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Copyright's Excess Revisited

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COPYRIGHT'S EXCESS REVISITED

By: Glynn S. Lunney, Jr.

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For three hundred years, we have enacted and expanded copyright protection based upon a simple premise: more copyright protection will yield more incentives for copyright owners, and more incentives for copyright owners will yield more and better original works of authorship. Despite being the fundamental premise on which copyright was and is based, the incentives-based premise for copyright has, for three hundred years, gone both untested and unchallenged—untested and unchallenged, that is, until 2018. In that year, my book, *Copyright's Excess: Money and Music in the US Recording Industry*,¹ presented a detailed empirical examination of copyright's fundamental premise in the music industry over more than fifty years from 1962 through 2015. During this fifty-four year period, legislation first provided copyright protection for sound recordings made after February 15, 1972, and then technological developments, specifically the rise of file sharing in 1999, undermined such protection.² This rise and fall of the sound recording copyright coincided with a general rise and fall in industry revenue from sales of recorded music. From the start of the study period in 1962 until its end in 2015, revenue from sales of recorded music in the United States initially rose sharply from under \$4 billion in constant 2013 dollars (\$2013) in 1962 to over \$20 billion (\$2013) in 1999.³ After that point, with the advent of file sharing, revenue began to fall.⁴ By 2014, revenue from shipments of recorded music had fallen to under \$7 billion (\$2013).⁵

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1. GLYNN LUNNEY, *COPYRIGHT'S EXCESS: MONEY AND MUSIC IN THE US RECORDING INDUSTRY* (2018).

2. *See id.* at 59–83.

3. *See id.* at 68 (relying on data from the Recording Industry Association of America).

4. *Id.* at 75.

5. *Id.*

The rise and fall of the sound recording copyright, and the corresponding rise and fall in the incentives copyright helped provide for music, presents a near-perfect natural experiment for testing copyright's incentives-based premise. If the incentives story is not just a story, we should find a corresponding rise and fall in the quantity and quality of popular music. Moreover, that rise and fall in music output should be just as unmistakable as the rise and fall in revenue. In *Copyright's Excess*, I used four different measures of the quantity and quality of music released to test copyright's premise: (1) SoundScan's count of albums released each year; (2) *Rolling Stone's* list of the greatest albums of all time; (3) the number of unique songs appearing annually on Billboard's Hot 100 chart; and (4) the stream count for the most popular songs appearing on the Hot 100 chart before 2006 based upon worldwide Spotify streams in 2014.⁶ Yet, none of these measures of the quantity and quality of music output showed a corresponding rise and fall. More incentives did not lead to more and better music. Less incentives did not lead to less and worse. Indeed, where there was a statistically significant correlation between money and music, it was negative.⁷ More incentives led to less music, and less incentives led to more, all else constant.

Since the book's publication, I have presented this startling finding in a variety of settings and discussed it with my academic copyright colleagues at two roundtables focused on the book: the first at Notre Dame Law School and the second at Texas A&M School of Law. As a result of the second roundtable, three of my academic colleagues in the field of copyright have been kind enough to write essays critiquing, building on, and exploring the book, its approach, and its conclusions. The editors of Texas A&M's *JOURNAL OF PROPERTY LAW* have agreed to publish these essays and have allowed me an opportunity to respond to the concerns and questions these essays raise, as well as others I have heard in the course of presenting my findings.

Broadly speaking, these concerns break down into three categories. First, a number of colleagues, including Professor Guy Rub in his essay, have raised questions as to the data on which I rely and the conclusions which I draw. Second, a number of colleagues, including Professor Ann Bartow in her essay, have suggested that the methodology might be used to provide guidance on other issues within copyright law. Third, a number of colleagues, including Professor Elizabeth Rosenblatt in her essay, have reminded me that the incentives theory is not the sole basis for copyright. Even if more money does not, in fact, lead to more and better music, other

6. *Id.* at 84–121.

7. *Id.* at 95–99, 112–18, 125–33, 135–38.

considerations, such as social or distributive justice, might justify our existing, or at least some measure, of copyright protection.

In this Essay, I shall attempt to address each of these concerns. At the outset, however, I would note that none of them undermine the core contention of the book that, at least for the music industry over the last six decades, copyright's fundamental premise was wrong. More incentives did not lead to more and better music. To the contrary, popular music from the low revenue 1960s, before Congress enacted a sound recording copyright, and from the low-revenue 2000s, after file sharing effectively gutted it, was every bit as good as, if not better than, popular music from the peak revenue 1990s. For myself, I will listen to the top artists from the 1960s, such as the Beatles, or from the post-file sharing era, such as Taylor Swift, over the top artists from the peak revenue 1990s, such as Jay-Z and Kenny Chesney, any day. And it is not just me. All of the available measures of music output agree that the music from the high-revenue 1990s was just not as good as music from the lower revenue decades.

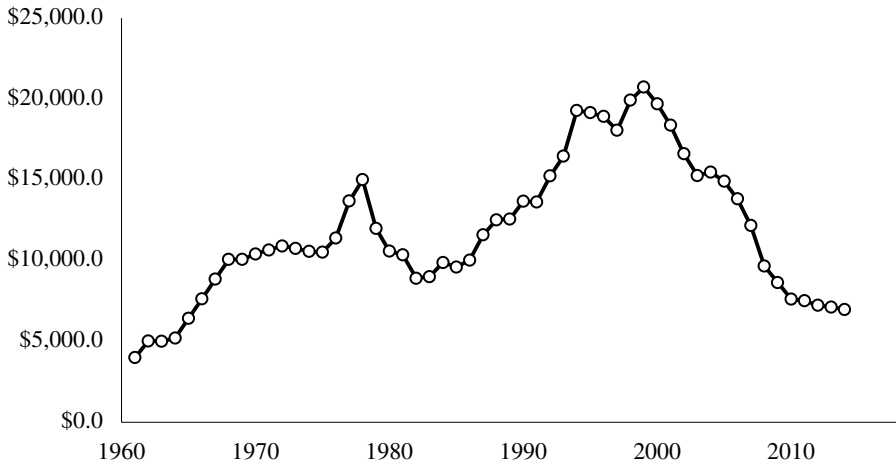
As a starting point for this Essay, in Section I, I will present new data on the musical preferences of Spotify listeners that confirms and reinforces the core findings of *Copyright's Excess*. In Section II, I will then move to address some of the concerns and questions that my colleagues have raised. In Section III, I will briefly conclude.

I. MONEY AND MUSIC: MORE SPOTIFY EVIDENCE THAT MORE INCENTIVES DID NOT YIELD MORE OR BETTER MUSIC.

Since the start of the modern rock era in 1962, more incentives did not lead to more and better music. They led to less. In reviewing my research, I found additional data on Spotify streaming in 2014 that confirms my initial results. Before presenting it, however, I would like to briefly explain the three reasons why the recording industry over the last sixty years makes an excellent case for testing copyright's fundamental premise. First, with the recording industry, the artist is readily identifiable. Who recorded and is performing a song is usually readily apparent. Unlike, for example, popular novels, there is little risk that a recording artist is relying on others to record or perform the song for her and simply putting her name on the finished product. Second, data is publicly available regarding the quantity and quality of music output. Except for the SoundScan album count, all of the data on which I rely in the book is publicly available. Anyone can replicate, extend, or if I made a mistake somewhere, correct my results. Third, revenue for the recording industry changes sharply over the period I studied. Moreover, there is both a rise and fall over time. In other copyright industries, one can argue that the rise of file sharing may have slowed the rate at which revenue was increasing. In the recording industry, however, there is a very sharp decline in revenue after file sharing is introduced. Figure 3.6 in the book, reprinted here

as Figure 1, illustrates this sharply changing revenue picture for the recording industry and presents revenue from shipments of recorded music in constant 2013 dollars (“\$2013”).⁸

FIGURE 1. MUSIC SALES (ALL FORMATS) IN THE UNITED STATES (CONSTANT 2013 DOLLARS, IN MILLIONS): 1961-2014



The revenue data in the figure, together with Congress’s decision to establish a second recording copyright for recordings made after February 1972 and the rise of file sharing in 1999, enables us to divide the fifty-four years I studied into four distinct eras. First, we have a low revenue period before the recognition of the sound recording copyright. During this period, from 1961 through 1971, revenue from shipments of recorded music in all formats averaged \$7.6 billion (\$2013) per year. Second, following the recognition of the sound recording copyright, we have a period of relatively steady revenue from 1972 through 1986. While there are some ups and downs in revenue during this period, particularly the odd jump in 1978, revenue during this period averaged a more-or-less steady \$10.9 billion (\$2013) per year. Third, beginning from 1987 through 1999, a combination of law, markets (a favorable economy), and technology (the introduction of the CD) drove revenue to its peak of over \$20 billion (\$2013) in 1999. During this period, revenue was steadily rising and averaged \$16.3 billion (\$2013)—a 50% increase over the 1970s and 1980s, and a 115% increase over the 1960s. Fourth, following the rise of file sharing in 1999, revenue began to decline sharply. By 2014, it had fallen to below \$7 billion (\$2013)—a decline of 66% from its peak and a level not seen since 1966. From 2000 through 2014, revenue averaged just \$12 billion (\$2013) annually—a 26% decrease from the peak revenue 1990s.

8. *Id.* at 81.

With this sharp and dramatic rise and fall in revenue, copyright's fundamental premise suggests that we should see a correspondingly sharp and dramatic rise and fall in the quantity and quality of music output. Yet, we do not. While it is difficult to measure music output in ways that account for changing quantity and quality simultaneously,⁹ the rise of streaming services, such as Spotify and YouTube, offers some of the best evidence. When a Spotify customer chooses to stream one song, rather than another, that provides direct evidence that the customer derives more satisfaction from listening to that song than she would have derived from listening to any other song available on Spotify. With a complete set of the data available to Spotify, we could determine precisely to which songs Spotify customers are listening, how each song's popularity fades over time, and how copyright's incentives are distributed across the songs available through Spotify. If we are serious about designing an efficient copyright system that actually "promotes the progress of Science," such data represents material, indeed critical, information. Unfortunately, Spotify has released only limited data on streaming preferences in a readily accessible fashion.

In the book, I used information Spotify released in 2015 on the top 1,001 songs that appeared on the Billboard Hot 100 before 2006.¹⁰ The information identified the top 1,001 of these songs, based upon their stream count in 2014, each song's worldwide total stream count in 2014, and the year in which each song first appeared on the Hot 100. Using this data, I grouped the songs by the year in which they appeared on the Hot 100 and created a dataset containing song count, total stream count, and average stream count for each year from 1961 through 2005 for these 1,001 songs. I used this data set for two purposes. First, I used it to test copyright's incentives-based premise directly. In this regard, the Spotify data confirmed the conclusion reached using the other three data sets: More incentives did not yield more and better music.¹¹ Second, I also independently used it to verify that each Hot 100 hit generated similar levels of age-adjusted consumer satisfaction.¹² The Spotify data thus established that the

9. See *id.* at 84–85.

10. Matt Daniels, *The Most Timeless Songs of All Time: Using Spotify to Measure the Popularity of Older Songs* (<https://pudding.cool/2017/03/timeless/index.html>) (last visited October 13, 2019) [<https://perma.cc/5866-GPE5>].

11. See LUNNEY, *supra* note 1, at 112–18, 122–33.

12. *Id.* at 118, 129 ("In addition to examining the relationships between revenue, file sharing, and music output directly, the average stream regression results also allow us to reject the hypothesis that the changes in turnover on the Hot 100 chart were due to increased production of a subset of super-popular songs as revenue rose, followed by decreased production of such songs as revenues fell. There is no statistically significant correlation between sales of recorded music in one year and the average number of streams for songs in the top 1001 list the next. This result confirms our preliminary analysis; there was not increased production of a subset of super-popular songs in the 1990. With the 'super-popular song' hypothesis rejected, we can treat a

number of unique songs that appeared on the weekly Hot 100 chart over the course of a year was an unbiased measure of the quantity and quality of music output.¹³

In going back and reviewing my work, I discovered that Spotify not only released data on the top 1,001 songs on the Hot 100 before 2006, but worldwide 2014 stream counts for the top 1,001 songs on the Hot 100 for the 1950s, the 1960s, the 1970s, the 1980s, the 1990s, and the period from 2000 through 2005.¹⁴ From this data, I was able to identify the top 3,823 of these songs,¹⁵ by worldwide 2014 stream count. This more than tripled the number of songs over my original Spotify data set. I grouped these songs by the year on which they first appeared on the Hot 100 chart and determined the total song count, total stream count, and average stream count for each year from 1960 through 2005. I then ran the same regressions I performed and reported in the book using the larger data set to see if anything changed.

Nothing changed. The larger data set confirmed my initial conclusions. More incentives were not correlated with more and better music. More incentives were correlated with less, all else constant. For this essay, I will present the total stream count data from the larger data set to illustrate and reinforce my initial analysis. To begin, Figure 2 presents the total stream count for each year with the larger Spotify data set.

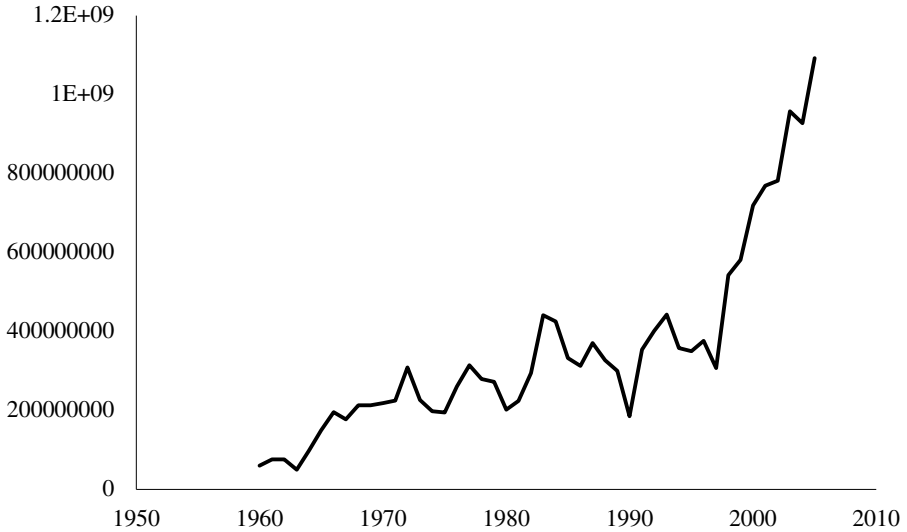
Billboard Hot 100 hit as a consistent and unbiased measure of high quality music output. We can therefore use chart turnover, measured by the number of new songs, on the Hot 100 chart each year as an effective proxy for high quality music output.”)

13. *Id.*

14. *See also* Daniels, *supra* note 10.

15. *Id.* There are five thousand-five songs from 1960 through 2005 in the data. Unfortunately, I could not initially use the whole data set. The data has the top one thousand-one songs from 2000 through 2005 and the top one thousand-one songs from each of the other decades, 1960s, 1970s, 1980s, and 1990s. Because the most popular songs from the 2000s cut off at the thousand and first song, I couldn't be sure where the thousand and second song from the 2000s would fit on the list. The one thousand oneth most streamed song on Spotify worldwide in 2014 from the period 2000 through 2005 was The Christmas Shoes, *New Song*, with 711,122 streams. Thus, only those songs that first appeared on the Hot 100 chart from 1960 through 2005 that had at least 711,122 streams worldwide on Spotify in 2014 made the chart. Of the 3,823 songs that made the list, 976 first appeared on the Hot 100 chart from 2000 through 2005, 962 first charted in the 1990s, 811 first charted in the 1980s, 697 first charted in the 1970s, and 377 first charted in the 1960s.

FIGURE 2. MUSIC OUTPUT: TOTAL STREAMS ON SPOTIFY WORLDWIDE IN 2014 FOR TOP 3,823 SONGS FROM 1960 THROUGH 2005 BY YEAR OF HOT 100 APPEARANCE



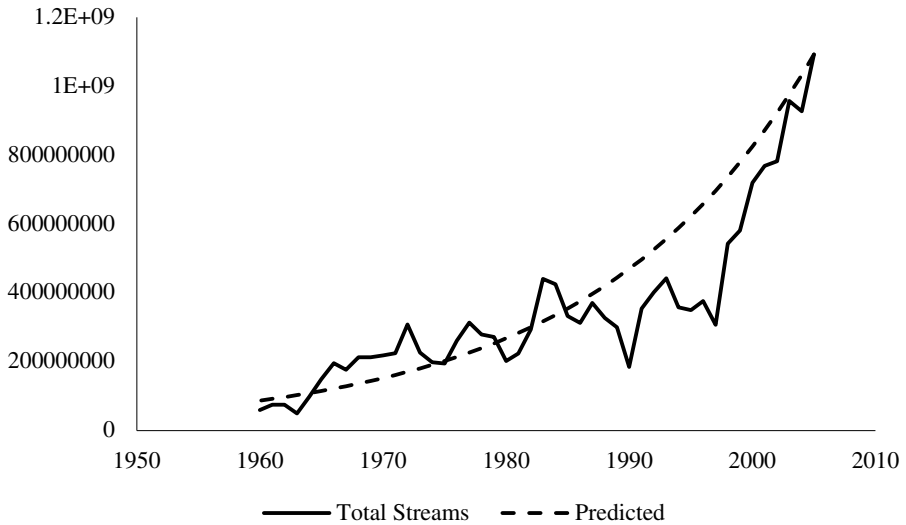
As we saw in the smaller, original data set,¹⁶ there is a time trend in the data. More recent songs received more streams.¹⁷ As with the original data set, even with the time trend, the data visually refutes the correlation copyright's premise insists we must find. The stream count does start to rise sharply in 1998-1999 just as file sharing begins. However, there is no apparent jump in stream count during the 1990s that would correspond to the rise in industry revenue that began in the late 1980s. Nevertheless, in order to use the data set to test copyright's incentives-based premise rigorously, we must go beyond visual appearances. To use the data set for regression analysis, we must first remove the time trend from the data. If we assume an exponential decay in popularity following a song's initial release,¹⁸ then Figure 3 presents the best fit estimate of the predicted total stream count we should expect to see for each year.

16. *Id.* at 112-17.

17. Moreover, some of the most popular artists of the 1960s and the 1970s, including the Beatles and AC/DC, were not available on Spotify in 2014. *Id.* at 112.

18. The exponential decay function, with an adjusted R^2 of 0.922, fits the data better than the cubic and quadratic time functions I used to model a song's popularity over time in the book. The cubic and quadratic time function models had an adjusted R^2 that ranged from 0.612 to 0.643 for the smaller Spotify total stream count data. *Id.* at 225.

FIGURE 3. MUSIC OUTPUT: ACTUAL AND PREDICTED TOTAL STREAMS FOR SPOTIFY TOP 3,823 SONGS BY YEAR OF HOT 100 APPEARANCE

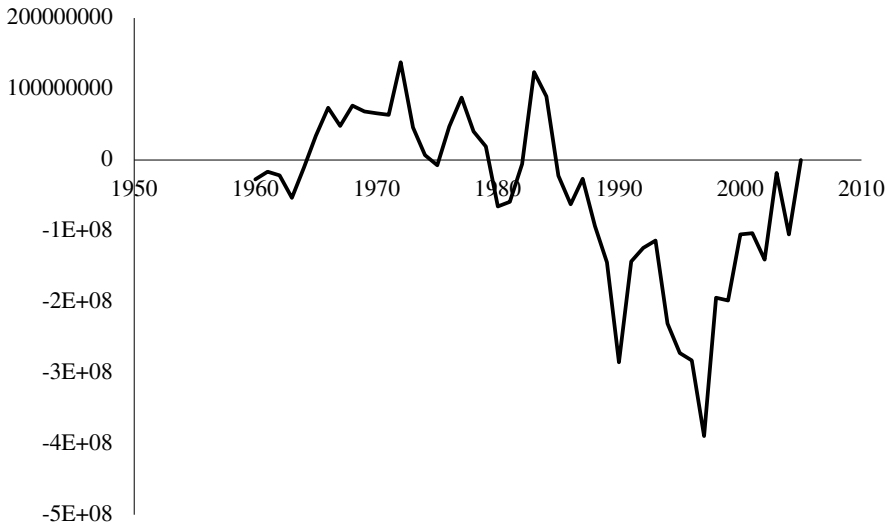


With an adjusted R-squared of 0.922, using an exponential decay function to model the time- or age-based decline in music's popularity provides a good fit to the data. To determine consumers' age-adjusted satisfaction from the top Hot 100 hits in a given year, we subtract the predicted total stream count from the actual. By doing so, we obtain a residual total stream count. This residual count provides a direct measure of the quality and quantity of the most popular music released in each year.¹⁹ If the residual stream count is positive for a given year, then the music from that year was either initially more popular than music from other years, or its popularity decayed more slowly, or some combination thereof. If, on the other hand, the residual stream count is negative, then the music from that year either was initially less popular than music from other years, its popularity decayed more rapidly, or some combination thereof. Thus, the age-adjusted residual provides a direct measure of the quality and quantity of the most popular music produced in a given year.

Using the larger data set, Figure 4 presents the residual total stream count for each year from 1960 through 2005.

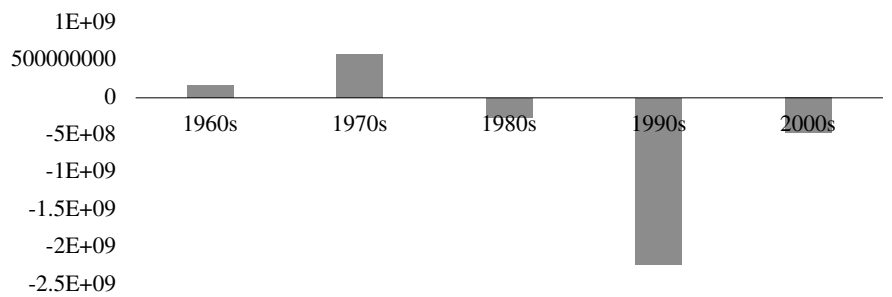
19. See *id.* at 125.

FIGURE 4. MUSIC OUTPUT: RESIDUAL TOTAL STREAMS FOR SPOTIFY TOP 3,823 SONGS BY YEAR OF HOT 100 APPEARANCE



As Figure 4 immediately illustrates, among the four and a half decades the data covers, the 1990s were the worst in terms of the age-adjusted satisfaction derived from listening to music on Spotify in 2014. Either music from the 1990s created less satisfaction among music listeners all along, or the satisfaction associated with 1990s music fell off more rapidly than it did for the other decades, or perhaps, both.²⁰ While Figure 4 plainly reveals the falloff in music quality and quantity during the 1990s, we can illustrate the falloff, perhaps a bit more clearly, by summing the residuals for each decade. Figure 5 depicts the cumulative residuals for each decade.

FIGURE 5. MUSIC OUTPUT: SUMMATION BY DECADE OF AGE-ADJUSTED RESIDUALS FOR TOTAL STREAM COUNTS FOR THE MOST POPULAR 3,823 SONGS BY YEAR OF HOT 100 APPEARANCE

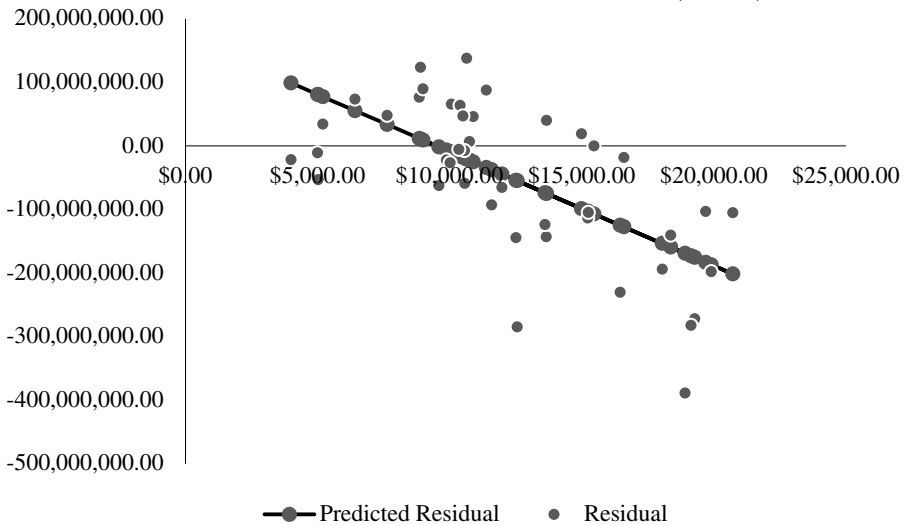


20. If we had a world-wide stream count for the most popular ten thousand songs on Spotify annually based upon streaming in each year from 2006 through 2018, we could determine which. But that data is not yet available.

Like Figure 4, Figure 5 demonstrates that the hit songs from the 1990s provided the least satisfaction to Spotify listeners on an age-adjusted basis in 2014.

Not only are the 1990s the worst visually, but by taking the residual as a direct measure of the age-adjusted satisfaction Spotify customers derived from listening to these songs in 2014, we find a statistically significant and negative correlation (coefficient=-17,0969.7, $p < 0.0001$) between revenue in one year and age-adjusted satisfaction with the music from the next. In other words, higher revenue in one year was associated with music in the next that provided less satisfaction, as measured by Spotify age-adjusted worldwide stream count in 2014, all else constant. Lower revenue, on the other hand, was associated with music that provided greater satisfaction, all else constant. We can illustrate this relationship by using ordinary least squares to regress the actual residual stream count against the previous year's revenue (\$2013). From the results of this regression, we can calculate the predicted residual stream count, or age-adjusted consumer satisfaction with music, as a function of the previous year's revenue. Figure 6 presents the results and plots the actual residual stream count and the predicted residual stream count for each year against revenue (\$2013) from shipments of recorded music in the United States in the previous year.

FIGURE 6. MORE MONEY, LESS MUSIC: ACTUAL AND PREDICTED RESIDUALS AS A FUNCTION OF THE PREVIOUS YEAR'S REVENUE FROM SHIPMENTS OF RECORDED MUSIC (\$2013)



As Figure 6 illustrates, there is a negative correlation between industry revenue in one year and music output in the next. When industry revenue was high in a given year, consumers derived less age-

adjusted satisfaction from the music released in the next. When it was low, they derived more. Using this larger Spotify data set, we reach the same conclusion that I reached with the smaller Spotify data set and with the three other measures of music output in my book. In the United States recording industry, more incentives in one year were associated with less and lower quality music in the next, all else constant.

This suggests that copyright, at least in the recording industry, has been nothing but theft. Because of copyright, consumers paid the recording industry vastly more money in the 1990s than in the 1960s, 1970s, 1980s, or 2000s for recorded music. Compared to the other decades, the more effective copyright of the 1990s took between \$43 and \$83 billion (\$2013) out of consumers' pockets and gave it to the recording industry. In return for that substantial wealth transfer, copyright promised those consumers more and better music. However, copyright failed to keep its promise. Indeed, rather than receive more and better music in return for that very large wealth transfer, music lovers received less and lower quality music. Copyright took money from music consumers and gave them nothing, indeed, less than nothing in return.

The question then becomes: Why did more incentives lead to less music? While the available data could not answer that question completely, it did suggest an important part of the answer: the distribution of demand and hence the distribution of incentives that copyright generates for the recording industry are highly skewed. The markets are not quite winner-take-all, but they are certainly winner-takes-most. The top 1% of the artists take home somewhere between 40 and 90 percent of the revenue.²¹ As a result, instead of going to the marginal artist or work, most of the incentives copyright provides go to overpaying our most popular superstars.

This creates two distinct problems. First, by providing very little in the way of incentives to works of authorship at the margins of profitability, copyright fails to encourage the authorship and distribution of additional original works at those margins directly. Instead, copyright primarily ensures that consumers will overpay for the most popular works—works that would have been produced in any event with no or far less copyright protection. This is not merely wasteful. Rather, it

21. See BUZZ ANGLE MUSIC, 2018 YEAR-END REPORT 31-33 (2018), <https://www.buzzanglemusic.com/wp-content/uploads/BuzzAngle-Music-2018-US-Report-Industry.pdf> [<https://perma.cc/BJ66-Z3DM>] (showing that: (i) the top 0.39 percent of albums accounted for 61.3 percent of total album sales in 2018; (ii) the top 0.75 percent of songs accounted for 76.5 of song sales; and (iii) the top 1.38 percent of songs accounted for 92.4 percent of the streams); *Performing Rights, MONOPOLIES AND MERGERS COMM'N* 65 (1996) (for the performing rights society in the United Kingdom in 1993, "the highest-earning 1.3 per cent of PRS writer members received nearly 41 per cent of comparable distributions, and the highest-earning 19.5 per cent accounted for some 92 per cent.").

creates the second problem: overpaying our most popular authors and artists, like other forms of monopoly rents, imposes significant social costs. In addition to the familiar deadweight and rent-seeking losses associated with monopoly rents, it can also push our most popular superstars onto the backward-bending portion of the labor supply curve.²² When it does, copyright directly reduces the creative output of our most popular authors and artists. Thus, copyright fails to provide much encouragement to the average work at the margins of profitability and actively discourages our most popular artists and authors from working hard.

Both of these problems arise because copyright provides the same protection to the marginal and non-marginal works alike. If a work at the margins of profitability needs one more year of copyright protection to achieve expected profitability, then to give that marginal work one more year of protection, copyright also gives the non-marginal work one more year of protection. So long as copyright protection remains uniform, copyright will continue both: (1) to fail at encouraging additional works at the margins; and (2) to force consumers to overpay for the most popular works.

Consider a simple example. Imagine that we have two artists, TS and KP. Each has a song she would like to release at an expected cost of \$1. As it turns out, TS's song will prove more popular than KP's and will outsell it at a ratio of 10 to 1.²³ In a world without any copyright at all, TS expects to earn exactly \$1 from releasing her song.²⁴ Given the popularity ratio, KP expects to earn \$0.10. Under these assumptions, TS will expect to cover her costs for releasing her song²⁵

22. As I explain in the book,

The backward-bending labor supply curve arises from the interaction of two, countervailing marginal effects. When wages are low, an initial wage increase leads individuals to devote more time to working, as the higher wage leads individuals to substitute work for leisure (the "substitution" effect). As wages continue to rise, however, higher wages generate higher income, which leads in turn to increased demand for a variety of goods including leisure (the "income" effect). Once wages increase to the point where the desire for leisure from the income effect outweighs the desire for work from the substitution effect, further wage increases actually lead to less time spent working. At that point, the labor supply curve begins to bend backward.

See LUNNEY, *supra* note 1.

23. As I showed, the actual ratio between the incentives copyright provides the most popular work and the incentives it provides the average or marginal work is far higher than ten to one. See *id.* at 20–22 (calculating a ratio of between 1147.34:1 and 66,666.67:1).

24. The most commonly offered reason why TS might earn some revenue in the absence of copyright is lead-time advantage. It takes some time for would-be competitors both to discover which songs to copy and then to make those unauthorized copies available. A better reason is that consumers know it is in their self-interest to support the artists whose music they love. Otherwise, those artists will not produce music. Thus, consumers will often pay for music even when they could obtain an unauthorized copy for less, or even, for free.

25. Costs include a reasonable return on TS's investment.

and will therefore release it even without copyright. In that sense, TS's song is non-marginal. It does not need copyright to ensure its expected profitability and hence release. Under the assumptions we have made, it will be authored and distributed with no copyright protection at all. KP, on the other hand, does not expect to cover her costs in the absence of copyright and hence will not release her song. In that sense, KP's song is marginal. It needs copyright to ensure its expected profitability. If we could provide KP with exactly that copyright protection necessary for her to cover her reservation costs, without providing any copyright protection to TS's song, that would represent a straightforward Pareto improvement. However, that is not what copyright does. If we give one-year of copyright protection to KP's song, then we also give it to TS's song.

As a result, if we enact a short and relatively narrow copyright regime that would double KP's expected revenue from \$0.10 to \$0.20, that regime would still not provide sufficient incentive to KP to ensure her song's release. Such a copyright regime would fail to provide sufficient incentives to the marginal work and hence fail to increase creative output at the margins directly. At the same time, enacting such a copyright regime would double TS's expected return from \$1 to \$2. However, overpaying TS will not increase creative output. Under our assumptions, TS would cover her costs and thus release her song even without copyright. Giving her song copyright protection ensures only that TS will recover twice her expected cost. Providing TS with even a short and narrow copyright merely forces consumers to overpay TS for her song. Perhaps more copyright is the answer. But let us assume that even if we enacted the broadest and longest possible copyright regime, that regime would increase KP's expected revenue by 800%, from \$0.10 to \$0.90. Under that assumption, even the broadest possible copyright would still not provide sufficient incentive to KP to ensure her song's release. However, it would vastly increase the extent to which music lovers are overpaying for TS's song.

Of course, there are stories we tell ourselves as to why overpaying TS might lead to more and better music. Maybe we cannot tell *ex ante* whether TS or KP's song will prove more popular. Maybe overpaying TS will lead to a larger pool of TS wannabes competing to become the next TS, thereby ensuring that we get the best superstars moving forward. Maybe a record label is funding both songs and will use the excess profits from TS's song to cover its losses on KP's. Maybe. But these are just stories, and unfortunately, they do not hold up in the face of empirical testing. As I discussed in the book, the decisions of artists and record labels as to which songs to include on an album and which singles to release and in what order establishes that artists and record labels have pretty good *ex ante* information on which songs will

become hits.²⁶ Moreover, the data establishes that more revenue to the music industry did not lead to more and better hit songs, new artists, or increase artist productivity moving forward. Thus, while the copyright as lottery and copyright as cross-subsidization mechanism may be good stories, the data does not support them.

In my book, I did not test whether more industry revenue led to more superstars directly. I tested only for a correlation between revenue and the number of new artists who charted at least once on the Hot 100.²⁷ Yet, it is easy enough to use the data I gathered and to extend the methodology I used to test whether there is a correlation between revenue from shipments of recorded music and superstar creation. To distinguish the true superstars, let us define a superstar recording artist as one that has ten Billboard Hot 100 hits, as principal artist,²⁸ in the first ten years of their career.²⁹ Given that definition, we can count the number of superstar artists and group them by the year they had their first Hot 100 hit. Doing so gives us Figure 7.

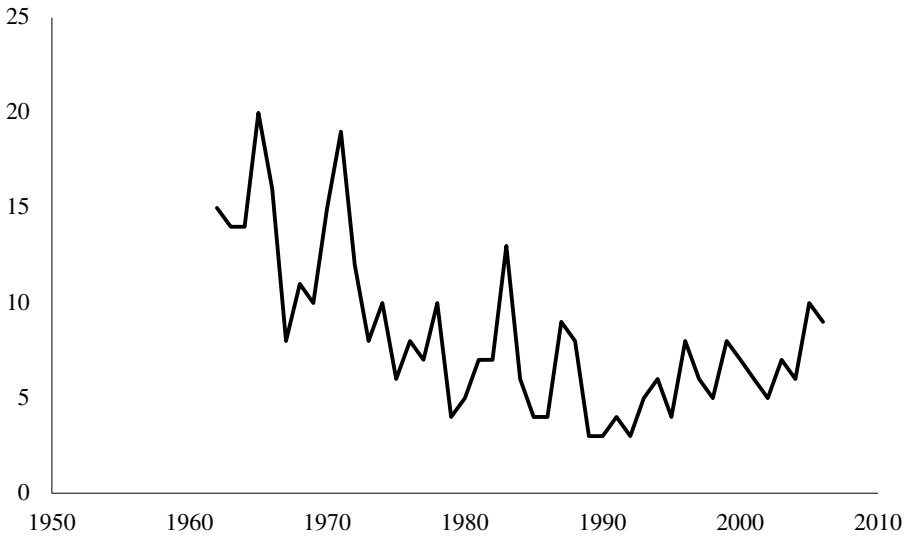
26. *See id.* at 50–53.

27. In the book, I tested for and did not find a statistically significant correlation between revenue in one year and the number of new artists making their first appearance on the Hot 100 chart in the next. *Id.* at 99–102, 141–42.

28. I do not count appearances as featured artist in the analysis for several reasons. First, any productivity measure must begin with a unit of work or production. The work of a principal artist is different from the work entailed in an appearance as a featured artist. Second, there is a sharp rise in featured artist appearances that begins on the Hot 100 charts in the mid-1990s. In the ten-year period from 1985 through 1994, there were, on average, 18.3 songs with featured appearances on the Hot 100 chart. A rise that began that plateaued in 2003. Following that rise, in the twelve-year period from 2003 through 2015, there were, on average, 190.3 songs with featured appearances on the Hot 100 chart. Whether the increase in featured appearances reflects the rise of hip hop, technological developments, or something else is unclear. Yet, if I count appearances, rather than appearances as principal artist, that would bias the productivity data towards artists that first appeared on the Hot 100 chart after the rise in featured appearances began.

29. I have also performed the same regressions defining a superstar as an artist who has five Hot 100 singles as the principal artist in the first ten years of their career. Same results. More revenue was negatively and statistically correlated with the number of such superstars.

FIGURE 7. SUPERSTAR ARTIST COUNT: BY YEAR, 1962–2006

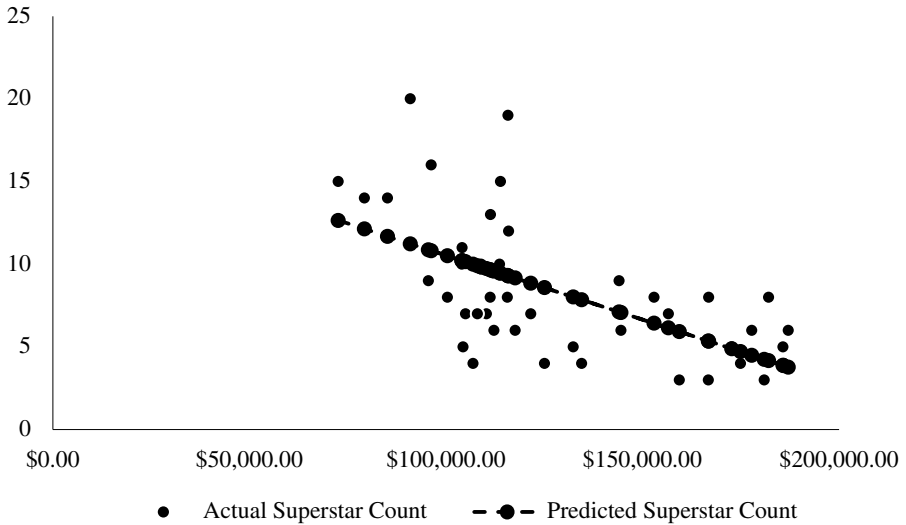


With this count, we can use a regression analysis to test whether overpaying our superstars in one year led to more and better superstars in the next. To do so, I regressed the number of superstars in each year against the ten-year industry revenue³⁰ (\$2013) from shipments of recorded music beginning the year before the year at issue.³¹ Doing so, I found a negative and statistically significant correlation (coefficient=-0.000078, $p < 0.0001$) between the ten-year industry revenue in one year and the number of superstars who had their first Hot 100 hit the following year. At least for the United States music industry since 1962, the story that overpaying superstars such as TS will lead to a larger pool of TS wannabes and thus more and better superstars in the future proved false. The more we overpaid our superstars in one year, the fewer superstars we got in the next, all else constant. Figure 8 illustrates these regression results by plotting the number of superstars in a given year against the ten-year industry revenue beginning the year before.

30. I use a ten-year period to correspond to the ten-year period in which I am counting to see if an artist has had ten Hot 100 hits. The results are the same if I switch to a five-year period for both revenue and Hot 100 hits.

31. I have done both the five- and ten-hit superstar regressions against both one-year and ten-year industry revenue. All four regressions yield a negative and statistically significant correlation between revenue and the number of superstars. I report the results for the ten-year industry revenue regression in the text because it had a higher adjusted R^2 .

FIGURE 8. MORE MONEY, FEWER SUPERSTARS: ACTUAL AND PREDICTED SUPERSTAR COUNT AS A FUNCTION OF TEN-YEAR INDUSTRY REVENUE (IN MILLIONS, \$2013)



As Figure 8 reveals for the recording industry from 1962 through 2006, more revenue to the industry did not lead to more superstars. As the ten-year revenue rose for the recording industry, the number of new superstars fell, *ceteris paribus*.

Taken together, this new data and the data I presented in *Copyright's Excess* establishes that Congress should abolish the sound recording copyright now. As it stands, the sound recording copyright has used the threat of government force to take billions of dollars from the pockets of music consumers and give it to a relative handful of superstar artists, producers, and record labels. In return for this vast wealth transfer and despite copyright's promise, music lovers did not receive more and better music. They received less and worse.

II. YOUR QUESTIONS AND CONCERNS ADDRESSED

As I have presented my research and results, a number of questions and concerns have arisen. The first concern is the data and the conclusions that I draw. The second concern is the applicability of the approach to other issues in copyright. The third concern is whether the incentives-based view of copyright is the only viable perspective.

A. *The Data is Not Perfect and Also Not Complete But Supports My Conclusions*

With respect to the data, I am the first to admit that the data is imperfect and incomplete.³² On the revenue side, I do not have income data for individual artists, nor do I have data for every source of revenue for the industry as a whole. As a result, I rely on the RIAA's reported shipments of recorded music both as a measure of revenue to the industry, as a whole, and as a proxy for the effective wage a top artist will receive for releasing a hit song. Some of the concerns raised, such as the labels obtaining ownership shares in Spotify in return for licensing their copyrighted content, are both too small in dollar value and too far outside the time period studied to prove worrisome.³³ However, others are more problematic.

Professor Rub, for example, questions whether sales of recorded music are a good proxy for the income of the top artists. Particularly, in the post-file sharing era, artists and record labels have focused more on touring and other revenue sources in order to replace lost sales.³⁴ The nature of a record deal has also changed. Labels now insist new artists sign 360 degree deals, where the label gets a cut of all of the artist's revenue, whatever the source. Because of these changes, Professor Rub worries that there may not be the same relationship between individual artist income and industry revenue across the study's time-frame. Importantly, even if Professor Rub were right, this concern would not be not relevant for my empirical tests of copyright's fundamental premise. In testing whether more incentives lead to more and better music, overall industry revenue is the measure we want to use. If there is a change in the relationship between industry revenue and top artist income, that may, however, be relevant to the mechanism I propose to explain the negative correlation the data shows. Another concern I have heard is that the revenue peak in the 1990s was due to consumers buying CDs to replace deteriorating vinyl collections.³⁵ In contrast to Professor Rub's concern, this concern

32. See LUNNEY, *supra* note 1, at 119–20.

33. Warner Music Group, for example, sold its stake in Spotify in 2018 for \$500 million. See Jem Aswad, *Warner Music Group Sells its Entire Stake in Spotify*, VARIETY (Aug. 17, 2018) <https://variety.com/2018/biz/news/warner-music-group-sells-entire-stake-in-spotify-1202897605/> [<https://perma.cc/G932-VAD9>]. On the revenue side, the study time period ended in 2014 because of the one-year time lag. Moreover, in the face of a decline in annual sales of recorded music from just under \$21 billion (\$2013) in 1999 to just under \$7 billion, a one-time \$500 million cash infusion is a drop in the bucket.

34. I acknowledge these other revenue sources in the book. See, e.g., LUNNEY, *supra* note 1, at 77.

35. In raising this concern, the implicit assumption must be that revenue from such replacement purchases would play no role in incentivizing the production of new music. In that sense, the second point, even if true, only supports my thesis that most of the incentives copyright generates do not go towards encouraging the creation of additional new music at the margins.

goes both to my test of copyright's fundamental premise and the mechanism I propose to explain the negative correlation between incentives and music output.

Fortunately, data can address both concerns. While not complete or perfect, the available data tends: (1) to suggest that overall industry sales are a rough, but workable, proxy for top artist income; and (2) to reject the second point. In my book, Figure 6.5 shows, according to publicly available SoundScan data, the fraction of total albums sales that the top ten best-selling albums captured each year from 1998 through 2015.³⁶ If the hypothesis that sales peaked in the 1990s because people were replacing their vinyl collections with CDs were true, then we would expect the top ten albums to capture a smaller percentage of total album sales in the 1990s than they did in the post-file sharing era. But they did not. In the three years from the 1990s for which SoundScan data is available, 1997–1999, sales of the top ten albums captured 6.44% of total album sales. In contrast, in the post file-sharing era, from 2000–2015, the top ten albums captured 4.88% of total album sales. If anything, this suggests that the decline in industry sales revenue from just under \$21 billion (\$2013) in 1999 to just under \$7 billion (\$2013) in 2014 was first, not due to the replacement of vinyl records with CD hypothesis, and second, understates the loss in income, at least from record sales, for the top artists.

Certainly, I would like to have additional and better data. In particular, the rise of the artist as a brand in the post-file sharing era seems a critically important piece of the revenue story. Yet, the question in the end is not whether the revenue data is perfect. Real world data never is (unless falsified). Instead, the question is whether the revenue data captures, albeit roughly and imperfectly, something real—that revenue for the industry and for the top artists generally rose from the 1960s through the 1990s and then, with the introduction of file sharing, began to fall. In this respect, even Professor Rub concedes that the movement in the industry revenue from sales of recorded music is both too large and too long-term to be discounted entirely. It may be, for example, that concert revenue jumped from \$2.3 billion (\$2013) in 2000 to \$5.1 billion in 2013, as Pollstar data shows.³⁷ It may also be that artists' share of total revenue increased from 8% in the late 1990s and early 2000s to 12% after 2008.³⁸ Even so, total revenue in 2000, consisting of \$19.7 billion in sales revenue and \$2.3 billion in concert revenue, was \$22.0 billion. 8% of that is \$1.76 billion. In contrast, total revenue in 2013 was only \$12.2 billion,

36. See LUNNEY, *supra* note 1, at 186.

37. Amy Watson, *Concert Ticket Sales Revenue in North America from 1990 to 2017*, STATISTA.COM, <https://www.statista.com/statistics/306065/concert-ticket-sales-revenue-in-north-america/> (last edited Aug. 26, 2019) [<https://perma.cc/CN4N-PEFC>].

38. Guy A. Rub, *Incentivizing Top-Musicians*, _ TEX. A&M J. PROP. LAW _ (forthcoming 2019) (manuscript at 9) (on file with periodical).

consisting of \$7.1 in sales revenue and \$5.1 billion in concert revenue. 12% of \$12.2 billion is only \$1.46 billion. Even with increased concert revenue and an increased share of total revenue, artist income still dropped from 2000 to 2014 by 17.4%. While not quite as dramatic as the drop in sales revenue for the industry as a whole over that period, the revenue data for the industry as a whole undoubtedly captures something real about changes in top artist income as well. It may be that the increase and decrease in top artist income did not precisely match the increase and decrease in industry revenue, but it likely followed the same general trend.

Moreover, two other points deserve particular emphasis. First, most of the changes in the industry's revenue structure arose as attempts to replace lost revenue following the rise of file sharing. As Professor Rub admits,³⁹ the increasing importance of touring, the increasing reliance on licensing revenue from the artist as brand, and the rise of 360 degree deals all began or accelerated in the mid-2000s. These changes come too late to undermine the regressions using the Spotify data. As discussed, the Spotify data sets only cover music that was released and hit the Hot 100 chart before the end of 2005. Whatever changes occurred in the revenue structure of the music industry after 2005 could play no role in explaining why music from the 1990s was disproportionately unpopular on Spotify in 2014. The Billboard Hot 100 data set, on the other hand, does extend through 2015. This raises the possibility that changes in the industry in the post-file sharing era may undermine our confidence in the regression results from that data set. Yet, if we are concerned that revenue structure changes post-2000 are material, we can simply omit that data from the regressions. Indeed, I have already done so. For both the Spotify and the Hot 100 chart data sets, I have cut-off the data in 2000 and simply re-run all of the relevant regressions. This permits a more direct apples-to-apples comparison, of the low revenue 1960s, through the mid-revenue 1970s and 1980s into the peak-revenue 1990s. While changes occurred in the industry during these forty years, they were less dramatic than those we witnessed as the industry struggled to deal with file sharing. When we re-run the regressions using the Spotify and the Hot 100 data sets, with the data cut off in the year 2000, the results remain the same. None of the regressions found a statistically significant and positive correlation, from the 1960s through 2000, between industry revenue and music output. To the contrary, and once again, where a statistically significant correlation between revenue and music output was found, it was negative.

Second, it is true that some of the data I would like to have to clarify the picture is simply not publicly available. However, that should not be used as a whip to beat my study. Rather, it should be used to

39. *Id.* (manuscript at 10–11).

force those who have that information to release it. Or if they refuse, to presume, as we do elsewhere in the law,⁴⁰ that the information would prove adverse to their position. As I have argued elsewhere, when copyright owners and industry players come to Congress, the courts, or an administrative agency and ask for help in expanding or enforcing copyright, they should first have to provide the information we need to resolve these issues rationally.⁴¹ How much money does copyright generate? To whom does it go? What does the public receive in return? I have measures of the satisfaction consumers derived from streaming nearly four thousand songs in one year, 2014, on one platform, Spotify. ASCAP, BMI, SESAC, Sound Exchange, and other market intermediaries have that data for every year and every song. To design a rational copyright regime, we need that data. As a result, when these entities come before, for example, the Copyright Royalty Board insisting that they need a higher royalty rate on streaming, the public is entitled to know what, if anything, the public has received for the rates the Board has approved in the past. There should be no copyright legislation, and indeed, no enforcement of the existing copyright regime, without full disclosure of how much incentives copyright generates, where they go, and what copyright and those incentives have bought us in terms of increased creative output.

With respect to the data, I have also heard the concern that the measures of music output are not perfect. With respect to the Hot 100 data, I have heard the concern that the unique song count for each year is not a reliable measure on its own of the quality and quantity of music output. I addressed this concern in the book,⁴² but will revisit it briefly. A bestsellers chart of any sort measures relative quality, not absolute quality. As a result, turnover on the chart, and hence the number of unique songs that appear on the chart in a given year, depends on the density of music output. If the release of a large number of songs of similar quality occurs in a year, density, and hence turnover, on the chart will be high.

This creates two types of problems with using a count of the number of unique songs that appear on the Hot 100 chart in a year as a proxy for the quantity and quality of music output in that year. First, turnover will be high so long as a large number of similar quality songs are released, whether the quality of those songs is high, low, or somewhere in between. In other words, if song density is high, a measure

40. Such a presumption has longstanding roots in the Anglo-American legal system. See *Armory v. Delamirie* (1722) 93 Eng. Rep. 664; 5 Strange 505 (“[T]he Chief Justice directed the jury, that unless the defendant did produce the jewel, and shew it not to be of the finest water, they should presume the strongest against him, and make the value of the best jewels the measure of their damages: which they accordingly did.”).

41. Glynn S. Lunney, Jr., *Copyright and the 1%*, 23 *STAN. TECH. L. REV.* _____ (forthcoming 2020).

42. See LUNNEY, *supra* note 1, at 97–99, 118, 129, 219–23.

of turnover such as a unique song count will also be high, whether the songs cluster around a high-quality or low-quality point. Second, and alternatively, using a unique song count may also lead us to infer that music output is increasing or decreasing when it is not. For example, the unique song count will decrease when density decreases. This may reflect a decrease in music output, but it may not. Density will also decrease when the quality of the best songs increases, reducing the extent to which the top songs cluster around a given quality level. In the book, I describe this possibility as the “super-popular” song hypothesis.⁴³ While these are real concerns, I addressed them in the book by using an external measure of peak song quality to ensure that the unique song count was not being driven by changes in the quality around which the top songs clustered.⁴⁴ Specifically, I used the average stream count data from the Spotify data set to show that the top Hot 100 hits from each year from 1962 through 2005 generated a similar level of age-adjusted satisfaction based upon streaming on Spotify in 2014. This allows us to use the unique song count from the Hot 100 chart as an unbiased measure of music output. With external verification of the absolute quality of the top Hot 100 hits across the time period, a higher unique song count in a year reflects greater density around a given peak quality, and hence higher music output in that year. A lower turnover or unique song count reflects lower density around the same peak quality, and hence lower music output.

With respect to the Spotify data, the concern that I have heard is that the Spotify stream count is biased by a generational issue. People who were young and therefore loved the music from the 1960s, 1970s, and 1980s, have grown up, had children, and shared their love for that music with their children. As a result, songs from those decades are disproportionately popular on Spotify in 2014 because they have two generations streaming them. In contrast, the generation that grew up loving the music from the 1990s has not yet had children, or at least, not children old enough to stream separately on Spotify. As a result, music from the 1990s is disproportionately unpopular because it has only one generation listening to it. I am not sure that the generational math quite works out that way. I am even less sure that parents are always successful in imparting their musical tastes to their children. But let us put those uncertainties aside.

Even if this generational issue is real, I have three responses. First, in the book, the cubic and quadratic functions I use to adjust the total stream count, song count, and average stream count for Spotify listeners' preference for newer music should correct for any such bias.⁴⁵ Moreover, in all of the more serious regressions in Chapter 5, I use the

43. *See id.* at 118, 129.

44. *See id.*

45. *Id.* at 115–18.

population of 15 to 19 year-olds as an explanatory variable.⁴⁶ It was never statistically significant.⁴⁷ Thus, even if the generational issue is real, I have accounted for it. Second, if the generational issue is real, it concedes my point. If people always like the music to which they listened in their teens or twenties—their peak courtship years, then there is no reason to expect that more money will ever yield more and better music. Our like or dislike of particular songs will be driven by what was otherwise going on in our lives when we first heard the song rather than the song's intrinsic quality. Third, more data can resolve this issue. If we had similar Spotify data on these songs from 2009 and 2019, rather than just 2014, then we would be able to determine whether a generational bias exists, and if so, its nature and extent. So once again, beating on my study for not gathering unavailable data is not the answer. Placing the burden of proof on those who have the relevant data is.

The last concern that I have heard is that some readers refuse to accept what the data is saying. If it does not confirm their *a priori* beliefs, then it cannot be true. Professor Rub, for example, insists that the backward-bending labor supply curve cannot explain the falloff in top artist productivity as revenue rises.⁴⁸ In his view, all of these top artists are so rich that they must work, not for money, but for the intrinsic satisfaction work brings.⁴⁹ But I believe that Professor Rub, and the studies he cites, mistakes observational bias for a universal truth. It is undoubtedly true that some wealthy people continue to work. It is also equally true that some wealthy people do not, or at least do not continue to work as hard. As I note in the book, Justin Bieber announced his retirement at age nineteen.⁵⁰ If you conduct a study to determine why the wealthy continue to work, then the study design necessarily limits the observational sample to those wealthy who continue to work. It necessarily omits those wealthy who do not continue to work. As a result, what you see in the study are the reasons some wealthy continue to work. You miss entirely the reasons why some wealthy do not.

It is undoubtedly true that intrinsic motivation plays an important role in creative output, particularly for those artists that we observe continuing to work even after they become wealthy. I state as much in the book.⁵¹ The question is whether money matters as well. On this question, the data produced a single, consistent answer: Money also matters. Every regression I ran confirmed a negative and statistically significant correlation between higher industry revenue and re-

46. *Id.* at 126–28, 136, 140.

47. *Id.*

48. *See* Rub, *supra* note 38, at 12–16.

49. *Id.*

50. LUNNEY, *supra* note 1, at 183.

51. *Id.* at 119–20 (noting that money, even if it is not the sole factor, matters).

duced productivity by the top artists.⁵² Now, the adjusted R-squared for these regressions was only 0.373 to 0.484.⁵³ In other words, variations in industry revenue explained less than half of the observed variation in productivity. That leaves plenty of room for varying levels of intrinsic motivation, talent, and other factors to matter as well. But this is not the result we would expect to find if the income for the top artists were so high that it no longer mattered at all. If these artists were so wealthy that money no longer mattered to any of them, there should be no relationship between revenue and productivity, just random noise.⁵⁴ Yet, that is not what we find.

Professor Rub's concerns do suggest an alternative to the backward-bending labor supply curve as an explanation for the consistent negative correlation between revenue and top artist productivity. Perhaps, when industry revenue rises, more of the top artists enter the field specifically for the money. Because these artists make music for the money, rather than for the intrinsic satisfaction of making music, they stop making music when they have enough money.⁵⁵ In contrast, in periods of low revenue, only those who truly love making music for its own sake enter the field. As a result, artists from those low revenue eras, such as the Beatles and Taylor Swift, continue to produce even after they become wealthy.

In the end, however, the appropriate policy response does not change regardless of whether the negative correlation arises from a backward-bending labor supply curve, a trade-off between extrinsic and intrinsic motivation as revenue rises or falls, or for some other reason entirely. Too much money, particularly too much money for the top artists, reduced music output. Therefore, we need to change the copyright regime to reduce the money flowing to the top artists.

B. *Can This Approach Answer All of Our Copyright Questions?*

Professor Bartow has an entirely different question: can this sort of rigorous empirical approach answer all of our copyright questions? She specifically wants to know if it can provide us guidance on the termination right. That is not an issue that I set out to explore in the book, but rigorous empirical analysis can answer at least three key

52. *Id.* at 103–04, 163–68.

53. *Id.* at 164.

54. *Id.* at 158.

55. Of course, this cannot be a complete explanation. If both intrinsically and extrinsically motivated artists enter the field in periods of high revenue, the intrinsically motivated would remain as the extrinsically motivated fall away. As I explain in the book, during periods of high revenue, the top ten new artists from the late 1980s through 1999 had low productivity in terms of Billboard Hot 100 hits as principal artist in the first ten years of their career across the board. See LUNNEY, *supra* note 1, at 167, 179. So, we would need to combine a switch in motivation with a crowding out story as well. In periods of high revenue, more extrinsically motivated artists enter the field and crowd out the more intrinsically motivated artists.

questions regarding the termination right if we can get the data. First, it can tell us something about whether, and to what extent, the availability or exercise of the termination right affects the initial creation and release of original works of authorship. Second, it can tell us something about whether the exercise of the termination right affects the re-release of original works of authorship that had become unavailable with the passage of time. Third, it can tell us how the incentives from the availability or exercise of the termination right are distributed. For example, does it simply make superstar artists and authors, who are already rich, that much richer? Or does it also help the average or marginal author? If so, what is the relative distribution of rents between those groups?

Between these questions, the data I gathered for my book can be used to answer only part of the first question. Specifically, I can look to see if there was a change in music output in 1978 when Congress enacted the termination right in section 203 of the Copyright Act of 1976.⁵⁶ While there are a variety of modeling techniques I could use to do so, the simplest is to add an instrumental variable to my existing regression models for the creation of the termination right. The instrumental variable is set to zero for the years before 1978 and set to one in and after 1978.⁵⁷ When I do so for the larger Spotify data set that I presented in Section I above, the establishment of the termination right in 1978 did not show a statistically significant correlation (coefficient=-6.8E07, $p=0.077$) with music output.

That the correlation is not statistically significant here is not as helpful as it was when even very sharp changes in industry revenue showed no statistical correlation with music output in the book.⁵⁸ At best, it could mean that the recognition of the termination right has no effect on the relationship between incentives and music output. In other words, taken at face value, the result suggests that the recognition of the termination right is purely a distributional issue. The termination right may control who, as between artist and record labels, receives the rents for songs that remain popular after thirty-five years (more or less), but it has no effect on music output at the outset. This would still leave important questions unanswered. For example, it only tests for recognition of the right, not its actual exercise. Because

56. 17 U.S.C. § 203 (1976).

57. This approach tests all of the changes wrought by the Copyright Act of 1976 at one time. Thus, it not only tests for whether the recognition of a termination right was associated with a change in music output, but also whether the longer copyright term that that 1976 Act adopted was associated with a change in music output. Moreover, the approach cannot separate the potentially conflicting effects various changes to the scope and duration of copyright protection may have had on creative output.

58. See LUNNEY, *supra* note 1, at 130 (“If we cannot find any relationship between changes in revenue and changes in music output, in the face of these substantial changes in revenue, then that itself is compelling evidence that copyright’s fundamental premise was not true.”).

the section 203 termination right could not be exercised until 2013, and my data ends in 2015, I have too little data to test whether the actual exercise of the termination right, as opposed to its recognition by Congress, had any effect on music output. More realistically, the lack of statistical significance may suggest that the output effect is too small to be measured given the limitations of our data.

Nevertheless, Professor Bartow is exactly right to ask the question she does. The broader point that I am trying to make in the book is that we, as lawyers, should stop relying on bedtime stories. The scientific method has been known and available for hundreds of years. There is no excuse for lawyers, or at the very least legal academics, not to apply it to rigorously test the stories we tell. Does copyright mean more incentives for copyright owners? Do more incentives mean more original works? Instead of assuming the answers to these questions, we should empirically test them. The answers, as my book suggests, may surprise us.

C. *What If I Do Not Believe in Incentives-Based Copyright?*

Professor Rosenblatt makes a third type of argument: incentives are not the sole justification for copyright. For her, even if I am right, that would not necessarily justify abolishing the sound recording copyright. Other considerations (in her case, social and distributive justice) might support either the existing sound recording copyright or at least some version of it. In the book, I frankly acknowledge that I was not going to explore these alternative excuses for copyright.⁵⁹ “Eat what you kill” or “reap where you have sown” may masquerade as natural rights or deontological reasoning, but they rely in truth on a not very well hidden consequentialist impulse. The underlying assumption is that following either rule puts more food on the table.

As for Professor Rosenblatt’s distributive justice approach, it always startles me that anyone could believe that copyright could be an effective tool to promote social or distributive justice. Anyone who has spent any time on a movie set will know that the societies that form on them are some of the least egalitarian societies in existence. A stark hierarchy exists between the big, name stars and directors and everyone else, and that hierarchy is ruthlessly enforced. It is no coincidence that the #me-too movement grew to prominence when it began to focus on the copyright industries.

We can, of course, tell stories about how so-and-so escaped a life of poverty and became a rich and successful big-name star. Is it not wonderful how copyright can promote social mobility in that way? But one of the main points of my book is to grow up and move beyond stories and anecdotes. If you look only at the king, life in a feudal monarchy does not seem so bad. Empirical analysis provides concrete

59. *See id.* at 56–57.

and comprehensive measures that can enable us to test whether more or less copyright would lead to more or less distributive equity, not just for this or that individual, but for society as a whole.

In this regard, economists typically rely on the Gini coefficient⁶⁰ as a measure of the extent to which income in a society is evenly distributed. In a society where everyone receives exactly the same income, the distribution of income in the society is perfectly even, and the Gini coefficient would be zero. In a society where one citizen earns everything, and no one else earns anything, the distribution of income is perfectly uneven, and the Gini coefficient would be one or one hundred percent. If we look at the world today, some countries have more income inequality. The Gini coefficients for these countries, countries such as Haiti, Lesotho, and South Africa, is over 60%.⁶¹ In others, income is more equally distributed. These countries, such as Germany, Norway, and Sweden, have Gini coefficients under 30%.⁶² The Gini coefficient for family income in the United States is 45%, falling between Iran at 44.5% and Saudi Arabia at 45.9%.⁶³

The empirical question Professor Rosenblatt is implicitly asking is whether having more of the national income in the United States run through the copyright regime would increase or decrease the Gini coefficient for the United States. While I did not attempt to answer this question in my book, empirics provide an unmistakable answer to this question. As discussed, the distribution of demand for, and hence income from, copyrighted works is highly skewed.⁶⁴ For example, Martin Kretschmer and his co-authors have twice surveyed UK authors to obtain estimates of their copyright incomes and its distribution, once in 2006 and again in 2018.⁶⁵ They found:

[In the 2018 survey, the] top 10% of writers still earn about 70% of total earnings in the profession but for primary occupation writers the Gini Coefficient (a measure of inequality) has increased from 0.63 in 2006 to 0.71 in 2018, and for all respondents from 0.74 in 2006 to 0.8 in 2018.⁶⁶

60. The coefficient is named after sociologist Corrado Gini who first proposed the coefficient in 1912 as a statistical measure of equal distribution. His original paper was published in Italian. Corrado Gini, *Variabilità e mutabilità* (1912). For an English-language version, see Corrado Gini, *Measurement of Inequality of Incomes*, 31 *ECON. J.* 124 (1921).

61. *The World Factbook*, CENT. INTELLIGENCE AGENCY, <https://www.cia.gov/library/publications/the-world-factbook/rankorder/2172rank.html> (last visited Jan. 5, 2019).

62. *Id.*

63. *Id.*

64. See *supra* text accompanying note 21.

65. MARTIN KRETSCHMER, ANDRES AZQUETA GAVALDON, JAAKKO MIETTINEN, AND SUKHPREET SINGH, *UK AUTHORS' EARNINGS AND CONTRACTS: A SURVEY OF 50,000 WRITERS* (2019), [<https://perma.cc/PJ6S-8J3T>].

66. *Id.* at 20.

By way of contrast, they found that the Gini coefficient for the distribution of income for skilled labor in the UK was 0.13.⁶⁷

Similarly, in a forthcoming article, I calculate the Gini coefficient for the distribution of players among 13,281 PC videogames available through Steam.⁶⁸ The distribution of players in that copyright market was even more skewed than the distribution of income for UK authors. The Gini coefficient for that market was 0.9925.⁶⁹

In the music space, the distribution of income and demand is also highly uneven. In 1996, the Monopolies and Mergers Commission in the UK published its report on performing rights societies (“PRS”). Although the Commission did not calculate a Gini coefficient, the report gave a distribution of royalties paid to the PRS writer members for 1993 in Table 5.2. Using the data in that table, the Gini coefficient for UK songwriter income in 1993 was 0.9591. In 2019, BuzzAngle Music released its year-end report on the United States music industry in 2018.⁷⁰ Again, it did not calculate the Gini coefficient directly. However, it provided data on the distribution of album sales, song sales, and song audio streams in the United States in 2018⁷¹—each of which can be used to calculate a corresponding Gini coefficient. Using the BuzzAngle data, the Gini coefficient for the distribution of album sales in the United States in 2018 was 0.9827. For the distribution of song sales, the Gini coefficient was 0.9280. For the distribution of song audio streams, the Gini coefficient was 0.9191.

For movies, we find a similarly unequal distribution of domestic box office revenue. Box Office Mojo has reported the distribution of box office revenue for 596 theatrical releases in the United States in 2019.⁷² For the domestic box office revenue through October 6, 2019, the Gini coefficient was 0.9209.

Thus, the story that copyright can help promote distributive justice by providing a source of income and a path out of poverty for poor and otherwise economically disenfranchised individuals is exactly wrong. When we move beyond a focus on a handful of sympathetic individuals who happen to have won the copyright lottery and examine whether income in our society as a whole would be more or less equally distributed if more of our national income were funneled through the copyright system, there can be only one answer. The dis-

67. *Id.*

68. See Lunney, *supra* note 41, at 40.

69. *Id.*

70. BUZZANGLE MUSIC, 2018 YEAR-END REPORT: U.S. MUSIC INDUSTRY CONSUMPTION (Jan. 3, 2019), <https://www.buzzanglemusic.com/wp-content/uploads/Buzz-Angle-Music-2018-US-Report-Industry.pdf> [<https://perma.cc/N26Z-UYL2>].

71. *Id.* at 31–33.

72. *Yearly Box Office: 2019 Domestic Grosses*, BOX OFFICE MOJO, (Oct. 7, 2019 2:15 PM) <https://www.boxofficemojo.com/yearly/chart/?page=1&view=release-date&view2=domestic&yr=2019&p=.htm> (last visited Oct. 7, 2019) [<https://perma.cc/E3UD-Q7Z5>].

tribution of income would become sharply more unequal than it currently is. Indeed, if all of our national income was distributed through markets with demand as skewed as the demand we see in the copyright industries, our Gini coefficient would blow right past such stalwarts of social and distributive justice as Lesotho, Haiti, and South Africa. The copyright regime does not promote distributive justice. It is distributive injustice writ large.

III. ABOLISH THE SOUND RECORDING COPYRIGHT NOW!

At a recent conference, a colleague asked me why I was so down on music copyright. After all, he insisted, we can all sign up for a streaming service and get all the music we want for only \$10 a month. That is a pretty good deal (from a certain, entitled perspective). As a former engineer, I have considerable sympathy for the proposition: “If it ain’t broke, don’t fix it.”

Yet, there are three reasons I am not content to accept the status quo. First, we only have the \$10 a month streaming services today because of unauthorized file sharing. As I explained in my book, it was file sharing that gave Steve Jobs the leverage to force record labels to break the album and make singles available for download on iTunes at a low price of 99 cents.⁷³ It is also the continued competitive threat of file sharing that makes streaming services available today at \$10 a month.⁷⁴ Second, while \$10 seems like a reasonable price in the abstract, particularly to those of us who lived through the 1990s when the only option if you wanted to listen to a song at your convenience was to buy a CD for \$20, \$10 a month may be far too much. The only way to know is to test empirically whether we could get more and better music, or even just the same music, at a streaming subscription price of \$5 a month, or free. Why should we pay \$10 if we can get the exact same music for five dollars or for nothing? The rigorous empirical study I presented in my book tends to establish that we can get more and better music for less. That suggests that \$10 a month is too high. Third, we should not make the mistake of assuming that just because we can get all the music we could want for \$10 a month today that we will continue to get streaming at that price tomorrow. The recording industry is continually striving to return to the high revenue 1990s. If they had their way, they would shut down the Internet entirely and force music consumers to pay \$20 for a CD once again. If that proves beyond their reach, then they will work to hook us all on streaming, and once they have, begin to raise its price through evermore onerous licensing terms. Neither the streaming services nor our elected government will stand against these price increases over the long-term. Right now, the only effective bulwark against future price

73. See LUNNEY, *supra* note 1, at 76–80.

74. *Id.* at 80.

increases is the threat of piracy. I worry that that is not a sustainable equilibrium.

The more rational approach, indeed, the only rational approach, is simply to abolish the sound recording copyright. Some of the best popular music of all time was created and released before the sound recording copyright became effective in February 1972. After Congress enacted the right, music output, both in quantity and quality, went downhill. Only with the advent of file sharing and the effective gutting of the sound recording copyright has creativity in the music industry begun to flourish again. We should not let this opportunity pass us by. We now have more and stronger evidence to justify abolition of the sound recording copyright than we ever had to justify its enactment. We should finish what file sharing has started and abolish the sound recording copyright.

