

Online Appendices for The Value of Silence: The Effect of UMG’s Licensing Dispute with TikTok on Music Demand

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A Reactions from Artists, TikTok Creators, and Users when Facing the Licensing Dispute

The UMG vs. TikTok licensing dispute, which led to the removal of UMG’s music from the platform, impacted artists, TikTok creators, and users. We describe below reported accounts of various reactions by these stakeholders. Notably, based on an extensive review of media accounts from the relevant timeframe, we do not find systematic behavioral changes by either artists, UMG, or content creators after UMG pulled its music from TikTok.

- **Artists:** A few UMG artists expressed frustration over the situation and the removal of their tracks from TikTok. For instance, UMG artist Noah Kahan voiced concerns in a TikTok video following the dispute, encouraging fans to pre-save his upcoming release (e.g., prompting users to add the unreleased song to their Spotify library ahead of its official launch, Coulter 2024; VOA News 2024). Other artists found ways to engage with their TikTok audiences through live sessions, behind-the-scenes content, and interactive posts on the platform to maintain visibility and tease their upcoming music releases. Some others, however, began shifting their music promotional efforts to alternative platforms, such as YouTube Shorts and Instagram Reels (Hüllbrock 2024; Myers and Milmo 2025).
- **Content Creators:** Many content creators were surprised and flustered to find their videos muted, as they had no prior warning about the removal of audio tracks. In response, some creators chose to delete their muted videos altogether, while a few others substituted the muted audio with royalty-free music or unofficial versions of the original soundtracks (e.g., creators re-record and re-release with them singing the song) to restore the audio component of their video post (music now blog 2024). Beyond the muted videos, creators also expressed frustration with the reduced selection of music, noting that it affected their creative choices and could potentially impact audience engagement (VOA News 2024). This is notable given that UMG tracks reportedly made up around 30% of the popular music available on TikTok (Ingham 2024).
- **TikTok users:** Reactions among TikTok users were mixed. Some users began noticing a lot more indie songs and emerging artists on their “For You” pages – TikTok’s main channel for content discovery. Others were confronted with an uptick in muted videos and a noticeable absence of popular artists like Drake and

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Noah Kahan, which led to decreased engagement with the platform. A number of users reported relatively little disruption to their experience, as their feeds adapted with mashups or unofficial versions of popular tracks repurposed by content creators (Coulter 2024).

B Additional Summary Statistics

Table A1: Summary Statistics of Daily Music Consumption on Spotify Prior to the Dispute

	Spotify Streams Prior to the Dispute			
	All	UMG	WMG	SME
count	146,293.0000	68,662.0000	33,911.0000	44,394.0000
mean	119,978.3079	135,221.8603	159,238.3167	66,169.8586
std	2,066,683.0972	2,253,350.8029	2,512,336.2364	1,188,039.9301
min	0.0000	0.0000	0.0000	0.0000
25%	26.8850	18.0000	34.1043	44.1416
50%	248.1250	176.9348	293.8261	331.2639
75%	2,297.3565	1,975.8389	2,735.2708	2,572.8370
max	206,052,002.4766	206,052,002.4766	205,245,387.4667	159,342,023.2523

Table A2: Summary Statistics of Daily Music Consumption on YouTube Prior to the Dispute

	YouTube Views Prior to the Dispute			
	All	UMG	WMG	SME
count	70,830.0000	30,648.0000	17,911.0000	22,695.0000
mean	1,505,510.9809	1,719,587.9793	1,082,980.4541	1,542,399.3178
std	20,278,849.4717	24,160,123.7349	16,824,912.9416	16,501,673.1106
min	0.0000	0.0000	0.0000	0.0000
25%	128.1429	115.3599	120.3333	156.5476
50%	966.5048	838.0595	822.3333	1,341.4286
75%	17,959.7778	15,875.9762	13,218.8077	26,751.0149
max	1,975,325,743.5000	1,975,325,743.5000	1,254,837,137.6364	998,910,250.6667

Table A3: Summary Statistics of Average Daily Music Consumption on Spotify By Tracks on TikTok Prior to the Dispute

	Spotify Streams Prior to the Dispute			
	All	UMG	WMG	SME
count	4,927,907.0000	2,254,247.0000	1,077,154.0000	1,625,395.0000
mean	300,501.7861	373,334.0056	392,491.5169	136,523.8600
std	6,440,240.9211	7,862,905.3919	5,719,925.5722	4,285,604.6607
min	0.0000	0.0000	0.0000	0.0000
25%	342.0000	312.0000	363.0000	378.0000
50%	2,072.0000	2,055.0000	2,022.0000	2,167.0000
75%	13,827.0000	15,246.0000	13,227.7500	12,704.0000
max	3,055,403,292.0000	3,055,403,292.0000	2,431,806,997.0000	2,653,174,557.0000

Table A4: Summary Statistics of Average Daily Music Consumption on YouTube By Tracks on TikTok Prior to the Dispute

	YouTube Views Prior to the Dispute			
	All	UMG	WMG	SME
count	445,721.0000	202,135.0000	96,585.0000	149,742.0000
mean	1,224,791.6472	1,216,980.5659	1,204,289.7286	1,235,678.8281
std	26,608,344.5891	23,242,857.7067	36,749,373.1383	22,531,849.8853
min	0.0000	0.0000	0.0000	0.0000
25%	177.0000	157.0000	177.0000	215.0000
50%	868.0000	769.0000	814.0000	1,072.0000
75%	5,069.0000	4,349.0000	4,533.0000	6,653.0000
max	7,120,032,301.0000	3,924,366,613.0000	7,120,032,301.0000	2,580,171,535.0000

Table A5: Summary Statistics of Average Daily Music Consumption on Spotify By Tracks Not on TikTok Prior to the Dispute

	Spotify Streams Prior to the Dispute			
	All	UMG	WMG	SME
count	10,568,574.0000	5,047,461.0000	2,435,271.0000	3,128,345.0000
mean	38,317.2926	31,494.4498	63,522.8081	29,832.8153
std	2,029,477.9006	1,543,226.6826	1,459,209.4030	2,903,318.4793
min	0.0000	0.0000	0.0000	0.0000
25%	10.0000	7.0000	14.0000	17.0000
50%	80.0000	52.0000	111.0000	122.0000
75%	556.0000	437.0000	870.0000	570.0000
max	4,048,914,853.0000	2,128,096,502.0000	1,099,802,506.0000	4,048,914,853.0000

Table A6: Summary Statistics of Average Daily Music Consumption on YouTube By Tracks Not on TikTok Prior to the Dispute

	YouTube Views Prior to the Dispute			
	All	UMG	WMG	SME
count	465,727.0000	195,065.0000	136,129.0000	137,211.0000
mean	413,506.9725	433,828.8282	264,244.7968	532,642.5672
std	13,605,372.6587	15,521,739.9788	10,748,767.5847	13,141,948.1819
min	0.0000	0.0000	0.0000	0.0000
25%	34.0000	30.0000	38.0000	38.0000
50%	135.0000	114.0000	158.0000	149.0000
75%	698.0000	551.0000	836.0000	823.0000
max	3,940,740,592.0000	3,940,740,592.0000	2,646,151,659.0000	2,192,757,135.0000

C Three-way Interaction Model for Heterogeneous Effects

In this section, we show the results from the heterogeneous analysis using interaction effects rather than segmenting our data. Table 7 shows the three-way interaction between a track’s absence or presence on TikTok prior to the dispute and the treatment (i.e., the removal of UMG’s music from TikTok). This is analogous to Table 7 in the main text and the results are consistent. We observe that for tracks previously not available on TikTok, the effect is significantly negative ($b = -0.0145$, $p < 0.001$ for Spotify streams in Column (1) and $b = -0.0242$, $p < 0.001$ for YouTube views in Column (2)). Conversely, for tracks that were available on TikTok prior to the dispute, the effect is significantly positive ($b = 0.0241$ ($= -0.0145 + 0.0386$), $p < 0.001$ for Spotify streams in Column (1) and $b = 0.0194$ ($= -0.0242 + 0.0436$), $p < 0.01$ for YouTube views in Column (2)).

Similarly, Table A8 documents the mechanism effects (through artists’ partial availability on TikTok) and is analogous to Table 8 from the main text, and shows consistent results. We can see that for tracks from artists with no presence on TikTok, the effect is not significant ($b = 0.0204$, $p > 0.1$ for Spotify streams in Column (1) and $b = 0.0483$, $p > 0.1$ for YouTube views in Column (2)). In contrast, for tracks by artists with partial presence on TikTok, the effect is negative ($b = -0.0152$ ($= 0.0204 - 0.0356$), $p < 0.05$ for Spotify streams in Column (1) and $b = -0.0288$ ($= 0.0483 - 0.0771$), $p < 0.001$ for YouTube views in Column (2)).

Table A7: Main Effect of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (three-way interaction)

	(1)	(2)
	log_Spotify_streams	log_YouTube_views
1.UMG#1.post	-0.0145*** (0.00257)	-0.0242** (0.00859)
1.Pre_on_TikTok	-0.0174*** (0.00244)	-0.241*** (0.0163)
1.UMG#1.Pre_on_TikTok	-0.00878** (0.00298)	-0.00466 (0.0222)
1.post#1.Pre_on_TikTok	0.0477*** (0.00344)	-0.121*** (0.00948)
1.UMG#1.post#1.Pre_on_TikTok	0.0386*** (0.00475)	0.0436** (0.0140)
_cons	5.574*** (0.000672)	6.055*** (0.00704)
Track FE	Yes	Yes
Date FE	Yes	Yes
N	24653297	1611685
R^2	0.9475	0.8840
aic	56213713.6	4563219.1
bic	56213788.7	4563280.6

Standard errors in parentheses

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

D Other Heterogeneous Treatment Effects

We explore whether the overall null effect observed in the full dataset masks any significant heterogeneity effects along dimensions beyond track availability on TikTok. Specifically, we explore whether the impact of the removal of UMG music from TikTok differs across tracks with varying popularity levels (measured by tracks’ Spotify streams/YouTube views pre-dispute) and across artist subgroups. For artists, we consider differences by popularity ($ArtistPopularity_i$, defined in §4.1 as the artist’s Spotify popularity score) as well as by career stage ($CareerStage_i$, defined in §4.1 as the artist’s career stage).

We begin by examining how the dispute may have differentially affected the music demand for more

Table A8: Main Effect of Removing UMG Music from TikTok on Music Demand: Tracks from Artists with TT Coverage v.s. not (three-way interaction)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	0.0204	(0.0165)	0.0483	(0.0532)
1.post#1.TT_avail_artist	0.0569***	(0.0108)	0.0729	(0.0384)
1.UMG#1.post#1.TT_avail_artist	-0.0356*	(0.0167)	-0.0771	(0.0539)
_cons	4.572***	(0.00400)	4.883***	(0.0163)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	16982133		787275	
<i>R</i> ²	0.9351		0.8976	
aic	38388046.6		1938675.5	
bic	38388090.5		1938710.2	

Standard errors in parentheses

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

popular tracks versus less popular tracks. To do this, we divide the sample based on average Spotify streams prior to the dispute. As shown in columns (1)-(2) of Table A9 below, for the more popular tracks, the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is positive and significant for streams on Spotify ($b = 0.0275$, $p < 0.001$), while for the less popular tracks as seen in columns (3)-(4), the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is negative and significant for streams on Spotify ($b = -0.0240$, $p < 0.001$). This suggests that more popular tracks prior to the dispute exhibit a positive (*substitution*) effect, i.e., they received greater streaming demand after being removed from TikTok’s music library. However, less popular tracks prior to the dispute exhibit a negative (*complementarity*) effect, i.e., they were adversely affected by UMG’s decision to remove music from TikTok.

Table A9: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: More Popular Tracks vs. Less Popular Tracks

	More Popular Tracks Prior to the Dispute		Less Popular Tracks Prior to the Dispute	
	(1) log_spotify_streams	(2) log_youtube_views	(3) log_spotify_streams	(4) log_youtube_views
1.UMG#1.post	0.0275*** (0.00244)	-0.0139 (0.00909)	-0.0240*** (0.00210)	0.00263 (0.00527)
_cons	8.201*** (0.000393)	8.125*** (0.00153)	2.939*** (0.000396)	3.680*** (0.00112)
<i>N</i>	12321650		801682	
<i>R</i> ²	0.9691		0.8039	
aic	12275590.5		2274884.3	
bic	12275604.8		21664694.2	

Standard errors in parentheses

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

Next, we explore heterogeneity based on the artists’ career stages. In Table A10, we categorize artists into three career groups: the reference group consists of developing and undiscovered artists; the medium career stage group includes mid-level and mainstream artists; and the advanced career stage group comprises

superstar and legendary artists. The regression results suggest that, relative to developing and undiscovered artists, mid-level and mainstream artists experience more substitution effects. This is evidenced by the significantly positive coefficient on the interaction term `1.UMG#1.post#artist_status_stage_med` ($b = 0.0212$, $p < 0.01$) for Spotify streams in Column (1) and ($b = 0.0686$, $p < 0.05$) YouTube views in Column (2). Lastly, we examine heterogeneity based on broader measures of artist popularity in Table A11. Consistent with earlier findings, tracks by more popular artists tend to experience stronger substitution effects, as indicated by the significantly positive coefficient on the interaction term `1.UMG#1.post#log_artist_sp_popularity` ($b = 0.0234$, $p < 0.01$) for Spotify streams.

Taken together, these results reveal substantial heterogeneity in user responses to the removal of UMG music from TikTok. The effects vary systematically by both track-level and artist-level popularity, with more popular content and artists benefiting from the removal, while less popular counterparts appear to be more adversely affected.

Table A10: Heterogeneous Treatment Effects of Removing UMG Tracks from TikTok on Music Demand: Artist Career Stage (Developing and Undiscovered Artists as the Reference Group)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
<code>1.UMG#1.post</code>	-0.0151*	(0.00672)	-0.0508*	(0.0258)
<code>1.post#artist_status_stage_med</code>	0.0190***	(0.00455)	-0.0491**	(0.0178)
<code>1.post#artist_status_stage_high</code>	0.0625***	(0.00462)	-0.0386*	(0.0178)
<code>1.UMG#1.post#artist_status_stage_med</code>	0.0212**	(0.00739)	0.0686*	(0.0278)
<code>1.UMG#1.post#artist_status_stage_high</code>	0.00436	(0.00763)	0.0214	(0.0284)
<code>_cons</code>	5.566***	(0.00144)	5.928***	(0.00703)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
N	24423376		1598683	
R^2	0.9475		0.8837	
aic	55722082.5		4533034.3	
bic	55722157.5		4533095.7	

Standard errors in parentheses

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

E Appendix for Parallel Pre-Trend Assumption

In this section, we test the parallel pre-trends assumption for all the model specifications used in the main text as well as the level models used for robustness checks in §5.3.3.

E.1 Parallel Trend Test for the Log DiD Specifications in §5.1

A key assumption of the DiD model is parallel trends: if the treatment group had not received the treatment, the trend in the treatment group's outcomes would have followed the same as the trend of the control group's outcomes (Angrist and Pischke 2009). Therefore, we compare the pre-treatment trends in music demand on Spotify and YouTube for the treatment and control groups by estimating a relative-time model (Autor 2003) at the daily level over our entire time window. As shown in Equation (A1), the model decomposes

Table A11: Heterogeneous Treatment Effects of Removing UMG Tracks from TikTok on Music Demand: Artist Spotify Popularity

	(1)	(2)
	log_Spotify_streams	log_YouTube_views
1.UMG#1.post	-0.0990** (0.0341)	0.138 (0.116)
1.post#log_artist_sp_popularity	0.0555*** (0.00488)	0.00605 (0.0177)
1.UMG#1.post#log_artist_sp_popularity	0.0234** (0.00825)	-0.0347 (0.0283)
_cons	5.494*** (0.00748)	5.901*** (0.0318)
Track FE	Yes	Yes
Date FE	Yes	Yes
N	24405072	1597548
R^2	0.9475	0.8836
aic	55697054.7	4529781.3
bic	55697099.7	4529818.2

Standard errors in parentheses

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

the pre-treatment periods into a series of period dummies, with one day prior to UMG music removal as the reference. Specifically, $Pre(\tau)$ indicates the τ th day prior to the UMG music removal (for $\tau = 1, 2, 3, \dots, 113$). The coefficient of the reference period, $Pre(1)$, is normalized to zero.

$$\begin{aligned}
 \log(Demand_{i\tau} + 1) = & Constant + \sum_{\tau=2,3,\dots,113} \beta_{\tau} * UMG_i * Pre(\tau) + \sum_{\tau=0,1\dots66} \alpha_{\tau} * UMG_i * Post(\tau) \\
 & + \sum_{\tau=2,3,\dots,113} \gamma_{\tau} * Pre(\tau) + \sum_{\tau=0,1\dots66} \lambda_{\tau} * Post(\tau) + track_i + \epsilon_{i\tau}, \quad (A1)
 \end{aligned}$$

where $Demand_{i\tau}$ is the demand of track i on the τ -th day prior to the UMG track removal from TikTok; UMG_i is 1 if track i belongs to UMG, and 0 otherwise; and $Pre(\tau)$ is an indicator for the τ -th day prior to the removal of UMG tracks from TikTok. The series of coefficients, β_{τ} , of the interaction $UMG_i \times Pre(\tau)$ captures the difference in music demand of track i between the treatment and control groups prior to treatment at period $Pre(\tau)$ relative to time period $Pre(1)$, i.e., one day before the removal of UMG tracks from TikTok. As we can see from Figure A1, some β_{τ} coefficients of the interaction $UMG_i \times Pre(\tau)$ before the dispute are significant.

In our case, the pre-treatment period is quite long (113 days), and there is a lot of variance in demand over time due to seasonality, holidays, platform-specific time-varying shocks to traffic, etc. As a result, naive relative-time trend tests can be noisy. Therefore, to investigate this further, we first fit a linear trend model to examine whether the trends for the treatment tracks (UMG) and the control tracks (SME and Warner) systematically differ during the entire pre-treatment period. Specifically, we estimate Equation A2 using the entire pre-treatment data to test for any differential time trends in the average demand between the two groups before the dispute. If no linear trend exists during the pre-treatment period, the coefficient β should be statistically insignificant. Here, t represents the number of days since the licensing dispute on January 31, 2024.

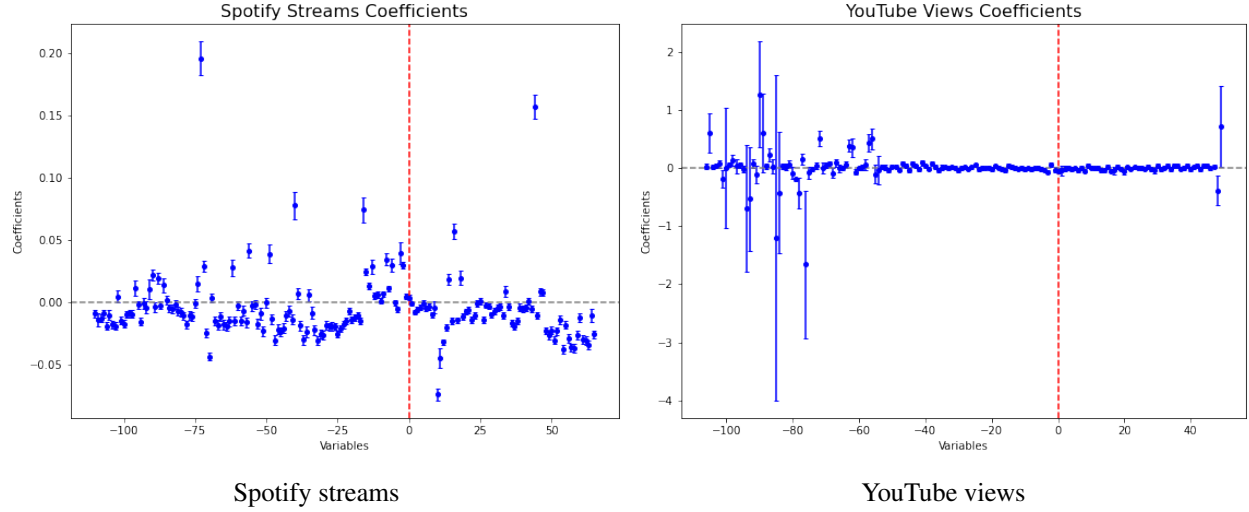


Figure A1: Relative-Time Model Estimation (All Tracks)

$$\log(Demand_{it} + 1) = \alpha + \beta * UMG_i * t + Track_i + Date_t + \epsilon_{it}, \quad (A2)$$

The results from this estimation are shown in Table A12. We see that the linear trend coefficient for Spotify demand in column (1) has a minuscule magnitude (i.e., approximately 1.45% of the coefficient in column (1) of Table 3) though significant, and the linear trend coefficient for YouTube demand in column (2) is insignificant. This suggests that it is very unlikely that the null effect in Table 3 is driven by the time trend before the dispute.¹

Nevertheless, to ensure that the estimated treatment effects are robust to the violations in the parallel trends assumption, we quantify the extent to which violations in parallel trends affect estimated treatment effects as a function of the magnitude of the violation. This approach, referred to as Honest Difference-in-Differences (Honest DiD), was proposed by Rambachan and Roth (2023) and is now the standard way to quantify the sensitivity of estimated treatment effects to parallel trends violations. Specifically, this approach allows us to evaluate the magnitude of the violation of parallel trends in the post-treatment that would be needed to nullify our treatment effect, considering the worst-case scenario over the pre-treatment periods.

In this approach, one need only impose restrictions on the possible differences in trends between treated and control groups. In our case, we perform a sensitivity analysis based on smoothness restrictions, where the change in slope of the differential trend between treated and control groups across two periods is bounded by the following formula (see Equation 8 in Rambachan and Roth (2023))

$$\Delta^{SD} := \{ \delta : |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M, \forall t \}, \quad (A3)$$

where δ_t refers to the difference in trends between the treated and control groups at time t, and M governs the

¹We also conducted a linear trend analysis of the treatment effects, and we do not observe any significant trends in the treatment effects over time.

maximum allowable error of the linear extrapolation, bounding how much the slope of δ can change between consecutive periods. Thus, such a restriction serves as a discrete analog to bounding the second derivative of trends between the treated and control groups. In the special case where $M = 0$, $\Delta^{SD}(0)$, the difference in trends between treated and control groups is exactly linear (or parallel).

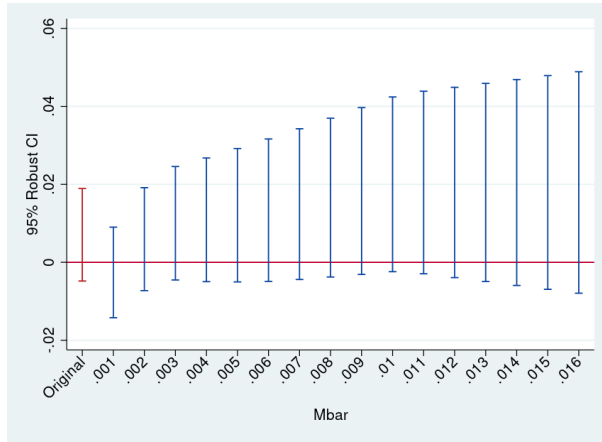
We present a set of Honest DiD estimates with varying M values in Figure A2, where the red bars represent corresponding 95% confidence intervals when allowing for per-period violations of parallel trends of up to M . Notably, even when we allow the M to be 0.16, which is 3,764 times greater than our current linear trend in the pre-treatment period, the main effect is still null for both Spotify streams and YouTube views.

Table A12: Linear Trend for All Tracks (Log-Specification)

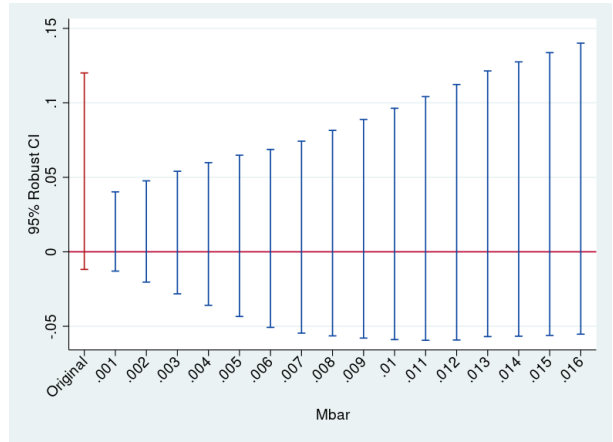
	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#Days_to_feud	-0.0000425*	(0.0000210)	-0.000284	(0.000183)
_cons	5.553***	(0.000561)	6.133***	(0.00369)
Date FE	Yes		Yes	
Track FE	Yes		Yes	
N	15352379		906890	
R^2	0.9461		0.8690	
aic	35589909.4		2737525.2	
bic	35589923.9		2737536.9	

Standard errors in parentheses

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



Spotify streams



YouTube views

Figure A2: Honest DiD Estimation for Music Demand (All Tracks)

E.2 Parallel Trend Test for the Log DiD Specifications in §5.2

Since we segment our data in estimating heterogeneity in treatment effects, we first estimate a relative-time model at the daily level over our entire time window. As we can see from Figure A3 and Figure A4, some β_τ coefficients of the interaction $UMG_i \times \text{Pre}(\tau)$ prior to the dispute are significant.

As before, we then fit a linear trend model to formally test the pre-trend assumption for the segmented

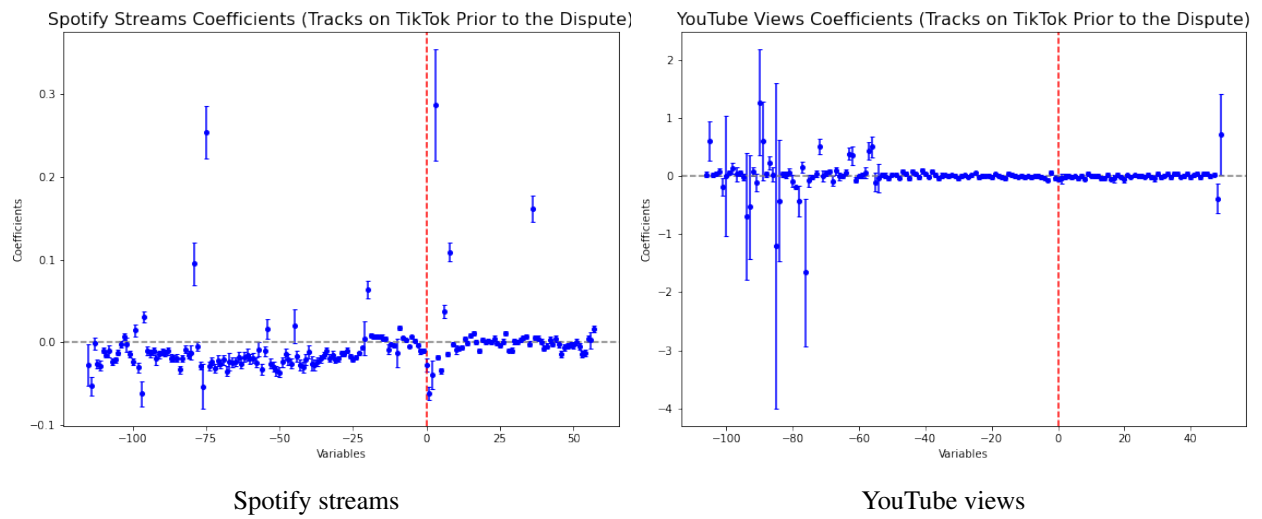


Figure A3: Relative-Time Model Estimation (Tracks on TikTok Prior to the Dispute)

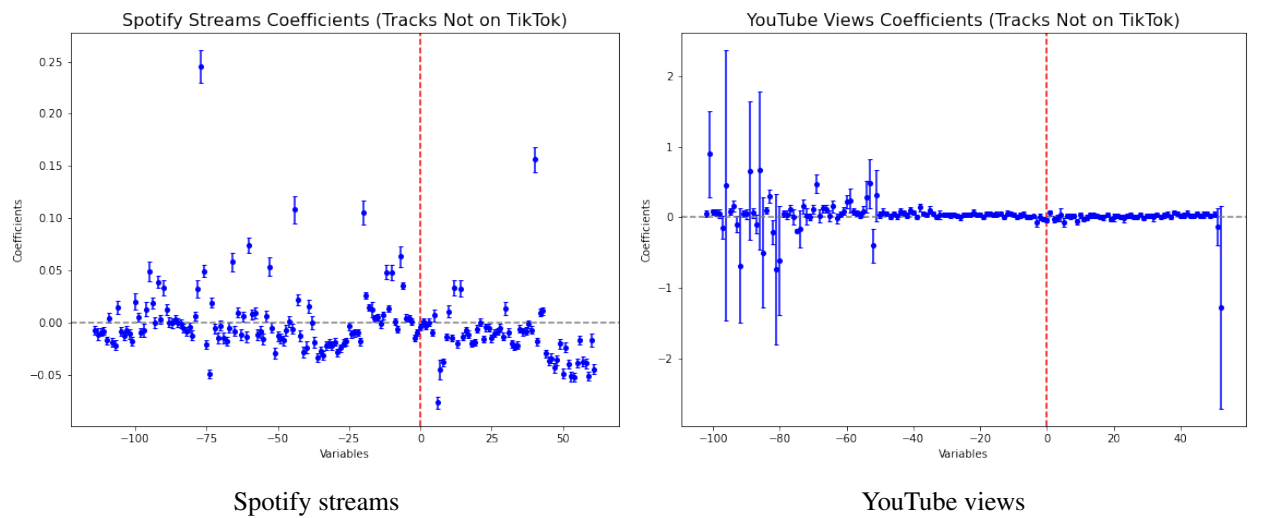


Figure A4: Relative-Time Model Estimation (Tracks Not on TikTok Prior to the Dispute)

data. As shown in Table A13, for tracks available on TikTok before the dispute, the linear trend coefficient for Spotify demand is significant but has a very small magnitude (i.e., approximately 0.3% of the coefficient in column (1) of Table 7). The linear trend coefficient for YouTube demand in column (2) is insignificant. This suggests that the substitution effect in Table 7 is unlikely to be driven by any pre-treatment time trend. Similarly, for tracks that were not available on TikTok before the dispute, the linear trend coefficient for Spotify demand is also significant but has a minimal magnitude (i.e., approximately 0.5% of the coefficient in column (3) of Table 7), while the linear trend coefficient for YouTube demand in column (4) is insignificant. Thus, it is very unlikely that the complementary effect in Table 7 is driven by any pre-treatment time trend.²

In Table A14, we observe that for tracks not available on TikTok from artists without any TikTok presence, neither the linear trend coefficient for Spotify demand in column (1) nor the coefficient for YouTube demand in column (2) is significant. Similarly, for tracks not on TikTok from artists with partial TikTok availability, the linear trend coefficient for Spotify demand is significant but has a very small magnitude (approximately 0.57% of the coefficient in column (3) of Table A14), while the YouTube demand coefficient remains insignificant in column (2). Therefore, it is unlikely that the effects in Table A14 are driven by any pre-treatment time trends.

We also present a set of Honest DiD estimate with varying M values in Figure A5 and Figure A6, where the red bars represent corresponding 95% confidence intervals when allowing for per-period violations of parallel trends of up to M. For tracks available on TikTok before the dispute, the positive estimates on Spotify stream estimates are nullified when M reaches 0.005, approximately 70 times greater than our current linear trend in the pre-treatment period. For tracks unavailable on TikTok before the dispute, the negative estimates on Spotify stream are nullified when M is 0.14, 1,774 times greater than our current linear trend in the pre-treatment period. Finally, as noted in footnote 6, there is less data available for YouTube than for Spotify; and we see that the results for YouTube are less robust, though generally similar to the estimates from the main text.

Table A13: Linear Trend for Tracks on vs. Not on TikTok Before the Dispute

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
l.UMG#Days_to_feud	0.0000711*	-0.000432	-0.0000789**	-0.000229
	(0.0000321)	(0.000292)	(0.0000264)	(0.000212)
.cons	7.676***	7.036***	4.563***	5.122***
	(0.000811)	(0.00568)	(0.000722)	(0.00417)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
N	4882808	443666	10469571	441905
R ²	0.9408	0.8513	0.9359	0.8838
aic	10981099.6	1385535.4	23637072.8	1168798.7
bic	10981113.0	1385546.4	23637087.0	1168809.7

Standard errors in parentheses

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

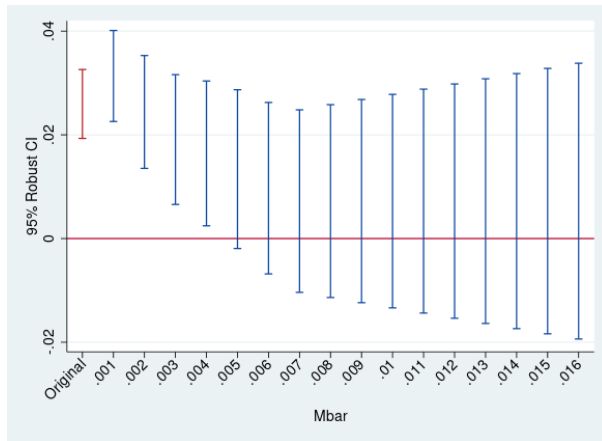
²We also conducted a linear trend analysis of the treatment effects, and we do not observe any significant trends in the treatment effects over time.

Table A14: Linear Trend for Tracks Not on TikTok Prior to the Dispute: Artists with No vs. Partial TikTok Availability

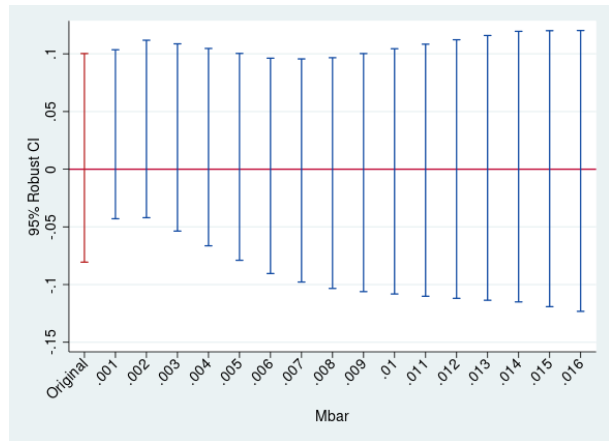
	Tracks from Artists with No TikTok Availability		Tracks from Artists with Partial TikTok Availability	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#Days_to_feud	0.000236 (0.000153)	0.00163 (0.00124)	-0.0000874** (0.0000268)	-0.000284 (0.000215)
.cons	4.164*** (0.00386)	5.158*** (0.0224)	4.574*** (0.000734)	5.121*** (0.00424)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
<i>N</i>	272739	12004	10196832	429899
<i>R</i> ²	0.9431	0.8948	0.9356	0.8835
aic	626047.6	32744.0	23006172.1	1135755.0
bic	626058.2	32751.4	23006186.2	1135765.9

Standard errors in parentheses

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



Spotify streams



YouTube views

Figure A5: Honest DiD Estimation for Music Demand (Tracks on TikTok Prior to the Dispute)

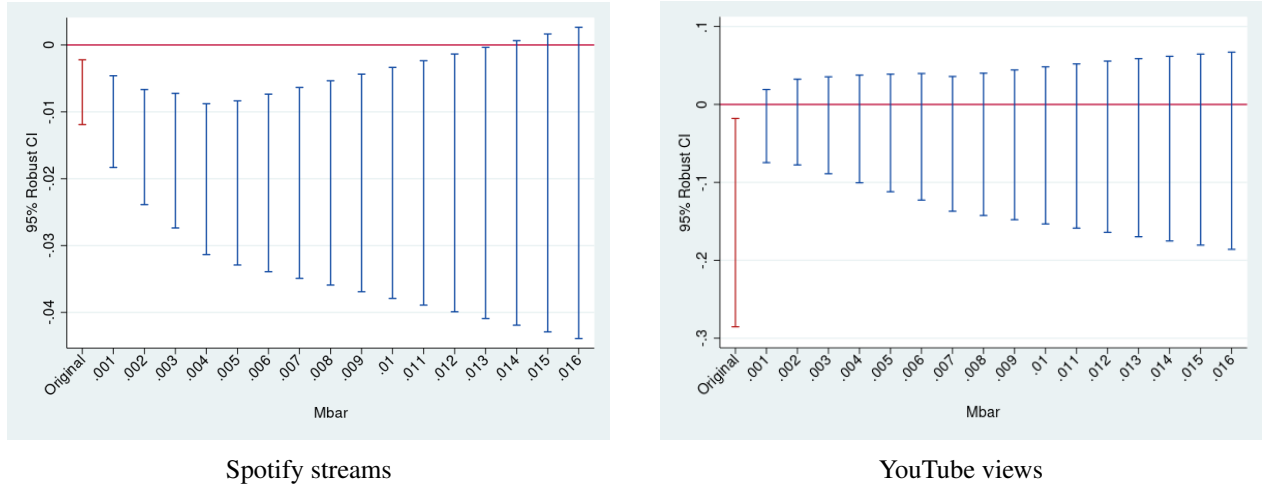


Figure A6: Honest DiD Estimation for Music Demand (Tracks Not on TikTok Prior to the Dispute)

E.3 Parallel Trend Tests for the Levels DiD Models

In this section, we estimate a linear trend model to assess the pre-trend assumption for our level specification using Equation A4. The results, presented in Table A15, show that the linear trend coefficients for both Spotify demand and YouTube views in columns (1) and (2) are insignificant, validating the parallel pre-trend assumption.

$$Demand_{it} = \alpha + \beta * UMG_i * t + Track_i + Date_t + \epsilon_{it}, \quad (A4)$$

Further, Table A16 presents the parallel trend tests for the heterogeneous DiD analysis in levels (by presence on TikTok prior to the dispute), with more details in Web Appendix §G.3. Again, since all linear trend coefficients are insignificant, we find no evidence for the violation of parallel trends in the levels-specification for estimating heterogeneity in treatment effect.

Table A15: Linear Trend for All Tracks (Levels-Specification)

	(1)		(2)	
	Spotify_streams		Youtube_views	
1.UMG#Days_to_feud	34.15	(66.36)	2430.6	(1509.7)
_cons	122744.1***	(1770.0)	854053.0***	(30502.4)
Date FE	Yes		Yes	
Track FE	Yes		Yes	
<i>N</i>	15352379		906890	
<i>R</i> ²	0.2692		0.4360	
aic	505642454.8		32633978.7	
bic	505642469.4		32633990.4	

Standard errors in parentheses

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

Table A16: Linear Trend for Tracks on vs. Not on TikTok Prior to the Dispute (Levels-Specification)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) Spotify_streams	(2) Youtube_views	(3) Spotify_streams	(4) Youtube_views
1.UMG#Days_to_feud	-119.3 (170.9)	2850.5 (3179.2)	-0.0196 (30.01)	913.2 (877.4)
_cons	297598.8*** (4322.5)	1267027.0*** (61852.8)	38451.6*** (819.7)	271687.1*** (17251.9)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
<i>N</i>	4882808	443666	10469571	441905
<i>R</i> ²	0.2888	0.4331	0.2486	0.4746
aic	165330605.2	16176519.9	330916160.0	15176520.1
bic	165330618.6	16176530.9	330916174.2	15176531.1

Standard errors in parentheses

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

Table A17: Linear Trend for Tracks Not on TikTok Prior to the Dispute: Artists with No vs. Partial TikTok Availability (Levels-Specification)

	Tracks from Artists with No TikTok Availability		Tracks from Artists with Partial TikTok Availability	
	(1) Spotify_streams	(2) Youtube_views	(3) Spotify_streams	(4) Youtube_views
1.UMG#Days_to_feud	412.3 (312.8)	-1951.2 (8398.8)	-10.42 (29.78)	967.5 (881.2)
_cons	104200.8*** (7877.4)	455182.0** (151195.3)	36686.1*** (815.2)	266173.9*** (17367.3)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
<i>N</i>	272739	12004	10196832	429899
<i>R</i> ²	0.2930	0.5156	0.2456	0.4735
aic	8844541.1	416625.2	321941994.2	14758328.3
bic	8844551.6	416632.6	321942008.3	14758339.3

Standard errors in parentheses

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

F Tests for Spillover Effects to the Control Group

One may be concerned that the treatment also has a spillover effect on our control group, resulting in a violation of the DiD model's SUTVA assumption. Note that the main mechanism by which the removal of UMG tracks could impact the control group is through music usage on TikTok. Therefore, for all the tracks in our dataset, we collect the number of newly uploaded videos using track i for each day t in our observation period and denote this variable as $TikTok_Video_Creations_{it}$. This data comes from Chartmetric.³

To test for spillovers, we analyze the distribution of these TikTok video creations in two ways. First, we conduct a two-sample t-test for the $\log(\text{number of daily video creations} + 1)$ on TikTok for the control group (i.e., tracks from SME and WMG) before and after the dispute. We find no significant changes in comparing creations between these two timeframes (before $\overline{\log(TikTok_Video_Creations_{it} + 1)} = 0.0405$,

³Please note that due to data limitations from our provider, we do not have track daily level TikTok video creation information from December 20, 2023, to January 30, 2024; as such, we use the data from October 10, 2023, to December 19, 2023, as the pre-treatment period.

after $\overline{\log(\text{TikTok_Video_Creations}_{it} + 1)} = 0.0408$, $p > 0.1$). In contrast, when we perform a two-sample t-test for the $\log(\text{number of daily video creations} + 1)$ on TikTok for the treatment group (i.e., tracks from UMG), is found to be negative and significant, suggesting a significant decrease in video creations after the dispute (before $\overline{\log(\text{TikTok_Video_Creations}_{it} + 1)} = 0.0326$, after $\overline{\log(\text{TikTok_Video_Creations}_{it} + 1)} = 0.0023$, $p < 0.001$). Indeed, the number of TikTok videos using UMG’s music effectively drops to zero after the dispute (except for a minuscule set of tracks; these exceptions are likely due to flagging issues at TikTok).

Next, we specify the following regression model to examine whether video creations using SME and WMG’s music tracks increased in a meaningful way in the post-dispute period.

$$\log(\text{TikTok_Video_Creations}_{it} + 1) = \alpha + \zeta * \text{Post}_t + \text{Track}_i + \epsilon_{it}, \quad (\text{A5})$$

where the key coefficient of interest is ζ . We estimate this regression for tracks from SME and WMG and present the results in Table A18. As we can see, ζ is insignificant, suggesting that the number of new TikTok videos using tracks belonging to these labels did not increase significantly after UMG’s music was pulled from TikTok.

Table A18: TikTok Video Creation Number Change After the Dispute (SME + WMG)

log_Video_Creations	
Post	0.000279 (0.00147)
.cons	0.0405*** (0.000728)
Track FE	Yes
<i>N</i>	4666475
<i>R</i> ²	0.2388
aic	3774666.7
bic	3774680.0

Standard errors are presented in parentheses and clustered at the track level

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

We further examine potential systematic shifts in Spotify and YouTube demand before and after the dispute by first plotting the daily Spotify streams and daily YouTube views across the treatment and control groups before and after the dispute in Figure A7. Descriptively, we observe no significant changes in demand on both platforms for tracks from SME and WMG after the dispute.

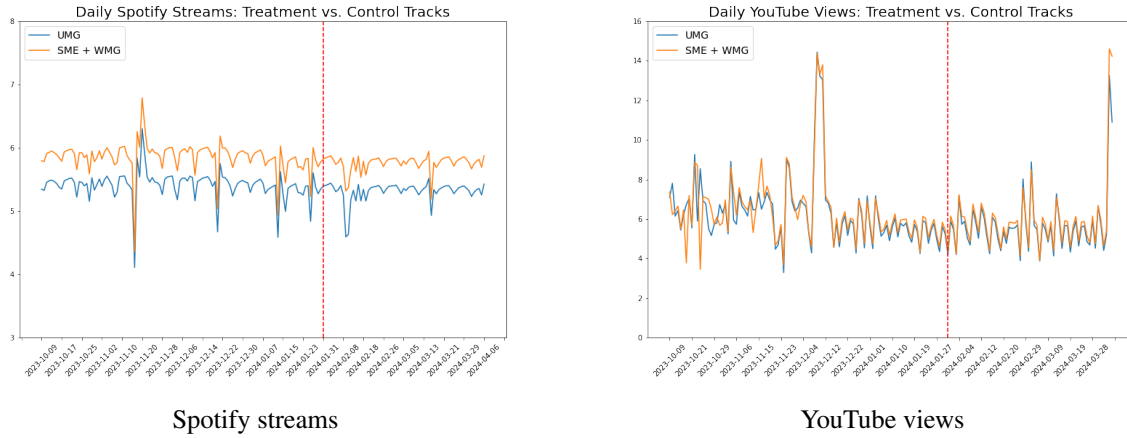


Figure A7: Spotify Streams and YouTube Views

Next, we run the following linear trend model (A6):

$$\log(Demand_{it} + 1) = \alpha + \beta * Post_t + \zeta * Post_t * t + Track_i + \epsilon_{it}, \quad (A6)$$

where ζ is the coefficient of interest. We estimate this regression for tracks from SME and WMG and present the results in Table A19. We find that there is a decrease in the demand (number of streams) for SME and WMG on Spotify after the dispute, which would be inconsistent with a hypothesis that the dispute led to a surge in demand for SME and WMG tracks on Spotify. Conversely, we do observe an increase in demand (number of views) for SME and WMG on YouTube after the dispute. However, it seems unlikely that the dispute led to a systematic increase in the demand for music from the control group on both Spotify and YouTube.

Table A19: Demand Change After the Dispute (SME + WMG)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
Days_to_feud	0.00117***	(0.0000142)	-0.0131***	(0.000120)
Post	0.176***	(0.00165)	0.250***	(0.00514)
1.Post#Days_to_feud	-0.00395***	(0.0000426)	0.00670***	(0.000152)
_cons	5.786***	(0.000868)	5.646***	(0.00470)
Track FE	Yes		Yes	
N	13036357		909095	
R ²	0.9048		0.8533	
aic	36730182.1		2783531.9	
bic	36730225.2		2783567.0	

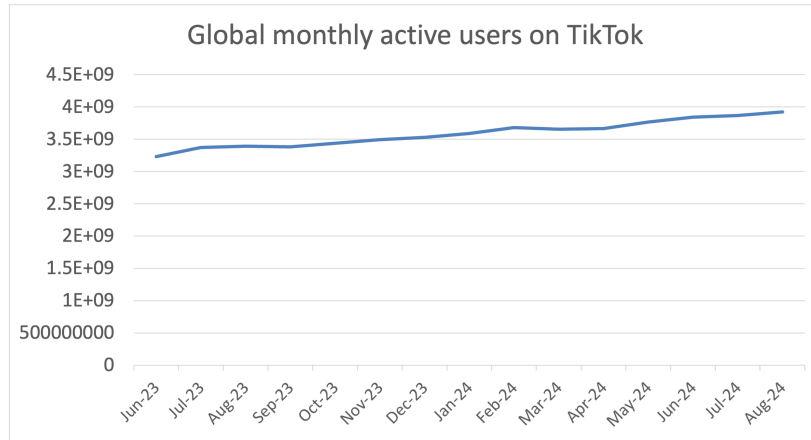
Standard errors are in parentheses and clustered at the track level

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

Lastly, to assess whether the dispute impacted TikTok usage, we collected global monthly active user data for TikTok before and after the dispute from App Annie,⁴ a third-party analytics tool that tracks app

⁴<https://www.data.ai/account/login/>

Figure A8: Global Monthly Active TikTok Users



usage from both the App Store and Google Play. As illustrated in Figure A8, TikTok’s monthly active users continued to grow even after the dispute,

In sum, these tests confirm that there are no significant spillover effects on the control group in this setting.

G Appendix for Specification Checks

G.1 Pre-treatment Demand Distributions for the Treatment and Control Groups

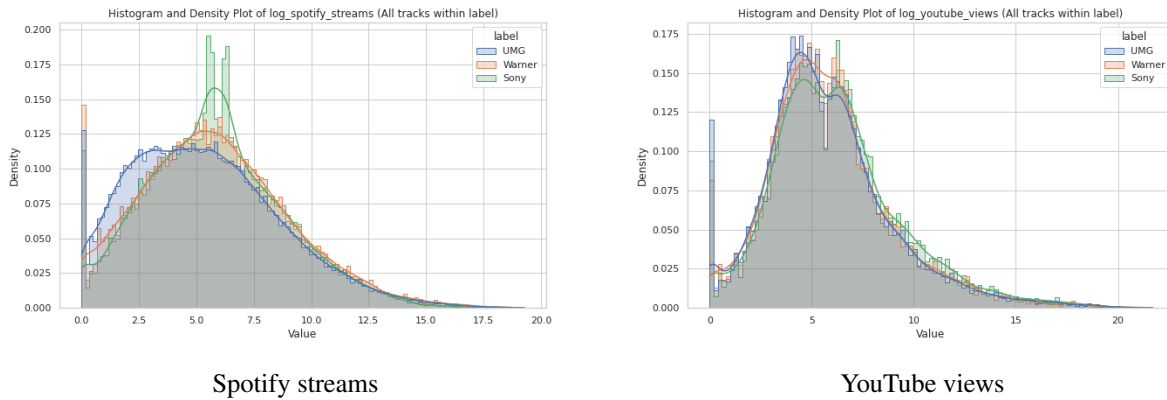


Figure A9: Pre-treatment Music Demand Distributions for the Big Three Labels

Figure A9 presents the pre-treatment distributions of the music demand on Spotify and YouTube for all three music labels. As we can see, there are no significant differences in the level of demand by music label on both platforms.

This is important because substantial differences in relative baseline outcome means can result in sign flips in a Difference-in-Differences (DiD) model, as shown by McConnell (2024). Specifically, McConnell (2024) outlines the conditions for a sign flip in DiD in Proposition 1, which occur when $0 < |\Delta_T - \Delta_C| < |\Delta_C \frac{E[Y_{T0}] - E[Y_{C0}]}{E[Y_{C0}]}|$. Here, $E[Y_{C0}] = E[Y_{it} | D_i = 0, T_t = 0]$ represents the expected demand for WMG’s and SME’s music before the licensing dispute, and $E[Y_{T0}] = E[Y_{it} | D_i = 1, T_t = 0]$ represents the expected

demand for UMG’s music before the licensing dispute. The terms $\Delta_C = E[Y_{it} | D_i = 0, T_t = 1] - E[Y_{it} | D_i = 0, T_t = 0]$ capture changes in music demand for WMG’s and SME’s music before and after the dispute, while $\Delta_T = E[Y_{it} | D_i = 1, T_t = 1] - E[Y_{it} | D_i = 1, T_t = 0]$ captures the changes in music demand for UMG’s music before and after the dispute. In our data, we compute Δ_T as 1,744,687.4, Δ_C as 1,017,079.3, and $\frac{E[Y_{T0}] - E[Y_{C0}]}{E[Y_{C0}]}$ as 0.2679. Since $|1,744,687.4 - 1,017,079.3| > |0.2679 * 1,017,079.3|$, the condition for a sign flip does not hold in our analysis.

G.2 Main Effects with Level DiD Models without Outliers

Here, we show the main effects when estimated with the levels DiD model for the two platforms after dropping the outlier observations for the respective platforms. In Table A20, we show the estimates when we drop the top 5% of outliers for a given platform, and in Table A21 we show the estimates when we drop top 10% of outliers. Both results remain directionally consistent with Table 9, but the magnitude decreases drastically when dropping outliers.

Table A20: Main Effect of Removing UMG Music from TikTok on Music Demand (levels-specification, Drop observations larger than 95 percentile)

	(1)	(2)
	Spotify_stream	YouTube_views
1.UMG#1.post	41.15*** (10.72)	29.61 (25.40)
_cons	3699.1*** (1.874)	2715.1*** (4.908)
<i>N</i>	23419919	1530003
<i>R</i> ²	0.9251	0.7725
aic	441568717.3	29529366.0
bic	441568732.2	29529378.2

Standard errors in parentheses

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

Table A21: Main Effect of Removing UMG Music from TikTok on Music Demand (levels-specification, Drop observations larger than 90 percentile)

	(1)	(2)
	Spotify_stream	YouTube_views
1.UMG#1.post	12.05*** (3.318)	-0.791 (7.371)
_cons	1449.9*** (0.582)	1118.8*** (1.438)
<i>N</i>	22186544	1448697
<i>R</i> ²	0.9256	0.8354
aic	364497706.3	23912341.3
bic	364497721.2	23912353.5

Standard errors in parentheses

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

G.3 Heterogeneous Treatment Effects with Levels DiD

In Table A22 below, we present the levels DiD analysis separately for tracks on TikTok and tracks not on TikTok prior to the dispute. The results are consistent with the heterogeneity analysis shown with the log DiD model in §5.2 for Spotify demand (i.e., number of streams).

Table A22: Main Effect of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (Levels-Specification)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) Spotify_streams	(2) Youtube_views	(3) Spotify_streams	(4) Youtube_views
1.UMG#1.post	2931374.5*** (495362.8)	53910.4 (112260.1)	-225423.4** (72121.8)	62492.4 (33994.3)
_cons	1154299.6*** (82678.5)	879572.2*** (22789.6)	219572.9*** (12888.9)	188057.3*** (6127.7)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	7671163	804253	16982133	787275
R^2	0.0185	0.4503	0.0145	0.5265
aic	316982804.1	28999886.7	655908557.8	26778734.6
bic	316982817.9	28999898.3	655908572.4	26778746.2

Standard errors in parentheses

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

G.4 Results after Rescaling Demand Variables

Even though our data satisfies the condition to ensure that the sign of the treatment effects will not flip when going from levels to logs specification (McConnell 2024), and our pre-treatment distributions of music demand on Spotify and YouTube are largely similar in levels (as shown in Web Appendix §G.1), we nevertheless consider another specification where the distributions are aligned in outcomes. Specifically, we rescale/recenter the outcome distribution of the treated group to align the baseline outcome means before applying the log transformation, as suggested by McConnell (2024). This rescaling is operationalized by the following specification:

$$Y_{it}^{RC} = \begin{cases} Y_{it} & \text{if } D_i = 0 \\ Y_{it} - (\bar{Y}_{T0} - \bar{Y}_{C0}) & \text{if } D_i = 1 \end{cases}, \quad (\text{A7})$$

where \bar{Y}_{T0} and \bar{Y}_{C0} represent the baseline outcome means for UMG's streams (the treatment group) and SME's and WMG's streams (the control group), respectively. This rescaling effectively shifts the mean of the treatment group distribution to match that of the control group. However, this has a selection effect on the estimation sample – rescaling causes observations in the treatment group to become negative; and these observations are dropped when we perform a log transformation of the rescaled variable.

As shown in Table A23, the result for Spotify demand in Column (1) and the result for YouTube demand in Column (2) are both positive and significant (and not null, as in the main log DiD model; see §5.1). However, as noted above, the estimation results from the two analyses are not directly comparable since the rescaled estimation drops all the rescaled negative observations. We therefore run the standard (non-rescaled) log DiD model on this sample and confirm that the results of that model are positive too. That is, both the rescaled and non-scaled log DiD models give similar results, conditional on the estimation sample being the same.

Finally, we also use the rescaled approach to estimate the heterogeneous treatment effect models and show the results in Table A24. We see that the results are consistent with our heterogeneous treatment effects

reported in Table 7. Specifically, for tracks available on the platform prior to the dispute, the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is positive and significant for Spotify streams in Column (1) ($b = 0.0788$, $p < 0.001$) and for YouTube views in Column (2) ($b = 0.160$, $p < 0.001$), suggesting that UMG music received increased streaming demand after being removed from TikTok’s music library. Conversely, for tracks not available on TikTok before the dispute, the estimated coefficient for 1.UMG#1.post, is negative and significant for Spotify streams ($b = -0.0461$, $p < 0.001$) and insignificant for YouTube views ($p > 0.1$), suggesting that UMG music experienced a decline in demand on Spotify following its removal from TikTok’s music library.

Table A23: Main Effect of Removing UMG Music from TikTok on Music Demand (Logs-Specification, Rescale)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	0.0521***	(0.00606)	0.0845**	(0.0278)
_cons	6.176***	(0.000153)	6.255***	(0.000376)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	14004256		947194	
<i>R</i> ²	0.9529		0.8974	
aic	31891713.6		2710734.4	
bic	31891728.1		2710746.2	

Standard errors in parentheses

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

Table A24: Main Effect of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (Log-Specification, Rescale)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0788*** (0.00708)	0.160*** (0.0315)	-0.0461*** (0.0121)	0.0419 (0.0555)
_cons	8.286*** (0.000366)	7.253*** (0.000689)	5.071*** (0.000138)	5.172*** (0.000285)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	4817342		9186402	
<i>R</i> ²	0.9479		0.9418	
aic	10518606.3		20795896.0	
bic	10518619.7		20795910.0	

Standard errors in parentheses

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

H Appendix for Other Robustness Checks

H.1 Sensitivity to Outliers

Here, we estimate the main effects and the heterogeneous treatment effects for tracks available on TikTok and not available on TikTok prior to the dispute for both Spotify and YouTube, after dropping observations with Spotify streams or YouTube views above the 99th percentile. Table A25 shows that the main effects are consistent with the results reported in Table 3, both indicating null effects. In Table A26, for tracks available on TikTok prior to the dispute, 1.UMG#1.post is positive and significant for streams on Spotify ($b = 0.0155$, $p < 0.001$) and views on YouTube ($b = 0.0283$, $p < 0.01$). Conversely, for tracks not available on TikTok prior to the dispute, 1.UMG#1.post, is negative and significant for Spotify streams ($b = -0.0158$, $p < 0.001$) and YouTube views ($b = -0.0283$, $p < 0.001$). These results are similar to the heterogeneous treatment effects presented in Table 7 in the main text.

Table A25: Main Effect of Removing UMG Music from TikTok on Music Demand (Drop 99 percentile)

	(1)		(2)	
	log_spotify_streams		log_youtube_views	
1.UMG#1.post	-0.00646	(0.00375)	-0.00216	(0.00688)
_cons	5.472***	(0.000375)	5.797***	(0.00131)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	24406707		1595299	
<i>R</i> ²	0.9457		0.8923	
aic	54330854.2		4173364.5	
bic	54330869.2		4173376.7	

Standard errors in parentheses

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

Table A26: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand (Drop 99 percentile, on TikTok vs. not on TikTok)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0155*** (0.00395)	0.0283** (0.0104)	-0.0158*** (0.00254)	-0.0283*** (0.00846)
_cons	7.553*** (0.000653)	6.672*** (0.00212)	4.550*** (0.000455)	4.862*** (0.00153)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	7492484		16914063	
<i>R</i> ²	0.9394		0.9337	
aic	15580334.5		37694162.1	
bic	15580348.3		37694176.7	

Standard errors in parentheses

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

H.2 Robustness Across Different Pre- Post-Treatment Time Windows

In our main paper, we estimate the main effects and the heterogeneous treatment effects for tracks on TikTok and not on TikTok prior to the dispute. These estimates are based on data covering a 180-day window, from October 10th, 2023 to April 7th, 2024. In this appendix, we assess the robustness of our results to alternative time windows. First, we shorten the length of the pre-treatment period from the 113 days used in the main paper to 90 days, 75 days, and 67 days. The corresponding estimates for the main effects are presented in Table A27, Table A29, Table A31, respectively. The heterogeneous treatment effects for these alternative pre-treatment periods are shown in Table A28, Table A30, and Table A32. Notably, shortening the pre-treatment period to 67 days yields a symmetrical design, with both pre- and post-treatment periods spanning 67 days.

We then vary the post-treatment period from the 67 days used in the main paper to shorter spans of 60 and 45 days. The main effects for these alternative post-treatment periods are presented in Table A33 and Table A35, with the corresponding heterogeneous treatment effects shown in Table A34 and Table A36.

Finally, to align more closely with the 9-week window used in Winkler et al. (2024), we vary both the pre-treatment and post-treatment periods to 30 days. The main and heterogeneous treatment effect estimates for this specification are presented in Table A37 and Table A38.

Across all these alternative time windows, our key findings remain largely consistent: the licensing dispute had a null, or a possibly small positive, effect on UMG’s demand on streaming platforms. Moreover, we continue to observe consistent heterogeneous treatment effects: tracks that had previously been available on TikTok exhibit a positive (*substitution*) effect, and tracks that had not been available on TikTok exhibit a negative (*complementarity*) effect.

Table A27: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 90 days, post-treatment window: 67 days)

	(1)		(2)	
	log_Spotify_streams		log_Youtube_views	
1.UMG#1.post	-0.00606	(0.00336)	-0.00362	(0.00698)
.cons	5.560***	(0.000478)	5.833***	(0.00144)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	21339818		1482745	
<i>R</i> ²	0.9455		0.8991	
aic	49545573.3		3968320.7	
bic	49545588.2		3968332.9	

Standard errors in parentheses

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

Table A28: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 90 days, post-treatment window: 67 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0217*** (0.00438)	0.0261* (0.0107)	-0.0180*** (0.00275)	-0.0255** (0.00838)
_cons	7.732*** (0.000831)	6.770*** (0.00231)	4.555*** (0.000571)	4.786*** (0.00166)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	6744601	761000	14593346	712882
<i>R</i> ²	0.9410	0.8775	0.9323	0.9078
aic	15005322.4	2167281.1	33485773.7	1635549.7
bic	15005336.1	2167292.6	33485788.2	1635561.1

Standard errors in parentheses

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

Table A29: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 75 days, post-treatment window: 67 days)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	-0.00591	(0.00348)	-0.000616	(0.00683)
_cons	5.554***	(0.000529)	5.790***	(0.00145)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	19397648		1434692	
<i>R</i> ²	0.9462		0.9088	
aic	44829873.9		3680228.6	
bic	44829888.7		3680240.7	

Standard errors in parentheses

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

Table A30: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 75 days, post-treatment window: 67 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0221*** (0.00442)	0.0298** (0.0105)	-0.0176*** (0.00276)	-0.0238** (0.00826)
_cons	7.732*** (0.000932)	6.722*** (0.00233)	4.561*** (0.000629)	4.750*** (0.00169)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	6073013	735310	13322653	690190
<i>R</i> ²	0.9425	0.8908	0.9333	0.9157
aic	13376471.5	2000079.6	30387947.3	1515111.9
bic	13376485.2	2000091.1	30387961.7	1515123.3

Standard errors in parentheses

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

Table A31: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 67 days, post-treatment window: 67 days)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	0.00588*	(0.00234)	0.00177	(0.00676)
_cons	5.611***	(0.000546)	5.770***	(0.00153)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	18466339		1348868	
<i>R</i> ²	0.9571		0.9239	
aic	38005104.0		3192867.1	
bic	38005118.7		3192879.3	

Standard errors in parentheses

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

Table A32: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 67 days, post-treatment window: 67 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0242*** (0.00433)	0.0333** (0.0102)	-0.00280 (0.00173)	-0.0208** (0.00797)
_cons	7.832*** (0.000972)	6.667*** (0.00242)	4.606*** (0.000655)	4.719*** (0.00175)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	5703300	686104	12627624	643540
<i>R</i> ²	0.9529	0.9157	0.9429	0.9324
aic	10954406.1	1653715.7	26607007.5	1251797.8
bic	10954419.6	1653727.2	26607021.8	1251809.2

Standard errors in parentheses

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

Table A33: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 113 days, post-treatment window: 60 days)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	0.000523	(0.00215)	-0.00811	(0.00738)
_cons	5.572***	(0.000349)	5.920***	(0.00135)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	23641356		1570470	
<i>R</i> ²	0.9470		0.8823	
aic	54228900.2		4474493.8	
bic	54228915.1		4474506.0	

Standard errors in parentheses

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

Table A34: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 113 days, post-treatment window: 60 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0245*** (0.00401)	0.0203 (0.0112)	-0.00979*** (0.00251)	-0.0279** (0.00869)
_cons	7.739*** (0.000619)	6.832*** (0.00220)	4.594*** (0.000416)	4.926*** (0.00151)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	7356941	782501	16284414	767809
<i>R</i> ²	0.9422	0.8616	0.9346	0.8965
aic	16160771.5	2334067.1	36978566.9	1901896.3
bic	16160785.3	2334078.7	36978581.5	1901907.9

Standard errors in parentheses

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

Table A35: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 113 days, post-treatment window: 45 days)

	(1)		(2)	
	log_Spotify_streams	log_YouTube_views	log_Spotify_streams	log_YouTube_views
1.UMG#1.post	0.00610** (0.00208)	-0.0150* (0.00746)		
_cons	5.574*** (0.000273)	5.962*** (0.00114)		
Track FE	Yes	Yes		
Date FE	Yes	Yes		
<i>N</i>	21472343	1404356		
<i>R</i> ²	0.9464	0.8765		
aic	49591764.4	4089905.0		
bic	49591779.2	4089917.1		

Standard errors in parentheses

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

Table A36: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 113 days, post-treatment window: 45 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0264*** (0.00391)	0.0126 (0.0114)	-0.00219 (0.00241)	-0.0332*** (0.00871)
_cons	7.732*** (0.000479)	6.874*** (0.00187)	4.598*** (0.000325)	4.972*** (0.00128)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	6682619	695458	14789723	688733
<i>R</i> ²	0.9411	0.8545	0.9348	0.8921
aic	14881512.4	2121687.7	33643671.6	1744318.9
bic	14881526.2	2121699.2	33643686.1	1744330.3

Standard errors in parentheses

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

Table A37: Main Effect of Removing UMG Music from TikTok on Music Demand (pre-treatment window: 30 days, post-treatment window: 30 days)

	(1)		(2)	
	log_Spotify_streams	log_YouTube_views	log_Spotify_streams	log_YouTube_views
1.UMG#1.post	0.0199*** (0.00150)	-0.00150 (0.00575)		
_cons	5.594*** (0.000334)	5.632*** (0.00124)		
Track FE	Yes	Yes		
Date FE	Yes	Yes		
<i>N</i>	8065786	660717		
<i>R</i> ²	0.9509	0.9494		
aic	17829247.0	1248539.2		
bic	17829260.9	1248550.6		

Standard errors in parentheses

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

Table A38: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (pre-treatment window: 30 days, post-treatment window: 30 days)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0286*** (0.00259)	0.0315*** (0.00929)	-0.0170*** (0.00180)	-0.0288*** (0.00691)
_cons	7.851*** (0.000556)	6.572*** (0.00211)	4.663*** (0.000407)	4.676*** (0.00140)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	2356494	328027	5709292	329485
<i>R</i> ²	0.9451	0.9356	0.9378	0.9517
aic	4976122.8	696747.3	12727449.1	515693.1
bic	4976135.5	696758.0	12727462.7	515703.8

Standard errors in parentheses

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

H.3 Controlling for Time-Varying Factors

One potential concern regarding the main analysis is that track fixed effects may not fully capture time-varying factors that influence music demand on Spotify and YouTube, which could potentially challenge the validity of our substitution argument. To address this, we conduct a robustness check that explicitly accounts for such time-varying factors. Specifically, we collect daily media coverage data for the Big Three Music Labels – UMG, Warner, and Sony – and their top artists using Factiva, a comprehensive digital archive of over 33,000 global news sources, including newspapers, industry publications, and websites. We construct the following keyword queries to capture relevant media coverage for each music label in Factiva:

- UMG: “(taylor swift or the weeknd or drake or lady gaga or lana del rey or billie eilish or justin bieber or sabrina carpenter or post malone or ariana grande and) and universal music group”
- WMG: (ed sheeran or bruno mars or dua lipa or zach bryan or teddy swims or charli xcx or lizzo or benson boone or maria becerra or gunna) and warner music group
- SME: (beyoncé or harry styles or doja cat or travis scott or rosálía or britney spears or calvin harris or future or 21 savage or the kid laroi) and sony music entertainment

Figure A10 plots the resulting daily media coverage over time. Notably, we observe a distinct spike in media coverage for UMG and its affiliated artists around the dispute period.

To incorporate these time-varying factors into our analysis, we include the daily media coverage measures as additional controls in our model. Table A39 shows that the main effects are consistent with the results in Table 3, both indicating null effects. We further explore the heterogeneous treatment effects in Table A40. For tracks available on TikTok prior to the dispute, 1.UMG#1.post is positive and significant for streams on Spotify ($b = 0.0245$, $p < 0.001$) and views on YouTube ($b = 0.0210$, $p < 0.1$). Conversely, for tracks not available on TikTok prior to the dispute, 1.UMG#1.post, is negative and significant for streams on Spotify ($b = -0.00995$, $p < 0.001$) and views on YouTube ($b = -0.0260$, $p < 0.01$). These results are similar in both magnitude and direction to the heterogeneous treatment effects reported in Table 7 of the main text.

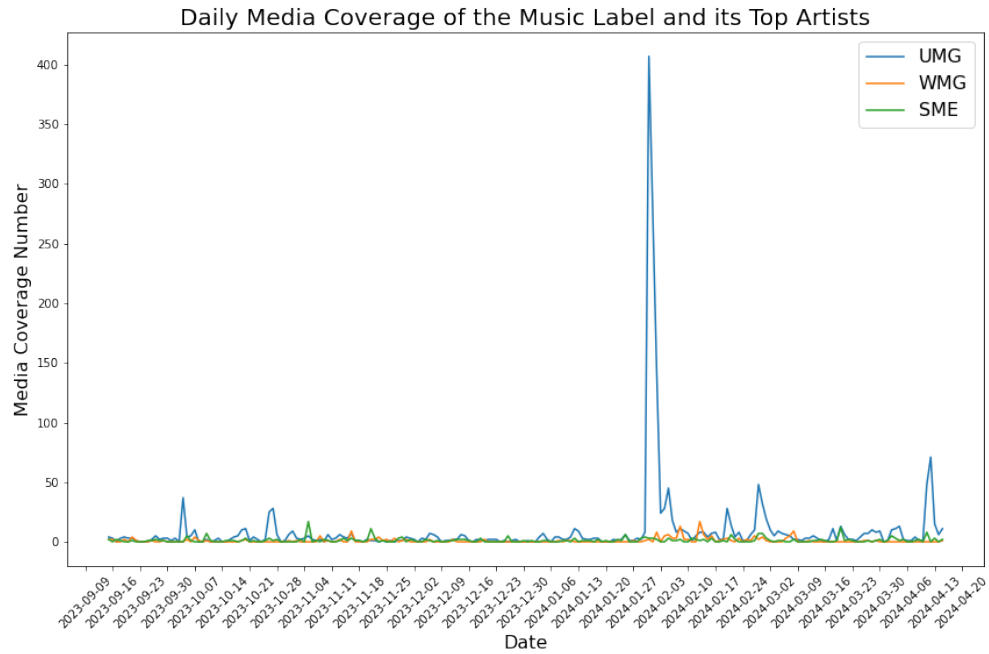


Figure A10: Daily Media Coverage

Table A39: Main Effect of Removing UMG Music from TikTok on Music Demand (Controlling for Daily Media Coverage)

	(1)		(2)	
	log_spotify_streams_total_daily		log_youtube_views_total_daily	
1.UMG#1.post	0.000644	(0.00215)	-0.00666	(0.00754)
log_media_coverage	-0.00554***	(0.000290)	-0.000212	(0.00151)
_cons	5.577***	(0.000497)	5.908***	(0.00179)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	24653297		1611685	
<i>R</i> ²	0.9475		0.8838	
aic	56222964.1		4565600.2	
bic	56222994.1		4565624.8	

Standard errors in parentheses

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

Table A40: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok (Control for Daily Media Coverage)

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_spotify_streams	(2) log_youtube_views	(3) log_spotify_streams	(4) log_youtube_views
1.UMG#1.post	0.0245*** (0.00395)	0.0210 ⁺ (0.0116)	-0.00995*** (0.00254)	-0.0260** (0.00880)
log_media_coverage	-0.00283*** (0.000502)	0.000687 (0.00243)	-0.00638*** (0.000353)	-0.000740 (0.00172)
.cons	7.743*** (0.000911)	6.820*** (0.00286)	4.598*** (0.000580)	4.914*** (0.00206)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
<i>N</i>	7671163	804253	16982133	787275
<i>R</i> ²	0.9429	0.8634	0.9351	0.8976
aic	16728357.3	2384708.3	38388046.9	1938694.2
bic	16728385.0	2384731.5	38388076.2	1938717.4

Standard errors in parentheses

⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

H.4 TikTok Video Creations in the Post-Treatment Period

Here, we examined the number of TikTok video creations for UMG tracks in our dataset. We found that only 303 UMG tracks continued to show positive video creation numbers after February 6th, 2024, with most of these remaining 303 tracks were removed by February 27, 2024. This was likely due to the fact that after the dispute commenced on February 1st, 2024, and the vast majority of its tracks were removed on that date, UMG subsequently also required the removal of songs by songwriters under contract to Universal Music Publishing Group (Variety 2024). While this second removal affected only a small number of tracks in our data, it could, in principle, affect the estimated treatment effects.

To address this concern, we conducted another analysis where we excluded the 303 tracks that had not been removed by February 6, 2024. Using this restricted sample, we estimate the main effects and the heterogeneous treatment effects for tracks on TikTok and not on TikTok prior to the dispute for both Spotify streams and YouTube views. Table A41 shows that the main effects are consistent with the results in Table 3, both indicating null effects. In Table A42, for tracks available on TikTok prior to the dispute, 1.UMG#1.post is positive and significant for streams on Spotify ($b = 0.0219$, $p < 0.001$) and views on YouTube ($b = 0.0229$, $p < 0.05$). Conversely, for tracks not available on TikTok prior to the dispute, 1.UMG#1.post is negative and significant for streams on Spotify ($b = -0.0142$, $p < 0.001$) and views on YouTube ($b = -0.0267$, $p < 0.01$). These results are similar in both magnitude and direction to the heterogeneous treatment effects presented in Table 7 in the main text.

Table A41: Main Effect of Removing UMG Music from TikTok on Music Demand (Log-Specification)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	-0.00346	(0.00219)	-0.00571	(0.00737)
_cons	5.561***	(0.000383)	5.895***	(0.00139)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	24603815		1606391	
<i>R</i> ²	0.9472		0.8834	
aic	56084961.3		4543048.9	
bic	56084976.3		4543061.2	

Standard errors in parentheses

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

Table A42: Heterogeneous Effects of Removing UMG Music from TikTok on Music Demand: Tracks on vs. Not on TikTok

	Tracks on TikTok Prior to the Dispute		Tracks Not on TikTok Prior to the Dispute	
	(1) log_Spotify_streams	(2) log_YouTube_views	(3) log_Spotify_streams	(4) log_YouTube_views
1.UMG#1.post	0.0219*** (0.00406)	0.0229* (0.0112)	-0.0142*** (0.00257)	-0.0267** (0.00869)
_cons	7.719*** (0.000674)	6.803*** (0.00226)	4.591*** (0.000459)	4.911*** (0.00157)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
<i>N</i>	7626272		16977542	
<i>R</i> ²	0.9423		0.9350	
AIC	16615456.9		38376824.6	
BIC	16615470.7		38376839.2	

Standard errors are presented in parentheses and clustered at the track level

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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