Making the Cut: Accounting for heterogeneous consumer behavior when developing copyright enforcement regimes that include internet disconnection

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Abstract

The problem of copyright enforcement has always been a substantial challenge, especially in goods like digital music files where licit and illicit versions are almost totally interchangeable (save the possible perceived good of paying the creator). One solution that industry groups have advocated for and even piloted is the mechanism of a legal punishment regime that includes internet disconnection. While there are a host of factors associated with such a scheme, one that has been effectively overlooked is the potential harm to the industry of disconnecting infringers who are themselves also consumers of licit goods.

The aim of this project was to build a framework to better ask the question of how to deal with customers who are also infringers. Along the way, we determined that the most important consumer attribute to consider in a disconnection regime is the consumer’s added value per infringement; since rate of infringement is the only fault line along which a non-corrupt government could bring about disconnection, it becomes the essentializing feature of consumer groups.

Once our taxonomy of nine consumer types was laid out, we modeled each of their behavior and harm levels. With our categories in place, we then built two simulated populations and observed that different mixes of consumer behaviors lead to different optimal thresholds, indicating that legal strategies ought account for this sort of consumer behavior. Finally, we laid out possible extensions, in particular the problem of deterrence and ways to use physical data. While not representative of any particular locale, our account demonstrates the value of further study.
Introduction

The problem of funding new, original content has been a major struggle, both theoretical and practical, for market economies since their inception. One solution, copyright, essentially provides a state monopoly on copies of certain content, provided the creator meet various constraints. It is illegal, for instance, to reprint a copyrighted book without the consent of the copyright holder. With start-up and production costs high, creators of reproducible works tend to contract with publishers and or distributors who tend also toward being responsible for ensuring respect for the associated copyrights. This has meant that, from the era of home cassette recorders forward, publishers have found themselves increasingly adversarial toward consumers, who they both depend on as its revenue stream and fears as competition.

The age of digital content has irrevocably transformed this relationship, affecting no medium as much as music. With the rise of Napster and iTunes, the dominance of the album format took a staggering hit in favor of singles. Unlike books, where certain advantages (ease of markup, tangibility) have been difficult to replicate, digital music (at sufficient quality) is nearly indistinguishable from its analog counterpart and, unlike movies, even high quality songs take up relatively little file space and are compatible with a wide range of devices. To the chagrin of publishers, however, digital music is nearly impossible to control. With the rise of the Amazon mp3 market, Digital Rights Management (DRM) technology, which allowed content producers to license individual song files after the point of transfer, could no longer be applied to music files in a way that was viable in the market. In the American market, leader iTunes has elected to drop DRM altogether from its music store. In the world of music files, the consumer is the owner.

That copyright enforcement for digital music files can practically not be conducted as prevention has encouraged content producers to seek punishments for infringers. The Recording Industry Association of America, for example, spent $90 million on lobbying between 2000 and 2011, and frequently pursues lawsuits. When it pursues private solutions, the RIAA is still as quick to chase customers as innovation; in 2011 it founded the
Center for Copyright Information with the Motion Picture Association of America and five leading internet service providers, whose primary purpose so far has been to implement a “six strikes” program leading to sanctions for accused infringers. More ambitiously, in France, the HADOPI law (passed in 2009, repealed in 2013) set up a “three strikes” program that ended in mandatory account suspension for a third offense. The rhetoric of the content producers focuses on converting infringers to paying customers but so far does little to acknowledge the frequently asserted claim that many infringers already do pay for at least some content.

Purpose

While the theoretical literature in and around the topic has tried to explore the possible market effects of infringement, and the empirical literature frequently examines the holistic market behavior of infringers, there has so far been a dearth of literature bridging the two. Peitz and Waelbroeck (2006) open the door in its construction of plausible infringement utility via the discovery mechanism, but there is still substantial room for expansion. Our goal here is to outline a theoretical framework to address the specific problem of determining when it might or might not be economically advantageous for a content provider to pursue disconnections for infringers. To this end, we build a vocabulary for discussing the spectrum of positive and negative infringer behavior and simulate test populations in order to demonstrate the applicability of our framework to different markets.

Since this is still something of a broad problem, it is worth further constraining our scope. We choose to examine here exclusively the phenomenon of legally-mandated disconnection schemes, and in particular the fact of removing infringers from the consumptive ecosystem. If we believe that at least some infringers are also sources of some revenue, we face something of an optimization problem; figuring out how to design rules for a disconnection regime depends on the consumptive tendencies of the population.

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2 Peitz and Waelbroeck. "Why the music industry may gain from free downloading" (2006)
Since no data are currently publically available concerning a granular distribution of illicit downloading habits, we turn to simulation in order to demonstrate the working of our framework. While those who conduct (and frequently suppress)\textsuperscript{3} private surveys will probably never have incentives to publish their data for the greater academic community, we hope primarily to show two things:

- The plausible ramifications of a population with mixed styles of infringer behavior must be considered as one evaluates whether (and which) disconnection policies to support.
- The framework that we outline provides a helpful vocabulary for analyzing the implications of such a study.

To this end, we outline nine characteristic types of infringers, and then run a number of simulations, in test populations of 100,000. We determine that the different types of infringers do different amounts of harm per infringement, and have different tendencies to infringe at all. Between simulations, we vary only the proportions of the population that belong to each type of infringer.

**Design**

We are, at this point, primarily concerned with the question of which infringer-disconnections, if any, could result in positive net revenue for a creative industry on condition of their disconnection. To this end, we construct an ecosystem that acknowledges the mechanisms under which a disconnection regime might plausibly function, and describe different sorts of consumers. We start with the following assumptions:

A. We are monitoring a fixed population that is punished in a single time step.

\textsuperscript{3} Enigmax. "Suppressed Report Found Busted Pirate Site Users Were Good Consumers.” (2011)
B. The disconnection criteria are applied fairly (no one who fails the criteria for
disconnection is punished and everyone who meets the criteria is punished)

C. in a non-corrupt legal regime, the criteria for disconnection must be a related to the
number of infringements in some set time period (a month, a year, lifetime, etc),
rather than the rate of infringement to legitimate consumption or any other criteria.

The shape of deterrence:

We recall that our agents are rational utility-maximizing actors, which until the
moment of punishment have varying appraisals of whether the systemic threat will be
executed on (given the track record so far, it is not irrational to assume that one will not
currently be disconnected under such a regime). This means that an agent’s deterrence is
essentially a binary: either they are deterred (reducing rate of infringement until they fall
below the disconnection threshold), or they are not and behave as usual. We can then
describe deterrence as a transformative effect on the population, and simply examine the
resultant population, where those who have been deterred have their new properties. It is
worth anticipating here, as well, that once the disconnection step has occurred, none of the
remaining agents (who per assumption B do not qualify for disconnection) has any reason
to modify their behavior. The net difference between the population before and after
deterrence, which is beyond the scope of our examination, must obviously be considered
when we discuss the net effect of a disconnection regime.

The goal of the consumer model is relating net damage to rate of infringement

It is essential, before we continue, to defend the counterintuitive assumption that
we are only concerned with the relationship between an infringer’s rate of infringement
and net damage, rather than any other set of values.

Given assumption A, we know that we need only deal with that segment of the
population which knows how to download. Those who are unable will never be
disconnected, and their value to the industry is (in a conservative estimate) insulated from
the behaviors of infringers. Assumption B lets us essentialize into two transition points:
first, the moment in which deterrence occurs (transforming the population) and second, the moment in which disconnection occurs (reducing the population). We discuss the second event here.

Assumption C means that, if our industry is attempting to bring about a change that is revenue-positive, the only non-deterrent good is from eliminating the net harm associated with those who infringe beyond a certain rate. This does mean that if the expected value of harm does not correlate positively to a consumer’s quantity (rate) of infringement, there is no regime whose disconnection step will net positive for the producer.

We can further decompose our key ratio (net damage/rate of infringement) into the following functions on the infringer level:

- Revenue (from an infringer’s legitimate purchases) as a function of rate of infringement
- Absolute harm (from an infringer’s infringements) as a function of rate of infringement

We can term these categories an infringer’s “customer” and “pirate” types, and note that each infringer must have some function for each, and that these functions are not necessarily coupled with one another. We can then work out a taxonomy for each, and build a matrix to discuss the policy implications of the intersections. Each theoretical form is accompanied by the narrative of an archetypal infringer. It bears noting here that our model assumes that the fact of infringing cannot itself be a good, so there is no case in which absolute harm correlates negatively with infringement.

**Customer Archetypes**

1) *Absolute revenue does not correlate with infringement:* “the fixed budget.” This type of customer does not purchase as a result of infringement but perhaps purchases from some producers exclusively or spends a fixed amount on media and
infringes to fill the rest of his desired consumption. If he finds infringement easier, he will consume more, and if he finds it harder, he will consume less, but in no case will this affect what he ultimately pays for.

2) *Absolute revenue correlates negatively with infringement:* “the path of least resistance.” This type of customer feels a very minimal utility from the act of purchasing, and so only purchases when infringement is too difficult. His total consumption is fixed or near-fixed, he infringes whenever he can, and purchases when he cannot.

3) *Absolute revenue correlates positively with infringement:* “the explorer.” This long-discussed type of customer infringes in order to explore how the available products suit his tastes, and then purchases the ones he likes. The more he listens illicitly, the more frequently he discovers products that he is happy to pay for.

**Pirate Archetypes**

1) *Absolute harm does not correlate with infringement:* “the private sharer.” This type of pirate infringes primarily as part of a network that is not on the public network, via physical media swaps or direct forms of communication like email attachments. Infringing does not inspire or facilitate further infringing, and indeed may not even be intended.

2) *Absolute harm correlates weakly positively with infringement:* “the leech.” This type of pirate knows how to take advantage of certain modes of infringement, but gives back as little as possible to his sources. He downloads for private use, but he does not feel bound either by loyalty to his sources nor to the sort of code of ethics that tends to coalesce around P2P communities.

3) *Absolute harm correlates strongly positively with infringement:* “the infringing community member.” This type of pirate is technically competent, and perhaps willing to spend money on increasing his ability to infringe, paying for memberships

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4 Peitz and Waelbroeck (2006)
in private trackers, seedboxes, or preferred access to cyberlockers that are
unfriendly to content removal. In his acts of infringing, this type of pirate actively
facilitates services which make piracy more accessible and therefore desirable to
other users.

**Composite Archetypes**

As discussed before, every infringer has a customer and a pirate type. When taken
together, these give us a model of how each type affects the ecosystem as total
infringements increase. In the following section, each archetype is specified as (X,Y) where
X and Y are the Customer and Pirate types as discussed above, respectively.

A: (1,1) *Net revenue does not correlate with infringement:* “the grandfather.” This
person consumes what they will consume, and accepts illicit content from sources
close to him, but doesn’t see it as a substitute for paid content.

B: (1,2) *Net revenue correlates weakly negatively with infringement:* “the fan.” This
person pays for certain varieties of content, and downloads others. If illicit access
became more difficult, he would consume less of the content that he is unwilling to
pay for.

C: (1,3) *Net revenue correlates strongly negatively with infringement:* “I’ll pay for it
someday, I swear.” This person may espouse a sense of ethical responsibility, but
not one he is willing to pay separately for. The amount that he purchases is a
budgetary constraint, the amount that he downloads illicitly is a consumptive
constraint.

D: (2,1) *Net revenue correlates negatively with infringement:* “the receiver.” This
person sees licit and illicit content as wholly interchangeable, but does not seek
illicit content, simply failing to purchase if an illicit version finds its way into his
circle.
E: (2,2) *Net revenue correlates negatively with infringement:* “limewire user.” This person does not intend to pay for anything that he can find illicitly, but is probably limited in his interest and efficacy.

F: (2,3) *Net revenue correlates strongly negatively with infringement:* "enthusiastic infringer" This person might actually see a positive utility in the act of piracy itself that is separate from the content being consumed.

G: (3,1) *Net revenue correlates positively with infringement:* “the risk-averse consumer.” This person buys what he knows he likes, but he doesn’t care to find new things unless he happens upon them by one of his personal extralegal channels.

H: (3,2) *Net revenue correlates positively with infringement:* “try before you buy.” This person is a targeted infringer, downloading things primarily as an evaluation before purchase.

I: (3,3) *Net revenue does not correlate with infringement:* “the insatiable enthusiast.” This person consumes as much content as he can, from all sources, and while he is happy to pay for it, he is similarly loyal and respectful to his infringing discovery community. He sometimes purchases more for having tried music, but sometimes fails to purchase because the illicit content is an adequate substitute.

**Quantifying the Value of Infringement**

As discussed in the previous section, customer types are defined by the expected net value to the producer per infringement, which we now anticipate numerically. Peitz and Waelbroeck⁵ and Waldfogel⁶ lay out some groundwork, imagining the average harm via displaced sale so be from 0.15 to 0.3 songs per song, and establishing that in a large enough market, a distributor can sell more with sampling. We note, however, that not all value is necessarily from direct sampling (for instance, second or third-order sampling of an album or artist, or sharing with other purchasers), and that not all harm is direct displaced sale.

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⁵ Peitz and Waelbroeck (2006)
⁶ Joel Waldfogel. Music file sharing and sales displacement in the iTunes era (2010)
(for instance, in a p2p network, an infringer may “seed” and thereby increase available bandwidth for further infringers). With this in mind, we assign the following best estimates for customer value per infringement (measured in units of content per infringement):

\[
\begin{align*}
A & : 0 \\
B & : -0.2 \\
C & : -0.5 \\
D & : -0.3 \\
E & : -0.3 \\
F & : -0.5 \\
G & : +0.4 \\
H & : +0.6 \\
I & : 0
\end{align*}
\]

**Quantifying number of infringements**

In the same manner as infringement value, infringement rate corresponds in some way to infringer type, but it must necessarily be more complex, as even infringers of the same style consume vastly different amounts of content. To address this, we determined to assign individual propensity to infringe according to a distribution. Because the log-normal distribution ranges from zero to infinity, but features a strong right skew, it was a strong choice for every category, leaving the mean and standard deviation to be estimated. The following mean, standard deviation pairs are plausible estimates for the infringement patterns of each category (though better models would dramatically improve the utility of the system for an actual population):

\[
\begin{align*}
A: & \ -1.5, \ 0.8 \\
B: & \ -0.5, \ 1.1 \\
C: & \ 1.0, \ 0.8 \\
D: & \ -2.0, \ 1.5 \\
E: & \ 2.0, \ 0.8 \\
F: & \ 3.0, \ 0.95 \\
G: & \ -0.1, \ 1.1 \\
H: & \ 0.0, \ 1.15 \\
I: & \ 1.5, \ 1.35
\end{align*}
\]

**Assembling the Ecosystem**

Once we have the category attributes estimated, we can measure in some simulated populations. We operate on populations of 100,000, as they are large enough that trials with the same settings turn out relatively similar. For demonstrative purposes, we lay out
two sets of plausible proportions of the infringer categories, to show the importance in aggregate.

Simulation 0:

A: 5%  B: 15%  C: 10%
D: 20%  E: 10%  F: 10%
G: 15%  H: 10%  I: 5%

Simulation 1:

A: 10%  B: 7.5%  C: 5%
D: 7.5%  E: 12.5%  F: 12.5%
G: 20%  H: 15%  I: 10%

In each simulation, each member of the population is assigned two random seeds. The first results in a category (allocated as above), and the second results in a number of infringements (based on the category's distribution, rounded to whole). From these, we can calculate the infringement-related value for each consumer, and then the total for each population. Finally, we can test out threshold values to see where each population’s optimal cutoffs are, and the results at each level.

Results

While less dramatic than we might have hoped, the results are still illustrative of the importance of population composition to threshold-setting. Before we discuss the specifics, however, we take a look at the broadest measures for comparing the populations to each other. Table 1 details a few such measures: the percentage of the population that infringes at all, the mean number of infringements, and the mean value-from-infringement. It bears reiteration that infringer categories describe distributions of infringements, so the sizeable non-infringing population is anticipated. Also notable is that in both populations, the mean
infringement value with no disconnection is negative; that is, the aggregate harm is larger than the aggregate purchase for the populations at large when all levels of infringement are permitted.

**Table 1: Aggregate Measures**

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Simulation 0</th>
<th>Simulation 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Infringers in Population</td>
<td>65%</td>
<td>72%</td>
</tr>
<tr>
<td>Mean # Infringements</td>
<td>5.70737</td>
<td>7.23424</td>
</tr>
<tr>
<td>Mean Infringement Value (units of content)</td>
<td>-1.889456</td>
<td>-2.161225</td>
</tr>
</tbody>
</table>

It is illustrative to break down the populations by infringer category to show that the categories themselves behave the same in both. Table 2 demonstrates this.

**Table 2: Category Measures**

<table>
<thead>
<tr>
<th></th>
<th>Sim0 Count</th>
<th>Sim1 Count</th>
<th>Sim0 % Infringers</th>
<th>Sim1 % Infringers</th>
<th>Sim0 Mean #</th>
<th>Sim1 Mean #</th>
<th>Sim0 Mean Val</th>
<th>Sim1 Mean Val</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>4927</td>
<td>10008</td>
<td>15%</td>
<td>15%</td>
<td>0.165212</td>
<td>0.165268</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>14992</td>
<td>7496</td>
<td>56%</td>
<td>56%</td>
<td>1.056564</td>
<td>1.033751</td>
<td>-0.21131</td>
<td>-0.20675</td>
</tr>
<tr>
<td>C</td>
<td>10012</td>
<td>4959</td>
<td>98%</td>
<td>99%</td>
<td>3.779465</td>
<td>3.771123</td>
<td>-1.88973</td>
<td>-1.88556</td>
</tr>
<tr>
<td>D</td>
<td>20150</td>
<td>7462</td>
<td>19%</td>
<td>19%</td>
<td>0.34134</td>
<td>0.315599</td>
<td>-0.1024</td>
<td>-0.09468</td>
</tr>
<tr>
<td>E</td>
<td>9976</td>
<td>12482</td>
<td>100%</td>
<td>100%</td>
<td>10.2512</td>
<td>10.15831</td>
<td>-3.07536</td>
<td>-3.04749</td>
</tr>
<tr>
<td>F</td>
<td>10012</td>
<td>12463</td>
<td>100%</td>
<td>100%</td>
<td>30.95605</td>
<td>31.65121</td>
<td>-15.478</td>
<td>-15.8256</td>
</tr>
<tr>
<td>G</td>
<td>14931</td>
<td>19844</td>
<td>70%</td>
<td>71%</td>
<td>1.597817</td>
<td>1.640798</td>
<td>0.639127</td>
<td>0.656319</td>
</tr>
<tr>
<td>H</td>
<td>9982</td>
<td>15226</td>
<td>73%</td>
<td>73%</td>
<td>1.888199</td>
<td>1.941153</td>
<td>1.132919</td>
<td>1.164692</td>
</tr>
<tr>
<td>I</td>
<td>5018</td>
<td>10060</td>
<td>95%</td>
<td>94%</td>
<td>10.85333</td>
<td>10.89304</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
With that groundwork laid, we can discuss the results of interest. To get the threshold results, we count the total value of everyone in the population who is below the disconnection cutoff, and then divide by the original population size (100,000).

Table 3: Threshold Results

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Simulation 0 mean infringement value</th>
<th>Simulation 1 mean infringement value</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Cutoff</td>
<td>-1.889456</td>
<td>-2.161225</td>
</tr>
<tr>
<td>At least 1 infringement</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>At least 2 infringements</td>
<td><strong>0.015012</strong></td>
<td><strong>0.04984</strong></td>
</tr>
<tr>
<td>At least 3 infringements</td>
<td>0.011488</td>
<td>0.077724</td>
</tr>
<tr>
<td>At least 4 infringements</td>
<td><strong>-0.003317</strong></td>
<td><strong>0.084927</strong></td>
</tr>
<tr>
<td>At least 5 infringements</td>
<td>-0.026657</td>
<td>0.079327</td>
</tr>
<tr>
<td>At least 6 infringements</td>
<td>-0.052532</td>
<td>0.063342</td>
</tr>
<tr>
<td>At least 7 infringements</td>
<td>-0.083132</td>
<td>0.040296</td>
</tr>
<tr>
<td>At least 8 infringements</td>
<td>-0.113813</td>
<td>0.013381</td>
</tr>
<tr>
<td>At least 9 infringements</td>
<td>-0.144669</td>
<td>-0.014211</td>
</tr>
<tr>
<td>At least 10 infringements</td>
<td>-0.175854</td>
<td>-0.046089</td>
</tr>
</tbody>
</table>

We make a few important observations. First, any threshold at all seems to be net revenue positive. At no point in either of these simulations does any cutoff make things worse for the industry - the few infringers at the very top more than account for the positive-valued infringers below. Second, the simulations resulted in different optimum thresholds (highlighted in blue), with a substantial cost for misidentifying the population (highlighted in red). Third, in neither population is either three or six the optimum number.
We save further discussion for the next section, noting here only that the full data for the simulations are included as “.csv” files in the full package for this project.

Conclusion

The problem of encouraging legal measures, with its high cost and limited public appeal will always be a fraught one for content providers. Despite the high stakes, however, there has been little academic work establishing the value of such a scheme for the content providers. Here, we attack one facet of this problem by conceding one of the most hotly contested points in this dispute (that there are measurable harms associated with copyright infringement in some circumstances). We aim here to open a dialogue concerning mixed-behavior populations and broad legal solutions.

While the data simply do not exist in a publically-available form to reasonably determine either the relative harm or tendency to infringe in them, our categories seem to be of an appropriate granularity. In particular, the choice to divorce positive and negative behaviors in a constructed consumer model is apparently a novel one for this domain, and one that lends to a much more charitable and robust vocabulary for analyzing infringers.

Finally, given the relatively conservative (disconnection-favoring) estimates for the attributes of the consumer categories, the simulations were fairly colorful. The two important successes are showing that (a) our analytic framework provides important additional information over the usual, coarser categorization of infringers and non-infringers and (b) proportions of a finite number of consumer types in a population have a marked effect on the optimal place for a disconnection threshold.

Further Study

While this unfortunately may never fall within the realm of academia at large, we hope that our work will at least inspire analysts in the content industries to develop a richer understanding of consumer behavior. As we have outlined, one of the most important areas to improve is the collection and inclusion of additional data. Additional work on this topic could also discuss the role of deterrence in order to value it
appropriately. Finally, this schema could be extended to account for non-uniform enforcement and multiple time-steps, with not all infringers being removed or potential infringers being added to the population.
Works Cited


