Working Paper 25-014

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Abstract

Social media platforms like TikTok have transformed how music is discovered, consumed, and monetized. This study examines the implications of the dispute between TikTok and Universal Music Group (UMG), which resulted in UMG excluding its music from TikTok from February to May 2024. UMG claimed that TikTok's compensation was inadequate, as presence of its tracks on the platform potentially reduced revenue that could be generated elsewhere. Conversely, TikTok argued that their compensation was appropriate, emphasizing the promotional and discovery benefits for artists. To examine the validity of these conflicting viewpoints, we conduct a Difference-in-Differences analysis, using tracks from Sony and Warner as a control group. We generally find that removing UMG music from TikTok did not significantly alter the overall demand for UMG tracks on streaming platforms like Spotify and YouTube. However, there is significant heterogeneity across tracks: previously available tracks on TikTok experienced a 2-3% increase in consumption when removed, indicating a *substitution effect*, predominantly encompassing more popular tracks from well-known artists. Conversely, UMG tracks not previously available on TikTok saw a 1-3% decrease in streams, indicating a *complementary effect*, mainly encompassing less popular tracks from lesser-known artists. Further analysis suggests that the *complementary effect* is driven by TikTok's role in promoting and discovering artists with a partial presence on the platform. An economic impact analysis shows that TikTok significantly undercompensates UMG, aligning with the terms of a new licensing agreement between the parties. This study provides valuable managerial implications for music labels, social media platforms, streaming services, and artists.

Keywords: Social media, Music Streaming, Content Monetization, Music Consumption, TikTok, Digitization

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1 Introduction

On February 1, 2024, TikTok users like @mariona.roma woke up to a grim reality. Effective that date, Universal Music Group (UMG), the label representing numerous artists – like Taylor Swift, Adele, and Drake – had pulled the soundtracks of all of its artists from TikTok's music library. Consequently, all videos that had used these tracks, including several by @mariona.roma, went silent. The silence disrupted the platform's dynamics: dancers moved without the usual beat drops and creators lip-synced to silence, highlighting the indispensable role of sound in content creation and the potential consequences of such disputes on the creative community. The situation sparked widespread disappointment and consternation among creators and followers alike (Kuo 2024).

UMG's dramatic action followed months of efforts to negotiate a new licensing agreement with TikTok. At the heart of the dispute between the parties, was UMG's claim that the previous agreement was, in its own words "unfair" (Universal Music Group 2024a)– as it failed to adequately compensate the label and its artists and songwriters for the use and consumption of tracks on the social media platform. In particular, while TikTok would pay the label a certain amount each time a creator incorporated a UMG track into their video, there was no further compensation. This meant that while the videos that included these music tracks were viewed thousands and sometimes millions of times by TikTok users, UMG and its artists/songwriters did not benefit from this consumption. Moreover, even though TikTok videos tend to be short and typically only feature part of a music track, still, repeated exposure to a particular song may reduce the desire to listen to this song again on other streaming platforms, such as Spotify and YouTube. If this is the case, UMG and its talent may be negatively affected by this cross-effect on demand. Notably, music streaming platforms usually compensate labels and artists every time a track is streamed (i.e., listened to). Given that streaming represents over 84% of music labels' revenues (RIAA 2024), any potential cannibalization can have significant financial implications for music labels.

For its part, TikTok believed that the compensation it had been paying was, in fact, "fair". The core of its argument was that being featured on TikTok was a boon for music labels, artists, and songwriters because such exposure could help promote the tracks and assist the artists in getting discovered (TikTok News 2024a), which would, in turn, spur greater demand on other channels. Furthermore, the growth of short-form video platforms has made TikTok an increasingly important channel for advertising (Yang et al. 2023). In a sense, TikTok intimated a potential for a positive cross-effect on music demand on other platforms.

In this paper, we empirically examine the conflicting arguments made by each party and, more broadly, address the issue of how major content owners like UMG—which holds a large number of music copyrights and trademarks—should consider the impact of social media consumption on the demand for their content on paid streaming platforms. Identifying the causal impact of social media consumption on outcomes/demand on other outlets is typically challenging due to potential endogeneity issues often associated with online user behavior (Godes and Mayzlin 2004). To overcome such endogeneity issues, we leverage the dispute between UMG and TikTok as a unique natural quasi-experiment. Specifically, given that the other two major labels that constitute the so-called 'Big Three' (Rys 2024), Sony Music Entertainment (SME) and Warner Music Group (WMG), did not remove their music from TikTok during this time frame, we can use their tracks as a control group to causally examine how precluding UMG tracks from TikTok affects the demand for UMG tracks on music streaming platforms, such as Spotify and YouTube. This context allows us to conduct a Difference-in-Differences (DiD) analysis to evaluate the effect of the treatment (i.e., exclusion of UMG music from TikTok) on our outcome of interest (i.e., demand for UMG tracks on streaming platforms). If the exclusion of UMG's tracks from TikTok results in a relative positive impact on Spotify streams and YouTube views, compared with non-exclusion, one can infer a substitution (or cannibalistic) effect of TikTok on streaming demand; thus supporting UMG's concerns. Conversely, if there is a relative negative impact, it implies a complementary effect, which aligns with TikTok's reasoning regarding the promotion and discovery role of its social media platform.

We compiled a dataset by drawing on multiple sources, including the websites of the Big Three record labels, as well as two music information aggregators, Soundcharts and Chartmetric (Soundcharts 2024; Chartmetric 2024). We start with a comprehensive list of the artists affiliated with the Big Three labels, based on information from the labels' official websites and Wikipedia. We then use Soundcharts and Chartmetric to obtain a listing of all the music tracks for each artist, which gives us a total of 235,741 tracks (across the three labels). Next, for each track, we obtain a set of relevant track-specific and artist-specific information, e.g., the career stage of the artists, track release date, and availability on TikTok in the pre-dispute period. Finally, for each track, we also collect data on its daily streaming demand – Spotify streams and YouTube views – over a six-month period from October 10th, 2023, to April 7th, 2024.

In our main analysis, we conduct a log Difference-in-Differences analysis leveraging the silencing of UMG's tracks on TikTok on February 1st, 2024, as a quasi-natural experiment. We find that, on average, the silencing of UMG's music on TikTok did not have a significant impact on the overall demand for UMG tracks on Spotify and YouTube compared to the counterfactual scenario where UMG tracks are allowed on TikTok. However, this null effect masks considerable heterogeneity. In particular, we focus on one dimension that is likely to impact the estimated treatment effects – the availability vs. the non-availability of tracks on TikTok prior to the dispute. Descriptively, these two groups are systematically different – tracks on TikTok (pre-dispute) tend to be more popular and by more successful artists, whereas tracks not on TikTok tend to be less popular and less likely to be performed by big-name artists. For example, in our data, an average track available on TikTok is streamed about 2,353 times daily on Spotify (in the pre-treatment period), while an average track not available on TikTok is only streamed about 82 times daily.

For tracks that were available on TikTok prior to the dispute, removal from TikTok led to a 2-3% *increase* in the consumption on Spotify and YouTube. This suggests a *substitution effect* for tracks that had been available on TikTok and indicates that TikTok may cannibalize the consumption of popular songs that would otherwise occur on revenue-sharing platforms like Spotify and YouTube; thus supporting UMG's concerns that TikTok had not been adequately compensating its artists and songwriters. In contrast, tracks that were not available on TikTok prior to the dispute experienced a roughly 2% *decrease* in their consumption on Spotify and YouTube as a result of UMG's action. This points to a *complementary effect*, indicating that UMG tracks not previously on TikTok could potentially benefit from the label placing music on the platform. Further analysis suggests that this *complementary effect* is likely due to the promotion and discovery role TikTok could be playing because it is mainly driven by artists with a partial presence on TikTok, i.e., some of their songs are available for use by TikTok creators, whereas others are not. In the case of such artists, social media users may first discover the artist via one (or more) of their songs embedded in TikTok videos and then seek out additional music by the artist on other streaming platforms like Spotify, where they might explore the artist's other tracks that are not available on TikTok. Taken together, our findings support the arguments of both UMG and TikTok, albeit for different groups.

We present an extensive set of robustness checks for the results in §5.3, including examining the validity of the parallel trends assumptions for all the models estimated and considering alternative specifications. We largely find converging support for our analysis and findings. In particular, when we split the tracks by presence on TikTok, the results are always consistent across all model specifications and samples. Hence, these heterogeneous results form the basis of our economic impact calculations and policy conclusions discussed below.

Lastly, we quantify the economic implications of our findings by conducting a simple back-of-envelope set of calculations. Based on the heterogeneity analysis discussed above, we know that – (1) for music already on TikTok, there is a *substitution effect* on Spotify, which implies a revenue gain if UMG's music were to be banned from TikTok, and (2) for music not on TikTok, there is a *complementarity effect*, which implies a revenue loss if UMG's music were to be banned from TikTok. Therefore, we calculate the expected annual revenue gain from the former group and the expected annual revenue loss from the latter group, and sum them together to obtain an estimate of the overall revenue impact on UMG. We find that if UMG's music is excluded from TikTok, the potential revenue gains from the typical tracks already on TikTok would easily outweigh the losses from the typical tracks not on TikTok. Specifically, we calculate the annual revenue gain from such a silencing move to be around $899 million USD, which is much lower than the approximately 111 million USD that TikTok was paying UMG prior to the dispute (Universal Music Group 2024a). In the "aftermath" of the dispute, and consistent with our findings, on May 1st, 2024, UMG and TikTok announced a new licensing agreement (Universal Music Group 2024b) that promises to "improve remuneration for UMG's songwriters and artists".

Our paper makes several contributions to the literature on cross-platform digital content consumption and the economic implications of social media platforms on the monetization of copyrighted content. First, substantively, we show that there are both substitution and complementarity effects in cross-platform consumption of digital content and that social media firms like TikTok can both help and hurt consumption in other channels. In particular, we find that streaming demand for popular content can suffer from direct exposure on social media (i.e., a *substitution effect*), whereas streaming demand for less popular content can benefit from social media (i.e., a *complementarity effect*), provided that some of the artists' tracks receive exposure on the platform. Second, from a managerial and economic perspective, we show that these two opposing cross-effects imply that content owners need to make an informed decision based on which of them dominates in their setting, taking into account the full portfolio and the lifecycle stage of their content. In our case, we find that the potential streaming revenue gains from excluding UMG's music from TikTok outweigh the compensation from TikTok at the time of the licensing dispute. Taken together, these findings provide guidance to content owners and social media platforms on evaluating and setting pricing and licensing terms.

The rest of the paper is organized as follows. In the next section, we discuss the related literature, and in §3, we delineate our research context by providing more detailed information on the main players involved and the nature of the licensing dispute that transpired between UMG and TikTok. In §4, we describe our data collection process and summarize the data features. §5 lays out our empirical framework, describes the main findings, and provides the details of the robustness checks. In §6, we offer an assessment of the economic implications of our findings for UMG and TikTok. Finally, in §7, we summarize the paper's findings and suggest managerial implications for the various stakeholders involved.

2 Related Literature

Our work is related to the small but growing literature in marketing and economics that examines the impact of digital platforms on music consumption and revenue generation across platforms. This work largely focuses on the impact of YouTube on music sales and so far, the findings are mixed. Hiller (2016) analyzes the temporary removal and subsequent reinstatement of Warner Music content on YouTube in 2009 and finds that the availability of popular albums on YouTube displaces Warner album sales. In contrast, Kretschmer and Peukert (2020) find that restricting access to online videos can decrease recorded music sales while enabling access tends to increase sales, as evidenced by two natural experiments in Germany—the 2009 blocking of all music videos on YouTube due to a legal dispute and the subsequent introduction of Vevo, which provided access to a large catalog of music videos. More specific to music streaming, Wlömert et al. (2024) show that while the availability of user-generated content using a specific track generally increases demand across other streaming platforms, it can cannibalize sales for new and hit releases, thereby negatively impacting overall revenue.

Our work both speaks and contributes to this debate by considering the impact of a different platform on music demand – TikTok, as it increasingly becomes a game changer in the music industry (Whateley 2023). There are a few important differences between TikTok and YouTube that can affect the substantive findings. On the one hand, unlike on YouTube, where users typically engage with entire songs/tracks, on TikTok, the music is typically embedded in user-generated videos as a backdrop, and only a small portion of the full song is featured.[1] Thus, it is unclear whether TikTok can serve as a relevant channel for music consumption when compared with standard streaming services. On the other hand, TikTok is deeply rooted in music, and its scale is unprecedented. As indicated by UMG in their open letters (Universal Music Group 2024a), "music is at the heart of the TikTok experience," and "TikTok is trying to build a music-based business." Further, there are over 34 million videos posted daily on TikTok and 85% of these feature music. Thus, TikTok surpasses all other social media platforms on this measure (i.e., content that features music), including YouTube, Instagram, and Facebook (Taylor 2024; Smith 2024; Whateley 2023). As such, even small changes in the platform may have a substantial impact on demand outside the platform. In this paper, we empirically investigate whether and how music availability on TikTok impacts streaming demand on Spotify and YouTube.

Research on this specific phenomenon, i.e., the effect of TikTok-like short-form video platforms on streaming demand, remains limited. Perhaps the works most relevant to our research are the following three papers. First, Yang et al. (2024) examined an exogenous boycott event in April 2021 that forced Douyin (the Chinese version of TikTok) to more proactively remove condensed TV series clips from the platform. They find that the removal of these clips reduced the demand for corresponding full-length original works on a

[1] Official videos featuring the full-length version of a music track are also licensed to TikTok, but the vast majority of the views for tracks come from user-generated videos where the track is embedded as background music.

major video streaming platform by approximately 3%, suggesting positive spillover effects from Douyin, consistent with a promotional effect. However, our findings indicate that TikTok does not influence the demand for music streaming in the same way. A notable distinction between TV and music streaming on short-form video platforms like TikTok concerns licensing aspects. Specifically, unlike TV streaming, where content is often edited into condensed clips by users without obtaining copyright permissions from the original TV series provider, the use of music on TikTok is governed by enforced licensing agreements.[2] This practice necessitates music labels to consider the "fair value" of licensing their music to TikTok, given the potential for millions of social media users to consume it for free. Second, an early version of a concurrent paper by Winkler et al. (2024) uses weekly music streaming data from a different source over a 9-week period and finds that the removal of UMG tracks had a positive effect on music streams. While they employ a similar log DiD specification to ours, they use weekly data and do not focus on the sources of heterogeneity that we do. Finally, in a recent working paper following ours, Bairathi et al. (2024) examine the same empirical context using weekly streaming data from one of our data sources over a 10-week period and report that the removal of UMG tracks had a negative effect on music streams previously available on TikTok. They employ a synthetic levels DiD specification and argue that our null/positive effects are likely due to our use of the log DiD specification, which can flip the sign of the estimated treatment effect under certain conditions (McConnell 2024). We conduct numerous robustness checks to examine whether this could be the case (including running levels DiD, rescaled DiD, and testing for the condition for sign flipping across specifications; see §5.3.2 for details), and find that the overall main treatment effects (across all tracks) are always null/positive, and the treatment effects on the subset of tracks already on TikTok (the specific subset of music that is the focus of Bairathi et al. (2024)) are consistently positive irrespective of the specification used. That is, we find no evidence of negative treatment effects for tracks on TikTok prior to the dispute.[3] We further note that our findings are consistent with the new agreement later reached between the parties, wherein TikTok increased the compensation to UMG artists (TikTok News 2024b; Universal Music Group 2024a,b). It should be noted that if treatment effects were indeed negative on the whole (which suggests an overall complementary effect), there would be no economic rationale for TikTok to increase its compensation to UMG.

3 Research Context

We now describe our research context, including the main players and the licensing dispute, which is the focus of this study.

3.1 Main Players

We start by describing the three main players, their sources of revenue, and their incentives.

[2]A separate stream of literature has examined the effects of illegal online copyright activities – commonly known as piracy – and their impact on demand for movies. For instance, Lu et al. (2020) find that pre-release piracy on websites can generate online word of mouth but is linked to lower film revenues. Similarly, Adermon and Liang (2014) find that pirated music is a strong substitution for legal music, but this substitute effect is less pronounced for movies. The main difference between these settings and ours is that the content available on TikTok is generally legally used and forms a source of revenue for UMG. As such, the findings from these papers may not directly translate to this setting, especially since the incentives and behavior of users who consume this content legally on TikTok are likely different from those who engage in illegal piracy.

[3]While we cannot definitely pinpoint the reasons for the negative treatment effect in Bairathi et al. (2024), it is possible that it stems from a combination of data and modeling choices, e.g., our sample spans over a 25-week period, and our unit of analysis is at the daily-level, which gives significant power, whereas their analysis uses weekly data over a 10-week time period.

- **TikTok:** TikTok is a short-form video hosting service and one of the largest social media platforms with more than 1 billion active monthly users in over 140 countries (Woodward 2024). The platform is powered by user-generated content, where users create/post, share, and consume short videos. An interesting aspect of these videos is that they often use soundtracks from music labels as their backdrop (Novecore Blog 2023). This has sparked a unique video creation phenomenon on TikTok – when a video or a meme gains popularity, other creators on TikTok often jump on the bandwagon and adapt the original video to create new content, typically using the same sound as in the original post. A prime example of this phenomenon is Fleetwood Mac's resurgence in popularity. Their 1977 album, Rumours, re-entered the charts after an obscure TikTok user posted a laid-back clip of himself skateboarding and sipping Oceanspray cranberry juice, all while grooving to the band's hit song "Dreams" (TikTok 2020). This sound clip inspired millions to create similar videos, cementing the song's iconic status on the platform (TikTok Newsroom 2019). As a result, many now view TikTok as a channel for users to (re)discover, share, and enjoy music.

  TikTok's primary source of revenue is advertising. Hence, the more users spend time on and engage with the platform, the better off it is (Iqbal 2024). As such, the creation, sharing, and consumption of engaging content that draws and keeps users in the system positively impacts TikTok's relevance to advertisers and revenues. Music is often a major component of such engaging content on TikTok (TikTok 2021).
- **Music Labels:** As described earlier, much of the sound used in TikTok videos comes from music licensed to the platform by the labels. There are three record labels that dominate the global music industry, also referred to as The Big Three Record Labels – Universal Music Group (UMG), Sony Music Entertainment (SME), and Warner Music Group (WMG). UMG leads with a market share of 33.90%, followed by SME at 26.91%, and WMG at 15.98% (Rys 2024). Each of these labels represents a variety of well-known recording studios and artists. For example, UMG includes major labels such as Interscope Records, Republic Records, Capitol Music Group, Abbey Road Studios, and prominent artists such as Taylor Swift, Billie Eilish, and the Weeknd (Universal Music 2024). Similarly, SME's portfolio includes Columbia Records, RCA Records, Arista Records, and Epic Records, which represent legendary figures such as Michael Jackson, Celine Dion, and Mariah Carey (Sony Music 2024a). Meanwhile, WMG operates labels that include Atlantic Records, Warner Records, and Parlophone Label Group, with top artists such as Ed Sheeran, Madonna, and Fleetwood Mac (Warner Recorded Music 2024).

  Music labels generate revenue from three primary sources: streaming services (such as YouTube, Spotify, and Apple Music), music sales, and licensing and synchronization fees (where the label allows partners such as social media platforms, movies, and video games to use their music) (Callaghan 2024). Streaming dominates the other two sources and accounts for over 84% of revenues (RIAA 2024).

  Conceptually, these revenue streams can act as both complements and substitutes for each other. For example, if a consumer learns about a track on TikTok, s/he may stream it on Spotify; alternatively, if a consumer mostly uses TikTok to consume music, s/he may not seek or purchase/stream music on other channels. Thus, record labels need to have a good understanding of how each of these revenue sources affects the others in order to make informed pricing decisions for each of them.
- **Streaming Services:** Music streaming services are platforms where users can watch and listen to music. Spotify and YouTube are two of the largest streaming platforms. Spotify offers over 100 million tracks

and has more than 615 million users across more than 180 markets (Spotify 2024a). Similarly, YouTube, has a vast array of video content, which often contains music, and attracts more than 2 billion visitors monthly (YouTube News 2023). Streaming platforms license tracks from music labels and monetize this by serving ads to listeners, as well as through subscription packages (for ad-free listening).

3.2 The UMG vs. TikTok Licensing Dispute

As social media platforms like TikTok have become a primary venue for exposure to and consumption of music, they represent a double-edged sword for music studios and labels. On the one hand, they can serve as a channel for music discovery and promotion, which may lead to increased demand on streaming platforms, thereby boosting the revenues of music labels. On the other hand, if users who consume music through TikTok substitute away from streaming the music elsewhere, for example, due to the fact that viewing content on TikTok is free and users' repeated exposure to the same music may lead to "wear-out" (Pechmann and Stewart 1988), then the effect of TikTok on music labels' revenues can be negative. With younger users spending more and more time on TikTok (Duarte 2024), labels may indeed harbor such apprehensions.

Fueled by these concerns, in early 2024, the largest music label, UMG, alleged that TikTok did not fairly compensate UMG's artists and songwriters for using their music in the extant agreement (Curto 2024). It noted that, despite TikTok's massive user base, rapidly increasing advertising revenue, and growing reliance on music-based content, TikTok contributed only about 1% to UMG's total revenue in 2023 (Universal Music Group 2024a). As a result, after unsuccessful negotiations, on January 30, 2024, UMG announced the termination of their licensing agreement with TikTok (Universal Music Group 2024a). This breakdown in negotiations meant that starting on February 1, 2024, TikTok users could no longer access UMG's music catalog. There were several immediate consequences of this termination, including the removal of UMG artists' music videos from TikTok, the removal of the tracks' music page, and the blocking of TikTok users from leveraging this music in new video creations. Moreover, existing TikTok videos featuring UMG songs were muted, rendering them silent.

This dispute lasted till May 1st, 2024, when UMG and TikTok successfully renegotiated their licensing agreement (Universal Music Group 2024b). As a part of the new agreement, TikTok agreed to deliver improved remuneration for UMG's songwriters and artists (Aswad 2024).

4 Data

Our data for the analysis comes from multiple sources, including the websites of the Big Three record labels, as well as Soundcharts and Chartmetric (Soundcharts 2024; Chartmetric 2024). Soundcharts and Chartmetric are platforms that provide historical and real-time data tracking and analytics for music tracks across streaming services and social media. Soundcharts integrates data from a wide array of sources and offers track metadata, streaming information, label details, etc. Chartmetric provides insights into track usage on social media platforms like TikTok and also offers proprietary artist-level metrics such as the *Career Stage Score*. We describe the data collection process in detail below.

First, we compiled a list of all the artists who have worked with the Big Three Record Labels from a combination of the labels' official websites and their Wikipedia pages (Wikipedia 2024, 2023a,b; Warner Records 2024; Warner Music Store 2024; Sony Music 2024b; Universal 2021). This gives us a total of 2862 artists who have worked with at least one of these labels. Next, we use Chartmetric to obtain information on each artist's characteristics (e.g., their career stage, how many music tracks they have made so far) and use Soundcharts to obtain a complete list of all the music tracks recorded by the artist over their career. Further, for each track, we collect additional information, including its label (e.g., UMG, Sony, Warner, or some other label), its release date, and a global track identifier (i.e., ISRC). Overall, this process gives us 235,741 tracks across the three main music labels.

In addition, we use Chartmetric to ascertain whether each of the tracks in our sample has a corresponding music URL on TikTok and to monitor the number of videos posted on TikTok that feature each track. This data is crucial for understanding the differential impact of the licensing dispute on UMG tracks that were available on TikTok vs. those that were not available on TikTok at the start of the dispute (February 1, 2024). The former tracks were removed from TikTok's music library due to the dispute, which resulted in the muting of videos that leveraged these tracks. The latter tracks, which were not on TikTok prior to the dispute, could not be added to the platform as a result of the dispute. In contrast, tracks from SME and WMG remained unaffected, i.e., videos using their tracks already on TikTok were still available, and tracks that were not on TikTok could still be uploaded and used for video creations on the social media platform during the timeframe of the study.

Finally, we use Soundcharts to collect data on the performance of all the 235,741 tracks belonging to the Big Three record labels on the two main streaming platforms, Spotify and YouTube. Since the start of the licensing dispute (i.e., the exclusion of UMG's music from TikTok) happened on Feb 1st, 2024, we focused on about a four-month period prior to the start of the dispute and a two-month period after the dispute commenced as a timeline for analysis. Specifically, our data collection covers a 180-day period from October 10th, 2023, to April 7th, 2024.

In §4.1, we summarize the track-level data, and in §4.2, we describe the time-varying data available for each track, including the daily usage on TikTok and the daily music consumption on Spotify and YouTube.

4.1 Time Invariant Track Information

We now describe the time-invariant attributes of the tracks in our data.

- $TrackName_i$: The name of track i.
- $ISRC_i$: The unique global identifier for track i, which we use to map tracks across different data sources.
- $Label_i$: Categorical variable denoting track i's label (i.e., UMG, Sony, or Warner). Of the 235,741 tracks, 113,808 are from UMG, 53,157 from Sony, and 70,247 from Warner.
- $PrevOnTikTok_i$: Categorical variable denoting whether track i has a music url on TikTok or not prior to the dispute. Of the 235,741 tracks, 28.59% were available on TikTok prior to the dispute, and the rest were not.
- $ReleaseDate_i$: The release date of track i.
- $ArtistName_i$: The artist name of track i.
- $CareerStage_i$: The artist's career stage of track i. It consists of six levels: undiscovered (1.32%), developing (18.50%), mid-level (19.15%), mainstream (36.94%), superstar (17.86%), and legendary (6.23%). More detailed definitions for the career stages are available at Chartmetric (2022).

4.2 Daily Track Consumption on Spotify and YouTube

There are two main metrics of demand from a music label's perspective – streaming and sales. We focus on streaming demand because it accounts for over 84% of the revenue for music labels and continues to grow (RIAA 2024). In contrast, while music sales used to be a significant source of revenue for labels in the past, it is no longer the case – digital music sales only account for 4% of revenues while physical sales (e.g., CDs and LPs) account for 11% of revenues. Streaming is thus the main source of revenue for music labels and accounted for $47.7 billion dollars in global revenue in 2023 (Curry 2023). From consumers' perspective, streaming has grown to be a key channel for music consumption. Collectively, Americans streamed around 4.1 trillion songs in 2023 (Luminate 2023).

Among streaming services, Spotify is the market leader, with over 30% market share and over 615 million monthly active users (Duarte 2024; Spotify 2024a) The next four contenders consist of YouTube, Tencent, Apple Music, and Amazon Music – all with market shares between 12–15% (Curry 2023). In this study, we utilize the daily demand data for Spotify and YouTube, which together represent about 46% of global streaming demand.[4]

Table 1: Summary Statistics of Daily Music Consumption

	Spotify Streams			
	All	UMG	WMG	SME
Mean	634,913.19	795,462.83	828,446.87	237,157.08
Std.	137,148,828.34	170,898,434.03	141,701,582.08	38,489,235.14
Min	0.00	0.00	0.00	0.00
25%	23.00	15.00	30.00	37.00
50%	228.00	162.00	280.00	291.00
75%	2,136.00	1,848.00	2,688.00	2,268.00
Max	231,194,640,582.00	231,194,640,582.00	149,510,335,746.00	53,635,410,309.00
Count	24,653,299.00	11,616,941.00	5,649,017.00	7,500,906.00
	YouTube Views			
	All	UMG	WMG	SME
Mean	585,870.40	603,582.08	468,778.16	651,359.80
Std.	17,397,774.24	17,199,710.54	19,835,429.48	15,253,726.31
Min.	0.00	0.00	0.00	0.00
25%	55.00	49.00	54.00	66.00
50%	281.00	240.00	268.00	370.00
75%	1,749.00	1,529.00	1,544.00	2,299.00
Max.	7,120,032,301.00	3,940,740,592.00	7,120,032,301.00	2,580,171,535.00
Count	1,611,996.00	702,731.00	413,641.00	505,379.00

For the time period of the analysis, for each track in our data, we gather the following demand information: (1) the number of daily streams on Spotify, which is counted as the number of times the track was listened to for 30 seconds or more on a given day (Spotify 2024b), and (2) the number of views on YouTube, which is counted as the number of times a video is watched for at least 30 seconds on a given day (Tuberanker 2022).[5]

[4]The main reason for not including data from Apple Music, Amazon Music, and Tencent is that there are no reliable providers with access to data from these firms.

[5]We note that there are a few days during the observation period when such data are not available, especially for YouTube; as a result, the amount of data available for YouTube is much less than that for Spotify, which can make the findings less robust for

Table 2: Summary Statistics of Average Daily Music Consumption By Track

	Spotify Streams			
	All	UMG	WMG	SME
Mean	640,831.31	802,095.96	840,203.37	234910.86
Std.	12,576,347.91	15,586,764.95	13,100,757.83	3,747,620.22
Min.	0.00	0.00	0.00	0.00
25%	44.73	34.03	51.33	62.01
50%	495.95	454.52	529.25	538.70
75%	7,162.74	7,539.85	7,178.60	6837.40
Max.	1,617,088,443.72	1,617,088,443.72	1,035,367,900.22	432590084.77
Count	235,741.00	113,808.00	53,157.00	70,247.00
	YouTube Views			
	All	UMG	WMG	SME
Mean	1,187,000.55	1,386,643.76	841,014.49	1,184,101.24
Std.	17,507,606.62	21,812,208.59	13,788,935.08	12,830,384.93
Min.	0.00	0.00	0.00	0.00
25%	116.55	104.29	110.08	142.83
50%	853.16	734.85	736.26	1183.33
75%	13,996.12	12,419.48	10,300.78	20569.77
Max.	1,550,815,406.50	1,550,815,406.50	776,462,899.70	598,164,778.00
Count	71,179.00	30,783.00	18,026.00	22,796.00

The summary statistics of these two demand metrics for the entire observation period (across all tracks and periods) are shown in Table 1. We find that these distributions are quite skewed with long tails, i.e., some tracks (on some days) get extremely high demand, running into billions of streams/views, but the bulk of the daily streams/views are much smaller. The median demand for a track on Spotify is 228 daily streams, whereas the median demand on YouTube is about 281 views per day. We also calculate the average daily demand by track and present these track-level summary statistics in Table 2. Additionally, we show the summary statistics of daily music consumption on Spotify and YouTube for the pre-treatment period in Tables A1 and A2 in Web Appendix A.

5 Empirical Analysis

We now present our empirical analysis and findings.

5.1 Main Effect on Music Demand

The breakdown of the licensing agreement between UMG and TikTok provides a quasi-natural experiment for our study. In this context, the treatment is the exclusion of UMG's music from TikTok. Consequently, UMG tracks that were previously available on TikTok were removed, videos leveraging those tracks were muted, and UMG tracks not yet on TikTok were blocked from being uploaded to or used on TikTok. As such, UMG tracks form our treatment group, while tracks from Sony and Warner, which remained available during the licensing dispute, serve as the control group.

We use a Difference-in-Differences (DiD) specification, which is a widely applied strategy for evaluating the effect of an intervention or treatment (e.g., the exclusion of UMG music from TikTok) on an outcome

YouTube. Nevertheless, the empirical results are largely consistent across both platforms.

variable of interest (e.g., Spotify streams and YouTube views). A DiD analysis estimates the treatment effect by comparing the difference in the changes in the outcome variable between the two groups (i.e., treatment and control). Our estimation relies on the following DiD specification:

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

where our dependent variable $Demand_{it}$ is the music consumption of track i on the day t on a streaming service, i.e., the number of streams on Spotify or the number of views on YouTube. We logged our dependent variable $Demand_{it}$ to address skewness and because we are primarily interested in understanding the outcome in percentage terms (Fouka 2020). UMG_i is an indicator equal to 1 if track i belongs to UMG and 0 otherwise. $Post_t$ equals 1 if date t is after Jan. 31, 2024, and 0 otherwise. The coefficient of interest is β, which represents the effect of track i belonging to the treatment group (i.e., exclusion from TikTok) on its streaming demand relative to the counterfactual scenario where the track is allowed on TikTok. $Track_i$ captures track fixed effects and $Date_t$ captures date fixed effects.

Table 3: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Log-Specification)

	(1)		(2)	
	log_Spotify_streams		log_YouTube_views	
1.UMG#1.post	-0.00293	(0.00219)	-0.00684	(0.00738)
_cons	5.572***	(0.000383)	5.908***	(0.00140)
Track FE	Yes		Yes	
Date FE	Yes		Yes	
N	24653297		1611685	
R^2	0.9475		0.8838	
AIC	56223334.0		4565598.3	
BIC	56223349.0		4565610.5	

Standard errors are presented in parentheses and clustered at the track level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 reports the results from the estimation of the DiD model shown in Equation (1). Column (1) features the results for Spotify demand, and column (2) for YouTube demand. As we can see, the main effect for both streaming platforms is insignificant. Later, in §5.3.2, we run a series of robustness checks on this analysis using the demand directly as the outcome (instead of *log* of the demand variable) and find consistent results; albeit under some specifications the effect can be slightly positive, and its magnitude is sensitive to outliers and subject to model fit issues. This could be because some alternative specifications pick up the actual level of change, which may be negligible in percentage terms under the log-specification (see more details in §5.3.2). Overall, this suggests that the main effects are either null or tend to be slightly positive.

5.2 Heterogeneity in Treatment Effects

We now explore whether the overall null effect from estimating Equation (1) on the full dataset masks any significant heterogeneity effects across different subgroups. In particular, one dimension that is likely to have an impact is the presence of the track on TikTok prior to the dispute (as captured by the $PrevOnTikTok_i$ variable described in section §4.1). For brevity, we present the main analysis with the log DiD specification estimated over different subgroups here. However, we perform a series of exhaustive robustness checks on the heterogeneity analysis and show that the results are valid and consistent elsewhere in the paper. Please see Web Appendix §C.2 for parallel pre-trend tests for the heterogeneity analysis, Web Appendix §B for analogous models with three-way interactions, and §5.3.2 for heterogeneity analysis with a levels DiD model.

Table 4: Summary Statistics of the Pre-Period Daily Streams on Spotify: For Tracks Previously on vs. Not on TikTok

	Tracks On TikTok			
	All	UMG	WMG	SME
Mean	315,855.59	390,506.33	412,278.51	147,521.24
Std.	3,577,350.31	4,014,790.74	4,390,629.02	1,932,599.51
Min.	0.00	0.00	0.00	0.00
25%	414.49	381.25	426.98	465.52
50%	2,352.98	2,347.60	2,224.82	2,492.81
75%	15,774.07	17,492.10	14,613.04	14,687.75
Max.	207,011,949.09	207,011,949.09	204,661,701.70	176,290,048.31
Count	76,210.00	35,837.00	16,124.00	24,784.00
	Tracks Not On TikTok			
	All	UMG	WMG	SME
Mean	26,847.57	20,064.03	49,677.27	19,312.21
Std.	563,714.03	489,733.96	841,793.40	345,692.80
Min.	0.00	0.00	0.00	0.00
25%	12.45	8.66	16.63	19.91
50%	82.50	53.58	115.96	125.22
75%	545.34	417.56	828.87	575.61
Max.	70,654,006.15	70,654,006.15	62,790,995.68	23,573,607.25
Count	159,529.00	77,961.00	36,943.00	45,412.00

We start by examining whether the following two groups – tracks that were previously available on TikTok prior to the dispute and tracks that were not available on TikTok prior to the dispute – are different from each other and, if so, how. First, we look at their pre-treatment demand level. Table 4 shows the track-level average daily streams on Spotify, and Table 5 shows the track-level average daily views on YouTube for each group. As we can see, the two groups are systematically different – tracks already on TikTok tend to be more popular than those not on TikTok. For example, an average track available on TikTok is streamed about 2,353 times daily on Spotify, while an average track not available on TikTok is only streamed about 82 times daily. Next, we examine the distribution of artists by career stage across the two groups; see Table 6. One interesting observation is that tracks on TikTok before the dispute are almost three times more likely to be from superstar artists. Overall, it seems that tracks on TikTok (pre-dispute) tend to be more popular and from more successful artists compared to tracks that were not on TikTok.

We now estimate the DiD specification in Equation (1) separately on these two groups of tracks and present the results in Table 7. Columns (1) and (2) display the regression results, whereby the treatment group consists of UMG tracks that were on TikTok prior to the dispute, and the control group comprises Sony and Warner tracks that were also on TikTok prior to the dispute. Columns (3) and (4) display the regression results, whereby the treatment group consists of UMG tracks that were not available on TikTok prior to the dispute, while the control group comprises Sony and Warner tracks that were not available on TikTok prior to the

Table 5: Summary Statistics of the Pre-Period Daily Views on YouTube: Tracks on vs. Not on TikTok

	Tracks On TikTok			
	All	UMG	WMG	SME
Mean	2,266,162.71	2,521,786.56	1,929,246.62	2,124,830.49
Std.	25,524,351.74	29,363,078.30	24,339,947.32	20,071,621.06
Min.	0.00	0.00	0.00	0.00
25%	431.92	361.03	451.85	532.80
50%	2,866.90	2,411.70	2,775.82	3,655.05
75%	50,029.87	43,286.78	45,614.38	61,585.50
Max.	1,456,073,743.67	1,456,073,743.67	1,254,837,137.64	860,206,470.33
Count	37,610.00	16,815.00	8,106.00	12,933.00
	Tracks Not On TikTok			
	All	UMG	WMG	SME
Mean	192,912.49	184,120.79	150,590.16	247,317.41
Std.	3,860,745.93	4,464,133.07	2,269,940.25	4,163,567.92
Min.	0.00	0.00	0.00	0.00
25%	53.67	49.00	58.17	57.82
50%	203.11	171.64	240.71	225.17
75%	1,625.71	1,292.90	1,868.47	1,893.76
Max.	324,861,858.00	324,861,858.00	108,417,081.40	250,395,317.67
Count	33,154.00	13,796.00	9,791.00	9,747.00

dispute. We discuss both sets of results in turn below.

The dispute had a differential implication for the various music labels in our data. As we can see from columns (1) and (2) of Table 7, the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is positive and significant for streams on Spotify (b = 0.0229, $p < 0.001$) and views on YouTube (b = 0.0216, $p < 0.1$). This indicates that the removal of UMG tracks on TikTok prior to the dispute led to a 2.32% (=$e^{0.0229} - 1$) increase in the demand for these specific tracks on Spotify and a 2.18% (=$e^{0.0216} - 1$) increase in their demand on YouTube compared to the counterfactual scenario where UMG tracks were to continue to be available on TikTok. This suggests a *substitution effect* for tracks that were available on TikTok prior to the dispute, indicating that these tracks received greater streaming demand after being excluded from TikTok's music library.

Table 6: Artist Career Stage Distribution for Tracks Available on vs. not Available on TikTok Prior to the Dispute

Artist Career Stage	Tracks on TikTok	Tracks Not on TikTok
mainstream	0.3783	0.4250
superstar	0.3096	0.1292
legendary	0.1818	0.2304
mid-level	0.0972	0.1168
developing	0.0326	0.0965
undiscovered	0.0004	0.0022

These findings echo the concerns of music labels and provide evidence in support of the cannibalizing impact of TikTok on popular tracks and artists. At the core of the dispute was UMG's allegation that TikTok did not adequately compensate its artists and songwriters. For example, Music Business Worldwide (MBW)

Table 7: Main Effect of Excluding UMG Tracks 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	0.0229***	0.0216+	-0.0142***	-0.0266**
	(0.00405)	(0.0112)	(0.00257)	(0.00869)
_cons	7.741***	6.820***	4.593***	4.914***
	(0.000676)	(0.00227)	(0.000459)	(0.00157)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	7670998	804222	16982133	787275
R^2	0.9429	0.8634	0.9351	0.8976
AIC	16724381.7	2384634.5	38388391.9	1938692.4
BIC	16724395.5	2384646.1	38388406.5	1938704.0

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

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

used data from Chartmetric to analyze the Top 1,000 most popular TikTok videos featuring Kate Bush's "Running Up That Hill" and found that these videos collectively garnered almost 5 billion views/plays on TikTok. However, unlike streaming platforms such as Spotify, where musicians get paid based on the total number of streams, TikTok's royalty payment system is based on the number of video creations that use a song (Hypebot 2023), which is typically orders of magnitude lower. Notably, while Kate Bush's track garnered nearly 5 billion unpaid views on TikTok, it was streamed only 400 million times on Spotify, despite being Spotify's global No.1 track for weeks. While this is just one anecdotal observation, examples like this abound and suggest that TikTok likely has a cannibalization/substitution effect on popular songs that would otherwise be consumed more heavily on revenue-sharing streaming platforms like Spotify (Ingham 2022).

Next, columns (3) and (4) in Table 7 show the estimation results for those tracks that were not available on TikTok prior to the dispute. Here, the treatment status indicator, 1.UMG#1.post, is negative and significant for both streams on Spotify (b = -0.0142, p $<$ 0.001) and views on YouTube (b = -0.0266, p $<$ 0.01). This implies that UMG tracks that were not available on TikTok prior to the dispute experienced a 1.41% (=$1 - e^{-0.0142}$) decrease in Spotify streams and a 2.62% (=$1 - e^{-0.0266}$) decrease in YouTube views in the period after the dispute. This suggests a *complementary effect* for tracks that were not available on TikTok prior to the dispute, indicating that these tracks were adversely affected by UMG's decision to exclude its tracks from TikTok.

This finding can be viewed as supporting the promotional and discovery role of TikTok, especially for content not already on the platform, which tends to be less popular and originate from less renowned artists. By banning TikTok users from incorporating any UMG music into their videos, the label likely hindered tracks by some of its artists from being discovered by a larger audience. In particular, TikTok users may discover artists who are new or previously unknown to them through their available tracks on TikTok. After becoming familiar with these artists, users may search for them on other music streaming platforms, such as Spotify, and discover other tracks by these artists that are not on TikTok. For instance, music producer L Dre witnessed a remarkable rise in his Spotify monthly listeners after his track "Steven Universe" was incorporated in over 10 million TikTok video creations, prompting fans to explore his other music on Spotify (Cirrkus 2022).

We next test TikTok's afore-described promotional and discovery role for artists with partial track availability on the platform. We do so by further segmenting the tracks not available on TikTok in the pre-dispute period into two subgroups – tracks from artists who had no tracks on TikTok prior to the dispute and tracks from artists who had some of their tracks available on TikTok prior to the dispute. We then examined how the exclusion of UMG tracks from TikTok affected the demand for music streaming for these two subgroups. As before, we estimate the DiD model in Equation (1) on these two subgroups separately and present the results in Table 8. Columns (1) and (2) display the results for tracks from artists with no TikTok presence prior to the dispute, while columns (3) and (4) show the results for tracks by artists with partial TikTok coverage.

First, for artists who have no prior tracks on TikTok, we do not observe any significant impact; see columns (1) and (2) of Table 8, where the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is insignificant. That is, for artists with no TikTok presence, the exclusion of UMG tracks from TikTok has no significant impact on their Spotify and YouTube demand. In contrast, for artists who had partial TikTok availability (through their other tracks), there is a significant negative impact of the dispute – see columns (3) and (4) of Table 8, where the estimated coefficient of the treatment status indicator, 1.UMG#1.post, is negative and significant. Together, these results suggest that the negative, or complementary, effects estimated in columns (3) and (4) of Table 7 are mainly driven by tracks from artists who had some presence on TikTok before the dispute. This further supports the hypothesis that TikTok can serve as a promotional and discovery channel for artists (TikTok News 2024b) – when they gain some traction on TikTok through certain tracks, their other tracks (which are not on TikTok) tend to be discovered and streamed elsewhere. Though this analysis is not a formal test, it provides some evidence for the idea that TikTok possibly plays a complementary, promotional, and discovery role for artists, particularly for their tracks that are not available on the social media platform.

Table 8: Main Effect of Excluding UMG Tracks from TikTok on Music Demand for Tracks Not on TikTok Prior to the Dispute: Artists with Partial vs. No 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#1.post	0.0207	0.0452	-0.0153***	-0.0289**
	(0.0165)	(0.0544)	(0.00260)	(0.00881)
_cons	4.191***	4.955***	4.604***	4.912***
	(0.00288)	(0.00921)	(0.000465)	(0.00159)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	449179	21450	16532954	765823
R^2	0.9417	0.9059	0.9349	0.8974
AIC	1045504.5	55331.2	37335563.2	1882757.9
BIC	1045515.5	55339.2	37335577.9	1882769.4

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

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

In summary, we find that TikTok has a differential effect on music tracks depending on whether they had vs. had not been available on the platform prior to the dispute. For the former type of tracks, there is a *substitution effect*, i.e., they received greater streaming demand after being excluded from TikTok's music library. These tracks tend to be more popular and come from more well-known artists. However, for the latter type of tracks, there is a *complementary effect*, i.e., they were adversely affected by UMG's decision to exclude its tracks from TikTok. These tracks tend to be less popular and less likely to be recorded by super-star artists. We further find that the complementary effect is likely driven by the promotion and discovery role TikTok can play for artists with a partial presence on TikTok – once their tracks that had previously been available on TikTok were removed, this had a negative impact on the streaming of their other tracks not previously available on the social media platform. Together, these findings support the arguments of both TikTok and UMG, albeit for different subgroups.

5.3 Robustness Checks

We now present a series of robustness checks on the analysis presented above. First, in §5.3.1, we test the assumptions required for the validity of the DiD models we used and then in §5.3.2 we consider a variety of alternative model specifications.

5.3.1 Model Assumptions and Validity Tests

The validity of the DiD model we employed in our analysis depends on a few key assumptions. We briefly describe these assumptions and our empirical tests to validate them in the main text below, with further details available in Web Appendix (§C, §D, and §E).

Parallel pre-trend: A key assumption of the DiD model pertains to parallel pre-treatment trends: if the treatment group had not received the treatment, the trend in the treatment group's outcomes would have been the same as the trend in the control group's outcomes (Angrist and Pischke 2009). Therefore, we run a linear trend model to test whether the parallel pre-trend assumption is satisfied (on both Spotify and YouTube) for both the main effects and heterogeneous treatment effects models. We find that the assumption is largely satisfied, with trends being either insignificant and/or very small (compared to the magnitude of the estimated treatment effects, e.g., 0.3%–1.5% of the size of the treatment effect). Please see Web Appendix C for details. In principle, it is feasible to correct for small differences in trends using matching. However, in practice, matching can introduce its own source of bias (Daw and Hatfield 2018) and should only be used when there are meaningful differences in pre-treatment trends (which is not the case in our setting). Moreover, we have 113 days of pre-treatment data, and it is not practical to match over such a long horizon. As such, we would need to aggregate the data to weekly/monthly levels to effectively match on pre-trends, and this will lead to a significant loss of power in addition to introducing match-related bias issues. Further, as we later discuss in §5.3.2, the results are consistent even when we use other specifications.

Level differences between treated and control groups: In addition to the parallel pre-treatment trend, it is usually a good idea to confirm that the levels of the treatment and control groups in the pre-treatment period are comparable (McKenzie 2020). Though not strictly required, this provides additional assurance for the validity of the DiD analysis. To that end, in Web Appendix E.1, we plot the distributions of the daily demand of tracks from all three music labels – UMG, SME, and WMG, and confirm that these distributions are largely similar in levels. Moreover, we recenter the outcome distribution of the treated group to align the baseline means and rerun the analysis after ensuring there is no disparity between the treatment and control groups. Our findings remain consistent after rescaling, as detailed in Web Appendix E.4 for details.

SUTVA: Another potential concern is that the treatment has a spillover effect on the control group, resulting in a violation of the SUTVA (Stable Unit Treatment Values Assumption) required for the DiD model. In particular, in our setting, one concern could be that when UMG's music disappeared from TikTok, users on the platform may have switched to music from SME and WMG, leading to a substantial upswell in their TikTok usage (which in turn could have impacted the control group's demand on Spotify and YouTube). To examine if this is the case, we collect data on the number of new TikTok videos uploaded daily that use music from different music labels before and during the treatment period. We do not see any significant jump in the use of SME and WMG's music after the dispute. Furthermore, we analyzed Spotify streams and YouTube views for SME and WMG's music by fitting a linear trend model to examine whether the silencing of UMG's music led to a significant surge in demand for SME/WMG tracks in the post-dispute period. However, our analysis did not reveal any consistent demand shifts across both platforms. Lastly, we examined global downloads and usage of the TikTok app before and after the licensing dispute, finding continued growth in monthly active users despite the licensing dispute. Thus, it is unlikely that there were any significant spillover effects on the control group during the treatment period. See Web Appendix D for details of the analysis and results.

In sum, we find that the data patterns are generally supportive of the identification strategy. However, some of the identifying assumptions are not directly testable with our data, even though they are unlikely to have been violated. First, the licensing dispute only lasted around three months, and significant changes—such as those in algorithms and competitors—typically require more time and effort to manifest. We do not observe any coinciding changes in demand- or artist-driven factors that would suggest endogeneity in the timing of Universal's music withdrawal from TikTok. Moreover, other major labels like Sony, Warner, and various independent labels did not alter their policies regarding TikTok during this period. We also did not see any anecdotal/empirical evidence that suggests that Universal withdrawal of its content from TikTok triggered any immediate changes in Spotify's/YouTube's recommendation algorithms since algorithmic adjustments usually take time to develop, test, and implement. Nevertheless, we acknowledge that we cannot empirically rule out these considerations.

5.3.2 Specification Checks

So far, we used a logged dependent variable in our analysis. We did so because of the nature of the data, which is highly skewed, and as we are primarily interested in understanding the outcome in percentage terms (Fouka 2020). However, a recent working paper by McConnell (2024) suggests that using a log specification in DiD model, as opposed to a levels-specification, can result in the sign of the treatment effect flipping under certain conditions (especially when the mean levels of the treated and control groups show large differences in the pre-treatment period). To examine whether this is a concern in our setting, we consider additional tests and alternative specifications.

First, we examine the extent to which the outcome distributions for the treated and control groups are different. Although we observe some differences, they are relatively very small in magnitude. Nevertheless, we formally test whether the moments in our data satisfy the condition for sign flipping when going from levels to logs. We find that the condition for sign flipping is not satisfied in our data, i.e., based on the data patterns, we would not expect the sign to flip. See Appendix §E.1 for details.

Second, we estimate a DiD model in levels as follows:

$$Demand_{it} = \alpha + \beta * UMG_i * Post_t + Track_i + Date_t + \epsilon_{it}, \tag{2}$$

Table 9 presents the results from estimating the levels-specification DiD model in Equation (2). Column (1) suggests that the demand for UMG's music tracks on Spotify increased by 684,307.2 compared to the counterfactual scenario where tracks would remain available on TikTok. Column (2) shows the effect of the results on YouTube demand, which is null. We also confirm that the parallel trend assumption holds for both these level models; see Web Appendix §C.3 for details.

The main difference between this analysis and that from §5.1 is the large positive treatment effect on Spotify. Based on the daily average pre-treatment demand for UMG streams on Spotify (135,222, per Table A1 in Web Appendix A), this translates into a 506% increase in daily streams on Spotify. This unreasonably large effect likely stems from the poor fit and extreme skewness of our data; notice that the R^2 for Spotify demand in column (1) of Table 9 is considerably lower than the log specification results in Table 3. To examine the extent to which this effect is driven by outliers, in Table 10 we also report results for the case where observations with Spotify streams above the 99th percentile were excluded. These results remain directionally consistent with Table 9, but R^2 improves significantly, and the coefficient decreases by orders of magnitude. This implies a high degree of sensitivity in the magnitude of the estimated treatment effects when using a levels-specification in the DiD model.[6] Overall, these results suggest that the licensing dispute had a null, or a possibly small positive, effect on UMG's demand in streaming platforms.

We also replicate the heterogeneity analysis for the levels DiD and find that all the results are consistent with our earlier findings reported in Table 7; see Table A19 in Web Appendix §E.3 for details. That is, we find that as a result of the dispute, tracks that had been available on TikTok see a positive (substitution) effect, and tracks that had not been available on TikTok see a negative (complementarity) effect. In a recent working paper following ours, Bairathi et al. (2024) use a levels-specification on a weekly DiD model, focus only on tracks available on TikTok, and document a negative treatment effect for those tracks. However, in spite of multiple stress tests, we consistently see a positive treatment effect for tracks on TikTok – including the levels DiD analysis described above, the log DiD analysis described in §5.2, and an additional rescaled analysis described in Web Appendix §E.4 where we scale the outcome variable to align the baseline outcome means before the log transformation.[7] Further, as we will discuss in §6 below, our findings and treatment effects are largely consistent with the eventual resolution of the dispute (unlike the negative effects on Spotify demand found in Bairathi et al. (2024)), since TikTok increased the compensation for UMG artists. Finally, since the results for the analysis by subgroups (of tracks available vs. not available on TikTok) are always consistent across all types of robustness checks, we will focus on these heterogeneous effects in our economic impact discussion section.

[6]We also report results excluding observations above the 95th and 90th percentiles of Spotify streams in Web Appendix E.2, where all results remain directionally consistent with Table 9, but decrease in magnitude even more drastically.

[7]According to (McConnell 2024), rescaling the outcome distribution of the treated group so that it is re-centered to align baseline outcome means before applying the log transformation avoids issues with sign flips by ensuring that the differences in the levels of the distributions of the outcome and treated variables are aligned.

Table 9: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Levels-Specification)

	(1)		(2)	
	Spotify_streams		YouTube_views	
1.UMG#1.post	684307.2***	(163345.7)	15855.4	(71044.9)
_cons	515134.4***	(28591.5)	582512.0***	(13467.0)
N	24653297		1611685	
R^2	0.0124		0.4281	
aic	993492724.8		57412769.5	
bic	993492739.9		57412781.8	

Standard errors in parentheses

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

Table 10: Main Effect of Excluding UMG Tracks from TikTok on Music Demand (Levels-Specification, Dropping Observations Larger than 99 Percentile)

	(1)		(2)	
	Spotify_streams		YouTube_views	
1.UMG#1.post	312.3**	(98.41)	635.0	(566.3)
_cons	18112.6***	(17.18)	20820.0***	(108.0)
N	24406707		1595299	
R^2	0.9047		0.4214	
aic	571635472.8		41644196.7	
bic	571635487.9		41644209.0	

Standard errors in parentheses

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

6 Economic Impact

We now present a simple back-of-the-envelope assessment of TikTok's economic impact on a music label's streaming revenues based on our estimates and data. For this analysis, we use the heterogeneous estimates from §5.2.

First, we calculate the impact on UMG's annual streaming revenue from Spotify in the scenario where its tracks are excluded from TikTok. Based on the findings in section §5.2, we know that: (1) For music available on TikTok, there is a *substitution effect* on Spotify, which implies an incremental gain in demand if UMG's music is excluded from TikTok, and (2) for music not available on TikTok, there is a *complementarity effect*, which implies an incremental loss in demand if UMG's music is excluded from TikTok. To the extent that the baseline demand for these two groups is different, it is possible that the overall net impact on revenue is non-zero (i.e., not null). Therefore, we calculate the net impact on revenue impact from Spotify on an annual basis as follows:

$$\Delta\text{Revenue}^S = \text{Gain}^S - \text{Loss}^S. \tag{3}$$

We can further expand the two terms on the right-hand side as follows:

$$\text{Gain}^S = \sum_{i=1}^{N_{\text{OnTikTok}}} \beta^S_{\text{OnTikTok}} \times BaselineDemand^S_i \times 0.003 \times 365$$
$$\text{Loss}^S = \sum_{i=1}^{N_{\text{NotOnTikTok}}} \beta^S_{\text{NotOnTikTok}} \times BaselineDemand^S_i \times 0.003 \times 365,$$

where $\beta^S_{\text{OnTikTok}}$ and $\beta^S_{\text{NotOnTikTok}}$ are the incremental impacts on the daily demand for the two groups in the counterfactual scenario. Based on the parameters in columns (1) and (3) of Table 7, this translates to $\beta^S_{\text{OnTikTok}} = +2.32\%$ and $\beta^S_{\text{NotOnTikTok}} = -1.41\%$. Further, $BaselineDemand^S_i$ denotes track i's average daily demand on Spotify in the pre-treatment period, \$0.003 represents the per-stream average payment that Spotify pays the music label (RouteNote 2022), and 365 refers to the number of days in a year.[8] Note that the calculation is over the set of tracks in the two groups, and we know that $N_{\text{OnTikTok}} = 35,837$ and $N_{\text{NotOnTikTok}} = 77,961$. This yields $\text{Gain}^S = 340.87$ million USD and $\text{Loss}^S = 24.15$ million USD, for a net revenue gain of ≈ 316.72 million USD per year.[9] This suggests that by excluding its music from TikTok, UMG could gain over 300 million USD per year in revenues from Spotify.

We can do a similar calculation and derive the impact on the annual streaming revenue from YouTube as:

$$\text{Gain}^Y = \sum_{i=1}^{N_{\text{OnTikTok}}} \beta^Y_{\text{OnTikTok}} \times BaselineDemand^Y_i \times 0.001 \times 365$$
$$\text{Loss}^Y = \sum_{i=1}^{N_{\text{NotOnTikTok}}} \beta^Y_{\text{NotOnTikTok}} \times BaselineDemand^Y_i \times 0.001 \times 365,$$

Note that this is similar to the calculations performed for Spotify, with only a few minor differences. Specifically, based on the parameters in columns (2) and (4) of Table 7, we have $\beta^{\text{Y}}_{\text{OnTikTok}} = +2.18\%$ and $\beta^{\text{Y}}_{\text{NotOnTikTok}} = -2.62\%$. $BaselineDemand^Y_i$ refers to the average pre-treatment demand on YouTube for track i, and \$0.001 is the per-view payment from YouTube to the music label (Oksana 2023).[10] This yields $\text{Gain}^Y = 720.25$ million USD and $\text{Loss}^Y = 137.55$ million USD, for a net revenue gain of ≈ 582.7 million USD per year.[11]

In sum, the removal of UMG tracks from TikTok's music library leads to a net revenue gain of approxi-

[8]Note that Spotify pays artists between \$0.003 - \$0.005 per stream on average (RouteNote 2022). We choose \$0.003 as the payment to keep our calculations conservative.

[9]These numbers are calculated as follows. $\text{Gain}^S = (e^{0.0220} - 1) \times 390,506.33 \times 365 \times 0.003 \times 35,837$, where 390,506.33 represents the mean daily Spotify streams for UMG tracks already on TikTok based on our data per Table 4, and 35,837 denotes the number of such tracks. Similarly, $\text{Loss}^S = (1 - e^{-0.0142}) \times 20,064.03 \times 365 \times 0.003 \times 77,961$, where 20,064.03 represents the mean daily Spotify streams for UMG tracks not present on TikTok before the dispute based on Table 4, and 77,961 denotes the number of such tracks.

[10]On average, per-view payments are lower on YouTube compared to Spotify. Industry reports suggest that YouTube pays music studios between \$0.001 and \$0.003 per view, on average (Oksana 2023). As in the case of Spotify, we choose the lower end of this range to keep our calculations conservative.

[11]These numbers are calculated as follows: $\text{Gain}^Y = (e^{0.0216} - 1) \times 2,521,786.56 \times 365 \times 0.001 \times$ 35,837, where 2,521,786.56 represents the mean daily YouTube views for tracks already on TikTok based upon Table 5, and 35,837 denotes the number of tracks on TikTok. Similarly, $\text{Loss}^Y = (1 - e^{-0.0266}) \times 184,120.79 \times 365 \times 0.001 \times 77,961$, where 184,120.79 represents the mean daily YouTube views for tracks not on TikTok prior to the dispute based upon Table 5, and 77,961 denotes the number of such tracks.

mately \$899 million USD from streaming on YouTube and Spotify. We can contrast this number with the status quo at the time of the dispute. In 2023, UMG's annual revenue was approximately 11.11 billion USD, of which TikTok contributed only 1%, or approximately 111 million USD (Universal Music Group 2024a), which implies a revenue loss of approximately \$788 million USD. Taken together, these calculations suggest that UMG's presence on TikTok results in a significant net loss in streaming revenues from other platforms like Spotify and YouTube, even if our calculations err somewhat on the side of supporting UMG's claims. Notably, on May 1st, 2024, UMG and TikTok announced a new licensing agreement (Universal Music Group 2024b) that promises to "improve remuneration for UMG's songwriters and artists," a move that aligns with our findings.

Table 11: Top 10 UMG Tracks's Views on TikTok based upon their 100 Most Popular Video Creations

Soundtrack	Artist	Total views
good 4 u	Olivia Rodrigo	24,833,494,359.0000
TWINNEM	Coi Leray	22,148,185,018.0000
happier	Olivia Rodrigo	12,659,661,006.0000
Happier Than Ever	Billie Eilish	11,763,840,240.0000
drivers license	Olivia Rodrigo	11,113,293,766.0000
Super Freaky Girl	Nicki Minaj	10,666,492,500.0000
Venom	Eminem	10,076,421,820.0000
Toosie Slide	Drake	9,725,194,834.0000
Supalonely	Gus Dapperton	8,255,200,000.0000
Believer	Imagine Dragons	7,777,127,228.0000

More broadly, our findings and analysis also invite further discussion on the optimality of the licensing/compensation model between social media platforms like TikTok and music labels like UMG. So far, UMG and other music labels do not receive any direct compensation for the number of views/streams on TikTok of a given track; rather, the compensation is based on the number of TikTok videos that used the track. As the aforementioned Kate Bush example highlights, these two metrics can be orders of magnitude different from each other. Recall that the top 1,000 TikTok videos featuring Bush's track "Running up the Hill" garnered nearly 5 billion views (Hypebot 2023). If UMG were to treat these views in a similar fashion to Spotify streams or YouTube views, then this would translate to a very significant lost monetization opportunity for UMG. While views of TikTok videos that use music tracks (as their audio backdrop) should likely be compensated at lower rates than YouTube/Spotify streams since the videos also include new original content made by TikTok users and often do not play the entire track, they could still represent a significant revenue stream for UMG.

To get a sense of the scale of this potential revenue, in Table 11, we list the top ten UMG tracks on TikTok based on the number of videos that use them. For each of these tracks, we show the total number of views that the top 100 videos using that track garnered. For example, the top 100 videos featuring the soundtrack "good 4 u" garnered over 24 billion views on TikTok. Together, the videos featuring the top ten UMG tracks garnered over 129 billion unpaid TikTok views. If UMG were to charge TikTok a streaming fee similar to YouTube (\$.001 per view), this would translate to a revenue gain of over 129 million USD, which is quite significant.[12] Note that this revenue calculation only considers the top 100 video recreations for the top 10 UMG tracks; if we were to consider the full UMG collection on TikTok and all their video recreations and views, this number would be much higher. As such, this estimate should be considered as a lower bound on the potential revenue gains from moving to this alternative revenue model (or to some combination of compensation for track usage in a video creation and the subsequent views of that creation). In sum, we find that pulling UMG's music from TikTok can lead to significant positive revenues from other sources and that UMG may be under-monetizing its music on TikTok by not charging for views directly. These findings also suggest that music labels can further sharpen their licensing agreements with social media platforms like TikTok without undercutting their streaming revenues.

Finally, we note that our economic impact calculations make a series of simplifying assumptions. As such, they are intended to give readers a sense of the scale of the economic impact (rather than serve as exact numbers) and should be taken with the appropriate caveats. For instance, we do not account for music streams on other platforms like SoundCloud (where UMG music is also available), and we also do not consider the potential impact on digital music sales (e.g., on Apple Music) or direct album sales. Additionally, our estimates are based on the short-term change in demand (within a few months of the removal of UMG's music from TikTok). It is unclear whether the long-term effects on streaming demand would be similar in magnitude. Furthermore, platforms like TikTok may provide artists and studios with other benefits not quantified in our analysis, e.g., a channel to shape the popular zeitgeist, a venue for interacting with fans and other artists, and an outlet for influencing popular trends in music and culture. Nevertheless, the analysis is intended to serve as a conservative first step in quantifying the impact of social media platforms like TikTok on music streaming demand and revenue and also to provide some insights into the potential profitability of alternative revenue models.

7 Conclusion

Our study focuses on a recent music licensing dispute between UMG and TikTok, which highlights important questions about the consumption, promotion, and monetization of music in the era of social media. At the heart of the dispute, UMG argued that TikTok's compensation is "unfair," because it failed to adequately compensate the label and its artists and songwriters for the usage of and exposure to tracks on the platform. In particular, extensive exposure and repeated consumption of music tracks on the platform could potentially diminish listeners' interest in other paid streaming services such as Spotify. Conversely, TikTok maintained that its platform "fairly" compensates artists by enhancing their visibility and fostering discovery, which in turn can boost demand across various music streaming platforms.

We leverage this dispute as a natural quasi-experiment, using UMG tracks that were excluded from TikTok as the treatment group and comparing them to tracks from Sony Music Entertainment (SME) and Warner Music Group (WMG), which remained available. Our Difference-in-Differences analysis shows that the removal of tracks that had been available on TikTok led to a 2-3% increase in the consumption of these tracks on Spotify and YouTube, indicating a *substitution effect* and supporting UMG's concerns about unfair compensation. Our findings suggest that these tracks tend to be more popular and come from more

[12] Both YouTube and TikTok are social media sites featuring video content and thus share certain similarities. As such, adopting YouTube's pricing model for TikTok seems more realistic than Spotify's higher pricing model.

well-known artists. Conversely, tracks not previously available on TikTok experienced a 1-3% decrease in streams on Spotify and YouTube, suggesting a *complementary effect*. These tracks tend to be less popular and less likely recorded by super-star artists. Our results further indicate that the *complementary effect* is possibly driven by the promotion and discovery role that TikTok can play for artists with a partial presence on the social media platform. Specifically, once their tracks that had previously been available on TikTok were removed, it negatively impacted the streaming of these artists' other tracks that were not previously available on TikTok. Taken together, the findings support the arguments of both UMG and TikTok, albeit with respect to different groups.

We further note that several of our results point to possible mechanisms driving the findings. For example, since the *substitution effect* is linked to the more popular tracks that had been available on TikTok prior to the dispute, it could reflect user "wearout" (due to repeated exposure); and since the *complementary effect* is associated specifically with tracks by artists that had partial availability on TikTok it could reflect a discovery and promotion role of the platform. Notwithstanding, future research can delve more deeply into the underlying forces responsible for these cross-demand effects.

Our back-of-envelope calculations indicate that UMG's annual revenue loss on Spotify and YouTube due to usage on TikTok is approximately $788 million USD.[13] This assessment does not account for potential losses on other platforms, like Apple Music and SoundCloud. Notably, on May 1, 2024, UMG and TikTok reached a new licensing agreement that promises to "improve remuneration for UMG's songwriters and artists"(Universal Music Group 2024b), aligning with our findings.

In closing, we point out that our work has noteworthy managerial implications for a number of key stakeholders. For music labels and copyright-protected content owners, our analysis underscores the importance of considering potential cross-effects between channels such as social media platforms and demand on other outlets such as streaming services. We observe that for relatively popular content, these channels often function as "substitutes," whereas for less popular content, they can exhibit "complementarity." Therefore, it is advisable for copyright-protected content owners to critically evaluate the net-net economic implications of such cross-effects and determine whether compensation should be based on track usage or viewership (or both). For social media platforms, our analysis suggests that these players should design features for better discovery and promotion of music tracks and serve less as "substitutes" with other channels so that music labels and artists will value being on the platform. For artists, our study highlights the importance of selecting which tracks to feature on social media platforms to minimize substitution and maximize discovery and promotion opportunities.

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Author(s) have no competing interests to declare.

[13]It is computed by subtracting TikTok's current approximate payment to UMG (i.e., $111 million (Universal Music Group 2024a)) from the potential annual revenue gain from silencing on TikTok (i.e., $899 million computed from § 6))

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Appendices

A Additional Summary Statistics

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

	Spotify_Streams Prior to the Feud			
	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 Feud

	YouTube_Views Prior to the Feud			
	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 Feud

	Spotify_Streams Prior to the Feud			
	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 Feud

	YouTube_Views Prior to the Feud			
	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 Feud

	Spotify_Streams Prior to the Feud			
	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 Feud

	YouTube_Views Prior to the Feud			
	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

B 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 A7 shows the three-way interaction between a track's absence or presence on TikTok prior to the dispute and the treatment (i.e., the exclusion 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 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 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 could 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 Excluding UMG Tracks 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.UMGl#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

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

C 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 and as well as the level models used for robustness checks in §5.3.2.

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

A key assumption of the DiD model is parallel pre-treatment trends: if the treatment group had not received the treatment, the trend in the treatment group's outcomes would have been the same as the trend in the control group's outcomes (Angrist and Pischke 2009). Therefore, we need to compare the pre-treatment trends in

Table A8: Main Effect of Excluding UMG Tracks 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	
N	16982133		787275	
R^2	0.9351		0.8976	
aic	38388046.6		1938675.5	
bic	38388090.5		1938710.2	

Standard errors in parentheses

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

music demand on Spotify and YouTube for the treatment and control groups.

One issue in our case is that 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 misleading. Therefore, we fit a linear trend model to examine whether the trends for the treatment tracks (UMG) and the control tracks (SME and Warner) are systematically different during the entire pre-treatment period. Specifically, we estimate Equation A1 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.

$$log(Demand_{it} + 1) = \alpha + \beta * UMG_i * t + Track_i + Date_t + \epsilon_{it}, \tag{A1}$$

The results from this estimation are shown in Table A9. We see that the linear trend coefficient for Spotify demand in column (1) has a tiny 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's very unlikely that the null effect in Table 3 is driven by the time trend before the dispute.

When parallel pre-trends assumption largely holds in the Difference-in-Differences analysis, matching is not necessary, and doing so can introduce some estimation bias (Daw and Hatfield 2018). Therefore, we do not consider any matching approaches to avoid introducing additional bias.

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

Since we segment our data in estimating heterogeneity in treatment effects, we also fit a linear trend model to formally test the pre-trend assumption for the segmented data. As shown in Table A10, 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

Table A9: Linear Trend for All Tracks (Log-Specification)

	(1) log_Spotify_streams		(2) 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

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

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.

In Table A11, 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 A11) , while the YouTube demand coefficient remains insignificant in column (2). Therefore, it is unlikely that the effects in Table A11 are driven by any pre-treatment time trends.

Table A10: Linear Trend for Tracks on vs. Not on TikTok Prior to 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
1.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

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

Table A11: Linear Trend for Tracks Not on TikTok Prior to the Dispute: Artists with Partial vs. No 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	0.00163	-0.0000874**	-0.000284
	(0.000153)	(0.00124)	(0.0000268)	(0.000215)
_cons	4.164***	5.158***	4.574***	5.121***
	(0.00386)	(0.0224)	(0.000734)	(0.00424)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
N	272739	12004	10196832	429899
R^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

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

C.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 A2. The results, presented in Table A12, 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.

$$Demand_{it} = \alpha + \beta * UMG_i * t + Track_i + Date_t + \epsilon_{it}, \tag{A2}$$

Further, Table A13 presents the parallel trend tests for the heteroegeneous DiD analysis in levels (by presence on TikTok prior to the dispute), with more details in Web Appendix §E.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 A12: 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	
N	15352379		906890	
R^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 A13: 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	2850.5	-0.0196	913.2
	(170.9)	(3179.2)	(30.01)	(877.4)
_cons	297598.8***	1267027.0***	38451.6***	271687.1***
	(4322.5)	(61852.8)	(819.7)	(17251.9)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
N	4882808	443666	10469571	441905
R^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 A14: Linear Trend for Tracks Not on TikTok Prior to the Dispute: Artists with Partial vs. No 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	-1951.2	-10.42	967.5
	(312.8)	(8398.8)	(29.78)	(881.2)
_cons	104200.8***	455182.0**	36686.1***	266173.9***
	(7877.4)	(151195.3)	(815.2)	(17367.3)
Date FE	Yes	Yes	Yes	Yes
Track FE	Yes	Yes	Yes	Yes
N	272739	12004	10196832	429899
R^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

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

D Tests for Spillover Effects to the Control Group

Finally, 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 exclusion 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.[14]

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(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

[14] Please 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.

comparing creations these two timeframes (before $\overline{log(TikTok\_Video\_Creations_{it}+1)}$ = 0.0405, after $\overline{log(TikTok\_Video\_Creations_{it}+1)} = 0.0408$, p > 0.1). In contrast, when we perform a two-sample t-test for the log(number of daily video creations + 1) on TikTok for the treatment group (i.e., tracks from UMG), and it's negative and significant, suggesting a significant decrease in video creations after the feud (before $\overline{log(TikTok\_Video\_Creations_{it}+1)}$ = 0.0326, after $\overline{log(TikTok\_Video\_Creations_{it}+1)}$ = 0.0023, p < 0.001). Indeed, the number of TikTok videos using UMG's music drops to zero effectively 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.

$$log(TikTok\_Video\_Creations_{it}+1) = \alpha + \zeta * Post_t + Track_i + \epsilon_{it}, \tag{A3}$$

where the key coefficient of interest is ζ. We estimate this regression for tracks from SME and WMG and present the results in Table A15. 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 A15: 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
N	4666475
R^2	0.2388
aic	3774666.7
bic	3774680.0

Standard errors are presented in parentheses and clustered at the track level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A16: 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	

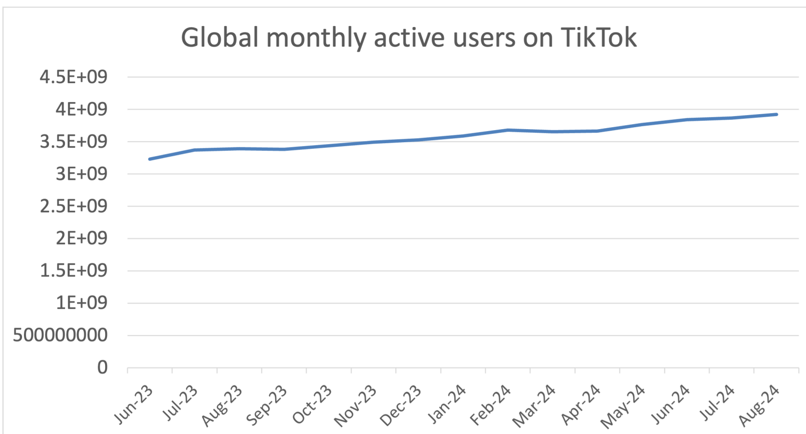
Standard errors are in parentheses and clustered at the track level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We further examine potential systematic shifts in Spotify and YouTube demand before and after the dispute using the following linear trend model (A4):

$$log(Demand_{it} + 1) = \alpha + \beta * Post_t + \zeta * Post_t * t + Track_i + \epsilon_{it}, \tag{A4}$$

where the key coefficient of interest is ζ. We estimate this regression for tracks from SME and WMG and present the results in Table A16. 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 the 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.

Figure A1: Global Monthly Active TikTok Users



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,[15] a third-party analytics tool that tracks app usage from both App Store and Google Play. As illustrated in Figure A1, 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.

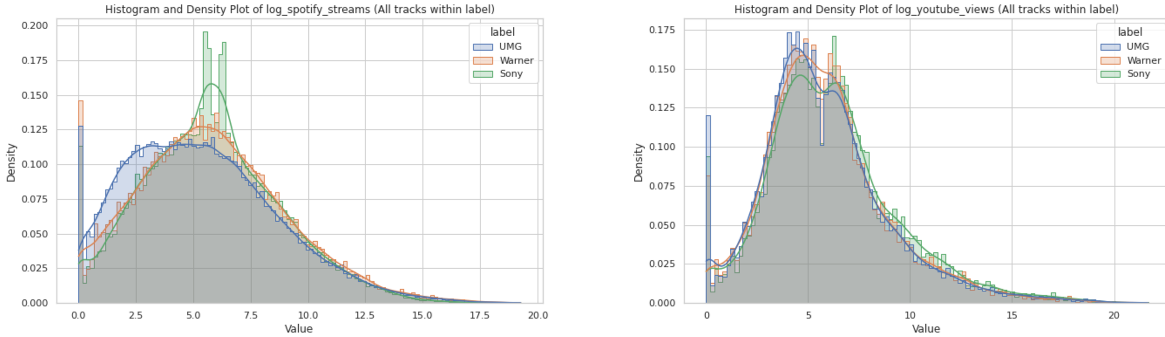
E Appendix for Specification Checks

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

Figure A2 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 $0 < |\Delta_T - \Delta_C| <$

[15] https://www.data.ai/account/login/



Spotify streams

YouTube views

Figure A2: Pre-treatment Music Demand Distributions for the Big Three Labels

$|\Delta_C \frac{(E[Y_{T0}]-E[Y_{C0}])}{E[Y_{C0}]}|$. Here, $E[Y_{C0}] = E[Y_{it} \mid D_i = 0, T_t = 0]$ represents the expected demand for WMG's and SME's music before the licensing dispute, and $E[Y_{T0}] = E[Y_{it} \mid D_i = 1, T_t = 0]$ represents the expected demand for UMG's music before the licensing dispute. The terms $\Delta_C = E[Y_{it} \mid D_i = 0, T_t = 1] - E[Y_{it} \mid D_i = 0, T_t = 0]$ capture changes in music demand for WMG's and SME's music before and after the dispute, while $\Delta_T = E[Y_{it} \mid D_i = 1, T_t = 1] - E[Y_{it} \mid D_i = 1, T_t = 0]$ 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.

E.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 A17, we show the estimates when we drop the top 5% of outliers for a given platform, and in Table A18, 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 A17: Main Effect of Excluding UMG Tracks 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)
N	23419919		1530003	
R^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 A18: Main Effect of Excluding UMG Tracks 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)
N	22186544		1448697	
R^2	0.9256		0.8354	
aic	364497706.3		23912341.3	
bic	364497721.2		23912353.5	

Standard errors in parentheses

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

E.3 Heterogeneous Treatment Effects with Levels DiD

In Table A19 below, we present the levels DiD analysis separately for tracks on TikTok and tracks not on TikTok prior to the dispute. The result are consistent with the heterogeneity analysis shown with the log DiD model in §5.2 for Spotify demand (i.e., number of streams).

Table A19: Main Effect of Excluding UMG Tracks 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***	53910.4	-225423.4**	62492.4
	(495362.8)	(112260.1)	(72121.8)	(33994.3)
_cons	1154299.6***	879572.2***	219572.9***	188057.3***
	(82678.5)	(22789.6)	(12888.9)	(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

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

E.4 Results after Rescaling Demand Variables

Even though our data satisfies the condition to ensure that the sign of 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 E.1), we nevertheless consider another specification where the distributions are aligned in outcomes. Specifically, we rescale/recentered 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:

$$Y_{it}^{RC} = \begin{cases} Y_{it} & \text{if} \quad D_i = 0 \\ Y_{it} - (\overline{Y}_{T0} - \overline{Y}_{C0}) & \text{if} \quad D_i = 1 \end{cases}, \tag{A5}$$

where $\overline{Y}_{T0}$ and $\overline{Y}_{C0}$ 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 A20, 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 from the estimation. 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 A21. We see that the results are consistent with our heterogeneous treatment effects 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 excluded 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 both Spotify and YouTube following its exclusion from TikTok's music library.

Table A20: Main Effect of Excluding UMG Tracks 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	
N	14004256		947194	
R^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 A21: Main Effect of Excluding UMG Tracks 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***	0.160***	-0.0461***	0.0419
	(0.00708)	(0.0315)	(0.0121)	(0.0555)
_cons	8.286***	7.253***	5.071***	5.172***
	(0.000366)	(0.000689)	(0.000138)	(0.000285)
Track FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
N	4817342	467297	9186402	466797
R^2	0.9479	0.8784	0.9418	0.9091
aic	10518606.3	1407105.7	20795896.0	1152781.0
bic	10518619.7	1407116.7	20795910.0	1152792.0

Standard errors in parentheses

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

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