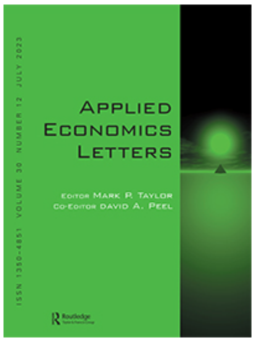

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Online video sharing and revenues during the pandemic. Evidence from musical stream data

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ABSTRACT
This study examines how instant online video sharing affects artists' musical streams during the pandemic. On average, the use of the TikTok app significantly increases artists' streams, by approximately 5%. This increase is even higher for male, European and dj Mag 2020 new entry artists.

KEYWORDS
Covid-19; streams; online video sharing; culture

JEL CLASSIFICATION
I1; L82; Z10

I. Introduction

Within only the last decade or so, social media platforms have significantly disrupted traditional modes of marketing and communication (Budzinski and Gaenssle 2018); the advent of the pandemic further boosted their use. The live events industry has been hit hard by Covid-19, so musical artists have flocked to new platforms providing instant online video sharing in order to attract and maintain consumer attention. Thus, TikTok snowballed into the most popular app in 2020 with a massive impact on the music business by creating a fan base, appeal,[1] streams (Spotify) and ultimately generating incomes (Aguiar and Martens 2016; Aguiar 2017; Aly-Tovar et al. 2020).

However, while a number of studies have investigated relationships between social media platform activity and economic outcomes, to date there has been little research on how an exogenous shock, such as the pandemic, shifts this relationship. We contribute to further extending the literature towards attention economics and the concepts of audience building (audience attraction and maintenance), by examining how an exogenous shock impacts artists' streams in the music industry (Wlömert and Papies, 2016). We fit a linear regression model with an interaction between Tik Tok use and pandemic period in order to explore how the effect of TikTok on streaming revenues changed after Covid.

II. Data

Our database consisted of dj-artists based on three criteria; (i) being listed as a dj on the djlist.com[2] for at least one genre, (ii) being listed as a dj on the djranking.org[3] salary list, (iii) being active on Facebook, Instagram and Resident Advisor for the last five years. We identified the top 300 most popular artists and tracked their daily Spotify streams for the period 1 January 2018 to 1 January 2022. Our stream data came from Songstats, an Internet based streaming-measurement platform.

Table 1 provides summary statistics on the sample, while Table 2 focuses on the years 2019 and 2020. We note a higher increase for TikTok users in each category. We also observe that each distribution is heavily right-skewed with the mean often orders of magnitude above the median.

Figures 1, 2, 3 and 4 show the growth of streams for the whole sample and for the subgroups of males, European artists and artists being new entries in the dj Mag list of 2020 relative to females, non-European artists and artists who in the dj Mag list of 2019 (pre

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A part of the work was conducted as a graduate student of the Department of Economics of Patras.

[1]Dj Mag list provides an important measure of success in its own right as it provides a proxy for an artist's fan base. This metric has become as important as traditional variables used to measure appeal.

[2]https://thedjlist.com/djs

[3]https://djrankings.org/about_rankings

Table 1. Descriptive statistics.

Variables	Frequency [1]	% [2]
TikTok app use		
Yes	113	37.67
No	187	62.33
Gender		
Males	253	84.33
Females	47	15.67
Europeans		
Yes	224	74.67
No	176	25.33
New Entries		
Yes	70	23.33
No	230	76.67

Notes: Authors' calculations.

Table 2. Spotify steams by subgroups.

		Year 2019		Year 2020		% Change
	N	Mean	Median	Mean	Median	Mean
Male artists						
TikTok = No	158	186,606	32,013	200,446	37,223	7.4%
TikTok = Yes	95	906,061	257,621	1,085,998	359,528	19.8%
All Male artists	253	459,346	57,537	535,029	74,762	16.4%
European artists						
TikTok = No	142	192,935	31,150	198,344	131,944	2.8%
TikTok = Yes	82	690,142	34,606	853,123	209,830	23.6%
All European artists	224	373,949	53,638	434,226	66,873	16.1%
New Entries						
TikTok = No	19	212,213	81,919	230,441	89,148	8.5%
TikTok = Yes	51	1,347,418	539,383	1,479,805	742,645	9.8%
All New Entries	70	1,039,291	309,842	1,140,692	390,567	9.7%

Source: Data drawn from Songstats platform.

Covid-19 poll) and not in that of 2020. Figures, which are on a monthly scale, present evidence of a shift in Spotify streams for each pair of variables.[4]

III. Empirical analysis

To investigate the effect of TikTok usage on Spotify streams, we estimate the following regression model:

$$\ln\mathrm{Streams}_{it} = \alpha\ \mathrm{After}_i + \beta\ \mathrm{After}_i \times \mathrm{TikTok}_i + \gamma\mathrm{TikTok}_i + \delta\mathrm{X}_i + \xi_m + \zeta_i + \varepsilon_{it} \quad (1)$$

where 'Streams$_{it}$' is the number of unique streams of artist i on Spotify in day t. After indicates days after 1[st] of March 2020. TikTok$_i$ refers to artists who used TikTok; X_i is a vector of variables, which includes demographic characteristics (i.e. age, gender); ξ_m is the months fixed effect; and ζ_i is the artist fixed effect. The coefficient of interest is β, which represents differential effects of the pandemic across artists additionally using or not using TikTok. In the simple model above, all artists in the TikTok group are implicitly considered equal in estimation, which implies β is the estimate of the additional impact of using TikTok after the pandemic. However, given that each artist in this group is also ranked by the dj Mag list of 2020, we followed the empirical strategy by Crosby, Lenten, and McKenzie (2018), and we also estimated a modified regression specification as follows:

$$\ln\mathrm{Streams}_{it} = \alpha\mathrm{After}_i + \lambda\mathrm{After}_i \times \mathrm{Ranked}_i + \gamma\mathrm{Ranked}_i + \delta\mathrm{X}_i + \xi_m + \zeta_i + \varepsilon_{it} \quad (2)$$

where 'Ranked' is the inverse of the actual ranking of the artist in the dj Mag poll and is converted to a number on the unit interval. This simple transformation associates a better outcome with a higher-ordinal number such that Ranked = [(−1)×Rank +101]/100, where Rank refers to the numeric dj Mag list rank.

Table 3 includes results from the aforementioned specifications, subsequently referred to as 'common effect' (columns 1–4) and 'ranked effect' (columns (5–7). Estimates of the β coefficient confirm that artists that continued to use the TikTok app to promote their work (i.e. live acts), during the pandemic marked a 5.1% increase in Spotify streams in relation to artists who did not use TikTok (column 4). Given that, streaming is a very complex facet of the music industry, the results of the 'ranked effect' specifications identify dj Mag list,[5] as an additional source of the increase of Spotify streams.[6] Column 7 is showing the differential effect of 'Ranked' before and after the Covid-19 pandemic. More specifically, an artist that achieve higher rankings in the list, has an increase of their Spotify streams by 19.9%.

Lastly, we also explore whether certain artist attributes affect the estimations outlined above. We examined sub-samples of our data according

[4]Different effects of the pandemic on the subgroups can shed light on the long-run effect of the pandemic on the shift in sources of revenues in the music industry.
[5]This voting list is the priming source on which new dj artists and their songs become discovered.
[6]Based on reports of TikTok's prevalence on dance music industry over the last 24 months, the use of this online tool by dj artists has a strong positive correlation with their rankings on dj Mag list for year 2021, in which no dj gigs took place due to Covid-19 restrictions.

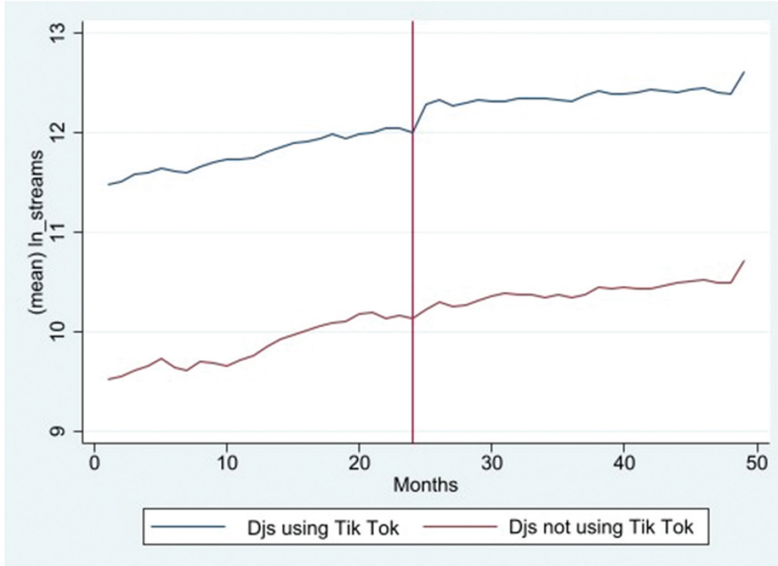

Figure 1. Spotify streams over time.

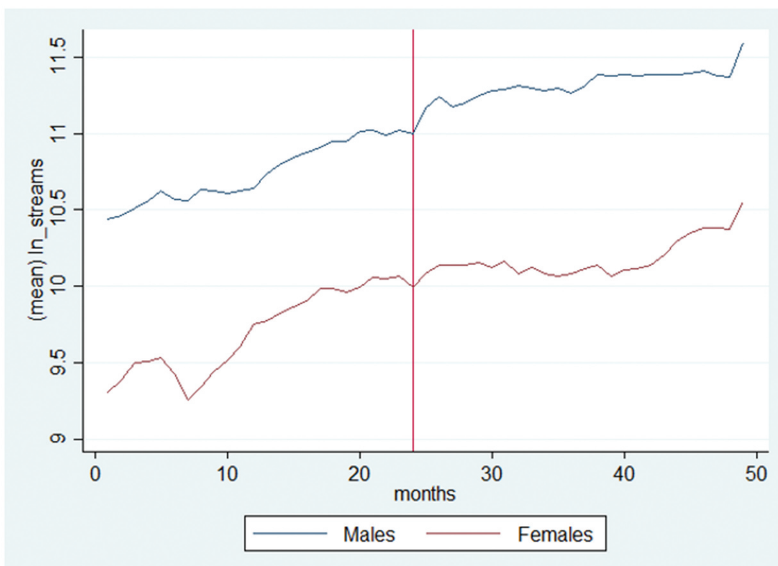

Figure 2. Spotify streams over time for male and female artists.

to (i) their gender (i.e. male and female), (ii) whether the artist was European and (iii) whether the artist was a new entry on the Dj Mag 2020 list. Table 4 supports a higher increase of Spotify streams for artists who are male, European and new entries. The aggregate combined results suggest an increase in stream growth, by approximately 29.6% (column 1), 17.4% (column 3) and 38.8% (column 5) for TikTok users being in the aforementioned categories, during the pandemic.

Limitations

Our study comes with limitations. The main pitfall of our empirical analysis concerns the potential endogeneity issue that occur when exploring cause-and-effect relationship in our estimations. Artists' existing trend for social media marketing strategies, may be the main reason why the error term can be correlated with the TikTok use after the Covid-19 occurrence. Hence, causality could be threatened, if dj artists coming from a particular musical genre and who are savvy

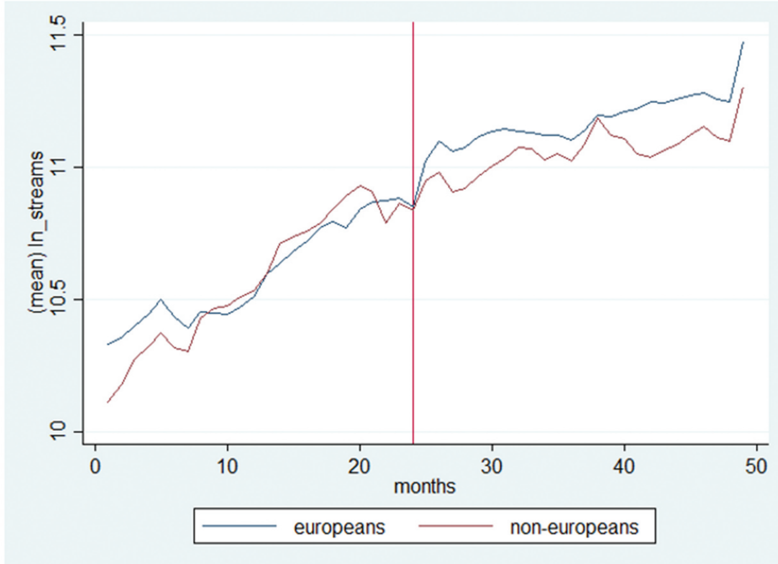

Figure 3. Spotify streams over time for European and nonEuropean artists.

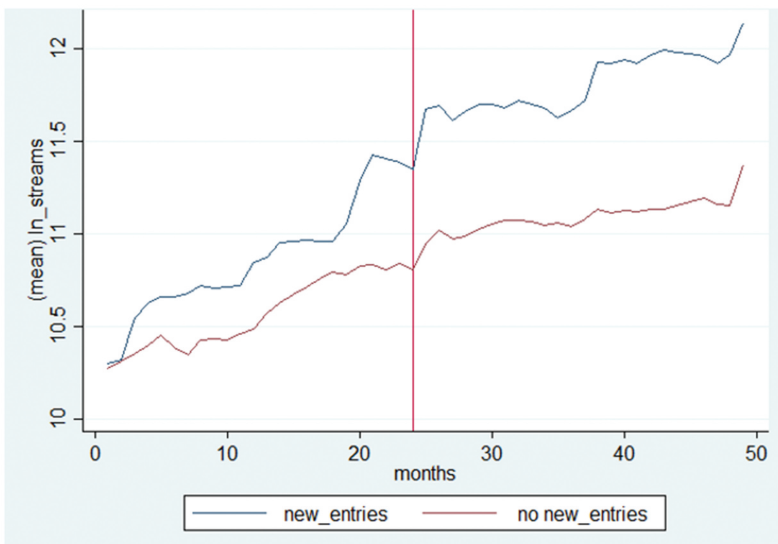

Figure 4. Spotify streams over time for new-entry artists and no-new entry artists.

about increasing Spotify streams are also the ones who are more likely to use TikTok. We tried to address this issue in three different ways. Firstly, our database consists of the most well-known dj artists, who they have more or less a similar profile of promoting their music and communicating with their audience. Secondly, we included artist and genre fixed-effects in order to minimize these sourced of potential endogeneity. Introducing individual fixed effects, allows to control for time invariant unobserved heterogeneity such as artists general interest on social media but this might rule out some artists learning more about digital apps and streaming over time. Lastly, we included in our models dj artists' Facebook, Instagram and

Table 3. Determinants of Spotify streams.

	Common effect				Ranked effect		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
After Covid-19	0.529***	0.537***	1.204***	1.241***	0.496***	0.510***	1.221***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.006)	(0.007)	(0.009)
Tik Tok user	1.925***	1.932***	1.701***	0.967***	0.887***	0.938***	0.858***
	(0.009)	(0.010)	(0.009)	(0.008)	(0.006)	(0.007)	(0.007)
After Covid-19 x Tik Tok user	0.042***	0.046***	0.050***	0.051***			
	(0.013)	(0.012)	(0.011)	(0.010)			
After Covid-19 x Ranked					0.386***	0.359***	0.199***
					(0.015)	(0.015)	(0.014)
Ranked in Dj Mag list 2020					0.799***	0.783***	0.818***
					(0.015)	(0.016)	(0.015)
Male Artists		1.060***	0.685***	0.441***		0.750***	0.456***
		(0.009)	(0.009)	(0.009)		(0.008)	(0.009)
Age		0.004***	0.008***	0.016***		0.018***	0.014***
		(0.003)	(0.003)	(0.003)		(0.003)	(0.003)
Cons	9.736***	8.732***	9.756***	8.227***	9.303***	7.979***	8.382***
	(0.008)	(0.015)	(0.030)	(0.027)	(0.007)	(0.015)	(0.028)
Genre Control	No	No	Yes	Yes			Yes
Country FEs	No	No	Yes	Yes			Yes
Entry on Dj Mag list 2018	No	No		Yes	Yes	Yes	Yes
Entry on Dj Mag list 2019	No	No		Yes	Yes	Yes	Yes
Entry on Dj Mag list 2020	No	No		Yes	Yes	Yes	Yes
Adjusted-R2	0.182	0.210	0.364	0.484	0.353	0.374	0.486
No. of artists	300	300	300	300	300	300	300
No. of observations	429,004	429,004	418,777	418,777	429,004	429,004	418,777

Source: Data drawn by Songstats platform.
Notes: The dependent variable is the logarithm of the number of streams in Spotify digital platform. All specifications include artist and month fixed effects. All Specifications control for artists' social media fans. Standard errors are in parenthesis and clustered at the artist level.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 4. Sub-Sample analyses by artist attributes.

	Males		Europeans		New Entries	
	Yes	No	Yes	No	Yes	No
	[1]	[2]	[3]	[4]	[5]	[6]
After Covid-19	1.298***	0.596***	1.165***	1.511***	1.714***	0.572***
	(0.017)	(0.007)	(0.010)	(0.019)	(0.017)	(0.007)
Tik Tok user	0.640***	1.069***	0.961***	1.202***	1.076***	1.027***
	(0.021)	(0.010)	(0.010)	(0.021)	(0.032)	(0.009)
After Covid-19 x Tik Tok user	0.296***	0.015*	0.174***	−0.282***	0.388***	0.015*
	(0.016)	(0.011)	(0.011)	(0.019)	(0.017)	(0.010)
Male Artists			0.668***	−0.326***	−2.292***	0.517***
			(0.010)	(0.023)	(0.081)	(0.010)
Age	−0.010***	0.022***	0.020***	0.002**	−0.014***	0.015***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)
Cons	8.650***	8.787***	8.324***	6.999***	13.948***	8.632***
	(0.064)	(0.019)	(0.029)	(0.075)	(0.055)	(0.020)
Genre Control	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	No	No	No	No
Entry on Dj Mag list 2018	Yes	Yes	Yes	Yes	Yes	Yes
Entry on Dj Mag list 2019	Yes	Yes	Yes	Yes	Yes	Yes
Entry on Dj Mag list 2020	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R2	0.488	0.317	0.485	0.577	0.396	0.478
No. of artists	253	47	224	76	70	230
No. of observations	354,213	64,564	310,545	108,232	31,929	405,628

Source: Data drawn by Songstats platform.
Notes: The dependent variable is the logarithm of the number of streams in Spotify digital platform. All specifications include month and artist fixed effects. All Specifications control for artists' social media fans. Standard errors are in parenthesis and clustered at the artist level.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Resident Advisor number of fans[7] as a way to control for differences on social media promotion strategies (Potts et al. 2008).

Conclusions

This study has studied the additional impact of using TikTok after the Covid-19 occurred and revealed that the use of TikTok as an online video sharing tool significantly increased Spotify streams, especially for male and European artists, during the pandemic. As a long-term effect, we found that the dj Mag 2020 artist ranking and the new entry status may be a result of using TikTok. While our findings are consistent with media tools affecting artist revenues and album sales, we cannot entirely rule out the influence of other contemporaneous changes in the music industry (Mortimer, Nosko, and Sorensen 2012).

A more general finding is that readily observable music stream metrics provide useful information that researchers can incorporate into studies of consumer behaviour and for better understanding digital music consumption (Peukert 2019). There are many possible practical implications of this type of data, which may establish a robust causal relationship between media tools and revenues, which we leave as an open invitation for future research outlines.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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[7]Data drawn by https://chartmetric.com/

Appendix A

By taking into consideration that a musical stream data from Spotify is counted when someone listens for 30 seconds or more, we present also negative binomial regression estimates[8] in which results are based on the relevant count data (using the logarithmic values of the Spotify streams).[9] Table A1 shows the results.

Table A1 Negative binomial estimations on Spotify streams.

	Common effect				Ranked effect		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
After Covid-19	0.514***	0.557***	1.104***	1.114***	0.511***	0.504***	1.116***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.006)	(0.008)
Tik Tok user	1.164***	1.646***	1.672***	0.857***	0.730***	0.986***	0.778***
	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)	(0.006)
After Covid-19 x Tik Tok user	0.045***	0.050***	0.053***	0.054***			
	(0.010)	(0.009)	(0.011)	(0.011)			
After Covid-19 x Ranked					0.321**	0.310***	0.133***
					(0.012)	(0.013)	(0.012)
Ranked in Dj Mag list 2020					0.625***	0.650***	0.714***
					(0.009)	(0.008)	(0.008)
Male Artists		0.719***	0.701***	0.664***		0.720***	0.450***
		(0.009)	(0.009)	(0.009)		(0.007)	(0.009)
Age		0.002***	0.009***	0.018***		0.017***	0.013***
		(0.003)	(0.003)	(0.003)		(0.002)	(0.002)
Cons	2.248***	2.266***	2.556***	2.262***	2.229***	2.108***	2.135***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)	(0.014)	(0.003)
Genre Control	No	No	Yes	Yes			Yes
Country FEs	No	No	Yes	Yes			Yes
Entry on Dj Mag list 2018	No	No		Yes	Yes	Yes	Yes
Entry on Dj Mag list 2019	No	No		Yes	Yes	Yes	Yes
Entry on Dj Mag list 2020	No	No		Yes	Yes	Yes	Yes
Pseudo-R2	0.033	0.037	0.038	0.038	0.353	0.374	0.050
No. of artists	300	300	300	300	300	300	300
No. of observations	429,004	429,004	418,777	418,777	429,004	429,004	418,777

Source: Data drawn by Songstats platform.
Notes: The dependent variable is the logarithm of the number of streams in Spotify digital platform. All specifications include artist and month fixed effects. All Specifications control for artists' social media fans. Standard errors are in parenthesis and clustered at the artist level.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

[8]The large value for chi-square in the Goodness of fit (gof) was an indicator that the Poisson distribution is not a good choice. A significant ($p < 0.05$) test statistic from the gof indicates that the Poisson model is inappropriate. We used nbreg Stata command which fits a negative binomial regression model for a nonnegative count dependent variable. In this model, the count variable is believed to be generated by a Poisson-like process, except that the variation is allowed to be greater than that of a true Poisson. This extra variation is referred to as overdispersion.
[9]We expect similar to OLS results because on the distribution of Spotify we had not many zeros and low values close to zero values.