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COPYRIGHT, INCENTIVES, AND POPULAR MUSIC COMPOSITION

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Abstract. The rise of file sharing and the subsequent collapse in sales of recorded music offer a rare glimpse into a counterfactual world where copyright, for a time, was weakened. Comparing creative output before and after this exogenous shock allows us to test empirically whether incentives to copyright owners were correlated with creative output. In this article, I extend previous work on this issue from recording artists to songwriters and search for a correlation between incentives and popular music composition. In particular, I test three hypotheses. First, I test whether more incentives were associated with more or better popular musical compositions. Second, I test whether more incentives were associated with more entry by new composers into the market for writing hit songs. Third, I test whether more incentives were associated with higher productivity from those new composers. For the first time, for the modern music industry, I find a positive and statistically significant correlation between revenue and music output for one measure of popular music composition. However, the correlation is not robust and having run hundreds of regressions searching for such a positive correlation, not unexpected. Beyond this one, isolated result, regression analysis finds no correlation between incentives and entry by new hit songwriters. And regression analysis finds a statistically significant and robust correlation between more incentives and both (i) lower quality hit songs; and (ii) reduced productivity from new hit songwriters, *ceteris paribus*.

1. Introduction

In the United States, copyright's fundamental premise is that increased revenue for copyright owners will lead to more and better original works of authorship for the public.[1] Although fundamental to copyright, for most of copyright's history, this premise has not been so much proven, as assumed. The advent of file sharing, however, represents

[1]See *Kirstaeng v. John Wiley & Sons, Inc.*, 579 U.S. 197, 204 (2016) ("As Fogerty explained, 'copyright law ultimately serves the purpose of enriching the general public through access to creative works." 510 U.S., at 527; see U.S. Const., Art. I, § 8, cl. 8 ('To promote the Progress of Science and useful Arts')."); *Sony Corp. of Am. v. Universal City Studios, Inc.*, 464 U.S. 417, 429 (1984) ("The monopoly privileges that Congress may authorize are neither unlimited nor primarily designed to provide a special private benefit. Rather, the limited grant is a means by which an important public purpose may be achieved. It is intended to motivate the creative activity of authors and inventors by the provision of a special reward . . . ."); *Twentieth Century Music Corp. v. Aiken*, 422 U.S. 151, 156 (1975) ("The immediate effect of our copyright law is to secure a fair return for an 'author's' creative labor. But the ultimate aim is, by this incentive, to stimulate artistic creativity for the general public good."); *United States v. Paramount Pictures., Inc.*, 334 U.S. 131, 158 (1948) ("The copyright law, like the patent statute, makes reward to the owner a secondary consideration."); *Fox Film Corp. v. Doyal*, 286 U.S. 123, 127 (1932) ("The sole interest of the United States and the primary object in conferring the monopoly lie in the general benefits derived by the public from the labors of authors.").

an exogenous shock that offers an opportunity to test the presumed correlation between incentives and creative output. For the music industry, in particular, revenue from sales of recorded music fell by roughly two-thirds in constant dollar terms following the introduction and rise of file sharing. That sharp fall provides a rare glimpse into a counterfactual world where copyright protection was, for a time, substantially weakened and allows us to test empirically for a correlation between revenue, as a proxy for incentives, and music output in a modern context.[2]

A number of scholars, myself included, have tested for such a correlation in the wake of file sharing and so far, have found no correlation between revenue from music sales and music output (Handke, 2012; Lunney, 2016, 2018; Waldfogel, 2012a, 2012b). Despite a 66.4 percent decline in revenue from music shipments in the United States from 1999 to 2014, from $20.7 billion in 1999, in constant 2013 dollars ("$2013"), to only $7.0 billion ($2013) in 2014, the sky did not fall. To the contrary, the initial studies found no observable difference in popular music output (Handke, 2012; Waldfogel, 2012a, 2012b).[3] Later studies examined the issue more thoroughly over a longer time frame (Lunney, 2016, 2018, 2019, 2020).[4] They used regression analysis, employed multiple measures of music output, and accounted for other factors that might account for variations in music output, such as the rise in market share of Clear Channel. Yet, these studies found no statistically significant and positive correlation between revenue in one year and music output in the next. To the contrary, where a statistically significant correlation was found, the correlation was negative (Lunney, 2018, 2020, 2021). Increased revenue from record sales in one year was associated, *ceteris paribus*, with reduced music output in the next.

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[2]Giorcelli and Moser (2020) found a correlation between the adoption of copyright and the production of operas in the Napoleonic era. While their conclusions nicely align with widely held a priori beliefs that some copyright is desirable but longer copyright is not, there are aspects of their analysis that trouble me. Whatever the merits of their analysis, however, it is difficult to generalize results from very different historical circumstances.

[3]Handke (2012) examined the release of new albums in Germany from 1984 through 2006 and found that neither the quantity nor quality of original sound recordings fell after the rise of file sharing. Waldfogel (2012a) examined the number of albums released and critics' evaluations of albums released in the United Sates from 1980 through 2010 and found that neither the quantity nor quality of the releases changed after the rise of file sharing.

[4]Lunney (2018) examined the number of albums released, the number of unique songs appearing on the Billboard Hot 100 chart, and Spotify stream counts for Hot 100 hits 1962 through 2015 and found. Lunney (2020) extended the Spotify stream count analysis from 1,001 Hot 100 songs to 3,823 songs. Lunney (2021) extended the analysis from an end date of 2015 to an end date of 2019 and from 3,823 Hot 100 songs streamed on Spotify in 2014 to 6,200 Hot 100 songs streamed on Last.fm in the summer of 2020.

In this article, I extend that previous empirical work in two ways. First, I extend the time-frame for analysis of music output through 2023. Beginning in 2016, the steady decline in revenue that followed the rise of file sharing finally ended, and revenues from music shipments as a whole began to rise as the gains from streaming overtook the losses from file sharing. While revenues have not yet returned to the peak levels of the late 1990s, the RIAA reports shipment revenue of $13.6 billion ($2013) in 2021. That is only 68.2 percent of the revenue at its peak in 1999 ($2013), but nearly doubles the shipment revenue the music industry received in 2014 and 2015 ($2013). Second, I extend the analysis from; (i) recording artists and the sound recording copyright that protects an artist's particular rendition of a song to (ii) composers and the musical work copyright that protects the song's composition generally. While the sound recording is protected under copyright in the United States, it is protected in much of the world not under copyright, but as a related right. Even in the United States, copyright has protected sound recordings only since 1972.[5] Thus, some might discount a study focused on the recording industry and sound recordings as not central to copyright. In contrast, the composer's musical work is both a core component of copyright worldwide and in the United States has received copyright protection since 1831.[6] A study finding no, or a negative, correlation between incentives and creative output for popular musical compositions cannot be so readily dismissed as outside of copyright's core.

Through these two extensions, I seek to answer three questions: First, does this additional data show any correlation between more revenue and more or better popular music? Second, does the data show that more revenue led to more composers entering the popular music market? Third, does the data show that more revenue led to increased productivity for the composers of popular music? Perhaps unsurprisingly, given the existing empirical studies, the answer to each of these three questions is, with one isolated exception, no.

[5]Congress did not formally protect sound recordings under federal copyright law until 1971 for recordings fixed after February 15, 1972. *Sound Recording Amendment*, Pub. L. No. 92-140, § 3, 85 Stat. 391, 392 (1971).

[6]See *Copyright Act of 1831*, ch. 15, § 4, 4 Stat. 436, 436 (adding musical compositions to the list of protected works). Musical compositions had in some instances been registered for copyright protection, apparently as "books," prior to 1831. See *Clayton v. Stone*, 5 F. Cas. 999, 1000 (C.C.S.D.N.Y. 1829) (No. 2,872); Federal Copyright Records 1790-1800, at xvi (James Gilreath ed., 1987).

Section 2 begins with a review of the existing literature. Section 3 examines the exogenous shock that arose from file sharing and explains the different revenue sources available to recording artists and composers. Section 4 presents two direct measures of music output, unique song counts from the Billboard Hot 100 and age-adjusted stream count residuals for the year-end Billboard Hot 100, as well as two indirect measures of music output, new composers and composer productivity, and identifies the data's limitations. Section 5 presents the regression models and empirical results. Section 6 concludes.

2. Existing Literature

Although there has been an extensive literature on the implications of file sharing for the music industry, the vast majority of that literature has focused on the question whether, and if so, to what extent file sharing reduced authorized sales of music or other copyrighted products (Peitz and Waelbroeck, 2004; Liebowitz, 2006; Rob and Waldfogel, 2006; Adermon and Liang, 2014). Yet, from the perspective of copyright policy or welfare analysis more generally, whether file sharing did or did not reduce revenue to copyright owners is largely a sideshow.[7] The purpose of copyright is not to enrich copyright owners. Rather, the purpose of copyright is to ensure the public access to a wide and varied supply of original works of authorship, whether books, movies, or music.[8] Unless we assume that music industry revenue directly correlates with creative output, a decline in revenue to copyright owners is not relevant to a discussion of copyright policy.

Yet, when we look for research that focuses on whether file sharing and the subsequent decline in revenue decreased the production of high-quality music, we find far fewer studies (Handke, 2012; Lunney, 2018; Waldfogel, 2012a). While fewer in number, these studies

[7]In the United States, Congress is authorized to enact copyright for a singular purpose: "to promote the Progress of Science." *U.S. Const.* Art. I, Sec. 8, Cl. 8.

[8]See *Sony Corp. of Am. v. Universal City Studios*, Inc., 464 U.S. 417, 429 (1984) ("The monopoly privileges that Congress may authorize are neither unlimited nor primarily designed to provide a special private benefit. Rather, the limited grant is a means by which an important public purpose may be achieved. It is intended to motivate the creative activity of authors and inventors by the provision of a special reward . . . ."); *Twentieth Century Music Corp. v. Aiken*, 422 U.S. 151, 156 (1975) ("The immediate effect of our copyright law is to secure a fair return for an 'author's' creative labor. But the ultimate aim is, by this incentive, to stimulate artistic creativity for the general public good."); *United States v. Paramount Pictures.*, Inc., 334 U.S. 131, 158 (1948) ("The copyright law, like the patent statute, makes reward to the owner a secondary consideration."); *Fox Film Corp. v. Doyal*, 286 U.S. 123, 127 (1932) ("The sole interest of the United States and the primary object in conferring the monopoly lie in the general benefits derived by the public from the labors of authors.").

focus on copyright's true purpose – ensuring creative output. On that key issue, all of them find that the production of high-quality music continued despite the decline in revenue that followed the rise of file sharing. Initial studies by Christian Handke and Joel Waldfogel analyzed the release of new albums before and after the rise of file sharing – Handke in Germany from 1984 through 2006, and Waldfogel in the United States from 1980 through 2010 (Handke, 2012; Waldfogel, 2012a). Both found that, despite the sharp decline in revenue, the number of new albums released annually continued to grow in both Germany and the United States. Both recognized that a mere quantitative measure, such as an album count, is not sufficient on its own to measure music output. To measure music output, we must also account for variations in quality. Unfortunately, the rise of file sharing rendered traditional measures of quality, such as gold or platinum status, that relied on unit sales, unreliable (Lunney, 2018, at 84-85). Both Handke and Waldfogel therefore developed their own, hopefully time-invariant, approaches to determining music quality. Specifically, Handke used the time consumers spent listening to music, and Waldfogel used critics' evaluations of the albums released, as a proxy for, or as a measure of, music quality. Both, again, found that the quality of music output remained unchanged following the rise of file sharing.

These initial studies did not attempt to sort out the role that file sharing and the contemporaneous decline in sales revenue may have played as against other potentially competing factors. As both of these scholars acknowledged, other external shocks affected the music market over the same time period. Nor did they attempt to show that music output would not have been higher but for the rise of file sharing and the contemporaneous decline in sales revenue. Rather, their work was meant to respond to the "sky is falling" rhetoric of copyright owners at the time and show, at least as a starting point, that file sharing had not destroyed entirely the music industry's capacity to produce original and high-quality music.

In 2018, I published a more comprehensive analysis of the relationship between file sharing, industry revenue, and popular music output (Lunney, 2018). The analysis covered a longer time period, from 1962 through 2015. While it also relied on album release counts

and critical evaluations, it introduced two new measures of music output, designed to account for both quantity and quality. First, it used the number of new or unique songs that appeared on the Billboard Hot 100 chart each year as a proxy for high-quality music output. In essence, the number of new songs on the Hot 100 chart suggests how many songs are good enough to compete for a spot on the Hot 100 each year. More great songs, more turnover, and hence a higher unique song count. Fewer great songs, less turnover and hence a lower unique song count. However, this measure has a weakness. It measures quality relative to other contemporaneous songs. In a given year, the best songs might be, in absolute terms, low quality. Or, alternatively, the best songs in a year might be high quality. Relying on song count alone creates a risk of mistaking a bad year, where there are large number of songs competing for Hot 100 slots and hence high turnover, but they are all, in absolute terms, low quality, for a good year, where there are the same large number of songs competing for Hot 100 slots and hence the same high turnover, but they are all, in absolute terms, high quality. To account for this risk, we need an external check on quality.

To provide this check and also to serve as an independent measure of the quality of music output, I introduced a second approach: stream counts for the most popular songs from a given year. Unlike the unique song count on the Hot 100 chart or other proxies for quality, such as critics' evaluations, a stream count provides a direct proxy for listener satisfaction. The more listeners who choose to stream a song and the more often they chose to stream it provides a direct measure of the satisfaction a listener derives from that song. If listeners choose to listen to one song rather than another, that song will have a higher stream count than the other. The higher stream count for the first song suggests that listeners are deriving more satisfaction from listening to the first song than the second. In that sense, we can say that the first song is higher quality than the second.

Comparing stream counts directly works well for two songs released in the same year. However, it does not work as well for comparing a song released this year to one released ten years ago. The popularity of even the best songs tends to fade with time. As a result, if we look at stream counts during January 2025 for the most popular songs from 2020,

those stream counts will be higher than stream counts for the most popular songs from 1980 simply because the 2020 songs are more recent.[9] In order to account for this decay over time in popularity, I fit various time functions to the actual stream counts that the most popular songs from each year, as identified by the Billboard Hot 100 year-end chart, experienced to find the function that best matched the observed decay in stream counts over time. I then subtracted this best fit decay curve from the actual stream counts for the best songs from each year to get a residual. This residual provides a direct and time invariant measure of whether the best songs from a given year are streamed more or less than we would expect given their age. In that sense, this residual provides a measure of the age-adjusted satisfaction associated with a year's best songs. If the best songs from a given year are streamed more often than expected given their age, the residual will be positive. A positive residual suggests that listeners are deriving more satisfaction from a year's best songs than we should expect given their age. If a year's best songs are streamed less often than expected given their age, the residual will be negative. A negative residual suggests that listeners are deriving less satisfaction from a year's best songs than we should expect given their age. As a result, the residual provides a direct and unbiased numerical measure of the quality of the top songs from a given year that can be compared across time to the residual for the top songs from other years. In addition, it also provides the independent check on song quality needed to refute the possibility that the high or low unique song counts that we observed on the Billboard Hot 100 chart were due to changes in the quality of the top songs competing for a spot on the Hot 100 (Lunney, 2018, at 118). The stream count residual data thus also enabled us to use the unique song counts as an unbiased measure of the quantity of high-quality music released each year.

With these two new measures of music output, which encompassed both quantity and quality, I performed regressions that accounted for the rise of file sharing and the associated decline in revenue. In addition, the regressions also accounted for other exogenous shocks to the music industry that may have affected music output during this period. I thus included additional independent variables in the regressions measuring: (i) the rise of Clear

[9]This pattern is found in the Spotify data and the Last.fm data (Lunney, 2018, at 114; Lunney, 2021, at 175, 178).

Channel; (ii) the size of the teenage cohort, ages 15-19, of the United States population; (iii) the rise of social media; (iv) the falling cost of music production; and (v) the overall performance of the economy. By accounting for these other shocks, I endeavored to isolate the effects of file sharing and revenue on music output.

Through hundreds of regressions with a variety of specifications, covering multiple time periods,[10] and relying on two independent sources of data for streaming counts,[11] I found no evidence to support copyright's fundamental premise. To the contrary, rather than a positive correlation between incentives and creative output, as copyright has long assumed, I repeatedly found either no statistically significant correlation, or where a statistically significant correlation was found, a negative correlation. More revenue in one year was associated with fewer and lower quality hit songs in the next, *ceteris paribus* (Lunney, 2018, 2020, 2021). At the same time, the rise of file sharing, independent of its effect on revenue, consistently showed a positive and statistically significant correlation with the quantity and quality of hit songs released each year. More file sharing was directly associated with more and better hit songs, *ceteris paribus* (Lunney, 2018, 2020, 2021).

In this article, I extend the time frame of this earlier work and extend the analysis to encompass not just recording artists, but songwriters as well. To begin, I examine how the revenue, and hence incentives, for songwriters differ from those of recording artists.

3. Industry Revenue: Artists vs. Composers

Songwriters receive revenue from two principal sources; (i) royalties on sales of recorded music, and (ii) public performance royalties. As mentioned in the introduction, the rise of file sharing led to a sharp drop in revenue from sales of recorded music in the United States. Using data from the Recording Industry Association of America, Figure 1 presents the rise

[10]Lunney (2018) covered the time period 1962 through 2015 for the Hot 100 unique song count and 1962 through 2005 for the stream count residual. Lunney (2021) extended the time period for both to 2019. To isolate the effect of revenue independent of other exogenous shocks, I also ran regressions covering the time period before file sharing arose, from 1963 through 1999.

[11]Lunney (2018) used stream count data that Spotify released for the most popular 1,001 songs streamed in 2014 that appeared on the Billboard Hot 100 chart before 2006. Lunney (2020) extended this to Spotify data for the most popular 3,283 songs streamed in 2014 that appeared on the Billboard Hot 100 chart before 2006. Lunney (2021) used stream count data for the year-end Hot 100 for each year from 1963 through 2019 scraped from Last.fm.

and fall of recorded music "shipments" from 1962 through 2023 in the United States.[12]

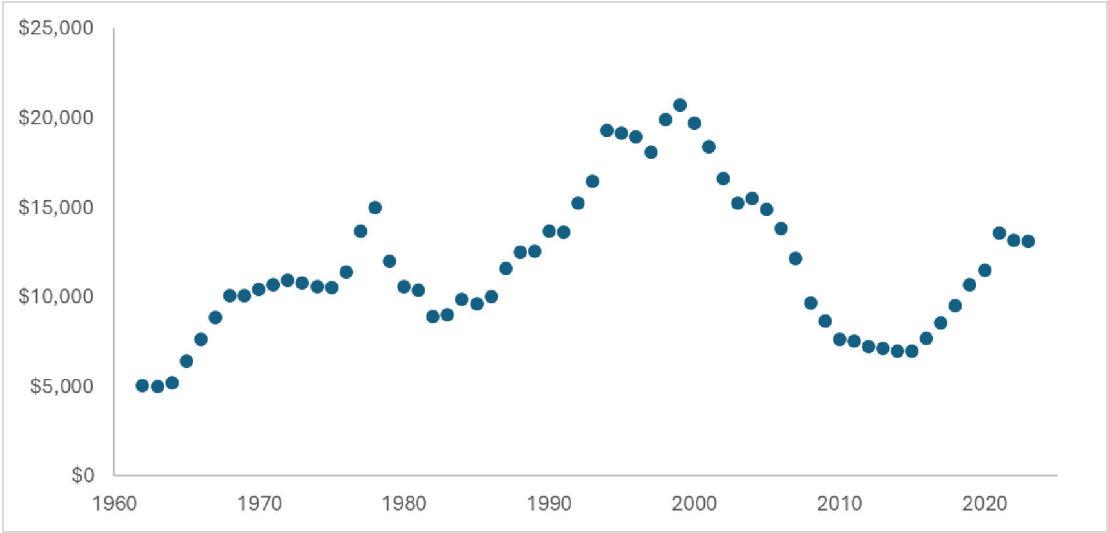

Figure 1. Shipments of recorded music in the United States: 1962-2023 (millions of dollars; $2013)

As Figure 1 shows, revenue in the United States from sales of recorded music rose from roughly $5 billion ($2013) in the early 1960s to roughly $20 billion ($2013) in the mid- to late-1990s. After Napster opened its virtual doors in 1999, revenue began to fall and fall sharply. By 2014, revenue from music sales in the United States had fallen to under $7 billion ($2013), a decline of 66.4 percent from its peak in 1999 and a level not seen since 1965. By 2016, gains in streaming revenue reversed the decline, and revenues for the music industry began to rise. By 2021, revenue from music shipments reached a post-file sharing peak of $13.6 billion ($2013) before tapering off slightly in 2022 and 2023.

For recording artists, these shipment numbers provide a rough proxy for the incentives copyright provides for producing original sound recordings.[13] But for musical composers, they are only part of the picture. Where the sound recording copyright owner enjoys

[12]Since 1973, shipment data comes from the RIAA Shipment database (available at www.riaa.com). For the years 1961 through 1972, it comes from a variety of secondary sources I have detailed elsewhere (Lunney, 2018, at 67 n.34). Adjustments to dollar values to constant 2013 dollars to account for inflation are done using the Bureau of Labor Statistics' CPI calculator (available at https://data.bls.gov/cgi-bin/cpicalc.pl).

[13]They are, to be sure, not the only revenue stream that supports performing artists. Live performance, merchandise, licensing music for or appearing directly in advertisements for trucks and other products, also provide revenue for recording artists.

only a limited right to control public performances of its work, musical work copyright owners enjoy a more complete right to control public performances (Lunney, 2018, at 62-67). As a result, when examining the relation between incentives and output, we must also consider for composers the public performance licensing fees. In the United States, public performance of music is principally licensed by two collectives; the American Society of Composers, Authors, and Publishers ("ASCAP") and Broadcast Music, Inc. ("BMI") (Lunney, 2010).[14] Rather than license public performances on a case-by-case basis, musical work copyright owners typically grant such a collective the authority to license the public performance of their works. The collectives, in turn, then issue blanket licenses to various business entities, from bars and restaurants, to radio stations, to concert venues and stadiums, to perform any music work in their respective repertoire or catalog in return for a negotiated percentage of the business entities' revenues.[15] The collectives collect the public performance royalties from all of these various business entities and then divvy the royalties up to their copyright owners based on how often each musical work in the collectives' catalog is publicly performed.

For composers, these public performance royalties are a significant source of income for composing original musical works. Figure 2 presents ASCAP's payouts to musical work copyright owners from 1961 through 2023 in constant 2013 dollars.[16]

[14]I recognize that there are other performing rights organizations, such as SESAC since 1931, and since 2013, Global Music Rights, since 2018, PRO Music Rights, and since 2019, AllTrack. But for purposes of this analysis, I focus on the two largest: ASCAP and BMI.

[15]Both ASCAP and BMI operate under consent decrees with the Department of Justice to limit their potential for anticompetitive behavior. See *United States v. Am. Soc'y of Composers*, No. 41 Civ. (S.D.N.Y. June 11, 2001) (available at http://www.ascap.com/reference/ascapafj2.pdf); *United States v. Broad. Music, Inc.*, No. 64 Civ. 3787 (S.D.N.Y. May 1, 2009). If a public performance venue believes that the rates ASCAP or BMI are charging is unreasonably high, they may challenge the rate as unreasonable in the Southern District of New York – the court with jurisdiction to enforce the consent decrees.

[16]Since 2014, ASCAP has published its payouts in its own annual reports. See, e.g., ASCAP, 2014 Annual Report 15 (available at https://www.ascap.com/~/media/files/pdf/about/annual-reports/ascap_annual_report_2014.pdf) (last visited August 5, 2024). For earlier years, Billboard magazine reports and other secondary sources were required, see Brabec and Brabec (2011), Billboard (1963), Billboard (2006); Billboard (2007a).

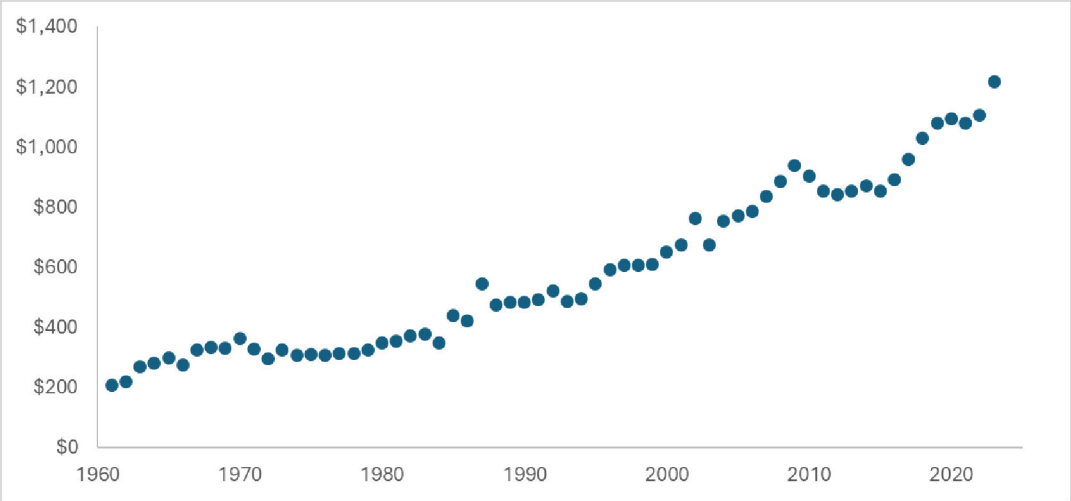

Figure 2. ASCAP payouts: 1961-2023 (millions of dollars; $2013)

As Figure 2 shows, public performance royalty payouts did not fall as a result of the rise of file sharing. To the contrary, public performance royalty payouts rose, more or less steadily, throughout the 1961 through 2023 time-frame. The most significant drop occurred from 2009 through 2012, when payouts declined from $937 million to $839 million ($2013), most likely due to the 2008-2010 Great Recession.

These public performance royalties also represent the composer's share of concert revenues. As revenue from record sales fell from 2000 through 2013, revenue from North American concerts grew from $2.30 billion in 2000 (adjusted to 2013 dollars) to $5.1 billion in 2013 (Lunney, 2018, at 9). While recording artists receive a profit share of concert revenues, composers receive only the public performance licensing royalty from the venue. Thus, any increased revenue from a shift towards live performance in the wake of file sharing is already included in the ASCAP data.

In any event, because composers earn revenue from both of these sources, record sales and public performance royalties, we must combine these two sources of revenue to obtain a complete, albeit rough, picture of the revenues, and hence incentives, available for the composition of popular music. To create this picture, I first multiplied the RIAA shipment data by 0.1, as a rough approximation of the licensing royalty that goes to the musical work copyright owner, either as a result of the mechanical license in section 115 of the

Copyright Act of 1976 or through the Harry Fox Agency.[17] Second, because; (i) data for BMI's royalty payouts was available only for the period 1996-2023[18] and (ii) averaged 95.1 percent of ASCAP's payouts for that period, I doubled ASCAP's payouts to estimate the total payouts for original musical works from the public performance royalty. Figure 3 presents the resulting composite composer revenue from these two sources for the United States from 1961 through 2021.

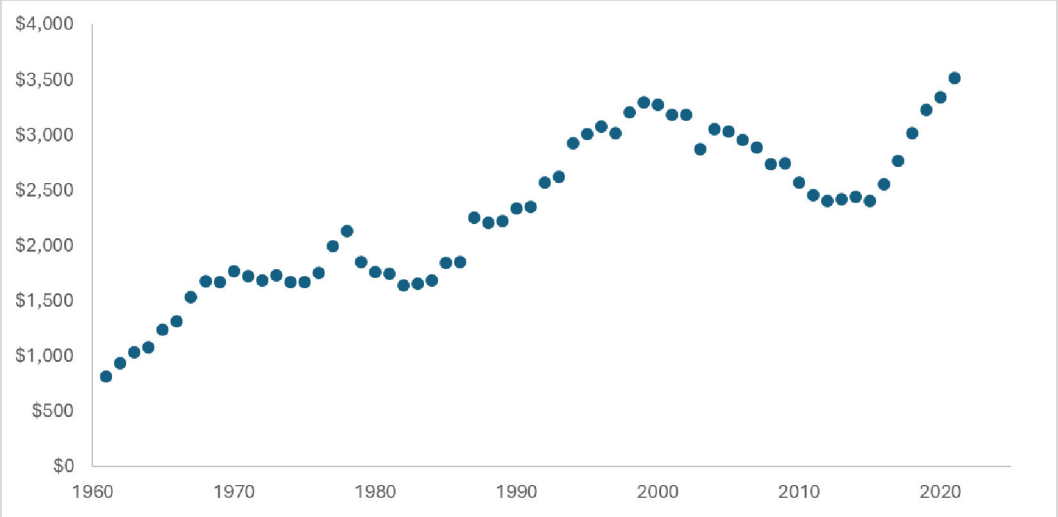

Figure 3: Composer revenue: 1961-2021 (millions of dollars; $2013)

As Figure 3 illustrates, revenue, and hence incentives, for the creation of original musical compositions did decline in the United States following the rise of file sharing. The decline was not as steep as that for recording artists and sound recording copyright owners, falling by only 27.0 percent from a peak of $3.3 billion ($2013) in 1999 to $2.4 billion ($2013) in 2015. Moreover, because public performance royalties continued to rise more or less steadily throughout the six decades under study, revenue, and hence incentives, for original music composition peaked not in 1999, as it did for recording artists, but in 2021. With

[17]Lunney (2018, at 60) notes that the mechanical license rate for reproducing physical or digital copies of a song was 9.1 cents, slightly less than ten percent of the 99 cent price iTunes and other websites charge for a digital single.
[18]For the years since 2008, BMI has released the data itself in its annual reports. BMI Annual Report 2021-2022. 2022 (available at https://www.bmi.com/pdfs/publications/2022/BMI_Annual_Review_2022.pdf) (last visited Aug. 17, 2024). For other years, secondary sources were used; see Brabec and Brabec (2011); Billboard (2007b).

the surge in revenue from streaming, musical work copyright owners were able to grow their revenues sufficiently to make-up the decline following the advent of file sharing.

While the decline in music composition revenue following the rise of file sharing is not as steep as that for record sales alone, the rise, fall, and rise again in composition revenue has enough variation to test whether the changes in composition revenue were associated with a measurable change in popular music output. As our next step, we turn to the task of measuring music output over the last six decades.

4. Measuring Music Output: Quantity and Quality

As discussed, there is no simple or fool-proof way to measure music output that encompasses both quantity and quality. Traditional measures of quality relied on unit sales, and associated gold or platinum certifications, and those became unreliable following the rise of file sharing. Nevertheless, as shown in previous work, a count of the unique songs that appear on the Billboard Hot 100 each year, combined with streaming counts for songs that appear on the year-end Hot 100, provide two measures of music output that can serve as effective proxies for the utility, pleasure, or satisfaction associated with the original music from a given year. Lunney (2018, 2020). A count of the unique songs that appear on the Billboard Hot 100 each year provides both a quantitative and qualitative measure of the number of songs released each year that are good enough to compete with the other top songs for a place on the Hot 100. While that song count is a measure of relative quality – how do the songs compare to other songs from that year – the stream count residual data for the year-end Hot 100 for each year provides a check that variations in the unique song count are not due to variations in absolute quality from year-to-year. The use of the stream count residual data thus, first, ensures that the unique song count provides a reliable and unbiased measure of original music output. And, second, the stream count residual data provides an independent measure of the quality of the top songs for each year. The number of times a song is streamed over a given time period establishes that a listener chose to stream music, rather than engage in some other activity, and chose to stream one song, rather than another. That listeners have made those choices repeatedly

for a particular song provides direct evidence of the intensity and level of utility, pleasure, or satisfaction that the song generates for listeners.

A few caveats warrant mention. First, the study focuses on songs that appear on the Billboard Hot 100. While the study encompasses 28,567 different songs that appeared on the Billboard Hot 100 from 1962 through 2022, that remains a narrow slice of the original music released each year. I focus on these most popular songs, however, because the demand for music is highly skewed. Like the markets for other copyrighted works, the market for original music tends to be winner takes all. In 2018, for example, the top 0.75 percent of song titles garnered 76.5 percent of song sales, and the top 1.38 percent of song titles garnered 92.4 percent of song streams.[19] Given the distribution of demand, measuring the quantity and quality of the most popular songs is likely to provide an effective proxy for the overall satisfaction associated with the original music released in a given year. In addition, while the measure does not purport to encompass the satisfaction associated with all the original music released in a given year, that is equally true for every year the study covers. While some songs outside the Billboard Hot 100 may generate significant satisfaction, either directly or by setting the stage for further musical development, such as the introduction of a new genre, that is as true for 1965 as it is for 1975 or 1985 or 1995 or 2005 or 2015. Thus, while the measures of music output on which this study relies focus on a narrow subset of the original music released in a given year, the measures are similarly narrow for each of the years in the study and thus likely to be unbiased across time.

Second, the stream count data for the year-end Hot 100 is scraped from Last.fm. To the extent the listeners who use Last.fm do not share the tastes of the average musical consumer, the stream count residual measure of music quality may reflect the idiosyncratic preferences of Last.fm listeners, rather than a true measure of music quality. In addition, because scraping is a mechanical process, errors or inconsistencies may be introduced into the data collection. Moreover, Last.fm sometimes offers multiple versions of a song. For

[19]Buzzangle Music (2018, at 31-33) shows 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.

example, Last.fm provides thirty links to versions of Beyoncé's 2003 hit *Crazy in Love*. The first listed version has a stream count (or as Last.fm calls it "scrobbles") of nine million; the second listed version has a stream count of only 3.8 million.[20] In other instances, Last.fm offers multiple listings but they link to the same version of the song with the same stream count. For example, Last.fm provides thirty links to versions of Christina Aguilera's 2003 hit *Can't Hold Us Down*, but eight of those links led to the same version with the same stream count.[21] To ensure consistency in the scraping process, the program scrapes only the version with the highest stream count. This creates some risk that a given song's stream count may be too low if the total streams are spread out across multiple versions of the song. Of course, scraping all the versions and adding their stream count together runs the risk of overcounting for songs like Aguilera's that list the same version of the song with the same stream count multiple times.

Despite these concerns, there is no reason to believe that any errors introduced into the stream count data as a result of these issues or any others will bias the stream count data in any particular direction vis-à-vis industry or composer revenue. The risk of multiple versions of a song diluting the stream count or of a mechanical error in the scraping process are the same for all of the songs in the data set. Moreover, for the overlapping years, the stream count data scraped from Last.fm is highly correlated with the stream count data Spotify released for the 3,823 most popular songs, based upon stream count in 2014, that appeared on the Hot 100 prior to 2006.[22] Because Spotify released its stream count for those songs directly, the Spotify stream count do not present the concerns the mechanically scraped Last.fm data does. As a result, the high correlation with the Last.fm data for

[20]Beyoncé, Crazy in Love, Last.fm (available at https://www.last.fm/search/tracks?q=beyonce+crazy+in+love) (last visited Feb. 15, 2025).

[21]Christina Aguilera, Can't Hold Us Down, Last.fm (https://www.last.fm/search/tracks?q=christina+aguilera+can%27t+hold) (last visited Feb. 15, 2025).

[22]The calculated correlation for the Spotify stream count residuals and for the year-end Hot 100 stream count residuals from Last.fm was 0.87 for both the four-year stream count residual data and the one-month stream count residual data. The two data sets do not include stream count residuals for an identical set of songs for each year. The Last.fm data includes stream count residuals for the year-end Hot 100 songs for each year. The Spotify data has the top 1,001 songs for each decade, where the Last.fm data includes stream count residuals for the year-end Hot 100 for each year. This creates two potential differences in the songs in the two data sets. First, the Spotify data may have stream count residuals for more or less than one hundred songs in each year, depending on the relative popularity of songs across a given decade. Second, the Spotify data, while it includes only those songs that made the Hot 100 chart at some point in the year, may include songs not on the year-end Hot 100.

the years the two data sets overlap suggests that, while we should remain aware of the potential limitations of the Last.fm stream count data, those limitations do not render the Last.fm data unreliable.

With these caveats in mind, Figure 4 presents the number of new or unique songs appearing on the Billboard Hot 100 from 1962 through 2022.

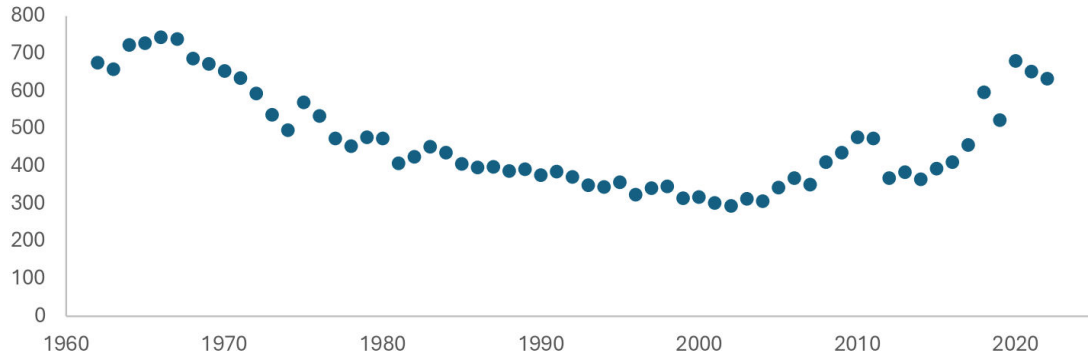

Figure 4: Unique song count on the Billboard Hot 100: 1962-2022

As Figure 4 demonstrates, the vast majority of songs appearing on the Billboard Hot 100 week-to-week are repeats. The Hot 100 chart is released weekly. Fifty-two weeks a year with 100 spots equals 5,200 potential spots each year. Yet, out of those 5,200 potential spots, the number of new, unique songs appearing in a given year on the Billboard Hot 100 peaked at 743 songs in 1966. From there, the number of unique songs appearing on the Hot 100 chart each year fell, more or less steadily, to a nadir of only 294 songs in 2002. From 2002, with the rise of file sharing, and in the 2010s, the growth of streaming, the number of unique songs appearing on the Hot 100 chart in a year began to grow, though not consistently or steadily. In 2020, the unique song count reached a post-file sharing peak of 680 unique songs, before trailing off just a bit in 2021 and 2022.

A visual inspection of Figure 4 provides little support for copyright's fundamental premise. The peak revenue in record shipments during the 1990s does not appear to drive any corresponding peak in the unique song count on the Hot 100 chart. To the contrary, the high unique song count years in Figure 4 belong either to the low revenue 1960s or to the post-file sharing years. In section IV, we will use regression analysis to

examine the long-assumed correlation between incentives and output more rigorously, but at least, at the outset, the Hot 100 unique song count reveals no immediately apparent correlation between increased revenue and increased creative output.

However, before we place too much weight on the unique song count data, it is important to remember that the Hot 100 chart provides a relative, not absolute, measure of song quality. It measures a song's quality relative to other contemporaneous songs competing for Hot 100 chart space. It does not measure a song's quality relative to songs from years before or years later. As a result, the long-term slow-down in chart turnover from 742 unique songs in 1966 to 294 in 2002, as well as the short-term slow-down from 474 unique songs in 2011 to 368 in 2012 or from 596 unique songs in 2018 to 523 in 2019 may be due to fewer higher quality songs competing for positions on the chart. Or any of these may be due to a small number of extremely high-quality songs sticking on the chart longer. Imagine Dragons' song *Radioactive*, for example, hit the Hot 100 chart in 2012 and remained on the chart for 87 weeks. Because it did so, turnover and hence the unique song count may be lower for 2012, 2013, and 2014, not because of reduced high quality music output, but because a few extremely high-quality songs refused to relinquish their position on the chart. Thus, before we can rely on the Hot 100 unique song count as a measure of high-quality music output, we must have some external measure of absolute song quality that addresses this concern.

As one such external measure and also as an independent measure of the quality of music output in each year, I also scraped Last.fm stream counts during a one-month period from August 27, 2024 through September 28, 2024 and during a slightly more than four-year period from August 7, 2020 through August 27, 2024. For each time period, I scraped the stream count from Last.fm for each song in the year-end Hot 100 songs for each year from 1963 through 2023 (for the one-month stream counts) or for 1963 through 2019 (for the four-year stream count). I then combined the stream counts for all of the year-end Hot 100 songs and divided by one hundred to get an average 1-month or 4-year stream count for the year-end Hot 100 songs in each year in the study. I used longer and shorter time periods to identify and account for any brief rises in a song's stream count due to

outside factors, such as the song appearing in a movie, television show, or commercial, or an artist's death. Figure 5a and 5b present the stream count data for the one-month and four-year stream count respectively.

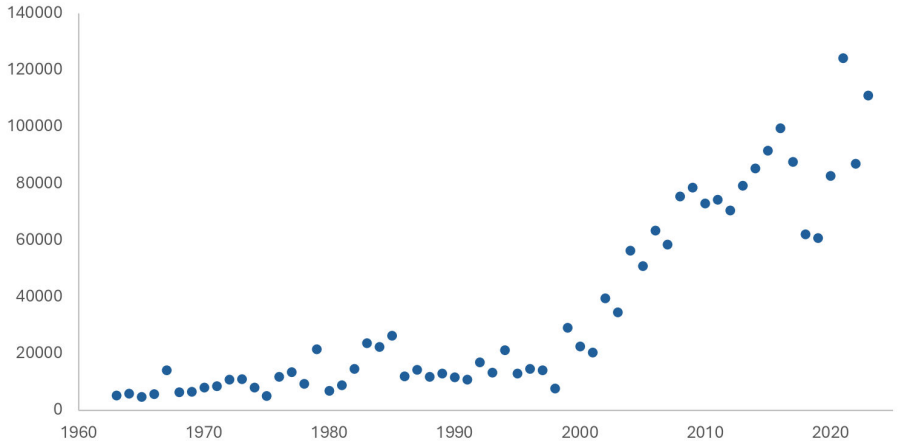

Figure 5a: 1-month stream count for the year-end Hot 100: 1963-2023

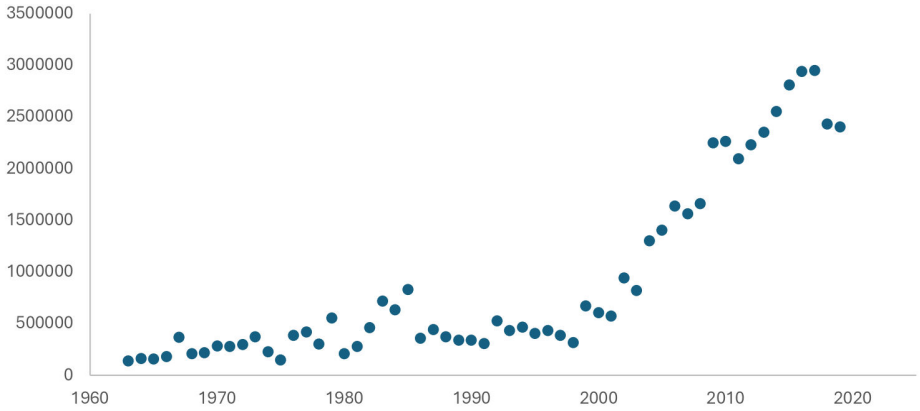

Figure 5b: 4-year stream count for the year-end Hot 100: 1963-2019

Visually, again, the stream count data provides no support for copyright's fundamental premise. When revenues from record sales peaked in the 1990s, there is no corresponding rise in the stream count for the most popular songs from those years. The years that stand out from the tail of the curve are the mid-1980s, from 1983 through 1985, when music industry revenues were low as a result of the recession associated with the second OPEC oil embargo. Interestingly, we see a steady rise in the stream counts for both the

one-month stream count data and the four-year stream count data beginning in 1999, just as Napster opened its virtual doors and revenues began to fall. That steady rise continues in the one-month count data until a fall begins in 2017 and in the four-year count data until a fall begins in 2018. Those falls in 2017 and 2018 come just after gains in streaming revenue began to outpace revenue losses associated with the rise of file sharing.

Both the one-month and four-year stream counts reflect an exponential decay in the popularity of music over time.[23] To enable a more direct determination of the satisfaction associated with the top hit songs from each year and to remove the time trend from the data to permit regression analysis, we can fit an exponential decay curve to each data set and then compare the actual stream count for each year to that year's expected stream count. The assumption here is that fitting an exponential decay curve to all of the year-end Hot 100 stream count data provides a measure of the average stream count we should expect from the top one hundred songs from each year as the songs age. By comparing the actual stream count for a year to the predicted stream count for that year, we can determine whether the quality of that year's top songs is above, equal to, or below the average time trend for all of the year-end Hot 100 songs in the study. If the actual stream count for the year is more than the expected stream count for that year, such that subtracting the predicted stream count from the actual stream count yields a positive residual, then the top hit songs from that year are being streamed, and hence generating satisfaction, more than expected given the age of the music and the average popularity, and its decay, of the year-end Hot 100 songs for all of the years in the study. In that sense, a positive residual indicates that the year-end Hot 100 songs from that year are higher quality than the average of all of the year-end Hot 100 songs in the relevant study period. Or if the difference is negative, that the top hit songs are being streamed, and hence generating satisfaction, less than expected given the age of the music and the average popularity, and its decay, of the year-end Hot 100 songs for all of the years in the study. Hence, a

[23] I tested other relationships for the decay in popularity over time, including, for example, linear and quadratic, and an exponential decay fit the data best.

negative residual indicates that a year's most popular songs are lower quality than the average quality of the songs in the study.

Figures 6a and 6b present the best fit exponential decay and the difference between the actual and predicted stream count (the residual or "Age-Adjusted Satisfaction") for each year's year-end Hot 100 songs.

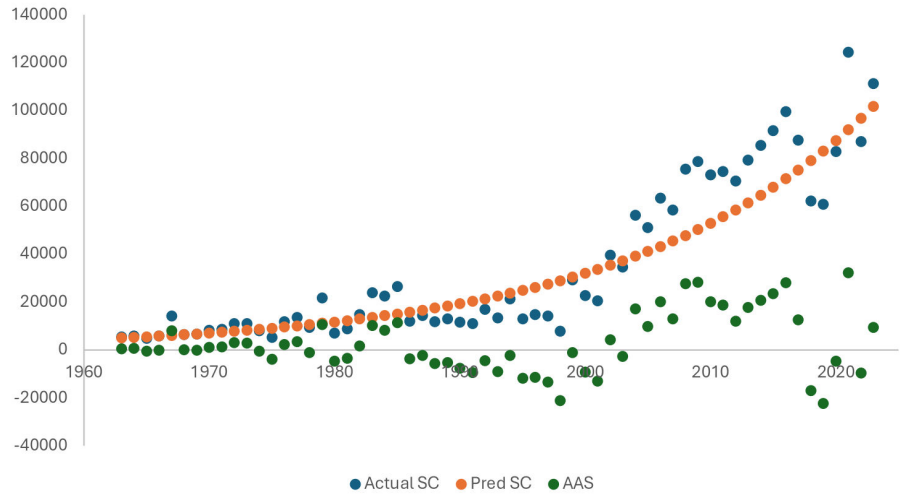

Figure 6a: 1-month stream count residual, time trend, and residuals (age-adjusted satisfaction) for the year-end Hot 100 (1963-2023)

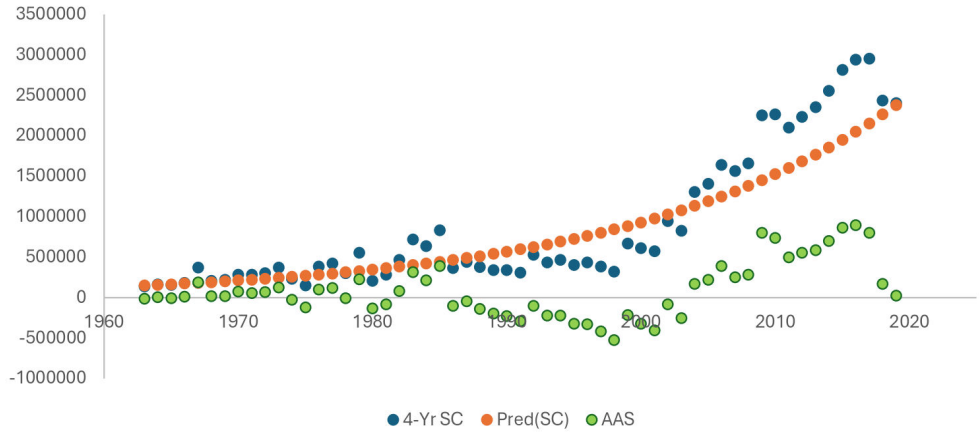

Figure 6b: 4-year stream count residual, time trend, and residuals (or age-adjusted satisfaction) for the year-end Hot 100 (1963-2019)

To simplify the Figures and focus on the key issue, Figures 7a and 7b present, on its own the residual or age-adjusted satisfaction, calculated by subtracting the predicted from the actual stream count residual, for each year's year-end Hot 100 songs.

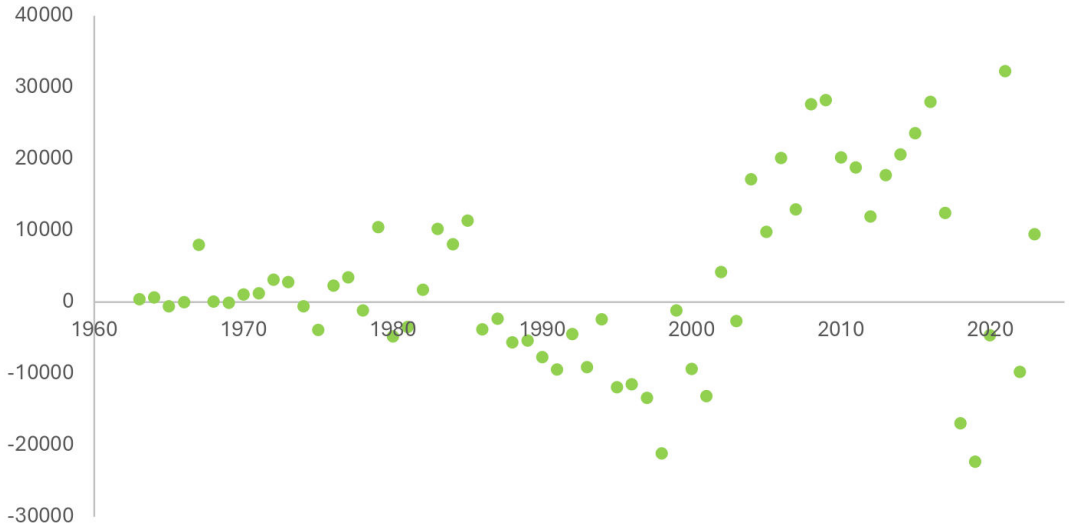

Figure 7a: 1-month age-adjusted satisfaction for the year-end Hot 100: 1963-2023

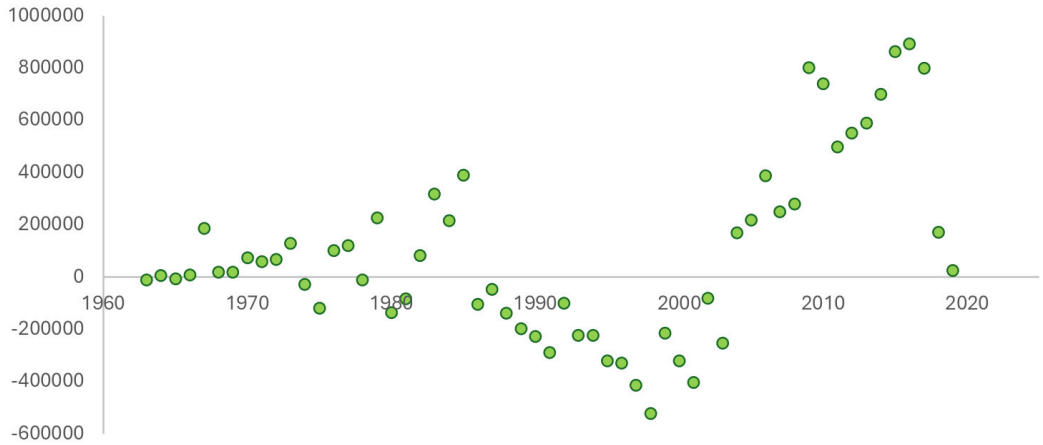

Figure 7b: 4-year age-adjusted satisfaction for the year-end Hot 100: 1963-2019

With the time trend removed from the stream count residual data, Figures 7a and 7b provide a direct indication of the extent to which the year-end Hot 100 songs for each year generate pleasure, utility, or satisfaction above, at, or below average for the year-end Hot 100 songs as a whole during the relevant time periods of 1963-2023 for the

one-month scrape and 1963-2019 for the four-year scrape. Where the difference between the actual stream count and the expected stream count (the residual or the "age-adjusted satisfaction") is positive, as it is in both data sets for the mid-1980s and from 2004 through 2017, that establishes that the year-end Hot 100 songs from those years are streamed on Last.fm more than we would expect given the age of the songs and the average time decay in popularity for all of the year-end Hot 100 songs in the relevant study period. Because those years over-perform relative to their age and relative to the average performance of the year-end Hot 100 songs in the study, we can say that the year-end Hot 100 songs from those years are higher quality. Consumers continue to listen to, and derive associated satisfaction from, these songs more than we would expect given the songs' age and how the rest of the year-end Hot 100 songs performed. In contrast, the age-adjusted satisfaction associated with year-end Hot 100 songs from the peak revenue 1990s is negative for both data sets. This suggests that the year-end Hot 100 songs from these years are lower quality. Consumers listen to the hit songs from the 1990s, and derive associated satisfaction, less than we would expect given the songs' age. Interestingly, for both data sets, after revenues began to rise again in 2016, the age-adjusted satisfaction associated with the year-end Hot 100 starts to fall.

A visual inspection of Figures 7a and 7b provides little support for copyright's fundamental premise. The peak revenue of the 1990s does not appear to drive any corresponding peak in the age-adjusted satisfaction of the year-end Hot 100 songs. To the contrary, the age-adjusted satisfaction associated with the year-end Hot 100 songs appears highest in the post-file sharing years and in the early 1980s. In section IV, we will use regression analysis to examine the long-assumed correlation between incentives and output more rigorously. But our initial visual inspection of the stream count residual data provides no support for copyright's fundamental premise.

Moreover, in addition to providing a direct measure of the quality of the year-end Hot 100 songs for each year from 1963 through 2023, the stream count residual data also provides an external and absolute measure of quality that validates the Hot 100 unique song count as a reliable and unbiased measure of the quality and quantity of popular music

released in each year. There is no evidence in Figures 7a and 7b that the slowing turnover on the Hot 100 chart from 1966 through 2002, or from 2011 to 2012, or from 2018 to 2019, is due to a cadre of super high-quality songs sticking on the Hot 100 list. Indeed, the age-adjusted satisfaction associated with the year-end Hot 100 songs for 2002 when the unique song count reached its nadir of 294 is statistically indistinguishable from those for 1966 and 2020 when the unique song count was 743 and 680, respectively.[24] Thus, the low unique song count from the 1990s through 2020 indicates there were simply fewer songs of sufficient quality, relative to the other songs from those years, to compete for a spot on the Hot 100, and the stream count residual data indicates that in absolute terms, those few songs that could compete were the same or lower quality than the songs competing for Hot 100 spots in the other years. We can therefore rely on the unique song count as a reliable and unbiased of high-quality music output. This is not to say that it is a perfect measure of high-quality music output – only that it provides some information on that issue and that information is unbiased with respect to periods of high or low industry revenue.

Because the unique song count provides a reliable and unbiased measure of music output, I also used the Hot 100 chart to count: (i) the number of first appearance composers for those unique songs; and (ii) for each such composer, the number of Hot 100 songwriting credits that they had within ten calendar years after their first. For the first, I used scraping and research assistants to determine the composers for each of the 26,653 unique songs that appeared on the Billboard Hot 100 from 1963 through 2019. To keep the data set manageable, I limited the number of composers for each song to ten.[25] For each of those years, I used a name matching algorithm, to determine how many composers had one of their songs appear on the Billboard Hot 100 for the first time. Figure 8 presents

[24]Using the four-year stream count residual data, the average residual or age-adjusted satisfaction was 91,049.6 with a standard deviation of 341,611. Only four years had a residual more than two standard deviations from the mean: 2009, 2015, 2016, and 2017. For the one-month stream count residual data, the average residual was 2,963.11 with a standard deviation of 12433.1. Only three years had a residual more than two standard deviations from the mean: 2009, 2016, and 2021. The enduring popularity of the year-end Hot 100 songs from these years suggests the possibility that a cadre of extremely high-quality songs slowed song turnover on the Hot 100 chart in these years. As a robustness check, I therefore ran regressions omitting these years from the unique song count regressions. That omission did not significantly change the regression results.

[25]Only 84 of the 24,444 unique songs in the study, or 0.34 percent, reached the limit of ten composers.

the results.

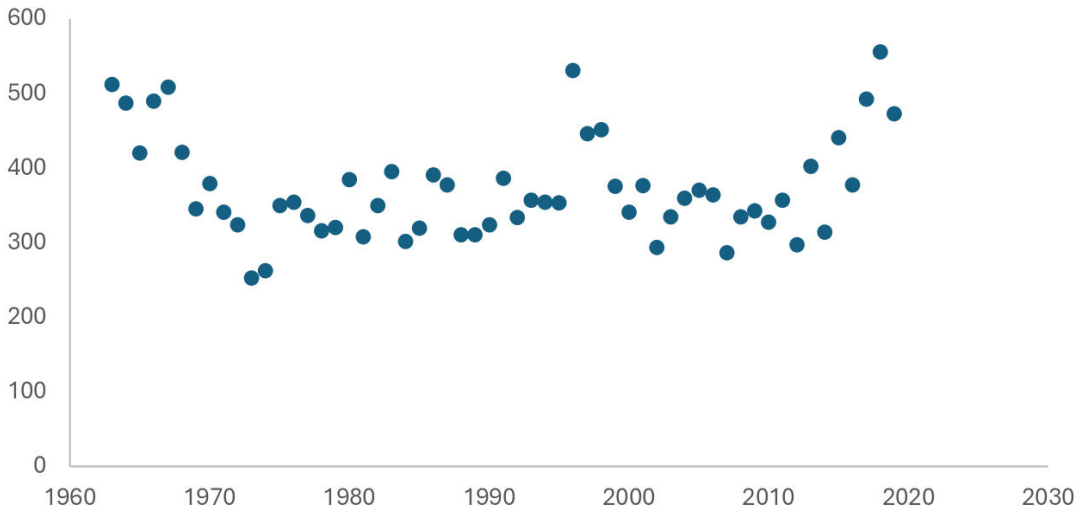

Figure 8: First appeance composers on the Billboard Hot 100: 1963-2019

Rather than present data that attempts to measure creative output directly, as the unique song count and stream count residual do, Figure 8 presents data on one of the key inputs for music production: new composers. Depending on productivity and the rate of market exit, the entry of new composers into the Hot 100 hit songwriting market can serve as an indirect measure of creative output. It also addresses directly the hypothesis that higher revenue for composers will lead more composers to enter the field.

As Figure 8 reveals, however, there seems to be no correlation between higher revenue and more hit songwriters entering the field. While revenue for music composition trended generally upward, with a significant downturn following the rise of file sharing in 2000, as we saw in Figure 3, the number of new composers who had their first hit song appear on the Billboard Hot 100 chart in a given year follows a different path. From an initial peak of 512 in 1963, the number of composers who had a songwriting credit on their first Hot 100 hit in a year fell to a largely flat average of 347.8 from 1970 through 2012, except for a brief jump from 1996 through 1998. And then beginning in 2011, the number of new entrants starts to rise again, rising to a second peak of 555 in 2018. The shape of the new composer curve follows more of a "U" or "W" pattern, without any regard for either the

generally upward trend we saw in ASCAP public performance royalty pay-outs in Figure 2 or that of overall composer revenue in Figure 3.

Moreover, we need to be careful with the generally upward trend in first appearance composers since 2011. Although it follows the generally upward trend of the composer revenue since 2011, copyright is not a full employment act for authors. The ultimate question is whether copyright: (i) generates more and better works of authorship; and (ii) their broader dissemination. As a result, we are using the entry of first appearance composers on the Hot 100 chart not as a desired end of its own, but as an indirect proxy for more and better music. Thus, the entry of more first appearance composers is desirable only if each new composer was similarly productive. In this regard, while we shall examine composer productivity directly below, it is worth noting that the average number of credited composers on a Hot 100 song has more than doubled from 1.86 in 1963 to 4.65 in 2018. Thus, to achieve the same creative output, it may take twice as many new composers in 2018 as it did in 1963. Figure 9 presents the average number of songwriters credited on each unique Billboard Hot 100 hit from 1963 through 2019.

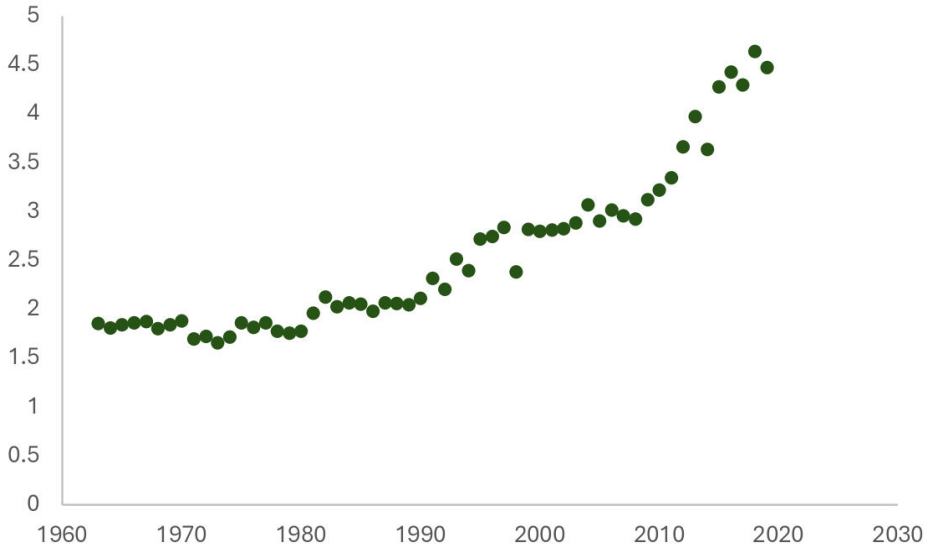

Figure 9: Average number of songwriters credited on a Hot 100 hit: 1963-2019

As Figure 9 reveals, the average number of songwriters receiving credit on a Billboard Hot 100 has increased from 1963 to 2019. From 1963 through 1981, the average number of songwriters credited on a Billboard Hot 100 hit fluctuated between 1.66 and 1.96. From there, the average number of songwriters credited on a Billboard Hot 100 hit rose to a peak of 4.65 in 2018.[26]

As the final measure of music output, I also used Hot 100 songs to determine the productivity of the average Hot 100 composer over time. Productivity can be defined as a given unit of work for given units of inputs, such as time.[27] For this analysis, I defined the given unit of a work as a songwriting credit on a Hot 100 song. Because I did not have any data on how writers divided credit on a given song, I divided the credit evenly among all credited songwriters. Thus, a composer who was the sole credited writer on a Hot 100 hit received one song writing credit for that song. If there were two credited songwriters, each received 0.5 song writing credits. If there were ten credited songwriters, each received 0.1 song writing credits. As for the second key aspect of productivity, I defined the unit of time as ten calendar years following a composer's first writing credit on a Billboard Hot 100 hit. While many songwriters had careers longer than the ten-year time limit, using the ten-year time limit allowed me to make productivity comparisons between songwriters who began their careers in the 1960s with those songwriters who began in the early 2000s. Without the ten-year time limit, the songwriters who began in the 1960s would appear more productive merely because they had longer careers. Because this time limit requires ten years of data after a composer's first appearance on the Hot 100, my present data set for productivity includes only those composers who had their first songwriting credit on a Hot 100 hit by 2010.

[26]One possible explanation for the increased number of songwriters on the average Hot 100 hit that deserves further study is the copyright-driven practice of crediting songwriters, sometimes long dead, of earlier songs from which a later song borrows or derives inspiration (Perot, 2025).
[27]Congressional Budget Office (1985, at 62).

Figure 10 presents the mean productivity for the first appearance composers for each from 1963 through 2010.

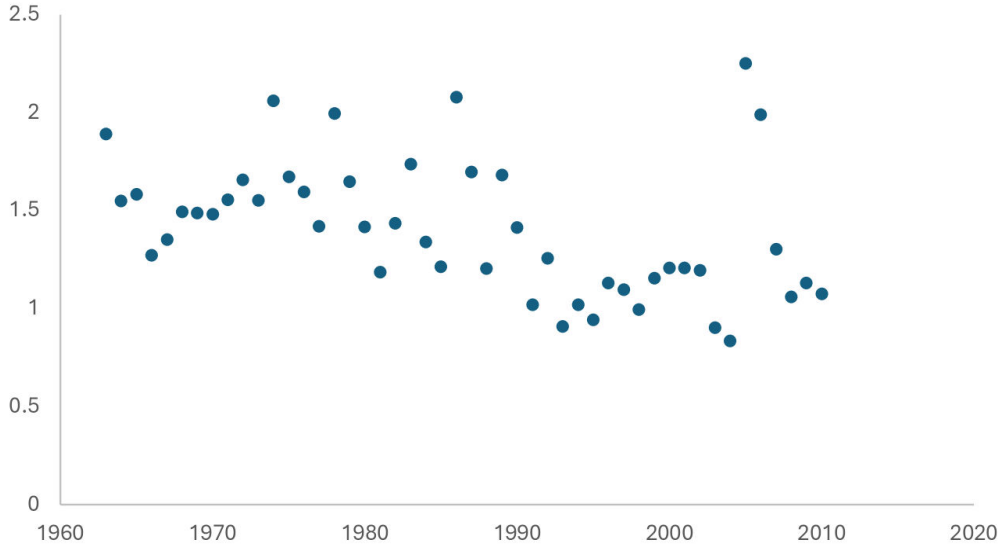

Figure 10: Mean productivity for first appearance composers: 1963-2010

Again, as with the other measures of creative output, we see no surge in productivity in connection with the surge in revenue during the 1990s. Composers who had their first songwriting credit for a Hot 100 hit from 1963 through 2010 would go on to garner a mean of 1.45, and a median of 1, Hot 100 songwriting credits within ten calendar years of that first appearance. There are some standout years, such as 1974, 1978, 1986, and 2005-2006, but the general trend in mean productivity from 1963 through 2007 is downward. As for the peak revenue 1990s, the mean productivity of composers who had their first Hot 100 songwriting credit during the 1990s was among the lowest mean productivities observed over the entire fifty-five-year period covered by this data.

Because of the winner take all nature of copyrighted markets, we should consider not just the mean productivity of the average Hot 100 composer, but should also examine the productivity of the most productive Hot 100 songwriters. Table 1 identifies the ten most productive Hot 100 songwriters, the year in which they received their first Hot 100 songwriting credit, and the number of Hot 100 songwriting credits they received over the

ensuing ten calendar years.[28]

First Hit	Songwriter	Hot 100 Credits/10 Years
1983	Diane Warren	69.83
1987	Babyface	68.88
1963	John Lennon	56.92
1963	Paul McCartney	55.92
2007	Taylor Swift	55.33
1978	Prince	46.5
1972	Jeff Lynne	43
2005	Lukasz Gottwald	42.17
2009	Aubrey Graham	41.23
1974	Billy Joel	40

Table 1: The Top Ten: Most Hot 100 Songwriting Credits in Their First Ten Years

Of the ten most productive songwriters over the ten calendar years following their first Hot 100 hit, three are from the 1980s, three are from the 1970s, and two each are from the 1960s and the mid-2000s. Interestingly, there is no one on the list who had their first Hot 100 hit in the 1990s.

If we move beyond the top ten, there are sixty-six songwriters who had more than twenty Hot 100 songwriting credits within ten calendar years of their first. If we sort these sixty-six songwriters into the decades according to each songwriter's first Hot 100 hit and count them, we get the number of the superstar songwriters from each decade. Figure 11 presents this data.

[28]As previously stated, for each Hot 100 hit, songwriting credits are divided evenly among the listed composers, limited to the first ten listed composers. If two songwriters are credited for a Hot 100 hit, they each receive 0.5 songwriting credits. If three are credited, they each receive 0.3333 credits. And so on.

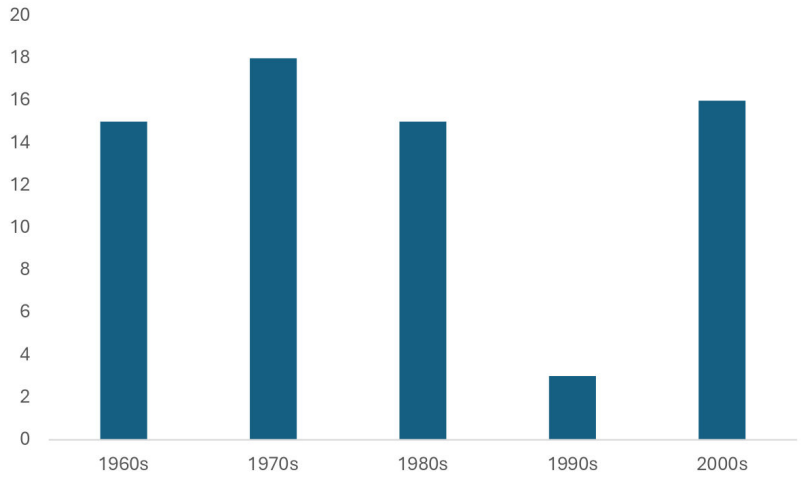

Figure 11: Number of superstar songwriters by decade

As Figure 11 reveals, the 1970s had the most superstar songwriters, with eighteen different songwriters garnering a total of at least twenty songwriting credits on Hot 100 hits within ten calendar years of their first Hot 100 hit. There are fifteen such superstar songwriters in the 1960s and 1980s, and sixteen in the first decade of the 2000s. The 1990s had only three.

In summary, for this study, I gathered data: (i) counting the unique songs that appeared on the Billboard Hot 100 each year from 1962 through 2022; (ii) scraping one-month and four-year stream count residuals for each song that appeared on the year-end Hot 100 for each year from 1963 through 2023 for the one-month stream count residual, or for the four-year stream count residual, from 1963 through 2019, from Last.fm; (iii) counting the number of new composers who had their first appearance as a credited composer of a Hot 100 hit for each year from 1963 through 2019; and (iv) calculating the mean productivity of those new composers for each year from 1963 through 2010. Visually, none of this data supports copyright's fundamental premise. None of these measures of creative output surge with the rise in revenue during the 1990s. None fall in the wake of file sharing.

Rather than rely on appearances alone, in the next section, I present regression results that test rigorously whether, over the last sixty years, there has been a positive correlation between incentives and creative output in the music industry, as copyright has long assumed.

5. A Search for Correlation: Incentives and Output

After running a wide array of regressions in search of a positive and statistically significant correlation between incentives and creative output for popular musical composition in the modern music era, I have finally found my first positive and statistically significant correlation. Specifically, there was a positive correlation between the first difference of composer revenue, lagged one year, and the first difference of the Hot 100 chart unique song count. In every other regression, either there was no statistically significant correlation between incentives in one year and creative output in the next, or where a statistically significant correlation could be found, it was negative. In particular, a negative correlation – that is more incentives in one year were associated with lower creative output in the next, *ceteris paribus* – was found: (i) between the level of incentives in one year, whether proxied by RIAA revenue or composer revenue, and the one-month Last.fm residual stream count in the next; (ii) between the first difference of composer revenue, lagged one year, and the first difference of the four-year Last.fm residual stream count; and (iii) between composer revenue in one year and our measure of mean new composer productivity in the next.

The regressions included models with three direct measures of creative output: (i) the Billboard Hot 100 unique song count (1962-2022); (ii) the one-month residual stream count for the year-end Hot 100 songs (1962-2023); and (iii) the four-year residual stream count for the year-end Hot 100 songs (1962-2019). I also tested for correlations with our indirect measures of creative output: (iv) the number of composers who received their first songwriting credit on a Hot 100 song in a given year (1963-2019); and (v) the mean productivity of those first appearance composers (1963-2010). For each of the five categories, I had annual observations, with the number of observations ranging from forty-eight for the fifth category to sixty-two for the second category.

My principal focus in the regressions was whether any of these dependent variables showed a correlation with incentives. As a proxy for incentives, I used either the music shipment data from the RIAA, shown in Figure 1, or the composer revenue data, shown in Figure 3, as an independent variable.[29] In addition, to isolate the role that incentives may play on creative output, I also attempted to account for other exogenous shocks that may have affected the music industry over the last six decades. I thus included independent variables in the regressions to account for other factors that may be affecting creative output. These additional independent variables seek to account for formal changes in copyright protection and thus include: (i) a dummy variable for the enactment of the Sound Recording Amendment of 1971; and (ii) a dummy variable for the enactment of the Copyright Act of 1976. They also seek to account for the practical effectiveness of copyright law in stopping unauthorized copying and thus include an estimate of the amount of file sharing traffic occurring in the United States taken from Cisco's Visual Networking Index. In addition, I accounted for the rise of Clear Channel radio. Its rise concentrated radio ownership and may have reduced the airplay opportunities for new music. Because airplay correlates with popularity and thus appearance on the Hot 100 chart, I included, as an independent variable, Clear Channel's market share over time, dividing Clear Channel's revenue from radio broadcasting (as set forth in its annual reports) by the total revenues from radio broadcasting in the United States (from the Census Bureau's Services Survey) to generate a rough estimate of the fraction of the radio market that Clear Channel controlled.[30] Descriptively, this variable began with Clear Channel receiving less than 1 percent of total radio broadcasting revenues through the early 1990s before rising to more than 20 percent of total radio revenue in the early 2000s, and then tailing off and holding

[29] As a robustness check, I also performed all regressions using the ASCAP payout ($2013) curve as the key independent variable that serves as a proxy for incentives. Except where expressly noted, the results were the same. Either there was no statistically significant correlation between ASCAP payouts in one year and the relevant measure of music creativity, or where there was a statistically significant correlation, it was negative.

[30] Clear Channel's share of radio revenue in 2010 was 17.03 percent, down slightly from its 17.16 percent share in 2009. Given that Clear Channel's revenue for radio broadcasting increased only slightly in 2011, 2012, and 2013, from $2.9 billion in 2010 to $3.1 billion in 2013, I assumed that Clear Channel's share of radio broadcasting remained constant from 2010 through 2022 at 17.03 percent. In addition, I could not find Clear Channel's radio revenue before 1990. In 1990, Clear Channel earned revenues from radio broadcasting of $69.6 million, representing less than one percent of the estimated revenue for radio as a whole. I therefore assumed that Clear Channel's share of radio revenue remained at the 1990 figure (or 0.96 percent) for the years before 1990.

steady at 17-18 percent by the late 2000s. Finally, I included independent variables for: (i) the size of the teenage cohort (ages 15-19) in the population; and (ii) the unemployment rate. I include the size of the teenage population both as a source for new composers and to reflect an ongoing preference that individuals may have for the music they listened to when they were teenagers. The unemployment rate is included to reflect economic factors that may drive demand for popular music. As the fall in shipments of recorded music in the early 1980s reflects, music purchases are a luxury good, and thus may fall when times are difficult. As I did in my prior work, Lunney (2018, at 124), I included, in the regressions, a cost variable decreasing over time, intended to reflect the falling cost of music production, but as it was not statistically significant in any of the regressions, I have omitted it from the reported regression results.

To estimate the correlation between output and each of these, I used an ordinary least squares model, and regressed the relevant measure of creative output, whether Unique Song Count, One-Month Residual stream count, Four-Year Residual stream count, New Artists, or Mean Number of Hits, against a linear combination of the independent variables. To avoid endogeneity, I used one-year lagged values for the RIAA music shipment and the composer revenue data. For robustness, I also performed regressions with one- and two-year lagged values for revenue. For each regression, I checked that the dependent variable was stationary using Dickey Fuller. Where the dependent variable was not stationary, I performed the associated regressions using first differences.

Before discussing the regression results, I should note that this is a very small data set, with between forty-eight and sixty-two observations for the dependent variables. This small size creates two principal difficulties. First, it sharply limits the regression techniques that we can use. Although ordinary least squares is not ideal for time series data, conventional time series analyses, such as the autoregressive integrated moving average approach, which might be more appropriate in theory, are not suitable for such a small data set.[31] Second, the small data set size may also limit the power of our regression

[31]For example, Box and Taio (1976) recommend between 50 and 100 data points for each period under study to use the ARIMA technique.

analysis. This will both generally limit our ability to separate correlations from noise and also emphasizes the need for parsimonious regression models. As we expand the number of potentially explanatory variables, we will quickly lose the ability to identify any statistically significant correlations, not because significant correlations do not exist, but simply due to the small size of the data set. For that reason, I have omitted a separate independent variable measuring the growth of social media. Despite the popular stories of superstars, such as Justin Bieber, being discovered on YouTube, and the emotional resonance of those stories, in previous work, I found no correlation between the rise of social media and the number of new artists entering the Hot 100 chart for the first time (Lunney 2018, at 140).

Of course, in any regression analysis, there is always a risk of omitted variable bias. Changes in live performance revenue or the rise of alternate channels of distribution and talent discovery or the switch to 360o contracts may be important factors in music production. Yet, we are not testing the effect of a small change in incentives. The RIAA revenue data drops by 66.4 percent from 1999 through 2014, by literally billions, and the composer revenue variable declines by 27.0 percent from 1999 through 2012, by over $800 million. These are substantial changes in the incentives copyright secures for creativity in the music industry. If copyright's fundamental assumption is correct, corresponding changes in music output should be immediate and readily apparent. If they are not, despite whatever changes in distribution costs or recording contracts, then incentives are not playing the central and vital role copyright has long assumed. With these cautionary notes in mind, we can now proceed to discuss the regressions and their results.

5.1. **Hypothesis #1: Mo' Money = Mo' Music?** While the regression results provide some support for this hypothesis, on balance, they reject the hypothesis. In support of the hypothesis, one of the six regression models found a positive and statistically significant correlation between incentives and creative output in the music industry over the last sixty years. Specifically, the regression results found a correlation between changes in incentives, proxied by the composer revenue data, in one year and changes in music output, proxied

by the Hot 100 chart unique song count, in the next. While this is the first model that yielded a positive and statistically significant correlation between incentives and creative output, I have spent a good part of the last decade running regressions that examine the rise of file sharing, the decline of music industry revenue, and creative output. Having run literally thousands of these regressions, a positive and statistically significant correlation was inevitable. Unfortunately, this regression result was not robust and was countered by statistically significant and negative correlations between incentives and music output in three of the other regression models. Specifically, there was a negative and statistically significant correlation between: (i) incentives in one year, proxied by the RIAA shipments data, and music output, proxied by the Last.fm one-month residual, in the next; (ii) incentives in one year, proxied by the composer revenue data, and music output, proxied by the Last.fm one-month residual, in the next; and (iii) changes in incentives, proxied by the composer revenue data, in one year and changes in music output, proxied by the Last.fm four-year residual, in the next. The remaining two regression models found no statistically significant correlation between incentives and music output. Taken as a whole, the results from the six regression models tend to reject the hypothesis that more incentives were associated with increased output of popular music compositions over the last six decades.

For this first set of regressions, we have three direct measures of more or better popular music and thus three dependent variables: (i) the Billboard Hot 100 unique song count; (ii) the one-month stream count residual for the year-end Hot 100; and (iii) the four-year stream count residual for the year-end Hot 100. For each of these dependent variables, I ran two sets of regressions. The first used the RIAA shipment data to examine whether sales of recorded music were correlated with popular music output. The second used the composer revenue data (from Figure 3). Obviously, each Hot 100 hit requires both a songwriter and a recording artist, although these two roles can sometimes be filled by the same person. The regressions using the RIAA shipment data extend the time period for the previous work done on the recording artist side of hit song production. The regressions using the composer revenue data break new ground and for the first time, examine the

songwriter side of hit song production. With three direct measures of music output and two proxies for incentives, I had six basic models testing the relationship between incentives and music output. For each such model, I ran multiple specifications, including or omitting additional independent variables, as well as multiple lags of the incentive variable, to test for robustness.[32]

We start with our Unique Song Count variable, which serves as an admittedly imperfect, albeit unbiased measure of the amount of high-quality music released each year. I performed the Dickey Fuller test on the Unique Song Count and cannot reject the possibility that this variable is non-stationary. Therefore, all regressions using the Unique Song Count as the dependent variable were run using first differences. Because we are using first differences for these regressions, the dummy variables for formal expansions of copyright protection in 1972 and 1978 are dropped from the regressions.

Variable	1 Δ(RIAA)	2 Δ(RIAA)	3 Δ(CR)	4 Δ(CR)
Constant	-9.5477 (0.178)	-9.442 (0.162)	-11.726 (0.098)	-11.707 (0.085)
Δ(Revenue)	0.00742 (0.175)	0.00791 (0.143)	**0.0838** **(0.045)**	**0.086** **(0.037)**
Δ(File Sharing)	**0.410** **(0.042)**	**0.398** **(0.045)**	**0.3966** **(0.032)**	**0.3802** **(0.036)**
Δ(Clear Channel)	-340.4 (0.412)	-	-362.75 (0.008)	-
Δ(Unemployment)	**17.628** **(<0.001)**	**17.481** **(<0.001)**	**17.048** **(<0.001)**	**16.786** **(<0.001)**
Δ(Teen Pop.)	7.65E-06 (0.585)	-	6.72E-06 (0.624)	-
Adj. R^2	0.171	0.187	0.204	0.218

Table 2: Regression Results for Unique Song Count: RIAA and Composer Revenue

Table 2 presents the key regression results for the unique song count using the RIAA revenue and composer revenue data for various combinations of independent variables, with p values in parenthesis. Columns 1 and 2 present representative regression results using the first difference of RIAA revenue as the revenue variable. Columns 3 and 4 present representative regression results using the first difference of Composer Revenue as

[32]Except where otherwise specifically noted, additional lags did not materially change the regression results.

the revenue variable. Coefficients, other than the constant, that are statistically significant at the 5 percent level are in **bold**.

Here it is. Finally. After running thousands of regressions searching for a positive and statistically significant correlation between incentives and creativity in the modern music industry, I have found one. While noteworthy, two cautionary notes should be emphasized. First, if you run enough regressions, sooner or later, you can find almost any result. Second, real world data is messy. It is chaotic, not orderly, and can often point simultaneously in multiple directions.

In evaluating the significance of this finding, I would note that the positive correlation reported in columns 3 and 4 is not robust. It is not robust to our measure of revenue. As Table 2 reflects, if I use the RIAA shipments data as the relevant measure of revenue, the correlation becomes statistically insignificant ($p = 0.141$). If I use ASCAP royalty payments as the relevant measure of revenue, the correlation becomes statistically insignificant ($p = 0.134$). It is not robust as to the model specification. If I drop either the file sharing or unemployment variables, or both, in an attempt to isolate the correlation between changes in composer revenue in one year and changes in the Hot 100 unique song count in the next, the correlation between composer revenue and the unique song count becomes statistically insignificant.[33] If I add a second lag of the first difference of composer revenue to the regression, the correlation between composer revenue and the unique song count becomes statistically insignificant ($p = 0.055$). Most importantly, it is not robust over time. If I regress the first difference of the unique song count against a constant and the first differences of the composer revenue, file sharing, and unemployment variables, the correlation between composer revenue and the dependent variable is not statistically significant if I run the regression using the data from 1964-2017 ($p = 0.160$). It becomes statistically significant if I run the same regression from 1964-2018 ($p = 0.030$). If I run the same regression from 1964-2019, the correlation becomes statistically insignificant

[33]If I drop the file sharing variable, $p = 0.141$ on the Composer Revenue coefficient. If I drop the unemployment variable, $p = 0.223$ on the Composer Revenue coefficient. If I drop both and regress the first difference of the Unique Song count against the first difference of Composer Revenue and a constant alone, $p = 0.474$ on the Composer Revenue coefficient.

again ($p = 0.178$). If I run the same regression from 1964-2020, the correlation becomes statistically significant again ($p = 0.041$). An examination of the data reveals that two outliers are driving the positive and statistically correlation reported in columns 3 and 4 of Table 2. Specifically, from 2017 to 2018 and from 2019 to 2020, the number of unique songs appearing on the Hot 100 chart increased by 140 and 157 songs, respectively. By way of comparison, the average yearly change for the entire sixty years under study is -0.7333 with a standard deviation of 43.45. When these two outliers are included in the regressions, the correlation between a change in composer revenue and a change in the unique song count is statistically significant. When they are omitted, the correlation is not statistically significant. This is troubling because, among other potential issues, recording artists began releasing all the singles simultaneously from an album in 2018, compared to their prior practice of releasing the singles over time.[34] The increase in the unique song count in 2018, rather than reflect more new music, may merely reflect the switch to a condensed release schedule.

But let us ignore these robustness concerns for now, and assume that the results in column four accurately capture the relationship between changes in revenue or file sharing traffic and changes in the unique song count – our proxy for high-quality music output. With that assumption, the question arises: On balance, did file sharing lead to increased or decreased music output? The regression results show two potentially offsetting effects. First, an increase in file sharing traffic was associated with a direct increase in the number of unique songs appearing on the Hot 100. The regression results do not say why this correlation exists. Perhaps, by providing free copies of songs to consumers, file sharing provided an advertising and popularity network effect – exposing consumers to new songs and enabling them to share those songs with others – that helps consumers discover and enjoy songs that they would not have without file sharing. But whatever the reason for the

[34]For example, Ed Sheeran released five singles each from his 2014 album, *x*, and his 2017 album, ÷. In both cases, the releases occurred over a year and thus some of the singles hit the chart in the year of the album's release and some the following year. In contrast, Ed Sheeran released eight singles from his 2019 album, *No. 6 Collaborations Project*. Yet, the releases occurred over three months, from May 10th to August 9, 2019, and all hit the Hot 100 chart in one year, 2019. Similarly, from his 2016 album *Stoney*, Post Malone released six singles over more than two years. By way of contrast, from his 2018 album *Beerbongs & Bentleys*, Post Malone released six singles over eight months and ten days.

correlation, if we use the coefficient for file sharing from column four, the 890 petabytes[35] per month rise in North American file-sharing traffic from 1999 to 2014 was associated with 338.38 additional new songs on the Hot 100 chart annually, *ceteris paribus*. Second, a decrease in composer revenue was associated with a decrease in the Hot 100 unique song count. If we assume that file sharing caused the reduction in revenue, then the rise of file sharing also indirectly reduced the unique song count. As an estimate of this indirect effect, composer revenue fell by $887 million ($2013) from 1999 to 2012. If we assume that file sharing caused all of that fall, that lost revenue was associated with 76.26 fewer new songs on the Hot 100 chart annually, using the coefficient in column four. Thus, accepting the results in column four of Table 2 as accurately capturing the relevant relationships, the rise of file sharing may have reduced composer revenue – a wealth transfer with no net welfare effects – but was associated on balance with a net gain of 262.12 additional new songs on the Hot 100 chart annually, *ceteris paribus* – a clear welfare gain, at least, to the extent the unique song count is an effective proxy for the quantity of high-quality music produced and released in a year.

I would note that, although the composer revenue correlation is not robust and may be the result of changes in single release practice, the correlation in column four reveals a proportionate relationship between reduced composer revenue and reduced music output. Specifically, the revenue loss of $887 million ($2013) from 1999 through 2012 represents 27.0 percent of the 1999 composer revenue. The estimated loss in music output associated with that reduction in composer revenue – 76.26 fewer new songs on the Hot 100 annually by 2012 – represents 23.9 percent of the 1999 unique song count. Nevertheless, that there is a positive and statistically significant correlation between composer revenue and music output, but not recording artist revenue and music output remains troubling. Releasing music requires both composer and recording artist. So before we put too much weight on the first positive and statistically significant correlation found between revenue and

[35]The typical music CD contains $650 - 700$ megabytes of data. A gigabyte is $1,000$ megabytes. A terabyte is $1,000$ gigabytes. And a petabyte is $1,000$ terabytes. As a result, if we assume that only 10 percent of the 890 petaybtes per month of file sharing traffic in North America in 2014 was of music, that's the equivalent of 127.1 million albums worth of music each month.

creative output for the modern music industry, let us consider the results from our other regressions.

When we move from the unique song count as a measure of the quantity of high-quality music released to the Last.fm stream count residual data, we return to the pattern I have previously found. Incentives either have no statistically significant correlation, or, in most of the regressions, a statistically significant and negative correlation, with music output. When we use the RIAA shipment data as the proxy for incentives and the age-adjusted satisfaction for the year-end Hot 100 songs from each year as a measure of the quality of the hit songs for each year, we find a negative and statistically significant correlation between incentives in one year and music quality in the next for the one-month stream count residual data, but no statistically significant correlation between changes in incentives in one year and changes in music quality in the next for the four-year stream count residual data. When we use composer revenue as the proxy for incentives, the correlation becomes statistically significant and negative for both the one-month and four-year stream count residual data. For both sets of regressions, whether we use RIAA shipment data or composer revenue data as the proxy for incentives, Dickey Fuller rejects non-stationarity for the one-month stream count residual residuals, but not for the four-year stream count residual residuals. For that reason, the regressions using the one-month stream count residual data are run in levels.[36] The regressions using the four-year stream count residual data are run in first differences.

Table 3 presents representative results from the one-month stream count residual data, in levels, and the four-year stream count residual data, in first differences, using RIAA shipment data as the proxy for incentives, with p-values in parenthesis. Coefficients that are statistically significant at the 5 percent level, aside from the constant, are in **bold**.

[36]I also ran the one-month stream count residual data regressions in first differences. In all of the results, there is no statistically significant correlation between incentives, whether proxied by RIAA shipment data or composer revenue, and the quality of the year-end Hot 100 songs for each year, proxied by the one-month stream count residual residuals.

Variable	One Month AAS	One Month AAS	Four Year AAS First Difference	Four Year AAS First Difference
Constant	-28393.4 (0.243)	16993.4 (<0.001)	-1037.94 (0.977)	2366.65 (0.056)
Record Sales	**-1.759 (0.0018)**	**-1.727 (<0.001)**	-44.752 (0.607)	-21.223 (0.325)
File Sharing	**-14.369 (0.033)**	**-12.181 (0.034)**	214.60 (0.832)	-
Clear Channel	**97277.42 (0.0023)**	**121431.5 (<0.001)**	945378.7 (0.122)	-
1972 SR © Dummy	-2820.79 (0.687)	-	-	-
1978 © Dummy	3702.26 (0.495)	-	-	-
Unemployment	936.25 (0.373)	-	24440.01 (0.429)	-
Teen Pop.	0.00214 (0.124)	-	0.0243 (0.717)	-
Adj. R^2	0.425	0.397	-0.057	-0.00023

Table 3: Regression Results for Stream count residual Data: RIAA Revenue

When we examine the correlation between incentives, here proxied by RIAA shipment data, and better music, here proxied by the age-adjusted satisfaction using Last.fm stream count residual data, we find a statistically significant and negative correlation for the one-month Last.fm stream count residual data, but no correlation between incentives and better music for the four-year Last.fm stream count residual data. Indeed, the negative adjusted R-squared in columns three and four of Table 3 suggests that changes in year-to-year recording artist incentives has no power to explain the observed changes in the year-to-year quality of the year-end Hot 100 over the years 1964-2019.

Also, of interest, the rise of Clear Channel was associated with a statistically significant increase in the quality of the year-end Hot 100 songs, *ceteris paribus*, at least in the one-month Last.fm regressions. The rise of file sharing was associated with a statistically significant decrease in the quality of the year-end Hot 100 songs, *ceteris paribus*, in the one-month Last.fm regressions.

If instead of RIAA shipment data as the proxy for incentives, we use composer revenue, we get a more consistent result. Holding all else constant, increased incentives in one year, now proxied by composer revenue, were associated with lower quality hit songs in the next. Table 4 presents representative results from the one-month stream count residual data and the four-year stream count residual data using composer revenue as the proxy for incentives, with p-values in parenthesis. Coefficients that are statistically significant at the 5 percent level, aside from the constant, are in bold. As previously stated, Dickey Fuller rejects non-stationarity for the one-month Last.fm residuals, but not for the four-year Last.fm residuals. As a result, the regressions using the one-month Last.fm residual or age-adjusted satisfaction as the dependent variable are run in levels, while the regressions using the four-year Last.fm residual are run in first differences.

Variable	One Month AAS	One Month AAS	Four Year AAS First Difference	Four Year AAS First Difference
Constant	-18687.1 (0.456)	20228.6 (<0.001)	19912.67 (0.573)	16733.65 (0.522)
Composer Rev.	**-12.357 (0.0021)**	**-12.140 (<0.001)**	**-433.77 (0.036)**	**-433.82 (0.019)**
File Sharing	-1.793 (0.713)	-0.282 (0.953)	-123.47 (0.892)	-
Clear Channel	**120751.3 (<0.001)**	**140136.2 (<0.001)**	-1312432 (0.515)	-
1972 SR © Dummy	-3628.1 (0.601)	-	-	-
1978 © Dummy	4603.51 (0.407)	-	-	-
Unemployment	1431.81 (0.145)	-	15863.36 (0.570)	-
Teen Pop.	0.00164 (0.235)	-	0.0367 (0.568)	-
Adj. R^2	0.421	0.384	0.028	0.081

Table 4: Regression Results for Stream count residual Data: Composer Revenue

When we examine the correlation between incentives, here proxied by composer revenue, and better music, here proxied by the age-adjusted satisfaction for the year-end Hot 100 using Last.fm stream count residual data, we find a statistically significant and negative correlation across all of the regressions. Holding all else constant, increased incentives in one year were associated with lower quality hit songs in the next. Also, of interest, the

rise of Clear Channel was associated with a statistically significant increase in the quality of the year-end Hot 100 songs, ceteris paribus, at least for the one-month Last.fm data.

In summary, if we focus on the key issue – do incentives increase creative output – our regression analysis yields a somewhat inconsistent answer. In total six different basic regression models were run. They used three proxies for music output: (i) the Hot 100 unique song count; (ii) the one-month Last.fm stream count residual; and (iii) the four-year Last.fm stream count residual. They used two proxies for incentives: (i) RIAA shipments; and (ii) Composer Revenue. Four of the models were run in first differences because the Hot 100 unique song count and the four-year Last.fm stream count residual variables were non-stationary. Of those four, one found a statistically significant and positive correlation between changes in incentives in one year, proxied by composer revenue, and changes in creative output, proxied by the Hot 100 unique song count. This is the first such correlation I have found in a decade of running these regressions. The result is not robust, but for those whose *a priori* views align with this result, the result is welcome news. On the other hand, one of these four also found a statistically significant but negative correlation between changes in incentives in one year, proxied by composer revenue, and changes in creative output, proxied by four-year Last.fm residuals. Two of the four found no correlation. The remaining two models were both run in levels because the dependent variable – the one-month Last.fm stream count residual – was stationary. Both found a statistically significant and negative correlation between incentives in one year, whether proxied by RIAA shipments or composer revenue, and creative output in the next, proxied by one-month Last.fm residuals. While one set of regression results supports the premise that more incentives will lead to more copyrighted works, five do not. And three find the exact opposite relationship. More incentives were associated in those three models with reduced creative output, *ceteris paribus*. On balance, then, we are still searching for consistent evidence that more incentives are associated with increased creative output in the modern music industry.

In the next section, we move on from seeking a correlation between incentives and music output directly, and examine whether there is a correlation between incentives and a key input to creative music output: the entry of new composers.

5.2. **Hypothesis #2: Mo' Money = Mo' Composers?** The second set of regressions tested the hypothesis that more incentives in one year will be associated with more entry into the market for writing Hot 100 hits in the next. Based upon the regression results, we must reject the hypothesis that more incentives in one year were associated with more new composers entering the market for writing Hot 100 hits in the next for the modern music industry. Through multiple specifications, regression analysis consistently found no correlation between revenue in one year and the number of new composers in the next. More money was not associated with more composers, *ceteris paribus*. We therefore reject the second hypothesis.

The regressions use a measure of new market entrants – the number of composers who had a songwriting credit on their first Hot 100 hit in a given year from 1963 through 2019 – as the dependent variable. We then regress that dependent variable against composer revenue and various combinations of other potentially explanatory independent variables. Dickey Fuller rejects non-stationarity for the First Appearance Composer count. As a result, all regressions using the variable were run in levels.

To begin the discussion, we isolate the relationship between incentives and entry. If we do so and regress the number of first appearance composers against a constant and the previous year's composer revenue, we find no statistically significant correlation between composer revenue in one year and the number of new composers who had their first Hot 100 writing credit in the next (-0.0098, $p = 0.475$). Moreover, the adjusted R-squared for the regression is less than zero. This indicates that variation in composer revenue explains none of the observed variation in new composer entry. In short, money didn't matter. Figure 12 presents this relationship, or more precisely, its absence, by plotting new entrants and predicted new entrants against the previous year's composer revenue.

The results shown in Figure 12 are unsurprising based upon the initial presentation of the data on songwriter entry in Figure 8. As we saw, the count of first appearance composers started over 500 in the early 1960s, then fell to below 400 from the 1970s through 2012 and then rose to over 500 again in the mid-2010s. Composer revenue, on the other hand, rose generally throughout the period, albeit with some reduction following the rise of file sharing.

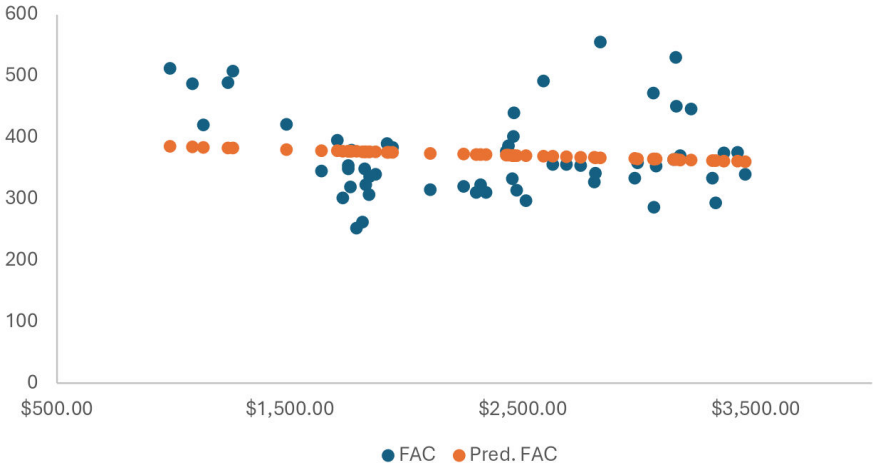

Figure 12: First appearance composer count vs. composer revenue (one-year lag), (in millions, $2013)

If we move beyond this focus on composer revenue alone and consider other possibly explanatory variables, the correlation between incentives and entry remains statistically insignificant. Table 5 presents the key regression results. Because this regression model focuses on new composer entry, all of the reported regression results rely on composer revenue, and not RIAA shipments, as the measure of incentives. Coefficients, other than the constant, that are statistically significant at the 5 percent level are in **bold**.

As the regression results in Table 5 reflect, more incentives in one year, here proxied by composer revenue, are not associated with additional new composer entry the next year.[37] More money did not yield more new composers – at least, not more new composers good enough to write a Hot 100 hit.

[37]Adding a second lag of composer revenue did not change the lack of a statistically significant correlation.

Variable	1	2	3	4
Constant	700.15 (<0.001)	413.78 (<0.001)	853.30 (<0.001)	880.92 (<0.001)
Composer Rev.	0.0236 (0.345)	0.0142 (0.368)	-0.00595 (0.709)	-0.0040 (0.755)
File Sharing	**0.126 (0.0012)**	**0.0593 (0.0152)**	**0.1122 (0.0022)**	**0.1123 (<0.001)**
Clear Channel	-263.58 (0.229)	-	-79.80 (0.687)	-
1972 SR © Dummy	-73.00 (0.087)	**-104.37 (<0.001)**	-	-
1978 © Dummy	5.299 (0.874)	-	-	-
Unemployment	-5.224 (0.394)	-	**-10.954 (0.0318)**	-
Teen Pop.	-1.5E-05 (0.063)	-	**-2.1E-05 (0.021)**	**-2.7E-05 (<0.001)**
Adj. R^2	0.341	0.233	0.320	0.282

Table 5: Regression Results for First Appearance Composers

Curiously, when the dummy variables are omitted from the model, the correlation between the size of the teenage population (ages 15-19) in the United States and new composer entry becomes negative and statistically significant. We would ordinarily expect a positive correlation, i.e. more new entrants when the teenage population is large, because a larger teenage cohort both provides a larger supply of potential new entrants and increases demand for new popular music. This result is therefore unexpected and requires further study. In all of the reported regressions, increasing levels of file sharing traffic is associated with increased songwriter entry. This may reflect that with the rise of the Internet, barriers to entry for new composers fell. But this too requires further study.

5.3. **Hypothesis #3: Mo' Money = Mo' Work?** The third set of regressions tested the hypothesis that more incentives in one year will be associated with more productivity by new composers entering the market for writing Hot 100 hits in the next. Based upon the regression results, we must reject this hypothesis for popular music compositions over the last six decades. Through multiple specifications, regression analysis consistently

found a statistically significant and negative correlation between incentives in one year and productivity among new composers entering the market in the next. More money was associated with less productivity, *ceteris paribus*. We therefore reject the third hypothesis.

In these regressions, our dependent variable is the mean productivity of new artists for each year, where productivity is total Hot 100 songwriting credits over the ten calendar years following a songwriter's first Hot 100 songwriting credit. As discussed, for each Hot 100 hit, songwriting credit is divided evenly among the listed songwriters. If there are two listed songwriters, each receives 0.5 credit. If there are ten listed songwriters, each receives 0.1 credit. Dickey Fuller rejects non-stationarity for this dependent variable. As a result, all regressions are run in levels.

To begin the discussion, we isolate the relationship between incentives and productivity. If we regress mean new composer productivity against a constant and the previous year's composer revenue, we find a statistically significant and negative correlation (-0.00021, $p = 0.00134$). Figure 13 presents this relationship by plotting mean productivity and predicted mean productivity against the previous year's composer revenue.

Figure 13: Mean new artist productivity vs. composer revenue (in millions, $2013)

While there are a few outliers in the data in Figure 13, more composer revenue in one year was associated with lower mean new composer productivity in the next, all else constant.

Variable	1	2	3	4
Constant	1.419 (0.097)	0.753 (0.341)	0.770 (0.238)	0.641 (0.313)
Composer Rev.	**-0.00046** **(0.0018)**	**-0.00026** **(0.00897)**	**-0.00031** **(0.0011)**	**-0.00026** **(<0.001)**
File Sharing	-0.00017 (0.752)	-0.00013 (0.738)	-0.00032 (0.556)	-0.00016 (0.621)
Clear Channel	1.078 (0.452)	-	0.704 (0.618)	-
1972 SR © Dummy	0.293 (0.222)	0.0547 (0.797)	-	-
1978 © Dummy	0.054 (0.765)	-0.0228 (0.899)	-	-
Unemployment	-0.0714 (0.0874)	-	-0.0314 (0.324)	-
Teen Pop.	5.95E-08 (0.186)	6.39E-08 (0.156)	**7.8E-08** **(0.033)**	**7.06E-08** **(0.042)**
Adj. R^2	0.235	0.195	0.227	0.230

Table 6: Regression Results for Mean New Composer Productivity

If we include additional possibly explanatory variables in the regression model, the correlation between incentives and productivity remains statistically significant and negative. Table 6 presents the key regression results, with composer revenue as the measure of incentives. Coefficients, other than the constant, that are statistically significant at the 5 percent level are in **bold**.

As Table 6 reflects, the correlation between composer revenue in one year and the mean productivity of new Hot 100 songwriters in the next is consistently statistically significant and negative across all of the specifications. Whether we include or omit the instrumental variables for formal expansions of copyright protection, the unemployment rate, or the rise of Clear Channel, more incentives in one year were associated with less productive new composers in the next, *ceteris paribus*.[38]

[38]If we add a second lag to the regression, the correlation between the first lag and productivity becomes statistically insignificant, but the correlation between the second lag and productivity is statistically significant and negative.

As for the other potentially explanatory variables, a larger teenage population (ages 15-19) was statistically significant and positively correlated with new composer productivity when the dummy variables for formal increases in copyright protection are omitted, but not statistically significant when those instrumental variables are included.

These results tend to confirm a hypothesis offered before.[39] As copyright increases the pay for our top authors, or here, composers, copyright pushes them onto the backward-bending portion of the labor supply curve. As we pay our top composers more, they spend less time on work and more time on leisure. They become, as the regression results in Table 6 consistently show, less productive. As a result, more money yields less, rather than more, original new music.

6. Copyright Sans Incentives?

From a social welfare perspective, file sharing has proven an unmitigated boon. File sharing has vastly increased access to existing music. As I testified to Congress, "file sharing put music in the hands of more Americans than any invention since the phonograph."[40] True, it likely cost the music industry billions in uncaptured revenue. That is not a welfare loss, however. Those billions that the music industry was unable to capture were not lost or destroyed. They did not vanish from the economy. No, they remained in consumers' pockets to be invested or spent on other things.

As for the longstanding fear[41] that without this revenue too little music would be created, it proved unfounded. While I finally found and present in this article the first regression

In the specification reported in column one of Table 7, if we add a second lag of composer revenue, its coefficient is -0.00083 ($p = 0.0275$).

[39] Lunney (2001, at 890) first posited this possibility in 2001. Scherer (2008, 2012) provided anecdotal support for it in connection with the provision of copyright protection for operas in the 19th century in Europe, focusing on one composer, Giuseppi Verdi. Lunney (2018) presented the first systematic examination of the possibility. With the rise of the sound recording right in the United States in 1971, record sales rose sharply through the 1990s, but this sharply reduced superstar productivity for the recording industry as a whole in the 1990s. With the rise of file sharing and the fall of the sound recording copyright beginning in 1999, record sales fell sharply through the 2000s, but superstar productivity increased (Lunney 2018, at 3-5, 168-69).

[40] *The Scope of Copyright Protection*, Hearing Before the Subcommittee on Courts, Intellectual Property, and the Internet, of the Committee on the Judiciary, House of Representatives, 113th Cong., 2d Sess., Serial 113-81, at 34 (Jan. 14, 2014).

[41] The Stationers' Company first articulated the fear to the Star Chamber in a 1586 petition to renew exclusive printing privileges in books (see *A Transcript of the Registers of the Company of Stationers of London*: 1554-1640 A.D., 1875).

model to show a statistically significant and positive correlation between changes in incentives in one year, proxied by composer revenue, and changes in creative output in the next, proxied by the Billboard Hot unique song count, for the modern music industry, even if we accept that result as accurate and correct, the same regression model shows, on balance, society gained more Hot 100 hits from the rise of file sharing than it lost due to the loss in composer revenue.

Moreover, we found such a positive and statistically significant correlation in only one of six regression models focusing on incentives and creative output directly. Of the remaining five, two found no statistically significant correlation between: (i) changes in RIAA shipments in one year and changes in the Hot 100 unique song count in the next; and (ii) changes in RIAA shipments in one year and changes in the four-year Last.fm stream count residual for the next. And three found a statistically significant and negative correlation between: (i) RIAA shipments in one year and the one-month Last.fm stream count residual in the next; (ii) composer revenue in one year and the one-month Last.fm stream count residual in the next; and (iii) changes in composer revenue in one year and changes in the four-year Last.fm stream count residual for the next.

On balance, then, our regression results do not find the sort of strong, consistent, and compelling evidence that file sharing reduced creative output in the modern music industry that copyright leads us to expect. It may have reduced revenue for both recording artists and composers alike, but after the rise of file sharing, the production of high-quality popular music either continued apace or increased.

With respect to the other issues examined, incentives had no statistically significant association with new composer entry. Before or after file sharing, individuals continued to choose songwriting as a field in which to devote their talents without regard to the level of, or changes to, composer revenue. Incentives did however have a negative and statistically significant correlation with composer productivity. When incentives were low, whether following file sharing or otherwise, the most talented songwriters were more productive.

For the modern music industry, proof of a strong and consistently positive connection between incentives and creative output that copyright has long assumed continues to

remain elusive. If anything, this study provides further evidence that more copyright protection and more incentives perversely leads to reduced creative output.

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