Promotional effects of recorded music and superstars on concert financial outcomes

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Abstract

Using a comprehensive data set of hand-collected observations of top touring performing artists, I examine the relationship between recorded music and concert financial outcomes. I find that music streaming derives substantive financial benefit to the top-100 touring artists. Using empirical estimates from a panel model with artist fixed-effects, an artist can derive an incremental $46K to $49K per show when achieving a 20% increase in music streaming. Additionally, using a 2SLS model with artist fixed-effects to account for potential endogenous promotional effects, I identify top performers ("superstars") who derive significant additional concert revenue because of their back-catalog of hit songs. These top performers earn an incremental $15K per show in response to every week they have a song from their catalog in the Billboard Top-20. These findings indicate that artists maintain the ability to use their musical and performance legacy to build lifelong earnings from their music and performance.

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1 Introduction

Disruptive market forces in the music industry have been a mainstay for several decades. The changing dynamics have made it challenging for performing artists to find reliable income sources to practice their craft. While technological innovation has expanded the availability of music and occasions for listening, it has heavily discounted the payments to artists and made them more dependent on revenue from live performance.

The flow of income in today's music industry has benefitted some more than others. Artists with deep song catalogs of hit songs derive hundreds of millions of dollars per year in revenue from touring and royalties. Recently, some of these artists, including Bob Dylan, Neil Young, Stevie Wonder, and Stevie Nicks, have sold their catalogs for a significant market premium to record labels and investors who forecast growth in future cash flows for these artists' copyrights. In contrast, others see much more modest financial benefits from their efforts.

In a broader economic context, many economists have highlighted this issue since Adam Smith. In particular, Alfred Marshall articulated the issue in his landmark book "Principles of Economics" (Marshall 1947) by saying that wage inequality stems from talented or "lucky" individuals who can scale their efforts by leveraging innovation and technology.

This discussion's vital subtext centers around why successful performing artists earn so much. Do traditional economic models explain why Ed Sheeran, who earned $211 million with 53 shows in 2019, earned so much more than Lizzo, who earned $11.1 million with 97 shows during the same period? And, what is it about an artist's music and promotion that explains such a large difference in financial outcomes? This paper explores the promotional effects of music streaming and the benefits that top talent redeem from their catalog of musical hits.

This paper also empirically tests the competing and complementary theoretical work on the superstar phenomenon by Sherwin Rosen and Moshe Adler. While Rosen believed an artist's success resulted from small advantages in talent, Adler postulated an artist's popularity and promotion as the source (Rosen 1981, Adler 1985).

This analysis includes integrating six comprehensive data sources formatted in quarterly time series from 2014 to 2019. The empirical approach consists of two estimators:

1. Panel model with artist fixed-effects to test the promotional effects of music streaming and social media buzz theorized in Adler's work.
2. Two-stage least squares (2SLS) with artist fixed-effects specification to control possible endogeneity in the music streaming trends.

The dependent variables predicted include revenue per show, average ticket prices, and percent of concerts sold-out. Key findings from the analysis identify music streaming, weeks with songs in the top-20, and potential superstar effects as key drivers of concert financial outcomes.

On its face, one might assess a simultaneous effect between concert revenue and music streaming. The data section of this paper addresses this issue and provides a series of steps taken to address the risk of non-trivial endogeneity. The findings indicate that even when controlling for artist and/or promotional effects, there are indications that music streaming and artists' musical catalog contribute to their concert revenues, ticket pricing, and likelihood to sell out. Additionally, through a 2SLS model with an instrument for music streams, we see indications that an artist's cumulative catalog of hit songs contributes to incremental revenue for top stars. Notably, Moshe Adler (Adler 2006) acknowledged that there is no objective measurement of the superstar phenomenon. In response, this paper does not define a regressor to measure talent directly;

instead, it explores indirect proxies such as back catalog of hit songs and historic concert financial heuristics to identify potential superstars.

2 Literature Review and Background

Sherwin Rosen (Rosen 1981) explored top talent's earnings potential when authoring his theoretical work on what he called the superstar phenomenon. That small differences in talent lead to outsized differences in earnings, and that availability of new technology fosters the best talents to broaden their market reach. Specifically for music, he theorized a convex relationship between talent and earnings where a performing artist with twice the talent could achieve four times the earnings potential. He also believed that top talents ("superstars") could uniquely set prices for concert tickets.

Moshe Adler (Adler 1985), inspired by the concept of consumption capital (Stigler and Becker, 1977), authored the theory that superstars' success was motivated by popularity and benefit from a snowball effect over time. Popularity, rather than talent, explains the outsized success of performing artists. He later expanded on this work in a book chapter of the Handbook of Cultural Economics (Adler 2006), where he highlighted the advantages of publicity rights that uniquely benefit superstars.

Much of the empirical testing of the superstar phenomenon (Chung and Cox 1994; Crain and Tollison 2002; Giles 2006; Adler 2006; Klein and Slonaker 2010; Filimon et al. 2011; Meiseberg 2014) has identified proxies for talent and popularity/presence (e.g., marketing and media) using recorded music such as music CD's, tapes, vinyl, et al. Only one identified in the literature review, Krueger (2005), has tested the theory on live-performance. An activity that makes up 80% of a performing artist's income (Krueger 2019) and was highlighted by Adler and Rosen as an observable success variable to identify superstars.

Krueger (2005) revisited Rosen's work to explain the rapid increase in concert ticket prices from 1996 to 2005. Using Rolling Stone's Encyclopedia of Performing Artists, he defined the talent variable (z) based on the millimeters of text in the Encyclopedia to explain changes in concert revenue, ticket sales, and price per ticket. While Krueger found that performing artists with more lengthy entries commanded higher values on all three dependent variables, he could not align the time series with the increase in concert ticket prices. He later concluded that price increases were likely motivated by the complementary effects of recorded music sales. With physical music sales declines of 15% (from $12.5B to $10.7B between 1996 and 2005), he concluded that performing artists were making up the losses by increasing concert ticket prices that some perceived had been intentionally suppressed to sell more tickets and expose more fans to a performing artist's music (Krueger 2005; RIAA.com 2020).

The industry is very different now than it was during the 1990s. Krueger, in particular, recognized this limitation in his 2005 paper. Artists now benefit from promotion on social media and music streaming has reduced search costs (Hyun, Hyuseokdara 2019) that Adler referenced as "establishing consumption capital" (Adler 1986). Growth of music streaming (from 27% of recording industry revenue in 2014 to 79% in 2019) and the availability of social media buzz via Google Trends facilitate an updated assessment of Adler and Rosen's theories.

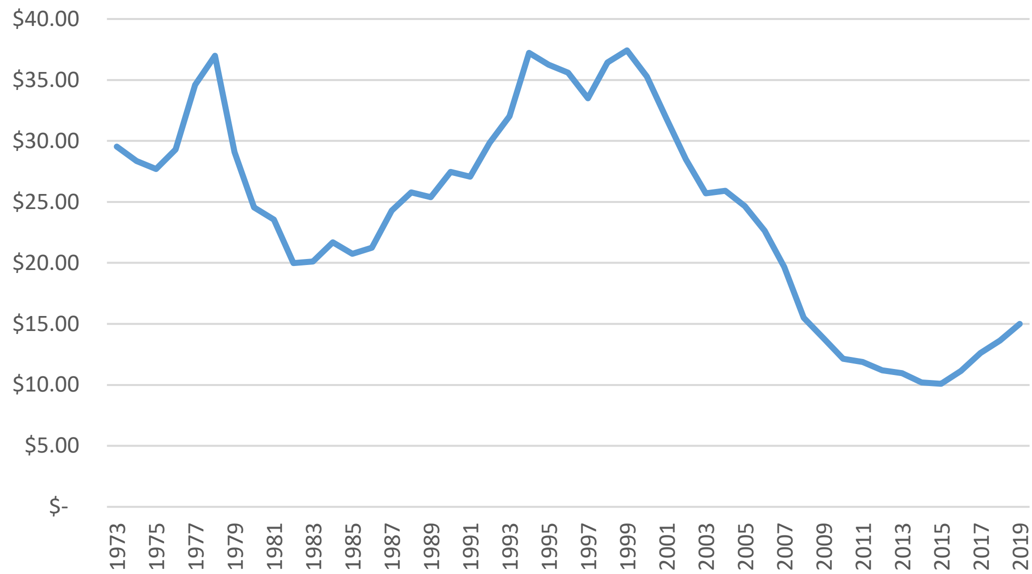
There is also some truth that performing artists have seen their recorded music payouts decline precipitously with the migration from C.D.s to music downloads and then to streaming. However, work done on the topic (Aguier, Waldfogel 2018) found that music streaming has provided a healthy disincentive to pirate music on any of a number of BitTorrent online sites. Thus, Aguier and Waldfogel concluded the benefit of piracy mitigation has effectively offset the past benefit performing artists received from C.D.s and downloads.

Industry disruption created by agreements between the four major labels (Sony, Warner Music, EMI, and Universal) and digital streaming platforms[1] (DSPs) have provided easy access to catalogs of 50 million+ songs (Igbal 2020) on any smart device or computer. Consumers can purchase monthly unlimited-use family plans for $14.99, individual plans for $9.99 or less, and in some cases, get a free subscription in exchange for receiving advertising. In particular, Spotify has pursued a landgrab strategy to become the dominant global distributor of music with 299 million total active subscribers globally, 170 million of which subscribe to the free ad-support service (Spotify.com).

With the migration of recorded music to DSPs, performing artists have voiced their displeasure with recorded music's low payouts. While contracts are paid based on a share of revenue, 2019 payments per stream ranged from $0.00069 to $0.019, depending on the DSP (Sanchez 2018). Figure 1 shows that, adjusted for inflation, U.S. households are spending less on recorded music now than at any point during the past five decades.

[1] Digital Music Platforms include Spotify, Apple Music, Amazon, Youtube, Tencent, and many other smaller brands

Figure 1 Recorded music spending per household in 1973 dollars (Adjusted for Inflation)



Note. Adapted from trends provided by U.S. Sales Database, RIAA.com; U.S. Household Count, Statista

In response, live performance has become the primary income source. Contrary to the music industry of 30-years ago, recorded music has become the table stakes for driving live performance revenue. As highlighted by Rosen (1981), Adler (1985), and others, this analysis's conclusions carry implications for talent in other industries. Status and compensation are driven by multiple forces, not just their efforts and direct productivity outcomes. This research addresses three key industry questions among the top-100 performing artists:

i. Does music streaming influence a performing artist's live concert revenue, ticket pricing, and selling out concerts?
ii. Do performing artists' star persona and/or hit-song legacy enhance their financial performance?
iii. Do Rosen's and Adler's theoretical work on the superstar phenomenon provide a construct for understanding today's music industry?

These questions will be analyzed in the Data and Empirical Analysis section (3); implications and conclusions will be outlined in the Discussion (4) and Conclusions (5) sections.

3 Data and empirical analysis

3.1 Data

To address the research questions, a data set of U.S. streaming and public performances was compiled with salient activities and characteristics of the top-100 performing artists (based on ticket sales) during 2019 according to Pollstar; a data source that ranks artist tours and collects worldwide concert ticket and sales data for each artist/band in the group.

Table 1 Data source characteristics

Source	Characteristics
Pollstar	Collect concert data back to 1999, includes Date, number of shows, revenue, ticket sales, minimum/maximum/average ticket price, venue, % of capacity sold, city/state/country
Alpha Data Music +	Streaming data: All weekly total, audio, video, and programmed digital streams by Spotify, Apple Music, Amazon, and all other major digital streaming platforms
Billboard Rankings (provided by Data.World)	Peak rankings and weeks in Hot 100 Billboard ranking of songs by week from 1959 to 2019. Sample filtered for all songs throughout career among the 2019 Pollstar top-100 performing artists
Google Trends	Monthly search trends for each top-100 performing artist in the U.S.
MusicBrainz.org	Album, E.P., Live Concert releases and profile of artist gender, primary genre, and years playing professionally for each top-100 performing artist

Among the top-100, nine were eliminated because they did not perform in the United States between 2014 and 2019. Some elite performing artists such as Taylor Swift, Bruno Mars, and U2 did not play enough dates during 2019 to be included in the top-100. However, many top-tier performing artists such as Elton John, Ed Sheeran, P!NK, Paul McCartney, the Eagles, and the Rolling Stones are included in Pollstar's top-100 during 2019; a sufficient count to test heterogeneity within the group.

U.S. Concert ticket sales, revenue, high/low pricing, and other concert characteristics were collected by date from January 1, 2014, through December 31, 2019. Additionally, weekly streaming, Billboard rankings, album releases, Google trending, artist characteristics, and macroeconomic data were compiled into an integrated data set. The data endpoints were chosen to mark when music streaming started becoming a dominant music distribution platform. The end date (December 31, 2019) precedes any possible headwinds from COVID-19 that essentially shut down in-person public performance as we knew it in 2020. Sample sizes for each source include 15,774 concerts, 29,224 weeks by artist for U.S. national streaming data, 21,739 Billboard ranking records from 1964 to 2019, 7,200 records of monthly Google Trending by artist, macro-economic data from 2014 to 2019, and artist characteristics such as years performing as well as the gender mix of headlining artist bands.[2]

Multi-artist festivals and international performances have been removed from the data. Concert revenue was then transformed into revenue per show and average ticket prices. Revenue per show was divided by the number of headline artists for the performance. The final data set includes 1,049 records by artist per quarter in which Pollstar recorded at least one performance. Music streams are transformed using natural logs and lagged one-quarter to capture the time series relationship of music streaming to dependent variables such as revenue per show, average ticket price, and percent of sellout concerts.

[2] Male =1 and Female =0 with mixed-gender brands assigned a value based on # of female headliners/total band headliners

Table 2 Descriptive statistics by quarter

Variable	Obs	Mean	Std.Dev.	Min	Max
Total streams (millions)	1042	117.00	214.00	0.00	2710.00
Tickets sold (millions)	1049	0.122	0.14	0.00	1.02
Gross revenue (millions $)	1049	9.70	13.00	0.01	156.00
Average ticket price ($)	1049	78.73	49.16	9.76	498.62
Minimum ticket price ($)	1049	69.76	878.99	8.50	28505.00
Maximum ticket price	1049	152.00	163.50	0.00	1977.40
Revenue per show ($)	1049	0.88	1.08	0.01	11.00
Percent sellouts	1049	0.49	0.38	0.00	1.00
Gender of headliner (Males)	1049	0.89	0.30	0	1
Years as a professional artist	1049	26.05	15.61	4	63
Total weeks in top 20	1049	101.95	135.61	0	503
Primary genre					
Pop music	1049	0.23	0.42	0	1
Rock	1049	0.26	0.44	0	1
Country	1049	0.21	0.41	0	1
Folk	1049	0.03	0.18	0	1
R&B	1049	0.08	0.27	0	1
Heavy Metal	1049	0.09	0.28	0	1
Christian	1049	0.06	0.24	0	1
Other	1049	0.04	0.21	0	1

Table 2 highlights many meaningful insights about performing artists. The average top-100 artist sells 122,000 tickets per quarter, with ticket prices ranging from $70 to $152 and selling out 49% of concerts. These artists have been playing professionally for 26 years on average. Some, such as The Rolling Stones and Paul McCartney, have played for 60 years or more. It is also noteworthy that among the top-100, only 11% of band members are female. This concurs with other reports in the media and literature (Watson 2019). Also, about 70% consider Pop, Rock, or Country to be their primary genre.

3.2 Observable trends from 2014 to 2019

When it comes to streaming growth, the top-100 artists have benefitted greatly at the hands of the rest of the industry over the past four years. The top-100 has seen a 5-fold increase in total streams and a 2-fold increase in their share of total industry streams since the beginning of 2016.

Live-concert revenue saw similar growth trends during the same period, with significant growth in concert revenue and sellouts during 2018 and 2019 (Table 3). While (Champarnaud 2014) theorized a leveling of prices for superstars' musical offerings, the empirical evidence points to steady growth of ticket prices. Among the top-100, this is undoubtedly influenced by capacity constraints since sellouts have increased in recent years.

Table 3 Concert financial metrics

			Growth rate		Annual growth rate of ticket prices		
	Revenue per show($ M)	Percent sellouts	Revenue per show	Percent sellouts	Mean price	Maximum Price	Minimum Price
2015	798.5	47%	15.4%	-19.6%	4.0%	16.2%	13.0%
2016	751.4	37%	-5.9%	-22.5%	9.8%	10.5%	4.9%
2017	777.1	35%	3.4%	-4.6%	-2.8%	8.4%	-6.1%
2018	983.5	56%	26.6%	59.0%	21.2%	23.1%	13.3%
2019	1,186.6	60%	20.6%	7.6%	1.5%	11.6%	-6.7%

Note. Source: Pollstar

While many performing artists like to state they earn little from the DSPs, Table 4 (Alpha Data Music +) shows that the top 70 artists made $1 million or more from streaming in 2019, while the bottom ten average less than $30,000. However, streaming earnings pale compared to concert revenue; for example, the median top-100 artist (the band Phish) made $34.7 million touring in 2019. So, for many, writing new music has become a complement for live performance vs. the opposite 30+ years ago (Hamlen 1991; Adler 1986; MacDonald 1988; Chung and Cox 1994;

Krueger 2005). Not to be overlooked is the disparity in streaming payouts, where the streaming payout for the average top-10 artist is 455X an average bottom-10 artist.

Table 4 Projected streaming revenue for the top 100 artists

Streaming rank among Top 100	Streams (millions)	2019 Payout per artist and writer ($ millions)
1 to 10	3,734.0	12,695.6
11 to 20	1,815.0	6,171.0
21 to 30	1,238.0	4,209.2
31 to 40	895.1	3,043.3
41 to 50	598.9	2,036.3
51 to 60	412.5	1,402.5
61 to 70	309.6	1,052.6
71 to 80	186.0	632.4
81 to 90	104.4	355.0
91 to 100	8.2	27.9

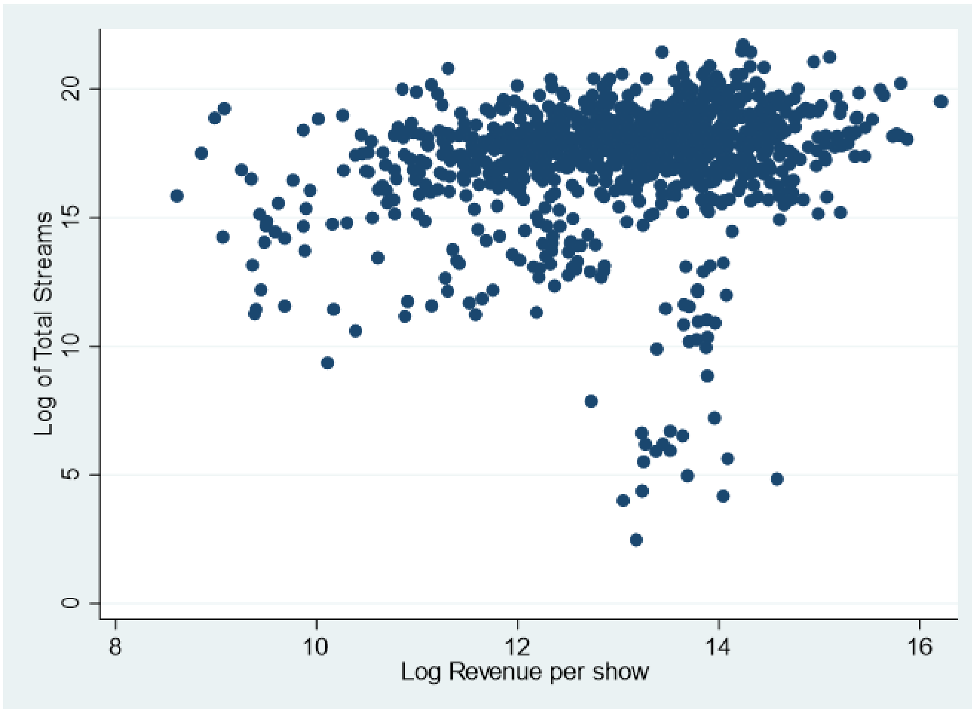
Note. Alpha Data Music +; Revenue estimated from DSP median amount paid to artists, writers, publishers, and record labels based on 2018 data. (Pastukhov 2019)

Preliminary analysis included an examination of simultaneity between concert financial metrics and music streaming. While one may hypothesize both are proxies for popularity, a scatterplot of log revenue and log streams (Figure 2) does not indicate a linear relationship. Several steps have been taken in model estimation to address possible endogeneity. They include:

1. Artist fixed-effects to mitigate variance in popularity effects between artists
2. IV instrument ($X_{it(IV)} = S(X_{it}) - X_{1t}$) was created to address pre-concert promotional effects
3. Inclusion of Google Trending for each artist as a control variable for trending popularity

It is believed that any simultaneous effects that remain are trivial and idiosyncratic. Out of an abundance of caution, the results have been tempered to avoid the risk of overstatement.

Figure 2 Scatterplot of music log music streams and concert revenue



3.3 Superstar identification

To identify superstars, a continuous and categorical metric was developed. The continuous metric is derived using a cumulation of weeks an artist had a song in the top-20 of Billboard's Hot 100.

As a robustness check, a tier 1 and 2 superstar categorical variable was also created by aggregating a data set of performing artists (n=81) for all concerts by the top-100 artists between 1999 and 2013 (the year before the start of the panel data set analyzed). Variables include artist identification, average ticket sales per show, cumulative weeks in Billboard top-20, the mean of average ticket prices, and percent of concerts sold out during the 1999 to 2013 pre-period. While using the pre-period may overlook more current superstar candidates, it was done to avoid endogeneity with regressors in the modeled timeframe.

All variables (except artist identification) were standardized and assigned into segments using K-Means Clustering with assignments of two to five segments. The five-segment solution (reduced to 3) was chosen based on meaningful discrimination of profiles and segments' size.

The segments were then approximated using several data heuristics that are intuitive to definitions for tier 1 and tier 2 superstars. These criteria include:

- Tier 1 performing artists: 100+ weeks in Billboard top-20 (vs. median of 62 for the top-100), $100+ average ticket price (vs. $46.50 median), and sell out 40%+ of concerts (vs. 31% median).
- Tier 2 performing artists: met the same criteria except that their average ticket price hurdle is greater than $40.

The criteria predict the original segments with 87% accuracy and bring parsimony to the groupings. The heuristic also makes it easier to extend the analysis to performing artists not included in the current data set. Extending the methodology to the 2014 through 2019 timeframe (Table 22 in Appendix), we discover younger artists including Ed Sheeran, Ariana Grande, Post Malone, Jonas Brothers, and Bad Bunny, in addition to several Country artists such as Florida Georgia Line, Carrie Underwood, and Jason Aldean have become tier 2 superstars. A key rationale for their omission is due to the timeframe (1999 to 2013) used to define superstars. At the time, they were earlier in their careers and had fewer top-20 hits.

The performing artist segment profiles (Table 5) demonstrate that tier 1 superstars maintain longer tenure, more than 3-times the revenue per show vs. non-stars, attain higher ticket prices (averaging $150 per ticket), and tend to play more shows. Tier 2 superstars tend to be more active in releasing albums and charge less than tier 1 for tickets. They also have the highest proportion of females (32% vs. only 19% for tier 1 and 8% for all other artists). The remaining artists play more shows, albeit with lower ticket prices and revenue per show. They are also more active in creating new releases. Notably, the skews for revenue, ticket pricing, and percent of sellouts correspond to the data heuristic definitions.

Ticket volume, revenue, and national/global reach derived by tier 1 performing artists highlight a very specialized level of talent. A performer such as Paul McCartney, who has sold out 92% of his 85 concerts during the past six years, charges upwards of $260 per ticket and has been an active professional performing artist for 63 years. Additionally, few in the top-100 have less than ten years of experience with professional performance. This concurs with (MacDonald 1988) that becoming a successful performing artist requires many years of building a fan base and a musical legacy.

Table 5 Superstar definition profile

	Tier 1 Stars	Tier 2 Stars	Rest of Top 100
Artist count	8	6	86
Number of shows per artist	160.0	86.4	124.9
Total tickets (millions) per artist	2.13	1.08	1.23
Gross revenue (millions $)	306.67	110.50	86.74
Gross revenue (millions $) per artist per show	2.30	1.20	0.71
Average ticket price ($)	$150	$113	$69
Percent sellouts	74.8%	49.4%	46.6%
Years as a professional artist	52.4	27.9	23.1
Gender of headliner (males)	80.9%	67.8%	91.7%
Weeks at Billboard #1	72	49	12
Weeks at Billboard #10	205	141	52
Weeks at Billboard #20	290	196	76
Weeks at Billboard #50	467	252	143
Weeks at Billboard #100	573	307	217
# of 2014 releases	0.25	0.33	0.51
# of 2015 releases	0.00	0.17	0.43
# of 2016 releases	0.50	0.17	0.38
# of 2017 releases	0.00	0.83	0.37
# of 2018 releases	0.25	0.33	0.52
# of 2019 releases	0.13	0.17	0.46
# of releases from 2014 to 2019 per artist	1.13	2.00	2.67

Note. Combined Data File, Profile based on 2014 to 2019 data, tier definitions created using 1999 to 2013 data

Tier 1 superstars place less effort on new releases. This is likely motivated by an attempt to rely on their old hits. Tier 2 superstars and the rest of the top-100 still show moderate recent release activity. This is likely due to the cohorts' need to build a catalog of hits and/or a need or desire to fuel greater streaming activity. Given that DSPs tend to promote new content, this finding is not a surprise (Music Ally 2020).

3.4 Panel model with artist fixed-effects specification

To account for performing artist interactions, a panel model with artist fixed-effects was chosen to examine the influence of music streaming and the superstar phenomenon on concert-related outcomes. These outcomes include revenue per show, average ticket prices, and percent of concerts sold out. Each outcome is denoted in the model specification as (Y_{it}). Tier 1 and 2 superstar regressors [$(\text{Superstartier1})_{it}$,$(\text{Superstartier1 and 2})_{it}$] identify the superstar effect of a person of particular notoriety. Weeks in the Billboard top-20 [$(\text{Cumulative Weeks in top-20})_{it}$] represents a rolling cumulation of weeks over time with songs ranked 20 or higher in the Billboard Hot 100 and therefore provides a proxy for a performing artist's musical legacy. Both Superstar Tiers and the Cumulative Weeks in the top 20 regressors were interacted with the log lag of music streams. Artist fixed-effects are suitable to address heterogeneity between artists.

Log lag of streams $(\text{streaming})_{it-1}$ capture the impact of broadcasting an artist's songs. Google Trending $(\text{Google Trending})_{it}$ highlights the influence of publicity (a.k.a social media buzz) pointed out by Adler (Adler 1985). Binary variables for quarter/year and streaming source trend corrections $(\text{Quarter/Year/Panel Data Corrections})_{t}$, album release during the current, past year $(\text{Current Year Release})_{it}$, $(\text{Last Year Release})_{it-n}$, and percent of solo headline concerts $(\text{Shows performing solo})_{it}$ were included as testable controls. Streaming trend corrections respond to adjustments in tracking by the streaming source (Alpha Data Music +) over time. These corrections include the addition and removal of specific data sources. Seven dummy variables were created to account for each of the corrections. The specific corrections are presented in the Appendix (Table 24).

The specification is:

$$Y_{it} = B_1 Ln(\textit{streaming})_{it-1} + B_2(\textit{Google Trending})_{it} + B_3(\textit{Quarter/Year/Panel Data Corrections})_t + B_4(\textit{Current Year Release})_{it} + B_5(\textit{Last Year Release})_{it-n} + B_6(\textit{Superstartier1})_{it} * B_1 Ln(\textit{streaming})_{it-1} + B_7(\textit{Superstartier1 and 2})_{it} * B_1 Ln(\textit{streaming})_{it-1} + B_8(\textit{Cumulative Weeks in top-20})_{it} * B_1 Ln(\textit{streaming})_{it-1} + B_9(\textit{Shows performing solo})_{it} + \varepsilon_{it}$$

Note. Y_{it} is transformed into a log for the models with dependent variables revenue per show and average ticket prices

Table 6 Revenue per show panel model with artist fixed effects

	1		2		3		4		5	
Ln(Rev. per show) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.273	***	0.265	***	0.261	***	0.259	***	0.275	***
Google Trending	0.006	***	0.006	***	0.006	***	0.006	***	0.006	***
Release$_t$			0.098	*	0.105	*	0.105	*	0.091	
Release$_{t-n}$			-0.014		-0.013		-0.013		-0.024	
Superstar(Tier1)*Ln(streams)$_{n-1}$					-0.101					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							-0.118			
Weeks in t-20*Ln(streams)$_{n-1}$									0.013	**
Solo performance					-0.112		-0.113		-0.111	
Constant	7.74	***	7.869	***	8.043	***	8.202	***	8.26	***
R-squared	0.317		0.32		0.323		0.323		0.327	
F-test	13.293		12.646		12.02		12.051		12.24	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

Note. *** p<0.01, ** p<0.05, * p<0.1, quarter, year, stream trend corrections included in full specification model in the Appendix

Table 7 Average Ticket Price panel model with artist fixed effects

	1		2		3		4		5	
Ln(Avg. Ticket pr.) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.085	***	0.085	***	0.085	***	0.084	***	0.094	***
Google Trending	-0.001		-0.001		-0.001		-0.001		-0.001	*
Release$_t$			0.006		0.008		0.008		-0.001	
Release$_{t-n}$			0.02		0.021		0.02		0.013	
Superstar(Tier1)*Ln(streams)$_{n-1}$					-0.014					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							-0.034			
Weeks in t-20*Ln(streams)$_{n-1}$									0.01	***
Solo performance					-0.029		-0.029		-0.028	
Constant	2.18	***	2.158	***	2.186	***	2.253	***	2.427	***
R-squared	0.287		0.288		0.288		0.289		0.305	
F-test	11.516		10.827		10.223		10.255		11.061	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

Note. *** p<0.01, ** p<0.05, * p<0.1, quarter, year, stream trend corrections included in full specification model in the Appendix

Table 8 Percent of Concerts Sold Out panel model with artist fixed effects

	1		2		3		4		5	
% sellouts$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.033	**	0.034	**	0.036	**	0.037	**	0.038	**
Google Trending	0.002	***	0.002	***	0.002	***	0.002	***	0.002	***
Release$_t$			-0.007		-0.012		-0.012		-0.014	
Release$_{t-n}$			-0.004		-0.005		-0.004		-0.007	
Superstar(Tier1)*Ln(streams)$_{n-1}$					0.037					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							0.05			
Weeks in t-20*Ln(streams)$_{n-1}$									0.003	
Solo performance					0.085	**	0.086	**	0.085	**
Constant	0.253		0.25		0.176		0.102		0.318	
R-squared	0.126		0.126		0.132		0.133		0.133	
F-test	4.129		3.873		3.844		3.872		3.877	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

Note. *** p<0.01, ** p<0.05, * p<0.1, quarter, year, stream trend corrections included in full specification model in the Appendix

3.5 Fixed-effect model analysis results and discussion

The statistical significance of lagged music streaming is consistent across all specifications. Concerts the following quarter see significant revenue increases (0.26% to 0.28% revenue increase for every percent increase in streams). So, a 20%[3] increase in streaming indicates the potential to increase per-show revenue between $46K and $49K for an average top 100 artists.

Additionally, concerts the following quarter see significant increases in average ticket prices (0.084% to 0.094% for every percent increase in streams) and sellouts (0.033% to 0.038% for every percent increase in streams). Google Trending plays a small but significantly positive role in increasing revenue per show, percent of seats sold, and percent of sellouts. The Solo act headliner control variable impacts the percent of sellouts (0.085% to 0.086%). Lastly, albums/E.P.s released in the current year positively impact revenue per show in some cases (0% to 0.11%).

The superstar phenomenon regressors are only significant in a few specifications. The top-20 regressor demonstrates a significantly positive effect on revenue per show and average ticket prices. Tier 1 and 2 superstar regressors are not significant.

The most informative finding are indications that music streaming contributes to concert revenue. And while streams alone make up a fraction of an artist's income, it provides a potential promotional effect on concert financial outcomes. Both present music streams and top-20-hits (over time) can drive incremental revenue. Lastly, based on the current model specification, the superstar phenomenon's influence appears limited to a performing artist's back catalog of musical hits to drive revenue and average ticket prices.

[3] 20% derived from conservative estimate for 2020 streams based on historic year-over-year growth: 43% in 2017, 44% in 2018, and 29% in 2019. Source: Nielson Music

3.6 Fixed-effect model limitations

Admittedly, the panel fixed-effect models overlook unobservable variance from pre-concert promotional activity referenced by (Adler 1985, 2006) that may be unique to specific artists and create an effect that is likely more pronounced among superstars. Data on advance concert date announcements and ticket "on-sale" dates are not widely available. Anecdotally, positive trends in streaming one-quarter in advance of the concert may reflect some of these unobserved promotional effects. In response, the impact of music streaming could be inflated for some artists.

3.7 Two-stage least squares (2SLS) model specification

While a fixed-effect panel model controls for artist effects, a 2SLS model specification also accounts for potential endogeneity in the log lag streaming regressor, which could be affected by unobservable promotional effects. The instrument created is the sum of streams by quarter for all the top-100 artists with the streams for artist$_i$ subtracted out:

$$\mathrm{Ln(streams)}_{n-1(IV)} = \sum_{j \neq i}^{N} (X_{it})$$

The following models were run with revenue, average ticket prices, and percent sellout as the dependent variables.

Table 9 Revenue per show 2SLS Model with artist fixed effects

	1		2		3		4		5	
Ln(Rev. per show) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams) $_{n-1(IV)}$	0.499	**	0.492	**	0.491	**	0.492	**	0.458	**
Google Trending	0.002		0.002		0.002		0.002		0.003	
Release $_{t}$			0.068		0.073		0.072		0.063	
Release $_{t-n}$			0.005		0.006		0.006		-0.012	
Superstar(Tier1)*Ln(streams) $_{n-1}$					-0.056					
Superstar(Tier1/2)*Ln(streams) $_{n-1}$							-0.07			
Weeks in t-20*Ln(streams) $_{n-1}$									0.017	**
Solo performance					-0.09		-0.091		-0.094	
F-score	11.59		11.13		10.62		10.67		10.84	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note. ** p<0.05, * p<0.1*

Table 10 Average Ticket Price 2SLS Model with artist fixed effects

	1		2		3		4		5	
Ln(Avg. Ticket pr.) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams) $_{n-1(IV)}$	0.174	**	0.175	**	0.175	**	0.175	**	0.154	**
Google Trending	-0.002	**	-0.002	**	-0.002	**	-0.002	**	-0.002	**
Release $_{t}$			-0.006		-0.005		-0.005		-0.01	
Release $_{t-n}$			0.028		0.028		0.028		0.017	
Superstar(Tier1)*Ln(streams) $_{n-1}$					0.003					
Superstar(Tier1/2)*Ln(streams) $_{n-1}$							-0.015			
Weeks in t-20*Ln(streams) $_{n-1}$									0.011	**
Solo performance					-0.02		-0.02		-0.022	
F-score	10.45		9.82		9.29		9.34		10.03	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note. ** p<0.05, * p<0.1*

Table 11 Sellout 2SLS Model with artist fixed effects

	1		2		3		4		5	
% sellouts$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1(IV)}$	0.11	**	0.112	**	0.113	**	0.111	**	0.103	**
Google Trending	0.001		0.001		0.001		0.001		0.001	
Release$_t$			-0.018		-0.023		-0.023		-0.024	
Release$_{t-n}$			0.003		0.002		0.002		-0.003	
Superstar(Tier1)*Ln(streams)$_{n-1}$					0.052					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							0.065			
Weeks in t-20*Ln(streams)$_{n-1}$									0.005	*
Solo performance					0.092	**	0.093	**	0.091	**
F-score	4.08		3.83		3.79		3.81		3.82	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note. ** p<0.05, * p<0.1*

The inclusion of a proxy for streaming category trends (streaming) $_{it-1(IV)}$ continues to display a significant relationship to concert revenue (with 0.46% to 0.5% impact for every 1% of increase), average ticket prices (with 0.15% to 0.18% impact for every 1% of increase), and sellout (with 0.1% to 0.11% impact for every 1% of increase).

Among the control variables, Google Trending demonstrates no impact on revenue as well as the likelihood to sell out and a slightly negative effect on average ticket prices. The Solo headliner variable also positively impacts the percent of concerts sold out (increasing sellouts by 0.09%).

Every additional week in the Billboard top-20 increases the effect of the log lag of streams on concert revenue by 0.017%. In absolute terms, a performing artist can derive an incremental $15K per show for every week in the Billboard top-20. So, an artist such as Ed Sheeran (with 314 weeks in the top-20 and a Weeks in top-20*Ln(streams)$_{n-1}$ value of 11.9) can earn $206K more per show than Luke Bryan (with 88 weeks in the top-20 and a Weeks in top-20*Ln(streams)$_{n-1}$ value of 0.92). Thus, a performing artist's back catalog provides a significant source of additional revenue.

3.8 Model analysis discussion

The panel and 2SLS model (both with artist fixed-effects) provide a complementary understanding of the key outcomes for public performance. Consistent throughout all specifications, the lagged streaming regressor contributes to concert revenue, ticket pricing, and selling out concerts. The impact of streaming can be seen even when including the impact of the model controls. And while the panel fixed-effect models may suffer from endogeneity, the use of an industry streaming instrument in the 2SLS specification further confirms the impact of streaming on concert financial outcomes.

Both models confirm that a performing artist's catalog of hit songs contributes to their ability to earn incremental concert income, charge higher ticket prices, and sell out their performances. By contrast, the superstar tiers do not contribute to concert financial outcomes.

3.9 Checking robustness of results

Data analysis included the exploration of a possible data anomaly that holds the potential for confounding the results. Of the 15,774 concert records Pollstar collected, 11,255 collected detailed concert metrics (tickets sold, gross revenue, ticket pricing, and percent of capacity sold). The missing records (n=4,519, 31% of records overall) vary significantly by performing artist (Table 23 in Appendix).

A panel model with artist fixed-effects was created using the following specification:

Percent missing concert record model with artist fixed-effects[4]

$$Y_{it} = B_1 Ln(\textit{streaming})_{it-1} + B_2(\textit{Google Trending})_{it} + B_3(\textit{Quarter/Year})_t + B_6(\textit{Supertartier1})_{it} * B_1 Ln(\textit{streaming})_{it-1} + B_7 (\textit{Supertartier1 and 2})_{it} * B_1 Ln(\textit{streaming})_{it-1} + B_8(\textit{Cumulative Weeks in top-20})_{it} * B_1 Ln(\textit{streaming})_{it-1} + \varepsilon_{it}$$

Note. Y_{it} is the percent of concert records with missing concerts where revenue, ticket prices, and percent of seats sold are missing in Pollstar

The model specification results include four versions testing different regressors: (1) log lag streaming, (2) tier 1 superstars * log lag streaming, (3) tier 1 and 2 superstars * log lag streaming, (4) Weeks in Billboard top-20 * log lag streaming. All models include control variables for Google Trending and quarter/year dummies to absorb potential time-series interactions. The results (see Appendix Table 19) demonstrate no significant effects on the regressors due to the missing data in the Pollstar records.

4 Discussion

This analysis highlights several findings on the economic dynamics of the music industry. First, music streaming plays a critical role in the scaling of market presence for performers that provides an ability to expand their reach around the globe. While some may argue that the direct payouts of music streaming are too low, music streams' promotional effect on concert revenue justifies the medium's role in a performing artist's career.

Additionally, a performer's elevation to superstar status requires a strong back-catalog of hit songs, as evidenced by the number of weeks performers' songs spent in the Billboard top-20.

[4] To address the potential for bias in the modeling results, a % of missing concert variable was created where 1 = concerts where revenue, ticket prices, percent of seats sold are missing in Pollstar and 0 reflects concert records where the variables are populated. The records were then aggregated by quarter and appended to the Combined File.

Observing the top-100 touring artists, accomplishing this requires decades of performing and (no doubt) a degree of luck. If you attend an Elton John or Paul McCartney concert, you will see fans respond on cue to the first bar of an old hit that dates back to childhood. Fans then sing in unison to many of the songs in the night's repertoire. Concerts for Elton John, Paul McCartney, and the Eagles run 2.5 to 3 hours (Stubhub.com 2020). For the Eagles, they draw on their hit songs as a band as well as solo performances by Don Henley, Joe Walsh, Deacon Frey (performing Glen Frey's songs), and Vince Gill (SongKick 2020). Cultivating this experience derives many benefits for superstar performers, including more revenue from sellout concerts and demand for premium-priced tickets.

Rosen's superstar phenomenon theory (Rosen 1981) concluded that performing artists will benefit from technological innovation to scale their market presence. As a result, small differences in talent will significantly impact a performer's revenue potential. Music streams and, in some specifications, Google Trending also indicate the relevance of Adler's theory (Adler 1985) on the influence of publicity in driving an artist's concert success.

In addition to demonstrating Rosen's theory, this work extends the literature by relating it to the current industry model of distribution and promotions (e.g., Google Trending as a proxy for social media and music streaming). It also dimensionalizes the superstar phenomenon as an expression of an artist's musical legacy (Schulze 2003; Adler 2006).

5 Conclusions

The results in this report outline a compelling case that success in the music industry is motivated by artists' streaming volume and is influenced by the perceived quality of a performer's catalog. Given the asynchronous relationship of a performer's talent to earnings, their ability to increase the creation of high-quality music should improve their financial prospects. But this does not necessarily mean there is a path for the top-100 non-superstars to become superstars. In other words, this work does not find a prototype or formula for becoming a superstar. While talent plays a primary role, there are undoubtedly other unobservable characteristics in play.

Given that 80 out of the top-100 artists have been performing for 10+ years, this work also highlights the ability of a performer's music to become a lifelong annuity. A performer's ability to build a catalog of hits provides a catalyst for deriving public performance income for decades.

The learning from this paper also carries implications for the industry's different stakeholders. While the strategic implications require further development, record labels will benefit from a better understanding of the nexus that superstar potential and musical content play in monetizing talent and creative works. Agents will be more effective in their representation by understanding the effective near and longer-term levers that will promote their clients' success. Lastly, promoters can establish greater confidence in planning dates and venue bookings that provide mutual benefit for helping artists sell capacity and optimize ticket pricing with an eye toward first-degree price discrimination that maximizes revenue.

Lastly, as Alan Krueger outlined (Krueger 2019), the music industry is important because it provides a microcosm for the broader economy. In a business environment where technology enables companies to scale globally, the founders and leaders of these organizations gain the opportunity to build enormous companies and personal wealth. Thus, the superstar phenomenon is not limited to a handful of industries like music and entertainment but can be extended to any industry where the unique talents (and luck) of a few can be leveraged to build extraordinary levels of wealth.

6 Compliance with ethical standards

Conflicts of interest/competing interests: The author manages a deceased Bluegrass/Folk artist's legacy unrelated to the data analyzed for this paper.

Stata code producing the attached results is available for review. However, several data sources are proprietary and cannot be shared.

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7 Appendices

Table 12 Revenue per show panel model (Full Specifications of Table 6)

	1		2		3		4		5	
Ln(Rev. per show)$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.273	***	0.265	***	0.261	***	0.259	***	0.275	***
Google Trending	0.006	***	0.006	***	0.006	***	0.006	***	0.006	***
2014-Q1	0		0		0		0		0	
2014-Q2	0.296		0.239		0.35		0.358		-0.217	
2014_Q3	0.438		0.384		0.51		0.516		-0.052	
2014_Q4	0.102		0.054		0.2		0.207		-0.363	
2015-Q1	0.073		0.037		0.177		0.183		-0.389	
2015-Q2	0.288		0.251		0.364		0.367		-0.144	
2015_Q3	0.425		0.397		0.509		0.503		0.088	
2015_Q4	0.209		0.186		0.299		0.294		-0.136	
2016-Q1	0.155		0.129		0.254		0.248		-0.19	
2016-Q2	0.209		0.119		0.223		0.217		-0.15	
2016_Q3	0.248		0.146		0.248		0.244		-0.114	
2016_Q4	0.022		-0.101		0		-0.002		-0.368	
2017-Q1	0.389		0.327		0.4		0.393		0.036	
2017-Q2	1.136		1.133		1.176		1.172		0.821	
2017_Q3	1.232	*	1.235	*	1.289	*	1.289	*	0.942	
2017_Q4	0.474		0.475		0.578		0.585		0.3	
2018-Q1	0.307		0.26		0.372		0.36		0.172	
2018-Q2	0.456		0.398		0.477		0.462		0.256	
2018_Q3	0.578		0.532		0.624		0.615		0.42	
2018_Q4	0.546		0.508		0.611		0.603		0.387	
2019-Q1	0.54		0.486		0.595		0.585		0.377	
2019-Q2	0.329		0.299		0.367		0.367		0.226	
2019_Q3	0.135		0.135		0.137		0.141		0.147	
2019_Q4	0		0		0		0		0	
Correction 1	0.007		0.006		0.009		0.009		-0.001	
Correction 2	-0.004		0.001		0.002		0.002		-0.003	
Correction 3	0.002		0.004		0.004		0.004		0.005	
Correction 4	-0.051		-0.057		-0.054		-0.054		-0.055	
Correction 5	0.006		0.004		0.001		0		-0.001	
Correction 6	0.041		0.045		0.045		0.046		0.037	
Correction 7	0.015		0.013		0.019		0.018		0.006	
Release$_t$			0.098	*	0.105	*	0.105	*	0.091	
Release$_{t-n}$			-0.014		-0.013		-0.013		-0.024	
Superstar(Tier1)*Ln(streams)$_{n-1}$					-0.101					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							-0.118			
Weeks in t-20*Ln(streams)$_{n-1}$									0.013	**
Solo performance					-0.112		-0.113		-0.111	
Constant	7.74	***	7.869	***	8.043	***	8.202	***	8.26	***
R-squared	0.317		0.32		0.323		0.323		0.327	
F-test	13.293		12.646		12.02		12.051		12.24	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

*Note.*** p<0.01, ** p<0.05, * p<0.1*

Table 13 Average Ticket Price panel model: (Full Specification of Table 7)

	1		2		3		4		5	
Ln(Avg. Ticket pr.) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams) $_{n-1}$	0.085	***	0.085	***	0.085	***	0.084	***	0.094	***
Google Trending	-0.001		-0.001		-0.001		-0.001		-0.001	*
2014-Q1	0		0		0		0		0	
2014-Q2	0.515		0.517		0.542	*	0.548	*	0.152	
2014_Q3	0.479		0.48		0.509		0.515		0.123	
2014_Q4	0.527	*	0.529	*	0.562	*	0.569	*	0.178	
2015-Q1	0.603	*	0.604	*	0.636	**	0.643	**	0.252	
2015-Q2	0.47	*	0.469	*	0.495	*	0.5	*	0.149	
2015_Q3	0.422		0.419		0.445		0.447		0.158	
2015_Q4	0.411		0.408		0.434		0.437		0.139	
2016-Q1	0.441		0.437		0.465		0.468		0.165	
2016-Q2	0.402		0.41		0.434		0.435		0.178	
2016_Q3	0.466		0.477		0.5		0.502		0.252	
2016_Q4	1.332	***	1.341	***	1.364	***	1.367	***	1.114	***
2017-Q1	0.89	***	0.896	***	0.913	***	0.913	***	0.663	**
2017-Q2	0.543	*	0.543	*	0.552	*	0.553	*	0.308	
2017_Q3	0.618	**	0.618	**	0.63	**	0.632	**	0.391	
2017_Q4	0.661	*	0.663	*	0.687	**	0.692	**	0.498	
2018-Q1	0.289		0.294		0.321		0.32		0.188	
2018-Q2	0.073		0.078		0.096		0.094		-0.051	
2018_Q3	0.233		0.238		0.26		0.26		0.122	
2018_Q4	0.309		0.313		0.337		0.337		0.185	
2019-Q1	0.337		0.342		0.368		0.368		0.222	
2019-Q2	0.067		0.071		0.086		0.088		-0.006	
2019_Q3	-0.042		-0.04		-0.04		-0.038		-0.03	
2019_Q4	0		0		0		0		0	
Correction 1	0.007		0.008		0.008		0.008		0.002	
Correction 2	0		-0.001		-0.001		0		-0.004	
Correction 3	-0.054	***	-0.054	**	-0.054	**	-0.054	**	-0.054	***
Correction 4	0.044	**	0.045	**	0.046	**	0.046	**	0.045	**
Correction 5	-0.021		-0.021		-0.022		-0.022		-0.023	
Correction 6	0.047	**	0.047	**	0.046	**	0.047	**	0.041	*
Correction 7	0.013		0.013		0.014		0.015		0.006	
Release $_t$			0.006		0.008		0.008		-0.001	
Release $_{t-n}$			0.02		0.021		0.02		0.013	
Superstar(Tier1)*Ln(streams) $_{n-1}$					-0.014					
Superstar(Tier1/2)*Ln(streams) $_{n-1}$							-0.034			
Weeks in t-20*Ln(streams) $_{n-1}$									0.01	***
Solo performance					-0.029		-0.029		-0.028	
Constant	2.18	***	2.158	***	2.186	***	2.253	***	2.427	***
R-squared	0.287		0.288		0.288		0.289		0.305	
F-test	11.516		10.827		10.223		10.255		11.061	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

*Note.*** p<0.01, ** p<0.05, * p<0.1*

Table 14 Percent of concerts sold out panel model: (Full Specification of Table 8)

	1		2		3		4		5	
% sellouts$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.033	**	0.034	**	0.036	**	0.037	**	0.038	**
Google Trending	0.002	***	0.002	***	0.002	***	0.002	***	0.002	***
2014-Q1	0		0		0		0		0	
2014-Q2	-0.36		-0.357		-0.431		-0.436		-0.548	
2014_Q3	-0.371		-0.368		-0.453		-0.457		-0.567	
2014_Q4	-0.232		-0.23		-0.328		-0.332		-0.441	
2015-Q1	-0.406		-0.404		-0.496		-0.5		-0.607	
2015-Q2	-0.272		-0.269		-0.344		-0.347		-0.446	
2015_Q3	-0.097		-0.094		-0.17		-0.169		-0.254	
2015_Q4	0.035		0.037		-0.038		-0.037		-0.123	
2016-Q1	-0.023		-0.02		-0.103		-0.102		-0.189	
2016-Q2	0.017		0.021		-0.051		-0.049		-0.127	
2016_Q3	0.059		0.062		-0.008		-0.007		-0.082	
2016_Q4	0.099		0.105		0.038		0.037		-0.035	
2017-Q1	0.126		0.128		0.08		0.082		0.006	
2017-Q2	-0.04		-0.039		-0.065		-0.064		-0.137	
2017_Q3	-0.082		-0.082		-0.117		-0.118		-0.189	
2017_Q4	-0.299		-0.299		-0.371		-0.375		-0.426	
2018-Q1	0.136		0.138		0.058		0.063		0.022	
2018-Q2	0.443		0.445		0.392		0.398		0.352	
2018_Q3	0.098		0.099		0.035		0.037		-0.005	
2018_Q4	0.152		0.153		0.08		0.083		0.036	
2019-Q1	0.231		0.233		0.156		0.16		0.115	
2019-Q2	0.107		0.108		0.062		0.061		0.037	
2019_Q3	0		-0.001		-0.001		-0.003		0.004	
2019_Q4	0		0		0		0		0	
Correction 1	-0.026		-0.026		-0.027		-0.027		-0.029	*
Correction 2	-0.009		-0.009		-0.009		-0.009		-0.01	
Correction 3	-0.004		-0.004		-0.005		-0.005		-0.005	
Correction 4	0.005		0.006		0.004		0.004		0.004	
Correction 5	0.029		0.029		0.031		0.032		0.031	
Correction 6	-0.024		-0.025		-0.024		-0.025		-0.026	
Correction 7	0.007		0.007		0.003		0.003		0.001	
Release$_t$			-0.007		-0.012		-0.012		-0.014	
Release$_{t-n}$			-0.004		-0.005		-0.004		-0.007	
Superstar(Tier1)*Ln(streams)$_{n-1}$					0.037					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							0.05			
Weeks in t-20*Ln(streams)$_{n-1}$									0.003	
Solo performance					0.085	**	0.086	**	0.085	**
Constant	0.253		0.25		0.176		0.102		0.318	
R-squared	0.126		0.126		0.132		0.133		0.133	
F-test	4.129		3.873		3.844		3.872		3.877	
Prob > F	0		0		0		0		0	
Number of obs	1008		1008		1008		1008		1008	

*Note.*** p<0.01, ** p<0.05, * p<0.1*

Table 15 Revenue per show 2SLS model (first stage): (Full Specification of Table 9)

$Ln(streams)_{n-1}$	Coef.	Std. Err.	t	P>|t|	[95% Conf Interval]	
Google Trending	0.01	0.002	6.33	0	0.007	0.013
2014-Q1						
2014-Q2	-26.408	2.852	-9.26	0	-32.006	-20.81
2014_Q3	-12.198	1.76	-6.93	0	-15.652	-8.743
2014_Q4	-10.575	1.647	-6.42	0	-13.807	-7.344
2015-Q1	-10.199	1.629	-6.26	0	-13.396	-7.002
2015-Q2	-9.107	1.268	-7.18	0	-11.595	-6.618
2015_Q3	-14.116	1.23	-11.48	0	-16.531	-11.702
2015_Q4	-16.148	1.387	-11.64	0	-18.87	-13.427
2016-Q1	-13.498	1.217	-11.09	0	-15.887	-11.109
2016-Q2	-5.092	0.822	-6.19	0	-6.705	-3.479
2016_Q3	-0.133	0.766	-0.17	0.862	-1.636	1.37
2016_Q4	-1.8	0.828	-2.17	0.03	-3.424	-0.175
2017-Q1	-3.707	0.731	-5.07	0	-5.142	-2.272
2017-Q2	5.399	0.882	6.12	0	3.669	7.13
2017_Q3	5.954	0.73	8.15	0	4.521	7.387
2017_Q4						
2018-Q1	-5.834	0.717	-8.14	0	-7.241	-4.426
2018-Q2	6.033	1.1	5.48	0	3.873	8.193
2018_Q3	3.348	0.629	5.32	0	2.113	4.583
2018_Q4	8.289	0.878	9.45	0	6.567	10.012
2019-Q1	12.041	1.127	10.68	0	9.829	14.253
2019-Q2	20.63	1.763	11.7	0	17.169	24.091
2019_Q3	21.046	1.924	10.94	0	17.27	24.822
2019_Q4	19.254	1.78	10.82	0	15.762	22.747
Correction 1	0.517	0.03	17.38	0	0.459	0.575
Correction 2	-0.063	0.04	-1.57	0.118	-0.141	0.016
Correction 3	0.006	0.047	0.13	0.899	-0.086	0.098
Correction 4	0.052	0.043	1.2	0.231	-0.033	0.137
Correction 5	-0.032	0.057	-0.57	0.566	-0.144	0.079
Correction 6	0.006	0.051	0.12	0.908	-0.095	0.106
Correction 7	0.075	0.034	2.23	0.026	0.009	0.141
$Release_t$	0.118	0.051	2.32	0.021	0.018	0.217
$Release_{t-n}$	-0.075	0.052	-1.44	0.151	-0.178	0.028
Solo performance	-0.092	0.072	-1.27	0.205	-0.234	0.05
Weeks in t-20*$Ln(streams)_{n-1}$	-0.028	0.005	-5.84	0	-0.037	-0.019
$Ln(streams)_{n-1(IV)}$	-15.094	1.217	-12.4	0	-17.483	-12.706
Number of obs	1,006					
F(35, 883)	92.11					
Prob > F	0					
Centered R-squared	0.785					
Uncentered Adj R-squared	0.785					
Root MSE	0.5971					

*Note.*** p<0.01, ** p<0.05, * p<0.1*

Table 16 Revenue per show SLS model with artist fixed effects: (Full Specification of Table 9)

	1		2		3		4		5	
$Ln(Rev. per show)_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
$Ln(streams)_{n-1}$	0.499	**	0.492	**	0.491	**	0.492	**	0.458	**
Google Trending	0.002		0.002		0.002		0.002		0.003	
2014-Q1										
2014-Q2	-1.935	*	-1.954	*	-1.966	*	-1.982	*	-1.956	*
2014_Q3	-1.781	**	-1.799	*	-1.799	*	-1.815	*	-1.782	*
2014_Q4	-2.133	**	-2.146	**	-2.131	**	-2.148	**	-2.108	**
2015-Q1	-2.191		-2.196	**	-2.188	**	-2.205	**	-2.159	**
2015-Q2	-1.137		-1.153		-1.156		-1.167		-1.241	
2015_Q3	0.33		0.304		0.313		0.31		0.05	
2015_Q4	0.057		0.035		0.043		0.04		-0.223	
2016-Q1	-0.021		-0.046		-0.029		-0.033		-0.298	
2016-Q2	-0.274		-0.328		-0.327		-0.335		-0.455	
2016_Q3	-0.342		-0.402		-0.404		-0.411		-0.495	
2016_Q4	-0.513		-0.588		-0.592		-0.597		-0.701	
2017-Q1	0.004		-0.034		-0.058		-0.065		-0.194	
2017-Q2	0.823		0.817		0.77		0.765		0.634	
2017_Q3	0.851		0.849		0.811		0.808		0.7	
2017_Q4										
2018-Q1	-0.144		-0.173		-0.165		-0.175		-0.073	
2018-Q2	0.053		0.016		-0.003		-0.015		0.051	
2018_Q3	0.125		0.097		0.089		0.081		0.173	
2018_Q4	0.066		0.042		0.043		0.035		0.109	
2019-Q1	0.045		0.012		0.017		0.007		0.094	
2019-Q2	-0.194		-0.212		-0.24		-0.244		-0.058	
2019_Q3	-0.279	*	-0.28		-0.358		-0.359		-0.012	
2019_Q4	-0.449		-0.451		-0.53		-0.533		-0.192	
Correction 1	-0.127		-0.126	*	-0.125	*	-0.126	*	-0.108	*
Correction 2	0.018		0.021		0.021		0.022		0.011	
Correction 3	-0.002		-0.002		-0.001		-0.001		0	
Correction 4	-0.063		-0.067		-0.065		-0.065		-0.064	
Correction 5	0.014		0.012		0.01		0.01		0.006	
Correction 6	0.041	**	0.043		0.043		0.044		0.034	
Correction 7	0.007	**	0.006		0.01		0.01		-0.004	
$Release_t$			0.068		0.073		0.072		0.063	
$Release_{t-n}$			0.005		0.006		0.006		-0.012	
$Superstar(Tier1)*Ln(streams)_{n-1}$					-0.056					
$Superstar(Tier1/2)*Ln(streams)_{n-1}$							-0.07			
Weeks in $t-20*Ln(streams)_{n-1}$									0.017	**
Solo performance					-0.09		-0.091		-0.094	
F-score	11.59		11.13		10.62		10.67		10.84	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note.** p<0.05, * p<0.1*

Table 17 Average Ticket Price SLS model with artist fixed effects (Full Specification of Table 10)

	1		2		3		4		5	
Ln(Avg. Ticket pr.) $_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams) $_{n-1}$	0.174	**	0.175	**	0.175	**	0.175	**	0.154	**
Google Trending	-0.002	**	-0.002	**	-0.002	**	-0.002	**	-0.002	**
2014-Q1										
2014-Q2	-0.842	**	-0.823	*	-0.826	*	-0.829	**	-0.818	**
2014_Q3	-0.872	**	-0.855	**	-0.856	**	-0.859	**	-0.844	**
2014_Q4	-0.832	**	-0.813	*	-0.811	*	-0.814	*	-0.794	*
2015-Q1	-0.767	*	-0.751	*	-0.751	*	-0.753	*	-0.728	*
2015-Q2	-0.568	*	-0.559	*	-0.561	*	-0.562	*	-0.611	*
2015_Q3	-0.089		-0.093		-0.093		-0.092		-0.254	
2015_Q4	-0.122		-0.127		-0.127		-0.126		-0.289	
2016-Q1	-0.102		-0.108		-0.106		-0.105		-0.27	
2016-Q2	-0.263		-0.242		-0.242		-0.244		-0.321	
2016_Q3	-0.241		-0.215		-0.216		-0.217		-0.273	
2016_Q4	0.647	*	0.673	*	0.671	*	0.671	*	0.605	*
2017-Q1	0.264		0.278		0.272		0.271		0.188	
2017-Q2	-0.055		-0.057		-0.068		-0.069		-0.153	
2017_Q3	-0.006		-0.01		-0.019		-0.019		-0.089	
2017_Q4										
2018-Q1	-0.363		-0.352		-0.35		-0.352		-0.292	
2018-Q2	-0.56		-0.548		-0.553		-0.555		-0.518	
2018_Q3	-0.419	*	-0.409	*	-0.41	*	-0.412	*	-0.358	
2018_Q4	-0.355		-0.346		-0.346		-0.348		-0.305	
2019-Q1	-0.332		-0.32		-0.319		-0.321		-0.271	
2019-Q2	-0.613	**	-0.607	**	-0.612	**	-0.614	**	-0.499	**
2019_Q3	-0.679	**	-0.679	**	-0.694	**	-0.696	**	-0.482	
2019_Q4	-0.651	*	-0.653	*	-0.668	*	-0.672	*	-0.463	
Correction 1	-0.046	*	-0.044	*	-0.044	*	-0.044	*	-0.033	
Correction 2	0.009		0.007		0.007		0.007		0.001	
Correction 3	-0.056	**	-0.056	**	-0.056	**	-0.056	**	-0.055	**
Correction 4	0.039	**	0.041	**	0.042	**	0.042	**	0.043	**
Correction 5	-0.018		-0.018		-0.018		-0.018		-0.021	
Correction 6	0.047	**	0.046	**	0.046	**	0.046	**	0.04	*
Correction 7	0.01		0.01		0.011		0.011		0.003	
Release $_t$			-0.006		-0.005		-0.005		-0.01	
Release $_{t-n}$			0.028		0.028		0.028		0.017	
Superstar(Tier1)*Ln(streams) $_{n-1}$					0.003					
Superstar(Tier1/2)*Ln(streams) $_{n-1}$							-0.015			
Weeks in t-20*Ln(streams) $_{n-1}$									0.011	**
Solo performance					-0.02		-0.02		-0.022	
F-score	10.45		9.82		9.29		9.34		10.03	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note.** p<0.05, * p<0.1*

Table 18 Percent of concerts sold out panel model (Full Specification of Table 11)

	1		2		3		4		5	
% sellouts$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Ln(streams)$_{n-1}$	0.11	**	0.112	**	0.113	**	0.111	**	0.103	**
Google Trending	0.001		0.001		0.001		0.001		0.001	
2014-Q1										
2014-Q2	-0.658		-0.65		-0.637		-0.623		-0.633	
2014_Q3	-0.664		-0.657		-0.657		-0.642		-0.65	
2014_Q4	-0.531		-0.525		-0.54		-0.525		-0.529	
2015-Q1	-0.714		-0.711		-0.719		-0.703		-0.704	
2015-Q2	-0.295		-0.29		-0.286		-0.276		-0.303	
2015_Q3	0.331		0.337		0.329		0.331		0.266	
2015_Q4	0.443		0.448		0.441		0.443		0.379	
2016-Q1	0.378		0.383		0.366		0.37		0.306	
2016-Q2	0.313		0.33		0.329		0.336		0.298	
2016_Q3	0.318		0.337		0.339		0.345		0.316	
2016_Q4	0.378		0.4		0.404		0.409		0.38	
2017-Q1	0.455		0.467		0.491		0.498		0.457	
2017-Q2	0.314		0.315		0.364		0.368		0.33	
2017_Q3	0.248		0.248		0.288		0.29		0.258	
2017_Q4										
2018-Q1	0.443		0.452		0.443		0.453		0.468	*
2018-Q2	0.766		0.777		0.796	*	0.807	*	0.812	*
2018_Q3	0.404		0.413		0.42		0.428		0.44	
2018_Q4	0.449		0.456		0.455		0.463	*	0.471	*
2019-Q1	0.523	*	0.532	*	0.528	*	0.537	*	0.548	**
2019-Q2	0.39		0.396		0.424		0.428		0.469	*
2019_Q3	0.319		0.32		0.398		0.399		0.481	
2019_Q4	0.308		0.308		0.387		0.391		0.465	
Correction 1	-0.071	**	-0.071	**	-0.071	**	-0.071	**	-0.067	**
Correction 2	-0.001		-0.002		-0.003		-0.003		-0.005	
Correction 3	-0.006		-0.006		-0.007		-0.007		-0.007	
Correction 4	0.001		0.002		0		0		0.001	
Correction 5	0.032		0.032		0.034		0.035		0.033	
Correction 6	-0.025		-0.025		-0.025		-0.026		-0.027	
Correction 7	0.004		0.005		0		0.001		-0.003	
Release$_t$			-0.018		-0.023		-0.023		-0.024	
Release$_{t-n}$			0.003		0.002		0.002		-0.003	
Superstar(Tier1)*Ln(streams)$_{n-1}$					0.052					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$							0.065			
Weeks in t-20*Ln(streams)$_{n-1}$									0.005	*
Solo performance					0.092	**	0.093	**	0.091	**
F-score	4.08		3.83		3.79		3.81		3.82	
Prob > chi2	0		0		0		0		0	
Number of obs	1006		1006		1006		1006		1006	

*Note.** p<0.05, * p<0.1*

Table 19 Robustness test of missing records

	1		2		3		4	
% Missing Concert$_{it}$	Coef.	Sig	Coef.	Sig	Coef.	Sig	Coef.	Sig
Google Trending	-0.005	***	-0.005	***	-0.004	***	-0.005	***
2014-Q1	0		0		0		0.131	**
2014-Q2	0.292	***	0.291	***	0.284	***	0.285	***
2014_Q3	0.133	*	0.134	**	0.126	**	0.128	**
2014_Q4	0.192	***	0.191	***	0.185	***	0.186	***
2015-Q1	0.133	*	0.131	**	0.126	*	0.129	*
2015-Q2	0.152	**	0.152	**	0.145	**	0.148	**
2015_Q3	0.238	***	0.238	***	0.231	***	0.234	***
2015_Q4	0.153	**	0.152	**	0.147	**	0.149	**
2016-Q1	0.137	**	0.136	**	0.131	**	0.135	**
2016-Q2	0.085		0.085		0.081		0.081	
2016_Q3	0.067		0.066		0.063		0.066	
2016_Q4	0.12	*	0.12	**	0.115	*	0.115	*
2017-Q1	0.034		0.034		0.03		0.042	
2017-Q2	0.027		0.026		0.023		0.025	
2017_Q3	0.122	**	0.122	**	0.119	**	0.121	**
2017_Q4	0.141	**	0.14	**	0.137	**	0.134	**
2018-Q1	0.144	**	0.142	**	0.141	**	0.143	**
2018-Q2	0.186	***	0.184	***	0.183	***	0.182	***
2018_Q3	0.11	*	0.11	*	0.107	*	0.107	*
2018_Q4	0.058		0.057		0.055		0.054	
2019-Q1	-0.069		-0.07		-0.071		-0.069	
2019-Q2	-0.042		-0.042		-0.043		-0.035	
2019_Q3	0.013		0.009		0.011		0.012	
2019_Q4	0		0		0		0	
Ln(streams)$_{n-1}$	0.003							
Superstar(Tier1)*Ln(streams)$_{n-1}$			0.067					
Superstar(Tier1/2)*Ln(streams)$_{n-1}$					0.014			
Weeks in t-20*Ln(streams)$_{n-1}$							0	
Constant	0.363	*	0.332	***	0.391	***	0.408	***
R-squared	0.102		0.103		0.102		0.099	
F-test	5.46		5.558		5.461		5.305	
Prob > F	0		0		0		0	
Number of obs	1276		1276		1276		1276	

*Note.*** p<0.01, ** p<0.05, * p<0.1*

Table 20 Superstar definition profile using the same methodology on 2014 to 2019 data

	Tier 1 Stars	Tier 2 Stars	Rest of Top 100
Artist count	7	15	69
Number of shows per artist	112.0	123.6	141.3
Total tickets per artist	1,586,097	1,826,921	1,290,294
Total revenue per artist	$240,000,000	$155,000,000	$89,500,000
Revenue per show	$3,039,033	$1,381,000	$736,715
Average ticket price	$164.41	$89.57	$75.69
% of sellout concerts	86.1%	71.4%	41.5%
Years playing professionally	49.7	24.7	24.4
Percent male	92.9%	80.0%	87.9%
Weeks at Billboard #1	75	46	10
Weeks at Billboard #10	214	160	42
Weeks at Billboard #20	288	233	60
Weeks at Billboard #50	431	343	108
Weeks at Billboard #100	526	443	161
# of 2014 releases	0.14	0.40	0.65
# of 2015 releases	0.29	0.53	0.75
# of 2016 releases	0.86	0.60	0.88
# of 2017 releases	0.71	0.47	0.72
# of 2018 releases	0.86	0.53	0.86
# of 2019 releases	0.71	0.87	0.58
# of releases from 2014 to 2019	3.57	3.40	4.45
Streams per artist (millions)	110.0	287.0	87.5
Primary genre			
Pop	28.6%	33.3%	29.0%
Rock	57.1%	26.7%	26.1%
Country	0.0%	20.0%	13.0%
Folk	0.0%	0.0%	2.9%
R&B	14.3%	20.0%	5.8%
Christian	0.0%	0.0%	8.7%
Heavy Metal	0.0%	0.0%	5.8%
Other	0.0%	0.0%	8.7%

Note. Combined Data File, Profile based on 2014 to 2019 data, tier definitions created using 2014 to 2019 data

Table 21 Superstar definition profile (1999 to 2013)

	Tier 1 Stars	Tier 2 Stars	Rest of top 100	
Artist list	Elton John	Pink	Ed Sheeran	Breaking Benjamin
	Bon Jovi	Muse	Metallica	Bad Bunny
	The Rolling Stones	John Mayer	BTS	Pentatonix
	Paul McCartney	Justin Timberlake	Shawn Mendes	Brad Paisley
	Spice Girls	Phish	Ariana Grande	Little Mix
	Billy Joel	Jennifer Lopez	Backstreet Boys	Westlife
	Eagles		Trans-Siberian Orchestra	Shinedown
	Celine Dion		Michael Bublé	Queen + Adam Lambert
			Hugh Jackman	MercyMe
			Post Malone	Andreas Gabalier
			Mumford & Sons	Eminem
			KISS	Tool
			Bob Seger	Chris Young
			Garth Brooks	Hozier
			Fleetwood Mac	Andrea Bocelli
			Jonas Brothers	Jason Aldean
			Florida-Georgia Line	Chayanne
			Andre Rieu	Maroon 5
			Iron Maiden	The Avett Brothers
			Eric Church	Jeff Dunham
			Zach Brown Band	Manuel Carrasco
			Travis Scott	Hillsong United
			Cher	Sebastian Maniscalco
			Hootie & the Blowfish	For King & Country
			Twenty-One Pilots	Rammstein
			Thomas Rhett	B2K
			Sandy & Junior	Kelly Clarkson
			New Kids on the Block	Disturbed
			Phil Collins	The World of Hans Zimmer
			Dave Matthews Band	ZZ Top
			Luke Combs	Maluma
			Luke Bryan	Marc Anthony
			Carrie Underwood	Rod Stewart
			Mark Knopfler	Greta Van Fleet
			Dead & Company	Anderson .Paak
			Khalid	Hits Deep Tour/Toby Mac
			Bryan Adams	Wisin & Yandel
			JoJo Siwa	Guns N' Roses
			Panic! At the Disco	Lizzo
			Florence + the Machine	Train
			Take That	Goo Goo Dolls
			Chris Stapleton	Newsboys
			Luis Miguel	

Note. Combined Data File, artists identified using K-means clustering of concert variables from 1999 to 2013 Details outlined in methodology section.

Table 25 Superstar definition profile using same methodology on 2014 to 2019 data

	Tier 1 Stars	Tier 2 Stars	Rest of top 100	
Artist list	The Rolling Stones	Ed Sheeran	Metallica	Pentatonix
	Elton John	Pink	BTS	Brad Paisley
	Fleetwood Mac	Bon Jovi	Muse	Little Mix
	Paul McCartney	Shawn Mendes	Backstreet Boys	Westlife
	Phil Collins	Ariana Grande	Trans-Siberian Orchestra	Shinedown
	Justin Timberlake	Post Malone	Michael Bublé	Queen + Adam Lambert
	Eagles	Bob Seger	Hugh Jackman	Celine Dion
		Jonas Brothers	Mumford & Sons	MercyMe
		Florida-Georgia Line	KISS	Andreas Gabalier
		Billy Joel	Garth Brooks	Tool
		Carrie Underwood	André Rieu	Chris Young
		Mark Knopfler	Iron Maiden	Hozier
		Bad Bunny	Eric Church	Andrea Bocelli
		Eminem	Zach Brown Band	Chayanne
		Jason Aldean	Travis Scott	Maroon 5
			Cher	The Avett Brothers
			Spice Girls	Jeff Dunham
			Hootie & the Blowfish	Manuel Carrasco
			Twenty-One Pilots	Hillsong United
			Thomas Rhett	Sebastian Maniscalco
			Sandy & Junior	For King & Country
			New Kids on the Block	B2K
			Dave Matthews Band	Kelly Clarkson
			Luke Combs	Winter Jam/Newsboys
			Luke Bryan	Disturbed
			John Mayer	The World of Hans Zimmer
			Dead & Company	ZZ Top
			Khalid	Maluma
			Bryan Adams	Marc Anthony
			JoJo Siwa	Rod Stewart
			Phish	Greta Van Fleet
			Panic! At the Disco	Anderson .Paak
			Florence + the Machine	Hits Deep Tour/Toby Mac
			Take That	Wisin & Yandel
			Chris Stapleton	Guns N' Roses
			Luis Miguel	Lizzo
			Breaking Benjamin	Train
			Jennifer Lopez	Goo Goo Dolls

Note. Combined Data File, artists identified using data heuristic created as part of K-means clustering of concert data during 1999 to 2013. Details outlined in methodology section.

Table 23 Percent of Pollstar records with missing data

	Populated Records			Populated Records	
Musical Artist	Yes	No	Musical Artist	Yes	No
Andreas Gabalier	0%	100%	Andrea Bocelli	80%	20%
Garth Brooks	14%	86%	Hits Deep Tour/Toby Mac	80%	20%
BTS	32%	68%	Shawn Mendes	80%	20%
Eminem	43%	57%	Bad Bunny	80%	20%
Anderson .Paak	45%	55%	Muse	80%	20%
Chris Young	45%	55%	Mumford & Sons	80%	20%
Luke Combs	47%	53%	Wisin & Yandel	81%	19%
Mark Knopfler	49%	51%	Elton John	83%	17%
Hillsong United	50%	50%	New Kids on the Block	84%	16%
Rod Stewart	51%	49%	Bob Seger	85%	15%
Khalid	52%	48%	Ed Sheeran	86%	14%
MercyMe	53%	47%	Ariana Grande	87%	13%
Goo Goo Dolls	55%	45%	Backstreet Boys	87%	13%
KISS	55%	45%	Metallica	89%	11%
Post Malone	58%	42%	Dave Matthews Band	90%	10%
The Avett Brothers	58%	42%	Hugh Jackman	90%	10%
Travis Scott	59%	41%	Hootie & the Blowfish	90%	10%
Kelly Clarkson	59%	41%	Guns N' Roses	90%	10%
Breaking Benjamin	59%	41%	John Mayer	91%	9%
Brad Paisley	60%	40%	Little Mix	91%	9%
Lizzo	60%	40%	Jennifer Lopez	91%	9%
Hozier	60%	40%	Phish	92%	8%
Train	63%	37%	Chayanne	92%	8%
Sebastian Maniscalco	64%	36%	Paul McCartney	93%	7%
Greta Van Fleet	65%	35%	Queen + Adam Lambert	93%	7%
Thomas Rhett	65%	35%	Marc Anthony	94%	6%
Luis Miguel	68%	32%	Bon Jovi	94%	6%
Chris Stapleton	68%	32%	Eagles	95%	5%
Disturbed	69%	31%	Manuel Carrasco	95%	5%
Florence + the Machine	70%	30%	Maluma	95%	5%
Eric Church	70%	30%	Jonas Brothers	96%	4%
Carrie Underwood	70%	30%	Justin Timberlake	96%	4%
Florida-Georgia Line	70%	30%	Fleetwood Mac	96%	4%
Shinedown	71%	29%	Michael Bublé	96%	4%
Celine Dion	71%	29%	Dead & Company	96%	4%
Panic! At the Disco	71%	29%	Pink	96%	4%
Twenty-One Pilots	71%	29%	The Rolling Stones	97%	3%
Luke Bryan	74%	26%	JoJo Siwa	98%	3%
Jason Aldean	74%	26%	Billy Joel	98%	2%
Bryan Adams	75%	25%	Trans-Siberian Orchestra	99%	1%
ZZ Top	75%	25%	Newsboys	99%	1%
Pentatonix	76%	24%	André Rieu	100%	0%
Zach Brown Band	77%	23%	Iron Maiden	100%	0%
Phil Collins	78%	22%	Cher	100%	0%
Jeff Dunham	78%	22%	Sandy & Junior	100%	0%
Maroon 5	79%	21%	For King & Country	100%	0%
Tool	80%	20%	B2K	100%	0%
			Total	71%	29%

Table 24 Alpha Data Music + corrections

- Correction 1: BestBuy and other retailers added (Q1 2015)
- Correction 2: Vivo replaced (Q1 2016)
- Correction 3: YouTube only reporting daily streams greater than 1,000 (Q2 2016)
- Correction 4: Amazon Music Unlimited Reporting Begins (Q4 2016)
- Correction 5: Version 2.5 Major Feature Enhancements: Shazam (Q2, 2017), later removed (Q1, 2018)
- Correction 6: Tidal data reporting ceases (Q3, 2017)
- Correction 7: New data provider: Pandora integrated into BuzzAngle Music (Now Alpha Data Music +)

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The complementary relationship between concerts and recorded music for top-performing artists

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Abstract

This paper examines the complementary effects of live concerts on incremental pre-and-post concert music streams in twenty-nine US cities. The work identifies that performers who have greater concert ticket demand, deeper hit-song catalogs, and/or are in the middle of their career experience stronger trends in their streams before and after their concerts in the markets where they perform. It also identifies that post-concert effects last up to ten weeks after the event. I hand-collected data of concert ticket sales, music streaming, and song rankings from the top sixty global performing artists. I then utilized a panel model empirical approach with artist and market fixed-effects to identify pre-concert promotional and post-concert decaying effects. This work will help top performing artists gain insight into the little-understood influence of live performance on the streaming of their recorded music.

Keywords Music . Music industry . music streaming . industry disruption
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1 Introduction

Musical performing artists are highly dependent on income from live performance, which makes up 80% of their income, according to Alan Krueger (2019). In light of recent challenges in touring, performers are exploring complementary strategies to monetize their music on digital music platforms. Hogue (2020) concluded that the cultivation of a catalog of hit songs not only provides a stable source of income but carries a significant promotional effect on future concert revenue. Building on the finding, this paper will examine the pre-concert promotional and post-concert effects on music streaming that decay over time. Past theoretical work has argued that an artist's popularity and financial prospects increase over time as they hone their performance skills. Adler (1986) and Rosen (1981) theorized that an artist's promotion and amplification of their talent can contribute to their personal and financial success.

This paper leverages novel, hand-collected data from March 2018 through June 2020 for the top-sixty global touring artists and leverages a series of industry sources. The empirical approach utilizes a time series panel model with weekly and monthly dummy variables to identify the impact and duration of concert streaming effects. The dependent variable is the log of music streams by artist and market.

Both pre-and-post concert effects highlight the multifaceted behavior that performers amplify through their recorded music. Pre-concert effects are no doubt driven by concert promotion. As fans hear the artist is coming to town and purchase tickets, they are more prone to listen to their music; particularly if the artist has a deeper catalog of hit songs. Performers also benefit from post-concert effects that decay over time, as fans reengage with the performer's music.

This paper explores several research questions regarding the influence of concert dates on music streaming. These include: Do concerts influence trends in pre-and-post concert music streaming within the same market? Are pre-and-post concert trends heterogenous across artists with differing ticket demand, catalog depth, and artists' years of performing? And, what is the magnitude of pre-concert promotional effects as well as the duration of decaying post-concert trends for music streaming?

I hypothesize that concert date promotion and performance do impact music streams for a top artist. Consistent with economic theory, it would be expected that performers with stronger ticket sales and deeper catalogs will see greater effects. Lastly, consistent with McDonald (1988), artists later in their careers will see a great increase in their streams given that they typically have a deeper catalog of hit songs. Secondly, younger artists should also see strong effects since fans are just discovering their music.

Creating a panel model with artist and market fixed effects, the analysis identifies significant pre-concert promotional effects. It also identifies post-concert effects of elevated streams that extend ten weeks after the concert date. Artists with higher ticket sales, more weeks on the Billboard 100, and are in the middle of their careers (17 to 29 years) see stronger streaming effects before and after their performance. By contrast, legacy artists who have played for 30+ years see less impact on their streaming activity in markets where they perform.

This paper makes a unique contribution to the academic literature because it dimensionalizes the contribution of live-concert performance on music streaming for top performing artists. While other researchers such as Pappies and Van Heerd (2017) have examined the contribution of concerts on physical distribution, none have examined the influence on digital music streaming. Nor have the heterogenous effects of demand for concert tickets, catalog depth, and years performing been examined.

2 Literature Review

Work done by Rosen (1981) and Adler (1986) on artist promotion has found a direct relationship between promotion and talent to income. Additionally, the notion of an iterative feedback loop was highlighted by Glenn MacDonald (1988), whereby a performing artist sees growth of their fan base and music as they hone their talent over time. Other researchers have highlighted a spill-over effect of concerts and festivals (Gazel 1997; Bracalente, Chirieleison, et al. 2011) on local economies. [i,ii] Pappies and Van Heerd (2017) conducted an extensive analysis in Germany exploring the feedback loop between live concerts and recorded music sales. Their work concluded that concert post-effects exist, albeit are smaller than the pre-concert promotional effects of recorded music on concert ticket sales. However, none have captured the complementary impact on pre-and-post concert music streaming. Before streaming, this behavior may have been suppressed by pre-planned radio programming and the lack of measurement of individual consumption. Now that music streaming has become the dominant mode of listening and is controlled primarily by individuals; this paper examines listenership trends in the weeks leading up to and after the concert.

A fitting analog would measure the effects of point-in-time events like the Super Bowl, the Grammys, or the Academy Awards. Hartmann and Klapper (2017) implemented a panel model with market and yearly effects to examine twenty weeks of post Super Bowl consumption effects. Their work identified that Super Bowl advertising does not influence consumption during the Super Bowl but instead creates a complementary relationship with sporting occasions by empirically demonstrating increased consumption during big sporting events later in the spring, such as the NCAA Tournament, MLB Opening Day, and NBA Playoffs/Finals.

Following Hartmann's and Klappers' approach, a series of weekly dummies were created up to 13 weeks after the concert. Additionally, to control for pre-concert promotion, 13 weekly dummies were included to control for trends in music streaming before the concert.

3 Data and empirical analysis

3.1 Data

The data set includes a series of hand-collected data of the top-sixty artists according to Pollstar's 2019 rankings based on ticket sales and music streaming within the top 29 US markets. The data comes from a number of sources (Table 1) and covers the time period from March 1st, 2018, through June 30th, 2020. It includes weekly market-level music streaming and concerts dates for each artist from venues within a 90-minute drive of the city center for each market.

Table 1 Data source characteristics

Source	Characteristics
Pollstar	Concert data includes Date, number of shows, revenue, ticket sales, minimum/maximum/average ticket price, venue, % of capacity sold, city/state/country
Music Connect	Streaming data: All weekly total, audio, video, and programmed digital streams by Spotify, Apple Music, Amazon, and all other major digital streaming platforms for top-29 concert markets in 2018 and 2019
Billboard Rankings (provided by Data.World)	Peak rankings and weeks in Hot 100 Billboard ranking of songs by week from 1959 to 2019. Sample filtered for all songs throughout career among the 2019 Pollstar top-100 performing artists
US Census	Incidence of gender age, race, ethnicity and population
MusicBrainz.org	Album, E.P., Live Concert releases and profile of artist gender, primary genre, and years playing professionally for each top-60 performing artist

The data set also includes songs from the Billboard Top 100 rankings, demographic data, and artist tenure. The sources have been aggregated and aligned by week to facilitate time-series analysis.

Table 2 shows total streams per week per artist per market average 213K with a peak of 23.2 million in LA during early February 2019 when Ariana Grande released her *Thank U, Next* album. Additionally, the markets included are large cities with an average population of 4.6 million, ranging from New York at 19.2 million to Salt Lake City at 1.2 million (Table 3). Artists in the group have performed songs that spent an average of 119 weeks in the Billboard Hot 100. The data set includes 1,843 concerts between March 1st, 2018, through December 31st, 2019, for which 1,549 included ticket sales.

Table 2 Data Frequencies at the artist week and market level

	N	Mean	min	max
Total streams per week	208,730	213,406	-	23,175,478
Population by market	208,730	4,559,786	1,232,696	19,216,182
Cumulative weeks in top 100	208,805	119	0	998
Tickets sold per concert	1,549	17,043	280	205500
Year: 2018	75,312	0.36	0	1
Year: 2019	89,007	0.43	0	1
Year: 2020	44,486	0.21	0	1
Years performing	60	26	4	63

Table 3 Twenty-nine markets included

Market	Population	Market	Population	Market	Population
New York	19,200,000	San Diego	3,338,330	Milwaukee	1,575,179
Los Angeles	13,200,000	Tampa	3,194,831	Raleigh	1,390,785
Chicago	9,457,867	Denver	2,967,239	New Orleans	1,270,530
DFW	7,573,136	St. Louis	2,801,423	Louisville	1,266,389
Houston	7,066,140	Charlotte	2,636,883	Salt Lake City	1,232,696
Washington	6,280,697	Pittsburg	2,317,600		
Miami	6,166,488	Cincinnati	2,219,750		
Philadephia	6,102,434	Kansas City	2,155,068		
Atlanta	6,018,744	Columbus	2,122,271		
Phoenix	4,948,203	Indianapolis	2,076,531		
Boston	4,873,019	Cleveland	2,048,449		
San Francsco	4,731,803	Nashville	1,933,860		

Tables 4 highlights the artists included. The top-sixty artists span a number of genres, with the supermajority playing primarily Pop and Rock-n-Roll.

Table 4 Top-60 artists based on concert revenue

Ed Sheerhan	KISS	Hootie & the Blow Fish	Bryan Adams
Pink	Bob Seger & the Silver Bullet Band	Twenty One Pilots	JoJo Siwa
Metallica	Garth Brooks	Thomas Rhett	Phish
Elton John	Fleetwood Mac	Sandy & Junior	Panic! At the Disco
BTS	The Rolling Stones	New Kids on the Block	Florence and the Machine
Bon Jovi	Jonas Brothers	Phil Collins	Take That
Muse	Florida Georgia Line	Dave Matthews Band	Chris Stapleton
Shawn Mendes	Andre Rieu	Luke Combs	Luis Miguel
Ariana Grande	Iron Maiden	Luke Bryan	Breaking Benjamin
Backstreet Boys	Eric Church	John Mayer	Bad Bunny
Trans-Siberian Orchestra	Paul McCartney	Billy Joel	Eagles
Michael Buble	Zach Brown	Carrie Underwood	Jennifer Lopez
Hugh Jackman	Travis Scott	Justin Timberlake	Pentatonix
Post Malone	Cher	Mark Knopfler	Train
Mumford and Sons	Spice Girls	Khalid	Goo Goo Dolls

Note . Source: Pollstar

Music streams among the top sixty artists increased during 2018 and 2019 before leveling off at lower levels during 2020 (Figure 1). Seasonality of concerts also plays a factor with more concerts performed during the summer months. Some of the peaks in streaming highlight blockbuster releases by specific artists such as Arian Grande's (Thank U Next album and singles: "7 Rings" and "Monopoly") in Q1 2019, Khalid's release of his Free Spirit album in April 2019, and Post Malone's single release of "Writing on the Wall" in September 2019. Additionally, pre-and-post concert effects play a role that will be controlled for in this work by aligning the time-series data to the weeks in the 13 weeks leading up to and the 13-weeks after the week of the concert. Concerts are disaggregated by performance whereby multi-night dates are each treated as unique concerts. Lastly, the primary role of the 2020 music streams are to capture post-effects. While artists performed through early March, the industry cancelled most concerts starting in early March due to the Covid-19 pandemic.

Figure 1 Streams and number of live concerts by month for top-60 performing artists

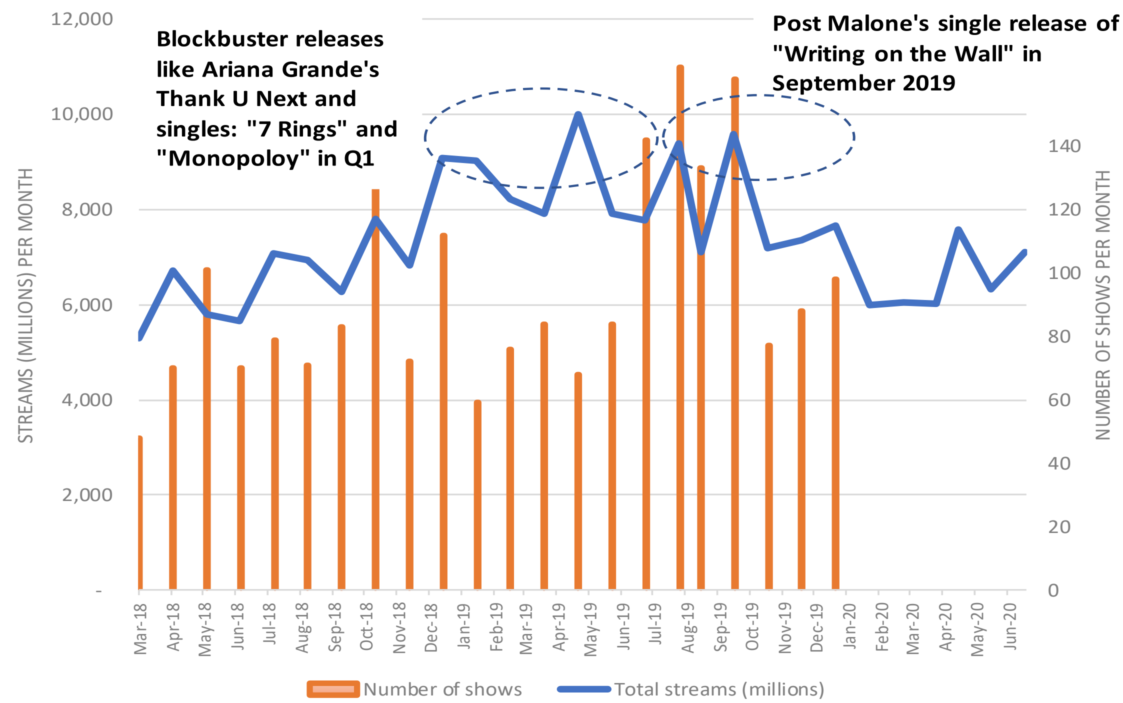
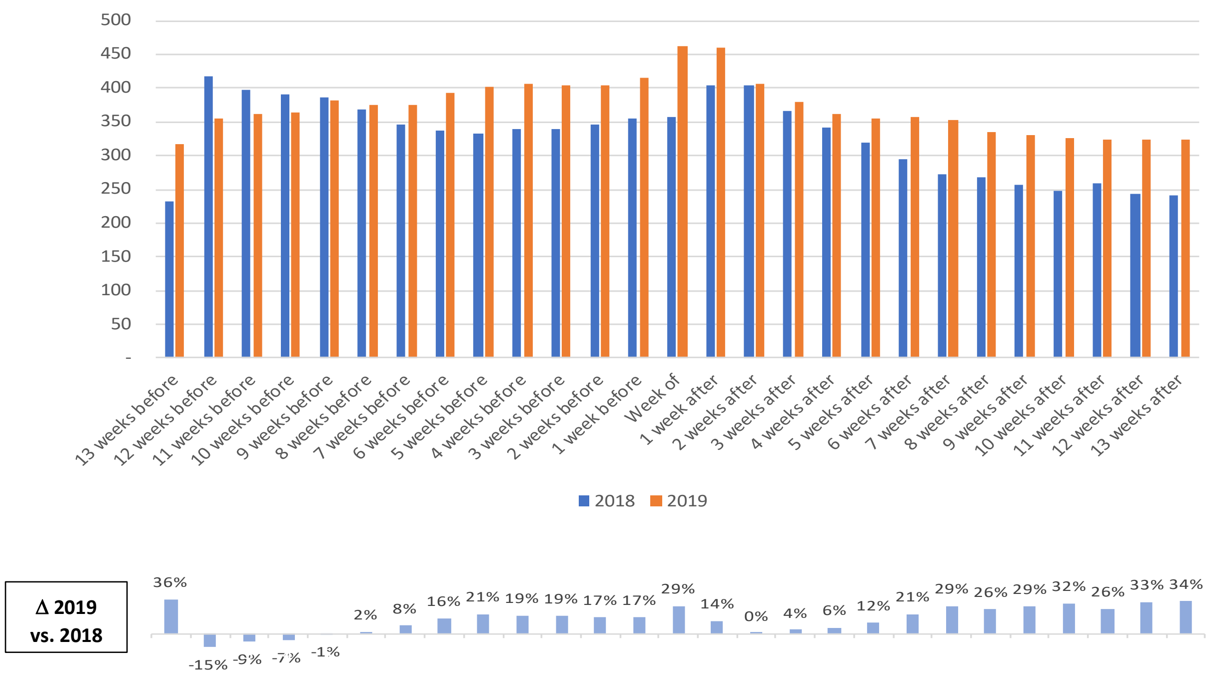


Figure 2 shows the trend of music streams pre-and-post concert. Consistent with the growth of music streaming overall, streaming activity in 2019 experienced double-digit growth vs. 2018. Weekly growth rates ranging from 0% to 34% indicate that while concert effects may be similar, the trends are higher in 2019 compared with 2018 data.

Figure 2 Total stream (millions) of top artists 13 weeks before to 13 weeks after concerts and year-over-year percent growth within market (below)



3.2 Panel model with artist and market fixed-effects specification

While parsimonious, the approach used by Hartman and Klapper (2017) effectively measures the weekly decay over time that is useful for measuring overall effects and examining heterogeneity in key cohorts via time-series interactions (e.g., ticket sales, depth of catalog, and artists' years of experience interacting with time series dummies). The cohort analysis consolidated the time effects to one month before and one month after the concert to capture heterogeneity during a timeframe most likely to experience elevated streaming effects.

The approach controls for pre-concert promotion sourced from ticket on-sale dates, radio promotion, and local artist public relations. Ticket on-sale dates are notoriously hard to track and a fundamental limitation of multiple works of research in this sector (Krueger 2005, Courty and Pagliero 2011, Mortimer et al 2012, Papies and Van Heerde 2017).

To account for differences among performing artists and cities, a panel model with artist and market fixed-effects was chosen to examine the influence of concerts dates on pre-and-post event trends in music streaming. The music streaming outcome is denoted in the model specification as ln(*Music streams*$_{itm}$). Specifications 1 is designed to highlight the promotional effects of upcoming concerts on streaming up to 3 months before the concert (*Concert during upcoming 3 months*$_{itm}$), week of the concert (*week of concert*$_{itm}$), and the post effects up to 3 months after the concert (*Concert within past 3 months*$_{itm}$). All specifications include control variables for month and year (δ_t) as well as artist and market fixed effects ($\alpha_{i,}$ μ_m).

$$\ln(\text{Music streams}_{itm}) = \beta_0 + \beta_1(\text{Concert during upcoming 3 months}_{itm}) + \beta_2(\text{week of concert}_{itm}) + \beta_3(\text{Concert within past 3 months}_{itm}) + \alpha_i + \delta_t + \mu_m + \varepsilon_{itm} \quad (1)$$

Specification 2 is created as a baseline for examining the heterogeneity of artist characteristics. It limits the pre-and-post concert effects up to one month before (*Concert during upcoming month*$_{itm}$), the week of the concert (*week of concert*$_{itm}$), and up to one month after the concert (*Concert within past month*$_{itm}$).

$$\ln(\text{Music streams}_{itm}) = \beta_0 + \beta_1(\text{Concert during upcoming month}_{itm}) + \beta_2(\text{week of concert}_{itm}) + \beta_3(\text{Concert within past month}_{itm}) + \alpha_i + \delta_t + \mu_m + \varepsilon_{itm} \quad (2)$$

Specification 3 deconstructs the lead-lag period to thirteen weeks before the concert *(weeks before the concert dummies*$_{itm}$*),* the week of the concert *(week of concert*$_{\mathbf{itm}}$*)*, and thirteen weeks after the concert *(weeks after the concert dummies*$_{itm}$*)*. The purpose in doing so is to examine the weekly lift preceding the concert followed by the weekly trend decay after the concert.

$$\ln(\text{Music streams}_{itm}) = \beta_0 + \boldsymbol{\beta_1}\textbf{(weeks before the concert dummies}_{\mathbf{itm}}\textbf{)} + \beta_2(\text{week of concert}_{\mathbf{itm}}) + \boldsymbol{\beta_3}\textbf{(weeks after the concert dummies}_{\mathbf{itm}}\textbf{)} + \alpha_i + \delta_t + \mu_m + \varepsilon_{itm} \quad (3)$$

Table 5 Panel model with artist and market fixed effects

	1			2			3		
$Ln(Streams)_{itm}$	Coef.	Sig		Coef.	Sig		Coef.	Sig	
lead 0 to 3 months_concert_$date_{itm}$	0.147	(0.003)	***						
Week of _concert_$date_{itm}$	0.407	(0.010)	***						
lag 0 to 3 months_concert_$date_{itm}$	0.077	(0.003)	***						
lead 1 month_concert_$date_{itm}$				0.154	(0.011)	***			
Week of _concert_$date_{itm}$				0.379	(0.010)	***			
lag 1 month_concert_$date_{itm}$				0.108	(0.010)	***			
lead13_concert_$date_{itm}$							0.102	(0.011)	***
lead12_concert_$date_{itm}$							0.087	(0.011)	***
lead11_concert_$date_{itm}$							0.088	(0.011)	***
lead10_concert_$date_{itm}$							0.098	(0.011)	***
lead9_concert_$date_{itm}$							0.098	(0.011)	***
lead8_concert_$date_{itm}$							0.097	(0.011)	***
lead7_concert_$date_{itm}$							0.110	(0.011)	***
lead6_concert_$date_{itm}$							0.123	(0.011)	***
lead5_concert_$date_{itm}$							0.141	(0.011)	***
lead4_concert_$date_{itm}$							0.164	(0.011)	***
lead3_concert_$date_{itm}$							0.193	(0.011)	***
lead2_concert_$date_{itm}$							0.234	(0.010)	***
lead1_concert_$date_{itm}$							0.363	(0.010)	***
Week of _concert_$date_{itm}$							0.381	(0.010)	***
lag1_concert_$date_{itm}$							0.256	(0.010)	***
lag2_concert_$date_{itm}$							0.188	(0.010)	***
lag3_concert_$date_{itm}$							0.151	(0.010)	***
lag4_concert_$date_{itm}$							0.123	(0.010)	***
lag5_concert_$date_{itm}$							0.085	(0.010)	***
lag6_concert_$date_{itm}$							0.056	(0.010)	***
lag7_concert_$date_{itm}$							0.043	(0.010)	***
lag8_concert_$date_{itm}$							0.030	(0.010)	***
lag9_concert_$date_{itm}$							0.025	(0.010)	**
lag10_concert_$date_{itm}$							0.018	(0.010)	*
lag11_concert_$date_{itm}$							0.011		
lag12_concert_$date_{itm}$							0.014		
lag13_concert_$date_{itm}$							0.007		
Constant	10.8	(0.005)	***	10.8	(0.005)	***	10.8	(0.005)	***
R-squared	0.158			0.148			0.166		
F-test	1292.204			1201.1			760.22		
Prob > F	0			0			0		
Number of obs	208711			208711			208711		

*Note.*** p<.01, ** p<.05, * p<.1*

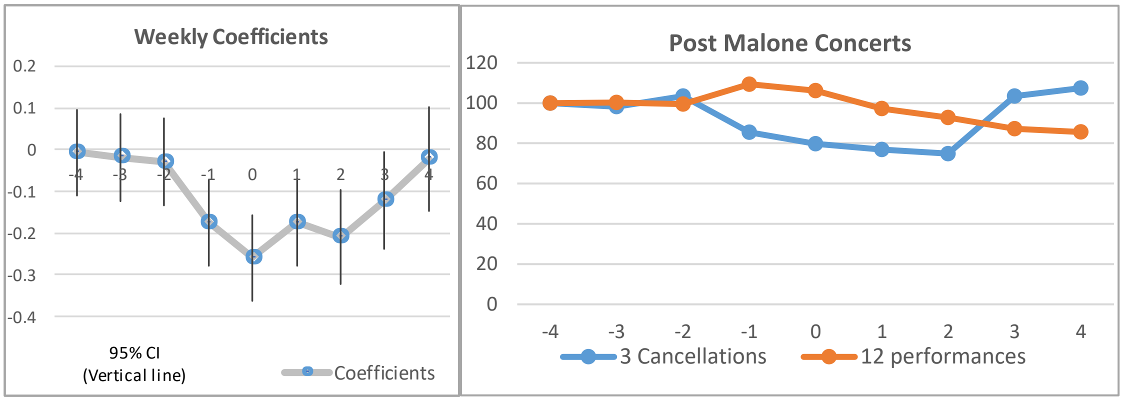
Model results in Table 5 indicate strong significance in both pre-and-post effects. Specification 1 coefficients outline a shape one would expect whereby the coefficient is .147 up to 3 months before the concerts, .407 the week of the concert, and decays to .077 during the three months after the concert. Specification 2 plays the role of a baseline model to be built upon with artist characteristics in the next section. Isolated to a more narrow timeframe, the model is better suited to incorporate interactive effects of artist characteristics. The results display a similar lift and decay pattern of Specification 1.

Specification 3 outlines the same trends with more granularity where the effects lift steadily during the thirteen-week pre-period, peaking the week of the concert, then declining to an insignificant level ten weeks after the concert.

A robustness test on Specification 3 that added times predictors for 14 and 26 weeks prior to the performance found the streaming effects are significant up to 26 weeks prior to the performance. However, the net impacts were small ($65 per week per artist). This confirmed that +/- 13 week of the performance provide sufficient timeframe for addressing the research questions.

I also completed a counter-factual analysis to confirm that when performers cancel concerts within weeks of the event, the impact on music streaming are diminished. I was able to collect 96 concerts from January through June 2020, of which 73 were cancelled. Panel model results in Figure 3 highlight that music streaming declined vs. previous streaming levels within two weeks of the concert and persisted until four weeks after the cancelled event. Further, I found a similar trend for Post Malone who hosted 12 concerts in January and February before having three concerts cancelled in March. The trend in his streaming mirrors the broader trend from the panel model.

Figure 3 Cancelled concerts in 2020



3.3 Panel model to identify heterogeneity of post-concert streaming by key cohorts

While identifying pre-and-post concert effects is meaningful, dimensionalizing the impact on key characteristics of performing artists, their music, and ticket sales hold promise for helping define an artist's strategy and expectations when they tour.

A panel model with year-month controls, artist, and market fixed effects was created to test this hypothesis. Cohort groups were interacted with the 1-month pre-and-post effects.

Specification 4 interacts the 1-month effects with ticket sales tiers (bottom, middle, and top tiers). Specification 5 interacts the depth of catalog using tiers of weeks in the Billboard Hot 100 (1 to 70, 71 to 270, and 271+). Specification 6 interacts tiers for those performing professionally for 4 to 16 years, 17 to 29 years, and 30+ years.

$$\ln(\text{Music streams}_{itm}) = \beta_0 + \beta_1(\text{Concert during upcoming month}_{itm})*(\text{lowest tier}) + \beta_2(\text{Concert during upcoming month}_{itm})*(\text{middle tier}) + \beta_3(\text{Concert during upcoming month}_{itm})*(\text{highest tier}) + \beta_4(\text{week of concert}_{itm})*(\text{lowest tier}) + \beta_5(\text{week of concert}_{itm})*(\text{middle tier}) + \beta_6(\text{week of concert}_{itm})*(\text{highest tier}) + \beta_7(\text{Concert within past month}_{itm})*(\text{lowest tier}) + \beta_8(\text{Concert within past month}_{itm})*(\text{middle tier}) + \beta_9(\text{Concert within past month}_{itm})*(\text{highest tier}) + \alpha_i + \delta_t + \mu_m + \varepsilon_{itm} \tag{4, 5, 6}$$

Note: Omitted parameter for ticket sales are cases without ticket sales and when artist_i did not perform in a market during the pre-and-post period and for weeks in the top 100: artists who have 0 weeks in the top 100.

Based on Rosen (1981), we would expect significant uplift in the trend for music streaming in markets where top artists perform. These effects should be more pronounced for those who have stronger ticket demand and deep catalogs of hits. Additionally, we would expect stronger pre-concert promotional effects among the same cohorts, according to Adler (1986).

Table 6 Panel model by ticket sale, weeks in top 100, and years playing cohorts with artist and market fixed effects

	4			5			6		
Ln(Streams)$_{itm}$	Coef.		Sig	Coef.		Sig	Coef.		Sig
Bottom tier sales									
lead 1 month_concert_date$_{itm}$	0.128	(0.010)	***						
Week of _concert_date$_{itm}$	0.289	(0.021)	***						
lag 1 month_concert_date$_{itm}$	0.066	(0.011)	***						
Middle tier sales									
lead 1 month_concert_date$_{itm}$	0.259	(0.011)	***						
Week of _concert_date$_{itm}$	0.424	(0.023)	***						
lag 1 month_concert_date$_{itm}$	0.17	(0.012)	***						
Top tier sales									
lead 1 month_concert_date$_{itm}$	0.35	(0.008)	***						
Week of _concert_date$_{itm}$	0.526	(0.017)	***						
lag 1 month_concert_date$_{itm}$	0.2	(0.009)	***						
1 to 70 weeks in top 100									
lead 1 month_concert_date$_{itm}$				0.088	(0.011)	***			
Week of _concert_date$_{itm}$				0.216	(0.010)	***			
lag 1 month_concert_date$_{itm}$				-0.209	(0.005)	***			
71 to 270 weeks in top 100									
lead 1 month_concert_date$_{itm}$				0.111	(0.008)	***			
Week of _concert_date$_{itm}$				0.155	(0.005)	***			
lag 1 month_concert_date$_{itm}$				0.097	(0.004)	***			
271 weeks+ in top 100									
lead 1 month_concert_date$_{itm}$				0.142	(0.009)	***			
Week of _concert_date$_{itm}$				0.015	(0.005)	***			
lag 1 month_concert_date$_{itm}$				0.214	(0.006)	***			
4 to 16 years performing									
lead 1 month_concert_date$_{itm}$							0.143	(0.016)	***
Week of _concert_date$_{itm}$							0.303	(0.016)	***
lag 1 month_concert_date$_{itm}$							0.103	(0.016)	***
17 to 29 years performing									
lead 1 month_concert_date$_{itm}$							0.311	(0.019)	***
Week of _concert_date$_{itm}$							0.602	(0.019)	***
lag 1 month_concert_date$_{itm}$							0.225	(0.019)	***
30+ years performing									
lead 1 month_concert_date$_{itm}$							-0.004		
Week of _concert_date$_{itm}$							0.276	(0.020)	***
lag 1 month_concert_date$_{itm}$							-0.018		
R-squared	0.161			0.171			0.15		
F-test	1102.74			1188.65			1013.07		
Prob > F	0			0			0		
Number of obs	208,711			208,711			208,711		

*Note.*** p<.01, ** p<.05, * p<.1*

The specifications highlight the heterogeneity for each artist characteristic that aligns with expected complementary effects. Specification 4 shows an increase in the lift of ticket sales among the mid and top tiers over the bottom tier and a more enduring lift post-concert. Specification 5 identifies the artists with deeper hit-song catalogs see strong pre-and-post concert effects. Artists with 270+ and 71 to 270 weeks of hits in the top 100 supersede the lift of those with fewer weeks in the top 100. In fact, those with 1 to 70 weeks in the top 100 see a negative outcome in their music streaming after the concert. Specification 6 highlights an interesting nuance. While artists who have performed 17 to 29 years see a stronger pre-and-post pattern than those with less playing experience, artists with 30+ years of playing experience have no significant pre-and-post concert effects.

Figures 3, 4, and 5 provide a visual depiction highlighting the greater coefficient trends for performers with stronger demand for tickets, more weeks on the Billboard 100, and in the middle of their careers.

Figure 4: Month pre and post-effects of concert on streaming (by tier of ticket sales)

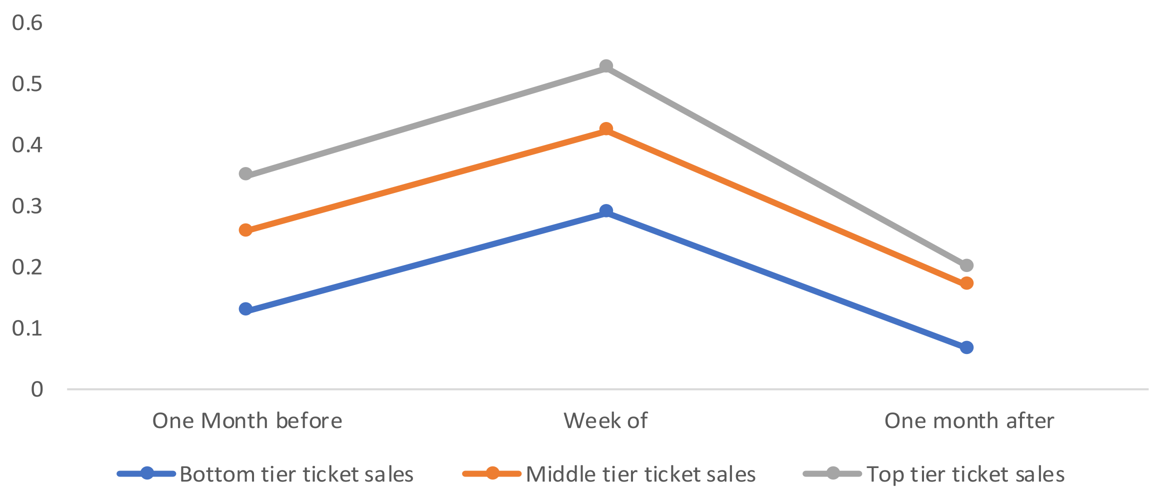


Figure 5: Month pre and post-effects of concert on streaming (by tier of weeks in top 100)

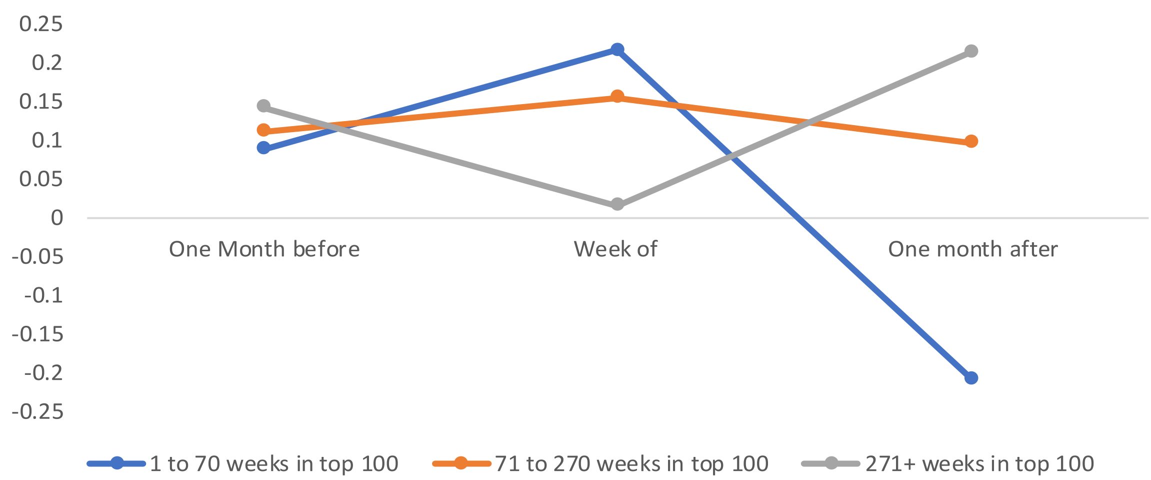
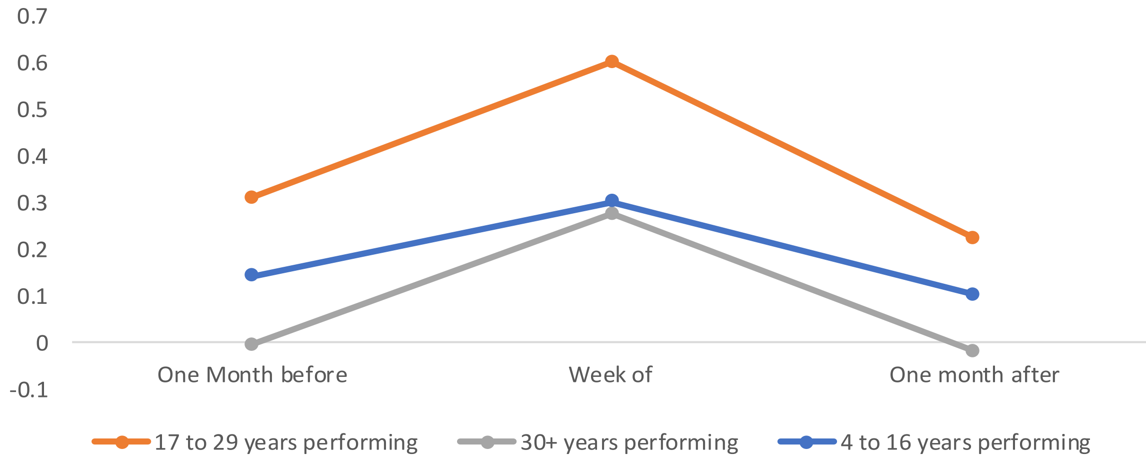


Figure 6: Month pre and post-effects of concert on streaming (by tier years performing)



Given censoring concerns among the 307 concerts with no data for ticket sales, a robustness check was run to assess if these concerts experienced different music streaming trends than the 1,549 concerts where ticket sales were available. This analysis found no difference in streaming trends between the groups.

4 Discussion

The lift in streams for performers with strong ticket sales and deep hit song catalogs suggests support for Rosen's (1981) theory that technology enables performing artists to expand their market. Likewise, the significant weekly leading effects among the same cohorts indicate the importance of promotional effects of top-performers theorized by Adler (1986). However, the implications for MacDonald's theory (1988) that performers redeem benefits with years of experience are inconclusive. While artists benefit from growing the depth of their catalog, the influence of years performing on pre-and-post concert effects peaks during the middle of top performers' careers.

Another implication of this analysis involves the absolute financial impact on artists. While specification 3 highlights a strong pre-concert effect and a post-concert decay of 10 weeks, what does this mean in terms of streams and dollars? Likewise, what does it mean for artists with deep hit catalogs and/or strong concert ticket sales?

The analysis includes pre-and-post periods of up to 3 months to capture the fuller impact in streams and dollar terms. Table 7 shows relatively modest effects of concerts on music streaming. With effects from ~$0 to $4,663 during the 3 months before and after the concert, performers stand to earn far more from the performance. A predecessor to this paper, Hogue (2020), found top artists can earn an incremental $46K to $49K per concert when achieving a 20% increase in music streaming. This also aligns with the finding of a similar analysis in Germany by Papies and Heerde (2017).

In summary, music streaming effects probably do not enter the discussion when a performer is booking concerts. However, the complementary effects of streaming may increase in the coming years as the medium grows and artists find innovative ways to expand the listenership of their recorded music.

Table 7 Streaming and revenue estimate

	Incremental streams (000)				Estimated incremental revenue			
Ln(Streams) $_{itm}$	Pre	Week of	Post	Total	Pre	Week of	Post	Total
Bottom tier ticket sales	342.4	42.9	-108.5	276.8	$1,164	$ 146	$ (369)	$ 941
Mid tier ticket sales	867.0	83.1	289.2	1239.2	$2,948	$ 282	$ 983	$4,213
Top tier ticket sales	1020.2	113.1	238.1	1371.5	$3,469	$ 385	$ 810	$4,663
1 to 70 cum weeks	186.7	104.3	-28.8	262.2	$ 635	$ 355	$ (98)	$ 892
71 to 270 cum weeks	414.0	137.3	115.3	666.6	$1,408	$ 467	$ 392	$2,266
271 weeks+ cum weeks	566.7	112.7	285.1	964.5	$1,927	$ 383	$ 969	$3,279
4 to 16 years performing	-106.1	69.1	-78.4	-115.4	$ (361)	$ 235	$ (266)	$ (392)
17 to 29 years	806.7	158.0	332.8	1297.5	$2,743	$ 537	$1,131	$4,411
30+ years performing	-5.0	69.1	-78.4	-14.3	$ (17)	$ 235	$ (266)	$ (49)

Note. Source for stream count: Music Connect. Revenue estimated from DMP median amount paid to artists, writers, publishers, and record labels based on 2018 data. (Pastukhov 2019)

5 Conclusions

This work suggests that live concerts complement music streaming before and after a performer's concert. Building steadily for three months before the concert highlights the benefit of artist promotion on promoting listenership. It endures after the concert for up to ten weeks after the concert. Performers who experience greater demand for tickets, with deeper hit song catalogs, and in the middle of their career (between 17 and 29 years) tend to see stronger pre-and-post effects. While absolute financial benefit is modest, these effects hold the potential to increase with the growth of media-on-demand. Also, streaming volume for hit songs is expected to have a long tail that will provide a source of income even after their performance days are over. Lastly, an artist's creation of hit-song compositions corresponds with a rise in the attractiveness of their concerts, contributing to a potential feedback loop of streams in markets where they perform.

Opportunities to extend this work include selecting a more extensive group of artists to see the influence of concerts on streams among more niche artists. Additionally, this is one of many potential applications for time-dummy event studies. Media releases and events in any number of technology industries could utilize the approach highlighted in this work.

6 Compliance with ethical standards

Conflicts of interest/competing interests: The author manages a deceased Bluegrass/Folk artist's legacy unrelated to the data analyzed for this paper.

Stata code producing the attached results is available for review. However, several of the data sources are proprietary and cannot be shared.

Special Thanks

Special thanks to Stephanie Bandel-Koroll and Greg Reish, Ph.D. from the Middle Tennessee State University Center for Popular Music Library for their assistance in acquiring data sets for this research paper.

7 Appendix

Table 8 Panel model with artist and market fixed effects (full version of table 5)

	1			2			3		
$Ln(Streams)_{itm}$	Coef.	Sig		Coef.	Sig		Coef.	Sig	
lead 0 to 3 months_concert_date$_{itm}$	0.147	(0.003)	***						
Week of _concert_date$_{itm}$	0.407	(0.010)	***						
lag 0 to 3 months_concert_date$_{itm}$	0.077	(0.003)	***						
lead 1 month_concert_date$_{itm}$				0.154	(0.011)	***			
Week of _concert_date$_{itm}$				0.379	(0.010)	***			
lag 1 month_concert_date$_{itm}$				0.108	(0.010)	***			
lead13_concert_date$_{itm}$							0.102	(0.011)	***
lead12_concert_date$_{itm}$							0.087	(0.011)	***
lead11_concert_date$_{itm}$							0.088	(0.011)	***
lead10_concert_date$_{itm}$							0.098	(0.011)	***
lead9_concert_date$_{itm}$							0.098	(0.011)	***
lead8_concert_date$_{itm}$							0.097	(0.011)	***
lead7_concert_date$_{itm}$							0.110	(0.011)	***
lead6_concert_date$_{itm}$							0.123	(0.011)	***
lead5_concert_date$_{itm}$							0.141	(0.011)	***
lead4_concert_date$_{itm}$							0.164	(0.011)	***
lead3_concert_date$_{itm}$							0.193	(0.011)	***
lead2_concert_date$_{itm}$							0.234	(0.010)	***
lead1_concert_date$_{itm}$							0.363	(0.010)	***
Week of _concert_date$_{itm}$							0.381	(0.010)	***
lag1_concert_date$_{itm}$							0.256	(0.010)	***
lag2_concert_date$_{itm}$							0.188	(0.010)	***
lag3_concert_date$_{itm}$							0.151	(0.010)	***
lag4_concert_date$_{itm}$							0.123	(0.010)	***
lag5_concert_date$_{itm}$							0.085	(0.010)	***
lag6_concert_date$_{itm}$							0.056	(0.010)	***
lag7_concert_date$_{itm}$							0.043	(0.010)	***
lag8_concert_date$_{itm}$							0.030	(0.010)	***
lag9_concert_date$_{itm}$							0.025	(0.010)	**
lag10_concert_date$_{itm}$							0.018	(0.010)	*
lag11_concert_date$_{itm}$							0.011		
lag12_concert_date$_{itm}$							0.014		
lag13_concert_date$_{itm}$							0.007		
Constant	10.8	(0.005)	***	10.8	(0.005)	***	10.8	(0.005)	***
R-squared	0.158			0.148			0.166		
F-test	1292.204			1201.1			760.22		
Prob > F	0			0			0		
Number of obs	208711			208711			208711		

*Note.*** p<.01, ** p<.05, * p<.1*

Table 8 Full Panel model with artist and market fixed effects (continued)

	1		2		3	
$Ln(Streams)_{itm}$	Coef.	Sig	Coef.	Sig	Coef.	Sig
Mar-18	0.38	***	0.399	***	0.38	***
Apr-18	0.399	***	0.42	***	0.398	***
May-18	0.431	***	0.454	***	0.428	***
Jun-18	0.415	***	0.439	***	0.415	***
Jul-18	0.428	***	0.457	***	0.431	***
Aug-18	0.473	***	0.502	***	0.475	***
Sep-18	0.456	***	0.486	***	0.456	***
Oct-18	0.487	***	0.513	***	0.484	***
Nov-18	0.573	***	0.596	***	0.571	***
Dec-18	0.585	***	0.611	***	0.588	***
Jan-19	0.47	***	0.493	***	0.474	***
Feb-19	0.587	***	0.612	***	0.587	***
Mar-19	0.637	***	0.663	***	0.635	***
Apr-19	0.631	***	0.664	***	0.634	***
May-19	0.634	***	0.673	***	0.638	***
Jun-19	0.376	***	0.418	***	0.374	***
Jul-19	0.166	***	0.206	***	0.161	***
Aug-19	0.177	***	0.216	***	0.174	***
Sep-19	0.157	***	0.194	***	0.156	***
Oct-19	0.155	***	0.185	***	0.156	***
Nov-19	0.237	***	0.259	***	0.237	***
Dec-19	0.272	***	0.287	***	0.27	***
Jan-20	0.161	***	0.169	***	0.163	***
Feb-20	0.193	***	0.199	***	0.197	***
Mar-20	0.174	***	0.177	***	0.176	***
Apr-20	0.474	***	0.474	***	0.474	***
May-20	0.373	***	0.373	***	0.373	***
Constant	10.803	***	10.803	***	10.803	***
R-squared	0.158		0.148		0.164	
F-test	1292.2		1200.63		751.5	
Prob > F	0		0		0	
Number of obs	208711		208711		208711	

**** p<.01, ** p<.05, * p<.1*

Table 9 Panel model by ticket sale, weeks in top 100, and years playing cohorts with artist and market fixed effects

	4			5			6		
$Ln(Streams)_{itm}$	Coef.		Sig	Coef.		Sig	Coef.		Sig
Bottom tier sales									
lead 1 month_concert_date $_{itm}$	0.128	(0.010)	***						
Week of _concert_date $_{itm}$	0.289	(0.021)	***						
lag 1 month_concert_date $_{itm}$	0.066	(0.011)	***						
Middle tier sales									
lead 1 month_concert_date $_{itm}$	0.259	(0.011)	***						
Week of _concert_date $_{itm}$	0.424	(0.023)	***						
lag 1 month_concert_date $_{itm}$	0.17	(0.012)	***						
Top tier sales									
lead 1 month_concert_date $_{itm}$	0.35	(0.008)	***						
Week of _concert_date $_{itm}$	0.526	(0.017)	***						
lag 1 month_concert_date $_{itm}$	0.2	(0.009)	***						
1 to 70 weeks in top 100									
lead 1 month_concert_date $_{itm}$				0.088	(0.011)	***			
Week of _concert_date $_{itm}$				0.216	(0.010)	***			
lag 1 month_concert_date $_{itm}$				-0.209	(0.005)	***			
71 to 270 weeks in top 100									
lead 1 month_concert_date $_{itm}$				0.111	(0.008)	***			
Week of _concert_date $_{itm}$				0.155	(0.005)	***			
lag 1 month_concert_date $_{itm}$				0.097	(0.004)	***			
271 weeks+ in top 100									
lead 1 month_concert_date$_{itm}$				0.142	(0.009)	***			
Week of _concert_date$_{itm}$				0.015	(0.005)	***			
lag 1 month_concert_date$_{itm}$				0.214	(0.006)	***			
4 to 16 years performing									
lead 1 month_concert_date$_{itm}$							0.143	(0.016)	***
Week of _concert_date$_{itm}$							0.303	(0.016)	***
lag 1 month_concert_date$_{itm}$							0.103	(0.016)	***
17 to 29 years performing									
lead 1 month_concert_date$_{itm}$							0.311	(0.019)	***
Week of _concert_date$_{itm}$							0.602	(0.019)	***
lag 1 month_concert_date$_{itm}$							0.225	(0.019)	***
30+ years performing									
lead 1 month_concert_date$_{itm}$							-0.004		
Week of _concert_date$_{itm}$							0.276	(0.020)	***
lag 1 month_concert_date$_{itm}$							-0.018		
R-squared	0.161			0.171			0.15		
F-test	1102.74			1188.65			1013.07		
Prob > F	0			0			0		
Number of obs	208,711			208,711			208,711		

*Note.*** p<.01, ** p<.05, * p<.1*

Table 9 Panel model by ticket sale, weeks in top 100, and years playing cohorts with artist and market fixed effects

	4		5		6	
$Ln(Streams)_{itm}$	Coef.	Sig	Coef.	Sig	Coef.	Sig
Mar-18	0.393	***	0.372	***	0.399	***
Apr-18	0.41	***	0.397	***	0.419	***
May-18	0.445	***	0.444	***	0.452	***
Jun-18	0.43	***	0.421	***	0.438	***
Jul-18	0.444	***	0.441	***	0.456	***
Aug-18	0.49	***	0.487	***	0.502	***
Sep-18	0.474	***	0.478	***	0.487	***
Oct-18	0.501	***	0.493	***	0.514	***
Nov-18	0.581	***	0.567	***	0.597	***
Dec-18	0.601	***	0.604	***	0.611	***
Jan-19	0.482	***	0.491	***	0.493	***
Feb-19	0.597	***	0.577	***	0.612	***
Mar-19	0.648	***	0.621	***	0.663	***
Apr-19	0.651	***	0.612	***	0.664	***
May-19	0.657	***	0.633	***	0.673	***
Jun-19	0.396	***	0.371	***	0.418	***
Jul-19	0.179	***	0.145	***	0.206	***
Aug-19	0.192	***	0.169	***	0.216	***
Sep-19	0.175	***	0.153	***	0.194	***
Oct-19	0.17	***	0.158	***	0.186	***
Nov-19	0.245	***	0.231	***	0.26	***
Dec-19	0.278	***	0.269	***	0.287	***
Jan-20	0.166	***	0.168	***	0.169	***
Feb-20	0.199	***	0.202	***	0.199	***
Mar-20	0.177	***	0.176	***	0.177	***
Apr-20	0.474	***	0.473	***	0.474	***
May-20	0.373	***	0.373	***	0.373	***
Constant	10.803	***	10.764	***	10.803	***
R-squared	0.161		0.171		0.15	
F-test	1102.74		1188.65		1013.07	
Prob > F	0		0		0	
Number of obs	208,711		208,711		208,711	

*Note.*** p<.01, ** p<.05, * p<.1*

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9 Compliance with ethical standards

Conflicts of interest/competing interests: The author manages a deceased Bluegrass/Folk artist's legacy unrelated to the data analyzed for this paper.

Stata code producing the attached results is available for review. However, several of the data sources are proprietary and cannot be shared.

Performing artist response to the Copyright Royalty Board rate increase and the Music Modernization Act

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Abstract

This paper examines the financial impact of the consecutive regulatory events of the Copyright Royalty Board rate increase in January 2018 and the passage of the Music Modernization Act in October 2018 on the release activity by the top 100 artists. This work identifies that the rate increase corresponded with a significant increase in musical track releases for a short eight-month period until the Music Modernization Act became law. Artists who are younger, had composed their music, and/or actively touring were more likely to increase their release activity. The analysis also identifies a handful of artists who have benefited from the new regulations.

Keywords Music. Music industry . music streaming . industry disruption

JEL Classification D12 . D22 . L82 . Z10

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1 Introduction

Top music performers are required to navigate an eco-system of incentives to derive revenue and manage their music catalog. Their primary source of income comes from live performance, where they earn an average of $853K per concert (2020). They also derive a substantive proportion of their income from recorded music streamed and downloaded on digital streaming platforms (DSP) like Spotify, Apple Music, and Amazon. While monthly streaming revenue is a fraction of what is earned for live performances, the earnings persist while an artist is not on the road.

Over the past few years, Federal regulation has sought to enhance the revenue earned for recorded music as well as to ensure accurate and efficient compensation. This paper explores the impact of two independent events: the January 2018 decision by the Copyright Royalty Board to increase rates paid to composers and the Music Modernization Act signed into law in October 2018. The latter provides greater payment transparency and ensures artists are fully paid for their music streams.

The Copyright Royalty Board rate increase (CRBRI) was designed to help remedy declining payments to creators as streaming became a dominant medium for music consumption. The Board proposed a staged increase from 10% to 15% of streaming platform revenue from 2018 to 2022. Several DSPs filed suit asking for relief. While the court did not side with the DSPs, it remanded the rate increase to the Board on procedural grounds; the issue has not been settled as of February 2022. Thus, any incentive response is based upon the perception and expectation that the defense of the CRBRI will succeed.

The passage of the Music Modernization Act (MMA) was designed to modernize the process of royalty payments for the digital age. While there had been previous reforms created by the Copyright Act of 1976 and the 1998 Digital Millennium Copyright Act, both had become outdated with the growth of music streaming. In response, several artists were considering class-action suits against the DSPs for copyright infringement. The MMA was designed to remedy this by creating the Music Licensing Collective, whose purpose was to collect and distribute artist royalties. The law also has provisions to set aside funds and a matching process for orphan copyrights where the rightful composer has not been identified. Lastly, it provides provisions for compensating owners of pre-1972 recordings.

To understand the source of incentives in commercial music, we need to recognize the potential roles of a commercial musician. Musical performing artists technically have rights to their performances on albums, concerts, and other recordings. However, in reality, many artists will waive those rights under artist and work for hire contracts with record labels/producers and performance venues in exchange for a contracted payment. That said, many artists maintain ownership and usage rights to at least a portion of their recorded performances. These may include live concerts, outtake videos of recording sessions, and social media content. It is critical that artists carefully weigh these types of performances when signing contracts, as they are entitled to release these performances and receive a royalty payment for their streaming. This is one of several motivations for bands like Phish, Metallica, and others who have released volumes of their live concerts.

A commercial musician can also be the composer of songs they perform. However, it should be recognized that some musicians view their primary profession as being that of a composer (a.k.a. songwriter) and are not performers with large followings. Under federal copyright law, when a composer writes a song and submits it for copyright, they are granted the right to select who will be the first to record it, and they will be paid royalties for recordings, live performance, derivative works, and reproduction of the song by any artist. The composer also has rights that vary by country, which are beyond the scope of this paper.

This paper explores the sources of income that composers and musical performing artists derive from their recorded music. Specifically, whether behavioral constructs such as Adam's Equity Theory and Vroom's Labor Expectancy Theory explain the motivation (or lack thereof) to compose and produce more music? With the availability of pre and post regulatory passage data, this paper examines the impact of the new regulations on artists' incentives to create more music.

This work's central question is whether the pair of regulations impacted artist production of recorded music? Also, other factors such as:

- Years performing professionally
- Percent of releases they composed
- Grammy nominations and awards throughout career
- Concerts during month
- Cumulative weeks in the Billboard top-20

influenced their release activity? The top 100 performing artists were selected given that, among all professional musicians, they are the group that will gain the greatest financial returns for their efforts. They have stronger notoriety and typically achieve a higher streaming baseline.

2 Literature Review

Economic literature widely holds that laborers respond rationally to financial incentives. The academic literature on incentives is lengthy and invites consideration as a lens for evaluating the response to the two regulatory events outlined. This study focuses on a series of cross-disciplinary theories: Vroom's Labor Expectancy Theory and Adam's Equity Theory.

Vroom's Labor Expectancy Theory is governed by workplace motivation that determines how laborers complete their work both in the present and the near future. The theory argues that motivation can be explained by three factors: expectancy, instrumentality, and valence (Lloyd and Mertens, 2018). Expectancy involves worker anticipation that a certain level of effort will yield a specific performance level. Instrumentality involves the expectation that attaining a specified performance level will result in an anticipated reward. Lastly, valence reflects how much a worker desires a particular outcome.

Applying the theory to a musical performer's career, a musician invests time in composing music and improving their performance to get booked for concerts and receive recorded music royalties (expectancy). It is hoped that the continued repetition of touring and composing will enable them to achieve higher levels of income and professional status (instrumentality). The magnitude of success is governed by how invested the performer is in their dual role of composing and touring (valence). While some performers want to achieve notoriety and celebrity, others enjoy touring and playing in more niche genres for fans in smaller venues.

Equity Theory assesses the career and job satisfaction of laborers. The theory posits that laborers contribute effort in exchange for rewards they receive. Laborers who are highly rewarded for their effort tend to be more satisfied with their chosen profession. However, laborers become dissatisfied when the rewards are not commensurate with the effort (Kollman, Stockmann, Kensbock, Peschl, 2019).

Equity Theory carries rich application in the music industry. Top 100 artists such as Ed Sheeran, Bon Jovi, and Post Malone have achieved broad levels of celebrity and financial rewards for their work. According to Equity Theory, they should have a high level of job satisfaction. By contrast, many composers believe that the DSPs have commoditized and underpaid them for their songs. These laborers are dissonant because they do not think they are being fairly paid and recognized for their work.

Additionally, I explored the hypothesis that performing artists respond to expected incentives. For instance, did performing artists become more productive on the news that the industry was lobbying for early versions of legislation that would become the MMA in December 2017 and January 2018? Or was there a measurable impact when the bill was introduced in the US Senate on April 10, 2018?

There is ample literature related to buy on the rumor sell on the news (BRSN) in the financial sector. The theory and the empirical evidence have been broadly covered in the finance literature (Lamont and Thaler 2003; Chopra, Lakonishok and Ritter, 1992; Dremen 2001; Tam, 2001). The hypothesis that expectation may have an equal or greater impact than the bill's passage will be examined in this paper.

Additional exploration of the academic literature found little written regarding the economic impact of the CRBRI and MMA. In particular, literature on the CRBRI or the MMA has been limited to the predicted effects of the policies.

3 Data and Empirical Analysis

3.1 Data

The empirical design of this work uses several sources of hand-collected data. Table 1 highlights artist-level data sources on track release productivity from January 2016 through March 2021 and artist years performing professionally reported by MusicBrainz.org. The data was combined with an abridged count of composer credits collected by the Music Licensing Collective. While imperfect due to observed incomplete self-reporting by artists and their agents, it provides a gauge of composer activity. Lastly, I incorporated concert activity, artist history for Grammy nominations and Awards, and cumulative weeks in the Billboard Top 20.

Table 1 Data source characteristics

Source	Characteristics
MusicBrainz.org	Album, E.P., Live Concert releases, track releases, and profile of artist gender, primary genre, and years playing professionally for each top 100 performing artist.
Music Licensing Collective	Database of composer credits for songs covered by federal copyright.
Pollstar	Concert data includes date, number of shows, revenue, ticket sales, minimum/maximum/average ticket price, venue, % of capacity sold, city/state/country.
Billboard Rankings (provided by Data.World)	Peak rankings and weeks in Hot 100 Billboard ranking of songs by week from 1959 to 2019. Sample filtered for all songs throughout career among the 2019 Pollstar top 100 performing artists.
Music Connect	Streaming data: All weekly total, audio, video, and programmed digital streams by Spotify, Apple Music, Amazon, and all other major digital streaming platforms for top-29 concert markets in 2018 and 2019
Grammy Awards	Record of Grammy nominations and awards from 1958 through 2019 awards given out in February 2020.

Table 2 outlines the artists included in the analysis. The list consists of the top 100 artists by global live concert annual revenue for 2019:

Table 2 Top 100 artists

	Ed Sheeran	Paul McCartney	Phish	Chayanne
	Pink	Zach Brown Band	Panic! At the Disco	Maroon 5
	Metallica	Travis Scott	Florence + the Machine	The Avett Brothers
	Elton John	Cher	Take That	Jeff Dunham
	BTS	Spice Girls	Chris Stapleton	Manuel Carrasco
	Bon Jovi	Hootie & the Blowfish	Luis Miguel	Hillsong United
	Muse	Twenty-One Pilots	Breaking Benjamin	Sebastian Maniscalco
	Shawn Mendes	Thomas Rhett	Bad Bunny	For King & Country
	Ariana Grande	Sandy & Junior	Eagles	B2K
	Backstreet Boys	New Kids on the Block	Jennifer Lopez	Newsboys
	Trans-Siberian Orchestra	Phil Collins	Pentatonix	Kelly Clarkson
Artist list	Michael Bublé	Dave Matthews Band	Brad Paisley	Disturbed
	Hugh Jackman	Luke Combs	Little Mix	The World of Hans Zimmer
	Post Malone	Luke Bryan	Westlife	ZZ Top
	Mumford & Sons	John Mayer	Shinedown	Maluma
	KISS	Billy Joel	Queen + Adam Lambert	Marc Anthony
	Bob Seger	Carrie Underwood	Celine Dion	Rod Stewart
	Garth Brooks	Justin Timberlake	MercyMe	Greta Van Fleet
	Fleetwood Mac	Mark Knopfler	Andreas Gabalier	Anderson .Paak
	The Rolling Stones	Dead & Company	Eminem	Hits Deep Tour/Toby Mac
	Jonas Brothers	Khalid	Tool	Wisin & Yandel
	Florida-Georgia Line	Goo Goo Dolls	Chris Young	Guns N' Roses
	Andre Rieu	Train	Hozier	Lizzo
	Iron Maiden	Bryan Adams	Andrea Bocelli	
	Eric Church	JoJo Siwa	Jason Aldean	

Note: Rammstein, Roland-Kaiser and Banda Sinaloense MS de Sergio Lizarraga were not included in the list

Time-based variables were defined to identify the pre-regulatory period from January 2016 through January 2018, the pre-MMA/post CRBRI period between the passing of the Copyright Royalty Board rate increase announcement and passage of the MMA (February 2018 through October 2018), and the post-period after the enactment of the MMA (November 2018 through March 2020). The data set is aggregated monthly to smooth the time series. It includes 4,947 observations (Table 3). The data set ends in March 2020, before the effects of the COVID pandemic impacted the release of recorded music. A transformed variable was created to capture the ratio of composer song credits to cumulative track releases. Given the inaccuracy of both the MusicBrainz and Music Licensing Collective sources, some ratios exceed 1 for 16 out of the top 100 artists and should be viewed as relative.

Table 3 Data frequencies

Variable	Obs	Mean	Std. Dev.	Min	Max
Monthly Track count	4947	2.519	19.442	0	623
Number of concerts per month	4947	1.811	4.28	0	77
Dummy variable for CRBRI	4947	0.176	0.381	0	1
Dummy variable for MMA	4947	0.333	0.471	0	1
Open-category Grammy awards during career	4947	0.186	0.524	0	3
Weeks in Billboard top 20	4947	88.22	125.075	0	516
Played professionally:					
4 to 5 years	4947	0.031	0.173	0	1
6 to 10 years	4947	0.134	0.341	0	1
11 to 15 years	4947	0.113	0.317	0	1
16 to 20 years	4947	0.093	0.29	0	1
21 to 25 years	4947	0.093	0.29	0	1
26 to 30 years	4947	0.134	0.341	0	1
31 to 35 years	4947	0.082	0.275	0	1
36 to 40 years	4947	0.062	0.241	0	1
41+ years	4947	0.258	0.437	0	1
Composer credit to track release ratio	4947	1	4.365	0	26
1st quarter	4947	0.294	0.456	0	1
2nd quarter	4947	0.235	0.424	0	1
3rd quarter	4947	0.235	0.424	0	1
4th quarter	4947	0.235	0.424	0	1

Observation of track count releases over time shows high skewness, with most artists reporting 0 releases during most months and a small handful releasing more than 500 tracks in some months. A closer examination of these outliers identifies a mixture of bands like Fleetwood Mac and ZZ Top releasing box sets, or Metallica releasing a series of historic live concerts. No attempt was made to cap the top end of the distribution.

Figure 1 Histogram of track counts (omitting 0)

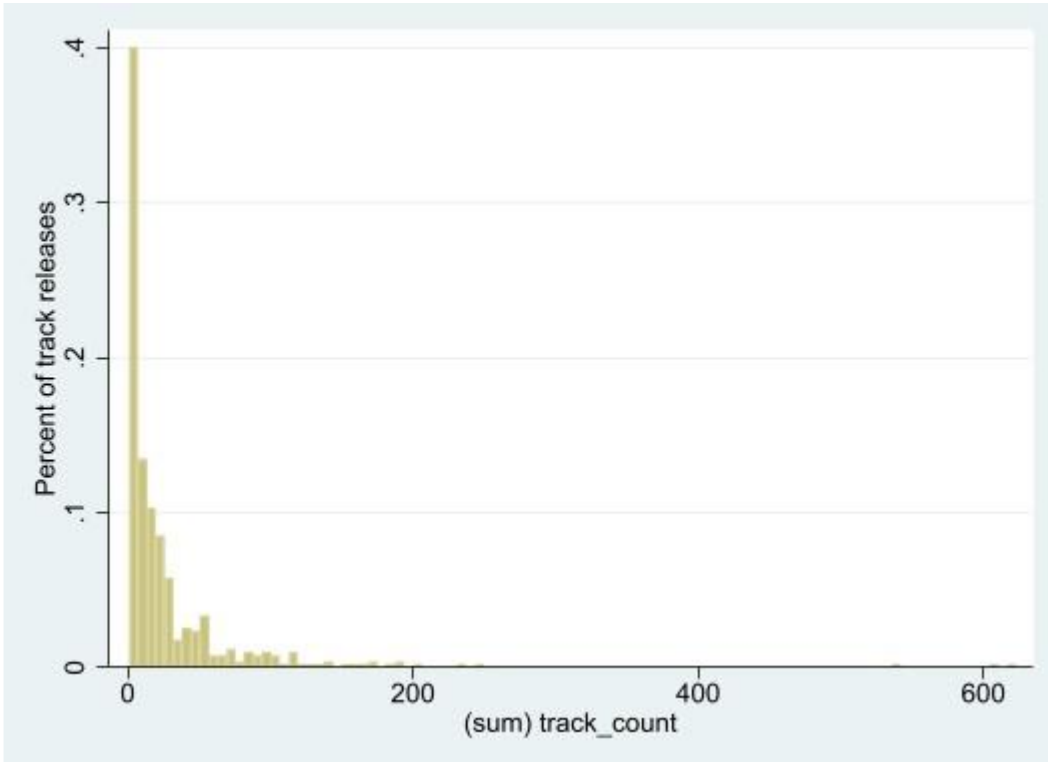
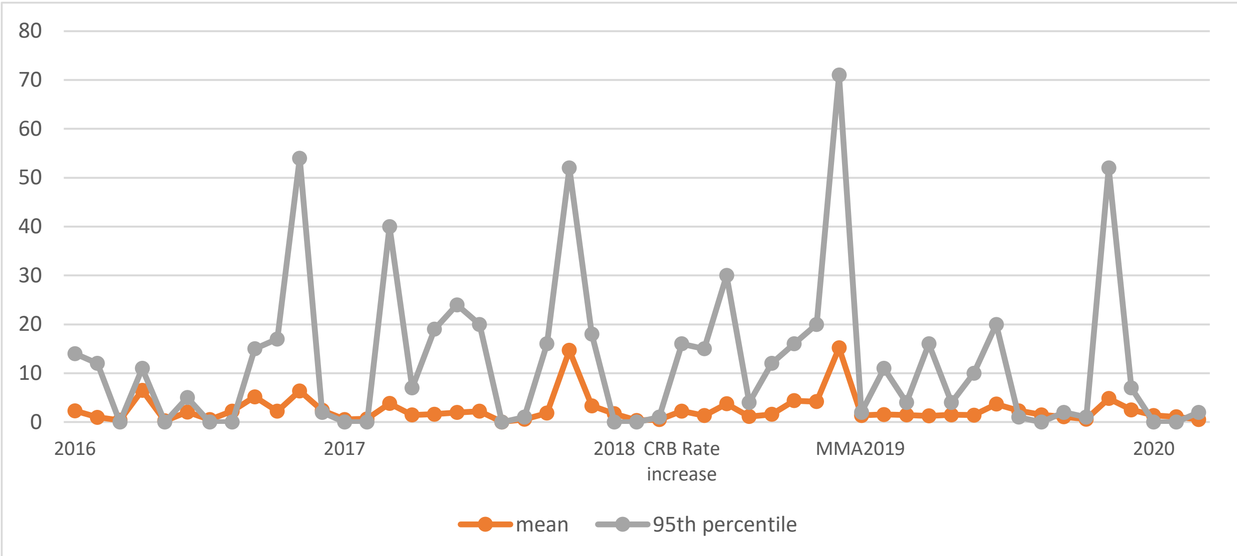


Figure 2 also highlights release seasonality. Historically more releases happened during the 2nd and 4th quarters. This should be controlled in modeling to avoid time-series interactions with the two regulatory events.

Figure 2 Trendline of mean, 95th and 99th percentile



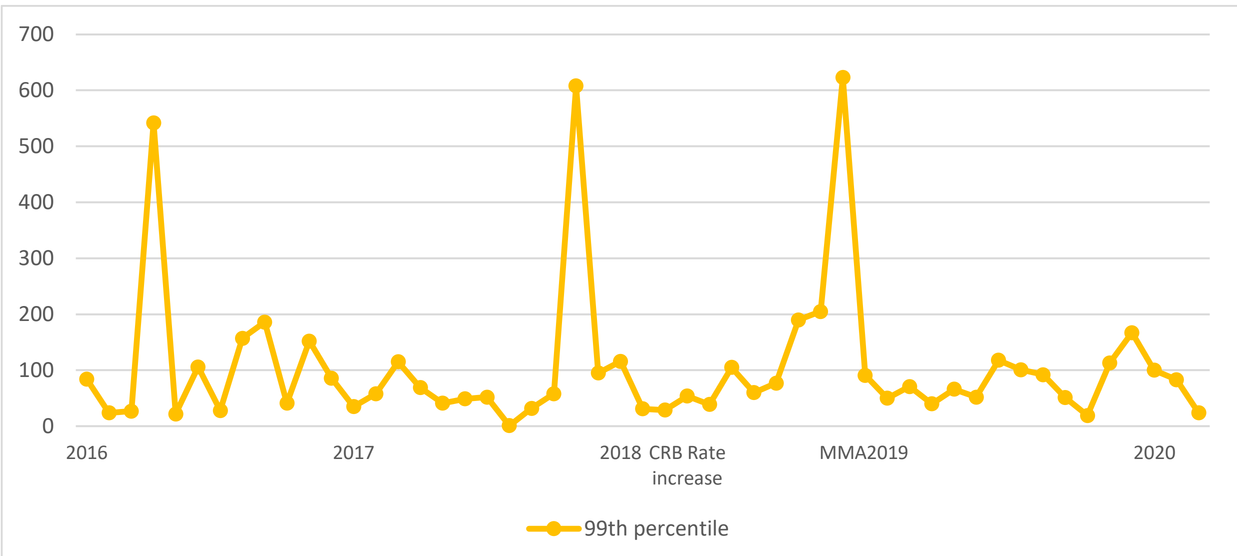
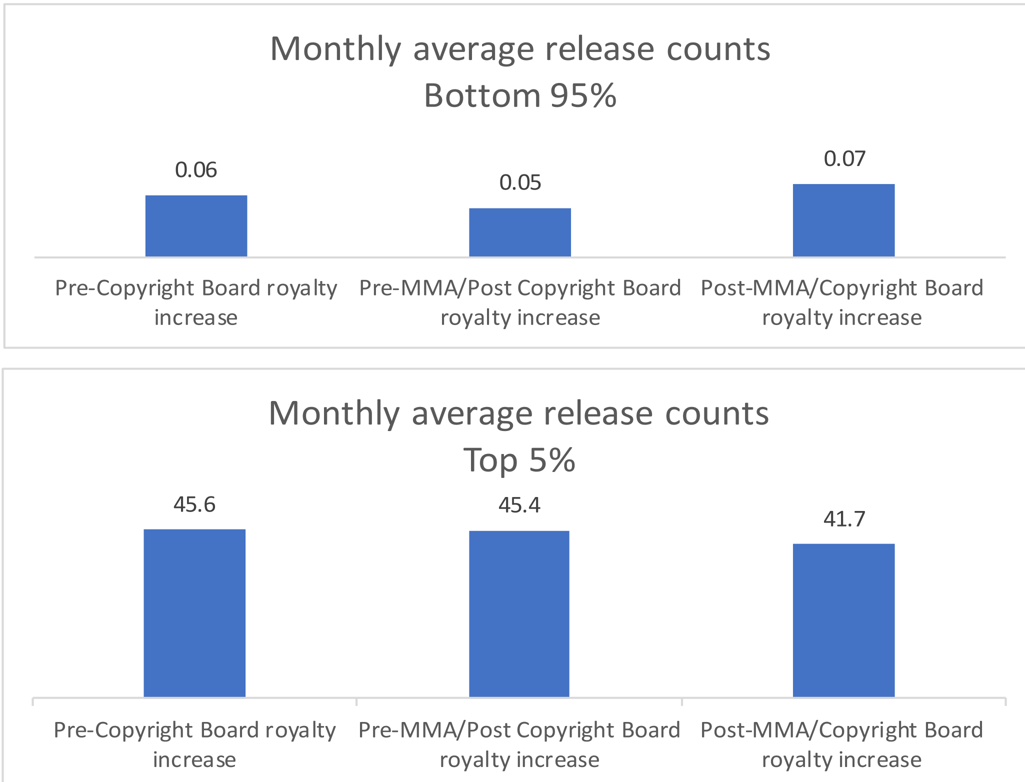


Figure 3 highlights that while the data suffers from skewness, the difference in track count releases among the top 5% of monthly release counts does not vary dramatically after vs. before the regulatory events. This should alleviate a concern that any increases are caused by the top end of the distribution.

Figure 3 Distribution of monthly track count for the bottom 95% vs. top 5%



3.2 Negative-binomial count model with artist fixed-effects specification

A negative binomial model was used to determine the impact of the regulatory events on artist productivity, leveraging the count of artist release activity (track counts) as a dependent variable. Specification 1 provides a simple estimation that identifies the time effects of the CRBRI and the later passage of the MMA combined with the royalty increase. Specification 2 examines the impact on key cohorts such as years performing, composer credits, current live concert activity, and catalog success with cumulative weeks in the Billboard Top 20 and Grammy Award recognition. Predictors g_{it} controls for artist fixed-effects and $\textit{Quarterly Seasonality}_{it}$ controls for seasonal effects. Given the fourth quarter is an active month for releases, activity fluctuates between November and December depending on the year. Rolling up the seasonality to quarterly provides a smoothing effect to address this.

$$Monthly\ release\ count_{it} = a_{it} + CRB\ Rate\ Increase_t + \ Music\ Modernization\ Act\ passage_t + \ Quarterly\ Seasonality_t + g_{it} + \ e_{it} \quad (1)$$

$$Monthly\ release\ count_{it} = a_{it} + CRB\ Rate\ Increase_t * artist\ cohort_i + \ Music\ Modernization\ Act\ passage_t * artist\ cohort_i + \ Quarterly\ Seasonality_t + g_{it} + \ e_{it} \quad (2)$$

Table 4 provides output for specification 1 and identifies a significant relationship that corresponds with .266 marginal effects after the CRBRI was announced. By contrast, adding the passage of the MMA did not impact release activity among the top 100 artists at least through March 2020.

Table 4 Negative binomial model with artist fixed effects

track_count	coeff. St Err.
2018 CRB Rate Increase	0.266*
	(0.13)
MMA Passage	0.049
	(0.12)
2nd quarter	0.441**
	(0.15)
3rd quarter	0.282
	(0.16)
4th quarter	0.774***
	(0.14)
Constant	-4.129***
	(0.13)

* p<0.05, ** p<0.01, *** p<0.001

Artist characteristics were then interacted with the CRBRI and the MMA variables. Table 5 highlights that younger artists, active as composers, and actively touring were more likely to increase their

Table 5 Negative binomial model by artist characteristics

$track\_count_{it}$	1 coeff./se	2 coeff./se	3 coeff./se	4 coeff./se	5 coeff./se
Years peforming interaction					
4 to 10 years * CRBRI	0.971 ***				
	(0.24)				
4 to 10 years * MMA	0.382				
	(0.22)				
Top 50% of composer credits * CRBRI		0.316 *			
		(0.15)			
Top 50% of composer credits * MMA		0.043			
		(0.13)			
Cumulative open category Grammy wins					
1 * CRBRI			0.239		
			(0.35)		
2 * CRBRI			0.181		
			(0.52)		
3 * CRBRI			-12.491		
			(481.30)		
1 * MMA			0.434 ^		
			(0.24)		
2 * MMA			0.177		
			(0.38)		
3 * MMA			-0.787		
			(1.05)		
Concert during month * CRBRI				0.617 ***	
				(0.19)	
Concert during month * MMA				0.178	
				(0.16)	
Cumulative weeks in top 20 * CRBRI					0.232
					(0.22)
Cumulative weeks in top 20 * MMA					-0.209
					(0.26)
2nd quarter	0.454 **	0.445 **	0.471 **	0.429 **	0.457 **
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
3rd quarter	0.288	0.286	0.313 *	0.255	0.298
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
4th quarter	0.769 ***	0.77 ***	0.761 ***	0.744 ***	0.765 ***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Constant	4.122 ***	-4.111 ***	-4.098 ***	-4.102 ***	-4.083 ***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)

^.10, * p<0.05, ** p<0.01, *** p<0.001

release activity in response to the rate increase. By contrast, the MMA had little influence on any artist cohorts.

I then examined the expectation hypothesis through the lens of BRSN. To do this, I created two specifications. The first examines the period before and after the submission of the original bill and lobbying period: January 2018 (specification 3). While some activity happened in December 2017, most of the activity occurred in January of the following year. Specification 4 examines the period before and after the bill's introduction in the US Senate on April 10, 2018.

$$\begin{aligned} Monthly\ release\ count_{it} &= a_{it} + December\ Introduction\ and\ lobbying_t + \ Quarterly\ Seasonality_t \\ &+ g_{it} + e_{it} \quad (3) \end{aligned}$$

$$\begin{aligned} Monthly\ release\ count_{it} = \\ &= a_{it} + April\ Introduction\ in\ the\ Senate_t + \ Quarterly\ Seasonality_t + g_{it} \\ &+ e_{it} \quad (4) \end{aligned}$$

The results (Table 5) are marginal with coefficients in the 0.11 to 0.13 range. These results are only significant with 90% confidence.

Table 6 Negative binomial model by lobbying and legislative events

	3	4
	coeff./se	coeff./se
track_count$_{it}$		
December introduction and Lobbying	0.113	
	(0.10)	
April bill introduction		0.128
		(0.10)
2nd quarter	0.477 **	0.452 **
	(0.15)	(0.15)
3rd quarter	0.317 *	0.293
	(0.16)	(0.16)
4th quarter	0.771 ***	0.746 ***
	(0.14)	(0.14)
Constant	-4.139 ***	-4.123 ***
	(0.13)	(0.12)

Note. * p<0.05, ** p<0.01, *** p<0.001

Recognizing the limited response to the incentives created by the CRBRI and the MMA, I identified a handful of artists who released more post-CRBRI and MMA. Then, I examined the impact on their music streaming during the same periods. I then analyzed their lift in streaming relative to the growth of other Top 100 performers. Table 7 outlines the outcomes for ZZ Top, Luke Combs, and Florida Georgia Line. The biggest beneficiary is Luke Combs, who netted an incremental $15.3 million above his fair share (growth in streams vs. all Top 100) with 4.0 track releases before MMA/after CRBRI and 5.4 track releases per month post-MMA/CRBRI. ZZ Top also achieved $286.5K. On the contrary, Florida-Georgia Line experienced a loss of $722K vs. their fair share. But the group did see an increase in streams from 25.4 million per week post-MMA/CRBRI vs. 17.3 million per week during the pre-period.

Table 7 Case study of artists who increased their productivity

	Before MMA\CRBRI January 1, 2016 through January 29th, 2018	After CRBRI\before MMA January 30th, 2018 through October 12th 2018	After MMA\CRBRI October 13th, 2018 through March 31st 2020
Percent growth of music streams vs. pre period for top 100 artists		75%	49%
Group: ZZ Top			
Average track release per month	2.6	5.7	9.9
Raw weekly music streams (M)	1.6	3.0	3.4
Percent increase vs. pre-period streams		87%	114%
Incremental streams/revenue since CRBRI increase vs. top 100		+84.3M/$286.5K from January 30, 2018 to March 31, 2020	
Group: Luke Combs			
Average track release per month	1.2	4.0	5.4
Raw weekly music streams (M)	0.1	24.1	49.1
Percent increase vs. pre-period streams		20473%	41893%
Incremental streams/revenue since CRBRI increase vs. top 100		+4,505M/$15,139K from January 30, 2018 to March 31, 2020	
Group: Florida Georgia Line			
Average track release per month	1.2	0.4	2.4
Raw weekly music streams (M)	17.3	25.2	25.4
Percent increase vs. pre-period streams		46%	47%
Incremental streams/revenue since CRBRI increase vs. top 100		-212.3M/-$721.9K from January 30, 2018 to March 31, 2020	

Note . Sources: Streaming (MusicConnnect), Releases (Musicbrainz.org)

4 Discussion

The outcome of this research indicates that many top performers have been remiss in taking advantage of financial incentives enabled by the CRBRI and the passage of the MMA. Only during the eight months post-CRBRI/pre-MMA did the Top 100 release more music.

Consistent with Labor Expectancy and Equity Theories, performers who earlier in their career were motivated by career success allocated labor to release more music. According to the Labor Expectancy theory, the two regulations should have improved artists' motivation to produce, given greater expectancy and instrumentality of being rewarded for their work. However, an explanation for the lack of increased productivity could be that the artist's valence skewed negatively (e.g., performers did not see more music streaming as a desired outcome). This may have occurred for various reasons, including that the creative process can be long and unpredictable. Also, many of these artists were preparing for lucrative tour schedules in 2019, a very good year financially for these artists.

Equity Theory also applies in that the DSPs opposed the rate increase, and many are yet to pay the increased rates until the issue is settled. Additionally, the primary benefits of the MMA did not become apparent until the Music Licensing Collective began distributing payouts in January 2020. It could be that performers during this period continued to view uncertainty in the revenue they would generate.

Performers should consider options for monetizing their non-traditional recordings to engage more fans. Among the handful of performers I examined who produced more music post-CRBRI, the group received incremental streams and (for ZZ Top and Luke Combs) revenue for their efforts and use of their recordings.

5 Conclusions

While both the CRBRI and MMA received much fan-fair when passed, top performers' release activity only increased modestly for a short period post-CRBRI/pre-MMA. This is unfortunate, as there is some evidence performers who did take advantage of the incentives (either deliberately or by happenstance) had the potential to gain significant incremental revenue for their efforts. While artists should continue to retain ownership of the quality of their recorded performances, they should also examine innovative releases for recordings in their possession. They should also avoid assigning those rights in their contracts.

6 Compliance with ethical standards

Conflicts of interest/competing interests: The author manages a deceased Bluegrass/Folk artist's legacy unrelated to the data analyzed for this paper. With the exception of the MusicConnect data, Stata code and data available for review.

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