11277			-11265	
athrho (P2P)_(DETECT)		0.28 (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

7 Appendix

Table 6. Regression of the instrument on the covariates (Probit estimates)

VARIABLES	OFFMONITORED
GENDER	0.0712
	(0.0753)
AGE15-24	-0.156
	(0.125)
AGE25-34	0.102
	(0.116)
AGE35-49	0.130
	(0.101)
AGE50+	Ref.
INCOME1	0.0121
	(0.104)
INCOME2	-0.0402
	(0.0959)
INCOME3	Ref.
EDUCATION1	-0.139
	(0.112)
EDUCATION2	0.0404
	(0.0843)
EDUCATION3	Ref.
TASTE1	0.104
	(0.127)
TASTE2	0.0213
	(0.109)
TASTE3	0.00175
	(0.109)
TASTE4	
PEERPIRACY	-0.0138
	(0.0830)
FRAUD	-0.0628
	(0.0777)
Constant	-1.209***
	(0.148)
Observations	2,000

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