The Heterogeneous Effects of the Music Modernization Act and Co-Occurring Federal Regulation on the Release of New Music in the United States

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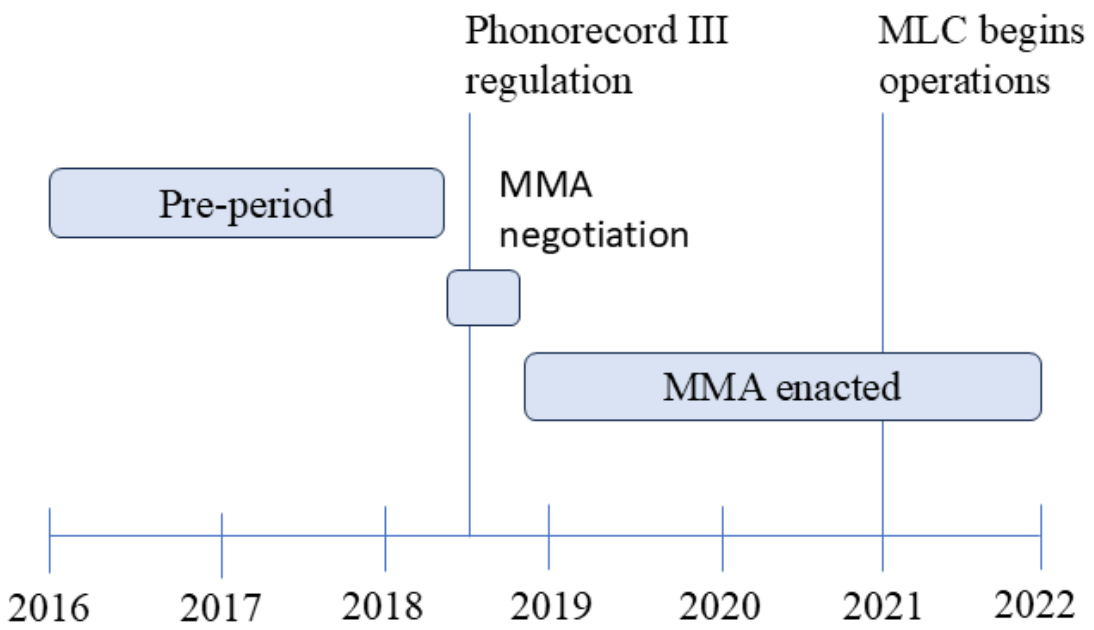
I examined the impact of the Music Modernization Act (MMA) and a co-occurring regulation on the release activity by composers and musical performers. The analysis uses a negative binomial count model with artist fixed effects to identify incremental release activity. Demographic and music copyright covariates were included to identify heterogeneity. While not impacting release activity overall, I identified increased release activity among composers (increasing with composer credits) as well as younger and female performers. These findings are observed in two instances: (1) during the post-period after the MMA was enacted and (2) during the negotiation period while the MMA was written and debated. Additionally, while there has been a significant increase in the release of singles, this phenomenon appears to be driven by the growth of music streaming. This work identifies the extent to which this new law and federal regulation have encouraged recording artists to increase their release activity.

Keywords: music, music industry, music streaming, industry disruption, federal regulation

BACKGROUND AND INTRODUCTION

Musical performing artists have long felt a lack of agency and believe they have been underpaid for their recorded music. In 2018, the Music Modernization Act became law and is designed to streamline the licensing and royalty payments for non-dramatic music copyrighted works. This law established the Mechanical Licensing Collective (MLC) to administer rights granted by the law, including matching previously unmatched composers' works and a provision to pay composer royalties for 'classics' defined as pre-1972 compositions not previously protected by federal law (Figure 1). During the same year, the Copyright Royalty Board, as part of its Phonorecord III proceedings, required digital service providers (DSPs) (e.g., Spotify, Apple Music, Amazon, and others) to increase rates paid to composers from 11.4% of service rates in 2018 to 15.1% by 2022.

FIGURE 1
TIMELINE FOR MMA AND PHONORECORD III RATE INCREASE



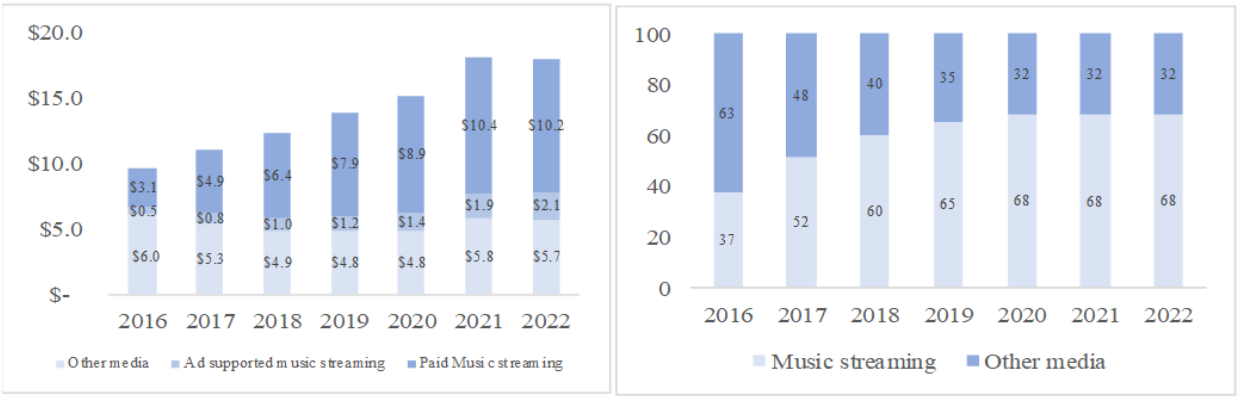
Note. An early draft of the Music Modernization Act began circulating in December 2017 but was not more widely socialized until 2018. Therefore, December 2017 is treated as part of the pre-period in this analysis.

This paper seeks to identify the impact of the co-occurring law and federal regulation on the productivity of performing artists. Does the increase in composer royalties and greater transparency of the collection process, following the MMA enactment, provide meaningful incentives for performing artists to release more music? Specifically, did performing artists (whether composers or not) release more music in response to the new law and regulation? Did male vs. female performers uniquely respond by releasing more music? How did the incidence of release formats change in response to the new law and regulation? Do composers who are younger or more prolific tend to release more music?

This analysis provides an empirical basis for the theoretical literature on creative markets (Potts & Cunningham, 2010; Marco-Serrano, et. al., 2014). Past work on the topic has identified four economic models relating the creative industries to the broader economy. First, if creative work contributes its fair share or greater to overall output as reflected by Potts and Cunningham's competitive, growth, and innovation models, then performers will show a willingness to invest more of their labor into releasing music. By contrast, if creative work contributes less than its fair share as reflected by their welfare model, the new law and regulation will likely have little effect as the primary incentive to release music. The economics of releasing during or after 2018 will be unchanged vs. pre-2018. While theoretically there could be other factors that may motivate increased release activity over a short period, if performers, composers, producers, and record labels see little economic benefit, they are unlikely to release more music in the long run.

While the annual revenue of recorded music has grown 8.9% annually since 2018, with music streaming becoming the dominant medium, no source provides royalty payouts available at an artist level. Therefore, this paper aims to assess whether enhanced transparency and rising composer shares increased performers' willingness to release more music.

FIGURE 2
RETAIL SALES IN REAL $ (BILLIONS) AND PERCENT OF TOTAL



Source: Recording Industry Association of America (RIAA), inflation adjustment based on 2022 dollars.

For the CRB Phonorecord III regulation to be an incentive, composers must believe that the market for streaming will expand. Unlike traditional supply and demand, where an equilibrium price is set, the regulation enhances composers' share of revenue. This means that if DSPs see declining revenue and/or more composers compete for their share of royalty revenue, composers may see decreasing royalty streams.

I use a negative binomial count model empirical approach on a comprehensive data set integrating multiple sources. It includes a panel model with an artist fixed-effects functional form when evaluating trends in age, gender, genre, and composer credits. While the univariate trendline among overall performers does not indicate a significant increase in release activity, the model suggests that key cohorts are showing signs of responding to the new incentives. Specifically, composers (with increasing numbers of credits), as well as younger and female artists, released more music after the MMA law and CRB regulation were enacted.

Admittedly, there is one US commercial music market influenced by the law and regulation, and I am not satisfied that an exogenous, representative control exists. I considered a series of possible markets and other criteria, but I am not satisfied that any of the options would avoid endogenous spillover effects. Therefore, the primary objective of this paper is to examine heterogeneity among groups displaying greater increases in release activity.

This paper presents a literature review in Section 2, followed by data and empirical analysis in Section 3, and discussion and conclusions in Sections 4 and 5.

LITERATURE REVIEW

The recorded music industry has faced a challenging transition from physical to digital music (Aguiar & Waldfogel, 2018; Christensen, 2022; Hogue, 2023). The industry was slow to embrace the migration from physical to digital media, given its vested interest in selling compact discs with high-profit margins. While successful infringement lawsuits and the launch of iTunes raised great hopes for the recorded music industry, the existing Federal regulatory structure needed updating to accommodate the shift to subscription-based music. It was not until the DSPs gained cooperation from the big three record labels to create easy-to-access platforms with reservoirs of over 100 million songs (Peoples, 2023).

The MMA provides a form of copyright enhancement by establishing the MLC as an objective third party to administrate their interests. Notably, the literature on copyright enhancements is inconclusive. Some (Haydari & Smead, 2015) find that copyright enhancements diminish productivity, while others concur that they have the opposite effect (Hu & Yin, 2022; Zhang & Shan, 2023).

Potts and Cunningham provide a meaningful theoretical framework for assessing economic outcomes for recorded music. Their paper theorizes four possible models for the creative industries (Potts and Cunningham, 2010):

- Welfare: Creative industries have a negative impact on the economy, such that they consume more resources than they produce ($dY/dCI<0$, where Y = value of the whole economy and CI = economic value of the creative industries).
- Competitive: A change in the size or value of the creative industries has a proportionate (but structurally neutral) effect on the whole economy ($dY/dCI=0$).
- Growth: Positive economic relation between growth in the creative industries and the growth in the aggregate economy ($dY/dCI>0$).
- Innovation: Re-conceptualizes the creative industries as a higher-order system that operates on the economic system (dY/dCI is undefined).

If the creative industries drive parity or higher rates of economic growth (as outlined in their competitive and growth models), then we would expect the MMA and the CRB rate increase to establish a financial incentive to release more music. By contrast, if music follows the welfare model (e.g., is a merit good) (Baumal & Bowen, 1966) where Economic growth drives the creative industries through a transfer of resources, then the law and regulation combination would have an insignificant effect on release activity because investment will flow to sectors providing greater economic value. While there may be short-term productivity gains due to other factors, in the long term, the increased labor will lack economic justification. To address possible short-term lifts, I included controls for seasonal and annual effects.

Therefore, this paper makes the strong assumption that if composers release more music during MMA negotiation and post-2018 enactment, it is likely due to expectations of future revenue streams (Salant et. al., 2023; Salant & Spenkuch, 2023). While artists may release music to increase their awareness, the MMA law and CRB regulation would not have changed the trajectory of release frequency. Also, with private investors showing an increased willingness to pay a premium for composers' catalogs since 2018, there is some indication of this expectation (Weintraub et. al., 2023). This assumption aligns with the economic theory of supply that the expectation of greater future earnings leads to a shift along the supply curve upward to the right.

DATA AND EMPIRICAL ANALYSIS

Data

The empirical design of this work integrates US artist and release data from several sources. Table 1 presents artist-level data sources on track release productivity for the US market from January 2016 to December 2022, as reported by MusicBrainz.org. The data was combined with an extract of 442.4 million songs identified by the US-based MLC database. The two files were merged using the artist identifier (aka IPI). The data set also includes weekly industry streaming data sourced from Luminate, an application that reports music streams for the US music industry.

The data are aggregated by quarter, and time-based variables were defined to identify the pre-regulatory period from the first quarter of 2016 through the fourth quarter of 2017. There are two post-periods defined. The first period is from the fourth quarter of 2018 through the fourth quarter of 2022, reflecting the time after the MMA was enacted. A second intermediary post-period (first through third quarter 2018) was also created, reflecting the pre-passage period when the Music Modernization Act was being lobbied, debated, and written (Figure 1).

TABLE 1
DATA SOURCE CHARACTERISTICS

Source	Characteristics	Cases
MusicBrainz.Com	US Album, E.P., Live Concert releases, track releases, and profile of artist gender, primary genre, and years playing professionally.	51,137 artists, 1,534,110 releases
Mechanical Licensing Collective	Database of recorded songs, the composer, performing artists, and publishers	442.4 million musical works, merged 128,160 works with matching IPI ID
Luminate	US Streaming data: All weekly total, audio, video, and programmed digital streams by Spotify, Apple Music, Amazon, and all other major digital streaming platforms for 2016 through 2022	378 weeks of total streams

Table 2 highlights the distribution of the variables of US release data included in the analysis. *Releases* reflect the number of unique artist releases per quarter. *Singles*, *albums*, and *EPs* reflect the unique type of releases. *Tracks* reflect the total number of songs released. *The total quarterly streams* reflect the industry's on-demand and programmatic audio and video streams. *Artist age* and *gender* are filtered among artists at a minimum age of 10 (1,288 records of artists reporting age 1 to 9 were filtered from the age predictors). Also, groups and production companies are excluded from the analysis. *Composer credits* reflect the number of composing credits registered in the Mechanical Licensing Collective's database, where 8.4% of performers are registered as composers. All composer analysis is filtered among single and group performers. Lastly, *genre*, sourced from MusicBrainz, is an overlapping variable as artists often release music in multiple genres.

TABLE 2
DATA FREQUENCIES

Variables	Obs	Mean	Std. Dev.	Min	Max
Singles	1,427,804	.035	.264	0	48
Albums	1,427,804	.038	.296	0	46
EPs	1,427,804	.012	.138	0	15
Releases	1,427,804	.086	.458	0	62
Tracks	1,427,804	.616	4.505	0	1000
Quarterly total streams (billions)	1,427,804	26.6	8.9	10.1	37.2
Artist age	572,544	35.91	18.018	10	105
Artist gender (male)	691,628	.737	.44	0	1
Percent w/composer credits	1,427,804	.084	.277	0	1
# of composer credits	119,588	216.459	804.358	1	45971

Variables	Obs	Mean	Std. Dev.	Min	Max
Genre					
Alternative	468,832	.017	.128	0	1
Bluegrass	468,832	.005	.072	0	1
Christian	468,832	.01	.099	0	1
Classical	468,832	.027	.162	0	1
Country	468,832	.028	.164	0	1
Electronic	468,832	.07	.254	0	1
Folk	468,832	.052	.222	0	1
Heavy metal	468,832	.136	.342	0	1
Jazz	468,832	.086	.281	0	1
Latin	468,832	.028	.164	0	1
Pop	468,832	.186	.389	0	1
Punk	468,832	.04	.196	0	1
R&B	468,832	.172	.377	0	1
Rock	468,832	.254	.435	0	1

Data Trends

Table 3 highlights the trends in release activity from 2016 through 2022. While artists are producing more singles, they are producing fewer albums, EPs, and tracks overall. Also, unsurprisingly, streaming activity increased throughout the period.

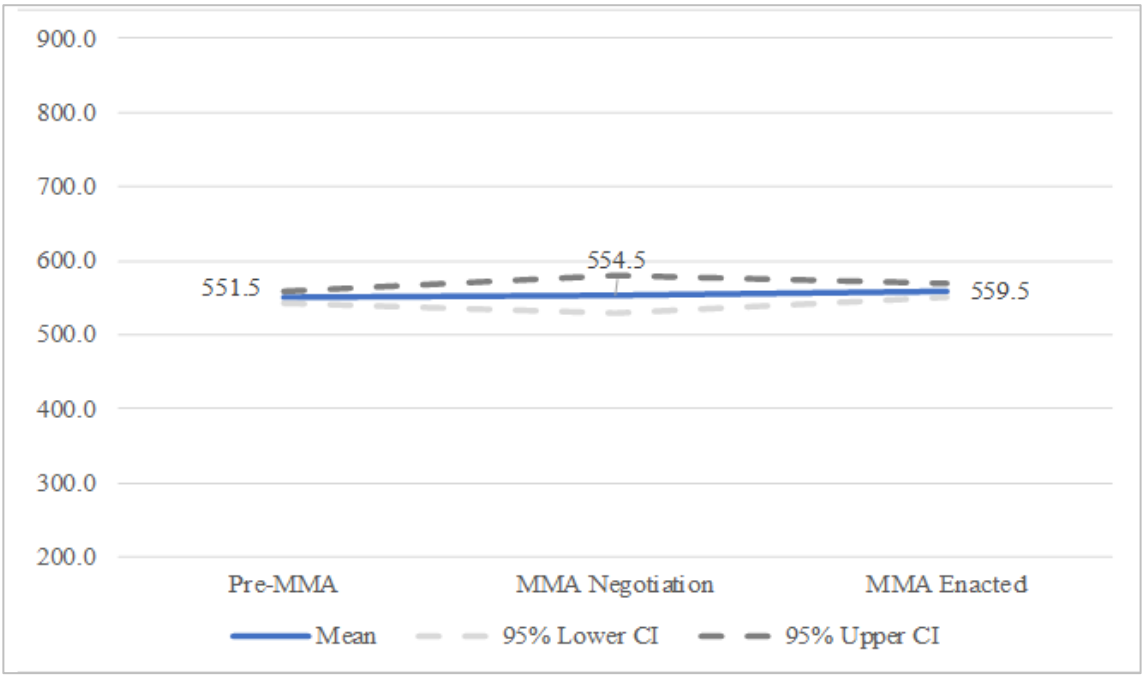
TABLE 3
AVERAGE QUARTERLY COUNTS OVER TIME

PRE/POST and Year	Pre-period (2016-2017)	MMA Negotiation (Q1-Q3 2018)	MMA Enacted (Q4 2018 - Q2 2023)*
Single releases	0.0303	0.0337	0.0347
Albums released	0.0468	0.0459	0.0352
Eps released	0.0140	0.0132	0.0108
Release count	0.0911	0.0934	0.0811
Track count	0.6011	0.5816	0.4760
Average quarterly Streams (billions)	134	263	329

Note. *Industry streams are from 2016 through Q4 2022. Luminate acknowledged a discrepancy in their data for Q1 2020. According to Luminate personnel, this anomaly was caused by changes in their data sources. Time-based controls in the estimations process were used to address this problem.

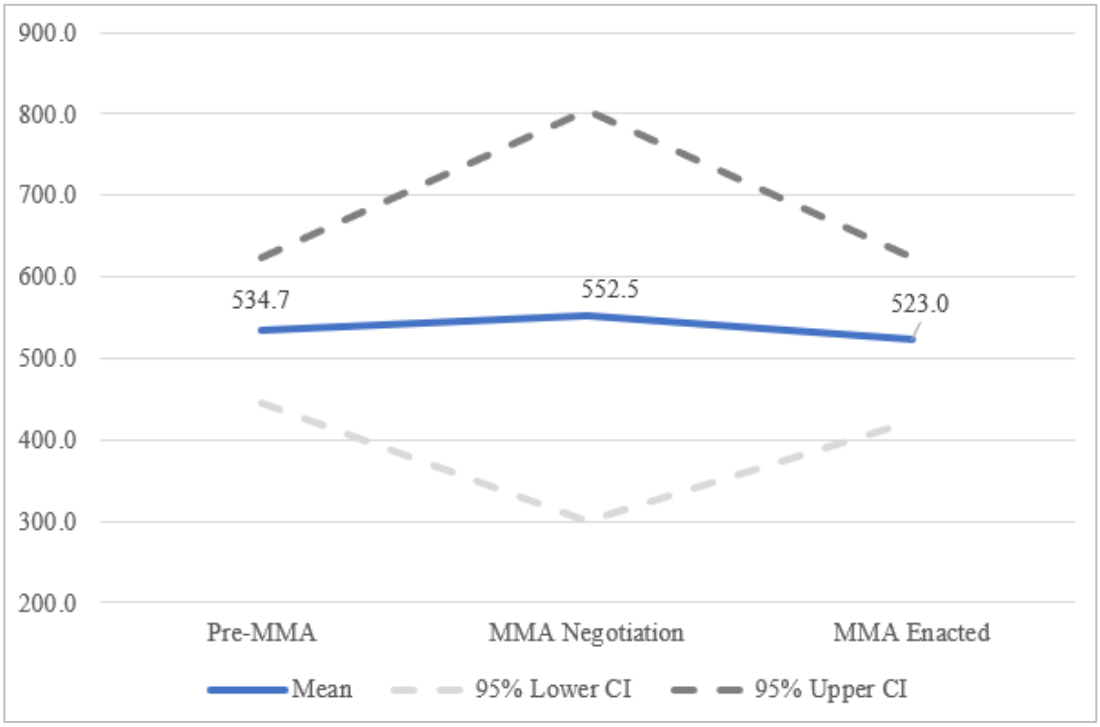
Exploring days between releases tells a similar story of little change in release activity before vs. after the MMA entered negotiations (Figures 3 and 4). Whether we look at performers or performing composers, days between releases are at parity.

FIGURE 3
DAYS BETWEEN MUSIC RELEASES (AMONG PERFORMERS)



Source: MusicBrainz.org. Note: data was disaggregated to date of each release.

FIGURE 4
DAYS BETWEEN MUSIC RELEASES (AMONG COMPOSING PERFORMERS)



Source: MusicBrainz.org. Note: data was disaggregated to date of each release.

Negative Binomial Count Model With Artist Fixed-Effects Specification and Results

While the univariate analysis does not paint an encouraging picture of how performing artists respond to the new law and rate increase regulation, the analysis lacks the appropriate controls to isolate possible effects. It thus leaves us with this paper's questions to be addressed. Specifically, does adding fixed effects identify trends at the artist level? Does including composing credits, gender, and age identify pockets of growing artist productivity? Does a natural log of total streams *ln(total streams$_t$)* (a proxy for streaming growth) explain a portion of any increase in release activity? Lastly, could it be that artists responded to the new incentives by producing more singles and/or music tracks? A negative binomial count model with a quarterly aggregation was specified using the following functional forms.

Empirical Functional Form

$$Y_{it} = a_{it} + MMA\ Negotiation_t + MMA\ Enacted_t + \ln(total\ streams)_t + Quarterly\ Seasonality_t + Annual\ Seasonality_t + g_{it} + e_{it} \quad (1)$$

$$Y_{it} = a_{it} + MMA\ Negotiation_t + MMA\ Enacted_t + \ln(total\ streams)_t + Age(16-24, 25+)_{it} + Age(16-24, 25+)_{it} * MMA\ Negotiation_t + Age(16-24, 25+)_{it} * MMA\ Enacted_t + Quarterly\ Seasonality_t + Annual\ Seasonality_t + g_{it} + e_{it} \quad (2)$$

$$Y_{it} = a_{it} + MMA\ Negotiation_t + MMA\ Enacted_t + \ln(total\ streams)_t + Gender_{it} + Age(16-24, 25+)_{it} + MMA\ Negotiation_t * Gender_{it} + MMA\ Enacted_t * Gender_{it} + MMA\ Negotiation_t * Age(16-24, 25+)_{it} + MMA\ Enacted_t * Age(16-24, 25+)_{it} + Quarterly\ Seasonality_t + Annual\ Seasonality_t + g_{it} + e_{it} \quad (3)$$

$$Y_{it} = a_{it} + MMA\ Negotiation_t + MMA\ Enacted_t + \ln(total\ streams)_t + MLC\ composer\ credits(1-49, 50-149, 150+)_{it} + MLC\ composer\ credits(1-49, 50-149, 150+)_{it} * MMA\ Negotiation_t * Age(16-24, 25+)_{it} + MLC\ composer\ credits(1-49, 50-149, 150+)_{it} * MMA\ Enacted_t * Age(16-24, 25+)_{it} + Quarterly\ Seasonality_t + Annual\ Seasonality_t + g_{it} + e_{it} \quad (4)$$

Identification for the two post periods is denoted by *MMA Negotiation$_t$* and *MMA Enacted$_t$*. The launch of the MLC operations in January 2021 was explored but determined to have no identifiable effects on music releases. Covariate ($\ln(total\ streams)_t$) was included to control for the exogenous growth of music streaming. Time-based controls (*Quarterly seasonality and Annual Seasonality)* were included to account for seasonality and unique events for each year during the 2016-2022 timeframe, including COVID-19. Alternative controls for COVID, including deaths and hospitalizations, were explored but it was found that quarterly and annual seasonality effectively controlled for these impacts. *MLC composer credits$_{it}$* were derived from the MLC database. Composer credits were grouped into those reporting 1 to 49, 50 to 149, and 150 or more composed songs throughout their career. The release date for each composition was not provided, so composer credits are based on a cumulative database snapshot as of June 5, 2023. Age range $(16-24, 25+)$ and gender were included as covariates to identify cohorts releasing more music. Artist fixed effects are denoted by g_{it}.

Each model includes dependent variables for the type of release. Albums are groups of recordings with eight or more songs, while EPs have 4 to 7 songs, and singles include 1 to 3 songs. Releases reflect a cumulation of all release types, and tracks encompass the number of tracks a performer released.

Model 1 (Table 4) shows how total music streams as a control dilute the limited impact of the new regulations on performers' release activity. If performers have responded to any incentive, streaming growth has encouraged them to release more singles. This makes sense and may indicate that performers view releasing music as a promotional tool to cultivate income through live performances and other sources.

TABLE 4
NEGATIVE BINOMIAL COUNT MODEL FOR MODEL 1

Release type	*Singles*		*Albums*		*EPs*		*Releases*		*Tracks*	
MMA negotiation	-0.195		-0.125		-0.453	*	-0.22	*	-0.227	*
	(0.14)		(0.13)		(0.21)		(0.09)		(0.09)	
MMA enacted	-0.256		-0.05		-0.464		-0.205		-0.213	*
	(0.17)		(0.16)		(0.26)		(0.11)		(0.11)	
ln(total streams)	1.123	***	-0.408		-0.176		0.218		0.199	
	(0.26)		(0.25)		(0.40)		(0.17)		(0.17)	
Constant	-29.798	***	8.365		2.348		-6.844		-9.246	*
	(6.54)		(6.25)		(10.22)		(4.22)		(4.25)	

* p<0.05, ** p<0.01, ***p<0.001
Note. (N/Wald Chi-sq): Singles: (497,900/544.4), Albums(664,125/443.3), EP(281,250/238.6), Release count(1,161,075/396.0),Tracks(1,157,250/378.7)

Interacting MMA with a performer's age highlights that younger artists were more responsive to the co-occurring law-regulation, as evidenced by their increased release activity in Model 2 (Table 5). In particular, artists ages 16 to 24 released more tracks compared to those ages 25 and above after MMA was enacted. This aligns with other research indicating that performers earlier in their careers tend to release more music to establish themselves in the industry (Hogue, 2023). This may also indicate that the MMA and CRB rate increase play an incremental complementary role in addition to existing incentives. Growth in productivity is also present among 16 to 24-year-olds during the MMA negotiation period.

TABLE 5
NEGATIVE BINOMIAL COUNT MODEL FOR MODEL 2 WITH AGE 16 TO 24 VS. 25+ INTERACTIONS

Release type	*Singles*		*Albums*		*EPs*		*Releases*		*Tracks*	
MMA negotiation	-0.211		-0.28		-0.187		-0.253	*	-0.275	*
	(0.18)		(0.18)		(0.32)		(0.12)		(0.12)	
MMA enacted	-0.243		-0.272		-0.197		-0.271		-0.298	*
	(0.22)		(0.22)		(0.38)		(0.15)		(0.15)	
Age 16 to 24	-0.218	***	-0.525	***	-0.209	*	-0.244	***	0.401	***
	(0.05)		(0.07)		(0.09)		(0.04)		(0.03)	
MMA negotiation *Age 16 to 24	0.204	**	0.375	***	0.348	**	0.31	***	0.353	***
	(0.07)		(0.10)		(0.13)		(0.05)		(0.05)	
MMA enacted*Age 16 to 24	0.378	***	0.667	***	0.377	***	0.542	***	0.581	***
	(0.05)		(0.08)		(0.10)		(0.04)		(0.04)	
ln(total streams)	1.209	***	0.248		-0.380		0.631	**	0.630	**
	(0.33)		(0.34)		(0.59)		(0.22)		(0.23)	
Constant	-31.88	***	-8.11		7.64		-17.198	**	-20.1	***
	(8.31		(8.65		(15.04)		(5.67)		(5.72)	

* p<0.05, ** p<0.01, ***p<0.001
Note. Filtered among single performing artists age 16+; Age 25+, Year: 2016, and Q1 are omitted variables
Note. (N/Wald Chi-sq): Singles: (290,792/688.8), Albums(328,080/229.9), EP(131,432/105.45), Release count(598,722/498.2),Tracks(595,862/1,487.0)

Adding an interaction by gender in Model 3 (Table 6) further highlights that, even after controlling for age, streaming growth, and age/MMA interactions, females were more motivated than their male counterparts, releasing more tracks, singles, albums, and releases. The inverse natural log (e^x) of the coefficients indicates women have been releasing 1.3 more singles, 1.1 more albums, 1.2 more releases, and 1.2 more tracks per quarter. This is an interesting finding for an underrepresented group in professional music (Table 2).

TABLE 6
NEGATIVE BINOMIAL COUNT MODEL FOR MODEL 3 WITH GENDER AND AGE INTERACTIONS

Release type	*Singles*		*Albums*		*EPs*		*Releases*		*Tracks*	
MMA negotiation	-0.203		-0.304		-0.211		-0.258	*	-0.279	*
	(0.19)		(0.18)		(0.33)		(0.12)		(0.13)	
MMA enacted	-0.257		-0.268		-0.249		-0.279		-0.304	*
	(0.22)		(0.22)		(0.40)		(0.15)		(0.15)	
Age 16 to 24	-0.182	***	-0.469	***	-0.191	*	-0.219	***	0.378	***
	(0.05)		(0.07)		(0.10)		(0.04)		(0.03)	
Gender: female	-0.026		-0.682	***	-0.174		-0.146	***	0.044	
	(0.06)		(0.06)		(0.13)		(0.04)		(0.02)	
MMA negotiation*Female	0.09		0.059		-0.076		0.07		0.084	*
	(0.05)		(0.06)		(0.10)		(0.04)		(0.04)	
MMA enacted*Female	0.225	***	0.109	**	-0.009		0.169	***	0.178	***
	(0.04)		(0.04)		(0.06)		(0.03)		(0.03)	
MMA negotiation*Age16 to 24	0.177	*	0.397	***	0.39	**	0.302	***	0.343	***
	(0.07)		(0.10)		(0.14)		(0.05)		(0.06)	
MMA enacted*Age16 to 24	0.319	***	0.666	***	0.383	***	0.506	***	0.547	***
	(0.05)		(0.08)		(0.11)		(0.04)		(0.04)	
ln(total streams)	1.199	***	0.178		-0.229		0.625	**	0.621	**
	(0.34)		(0.35)		(0.61)		(0.23)		(0.23)	
Constant	-31.642	***	-6.187		3.873		-17.015	**	-19.87	***
	(8.55)		(8.88)		(15.57)		(5.84)		(5.89)	

* p<0.05, ** p<0.01, ***p<0.001
Note. Filtered among single performing artists age 16+; Age 25+, Gender: Males, Q1, MMA negotiation*Males+, MMA enacted*Males, MMA negotiation*Age 25+, MMA enacted*Age 25+, and Year 2016 are omitted variables
Note. (N/Wald Chi-sq): Singles: (271,627/745.8), Albums(307,283/370.0), EP(172,736/105.8), Release count(556,702/551.4),Tracks(553,950/1,536.45)

Model 4 (Table 7) interacts the MMA time frames with composer credits by age. As expected, the production of musical tracks increases steadily for performers who own more composing credits. Younger composers (age 16 to 24) were more responsive during both the negotiation and the enactment periods. These younger composers with 50 to 149 composing credits were the most productive with more singles, albums, releases, and tracks. The inverse natural log (e^x) of the coefficients indicates younger composers have been releasing 1.7 more singles, 2.0 more albums, 1.8 more releases, and 2.1 more tracks per quarter.

TABLE 7
NEGATIVE BINOMIAL COUNT MODEL FOR MODEL 4 WITH AGE AND COPYRIGHT INTERACTIONS

Release type	*Singles*		*Albums*		*EPs*		*Releases*		*Tracks*	
MMA negotiation	-0.232		-0.341		-0.194		-0.292	*	-0.424	***
	(0.18)		(0.18)		(0.32)		(0.12)		(0.12)	
MMA enacted	-0.257		-0.309		-0.225		-0.291	*	-0.418	**
	(0.22)		(0.22)		(0.39)		(0.15)		(0.15)	
Age 16 to 24	-0.097	*	-0.314	***	-0.064		-0.071	*	0.63	***
	(0.04)		(0.06)		(0.09)		(0.03)		(0.03)	
50 to 149 composer credits	0.345	*	-0.118		-0.214		0.146		0.365	***
	(0.14)		(0.12)		(0.27)		(0.08)		(0.05)	
150+ composer credits	0.109		0.339	***	0.119		0.165	*	-0.164	***
	(0.11)		(0.10)		(0.22)		(0.07)		(0.04)	
MMA negotiation*16 to 24*1 to 49 credits	-0.051		0.195		0.041		0.04		0.129	
	(0.16)		(0.25)		(0.35)		(0.13)		(0.12)	
MMA negotiation*16 to 24*50 to 149 credits	0.217		0.378		-0.028		0.276	*	0.534	***
	(0.14)		(0.20)		(0.32)		(0.11)		(0.11)	
MMA negotiation*16 to 24*150+ credits	0.297		0.307		0.141		0.36	*	1.142	***
	(0.22)		(0.34)		(0.54)		(0.18)		(0.18)	
MMA enacted*16 to 24*1 to 49 credits	0.517	***	0.561	*	0.733	*	0.507	***	0.526	***
	(0.15)		(0.23)		(0.37)		(0.12)		(0.10)	
MMA enacted*16 to 24*50 to 149 credits	0.516	***	0.695	***	0.399		0.575	***	0.728	***
	(0.11)		(0.15)		(0.23)		(0.09)		(0.08)	
MMA enacted*16 to 24*150+ credits	0.007		0.044		0.215		0.109		0.989	***
	(0.21)		(0.33)		(0.49)		(0.17)		(0.16)	
MMA negotiation*25+*1 to 49 credits	-0.023		0.127		-0.103		0.03		0.116	*
	(0.09)		(0.08)		(0.17)		(0.06)		(0.06)	
MMA negotiation*25+*50 to 149 credits	0.024		-0.008		0.227		0.045		0.312	***
	(0.08)		(0.08)		(0.15)		(0.06)		(0.06)	
MMA negotiation*25+*150+ credits	0.161	*	0.048		-0.142		0.094	*	0.88	***
	(0.07)		(0.06)		(0.14)		(0.05)		(0.04)	

Release type	*Singles*		*Albums*	*EPs*	*Releases*		*Tracks*	
MMA enacted*25+*1 to 49 credits	0.206	**	0.025	-0.058	0.106	*	0.189	***
	(0.07)		(0.07)	(0.13)	(0.05)		(0.05)	
MMA enacted*25+*50 to 149 credits	0.065		0.017	0.149	0.057		0.205	***
	(0.06)		(0.06)	(0.12)	(0.04)		(0.04)	
MMA enacted*25+*150+ credits	0.084		0.015	0.037	0.046		0.821	***
	(0.05)		(0.04)	(0.09)	(0.03)		(0.03)	
ln(total streams)	1.212	***	0.251	-0.38	0.632	**	0.628	**
	(0.33)		(0.34)	(0.59)	(0.22)		(0.23)	
Constant	-32.113	***	-8.46	7.533	-17.4	**	-19.981	***
	(8.31)		(8.65)	(15.04)	(5.67)		(5.72)	

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

Note. Filtered among single performing artists age 16+; 1 to 49 composer credits, age 25+, Q1, and Year 2016 are omitted variables. (N/Wald Chi-sq): Singles: (290,792/705.1), Albums(328,080/220.4), EP(131,432/104.9), Release count(598,722/388.0),Tracks(595,862/3826.7)

I also explored the influence of genres on release activity to determine if some musical communities may be more responsive to the MMA and CRB regulation than others. This work was inconclusive. The models are presented in the Appendix (A1).

DISCUSSION

If we look at the overall performer community, there does not appear to be any impact of either the MMA enactment and/or CRB rate increase on artist release activity. This no doubt supports the narrative of music being a merit good (Baumal & Bowen, 1966; Potts & Cunningham, 2010). However, performers with composing credits (particularly younger composers) did respond by releasing more music. While younger composing performing artists have a greater incentive to establish themselves by releasing music, this cohort's post-MMA release of more singles, tracks, and albums may point to a complementary incentive for these performers. The expectation of future earnings may be a catalyst encouraging their musical creativity. While not identified in my data, some of this activity may be motivated by composers 'featuring' on other artists' songs.

Increased productivity by female performers highlights a finding that is not fully understood. One possibility is that given the underrepresentation of women in professional music, perhaps the MMA and CRB rate increase have played a complementary role in fostering greater expectation of financial upside for their recorded performances. In essence, their labor presents a market expansion opportunity for their underrepresented group. For context, among all MusicBrainz records with gender identified, only 23.3% of tracks are performed by female performers.

This highlights a mixed bag as it relates to the model framework for the creative industries (Potts & Cunningham, 2010). In reality, Potts and Cunningham's competitive, growth, and welfare models are all applicable to differing segments of music performers. The overall industry (and likely the narrative) is that the rate increases and pay transparency for recorded music have not changed release activity for the industry. However, younger performers, composers (particularly younger), and female performers are releasing more music.

The shift in releasing singles has risen in recent years, but no substantive evidence exists that the MMA and/or CRB rate increase influenced this trend. Rather, it appears to be a growing phenomenon more aligned with the growth of streaming (and possibly social media).

CONCLUSIONS

We do not know yet whether or not musical performing artists benefit economically from the new law and regulation. Yes, the retail music industry's revenue has grown robustly in recent years, but we do not know how this plays out in terms of individual artist royalties. If there is a financial incentive to release more music, it likely involves the expectation of increased future earnings. Additionally, the rate increase, combined with a more transparent payment process, may have played a role. Given that release activity increased in response to the MMA negotiation and enactment, as well as the CRB rate increase among composers, younger, and female performers, it appears that these performers see a meaningful incentive to contribute more labor to releasing music.

Further work will be needed to identify the phenomenon of anecdotal growth in artist collaborations (e.g., 'featuring') and the growing release activity of female artists.

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APPENDIX

TABLE A-1
NEGATIVE BINOMIAL COUNT MODEL AMONG COMPOSERS AND BY GENRE

Release type	*Singles*		*Albums*		*EPs*	*Releases*	*Tracks*
MMA negotiation							
Alternative	-0.266		-0.111		-1.132	-0.3	-0.299
	(0.39)		(0.45)		(0.93)	(0.30)	(0.31)
Bluegrass	0.936		-0.318		-40.078	-0.232	-0.183
	(0.76)		(0.53)		(3,280.74)	(0.42)	(0.42)
Christian	0.66		0		-0.603	0.133	0.104
	(0.46)		(0.40)		(0.90)	(0.29)	(0.29)
Classical	-0.476		0.033		0.36	-0.153	-0.171
	(0.42)		(0.22)		(0.46)	(0.19)	(0.19)
Country	0.049		0.019		-0.19	-0.051	-0.049
	(0.23)		(0.20)		(0.46)	(0.15)	(0.15)
Electronic	0.2		-0.453		-0.448	-0.095	-0.092
	(0.17)		(0.23)		(0.37)	(0.14)	(0.14)
Folk	0.072		0.23		-0.231	0.084	0.084
	(0.23)		(0.16)		(0.39)	(0.13)	(0.13)
Heavy Metal	-0.317		0.197		0.319	-0.053	-0.022
	(0.42)		(0.34)		(0.59)	(0.27)	(0.27)
Jazz	0.028		0.623	***	-0.538	0.263	0.267
	(0.30)		(0.17)		(0.46)	(0.14)	(0.14)
Latin	-0.342		-0.413		-39.762	-0.32	-0.317
	(0.21)		(0.45)		(3,016.61)	(0.19)	(0.20)
Pop	0.233	*	0.043		-0.016	0.074	0.066
	(0.11)		(0.12)		(0.24)	(0.08)	(0.08)
Punk	-0.848		0.261		0.087	-0.211	-0.089
	(0.79)		(0.62)		(1.31)	(0.46)	(0.46)
R&B	-0.001		0.061		0.207	-0.002	0.024
	(0.12)		(0.15)		(0.29)	(0.10)	(0.10)
Rock	-0.061		-0.071		-0.099	-0.125	-0.082
	(0.15)		(0.14)		(0.28)	(0.10)	(0.10)

* p<0.05, ** p<0.01, ***p<0.001
Note. Filtered among single performing artists age 16+; Q1, and Year 2016 are omitted variables
Note. (N/Wald Chi-sq): Singles: (36,625/398.1), Albums(39,975/282.4), EP(14,150/95.5), Release count(52,025/381.0),Tracks(51,950/915.7)

TABLE A-1
NEGATIVE BINOMIAL COUNT MODEL AMONG COMPOSERS AND BY GENRE CONTINUED

Release type	*Singles*		*Albums*		*EPs*		*Releases*		*Tracks*	
MMA enacted										
Alternative	-0.107		0.331		-0.477		0.214		0.214	
	(0.25)		(0.26)		(0.44)		(0.18)		(0.18)	
Bluegrass	-0.143		-0.319		-0.831		-0.504		-0.527	
	(0.62)		(0.35)		(0.84)		(0.28)		(0.29)	
Christian	0.413		-0.506		-0.17		-0.204		-0.165	
	(0.34)		(0.27)		(0.54)		(0.20)		(0.20)	
Classical	-0.514	*	0.006		-0.263		-0.2		-0.13	
	(0.26)		(0.14)		(0.33)		(0.12)		(0.12)	
Country	0.54	***	-0.032		-0.081		0.149		0.153	
	(0.15)		(0.13)		(0.29)		(0.10)		(0.10)	
Electronic	-0.049		0.031		-0.439		-0.077		-0.064	
	(0.12)		(0.13)		(0.24)		(0.09)		(0.09)	
Folk	0.189		-0.08		0.27		-0.056		-0.049	
	(0.15)		(0.11)		(0.24)		(0.09)		(0.09)	
Heavy Metal	-0.137		0.34		0.403		0.152		0.12	
	(0.26)		(0.22)		(0.42)		(0.17)		(0.17)	
Jazz	0.081		0.13		-0.314		-0.072		-0.039	
	(0.20)		(0.12)		(0.28)		(0.10)		(0.10)	
Latin	-1.023	***	-0.798	**	-0.433		-0.886	***	-0.791	***
	(0.15)		(0.29)		(0.75)		(0.13)		(0.14)	
Pop	-0.018		0.213	**	0.095		0.043		0.061	
	(0.07)		(0.08)		(0.16)		(0.05)		(0.06)	
Punk	-0.326		0.478		-0.488		0.021		0.065	
	(0.41)		(0.40)		(1.03)		(0.29)		(0.29)	
R&B	-0.086		-0.062		0.358		-0.057		-0.041	
	(0.08)		(0.09)		(0.19)		(0.06)		(0.06)	
Rock	0.044		-0.307	***	-0.428	*	-0.237	***	-0.183	**
	(0.10)		(0.09)		(0.19)		(0.07)		(0.07)	
ln(streams)	1.214		1.066		2.568		1.523	**	1.552	**
	(0.72)		(0.80)		(1.63)		(0.55)		(0.56)	
Constant	-32.001		-29.111		-67.812		-39.986	**	-43.218	**
	(18.36)		(20.37)		(41.41)		(13.96)		(14.23)	

* p<0.05, ** p<0.01, ***p<0.001
Note. Filtered among single performing artists age 16+; Q1, and Year 2016 are omitted variables
Note. (N/Wald Chi-sq): Singles: (36,625/398.1), Albums(39,975/282.4), EP(14,150/95.5), Release count(52,025/381.0),Tracks(51,950/915.7)