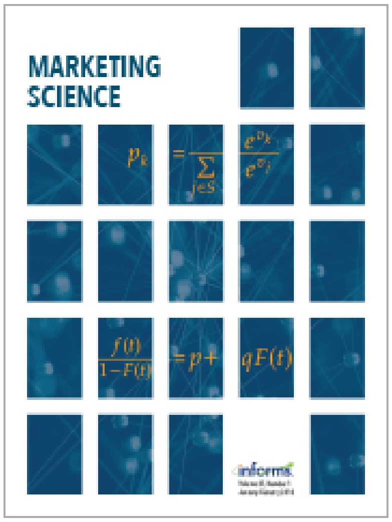

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Frontiers: The Interplay of User-Generated Content, Content Industry Revenues, and Platform Regulation: Quasi-Experimental Evidence from YouTube

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Abstract. An ongoing debate among firms, rightsholders, particularly in the music industry, and policymakers in the United States and the European Union concerns potential changes to the regulation of user-generated content (UGC) video streaming platforms (e.g., YouTube). Currently, safe harbor provisions protect platforms from liability for copyright-infringing content uploaded by users, and requirements for compensating rightsholders for UGC are weak, resulting in comparatively low payouts. At the same time, it is unclear how a change in these regulations would affect consumer demand for this content on other platforms with higher payouts (e.g., Spotify), that is, whether UGC platforms stimulate or displace demand on other platforms. We study a quasi-experiment that occurred when numerous songs became available as UGC on YouTube after an agreement between YouTube and the German royalty collecting society. Our analysis of an unprecedented data set covering 600,000 songs by 38,000 artists reveals an intriguing finding: Although UGC availability stimulates demand in other streaming channels for most songs, cannibalization occurs for recent releases and hit releases, turning the overall revenue effect negative. We discuss how policymakers can use these findings to understand the implications of changes in regulation, and how labels and artists can decide which content to block or allow on UGC platforms.

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Keywords: user-generated content • digital platform regulation • safe harbor • channel cannibalization • difference-in-difference • quasi-experiment • music streaming

1. Introduction

"The Copyright Office concludes that the balance Congress intended when it established the section 512 safe harbor system is askew."

U.S. Copyright Office (2020, p. 197)

User generated content (UGC) platforms such as YouTube, Facebook, Instagram, or TikTok play a key role in how users communicate and consume content. Their vast reach and dominant market positions leads to numerous regulatory challenges that need to balance, inter alia, (1) access to information, (2) protection of consumers, (3) interests of copyright holders, and (4) the power of gatekeepers (Goldfarb and Tucker 2019, Johnson et al. 2022). Initial regulations like the 1998 U.S. Digital Millennium Copyright Act (DMCA) and the 2000 European Union (EU) Electronic Commerce Directive protected UGC platforms from liability for copyright-infringing user uploads through so-called safe harbor provisions.

Although these lenient regulations allow UGC platforms to offer extensive content libraries to their users, rightsholders and policymakers have long been concerned that these regulations put rightsholders at a disadvantage, in part because the safe harbor provisions mean that platforms such as YouTube pay no or only little compensation to rightsholders (Liebowitz 2018, Blistein 2021). Policymakers in the United States are currently discussing changes to these regulations and, in its recent report to the U.S. Congress, the U.S. Copyright Office outlined the need to update Section 512 of the DMCA: the key section related to the safe harbor system (U.S. Copyright Office 2020, Stout and Manne 2022).[1] Likewise, in the EU, the 2019 EU Copyright Directive (CD) strengthens the rights of copyright owners by requiring UGC platforms to obtain authorization from the rightsholders for the use of copyrighted content.[2] However, the EU Copyright Directive still shields UGC platforms from liability for copyright violations as long as they make best efforts according to industry standards and the specific requirements for UGC platforms under the recently changed EU regulation are likely candidates for legal clarification (Quintais 2022).

These debates raise the question of how demand for the rightsholders' content would be affected if these regulations are changed, that is, to which extent demand in other channels would be affected if regulations were changed by either facilitating or restricting content provision via UGC platforms. In case of the music industry, the question is whether platforms such as YouTube *substitute* demand in other channels that do not host content uploaded by users (e.g., Spotify, Apple Music) or whether they *stimulate* demand in other channels through sampling or discovery (Kretschmer and Peukert 2020, Blistein 2021). These questions are particularly relevant because UGC platforms such as YouTube are either explicitly protected by safe harbor provisions (e.g., in the United States), or courts have ruled in favor of the platforms, stating that, for example, YouTube cannot be held legally responsible for user-uploaded content (Ingham 2016). This legal position likely allows these platforms to pay low royalty rates compared with other streaming services (e.g., Apple Music, Spotify) that do not primarily host UGC (Liebowitz 2018, Stout and Manne 2022).[3] These issues are also currently debated in the context of TikTok's impact on rightsholders and in negotiations over TikTok's share of ad revenue to be paid to the major labels (Cirisano 2022). Importantly, previous research does not provide conclusive insights on how changes in these regulations would affect demand for the rightsholders' content in other channels, and it is difficult to directly study demand reactions to regulations prior to their implementation. Moreover, the debate to date has largely overlooked the distributional effects of potential regulation on different types of artists, such as established artists or newcomers.

To contribute to this debate, we study a quasi-experiment that can act as a proxy for the direct analysis of a change in regulation. We do so by analyzing a supply shock in the German music market where hundreds of thousands of songs became available on a UGC platform overnight when GEMA, the German music royalty collecting society, and YouTube, the #1 on-demand music streaming service worldwide (Dredge 2020), settled a long legal fight in October 2016. This supply shock allows us to quantify how making UGC content available on a major UGC platform affects demand in other channels, and whether the overall net impact of making UGC available is positive or negative for content owners. We argue that this quasi-experiment is akin to a change in regulation that facilitates content provision via UGC, and it provides us the opportunity to understand possible consequences of potential changes in EU and U.S. regulation.

Ideally, we would be able to study a quasi-experiment, in which we observed the introduction of safe-harbor regulations into a market that previously did not rely on safe-harbor regulations, and we would require an untreated control group. Because such a quasi-experimental setting is not available, we study how making user-generated content available on a popular UGC platform affects demand for that content in other channels as well as total revenue. We then discuss what we can learn from this quasi-experiment for potential economic consequences of safe harbor regulations.

Our analysis rests on an unprecedented data set comprising more than 600,000 tracks by more than 38,000 artists, covering approximately 50% of the entire German market. The results indicate that making UGC available on YouTube had, on average, modest positive effects on premium streams (e.g., Spotify premium) and free ad-funded streams (e.g., Spotify free) on other platforms, and negligible effects on paid downloads. These average effects, however, mask substantial heterogeneity across songs; that is, the effects are negative for songs that have been successful prior to treatment and for new releases. In contrast, the effects are positive for less successful (long-tail) songs and older songs. Coupled with the skewed distribution of demand in the music market, this means that the total effect of UGC availability on *industry revenue* is negative, despite the seemingly positive effect on demand for the average song.

Overall, our analysis allows us to learn and infer whether and how an increase in UGC supply that is induced by a switch from a restrictive policy regime (that essentially bans UGC platforms from offering unlicensed content) to a more lenient regime (in which UGC platforms remunerate content), affects demand for the rightsholders' content.

2. Background

2.1. Institutional Background

The legal dispute between GEMA and YouTube dates back to April 2009, when YouTube stopped showing music videos provided as UGC in Germany after a

Figure 1. (Color online) YouTube Blocked Content Message

Notes. Before the agreement between GEMA an YouTube was reached, this message was shown to German YouTube users who requested a video that contained copyrighted music content. English translation: Unfortunately, this video is unavailable in Germany because it may contain music for which we could not reach an agreement with GEMA over its use. We are sorry for this.

17-month deal with GEMA came to a close. Under this deal, YouTube paid GEMA a fixed per-stream fee for its licensed videos. After efforts to renew the contract collapsed, users saw a blocked content message whenever they tried to play a video that contained potentially copyright-infringing music content (Figure 1).

The legal battle regarding the adequate remuneration of rightsholders lasted for more than seven years. YouTube argued based on the safe harbor regulation that, as a hosting provider (rather than a content provider), it cannot be held legally responsible for material its users upload. GEMA argued that YouTube should be held accountable for the unlicensed usage of copyrighted content on its platform. The disagreement was the subject of court cases, without a consistent ruling. An agreement between YouTube and GEMA was reached on October 31, 2016, the blocked content message was removed, and hundreds of thousands of UGC videos containing music content became available overnight, which we study as a quasi-experiment. Although the details of the deal were not disclosed, the case and the deal in 2016 received major press coverage (Eddy 2016). The dispute and the deal in 2016 only pertained to UGC videos. Videos provided by artists and labels themselves (i.e., firm-generated content), for example, as promotional music videos, were not part of this process (see Online Appendix A). In fact, some artists provided parts of their content on YouTube before the agreement was reached, which we consider in our following analysis.[4]

2.2. Theoretical Background

On the one hand, UGC video availability may have beneficial effects for songs and artists because it may act as a sampling source. Sampling is particularly relevant for music as an experience good (Zhang 2018). Given the vast assortment size in digital markets, UGC may inform consumers, resolving imperfect information that inhibits product discovery (Hendricks and Sorensen 2009). On the other hand, samples may displace purchases or consumption elsewhere, especially when free samples are close substitutes for the main product, which is likely for digital products (Halbheer et al. 2014).

Previous research with respect to the potential sampling and substitution effects of UGC video streaming is scarce and inconclusive. Hiller (2016) and Kretschmer and Peukert (2020) both analyze data from YouTube's early days (i.e., 2009) and find evidence that UGC on YouTube, on average, cannibalizes *album sales* (Hiller 2016) but stimulates *song sales* (Kretschmer and Peukert 2020).[5] However, their analyses are focused on the effects of UGC on *purchases* of CDs and downloads (not *streams*).

Our analysis of more than 600,000 songs covers the majority of all streams in the market, allowing us to explore heterogeneity across songs along several dimensions. The conceptual argument guiding the selection of moderators is that songs differ in the degree to which they may benefit from being discovered through sampling (Hendricks and Sorensen 2009) and reminder advertising (He and Klein 2023). (1) We expect that songs that are already popular prior to the treatment are less likely to benefit from sampling through UGC because consumers are likely to be already familiar with the music from previous encounters (Hendricks and Sorensen 2009, Zhang 2018). (2) We further expect that the treatment effect is contingent on the recency of a song's release. Recent releases are more salient and, thus, more accessible for consumers compared with older songs. In contrast, older songs are less top of mind and their discovery is facilitated via sampling (Zhang 2018). (3) Some videos are available as (promotional) music videos provided by labels or artists. We expect that songs that were available as firm-generated music videos prior to becoming available as UGC as part of the treatment will benefit less from sampling. Following a similar rationale as in (1) and (2), we expect (4) content from newcomer artists will benefit more from sampling, as well as (5) content from niche genres. Last, we expect (6) genres attracting a younger audience will see a less positive treatment effect because younger consumers are more likely to adopt the habit of consuming music via platforms such as YouTube.

3. Data

GfK SE, a large market research firm in Germany, provided demand information for all >600,000 songs published by three music labels. Jointly, these songs account for 21 billion streams during our observation period and represent approximately 50% of the German market. Our sample contains all tracks that (1) were

Table 1. Descriptive Statistics

Variable	Definition	Mean	Standard deviation	Minimum	Maximum
$PaidStreams_{it}$	Audio streams from paying users for song i in week t	483.07	7,847.49	0	3,274,500
$AdFundedStreams_{it}$	Audio streams from nonpaying users for song i in week t	167.17	3,580.84	0	1,637,039
$PaidDownloads_{it}$	Paid downloads for song i in week t	1.52	47.52	0	25,122
$SongPopularity_i$	Cumulative revenue from downloads and streams for song i in the 26 weeks before the quasi-experiment	111.03	2,057.25	0	559,140
$SongAge_i$	Weeks since song i has been released in week t of the quasi-experiment	616.10	530.93	0	3,930
Prior availability$_i$	=1 if promotional video was available on YouTube pretreatment	0.16	0.37	0	1
$Newcomer_i$	=1 if an artist's first release occurs in the year prior to the observation period	0.01	0.08	0	1
Niche genre$_i$	=1 if genre is from the least popular 75% of genres	0.21	0.41	0	1
Young genre$_i$	=1 if genre has young audience (rap, electro)	0.09	0.29	0	1

Note. Number of songs = 614,562; number of weeks = 52; N = 31,816,626.

released at least one month prior to the quasi-experiment, (2) accumulated at least 1,000 streams in total over the observation period, (3) generated at least one stream per month, and that we (4) observe for at least 6 months in total. This results in a final sample of 614,562 tracks by 38,344 distinct artists, which we observe at the song-week level 26 weeks before and after the quasi-experiment (May 2016 to the end of April 2017), that is, 31.2 million track-week combinations.

3.1. Dependent Variables

For each song, we observe on the weekly level the number of paid downloads across all major paid download stores ($PaidDownloads_{it}$; e.g., Amazon MP3), the number of streams via free, ad-funded streaming services ($AdFundedStreams_{it}$; e.g., Spotify Free), and the number of streams via paid subscription-based streaming services ($PremiumStreams_{it}$; e.g., Spotify Premium). These measures do not include streams from YouTube.

3.2. Independent Variables

The cooperating music labels provided a list indicating for each song i whether it became available as UGC on YouTube after the agreement between GEMA and YouTube in October 2016 (UGC_i). In total, 378,460 songs became available, and 236,102 remained unavailable as UGC on YouTube.

Table 1 summarizes the measurement of the moderator variables (Online Appendix C).

4. Estimation

Our identification exploits the agreement between GEMA and YouTube in October 2016 as a quasi-experiment (Goldfarb et al. 2022), in the course of which hundreds of thousands of copyrighted songs became available as UGC almost overnight (Eddy 2016). We assume that songs were not handpicked to be available on YouTube (e.g., to capitalize on a short-term unobserved demand shock), but that songs became available in bulk in response to this exogenous shock. Whether a song became available on YouTube as UGC depended mostly on existing legal arrangements between music labels and artists that were made prior to and independently of the occurrence of this specific event. Extensive discussions with managers at all three music labels confirmed that songs were not handpicked based on the perceived suitability to be available on YouTube as UGC. Given the large number of songs, it seems implausible that managers can reliably identify songs to capitalize on some potentially existing unobserved demand shock that may coincide with this quasi-experiment. In addition, long-term contracts between music labels and artists inhibit quick reactions and are costly to adapt. However, recognizing the fact that songs were not randomly selected, we augment our analysis with a matching approach to ensure comparability between treated and untreated songs.

Using the songs that remained unavailable on YouTube as a control group, we compare the demand on other consumption channels (streaming and paid downloads) for these songs relative to the (treated) songs that became available on YouTube using a difference-in-differences (DiD) specification:

$$\log(Y_{it}) = \delta UGC_i \times post_t + \beta UGC_i \times post_t \times \log(M_i) + \mu_i + \gamma_t + \varepsilon_{it}, \quad (1)$$

where Y_{it} is the dependent variable for song i in week t (i.e., $PaidDownloads_{it}$, $AdFundedStreams_{it}$, or $PremiumStreams_{it}$), and μ_i and γ_t are song- and week-level fixed effects.[6] We interact the treatment dummy UGC_i with a step dummy $post_t$, which turns 1 in the treatment period. Hence, δ captures the effect of the UGC availability on sales and audio streams relative to the control songs. The coefficient vector β captures how the treatment effect varies over our set of moderators M. To ensure that the treated and control songs are as comparable as possible, we augment (1) with an inverse probability of treatment weighting, similar to propensity score matching, which has been used, for example, in Datta et al. (2018) in a comparable setting.

$$\Pr(UGC_i = 1) = \Pr(\alpha_0 + Z_i\alpha + \eta_i > 0) \tag{2}$$

The expression $\Pr(UGC_i = 1)$ is the propensity score, that is, the propensity of being treated (i.e., being available as UGC), given the observed covariates. We use this propensity score to calculate the appropriate weights (Austin 2011, p. 409):

$$w_i = UGC_i + \frac{\Pr(UGC_i = 1)(1 - UGC_i)}{(1 - \Pr(UGC_i = 1))}, \tag{3}$$

which we then use to implement an inverse probability of treatment weighting approach by estimating Equation (1) with weighted least squares.

To estimate the selection Equation (2), we rely on song characteristics as covariates that are provided by Spotify and that characterize a song's musical content (e.g., tempo, valence). Additionally, we use the artist's fame, song length, and the focal song's demand in the week prior to treatment and in the first week of the observation period (Table C.1 in the online appendix).

Figure 2(a)–(c), displays the standardized mean differences for all covariates pre- and postmatching and suggests that the matching approach removes most of the observable differences between treated and control songs. Figure 3(a)–(c), shows that the developments in the outcome variables for the matched treatment and control groups before the treatment are very closely aligned, suggesting that the assumption of parallel trends is reasonable. In some weeks, slight deviations between the two lines are visible, but they do not follow a systematic pattern. The paid download market sees a downward trend, which is in line with the declining importance of this market (IFPI 2022), but this affects both treated and control songs. The leads and lags model estimates in Figure 4 show weekly treatment effects, with the treatment week serving as the reference week (i.e., the interaction between the treatment indicator and week dummies). In the absence of any diverging pretreatment trends, there should be no discernable patterns in these effects in the pretreatment period; that is, they should ideally be centered around zero (Todri 2021). Figure 4 supports this notion. A placebo test (Online Appendix E.1) yields a small coefficient, marginally significant at the 10% level. An additional analysis that we report in the online appendix (Table E.2) suggests that it is unlikely that the focal results arise due to potential deviations in the parallel pretreatment trends.

5. Results

5.1. Streams and Paid Downloads

Figure 3 suggests that after the quasi-experiment, untreated songs become somewhat less successful compared with treated songs in terms of premium streams (a) and ad-funded streams (b), whereas no notable change occurs for paid downloads (c).

The estimation results in Table 2 show that, on average, making UGC available on YouTube positively affects demand for *PremiumStreams* ($\delta_{\text{premium}} = 0.057$) and *AdFundedStreams* ($\delta_{\text{adfunded}} = 0.057$), with coefficients of moderate magnitude. For downloads, we estimate a weak and insignificant coefficient ($\delta_{\text{downloads}} = -0.002$).

However, Table 2 and Figure 5 show that these effects vary substantially across songs, and a consistent pattern emerges such that songs that are likely to

Figure 2. Covariate Balance Main Model

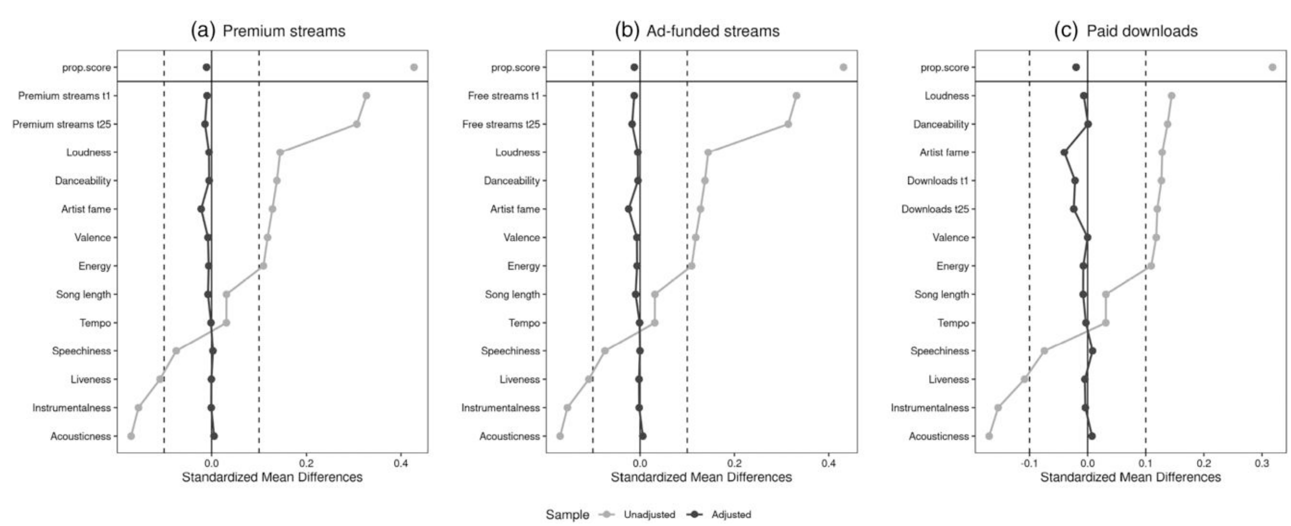

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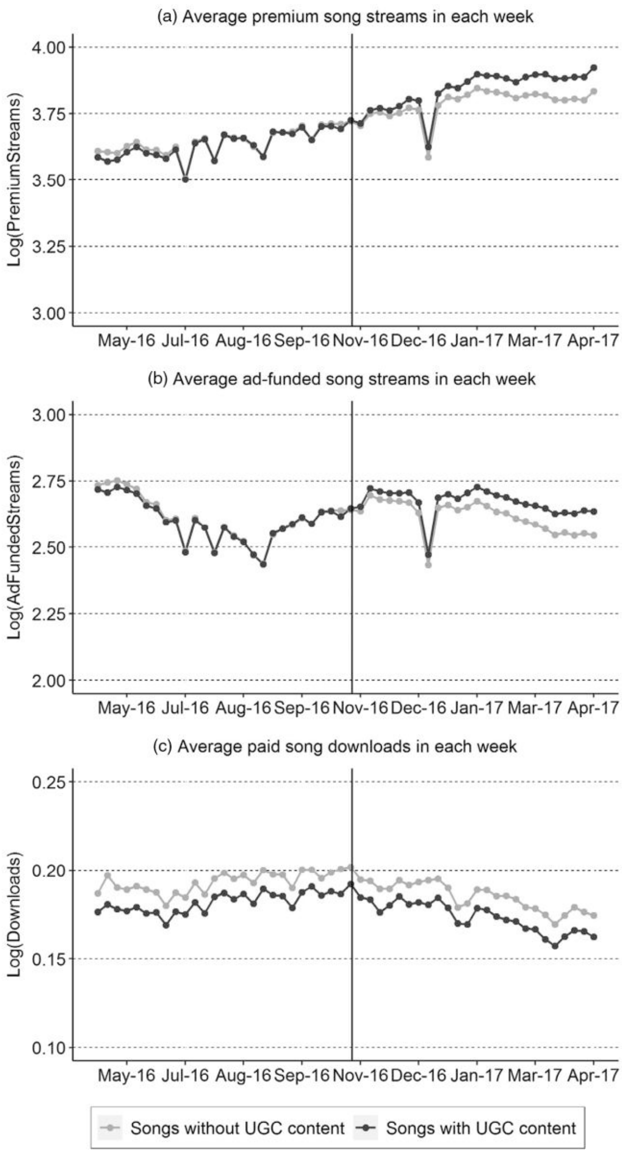
Figure 3. Model-Free Evidence



Notes. The vertical lines indicates the week of policy change. The lines show the mean for each group weighted by the weights obtained from the matching procedure.

benefit more from sampling and discovery see a stronger treatment effect. That is, the effect of making UGC available is less positive (more negative) for those songs that have been more successful prior to the quasi-experiment (β_1), and it is more positive for older songs (β_2). Furthermore, songs that were available as promotional music videos, uploaded by labels or artists prior to the treatment, barely benefit from UGC, suggesting that promotional videos reduce the extent to which songs can benefit from discovery through UGC (β_3). As expected, content from newcomer artists benefits more from UGC availability (β_4) as well as content from niche genres (β_5). Content in genres with a young audience, in contrast, benefits less, suggesting that younger audiences are more likely to use YouTube as a substitute for other streaming services (β_6).[7]

Figure 4 suggests that the treatment effects grow during the observation period. A potential explanation is that it takes time for consumers to realize and appreciate the availability of UGC. In addition, the additional exposure through discovery and sampling may lead to multiplier effects, for example, through an increased likelihood of being included on playlists.

5.2. Total Demand

We use the estimated coefficients to predict the total effect on demand (Table 3; Online Appendix D). Row V in Table 3 indicates that total demand in other channels is *lower* due to the availability of UGC on video streaming platforms.

This surprising finding that the total effect on demand is negative, although the main effect that we observe is positive (streaming) or insignificant (paid downloads) arises because – due to the specification in logs – the main treatment effect that we report in Table 2 gives us the *percentage* change in the dependent variable when a song is made available as UGC on YouTube. The negative interaction with song popularity means that successful songs lose. When a very successful song loses, say, 2% of its streams, this amounts to a much larger change in units compared with when a less successful song gains 2% in streams. Hence, the strong concentration that we observe in the market[8] means that, in conjunction with the negative interaction with song popularity, the total effect in terms of units can be negative while the average percentage effect can be positive.

5.3. Revenue

To obtain monetary values, we multiply the unit predictions (Table 3, rows III and IV) by the channel-specific earning per unit that artists and labels receive (Table 3, row VII). For paid streaming, we use a fixed payout rate (€0.006) per stream (Aguiar and Waldfogel 2021). The payout for ad-funded streams is lower, and we use an average fixed payout of €0.001 per stream (The Trichordist 2020). Assuming that the number of streams per user and the payout rate per stream remains approximately constant (Online Appendix D), we find displacement effects of approx. €15m per year for paid streaming (15%) and €730k per year for free streaming (15%). For paid downloads, based on the average song-level net price from GfK, we find a yearly decrease in revenue by €4.6m (i.e., 6%). In sum, we calculate an annual loss of approximately €20m due to the availability of UGC. In Online Appendix D, we show that it is unlikely that YouTube compensates for this loss through payments given the current magnitude of payouts per UGC stream.

Figure 4. Weekly Treatment Effects

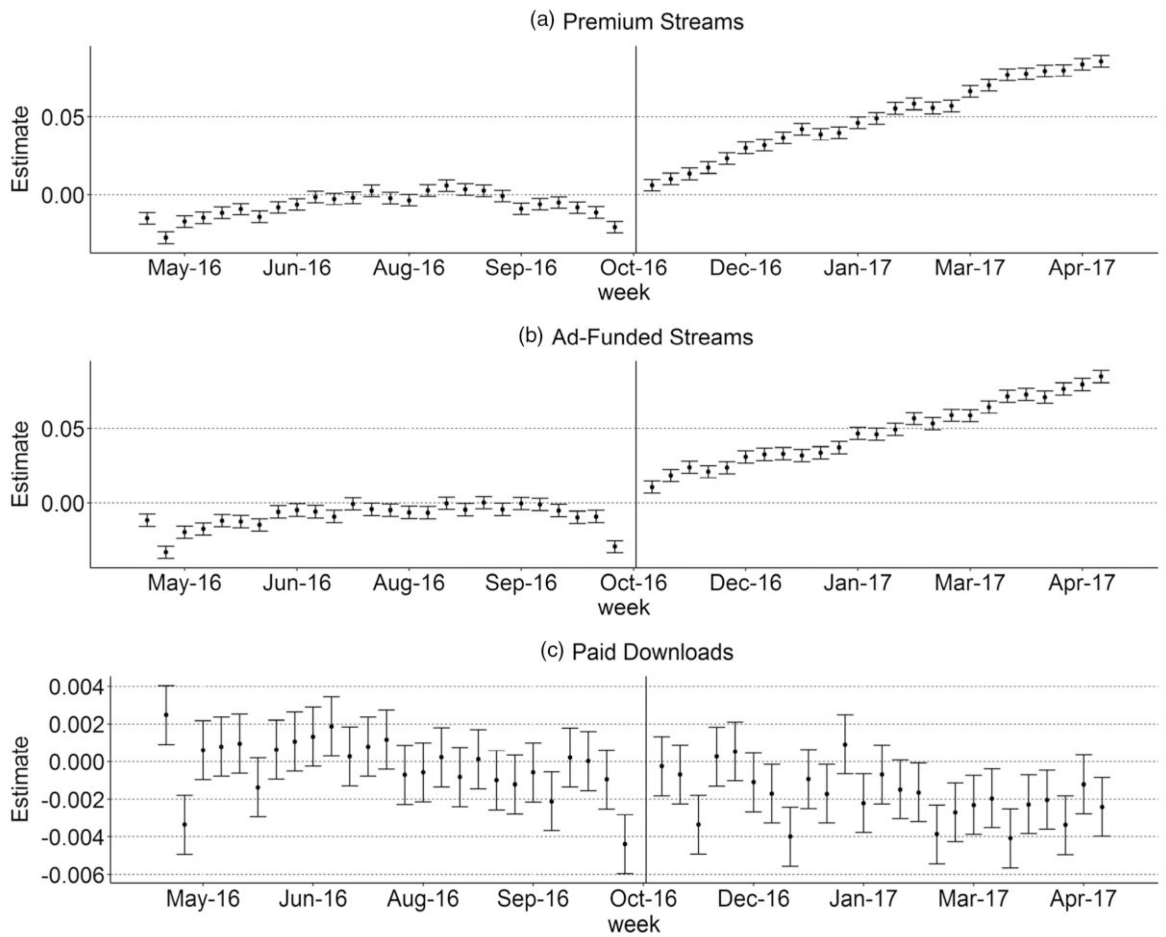


Table 2. Estimation Results

	Log(*PremiumStreams*)				Log(*AdFundedStreams*)				Log(*PaidDownloads*)			
Independent variables	(1a)		(1b)		(2a)		(2b)		(3a)		(3b)	
Treated × After (δ)	**0.057**	(0.005)	**0.062**	(0.009)	**0.057**	(0.005)	**0.059**	(0.008)	−0.002	(0.001)	−0.002	(0.001)
(…) × SongPopularity (β_1)			**−0.059**	(0.003)			**−0.046**	(0.003)			**−0.030**	(0.003)
(…) × SongAge (β_2)			**0.031**	(0.007)			**0.049**	(0.007)			**0.019**	(0.001)
(…) × Prior availability (β_3)			**−0.031**	(0.005)			**−0.025**	(0.005)			**0.026**	(0.003)
(…) × Newcomer (β_4)			**0.170**	(0.027)			**0.153**	(0.026)			0.006	(0.009)
(…) × Niche genre (β_5)			**0.058**	(0.021)			**0.057**	(0.018)			**−0.005**	(0.002)
(…) × Young genre (β_6)			**−0.083**	(0.009)			**−0.094**	(0.008)			**−0.018**	(0.003)
Song fixed effects	Yes				Yes				Yes			
Week fixed effects	Yes				Yes				Yes			
R^2	0.93		0.93		0.91		0.91		0.89		0.89	

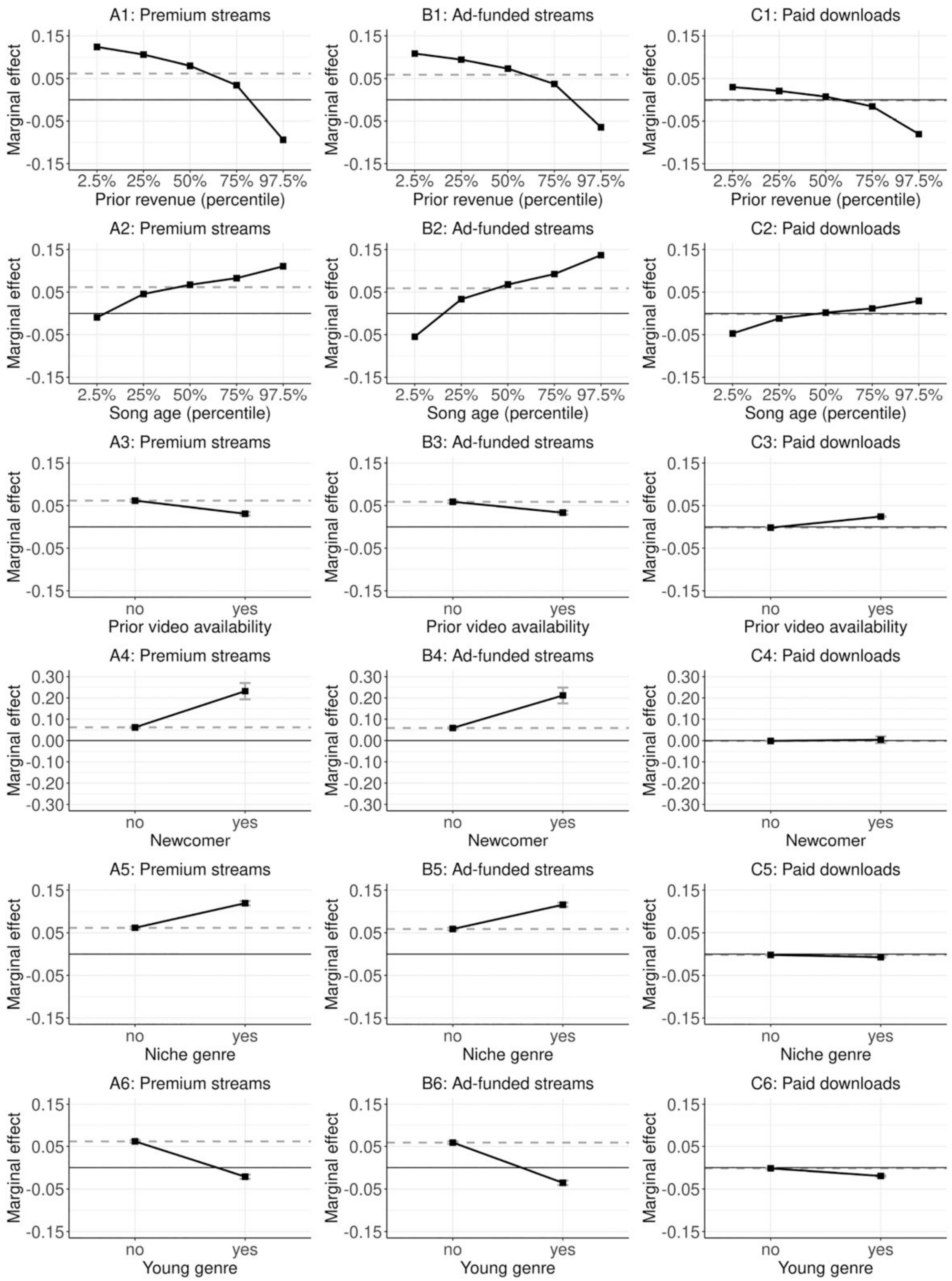
Notes. Clustered standard errors (by song and week) in parentheses. Continuous regressors (*SongAge* and *SongPopularity*) are standardized. Coefficients in bold are significant with $p < 0.01$. N = 31,816,626. Number of songs = 614,562. Models 1a, 2a, 3a are estimations of Equation (1), excluding interactions.

5.4. Robustness and Alternative Explanations

We assess the robustness of the results in several alternative model specifications. We provide the results in a condensed form in Table 4 and details in Online Appendix E.

(1) The placebo test yields a small positive coefficient in the case of premium and ad-funded streaming, weakly significant with $p < 0.1$ but insignificant at the significance threshold used throughout the remainder of the paper (Online Appendix, Table E.1). In an additional

Figure 5. Interaction Effects



Notes. The marginal effects on the respective y-axes represent the elasticity of demand in response to UGC availability on YouTube. The horizontal dashed lines show the average effects we report in Table 2. The error bars represent the 95% confidence interval (CI) for the respective effects, which we compute by adding/subtracting from the corresponding point estimate $t_{1-\frac{\alpha}{2}} * SE_{\frac{\partial Y}{\partial X}} = 1.96 * \sqrt{\mathrm{var}(\hat{\delta}) + Z^2 * \mathrm{var}(\hat{\beta}_\bullet) * +2 * Z * \mathrm{cov}(\hat{\delta}, \hat{\beta}_\bullet)}$ (Brambor et al. 2006, p. 70). Due to small standard errors, and overlap with the plot representing the point estimate, CIs may not be visible.

Table 3. Revenue Calculation

		PremiumStreams	*AdFundedStreams*	*PaidDownloads*	Total
		Panel A: Unit predictions			
I	Untreated week	326,175,491	96,575,409	1,400,154	
II	Treated week	277,112,503	82,535,469	1,309,512	
III	Untreated year	16,961,125,532	5,021,921,251	72,808,032	
IV	Treated year	14,409,850,134	4,291,844,374	68,094,609	
V	Unit effect year (IV − III)	−2,551,275,398	−730,076,877	−4,713,423	
VI	Percentage change (V/III)	−15%	−15%	−6%	
		Panel B: Revenue predictions			
VII	Price/payout per unit	€0.006	€0.001	n.a.[a]	
VIII	Untreated year (III × VII)	101,766,753 €	5,021,921 €	73,626,700 €	180,415,374 €
IX	Treated year (IV × VII)	86,459,101 €	4,291,844 €	68,985,890 €	159,736,836 €
X	Revenue effect year	−15,307,652 €	−730,077 €	−4,640,809 €	−20,678,538 €
XI	Percentage change (X/VIII)	−15%	−15%	−6%	−11%

[a]For the computation of revenue for song sales, we use each song's average price because, unlike for streams, the payouts vary across songs.

analysis (Online Appendix, Table E.2), we estimate treatment-specific trends in the pretreatment period and then calculate whether the treatment-specific trends from the pretreatment period can account for the focal results. The results suggest that it is unlikely that potentially nonparallel trends in the pretreatment period are responsible for the focal treatment effects that we report in the paper. (2) An alternative explanation for the focal finding could be changes in the artists' new release strategy. However, we do not find evidence that artists from the treatment and control groups adapt their new release strategy in differential ways (Online Appendix, Table E.3). (3) Table 4, robustness check 1, shows that the results are largely the same if we estimate the focal model (Equation 1) without IPTW. (4) In robustness check 2, we account for the different music labels in the matching equation. Again, this leaves the results unchanged. (5) In robustness check 3 we include a growth variable as a matching covariate, designed to capture short-term demand shocks that labels may use to select songs into the treatment and control groups. Again, this leaves the results largely unchanged.

We conclude that our results in Table 2 are robust against alternative explanations and competing model specifications.

6. Discussion

6.1. Key Findings

6.1.1. UGC Video Streaming Has a Modest Positive Average Effect on Demand. The main effects of the analyses suggest a modest positive average effect on demand in streaming channels and a negligible average effect on demand in the paid downloads market. Observers may come to the conclusion that UGC availability on YouTube has a small but beneficial effect on the music industry: a finding that would support the arguments of proponents of safe harbor provisions if heterogeneity across songs is ignored.

6.1.2. There Is Substantial Heterogeneity Across Songs. Although the effect is modest and positive for most songs, the effect is more positive for content for which conceptual arguments suggest higher gains from sampling and reminder advertising (He and Klein 2023), that is, older songs, songs that were less successful prior to treatment, from niche genres, from newcomer artists, and from genres that do not primarily attract a young audience. The effect is negative for new songs and those songs that were very successful prior to treatment. These findings suggest that UGC serves as a sampling tool for songs that need to be (re)discovered but not for songs that are salient and top-of-mind for consumers (new releases and hits), for which the need to be discovered is lower. We provide additional evidence for the proposed mechanism of YouTube being used for sampling and discovery in Online Appendix B.

6.1.3. UGC Video Streaming Negatively Affects Total Revenue. Although the average song-level effect of UGC availability on streaming demand is moderately positive, the total effect on demand and on *revenue* is negative. Although this finding may appear counterintuitive, it arises due to the market's demand distribution, which is heavily skewed toward successful songs. Coupled with the negative effect for these successful tracks, it means that the total effect of UGC content availability on industry revenue is negative, despite the seemingly positive average effect on demand.

6.2. Implications for Policymakers

First, hosting content on UGC video streaming platforms reduces demand for this content in other channels. Coupled with the observation that UGC video streaming platforms pay substantially lower payouts to artists and labels, the content provision on these UGC platforms comes at a cost for some content owners and other platforms like Spotify and Apple Music that do

Table 4. Robustness Checks

Independent variables	Main results			Robustness check 1: Without IPTW			Robustness check 2: Labels as additional matching covariates			Robustness check 3: Growth trajectory as additional matching covariate		
	Log (*Premium Streams*)	Log (*AdFunded Streams*)	Log (*Paid Downloads*)	Log (*Premium Streams*)	Log (*AdFunded Streams*)	Log (*Paid Downloads*)	Log (*Premium Streams*)	Log (*AdFunded Streams*)	Log (*Paid Downloads*)	Log (*Premium Streams*)	Log (*AdFunded Streams*)	Log (*Paid Downloads*)
Treated × *After* (δ)	0.062	0.059	*−0.002*	0.033	0.029	*−0.007*	0.059	0.057	*−0.002*	0.062	0.059	*−0.002*
(…) × *SongPopularity* (β_1)	−0.059	−0.046	−0.030	−0.059	−0.046	−0.030	−0.059	−0.046	−0.030	−0.059	−0.046	−0.030
(…) × *SongAge* (β_2)	0.031	0.049	0.019	0.031	0.049	0.019	0.031	0.049	0.019	0.031	0.049	0.019
(…) × *Prior availability* (β_3)	−0.031	−0.025	0.026	−0.031	−0.025	0.026	−0.031	−0.025	0.026	−0.031	−0.025	0.026
(…) × *Newcomer* (β_4)	0.170	0.153	*0.006*	0.170	0.153	*0.006*	0.170	0.153	*0.006*	0.170	0.153	*0.006*
(…) × *Niche genre* (β_6)	0.058	0.057	−0.005	0.058	0.057	−0.005	0.058	0.057	−0.005	0.058	0.057	−0.005
(…) × *Young genre* (β_5)	−0.083	−0.094	−0.018	−0.083	−0.094	0.018	−0.083	−0.094	−0.018	−0.083	−0.094	−0.018
Treated × *Trend* (β_6)												
Revenue effect	−15%	−15%	−6%	−17%	−17%	−7%	−15%	−15%	−6%	−15%	−15%	−6%
Total revenue effect		−11%			−12%			−11%			−11%	
Full results		Table 2			Table E.4			Table E.5			Table E.6	

Note. All coefficients are significant with $p < 0.01$, unless coefficient is printed in italics.

not host UGC content and that do not fall under safe harbor protection. Under the assumption that the existence of safe harbor regulations enables UGC video streaming platforms to make no or low payments to artists and labels (Liebowitz 2018), one may tentatively conclude that safe harbor regulations reduce overall demand for some artists (e.g., successful artists and new releases) and for platforms that do not fall under safe-harbor agreements.

Second, policymakers should be aware that UGC video streaming gives rise to redistributive effects to the extent that most content, in particular, niche content benefits, whereas hit songs and new releases lose market share. This is an aspect that has been overlooked in the debate thus far, and it may make demand in the industry less concentrated on superstars (Ingham 2021). This could also imply that a more restrictive regulation regarding the provision of UGC is likely to increase market concentration as a potentially unintended consequence.

Third, policymakers should be aware that the current payouts for UGC usage to rightsholders do not compensate for economic damage caused in other channels. UGC on YouTube had the lowest per-stream payout of all streaming services in 2019 (€0.0002, i.e., approximately 3% of the premium rate of €0.006), and these services accounted for 51% of the streams but for only 6% of all revenues (The Trichordist 2020). This is likely caused by the poor bargaining position of artists and labels: The safe harbor provisions imply that UGC platforms have an outside option because they are not legally required to make any payments to rightsholders (Liebowitz 2018), in contrast to other streaming services (e.g., Spotify) that cannot rely on the safe harbor provisions. Therefore, the more restrictive EU regulation, where UGC platforms need to ensure that users uploading content have the necessary rights to do so (Reynolds 2019), increases the negotiation power of rightsholders, which may lead to higher payouts.

Fourth, policymakers may use the results from this study to infer consequences for the regulation of other platforms and other markets. One of the fastest growing platforms at the moment, TikTok, operates under safe harbor protection, and is engaged in intense negotiations with rightsholders, who demand better compensation. At the same time, rightsholders are in a poor position for negotiations, likely due to safe harbor regulations (Liebowitz 2018). Another example is the Journalism Competition and Preservation Act (JCPA) that is currently being debated in U.S. Congress,[9] and which is intended to regulate the use of and compensation for journalistic content on online content distribution platforms like Facebook, Reddit, or TikTok. This regulation will likely not only have implications on how much content will be provided on these social media platforms, but also affect newspapers' other revenue streams. In addition, possible regulation or even bans of UGC platforms due to data privacy and security issues (e.g., TikTok; New York Times 2022) would likely have effects on other content distributors and on rightsholders' revenue. Based on our results, we would predict that a ban of a major UGC platform (such as TikTok) favors major artists but hurts smaller artists and niche content.

6.3. Implications for Rightsholders

First, our results show that UGC video streaming hurts total music industry revenues. At the firm level, it depends on the type of songs in a company's catalog. Labels with unknown artists and those with a deep back-catalog likely benefit from UGC. The "big" players, however, are likely to incur losses, which cannot be compensated by the large number of smaller players that will gain. For major labels, this is especially problematic because high marketing investments are required for the successful introduction of new releases of existing superstars and the development of new superstars.

Second, labels and artists can use the findings from our analysis to decide which content to allow (and monetize) on UGC platforms, and which content to block. In particular, they should allow and monetize long-tail content (newcomer artists, niche genres, older and less successful content), and should be more restrictive with superstar content.

Third, the heterogeneity in effects puts rightsholders in a delicate position for negotiations. Although major labels with many superstars in their portfolio should have an interest in restricting UGC content, labels and artists that provide niche content, in contrast, should be interested in UGC availability. This makes it difficult for rightsholders to confront policymakers and UGC platforms with one voice.

One limitation of this research is that we do not observe revenue sources other than recorded music; for example, it is possible that UGC stimulates demand for concert tickets. However, global recorded music revenues, of which streaming has the largest share, amounted to more than U.S. $25 billion in 2021 (IFPI 2022), making it a major source of income for artists. In 2019 (pre-COVID), global concert revenues were approximately at the same level (Statista 2021).

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Endnotes

[1] In addition, there is a related legal debate regarding the liability of UGC platforms for harmful user-generated content in the context of Section 230 of the Communications Decency Act (CDA) of 1996. Although technically different, it is important to note that Section 512 DMCA and Section 230 CDA "...are separate legal structures that work together to uphold certain protections for online service providers against claims arising out of user-generated content" (Shaheen and Canter 2023). Therefore, court decisions or legislative reform regarding Section 230 of the CDA could also affect how courts and legislators treat Section 512 of the DMCA.

[2] See Article 17(4) of the EU CD: https://eur-lex.europa.eu/eli/dir/2019/790/oj.

[3] Although UGC platforms claim that they pay substantial amounts to rightsholders (Blistein 2021), rightsholders argue that payments from UGC are insufficient compared with audio music streaming services (e.g., Apple Music, Spotify) (Levine 2020).

[4] Although the situation in the German market as of 2016/2017 may not be identical to a safe harbor, like, for example, the safe harbor according to the U.S. DMCA, the supply of songs on YouTube in the post-treatment period is very similar to international markets that operated under safe harbor in 2016/2017. Therefore, we view it as likely that consumers face very similar market conditions and supply in Germany after the treatment compared with markets with a safe harbor regulation. In addition, we could not find any evidence or reports that the payouts from UGC platforms (e.g., YouTube) in Germany were substantially higher than in other markets. Lastly, YouTube has argued during this legal dispute that it is merely a hosting provider that cannot be held legally responsible for user-uploaded content (Lomas 2013), and later German court rulings have mostly sided with YouTube (Ingham 2016). Against the background of these arguments, we think it is reasonable to consider the situation after the treatment as very similar compared with a market with a safe harbor regulation (see also Meyer 2016).

[5] Kretschmer and Peukert (2020) also analyze the effect of official music videos (firm-generated content) on streams (Online Appendix A).

[6] Following previous research (Kretschmer and Peukert 2020), we take the log of the dependent variable to account for the skewed nature of demand in the industry.

[7] In contrast to our expectations, songs with promotional videos on YouTube prior to treatment benefit in the download channel, which we attribute to the non-zero marginal cost of consumption for paid downloads, making it more likely that consumers opt for familiar

content to reduce consumption risk. Furthermore, the interaction in the download model with niche genre is negative, the effect size, however, is close to zero.

[8] In our sample, 80% of premium streams/ad-funded streams/downloads come from 3.7%/3.2%/1.2% of all songs.

[9] The JCPA is aimed at creating "a four-year safe harbor from antitrust laws" to allow news companies "to collectively negotiate with online content distributors [e.g., platforms] regarding the terms their content may be distributed by online content distributors." https://www.congress.gov/bill/117th-congress/senate-bill/673.

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