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Copyright and Economic Viability: Evidence from the Music Industry

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Copyright Statement

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Copyright provides a long term of legal excludability, ostensibly to encourage the production of new creative works. How long this term should last, and the extent to which current law aligns with the economic incentives of copyright owners, has been the subject of vigorous theoretical debate. We investigate the economic viability of content in a major content industry—commercial music—using a novel longitudinal dataset of weekly sales and streaming counts. We find that the typical sound recording has an extremely short commercial half-life—on the order of months, rather than years or decades—but also see evidence that subscription streaming services are extending this period of economic viability. Strikingly, though, we find that decay rates are sharp even for blockbuster songs, and that the patterns persist when we approximate weekly revenue. Although our results do not provide an estimate of the causal effect of copyright on incentives, they do put bounds on the problem, suggesting a misalignment between the economic realities of the music industry and the current life-plus-70 copyright term.

I. INTRODUCTION

Creative works are widely understood to have a "non-excludability" problem. Once published, books, songs, television shows, and movies are cheap to copy and share, which in many cases may limit the rightsholder's ability to appropriate the value of her work. Economic theory predicts that this will lessen incentives to write, sing, and make films. In

response, the law provides a limited property right in many kinds of creative work. Copyright provides a narrow and time-limited period of legal excludability, during which the owner of the right can prevent others from—among other things—copying, performing, displaying, or making derivatives of her work, and can therefore command above-marginal-cost returns in the marketplace. This policy mechanism prompts a canonical legal design question: For how long should a copyright last?

The duration of copyright has long been a fraught public policy question. Although there has been significant academic attention to the topic within both the economics and legal literatures, much of the debate has played out in the political sphere. After a succession of trade deals,[1] legislative extensions,[2] and Supreme Court decisions,[3] the current U.S. copyright term for most works now subsists for the lifetime of the author plus an additional 70 years.[4] (Corporate works—also known as "works for hire"—have a slightly different term, but for all intents and purposes enjoy a similar duration of protection.) While the political debate in the United States has tapered in recent years, concern about term length remains salient in many jurisdictions where it is still an active policy issue.[5] Proponents of longer terms argue that they are essential to incentivize new creations, and that they encourage owners to continue to be good stewards of their works long after initial release (Landes & Posner 2003). Opponents contend that long terms vastly over-reward a select few copyright owners and create an unnecessary thicket of conflicting property rights, stifling future creativity (Heller 2010).

Despite this long running debate, relatively little evidence has been introduced about the economic characteristics of commercial copyrighted works. Yet from a theoretical perspective, this is a key threshold question. As with other intellectual property (IP) rights, copyright is ostensibly designed to provide a financial incentive to produce creative works. However, for an individual creator or prospective copyright owner, the incentive operates only for the period during which its owner expects her work to be viable in the market. This detail prompts several empirical questions, on which there is surprisingly little hard evidence. How long does the typical copyrighted work maintain its commercial viability? Over what period should a creator, artist, or intermediary rightsholder expect a return?

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[1]See, e.g., TRIPS: Agreement on Trade-Related Aspects of Intellectual Property Rights, Apr. 15, 1994, Marrakesh Agreement Establishing the World Trade Organization, Annex 1C, 1869 U.N.T.S. 299, 33 I.L.M. 1197 (1994).

[2]See, e.g., Sonny Bono Copyright Term Extension Act (1998) [hereinafter CTEA].

[3]See Eldred v. Ashcroft, 537 U.S. 186 (2003), in which the Court upheld the constitutionality of the retroactive term extensions contained in the CTEA.

[4]The Berne Convention, to which most nations are party, provides for a minimum duration of 50 years plus the life of the author, but signatories are free to set longer terms. Berne Convention for the Protection of Literary and Artistic Works, Sept. 9, 1886, as revised in Paris on July 24, 1971 and amended in 1979, Art. 7.

[5]In recent years, the United States has used trade agreements as a vehicle to encourage other countries to extend the durations of IP protection. For example, the United States-Mexico-Canada trade agreement (so-called NAFTA 2.0) will extend Canadian copyright terms from 50 to 70 years plus the life of the author. See, e.g., Geist (2018).

To shed fresh light on these questions, we use a novel dataset from the commercial music industry that allows us to track sales and streaming volumes over time. As a particularly IP-intensive industry, music presents an important case study of the relationship between property rights and economic viability.[6] Using our highly granular, longitudinal dataset, we are able to track the economic lifecycle of a broad mix of individual musical works over time, ranging from pop smash hits to classical compilations. The results yield a rich picture of the typical window of appropriability for musical recordings. We find that most commercial music has a remarkably short "economic half-life": on average, a commercially released track loses almost 90 percent of its initial sales volume by the end of its second year of release. Strikingly, this pattern holds across genres and even for blockbuster releases, suggesting that the current copyright term is at odds with creative realities in a key content industry.

In a companion piece, two of us develop the doctrinal implications of our findings (García & McCrary 2019). That paper focuses on the normative implications of a period of commercial viability that is substantially shorter than the current U.S. copyright term. In this article, we turn to theory and empirics in more depth. We also introduce several extensions, exploring the role of "top-selling" albums and the relationship between time and revenue. We begin in Section II by surveying the theory and literature on intellectual property terms, as well as copyright in music specifically. In Section III we describe the data and introduce our empirical approach. In Sections IV and V we present our main results and several extensions, and conduct robustness and sensitivity checks on our findings. Section VI concludes.

II. Theory and Literature

Identifying the optimal term of copyright has long challenged economists and legislators alike. The classic utilitarian conception of IP law is a response to a well-known public goods problem in intellectual work (for canonical early discussion, see Arrow 1962). Creative work is (often) expensive to create but cheap to copy. To address this, IP provides a limited term of legal excludability, affording the rightsholder an opportunity to recoup her investment by earning a return above marginal cost in the marketplace during the exclusive period. The basic model implies that a stronger right will increase the share of a work's social value that an owner can appropriate. In theory, then, an increase in the length of the copyright term will be accompanied by an increase in the creative incentive that it provides (Varian 2005),[7] but there are several important caveats. First, longer terms are not cost-free: policymakers face a classic "incentive-access" tradeoff (Bracha &

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[6]In this sense, intensive refers to an industry with an unusually high ratio of IP-derived revenue to general revenue (Didwania 2018: 237).

[7]This article takes the core economic theory as given, but there is an important and growing literature that argues that creative incentives are much more heterogeneous and complex. For examples, see Buccafusco (2007), Raustiala and Sprigman (2006), Silbey (2014), and Buccafusco et al. (2014).

Syed 2014). On the one hand, we may be able to increase a copyright owner's incentives by strengthening the right and giving her greater pricing power. On the other hand, by doing so, we limit consumers' access to creative works and thus increase deadweight loss. We may also inhibit follow-on creation by other artists and creators (Scotchmer 2004). Second, and more relevant to this article, the incentive effect of copyright is neither boundless nor linear: for most works, we expect diminishing private returns to increases in intellectual property term length (Nordhaus 1967).

The extent of both the incentive effect and the costs of copyright are, in principle, empirically testable. On the question of cost, some attention has been paid to the effect of copyright on the availability and perceived quality of creative work. Exploiting the fact that works written before 1923 are in the public domain in the United States, Heald (2008, 2014) finds that copyright status is associated with a significant increase in the proportion of books that are out of print and functionally unavailable.[8] Similarly, Reimers (2019) uses a regression discontinuity to identify the effect of copyrights on the price and availability of literature, and concludes that copyright results in higher prices (and fewer editions) for popular works, and lesser availability among low- and medium-quality works. Reimers draws a mixed picture of the welfare effects of this tradeoff, finding that, in this case, the decrease in consumer surplus from reduced access to lower-quality works was not offset by increased profits for owners of popular books.

Buccafusco and Heald (2013) see a similar result with respect to availability in the audiobook market. They also show experimentally that copyrighted audiobooks are no more likely to be perceived by listeners as "high quality" than audiobooks derived from public-domain works, somewhat contrary to theoretical predictions that copyright owners will have an incentive to be better stewards of older works. However, the picture is complicated: in the musical context, MacGarvie et al. (2018) show that the expiry of copyright leads to a doubling of rereleases of the underlying work but has no effect on the availability of the original track on Spotify's streaming platform.

In the case of follow-on creation, new evidence from economic history suggests that copyright can limit the circulation of knowledge in the scientific community (Biasi & Moser forthcoming). Similarly, in the music industry, Didwania (2018) finds evidence that copyrighted musical works are sampled at less than half the rate of comparable public-domain tracks.

On the incentive side, there is rather less evidence. In legal scholarship, much of the literature has focused on IP's "negative space"—particular industries where innovation appears to flourish despite a lack of formal legal protection (for a recent survey, see Sprigman 2017). On the direct link between incentives and IP, some experimental work suggests a mixed picture of the effect, at least in controlled settings (e.g., Buccafusco et al. 2014). Elsewhere, economists offer historical empirical evidence to suggest that longer copyright terms lead to higher prices (Giorcelli & Moser 2020). In general, however, credible causal estimates are hampered by the long terms of existing copyrights and the lack of variation in the global policy environment, which has become increasingly standardized through international treaty-making (Li et al. 2018).

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[8]Heald (2019) finds similar results in the South African context, where copyright expiry is more recent.

Our article tackles the incentive side of the equation, but with a slightly different approach. Rather than attempting to identify the price effect of copyright, we take a step back and put bounds around the problem. We ask what level of financial incentive is actually provided in a key content industry—and, implicitly, whether the current law is a good fit to that economic reality. Several authors have tackled the question of depreciation in the music industry. Soloveichik (2013) uses Billboard sales rankings and RIAA time-to-certification data to infer a depreciation rate for purchased music. In a paper that develops a measure of the "quality" of commercial music, Waldfogel (2012) uses a similar methodological strategy to estimate depreciation rates for different musical vintages. In addition to the RIAA data, he uses longitudinal information on radio airplay to estimate that tracks receive, on average, 25 percent of their initial share of radio airtime after 10 years of release. However, because recording artists and labels are not compensated for plays of sound recordings on terrestrial radio, it is a somewhat indirect proxy for economic value and incentives.[9] These studies provide important bounds on the economic performance of music over time, but they use fairly coarse data. With the dataset we introduce in this article, we are able to take advantage of highly granular sales and streaming data to more accurately estimate depreciation curves for commercial music.

III. Data and Empirical Approach

Our main data were supplied by Nielsen, a data aggregation company that collates listening figures from a wide range of industry sources and online platforms. The datasets are two-fold. The first contains data for a random sample of albums released between 2008 and 2017. We have 1,200 albums in total, stratified by year of release (120 albums per year). For each album, we observe weekly counts of song sales and streams, aggregated at the album level, as well as physical and digital whole-album sales (again weekly). The second dataset is a random subsample of the first. It contains sales and streaming volumes of each individual track for 10 percent of the albums contained in Dataset 1. Once again, we observe weekly sales and streaming counts for each track, from the week of release until the end of 2017.[10]

We supplement the Nielsen sales data with hand-collected metadata that include each album's release date and genre, as well an indicator for whether it was previously released in some form. In the analyses that follow, we exclude all "previously released" works (which are primarily compilations and "greatest hits" albums). This leaves us with 916 albums and, at the song level, 1,528 tracks from 105 unique albums.

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[9]The underlying composition (or musical work) and particular recordings of it are conceptually and legally distinct, and are subject to slightly different rules. When a work is played on terrestrial (AM/FM) radio, the owner of the *musical work* receives a share of royalties pursuant to a statutory license, but the owner of the *sound recording* does not.

[10]Note that our sampling strategy leads to an unbalanced panel. The sample includes albums released throughout our window: every album is observed only from its entry into the dataset, which could be as early as January 1, 2008 or as late as December 22, 2017. As a result, we have between one and 520 observations for each unit: for example, we observe the full 520 weeks for an album released on January 1, 2008, but only 26 weeks for an album released in June 2017.

A. Descriptives

Our data include a wide variety of recorded music, from hit singles by well-known stars to compilations of children's music. The sample includes a representative array of genres, including rock (35 percent of albums), hip-hop and R&B (14 percent), country (9 percent), pop (7 percent), and others. Mirroring the broader population of music, a small portion of our data is compilations of previously released works—either greatest hits albums or multi-artist anthologies such as soundtracks—but the majority are new-release studio albums.

The distribution of recorded music sales has an extremely long tail, and there is enormous variation in the overall sales volume both between albums and over time. Table 1 shows summary statistics across our four outcome variables. At the high end, a single blockbuster album saw 175 million streams in a single week, but the majority of our observed weekly counts are quite low.

Significant changes occurred in the industry during our study window. Figure 1 shows industry revenue (rather than volume) by format, which gives a sense of the decade-long trend. In 2008, sales of downloaded digital music had already overtaken physical CDs as the dominant format by volume, but CDs remained the largest revenue stream for the industry. By the early 2010s, downloads overtook CDs in revenue terms, but streaming quickly caught up. By 2017, paid and ad-supported subscription services represented by far the most economically important distribution format.

To ensure that we capture these changing dynamics, we begin by analyzing the four modes of distribution—track sales, track streams, physical album sales, and digital album sales—separately. Most music in our dataset was offered for sale or download through all four media, but there are some exceptions—for example, certain releases were only distributed in whole-album format. We therefore exclude any unit from analysis if we do not observe at least one sale (or stream) through the distribution channel in question.

B. Empirical Strategy

Because our focus is on the duration of commercial viability, we are primarily interested in the decay rate—the relationship between sales volume and time—which leads to a general model of the form $\mathbb{E}[y_{it}|x_{it}] = f(x_{it})$. y_{it} is the observed sales or streaming volume for album (or track) i at week $t \in [0,519]$. $f(x_{it})$ includes functions of time since release. For the album-level data, we use "weeks since release" and its square root to account for nonlinearity in the relationship.

Table 1: Summary Statistics for Weekly Sales and Streaming Counts

	Mean	SD	*Min.*	*Median*	*Max.*
Digital album sales	217	2,469	0	9	507,238
Physical album sales	123	2,118	0	11	709,178
Track sales (by album)	1,288	8,254	0	76	655,153
Track streams (by album)	1,497,983	5,781,519	0	149,369	176,964,675

Figure 1:   Industry-wide revenue share by sales medium, 2008–2017.
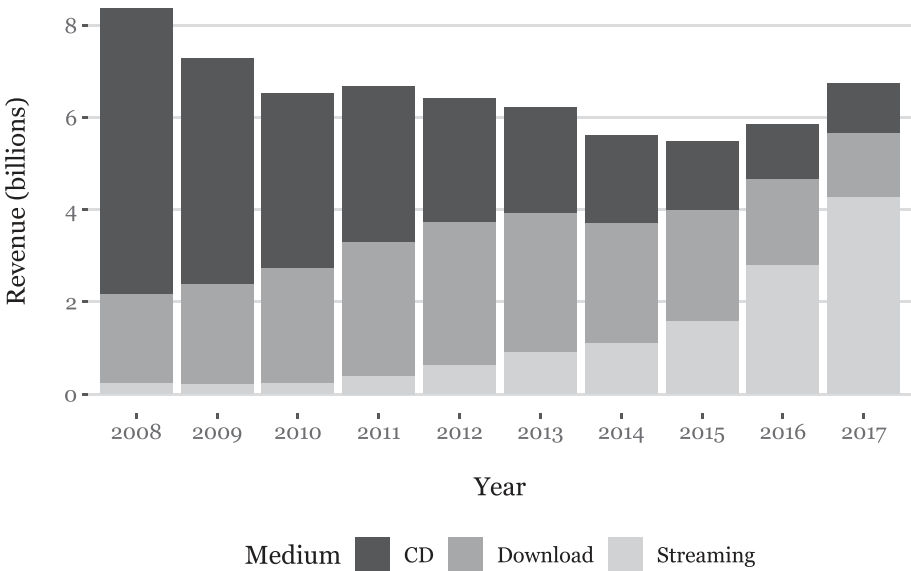
NOTE: Figure data are from the RIAA U.S. Sales Database, available at https://perma.cc/CV8F-XTYQ.

In practice, the album's release date is a slightly noisy measure because the constituent tracks are sometimes released at different times. Due to the structure of our data, any track whose unique identifier (a so-called ISRC[11]) is associated with an album will contribute to that album's total "count," regardless of when a sale or stream occurs. Lead singles, for example, are often released one to two months in advance of the rest of the album, which gives rise to "prerelease" counts of sales and streams for the collection. To maintain consistency across units, we start our analyses at the date on which the *album* was released, but in the Appendix we include robustness checks showing that extending our window back in time does not substantively change our results (Figure A2). For the track-level data, we can use the release date of each individual song—including those released prior to the full album—which avoids any truncation problem.

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[11]An ISRC, or International Standard Recording Code, is a unique identifier assigned to every individual *sound recording* (different recordings of the same underlying composition will each have their own unique ISRC). Technically speaking, an album is a collection of these underlying ISRCs, and the total number of album track sales is just the sales of the collection's individual ISRCs summed together. In principle, this means there could be some overlap between albums: that is, if a particular sound recording was included on multiple albums, we would "double count" it. In practice, our window is sufficiently short and our random sample sufficiently small that this is unlikely to occur. We also find substantively similar results at the level of individual tracks, allaying any concern about the effect of the aggregation.

There are several possible options for parametric estimation.[12] Since we are modeling counts, the natural choice is Poisson regression. A simple pooled Poisson model, $y_{it} = \exp(x_{it}\beta)$, is robust to violations of the customary distributional assumptions.[13] The negative binomial (NB2) model is a potential alternative, introducing a gamma-distributed dispersion parameter to relax the Poisson equidispersion assumption (Cameron & Travedi 1998).[14] In practice, though, we suspect that neither of the pooled estimators correctly models the underlying data, given the unobserved heterogeneity between albums. The between-album differences are significant, and they remain even when controlling for year of release (and, later, RIAA certification). The fixed effects Poisson estimator (FEP) introduced by Hausman et al. (1984) allows us to include album-level individual effects in a computationally tractable way, using within-album variation to estimate the average decay rate, such that $y_{it} = \alpha_i \exp(x_{it}\beta)$, where α_i is an individual effect that functions as an intercept shift.[15]

In the main text, we present FEP results. As a robustness check, in the Appendix we repeat our main analysis with the alternative estimators (Appendix Tables A1 and A2). In short, the results for track sales are insensitive to our choice of model. The results for track streams are broadly similar for the main specification, and only vary slightly when we introduce controls for blockbuster status (as described below). We use robust standard errors clustered at the album level to account for correlation over time within each album (Wooldridge 2002: 675).

Finally, we must account for the dramatic changes in overall use of each format during our study window. For example, the dramatic rise in subscription music services means that a recording may be streamed at a greater absolute rate over time, in large part because more people are using streaming services. Put differently, for any given album or song, the change over time can be attributed to both the underlying (secular) trends in the industry, and the variation that is inherent to the recording itself. For our purposes, we are primarily interested in the second component.

To disentangle the two effects, we use a measure of exposure in order to normalize the sales and streaming counts over time.[16] Ideally, we would adjust each of our observed

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[12]We also estimated a nonparametric fixed effects Poisson regression using a full set of week dummies in place of the continuous functions of time. The results are very similar, and we present the more parsimonious parametric models here.

[13]In particular, the Poisson model assumes that the mean and the variance of the outcome are equal, conditional on covariates, $\mathbb{V}[y_{it}|x_{it}] = \mathbb{E}[y_{it}|x_{it}]$. This does not hold in our data: across all distribution channels, the conditional variance is generally (much) larger than the conditional mean—a characteristic known as over-dispersion. This problem is common in applied settings, and the Poisson estimator is robust to violations. Our estimator is consistent so long as we correctly specify the conditional expectation function itself. (This is known as the quasi-maximum likelihood interpretation [Wooldridge 1999].)

[14]Our data have an excess of low but nonzero numbers, so we do not consider zero-inflated models.

[15]Note that $\exp(\eta_i)\exp(x_{it}\beta) = \exp(\eta_i + x_{it}\beta)$.

[16]We incorporate the exposure variable as an offset in the regression. In Figure A2, we demonstrate the effect of leaving out the offset.

Table 2:   Population Volumes for Each Medium (Millions)

Year		Track Streams	Track Sales	Digital Albums	Physical Albums
2008		—	1,000	63.6	371.4
2009		—	1,100	74.6	300.2
2010		—	1,200	85.8	257.2
2011		—	1,300	104.0	246.4
2012		—	1,400	116.8	205.2
2013	H1	53,050	707.4	61.3	78.3
2013	H2	53,050	621.4	56.7	103.3
2014	H1	82,250	649.8	54.7	63.3
2014	H2	82,250	550.8	62.9	92.7
2015	H1	131,600	558.8	56.4	53.0
2015	H2	178,500	436.9	52.9	83.8
2016	H1	208,700	412.8	48.2	45.8
2016	H2	223,600	330.9	36.9	66.6
2017	H1	284,700	306.9	35.8	42.2
2017	H2	333,400	247.2	30.6	61.1

NOTES: For years 2013—2017, half-yearly data are taken from RIAA's semi-annual reports. From years prior to 2013, yearly data are taken from RIAA sales data website, available at https://perma.cc/CV8F-XTYQ.

counts by the sum of all sales or streams in that week. Unfortunately, we have the aggregated data only in yearly (or sometimes half-yearly) increments, as shown in Table 2. We therefore approximate the total weekly streams by assuming that they are distributed uniformly within each aggregate group: that is, we simply divide the total by 52 (or 26 in the case of half-years).[17] Of course, this measure is not perfect—for example, we know that overall streaming is, in practice, increasing month-on-month during our study window—but it provides a reasonable approximation.

IV. MAIN RESULTS

A. Sales

Table 3 presents the first part of our main results: estimates for sales rates across four different media. Columns (1) and (2) show physical and digital album sales. Columns (3) and (4) show track sales, aggregated at the album level and individually, respectively. (Note that unlike ordinary linear regression, Poisson coefficient estimates are semi-elasticities, which require a little more work to interpret—specifically, a one-unit change in x is associated with percentage change in the outcome.) Whole-album sales (Columns (1) and (2)) show particularly steep declines in appropriability: average sales decrease to less than 5 percent of their initial peak only months after release and are negligible beyond the first year. As we might expect, sales of individual songs—including both

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[17]For example, in the first half of 2015, there were 131.6 billion unique streams. For each week, therefore, our measure assumes 131.6/26 = 5.06 billion total streams.

Table 3:   Estimates for Sales Depreciation (Fixed Effect Poisson)

	(1)	*(2)*	*(3)*	*(4)*
	Physical Albums	*Digital Albums*	*Track Sales (Album Level)*	*Track Sales (Song Level)*
Weeks since release	0.018 (16.5)	0.025 (16.0)	0.0058 (6.3)	0.0005 (0.4)
sqrt(Weeks since release)	−0.65 (−25.91)	−0.69 (−19.05)	−0.30 (−12.84)	−0.22 (−6.22)
Observations	219,282	222,311	211,705	388,926

NOTE: z-statistics in parentheses; standard errors clustered at the album level; includes album fixed effects. All models include the (logged) weekly population total of the respective sales medium, as an offset.

physical singles and digital track purchases—have a longer period of economic viability. On average, track sales volume declines to only 20 percent of its initial peak after one year of release, and slowly declines to a negligible volume through the remainder of our 10-year study window.

To demonstrate these relationships visually, we plot predicted decay rates from the models in Figure 2.[18] The bottom two panels compare album-level and song-level track sales, while the top two panels show results for whole-album purchases. We observe a somewhat longer shelf-life for sales of constituent tracks than we do for entire albums,[19] but the top-line results show a steep decline in the average sales performance of sound recordings, regardless of the distribution method.
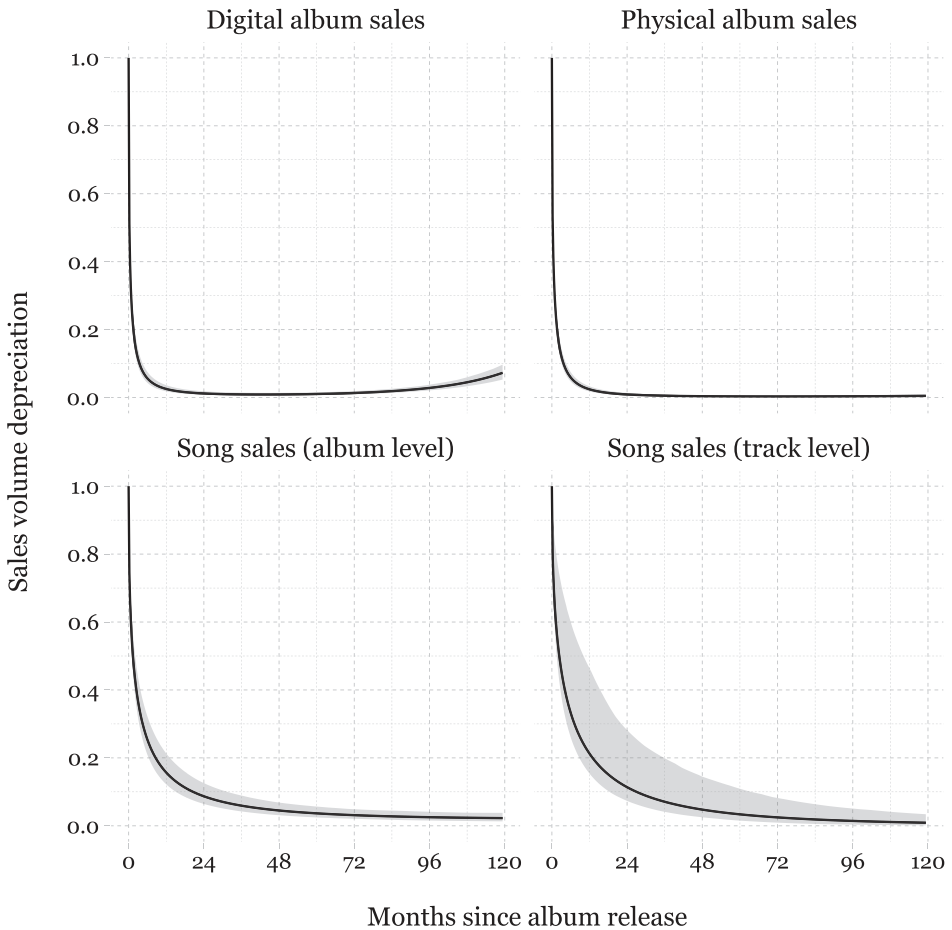
B. Streaming

Of course, direct sales are only one part of the modern music economy—and, in practice, they are an increasingly small one. The rise of subscription streaming services (Spotify, Google Play, Apple Music, etc.) appears likely to signal a qualitative shift in how listeners consume, and pay, for music. Although Spotify was founded in 2006 (and entered the U.S. market in 2008), it did not become commercially significant until the early 2010s. Indeed, some of the most popular modern subscription services are a relatively recent phenomenon: Apple Music and Google Play began operating in 2015, and Amazon Music in 2016. Unfortunately, this implies a limitation of our analysis. To be conservative, we take only 2015, 2016, and 2017 as "complete" streaming years, leaving a somewhat small

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[18]Uncertainty estimates are generated with a percentile block bootstrap (resampling on albums) at the 95 percent level.

[19]The continuing shift in purchasing patterns away from albums and toward individual tracks has interesting implications for the (in)efficiency of bundling. Specifically, it suggests that consumers respond differently when they are not constrained to buy preset bundles of songs (i.e., albums). Our data provide some evidence of this general change: over the full sample, the top 25 percent of albums account for 83 percent of CD sales, but the same fraction of albums accounts for almost 93 percent of individual track sales.

Figure 2:   Depreciation of sales volume.

Digital album sales   Physical album sales

Song sales (album level)   Song sales (track level)

Sales volume depreciation

Months since album release

number of observations—just 314 albums, with up to 154 weeks of data per album. This hinders our ability to make statistical inference. More importantly, this feature of the data betrays a deeper substantive problem: streaming simply has not been around very long, and it is too early to make any confident assessment of its economic significance. Still, we can offer some tentative initial observations.

In line with the sales results, streaming track plays decline monotonically over time, but as Figure 3 suggests, streaming appears to follow a slightly different trajectory from that of sales. Volumes fall more gently in the first year—albums retain, on average, around 25 percent of their initial volume a year after release. Over the medium term,

Figure 3: Depreciation of track streams, aggregated by album (2015–2017).
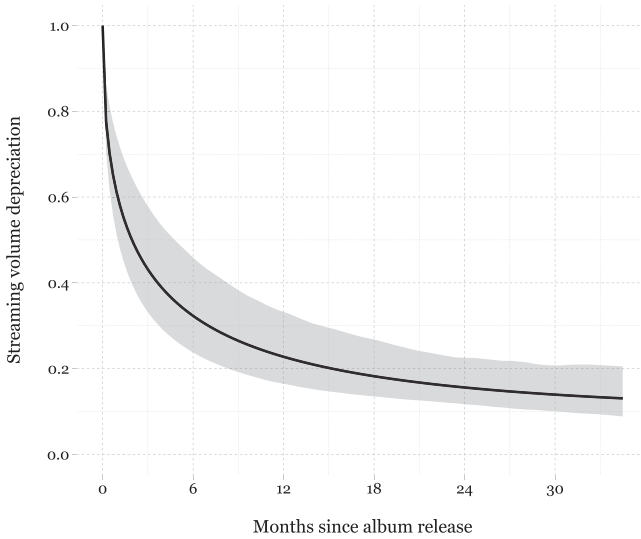
average streaming volumes begin to flatten out, settling at just below 20 percent of the initial volume. Although our study window is too short to tell the full story, this offers suggestive evidence that streaming presages a change in the economic lifespan of commercial music. On the other hand, it may be that listeners are actually consuming music in much the same way as before, but that we cannot observe it. Note that on a streaming platform we count every *listen*, but that for sales we observe only the first *purchase* of an album or digital download.[20] Without evidence on private consumption, it is difficult to disentangle these explanations. However, from the perspective of artist or record label incentives—the focus of this article—the effect of these changes on revenue streams is the most salient issue; we discuss this further below.

Finally, given that our sales models use the full 10-year period, one might be concerned that we are making an apples-to-oranges comparison; that is, that the streaming results are simply an artifact of the period studied, rather than a consequence of substantive differences between the two distribution channels. To check this, Figure A1 in the Appendix compares sales depreciation rates estimated using data for (a) the whole window (as above), and (b) only the 2015–2017 window. The curves track each other closely, suggesting that the streaming differences are indeed attributable to effects of the medium.

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[20]We thank Will Page, former Chief Economist at Spotify, for this point.

V. Extensions

A. *Top Sellers*

Thus far we have focused on the average performance over all works. In practice, however, the commercial music industry is known to have a very long tail. The majority of recorded music does not produce a significant return, while a small number of artists (and tracks) are extraordinarily successful (e.g., Barnett 2014: 398). Indeed, we observe precisely this pattern in our data. From a policy perspective, it is important to be attentive to this kind of cross-subsidization. If the industry is organized in such a way that record labels focus on blockbuster releases, then estimates of "average" economic half-life may mask consequential differences in the incentive structure of the industry (DiCola 2013; Rosen 1981; Elberse & Oberholzer-Gee 2007). How, then, does economic viability differ for the music aristocracy?

There are two (potentially complementary) ways that a work could be a commercial success. First, a song could sell for many years—the proverbial Beach Boys or Beatles hit single. These tracks are often repackaged and rereleased on "greatest hits" albums and other compilations, in addition to having their original albums actively marketed for much longer than the typical work. Second, a track could be an early chart-topper, selling a huge number of units soon after release. Given the limited 10-year window of observation, the structure of our data limits our ability to make inferences about the first mechanism.[21] We are, however, able to shed light on the second.

Fortunately, our sample includes multiple Gold-, Platinum-, and Diamond-award winning albums. Although the official certification is difficult to obtain, the Recording Industry Association of America (RIAA) is transparent about the criteria used to make the awards, which allows us to replicate the classifications.[22] We impute "top-seller" status to any album or track that could have received Gold or higher certification under the RIAA rules.[23] This accounts for 13.8 percent of the albums and 6.1 percent of the tracks in our dataset.[24]

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[21]This is an important question that we plan to revisit in future work.

[22]The rules are somewhat complex. Album certification is based on "album-equivalent units," which combine whole-album sales, track sales, and track streams (the latter two are discounted). Five-hundred-thousand "album-equivalent" units sold constitutes a Gold certification. For predominantly Spanish-language music, Gold certification is awarded at 30,000 units in recognition of the different size of the markets. We adopt the same approach in our imputed measure. However, a robustness check shows that our results are not sensitive to our decision to include Spanish-language albums (Appendix Table A3).

[23]We also conducted a manual check with the RIAA for albums released toward the end of our dataset, for which we observe an artificially short time period.

[24]Although this proportion may seem somewhat high, we note that our measure is deliberately over-inclusive. We include *any* album that passes the RIAA threshold, whereas in practice certification is awarded only on application, and only in certain cases (for example, Gold or Platinum status would not generally be awarded to multi-artist compilations). Because of this, the actual RIAA certification is somewhat noisy, whereas our "empirical" measure provides a clear picture of the economic performance of the album.

Using this indicator variable, we replicate the main specification with an additional interaction term, which allows top-selling and less popular albums to take on different rates of decline. Of course, by construction, the two types of music have very different absolute sales and streaming levels: the average non-blockbuster album sells around 3,000 tracks and streams 500,000 times in its first week of release, while the average block-buster album sells 45,000 and streams 8.4 million times. However—and crucially for our purposes—the *rates* of decline are remarkably similar, closely mirroring our main results. Figure 4 shows the depreciation rates for track sales (aggregated by album). In both cases, the albums' tracks lose more than 80 percent of their initial sales volume by the end of the first year.

Streaming volumes, shown in Figure 5, tell a similar story. A top-selling work maintains, on average, around 20 percent of its initial streaming volume after 12 months, while non-certified tracks stream around 30 percent of their opening volume at the same point. The slightly steeper fall for blockbusters is perhaps not surprising, given the different starting points. As with sales, the streaming depreciation graphs hide a substantial difference in *overall* volume between blockbusters and non-blockbusters. On average, the former saw 40 million streams in their first month, while the latter had just 2.3 million. (On the other hand, the differences are somewhat less marked for album sales—non-blockbusters sold an average of 20,000 digital and physical units in their first month vs. 125,000 for blockbusters.) All this said, we stress again that the short window of observation and small sample limits our ability to draw conclusions with confidence, and this is mirrored in the wide uncertainty intervals.

From the perspective of copyright policy, these are important—and perhaps surprising—results. Even if cross-subsidization is an important reality in the industry, these findings give little reason to think that copyright should treat blockbusters differently. In the context of duration, at least, the economics of blockbusters and run-of-the-mill releases do not appear to be so different.

B. Genres

Next, we consider the relationship between depreciation and genre. Figure 6 shows predictions from a model of the six most common genres in our sample: rock, hip-hop, pop, country, Christian, and Latin music. The model is similar to earlier analysis, with two adjustments. First, we use a pooled Poisson model, which allows us to predict actual volume, rather than just decay rates. Second, because genres have heterogeneous distribution channels (e.g., rock sells a higher proportion of albums, while hip-hop is a more streaming-focused genre), we use album-equivalent units as the dependent variable.[25]

We find the general pattern of decline to be much the same as in the results above, but there are some notable and intriguing differences across types of music. Hip-hop and pop exhibit relatively steep depreciation curves, dwindling to a small portion of their

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[25]This is the same measure introduced in Section V.A. It heavily discounts an individual stream relative to a whole-album sale to account for the very different revenue that accompanies each.

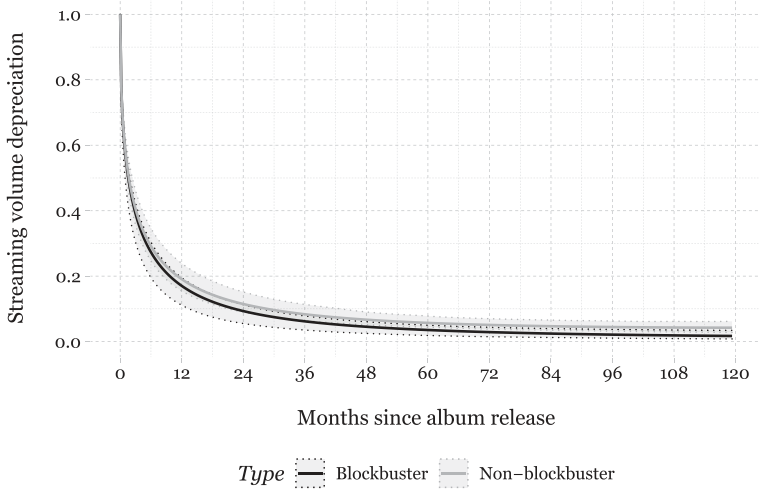*Figure 4:*   Track sales depreciation for blockbuster albums (aggregated at the album level).

Figure 5:   Track streaming depreciation for blockbuster albums (aggregated at the album level).
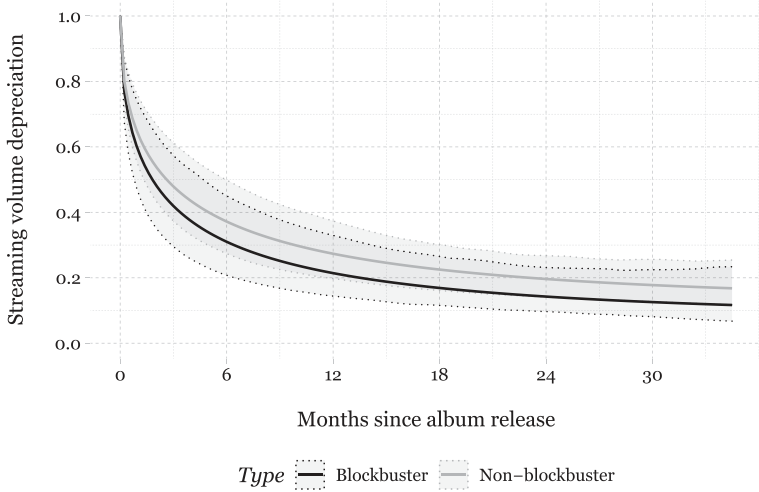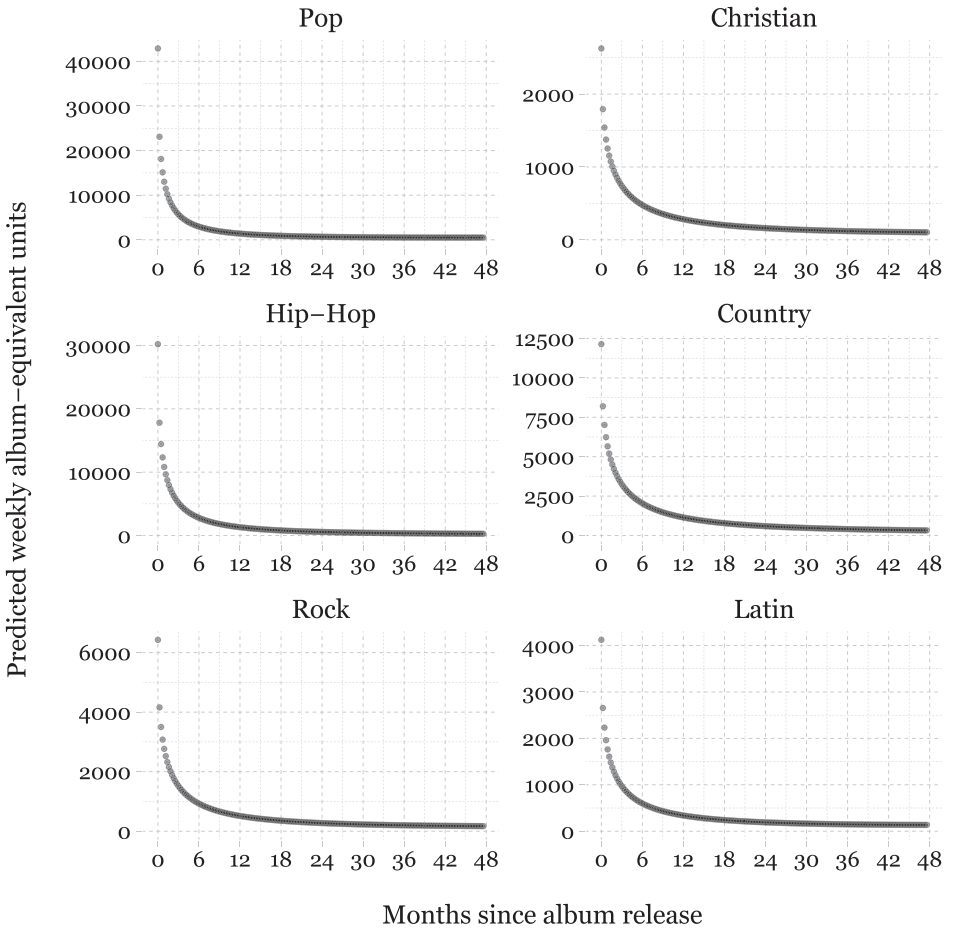
Figure 6: Relationship between genre and album-equivalent unit volume depreciation.

NOTE: Predicted outcomes are album-equivalent units, which is a weighted aggregation of sales and streaming channels. To highlight the difference in absolute levels, this model uses a pooled Poisson estimator, which allows us to predict counts, rather than just depreciation rates. However, the FEP estimate (omitted for brevity) has similar slope coefficients. Predictions beyond Year 4 of release are excluded for legibility.

initial unit volume by the second year of release—but they also start with substantially higher rates of absolute popularity. By contrast, country and rock music produce somewhat flatter depreciation curves.[26] Country music in particular holds its relative value

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[26]The commercial success of country music may be somewhat misrepresented here, given that its distribution leans unusually heavily on radio airtime.

longer into the window: for example, the model predicts that hip-hop and country music will have similar unit volume after six months, despite the former starting with triple the amount at release.

Still, our results and conclusions here are modest. After subsetting, the sample size for any individual genre is quite small. The direct implications for copyright policy are also somewhat ambiguous. Copyright is a uniform legal right as to sound recordings, and different genres of recorded music receive the same formal scope of protection. Although we argue that our findings militate in favor of a *general* music copyright term that is better calibrated to the economics of the industry, micro-targeting of specific genres seems likely to have distortionary effects on music production. For example, a longer copyright term for country music might induce inefficient overproduction of that genre, or "gaming" of genre classifications on the part of record labels and artists. (The notion of gaming the numbers is not novel in the music industry. For example, because the RIAA sets a lower Gold certification threshold for Latin music than for other genres—30,000 units vs. 500,000 units—some artists will incorporate a guest artist who may sing one verse in Spanish in order to classify the track as "Latin.") Nevertheless, it is intriguing that the most popular contemporary genres have steeper decay curves. This accords with anecdotal reports of a general shift in the economics of the industry toward ephemeral hits, in which more of a work's commercial value is realized early in its lifecycle.[27]

C. Revenue

Finally, we consider revenue. Thus far, our analysis has focused on sales (and streaming) volume, in line with the limitations of our data. (We have access only to streaming and sales counts, and do not observe revenue directly.) However, given the complex pricing and payout structures across different distribution channels, it is not necessarily obvious that revenue would follow the same decay patterns as unit counts. To probe this further, we construct a synthetic measure of the weekly revenue for each track and album.

To generate our revenue approximation, we assume a per-unit revenue multiplier for each medium:

$$revenue = 0.99 \times track\ sales + 0.0005 \times track\ streams + 9.99 \times digital\ albums + 12.99 \times physical\ albums.$$

In practice, physical revenue varies by album for many reasons—single or double CD, EP, popularity, idiosyncratic vendor pricing, and so on—and digital prices and payouts vary from platform to platform. For example, Spotify's average payout is currently around \$0.00437 per stream, while Apple Music's is \$0.00735. (These per-stream payouts vary further depending on whether they are served to paying or "freemium" consumers.) The numbers we use reflect broad industry averages, but to confirm that the results are not sensitive to our specific choice of multipliers, we also report estimates for lower and

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[27]See, e.g., Cliff (2019).

Table 4:   Estimates of Weekly Revenue

		Bounds	
	(1)	*(2)*	*(3)*
	Main Results	*Minimum*	*Maximum*
Weeks since release	0.0179	0.0180	0.0184
	(24.59)	(24.73)	(23.80)
sqrt (Weeks since release)	−0.587	−0.590	−0.592
	(−37.17)	(−37.37)	(−36.30)
Blockbuster (1/0)	2.018	2.013	2.019
	(12.89)	(12.86)	(12.88)
Blockbuster × Weeks since release	−0.00233	−0.00221	−0.00174
	(−1.53)	(−1.45)	(−1.11)
Blockbuster × sqrt(Weeks since release)	0.0687 (1.93)	0.0670 (1.87)	0.0598 (1.64)
Constant	11.24 (154.88)	10.99 (151.68)	11.50 (157.79)
Observations	230,109	230,109	230,109

NOTE: z-statistics in parentheses; standard errors are clustered at the album level.

upper "bounds" in Table 4.[28] Although our measure is a coarse approximation of the true revenue potential of a given recording, it provides a useful window into the relationship between unit volume and revenue.

To derive the revenue decay curves, we repeat our previous empirical strategy, this time estimating a pooled Poisson model.[29] Once again, we interact blockbuster status with time to allow the decay curves to differ. Table 4 shows our results, with the key findings reported in Column (1) (Columns (2) and (3) report bounds). In Figure 7, we plot the expected weekly revenue, as predicted by Column (1).

In line with our earlier results, we find that overall revenue decays remarkably quickly. Blockbuster albums see an average of $600,000 in revenue in their first week of release, which falls to $65,000 (11 percent) by the sixth month. As before, the decay curves of the non-blockbuster and top-selling albums follow a remarkably similar trajectory—indeed, the slopes are statistically indistinguishable.[30] However, the initial revenue for top-selling albums is, of course, much higher. By the end of Year 4, the average non-blockbuster has residual revenue of roughly $1,000 a week. The average blockbuster—approximately the top 10 percent of our data by sales volume—commands residual weekly revenue of around $8,000.

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[28]The "minimum" scenario uses values of $0.69, $0.0004, $7.99, and $9.99; the "maximum" scenario uses $1.29, $0.0009, $12.99, and $16.99, respectively.

[29]Note that although we are no longer modeling counts, the Poisson estimator can be equivalently thought of as a generalized linear model with a log link function, $\mathbb{E}[Y|X] = \exp(X\beta)$. Unlike a log-linear OLS regression, $\mathbb{E}[\log(Y)|X] = X\beta$, the Poisson model can easily accommodate observed values of zero, which are a common feature of our data.

[30]Using a Wald test, we fail to reject the null hypothesis that the slope interaction terms are jointly equal to zero ($p = 0.16$).

Figure 7:   Predicted weekly album revenue across all distribution channels.
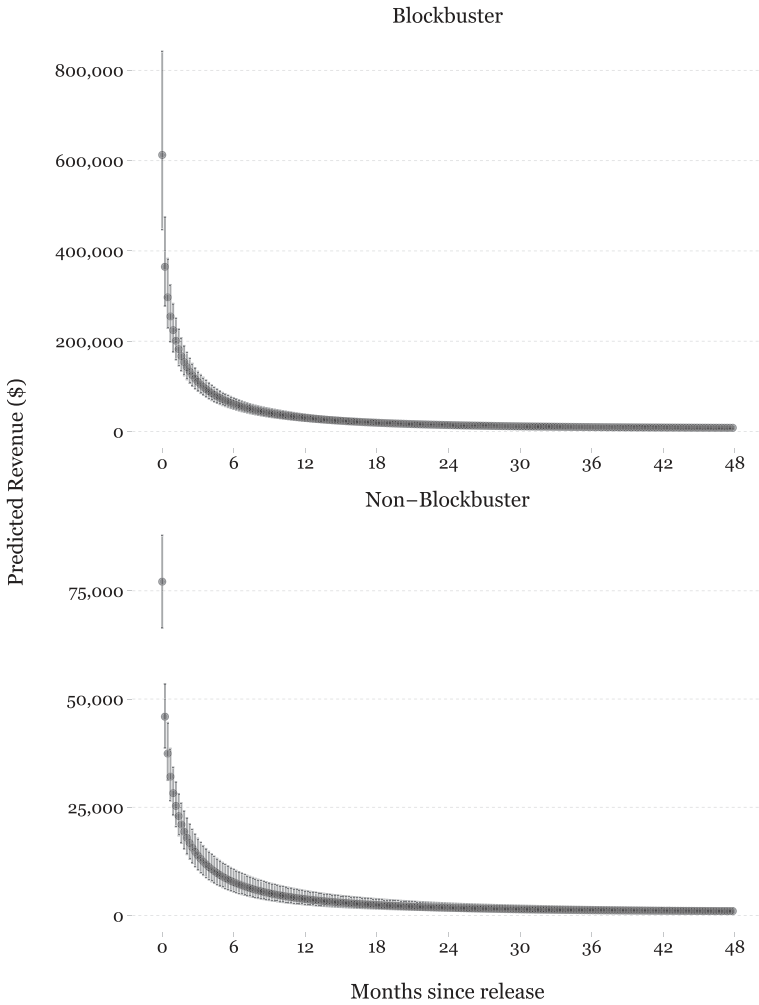
Finally, in unreported results, we consider the possibility that revenue depreciation rates are changing over time. Given the change in consumption patterns from physical CDs to digital streaming, we might suspect that the revenue decay curves would have appreciably changed over the course of our study window. However, we tested a model that interacted the slope coefficients with year of album release and found no appreciable difference in the average depreciation rates by stratum. This may be a feature of our (relatively small) dataset, or it may be that the full consequences of economic shifts in the industry are yet to be revealed.

VI. Discussion

Our top-line results show that album and song sales have a remarkably short period of economic viability. Sales of whole albums (both traditional CDs and digital) approach zero by the end of their first year of release. Individual tracks maintain meaningful sales volumes for longer—perhaps up to several years—but average track sales are negligible in the medium term, and almost zero by the end of our 10-year study period.

We also find indicative evidence that streaming services prolong the life of sound recordings. Our data suggest that the economic value of the average track declines more slowly through this medium. (From a revenue perspective, the incentive implications of this remain unclear, since streaming volume far exceeds sales volume, while per-sale earnings far exceed per-stream royalties.) Unfortunately, our conclusions about streaming are quite tentative. As a result of the small sample size and limited window of observation, we simply cannot make confident inferences. This is a clear avenue for further research as the music industry continues to evolve and further data on consumer behavior becomes available.

There are obvious limitations to our analysis. First, the findings are purely descriptive: nothing in our data allows us to directly assess the causal effect of copyright on sales, let alone on creators' or labels' incentives. The data provide a portrait of the economic environment faced by the industry, but we cannot directly observe the choices of artists and record labels.

Second, this is just a piece of the puzzle. Although music is a copyright-intensive industry, consumer sales and streams are only one component of revenues for commercial music. Statutory royalties paid to the owners of musical compositions and sound recordings are not accounted for in our data. Nor are the various contractual income sources—including sync licensing, touring, and endorsements—that can constitute a significant portion of an artist's revenues. In many cases, these contractual revenue streams are influenced by the copyright-related revenue streams. This impact varies, however, from artist to artist, and over the course of a career. Unfortunately, our results cannot reveal much quantitatively about these ancillary revenue sources because this information is not generally public.[31] Nevertheless, we think these data provide a reasonably good proxy for the overall popularity and revenue performance of the bulk of commercially recorded music.

Our analysis shows that the average work has exhausted its commercial potential long before the term of copyright protection expires. This might suggest—as we conclude—an inefficiency owing to overprotection, such that a more carefully calibrated term would strike a better balance between incentivizing creation and ensuring a robust public domain. An alternate interpretation might suggest that a work's lack of commercial value mitigates concerns stemming from overprotection. In other words, if a work is commercially worthless, what harm is there in that work remaining under copyright

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[31]One of us has taken a qualitative stab at it, however. In a forthcoming chapter, García (2020) interviews a series of artists and management teams to determine that copyright-derived income sources tend to be important both early on, and much later, in an artist's career, whereas contractually derived income plays a significant (and increasing) role at every stage.

protection? In a word: access. In the absence of a use requirement, copyright protection prevents a work from falling into the public domain regardless of whether the rightsholder is actively exploiting it or making it available. The literature has identified several categories of post-commercial works for which an extended period of copyright protection has an adverse impact on access. These include orphan works (works whose authors are either unknown or unidentifiable); mismanaged works (where a work's author is known but deceased, and the stewards are either delinquent or difficult to trace); and works by disadvantaged or marginalized authors. Works in the latter category, for example, often do not experience commercial success in their day, but may later prove to be valuable historical accounts of oppression (Reese 2012: 291).

Overall, we find the sharpness of the results quite striking. Our analysis provides a baseline for the commercial relevance of the typical sound recording and offers a rare window into the on-the-ground economics of a major content industry. As political debates about the appropriate term of copyright continue to roil in the international arena, empirical evidence provides an important, but inexplicably rare, check: Our findings suggest that current copyright terms are at odds with the economic reality of the majority of commercially recorded music.

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APPENDIX

A. Model Selection

Appendix Tables A1 and A2 present comparisons of the base model for pooled Poisson, negative binomial (NB2), and fixed effect Poisson estimators. We show both our base model and a model that includes an interaction for RIAA certification (as calculated in Section V.A). The three estimates are substantively similar.

Table A1: Comparison of Estimators with Album-Level Track Sales Data

	Base Model			Blockbuster Interaction		
	(1) Poisson	*(2)* NB2	*(3)* FEP	*(4)* Poisson	*(5)* NB2	*(6)* FEP
Week	0.01	0.01	0.01	0.01	0.00	0.01
	(5.97)	(7.17)	(6.26)	(5.43)	(4.96)	(5.39)
sqrt(Week)	−0.30	−0.30	−0.30	−0.28	−0.24	−0.27
	(−13.06)	(−12.57)	(−12.84)	(−12.23)	(−12.77)	(−12.00)
Blockbuster	—	—	—	2.97	3.11	—
				(14.67)	(12.20)	
Blockbuster × Week	—	—	—	−0.00	0.00	−0.00
				(−0.44)	(0.67)	(−0.16)
Blockbuster × sqrt(Week)	—	—	—	−0.02	−0.07	−0.03
				(−0.58)	(−1.31)	(−0.90)
Lnalpha	—	1.12	—	—	0.79	—
		(31.14)			(21.17)	
Observations	211,706	211,706	211,705	211,706	211,706	211,705

NOTE: z-statistics in parentheses. Poisson and negative binomial models include release-year fixed effects. Standard errors clustered at the album level.

Table A2: Comparison of Estimators with Album-Level Track Streaming Data, 2015–2017

	Base Model			Blockbuster Interaction		
	(1) Poisson	*(2)* NB2	*(3)* FEP	*(4)* Poisson	*(5)* NB2	*(6)* FEP
Week	0.01	0.01	0.01	0.02	0.00	0.01
	(2.20)	(1.32)	(1.53)	(3.09)	(1.04)	(1.69)
sqrt(Week)	−0.28	−0.22	−0.26	−0.37	−0.21	−0.23
	(−4.49)	(−4.30)	(−4.59)	(−4.45)	(−3.96)	(−4.78)
Blockbuster	—	—	—	2.66	2.82	0.00
				(9.65)	(10.76)	(.)
Blockbuster × Week	—	—	—	−0.01	−0.00	0.00
				(−1.41)	(−0.50)	(0.11)
Blockbuster × sqrt(Week)	—	—	—	0.10	−0.00	−0.04
				(0.90)	(−0.01)	(−0.46)
lnalpha	—	1.03	—	—	0.67	—
		(18.3)			(10.34)	
Observations	23,253	23,253	23,252	23,253	23,253	23,252

NOTE: z-statistics in parentheses. Poisson and negative binomial models include release-year fixed effects. Standard errors clustered at the album level.

B. Robustness Checks

1. Varying the Study Period for Track Sales

Figure A1:   Comparison of track-sales depreciation rates with longer and shorter study periods.

Window ▬ 2008–17   ▬ 2015–17
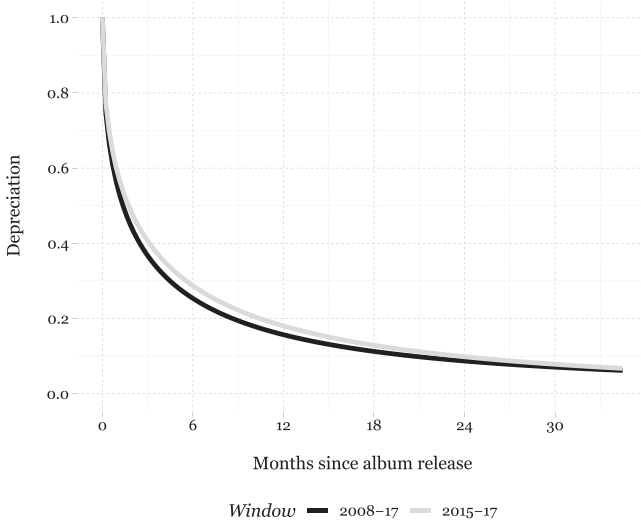
2. Offset Measure for Streams

Figure A2 shows the effect of failing to include a measure of exposure in the streaming analysis. The blue curve shows predictions for unadjusted counts; the red curve is our base model (normalized by total streams). The difference between the two estimates reflects the underlying secular trend caused by explosive growth in the streaming sub-scriber base throughout our study window.

Figure A2:   Comparison of streaming rates with exposure measure.
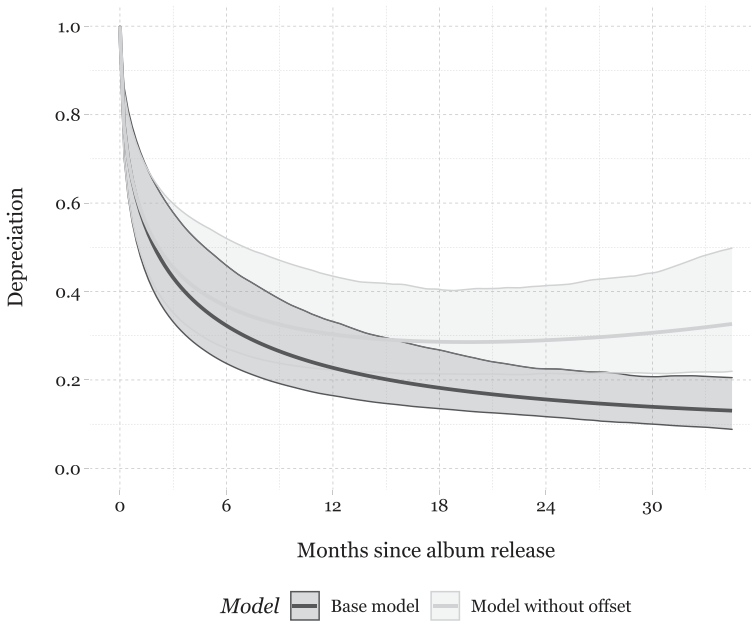
3. Windowing Effects

It is standard industry practice to release one or more "lead singles" ahead of the release of a full album or EP. This is typically done one to two months in advance of an album's release date, and usually includes a marketing plan that combines digital downloads, terrestrial and digital radio plays, and streaming availability.

Our main analysis—which begins the calculation of commercial viability at the release date of the *album*—does not consider sales and streams in the prerelease period. To the extent that our sample includes albums with many lead singles, this may understate the commercial viability of the works. To check that our results are robust to this prerelease period, Figure A3 repeats the main analysis on periods beginning two, four, and eight weeks prior to the album release date. The results are substantively similar.

Figure A3:   Effect on sales depreciation of starting the observation window prior to album release.

Months since album release

Window   •   t = 0 (Album release)   •   t–2   •   t–8
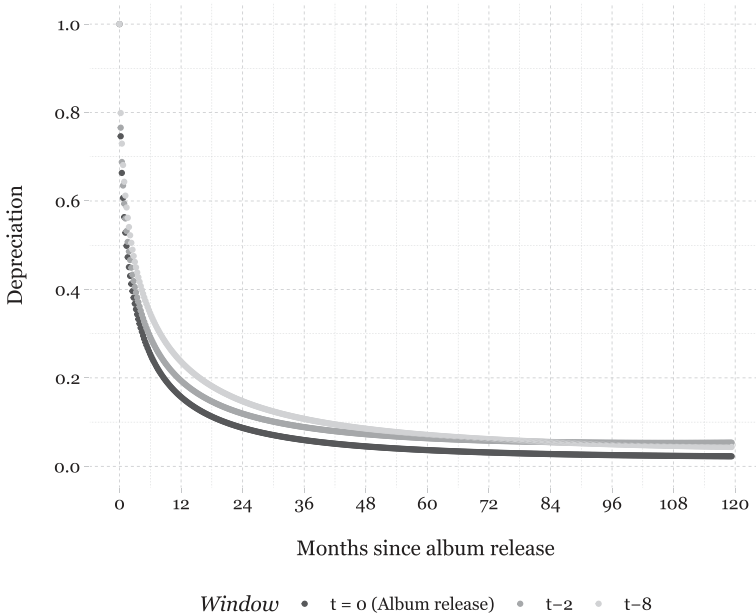
4. Blockbuster Measure

Table A3:   Comparison of Synthetic "Top-Selling" Indicator With and Without Spanish-Language Music

	Dependent Variable: Weekly Track Sales	
	(1) *Full RIAA Measure*	(2) *Non-Latin Subset*
Week	0.006 (5.390)	0.006 (5.520)
sqrt(Week)	−0.271 (−12.00)	−0.269 (−12.41)
Blockbuster × Week	−0.000 (−0.16)	−0.000 (−0.09)
Blockbuster × sqrt(Week)	−0.033 (−0.90)	−0.037 (−1.00)
Observations	211,705	211,705

NOTE: z-statistics in parentheses with standard errors clustered at the album level. Includes album-level fixed effects.