Copyright and the Production of Hip-Hop Music

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Abstract

Whereas the role of patents in cumulative innovation has been well established, little work has examined the impact that copyright policy may have on cumulative innovation in creative content industries. Utilizing U.S. federal court decisions that strengthened the breadth of copyright policy, this paper examines the implications of those decisions on the re-use of original content in the popular music industry, particularly hip-hop music. With a novel, self-collected data-set that tracks re-use through "digital sampling" in hip-hop music, I explore the impact that these federal copyright cases had on the production process of hip-hop music through changes in sampling practices. I find that digital sampling, wherein new musical works are created in part from existing sound recordings, significantly decreased following a 1991 decision that effectively strengthened rights for the original rights holder and restricted downstream re-use. Additionally, this policy change affected the creativity of new works by limiting the diversity of music that is re-used in new products. I also find that this effect on sampling was greatest in magnitude for the most prominent artists.

Keywords: Copyright, Intellectual Property, Content Industries

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1 Introduction

In recent decades, digital technologies have lowered production costs in creative content industries, especially music, and new digital channels for distributing content have emerged. Technological progress has contributed to the development of new styles and genres within the music industry, such as the advent of the digital sampler and the emergence of hip-hop music. New production technologies, such as the aforementioned digital sampling devices and more recent digital audio workstations (DAW), decrease the costs of re-use in creating new works that build off past works. However, the intellectual property rights regime may be at odds with the direction afforded by such advances in technology.

Music, like most forms of art, relies and builds upon the existence and ideas expressed in previous works. However, copyright, which protects specific rights associated with the creation of original works, imposes limits upon the ability of artists to re-use prior work in new contexts. The apparent strengthening of copyright over time has been of growing concern in the music industry, as even absent direct re-use, courts may find creators of new works to be infringing the rights of an older vintage. The recent jury decision that Robin Thicke's single "Blurred Lines" infringed the rights of Marvin Gaye's "Got To Give It Up" exemplifies this restriction over re-use, despite any direct copying, as does the less recent decision that George Harrison, in writing "My Sweet Lord," subconsciously plagiarized a work by Ronnie Mack.[1] While intellectual property rights regimes must weigh the moral rights for ownership as well as the economic incentives faced by potential innovators, concerns over the strength of granted rights are especially relevant when innovation is cumulative. As discussed in Scotchmer (1991), while downstream creators in a cumulative innovation context may bargain with inventors to license upstream rights for re-use, downstream incentives can often be deficient in a regime of strong, restrictive property rights. In contrast to

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[1] See *Pharrell Williams et al v. Bridgeport Music Inc et al*, Docket No. 2:13-cv-06004 (C.D. Cal. Aug 15, 2013) and *Bright Tunes Music v. Harrisongs Music* 420 F. Supp. 177 (S.D.N.Y. 1976)

the literature on cumulative innovation in patent-intensive industries (see e.g., Green and Scotchmer (1995); Williams (2013); Galasso and Schankerman (2015)), there is almost no evidence on copyright's effect upon innovation and creativity when it is cumulative.

This paper uses a novel dataset on a form of explicit re-use in popular music – known as digital sampling – to estimate the effect of U.S. copyright court decisions on sampling practices and cumulative creativity in the music industry. By comparing sampling trends before and after precedent-setting court decisions that restricted re-use, I find that the decision in *Grand Upright v. Warner Brothers Records* led to a mean drop of between 0.3 and 0.45 songs re-used in each new hip-hop track. Provocative results demonstrate that the 1991 *Grand Upright* decision also affected the creativity of new products, with fewer "novel" samples being used in the industry, while re-use of samples from songs that had previously been sampled became more common. I examine two sampling-related court decisions and find that only the first decision had a meaningful impact on the content of new products and the direction of re-use. Despite the large magnitude of the estimated decline in sampling, results are driven by changes along the intensive margin; there is no significant change in the propensity to use samples in a given song. Furthermore, I find that the magnitude of this decline was greater for more prominent artists.

1.1   Digital Sampling

While many genres of contemporary music may incorporate some form of "sampling," hip-hop music in particular began with a focus on sampling fragments of existing sound recordings to create new works.[2] The roots of modern sampling practices in popular music can be traced back to disc jockeys (DJs) manipulating vinyl records via turntables and cross-faders, using such equipment, DJs could loop over interesting segments of a song, or isolate

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[2]Sampling is defined in this paper as the re-use of a portion of an existing sound recording or musical composition in a new song or recording

particular instrumentals, such as the drum "break." These techniques extended beyond just replaying parts of the song in a recognizable manner – DJs can manipulate the playback of the record using techniques like "scratching" to create sound effects that are almost unrecognizable compared to the original recording. While such techniques were useful for live performances, the advent of digital sampling devices in the 1980s significantly enhanced producers' flexibility in recording new, sample-based music. By allowing artists to store, loop over, and sequence samples, the digital sampler helped transform hip-hop into a recorded, commercially-relevant art form.

Musicians that incorporate sampling may view the technique as more than routine appropriation or theft of an original sound recording, but the use of samples runs the risk of infringing at least two rights associated with the sampled work: (1) the copyright of the sound recording, and (2) the copyright of the underlying composition. While early hip-hop musicians up to late-1991 utilized unlicensed samples in a legal gray area (see discussion in McLeod and DiCola (2011)), federal copyright cases since 1991 have set precedent and highlighted the risk of infringement that comes with unlicensed sampling.

A recent theoretical literature has emerged that focuses on models of sampling, (or "remixing") wherein a downstream sampler bargains with an upstream creator whose original work is repurposed by the downstream agent (DiCola, 2010; Gans, 2015). While such literature is useful in considering the incentive constraints faced by upstream and downstream creators in alternative copyright policy scenarios, this paper builds upon these theoretical papers by providing the first quantitative evidence of how sampling and re-use is affected as copyright policy has effectively grown more restrictive.

1.2 Federal Copyright Decisions on Sampling

1.2.1 Grand Upright v. Warner Brothers Records

While there have been many copyright lawsuits over sampling, with the first notable case regarding the Beastie Boys' 1986 album *License to Ill*, many of these cases were settled out of court and hence provided no public precedent to set the contours of copyright policy with respect to sampling. The first case on sampling to be settled via court decision was *Grand Upright Music v. Warner Bros. Records, Inc.*, 780 F. Supp. 182 (S.D.N.Y 1991) (henceforth *Grand Upright*). This case concerned the rap artist Biz Markie's use of a sample from a Gilbert O'Sullivan recording on Markies album "I Need a Haircut." Judge Kevin Duffy, in ruling in favor of the plaintiff, Grand Upright Music, granted an injunction against the defendant, with whom Biz Markie was under contract. In his opinion, Duffy stated "Thou shalt not steal," essentially equivocating the digital sampling of music with theft. While the ruling did not provide an in-depth analysis of copyright law with respect to sampling, the infringement ruling highlighted the risk of sampling in the music industry. Prior to *Grand Upright* sampling in hip-hop had been likened to lawlessness in the Old West, as by Eothen Alapatt of Stones Throw Records: "it was a kind of Wild, Wild West situation where no one really knew the legalities. Everyone was just doing it."[3] By strengthening the breadth (or perceived breadth) of copyright in this respect, the ruling may have affected future sampling practices in the recording industry, a conclusion supported by interviews with industry participants found in McLeod and DiCola (2011). For example, McLeod and DiCola, in quoting entertainment lawyer Whitney Broussard, "For many years after ... they [Warner Bros.] wouldn't let you release anything that wasn't licensed. They had a sample committee that would listen to records to see if they could find undisclosed samples. So, they take that pretty seriously." McLeod and Dicola additionally argue that out-of-court settlements for infringement likely increased after 1991, as a successful defense appeared

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[3]As reported in McLeod and DiCola (2011)

unlikely after the broad ruling by Judge Duffy. Faced with the outcome of *Grand Upright*, record producers may either attempt to use unlicensed samples in their music and risk costly infringement claims based on this precedent, or pay lawyers to track down rights holders and bargain over a license to incorporate samples in their work.

1.2.2 Bridgeport Music v. Dimension Films

The second case of interest for this paper, that also set controversial precedent restricting the use of sampling, was *Bridgeport Music, Inc. v. Dimension Films*, 410 F. 3d 792 (6th Circuit 2005) (henceforth *Bridgeport Music*). This case, brought by the apparent rights holder for Funkadelic's "Get Off Your Ass and Jam," concerned the unauthorized usage of a three-note guitar sound from the Funkadelic recording in N.W.A.'s track "100 Miles and Runnin." The opinion of the 6th circuit determined that a *de minimis* defense against infringement did not apply to sound recordings. The court ruled in its opinion, "Get a license or do not sample. We do not see this as stifling creativity in any significant way." Again, this case anecdotally had a large effect on the advice given by lawyers practicing in the industry, as evidenced by McLeod and DiCola (2011) quoting one music lawyer "I would advise my clients before Bridgeport if they used a little snippet of a recording that was *de minimis*, 'That's fine; we dont have to clear it,' " whereas according to another lawyer post *Bridgeport Music* "they probably got even more conservative about clearing stuff. Basically, it said that even if you can't hear a sample of the sound recording, you still have to clear it."

The remainder of the paper provides a brief review of prior research (Section 2), examines copyright's expected effects on re-use (Section 3), explains the empirical framework, data, and identification strategy (Section 4), presents the empirical results (Section 5), and ends with concluding remarks (Section 6).

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2 Literature Review

The main contribution of this paper uncovers how the breadth of copyright policy shapes follow-on innovation in new products. Of particular relevance, this paper explores how copyright may contribute to hold-up when innovation is cumulative, and is one of the first papers to examine how copyright policy and digitization affect the content of new goods. While economists have been specifically interested in copyright for some time now (see e.g., Landes and Posner (1989)), the economic literature on copyright is relatively sparse compared to the range of intellectual property literature regarding patents. Much of the recent empirical work on copyright is motivated by the development of file-sharing and peer-to-peer technologies, focusing on the extent to which file-sharing did or did not displace legitimate record sales (Liebowitz, 2006, 2008; Oberholzer-Gee and Strumpf, 2007; OberholzerGee and Strumpf, 2010; Rob and Waldfogel, 2006). Another major stream of recent empirical work on copyright focuses on the effect of copyright's duration and implementation on creators' incentives and the supply of new creative goods (Hui and Png, 2002; Liebowitz and Margolis, 2004; Png and Wang, 2006; Kim, 2011; Li et al., 2013; Giorcelli and Moser, 2014).

From a broad perspective, this paper contributes to our understanding of the effects of intellectual property policy on innovation, where most work has focused on the patent system and academic research (Heller and Eisenberg, 1998; Kortum and Lerner, 1999; Sakakibara and Branstetter, 2001; Qian, 2007; Williams, 2013). This paper is similar in nature to Hall and MacGarvie (2010), which investigates the effect of federal court decisions on the scope of software patents. This paper, to my knowledge, is the first research to study how copyright policy affects the content of new products, and one of the first to examine copyright policy in a cumulative context.

Closely related work by Nagaraj (2016) has studied digitization and copyright in a cumulative innovation context, utilizing a natural experiment with the Google Books project

to estimate the negative impact of copyright on re-use of the *Baseball Digest* magazine in Wikipedia articles. However, Nagaraj (2016) focuses on upstream works that have fallen into the public domain, whereas this paper examines policy changes that affect the breadth of rights for existing copyrights. Given the unique dataset in this paper, I am additionally able to examine how copyright policy affects changes in commercially released new products, and further examine the manner in which works are repurposed.

A major contribution of this paper is to the aforementioned literature focusing on sequential music creation (e.g., sampling, remixes) and the role of the copyright system (McLeod and DiCola, 2011; DiCola, 2010; Menell, 2016; Gans, 2015). This empirical study builds off and complements these prior theoretically-focused examinations, and as the first such empirical research in this vein, provides quantitative estimates of how copyright policy has affected the sampling practices of industry participants.

The focus on sampling in this paper, a production practice in the music industry that was greatly enabled by technological change ties this research with the recent work studying digitization and its impact on the creative industries.[4] Research in this area has examined the impact of new, digitally-enabled distribution channels on music industry profits (e.g., Mortimer et al. (2012)), as well as the effect of digitization on the quality of new products in the music industry (e.g., Waldfogel (2012)). An expanding research stream in this area has focused on firms' efforts to protect their copyright goods under the threat of digital technology that enables unlicensed copying (Luo and Mortimer, 2016; Zhang, 2016). Field experiments in stock-photography enforcement and settlement have highlighted the role of communication in protecting IP assets (Luo and Mortimer, 2017), while observational studies have estimated the effective sales increase that results from rights enforcement through Digital Millennium Copyright Act (DMCA) takedown procedures (Reimers, 2016). Rather than focusing on digitization's interaction with illicit copying and piracy on the demand side,

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[4]Digital sampling was originally enabled by dedicated digital sampling devices, now digital software

this paper instead focuses on the supply side, exploring trade-offs between digitization and copyright on the production process.

Due to the cumulative innovation setting of this paper, it builds off the existing theoretical and empirical literature on cumulative innovation and patents, and extends upon this stream by providing empirical evidence of the effect of copyright on follow-on innovation (Green and Scotchmer, 1995; Scotchmer, 1991; Bessen and Maskin, 2009; Hall and Ziedonis, 2001). By examining the rate and direction of innovation after intellectual property rights become more restricted, this paper may also deepen our understanding of the costs and benefits of open-access for innovation in a novel, cumulative creativity setting (Furman and Stern, 2011; Murray and Stern, 2007).

3 How Copyright May Effect Cumulative Creativity

How might a strong copyright regime alter the direction of creative activity and complicate efficient licensing for re-use? First, the licensing of copyrights in a cumulative creativity context is complicated by a number of transaction cost hurdles that may lead to hold-up and inefficiency. Sample licensing incurs significant search costs from the onset of the licensing process. If a sound recording is licensed, both sets of rights holders for the sound recording and the underlying composition right must be identified and contacted before negotiations begin, and such a process can be far from trivial. Both of these distinct rights may be fragmented due to the collaborative nature of music production, with the composition right being at particular risk for fragmentation.[5] While in the best case all songwriters may be under contract with a single major publisher (e.g., BMG, Universal, EMI), the

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[5]For example, the recent Billboard chart-topping single "Can't Feel My Face" by The Weeknd has five separate songwriters associated with the underlying composition, according to the music database MusicBrainz.

situation is often much bleaker with control split among publishers, or with rights held in part by independent songwriters. Further complications may arise in practice - an artist being sampled may have a contract that requires express permission before their work may be sampled, or the original songwriter and publisher may no longer control the copyright in question.

Once all of the relevant rights holders are identified, a negotiations process begins with a number of complications in its own right. Even if rights holders are interested in cooperating with downstream samplers, negotiations may be complicated by the manner that the sample is used in the new work, or the context in which it is used. In worse cases, rights holders may have divergent interests, with a portion open to, or even reaching licensing terms, with some relevant party holding out.

Perhaps of greatest concern, and theoretical source of hold-up, relates to the timing of actions in the licensing negotiations. The transaction cost economics literature (e.g., Williamson (1985)) provides intuition here for how licensing will be affected when upstream rights are strong. Before the necessary samples and potential licensors are identified, artists must expend a significant amount of effort in searching for samples, and experimenting with samples during early stage production. An artist re-using existing work thus expends a considerable amount of effort before negotiations over sample licenses may begin, often creating a new song before negotiations open. Once a sample has been selected by the artist for their new work, their investment in creatively using the sample is highly specific to the relationship with the owners of the sampled copyright. This sunk investment, in combination with the *ex post* licensing typical in practice, creates a hold-up problem. With incomplete contracts, parties cannot realistically contract over licensing before potential downstream licensees sink their investment in production. This result positions downstream licensees at risk of being exploited by upstream rights holders, and should decrease the extent of sample usage.

Cournot's theory of complementary monopoly provides further intuition for how strong upstream rights may affect the direction of re-use downstream (Cournot, 1838; Economides and Salop, 1992). Cournot considers the case of two monopolists selling complementary goods (e.g., zinc and copper) used in a downstream market. When both of the monopolists act individually to maximize profits, equilibrium prices result that are greater than would be obtained from an integrated monopolist. In addition to the increased prices, total welfare decreases when the upstream producers act independently compared to the integrated case as the independent monopolists do not account for how their own actions affect demand for the other. Such a model is a useful example when considering the licensing of copyrights for producing derivative works (e.g., sample-based music). When upstream rights holders independently price licenses of complementary works, sub-optimal equilibrium may result. In creating derivative works, this situation can arise in two ways in the music licensing context. First, creators of derivative works may have to negotiate with multiple rights holders covering a single work when rights are fragmented. Second, complementarities exist between works when the derivative work is created. That is, after downstream artists invest in creating a derivative work with multiple samples, each upstream rights holder controls a complementary copyright that the downstream producer must license before their derivative work can be commercialized under restrictive re-use. Acting independently, the complementary rights holders price their licenses above the level obtained in an optimal equilibrium, leading to a royalty stacking scenario (Lemley and Shapiro, 2007). In response to sub-optimally high prices, it is expected that creators of derivative works will decrease the number of samples used per song in order to reduce the number of upstream complements and alleviate costs.

Given the above discussion, one may also expect the proposed effect on sampling to have differential impact across artist types. For example, artists and labels may differ in their willingness to infringe, or risk infringing, the copyrights of others through unlicensed sampling. Furthermore, successful artists may have greater resources and an increased ability to clear transaction cost hurdles and negotiate licenses. Absent data, the theoretical expectation in

this situation remains particularly unclear. On the one hand, successful artists may have the resources necessary to clear licenses when rights are restrictive. Such resources available to successful artists could include higher production budgets, as well as the availability of administrative and legal support for licensing samples. On the other hand, prominent artists have much greater exposure, and unlicensed sampling by high-profile artists may be easily identified by upstream rights holders. An analogous effect has been observed in the patent space, with non-practicing entities (NPE) litigation preferentially targeting cash-rich firms (Cohen et al., 2014). Because of this, major labels with which prominent artists are associated may be highly restrictive over artists' use of samples, and may monitor their releases closely to ensure they are not at risk of costly litigation. With these predictions in mind, it is uncertain which effect will dominate, and thus whether prominent artists will be more or less affected by restrictive sampling rights than less prominent artists. The exploration of this question thus depends on the empirical results in the following sections.

3.1 Licensing in Practice

In practice, licensing of copyrighted works may follow a number of paths depending upon the rights desired and the context of their desired usage. For some cases, compulsory licensing provisions exist in U.S. Copyright law – such as the right for artists to create "cover versions" of previously recorded musical works. In addition to compulsory licensing schemes, copyright collectives have been created in many countries that represent groups of copyright owners to manage the licensing of selected rights, as well as the collection of royalties. Performance rights organizations (PROs), such as ASCAP and BMI, are a notable example of copyright collectives, that specifically work to license and manage the public performance right (e.g., playing a song in a retail store) for participating copyright holders. However, in most cases, the licensing of copyrights must proceed in an *ad hoc*, un-standardized manner when prior works under copyright are incorporated into a new derivative work. Negotiations over this

right may proceed in either direction, a potential licensee may approach a rights holder to obtain a license to create a derivative, just as a rights holder may identify their unlicensed work in a published derivative work and seek out the infringing artist.

Two separate rights must be licensed in the context of sampling a sound recording, a "mechanical license" for the underlying composition, as well as a "master use" license for the rights associated with the sound recording itself. These two rights are often owned by separate parties, with the sound recording copyright typically controlled by the record label or performing artist(s), and the composition copyright typically vesting with the song writers or their publisher. When these rights are successfully licensed for use as samples, Broussard (1991) identifies five types of agreements that are typically encountered: gratis, buyouts, royalties, co-ownership, and assignment of copyright. Additionally, the form of the license agreement often differs for the right being licensed. While master user licenses typically take the form of "buyouts" (or flat fees), with royalty agreements being less common, royalty agreements and co-ownership agreements are the most common deals for licensing of the composition right. Along with the types of deals negotiated, Broussard (1991) highlights three main factors that influence the price of the negotiated sample license agreement - what is sampled, how the sample is used, and who is using the sample. Typically, in terms of what is sampled, price depends on the popularity of the original artist/song, as well as what part of the song is sampled (e.g., vocal/instrumentals, chorus, melody, etc.) and how recognizable the sampled section is. The negotiated price also depends on how the sample is repurposed in the new work, with higher rates associated with samples that are repeated throughout the song and samples that provide a great deal of the new derivative work's appeal. The final factor determining price, who is using the sample, generally depends on the prominence of the artist using the sample, with very commercially successful artists expected to pay a higher rate. However, with equal importance to "who" uses the sample, is whether the sampling artist sought prior permission to use the sample, with heavy penalty pricing imposed when the original rights holder finds infringing content and begins negotiations post-release.

4 Empirical Framework and Identification

4.1 Data and Measures

Data for this paper was collected from two sources, WhoSampled.com and Billboard. Data on music sampling was self-collected from the website WhoSampled.com. WhoSampled, which bills itself as "the world's largest community for fans of sampled music, cover songs and remixes," is a community-driven website where contributors upload information about samples used in songs. The database has information on 365,330 unique songs and 207,632 samples, provided by 14,230 contributors at the time of this draft. While the WhoSampled database also has information on cover songs and remixes, for the purposes of this study only sampling data was used. For each sample driven song in the database, WhoSampled provides a number of fields important to building this dataset: the artist, title, label, and date of release of the sampling ("follow-on") song, plus the artist, title, label, and date of the sampled song. Additionally, the WhoSampled database contains information on the genre of both the sampled and sampling song, as well as where in the song the sample is used, and where the sample is taken from in the original track. While the "importance" or "prominence" of the sample in the sampling song would be a useful measure for this study, the WhoSampled data unfortunately does not provide any such measures. Figure 1 depicts the typical track level data available on WhoSampled for a sample-using song. In addition to the high level details shown in Figure 1, the community provides additional detailed information for each specific sample used in a song, as shown in Figure 2.

The second source of data used for constructing this study's dataset comes from Billboard.com. Billboard provides weekly music industry top-charts for singles, and now ranks singles based upon digital sales, physical sales, radio play, and online streaming. For this paper, data from Billboard's "Hot R&B/Hip-Hop" charts were collected since Billboard began tracking this genre in the beginning of 1985. Each weekly chart contains a ranked list

of Hip-Hop/R&B singles, including the title of the ranked song and the song's artist(s).

To construct the dataset used herein, the list of hip-hop/R&B artists appearing on the Billboard charts since 1985 is merged with the artists from the WhoSampled data. The dataset then includes all sampling tracks found in the database since 1985. The main response variable, $samples_i$ is constructed by calculating the count of samples used in the sampling song i. An additional response variable, *new samples*, is constructed by calculating whether the sampling song i has any novel samples - samples of songs for which song i is the first sampling track - and equals 1 if song i contains 1 or more novel samples, 0 otherwise. Two treatment variables were created, *post-Grand Upright* which is a binary indicator variable that equals 1 if song i was released after *Grand Upright*, and *post-Bridgeport Music* that analogously equals 1 if song i was released after *Bridgeport Music*. Summary statistics for this data are shown in Table 1.

4.2   Estimation

To investigate the effect that a court decision has on the sampling practices in the music industry, I first focus on the raw count of samples used in a new song. In an ideal experiment to study this question, the econometrician would expose a randomly selected treatment group of sample-using musicians to more (or less) restrictive copyright policy for re-use of existing work. The econometrician could then compare the output of this treatment group to a control group that was not exposed to a change in policy. With this ideal setup, the econometrician could then simply estimate the change in the rate of sampling that is associated with stronger/weaker copyrights over re-use.

Unlike the ideal experiment, the identification strategy in this paper must deal with the fact that there is little heterogeneity in the treatment condition. During the period of the first court case, *Grand Upright*, sampling was primarily found in hip-hop music, and the

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vast majority of this music was being produced in the U.S. Strong assumptions about either pre-treatment sampling rates or treatment heterogeneity based upon jurisdiction of the court could be used to help identify the parameter of interest (e.g., using a differences-in-differences design). Instead, this paper takes a simple, transparent approach rather than relying on specious assumptions given the industry context. To estimate the effect of copyright court decisions on the rate of sampling, the rate of sampling is compared for songs released before and after the court decision. This pre/post strategy however raises concerns about potential confounding effects from unobserved time-trends in re-use, as any time-varying trend will be absorbed into our parameter estimate and bias the results. To deal with this, a shrinking time window is used around the court decision "treatment," to rule out confounding temporal trends. While this identification depends upon a maintained assumption regarding time trends within the window, similar strategies have been used in the past with success (e.g., Zhang and Zhu (2011)), and this strategy is suitable given the lack of appropriate control group. With a linear model, the following regression is used:

$$s_i = X_i'\beta + \gamma\mathbb{1}[i \text{ is post-court}] + \varepsilon_i \tag{1}$$

Where s_i is a count of samples in song i, $\mathbb{1}[i \text{ is post-court}]$ is a dummy indicator variable equal to 1 if the song is released after the court decision, and X_i is a vector of control variables. The available control variables are categorical variables for the main artist associated with song i and the label of song i. Since sampling was predominantly used in hip-hop music during the first court decision, the entire sample is restricted to the hip-hop music industry to keep the analysis consistent. The same identification strategy and framework shown in Equation 1 is used when investigating the impact of federal court decisions on the incidence of new samples being used in popular music.

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5 Results

The results of this analysis are presented in three parts. The first part of this section presents the estimates of the main treatment, the effects of *Grand Upright* and *Bridgeport Music* on the rate of sampling in hip-hop music. I demonstrate evidence for the mechanism of this effect, as it operates along the intensive margin. The analysis proceeds by presenting evidence of how *Grand Upright* affected the creativity of new works and the diversity of works being re-used. I conclude by examining how this main effect differs by artist type. The majority of the analysis in this section focuses on the *Grand Upright* case, as will be discussed below, due to the lack of effect that can be attributed to the later *Bridgeport Music* court decision.

5.1 The Rate of Sampling in Hip-Hop Songs

Figure 3 depicts the mean samples-per-song time trend since 1986, shown as the estimates of a fitted Poisson model. From Figure 3 we see that the average number of samples (per-song) peaks between 1989 and 1990, before beginning a sharp decline in 1991, a trend that continues until leveling off in the late 1990s - early 2000s. Such evidence lends support to *Grand Upright* spurring a change in sampling practices, but of note is the seeming lack of effect seen in the mid 2000s, where one would expect any effect from *Bridgeport Music* to appear. Some insightful comparisons can be made between the sampling trend shown in Figure 3 and the past trends in cover songs (Figure 4) and the rate of self-sampling (Figure 5). While such comparisons are imperfect control groups, they give one an idea of whether there were other general trends in re-use over this time period. Figure 4 shows the rate of cover songs per year as a total proportion of all songs released. Because cover songs are covered by a statutory licensing regime, the incentives to create cover songs should have been completely unaffected by the *Grand Upright* decision, and this does appear to be the case, as the rate of cover songs produced actually increased after 1991, before reaching a

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peak in the mid 2000s. Second, one can also examine trends in self-samples, that is, samples in which an artist repurposed part of their previous works. As shown in Figure 5, the decline in self-samples post-1991 was much lower than the decline in general sampling. It is of potential concern that any change in self-sampling is observed, but it must be re-iterated that ownership of musical copyrights are often fragmented. One could expect to see some effect of the court-imposed restrictions on self-samples, as just because an artist is associated with a work does not indicate that they control all of the rights needed to license it for re-use.

Table 2 presents the estimated change in sampling per hip-hop song due to the *Grand Upright* decision. Columns (1)-(3) of Table 2 restrict the estimation sample to a ±3 year window before and after the *Grand Upright* decision in order separate the effect of *Grand Upright* from any confounding long-term time trends. Column (1) includes no controls, and implies that *Grand Upright* led to a mean decline in sampling of 0.461 samples used per song. Record label controls are added in Column (2) to account for the unobservable influence on sampling coming from record label management, with the estimate negative effect of *Grand Upright* marginally shrinking to 0.444 fewer samples per song due to the decision. Artist controls are added in Column (3) to account for heterogeneity in artists' styles and use of sampling as a production process, but the results remain consistent, with the point estimates implying 0.422 fewer samples per song. All of these stated effects are statistically significant at the one percent level.

The ±3 year time window on either side of the *Grand Upright* decision may still allow for underlying time-trends in sampling practices to bias the parameter estimates. To lessen concerns about confounding time trends, the time window around *Grand Upright* shrinks to ±2 years in columns (4)-(6) of Table 2. Column (4) includes no controls, and implies that, conditioning on a ±2 year time down, *Grand Upright* caused a mean drop of 0.302 fewer samples per song. Column (5) includes label effects, with the result remaining consistent but shrinking to 0.275 fewer samples per song. Finally, the fully saturated model in Column

(6) includes both label and artist effects, with an estimates 0.320 fewer samples per song as a result of the *Grand Upright* decision. Results thus remain largely consistent across specifications, with all results significant at the one percent level, and leading to the inference that *Grand Upright* reduced re-use, and altered the direction of innovation in the industry.

The analysis of *Bridgeport Music*'s effect on the magnitude of sampling in hip-hop is shown in Table 3. Similar to the prior results on *Grand Upright*, Columns (1)-(3) of Table 3 restrict the estimation sample to a ±3 year time window around *Bridgeport Music*. However, in contrast to the large drop caused by *Grand Upright*, *Bridgeport Music* appeared to have no significant effect. Without controls, in Column (1), I estimate the effect of *Bridgeport Music* to be near zero at 0.020 fewer samples per song, and while this effect is economically insignificant, it is also statistically insignificant. While adding label controls in Column (2) brings statistical significance at the 5% level to the small estimated coefficient, the effect disappears once artist controls are added in Column (3).

Once I shrink the time window shrinks to ±2 years around *Bridgeport Music* in Columns (4)-(6) of Table 3, the effect of *Bridgeport Music* remains insignificant. The point estimates are further attenuated towards zero across specifications without controls (Column 4), with label controls (Column 5), and with both sets of controls (Column 6). Overall, due to the small, economically insignificant mean effect size across models, and the lack of statistical significance, it appears that if *Bridgeport Music* did in fact have an effect upon the rate of sampling in the industry, such effect is smaller than what can be detected given noise in my sample. The apparent lack of effect from the *Bridgeport Music* ruling is consistent with the industry rapidly adapting to a new sample-licensing model in the wake of *Grand Upright*, a model that precludes extensive re-use in the production process. As I cannot reject the null of no effect for most models estimating the impact of *Bridgeport Music*, the rest of the empirical analysis in this paper focuses upon the *Grand Upright* decision and its effect upon sampling practices in the industry.

5.2   Impact on the Probability of Sampling

I next disentangle whether *Grand Upright*'s effect manifested as a change in the proportion of songs that contained samples or instead a decrease in the magnitude of sampling across all songs. A new dependent variable is constructed that equals one if song i contains any samples, and 0 otherwise for songs that do not contain samples. Running a logistic regression using this outcome measure with my post-*Grand Upright* variable, as shown in Table 4, provides evidence that the court decision did not have any outright effect on the propensity of songs to contain samples, as I cannot reject the null hypothesis of no effect. Column (1) of Table4 includes no controls, and implies the odds of a song containing samples after *Grand Upright* is approximately 14% greater than before, but this effect is only significant at the 10% level. Controlling for label effects renders this effect statistically insignificant in Column (2), as with artist controls in Column (3). The fully saturated linear probability model in Column (4) also implies no statistically significant effect on the propensity for a song to contain samples post-*Grand Upright*, but with the point estimate remaining positive. Hence, from these consistent results, there is no evidence that *Grand Upright* had any negative impact on the probability that a new work utilized sampling in the production process.

It thus appears that the reduced sampling after *Grand Upright* was due to a reduction in the number of samples per track, not the proportion of songs containing samples after the decision. This result is consistent with a royalty stacking mechanism, whereby artists in the restrictive rights regime decrease the number of samples used per song in order to defray the sub-optimally high licensing costs that result from upstream complementary rights holders acting independently. Furthermore, these results also help to rule out an alternative interpretation that sampling was a fad that peaked in the 1990s then faded from popularity. I do not observe any decrease in the popularity of using sample-based production, instead, the decrease in sampling manifests along the intensive margin.

5.3 Impact on Creativity and Diversity of Samples

Given that *Grand Upright* had a dramatic effect on the content of new products in the music industry, it may have also affected the creativity and the diversity of works drawn upon. If *Grand Upright* made copyright more restrictive for artists wishing to re-use existing sound recordings, it may have pushed artists and labels to increasingly re-use work from rights-holders that either (1) did not assert their rights against re-use and derivative works, and/or (2) were apt to license their rights to hip-hop producers. Table 5 presents results with a new outcome variable that is equal to 1 if the observed song i has a sample of a song that was never previously sampled (henceforth a "novel" sample), and 0 otherwise.

Table 5 shows the effect of *Grand Upright* on the incidence of novel samples in hip-hop songs. From the evidence of these results, it is clear that *Grand Upright* had a negative impact on the creativity of new products in the industry and the diversity of re-used work. Columns (1) through Column (4) of Table 5 utilize linear probability models, while Column (5) depicts marginal effect estimates from logistic regression. Across specifications, the estimated effect of *Grand Upright* is statistically significant at the 1% level. Column (1) includes no controls, and implies that songs released post-*Grand Upright* were 4% less likely to include a novel re-use. When label effects are included in the model, the magnitude of this estimate grows to 5%, while controlling for artist effects implies that songs were 9% less likely to include a novel re-use as the result of restrictions put in place by *Grand Upright*. I estimate that songs are 10% less likely to use novel samples after controlling for both artist and label effects with a linear probability model. Very similar results are achieved with an alternative logisitic regression in Column (5), which estimates that the court decision lead to a 10.6% decrease in the use of novel samples while controlling for artist and label.

Thus, from these regression results, there appears to be a consistent negative effect of *Grand Upright* on novel samples being used to produce new music. Songs released after the

Grand Upright decision are, on average, about 10% less likely to utilize samples that have not been previously exploited. These results support the interpretation that the downstream restrictions from *Grand Upright* are leading artists to exploit samples from a less diverse pool of previously recorded music than would have been obtained under a less-restrictive regime. Thus, while I have already established that the effective policy changes from *Grand Upright* altered the rate of re-use in the music industry, these results demonstrate that the policy change also affected the direction of re-use, creativity, and innovation for new products.

5.4   Change in Sampling: Heterogeneity by Artists

Table 6 presents the results of examining how the *Grand Upright* decision affected more and less-prominent artists. I define musicians as prominent if they have previously released an RIAA certified gold album, a certification that is awarded albums that have sold at least 500,000 units. With this measure, I estimate that the change in sampling practices post-*Grand Upright* was greater in magnitude for these prominent artists, as the interaction between the post-*Grand Upright* indicator and the indicator for gold-certified artists is significant across all specifications. While the prominent artists not only were more so affected by the *Grand Upright* decision, these artists appear to practice a higher baseline rate of sampling per song pre-*Grand Upright* than less prominent artists.

Column (1) of Table 6 includes no controls, Column (2) and (3) respectively control for label and artist, and Column (4) controls for both label and artist effects. In models without artist fixed effects (Columns 1 and 3), Gold-certified artists have a higher baseline rate of sampling compared to less prominent artists, using between 1 and 1.4 more samples per song on average. Furthermore, across specifications, *Grand Upright* had a more extensive effect on sampling for prominent artists. Without controls, I estimate in Column (1) that the interaction between prominent artists and post-*Grand Upright* was approximately 0.5 fewer

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samples per song compared to base effect of *Grand Upright* at 0.25 fewer samples per song. When artist and label fixed effects in Column (4), this interaction effect grows in magnitude to 0.72 fewer samples per song, a result that is statistically significant at the 5% level.

These results clarify the theoretical-focused discussion in Section 3. It is *ex ante* ambiguous without data whether highly prominent artists would be more or less affected by restrictive copyright. While famous and/or successful artists may have the record label resources to overcome transaction costs and pay costly licensing fees, these artists also face greater scrutiny from major label management, which are wary to allow unlicensed sampling that risks infringement claims and damages. However, from my data and estimation strategy, it appears that any resource advantage these prominent artists have is dominated by the increased scrutiny and litigation risk they face when using samples without a license.

6 Conclusion

This research examines the impact of strengthened copyright breadth on re-use in the music industry. While the results of the analysis require maintained assumptions, this work provides evidence of how copyright policy affects the actual content and creativity of new products – demonstrating that the intellectual property right regime has altered not only the rate of re-use, but the direction as well. While I cannot estimate welfare in this context, this setting still allows me to uncover how copyright policy has altered the trajectory of new products. Concerns over appropriate copyright balance have never been more pressing. Digitization has nixed replication costs (Goldfarb and Tucker, 2017), enabling both demand-side replication (e.g., piracy) and supply-side re-use in a creative content industry that now generates over $2 trillion in global annual revenue. Future work in this area may further explore the welfare question, as well as focus on the other side of the samplee/sampler dyad - the upstream rights holders.

First, the empirical results indicate that there was a moderate decrease in sampling following the *Grand Upright* decision. Depending on the model used and time window around the event, the court decision is estimated to have caused sampling to decrease by approximately 0.3-0.4 samples per song on average, and the magnitude of this result is robust across models. An interesting result is the lack of a significant effect on re-use from the *Bridgeport Music* decision. While *Bridgeport Music* had a more dramatic effect on copyright policy itself, as it effectively changed policy within its jurisdiction (see McLeod and DiCola (2011)), it appears that the earlier *Grand Upright* decision had a more significant impact upon sampling and licensing practices within the industry. The evidence suggests that the first decision pushed labels to confront the risks associated with unlicensed sampling, cleared the path for infringement claims, and thus forced major record labels to rapidly adapt a licensing model for sample based music. Thus, while this paper fails to find any economically significant or statistically significant effect of *Bridgeport Music* on sampling in the industry, there does appear to be robust evidence that *Grand Upright* decreased the rate of sampling and re-use. Strikingly, the evidence shows that the court decision mainly affected derivatives and re-use through an effect on the intensive margin, with the magnitude of samples used per track dropping, and no apparent change in the probability of a new song containing samples. This effect highlights the royalty stacking problem in licensing for derivative works - with multiple upstream rights holders (complementary monopolies), downstream artists face high licensing fees and must decrease the number of samples used in order to offset high input costs. Thus, I find not only that the magnitude of sampling decreases when re-use is restricted, but also find evidence of the mechanism at work.

Perhaps most concerning, I have demonstrated that copyright policy altered the creativity of new products. After the decision in *Grand Upright*, music producers have drawn upon a less diverse pool of existing works for re-use in new music. This result could thus be interpreted as impeding the "Progress of Science and useful Arts," the U.S. constitutional basis for establishing copyright. Expanding the existing compulsory licensing regime (Menell,

2016) could remedy this stifling effect of the current restrictive regime. Objections to such policy interventions have focused on the moral right of artists to control the manner in which their works are exploited – but such objections have less basis in U.S. policy as compared to continental European copyright systems (Rigamonti, 2006).

Empirical evidence also confirms *Grand Upright* had a differential impact on more versus less prominent artists, with the regression analysis providing evidence that more prominent artists were affected to a greater extent by the court decision than other, less prominent artists. Such a result is particularly interesting due to the theoretical ambiguity of how stricter rights over re-use may effect artists. On the one hand, it may be that more prominent artists signed to major labels have the resources to license samples that independent, less prominent artists do not have. On the other hand, a separate effect can be theorized wherein less-exposed artists ("underground artists") are able to conduct unlicensed sampling without a high risk of infringement suits, and are thus able to continue sampling at a higher rate than those artists with greater financial and media exposure. However, from the empirical results shown in this paper, I see no evidence of the former dominating, instead finding that more prominent artists were affected more so by the decision.

The study of copyright strength in this context is a complicated issue, necessitating concerns over both moral rights as well as economic incentives. This paper does not attempt to provide a final answer on the matter or to calculate a welfare estimate. Instead, this study seeks to chip-off and answer one question - how did more restrictive rights over re-use affect the content of follow-on work? By answering this question, this paper may contribute to the discussion forming around copyright and the creation of derivative works, a spreading phenomenon enabled by digitization.

References

Bessen, J. and E. Maskin (2009, December). Sequential innovation, patents, and imitation. *The RAND Journal of Economics 40*(4), 611–635.

Broussard, W. C. (1991). Current and suggested business practices for the licensing of digital samples. *Loyola of Los Angeles Entertainment Law Review 11*, 479.

Cohen, L., U. Gurun, and S. D. Kominers (2014). Patent trolls: Evidence from targeted firms. *NBER Working Paper*.

Cournot, A.-A. (1838). *Recherches sur les principes mathématiques de la théorie des richesses par Augustin Cournot*. chez L. Hachette.

DiCola, P. C. (2010). Sequential musical creation and sample licensing. *Northwestern Law & Econ Research Paper* (10-06).

Economides, N. and S. C. Salop (1992). Competition and integration among complements, and network market structure. *The Journal of Industrial Economics*, 105–123.

Furman, J. L. and S. Stern (2011). Climbing atop the shoulders of giants: The impact of institutions on cumulative research. *American Economic Review 101*(5), 1933–63.

Galasso, A. and M. Schankerman (2015). Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics 130*(1), 317–369.

Gans, J. S. (2015). Remix rights and negotiations over the use of copy-protected works. *International Journal of Industrial Organization 41*, 76–83.

Giorcelli, M. and P. Moser (2014). Copyright and creativity: Evidence from Italian operas. *Available at SSRN 2505776*.

Goldfarb, A. and C. Tucker (2017, August). Digital economics. Working Paper 23684, National Bureau of Economic Research.

Green, J. R. and S. Scotchmer (1995). On the division of profit in sequential innovation. *The RAND Journal of Economics*, 20–33.

Hall, B. H. and M. MacGarvie (2010). The private value of software patents. *Research Policy 39*(7), 994–1009.

Hall, B. H. and R. H. Ziedonis (2001). The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND Journal of Economics*, 101–128.

Heller, M. A. and R. S. Eisenberg (1998). Can patents deter innovation? The anticommons in biomedical research. *Science 280*(5364), 698–701.

Hui, K.-L. and I. P. Png (2002). On the supply of creative work: Evidence from the movies. *American Economic Review*, 217–220.

Kim, J.-H. (2011). International convergence of copyright production. *The Review of Economics and Statistics 93*(4), 1432–1439.

Kortum, S. and J. Lerner (1999, January). What is behind the recent surge in patenting? *Research Policy 28*(1), 1–22.

Landes, W. M. and R. A. Posner (1989). An economic analysis of copyright law. *The Journal of Legal Studies 18*(2), 325–363.

Lemley, M. A. and C. Shapiro (2007). Patent holdup and royalty stacking. *Texas Law Review 85*, 1991.

Li, X., M. MacGarvie, and P. Moser (2013). Dead Poets Property - Does Copyright Increase the Price of Content. *Working Paper*.

Liebowitz, S. and S. Margolis (2004). Seventeen famous economists weigh in on copyright: The role of theory, empirics, and network effects. *bepress Legal Series*, 397.

Liebowitz, S. J. (2006). Economists examine file-sharing and music sales. *Industrial Organization and Digital Economy. MIT Press, Cambridge*.

Liebowitz, S. J. (2008). Testing file-sharing's impact by examining record sales in cities. *Management Science 54*(4), 852–859.

Luo, H. and J. H. Mortimer (2016). Copyright infringement in the market for digital images. *American Economic Review 106*(5), 140–45.

Luo, H. and J. H. Mortimer (2017). Copyright enforcement: Evidence from two field experiments. *Journal of Economics & Management Strategy 26*(2), 499–528.

McLeod, K. and P. DiCola (2011). *Creative License: The Law and Culture of Digital Sampling.* Duke University Press.

Menell, P. S. (2016). Adapting copyright for the mashup generation. *University of Pennsylvania Law Review 164*(2), 441.

Mortimer, J., C. Nosko, and A. Sorensen (2012). Supply responses to digital distribution: Recorded music and live performances. *Information Economics and Policy*, 1–38.

Murray, F. and S. Stern (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization 63*(4), 648–687.

Nagaraj, A. (2016). Does copyright affect reuse? Evidence from the google books digitization project. *Management Science*. Forthcoming.

Oberholzer-Gee, F. and K. Strumpf (2007). The effect of file sharing on record sales: An empirical analysis. *Journal of Political Economy 115*(1), 1–42.

OberholzerGee, F. and K. Strumpf (2010). File sharing and copyright. *Innovation Policy and the Economy 10*(1), 19–55.

Png, I. and Q.-h. Wang (2006). Copyright duration and the supply of creative work: Evidence from the movies. *Working Paper*.

Qian, Y. (2007). Do national patent laws stimulate domestic innovation in a global patenting environment? A cross-country analysis of pharmaceutical patent protection, 1978–2002. *The Review of Economics and Statistics 89*(3), 436–453.

Reimers, I. (2016). Can private copyright protection be effective? Evidence from book publishing. *The Journal of Law and Economics 59*(2), 411–440.

Rigamonti, C. P. (2006). Deconstructing moral rights. *Harvard International Law Journal 47*, 353.

Rob, R. and J. Waldfogel (2006). Piracy on the high C's: Music downloading, sales displacement, and social welfare in a sample of college students. *Journal of Law and Economics 49*(1), 29–62.

Sakakibara, M. and L. Branstetter (2001). Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms. *The RAND Journal of Economics 32*(1), 77.

Scotchmer, S. (1991). Standing on the Shoulders of Giants: Cumulative Research and the Patent Law. *Journal of Economic Perspectives 5*(1), 29–41.

Waldfogel, J. (2012). Copyright protection, technological change, and the quality of new products: Evidence from recorded music since napster. *Journal of Law and Economics 55*(4), 715–740.

Williams, H. L. (2013). Intellectual property rights and innovation: Evidence from the human genome. *Journal of Political Economy 121*(1), 1–27.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism*. New York, NY: The Free Press.

Zhang, L. (2016). Intellectual property strategy and the long tail: Evidence from the recorded music industry. *Management Science*. Forthcoming.

Zhang, X. and F. Zhu (2011). Group size and incentives to contribute: A natural experiment at Chinese wikipedia. *American Economic Review 101*(4), 1601–1615.

Figures and Tables

Figure 1: WhoSampled example

This screenshot depicts the community-provided sampling data from WhoSampled.com for the Beastie Boys song "Car Thief"

Figure 2: WhoSampled: Detailed Sample Information

Along with the high-level sampling data shown above, the community at WhoSampled also provides detailed information for each sample added to the database, shown here for the Beastie Boy's sample of Funk Factory's Rien Ne Va Plus

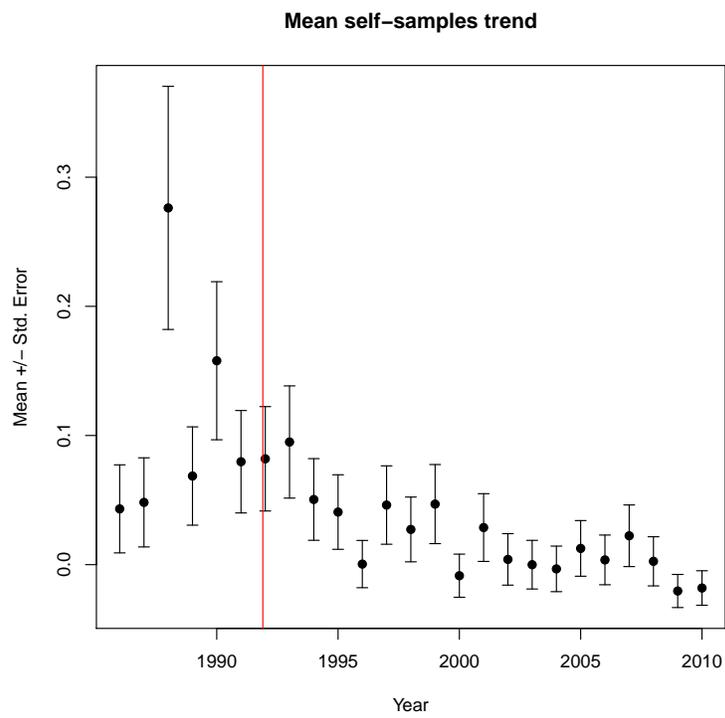Figure 3: Samples-per-song Time Trend

Mean samples trend
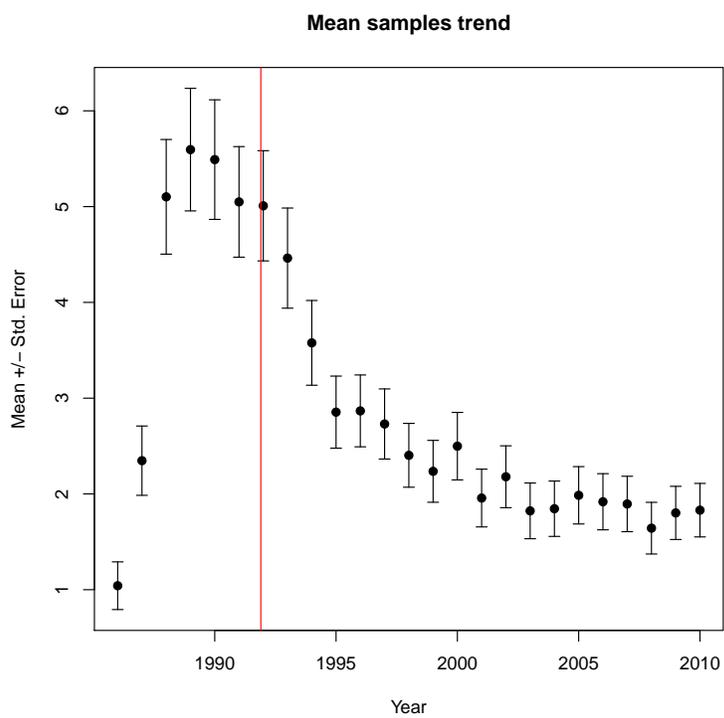
This figure illustrates time trend of samples used per song (shown as fitted Poisson-model marginal effects). The time of the *Grand Upright* decision (December 1991) is shown in red

Figure 4: Cover Song Time Trend

Rate of Cover Songs Per Year
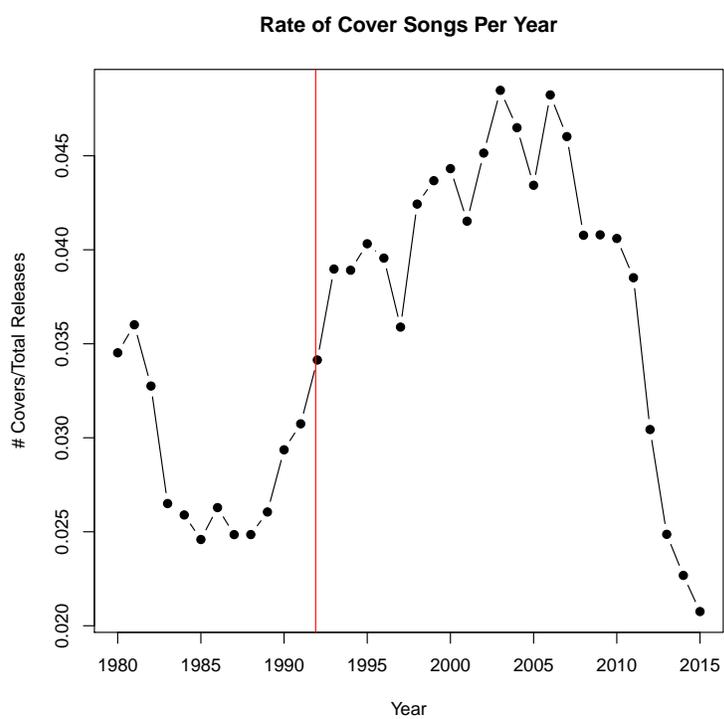
This figure illustrates time trend of cover songs per year, as a proportion of total songs released per year

Figure 5: Self Sampling Time Trend

Mean self−samples trend

This figure illustrates time trend of self-samples used per song (shown as fitted Poisson-model marginal effects). The time of the *Grand Upright* (December 1991) decision is shown in red

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Year of release	26,892	2002	8.25	1985	2015
Number of Samples	26,892	1.22	1.62	0	36
post-*GrandUpright*	26,892	0.86	0.35	0	1
post-*BridgeportMusic*	26,892	0.39	0.49	0	1
Contains New Samples	19,425	0.35	0.48	0	1

Table 2: Grand Upright Effect on Sampling

	±3 Year Window			±2 Year Window		
	Dependent variable:					
	Number of Samples					
	(1)	(2)	(3)	(4)	(5)	(6)
post-*GrandUpright*	-0.461***	-0.444***	-0.422***	-0.302***	-0.275***	-0.320***
	(0.060)	(0.070)	(0.095)	(0.074)	(0.077)	(0.104)
Constant	2.096***			2.070***		
	(0.048)			(0.063)		
Artist FE	No	No	Yes	No	No	Yes
Label FE	No	Yes	Yes	No	Yes	Yes
Observations	5,706	5,461	5,263	4,119	3,945	3,777

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays coefficients from linear probability model regressions in which the dependent variable is a count of samples used in song i. The main variable of interest, post-*GrandUpright* =1 for songs released after the *Grand Upright...* court decision that restricted re-use. Columns (1), (2), and (3) utilize a ±3 year window around the event to minimize confounding time trends. Column (2) controls for record label effects, while Column (3) controls for both artist and label. Columns (4), (5), and (6) shrink the time window further to ±2 years, with Column (6) fully controlling for label and artist effects

Table 3: Bridgeport Music Effect on Sampling

	Dependent variable:					
	Number of Samples					
	±3 Year Window			±2 Year Window		
	(1)	(2)	(3)	(4)	(5)	(6)
post-*BridgeportMusic*	-0.020	-0.077**	-0.044	-0.002	-0.060	-0.019
	(0.031)	(0.035)	(0.052)	(0.038)	(0.045)	(0.076)
Constant	0.967***			0.977***		
	(0.021)			(0.026)		
Artist FE	No	No	Yes	No	No	Yes
Label FE	No	Yes	Yes	No	Yes	Yes
Observations	5,772	5,070	4,797	3,998	3,511	3,285

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays coefficients from OLS regressions in which the dependent variable is a count of samples used in song i. The main variable of interest, post-*BridgeportMusic* =1 for songs released after the *Bridgeport Music...* court decision in 2005 that restricted re-use. Columns (1), (2), and (3) utilize a ±3 year window around the event to minimize confounding time trends. Column (2) controls for record label effects, while Column (3) controls for both artist and label. Columns (4), (5), and (6) shrink the time window further to ±2 years, with Column (6) fully controlling for label and artist effects

Table 4: Grand Upright Effect on Propensity to Sample

	(1)	(2)	(3)	(4)
	Logit	Logit	Logit	OLS
post-*GrandUpright*	1.136*	1.040	1.119	0.020
	(0.084)	(0.098)	(0.151)	(0.016)
Constant	2.735***			
	(0.158)			
Artist FE	No	No	Yes	Yes
Year Controls	No	Yes	No	Yes
N	4,119	3,615	2,907	4,112

Dependent variable: Contains Samples (1/0)

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This display displays odds-ratios from a logistic regression (Columns 1-3) and coefficients from an OLS regression (Column 4) in which the dependent variable is a binary (1/0) variable $= 1$ when song i contains samples, 0 otherwise. The main variable of interest, post-*GrandUpright* $=1$ for songs released after the *Grand Upright...* court decision that restricted re-use. Column (1) includes the main variable of interest, Column (2) adds label effects, and Column (3) controls for artist effects. Column (4) displays results from a linear probability model controlling for both artist and label effects.

Table 5: Novel Sampling

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit (M.E.)
	Dependent variable:				
	Contains Novel Sample(s)				
post-*GrandUpright*	-0.040**	-0.052***	-0.094***	-0.100***	-0.106***
	(0.016)	(0.018)	(0.021)	(0.024)	(0.023)
Constant	0.393***				
	(0.013)				
Artist FE	No	No	Yes	Yes	Yes
Label FE	No	Yes	No	Yes	Yes
Observations	4,195	4,009	3,995	3,851	3,337

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays coefficients from linear probability models (Columns 1-4) and marginal effects from a logistic regression (Column 5) in which the dependent variable is a binary variable, *Contains Novel Sample(s)*, that $= 1$ when song i contains samples that have not been previously used, 0 otherwise. A ± 3 year window around the *Grand Upright* court decision is used. These regressions include the main variable of interest, post-*GrandUpright* $=1$ for songs released after the *Grand Upright...* court decision that restricted re-use. Columns (1) includes no controls, Column (2) controls for label effects, Column (3) controls for artist effects, and Columns (4) and (5) controls for both label and artist.

Table 6: Heterogeneity by RIAA Gold Artists: 2 Year Window

		Dependent variable:		
		Number of Samples		
	(1)	(2)	(3)	(4)
post-$GrandUpright \times Gold_{jt}$	-0.491*	-0.530*	-0.641**	-0.719**
	(0.252)	(0.283)	(0.254)	(0.309)
post-$GrandUpright$	-0.247***	-0.195**	-0.195**	-0.125
	(0.074)	(0.079)	(0.076)	(0.092)
$Gold_{jt}$	1.424***	0.0812	1.002***	0.269
	(0.223)	(0.340)	(0.232)	(0.369)
Constant	1.855***			
	(0.062)			
Artist FE	No	Yes	No	Yes
Label FE	No	No	Yes	Yes
Observations	4,119	3,927	3,945	3,777

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table displays coefficients from OLS regressions in which the dependent variable is a count of samples used in song i. These regressions include the previous variable of interest, post-$GrandUpright$ =1 for songs released after the *Grand Upright...* court decision that restricted re-use. Additionally, an interaction term is added using the variable $Gold_{jt}$, which =1 when artist j has had an album certified "Gold" (500,000 units) prior to year t according to the RIAA. A ± 2 year time window around *Grand Upright...* is used for all the models in this table. Columns (1) introduces the *Gold* variable and the interaction term, Column (2) controls for artist effects, Column (3) controls for label effects, and Column (4) controls for both label and artist effects.