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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.

JEL Codes: I1, L82, Z10

Keywords: Covid-19, Streams, Online video sharing

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(a part of the work was conducted as a graduate student of the Department of Economics of Patras)

1. Introduction

Within only the last decade or so, social media platforms have significantly disrupted traditional modes of marketing and communication (Budzinski & Gaenssle, 2018); the advent of the pandemic further boosted their use. The live events industry has been hit hard by Covid-19, so 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, appeal¹, streams (Spotify) and ultimately generating incomes (Aguiar 2016,2017; 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 toward 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. We employ a simple difference-in-difference model to examine how TikTok use affects streams, appeal and therefore revenues.

2. Data

Our database consisted of dj-artists based on three criteria; (i) being listed as a dj on the [djlist.com](https://thedjlist.com)² for at least one genre, (ii) being listed as a dj on the djrankings.org³ 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 1-1-2018 to 1-1-22. 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.

--- Insert Tables 1-2 about here ---

Figs 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

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

(pre 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 variables⁴.

--- Insert Figures 1-4 about here ---

3. Empirical Analysis

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

$$\ln\text{Streams}_{it} = \alpha\text{Post}_i + \beta\text{Post}_i \times \text{Treatment}_i + \gamma\text{Treatment}_i + \delta X_i + \xi_m + \zeta_i + \varepsilon_{it}, \quad (1)$$

where “Streams_{it}” is the number of unique streams of artist *i* on Spotify in day *t*. Post indicates days after 1st of March 2020. Treatment_{*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 using or not using TikTok. In the simple model above, all artists in the treatment group are implicitly considered equal in estimation, which implies β is the estimate of the average treatment effect. However, given that each artist in the treatment group is also ranked by the dj Mag list of 2020, we followed the empirical strategy by Crosby et al. 2018, and we also estimated a modified difference-in-difference specification as follows:

$$\ln\text{Streams}_{it} = \alpha\text{Post}_i + \lambda\text{Post}_i \times \text{Ranked}_i + \gamma\text{Ranked}_i + \delta X_i + \xi_m + \zeta_i + \varepsilon_{it}, \quad (2)$$

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 treatment effect” (columns 1-4) and “ranked treatment effect” (columns 5-7). Estimates of the β coefficient confirm that artists that used 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). The results of the ‘ranked treatment effect’ specifications provide additional evidence for the long-term effects of TikTok use deriving from artists’ rankings. More specifically, TikTok appears to help artists achieve higher rankings in the list, which resulted in a further increase of their Spotify streams by 19.9% (column 7).

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

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.

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.

--- Insert Tables 3-4 about here ---

Conclusions

This study has 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 et al. 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.

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Graphs

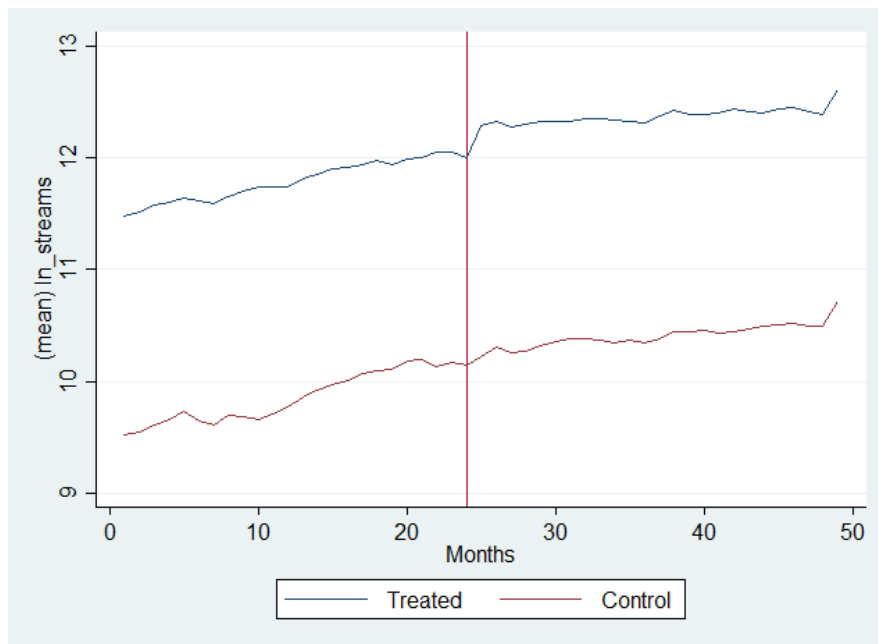


Figure 1. Spotify streams over time.

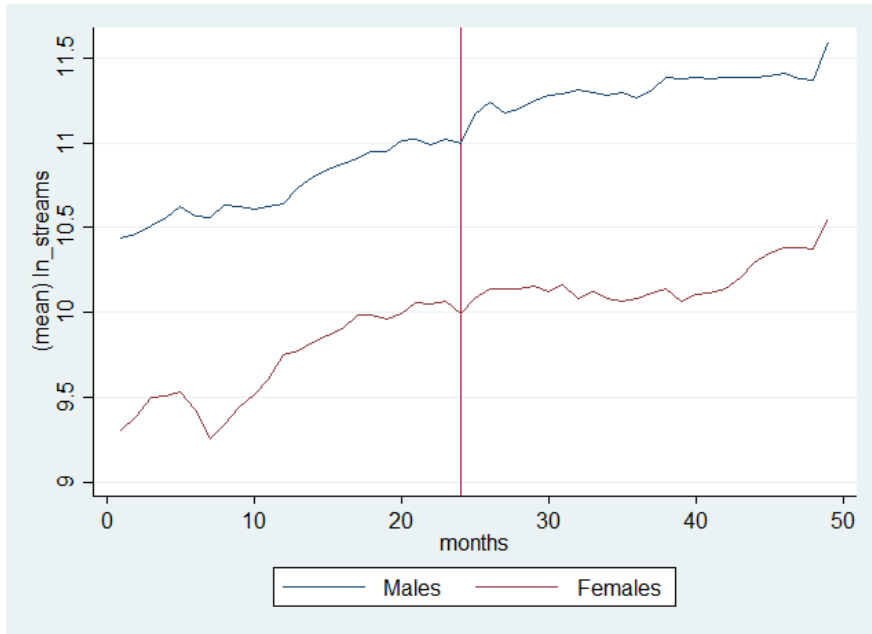


Figure 2. Spotify streams over time for male and female artists.

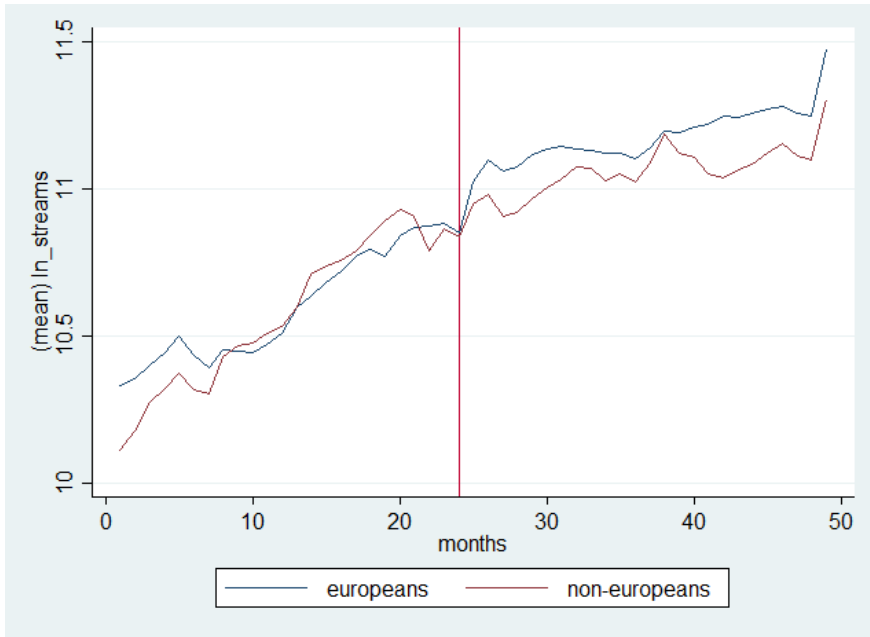


Figure 3. Spotify streams over time for European and non-European artists.

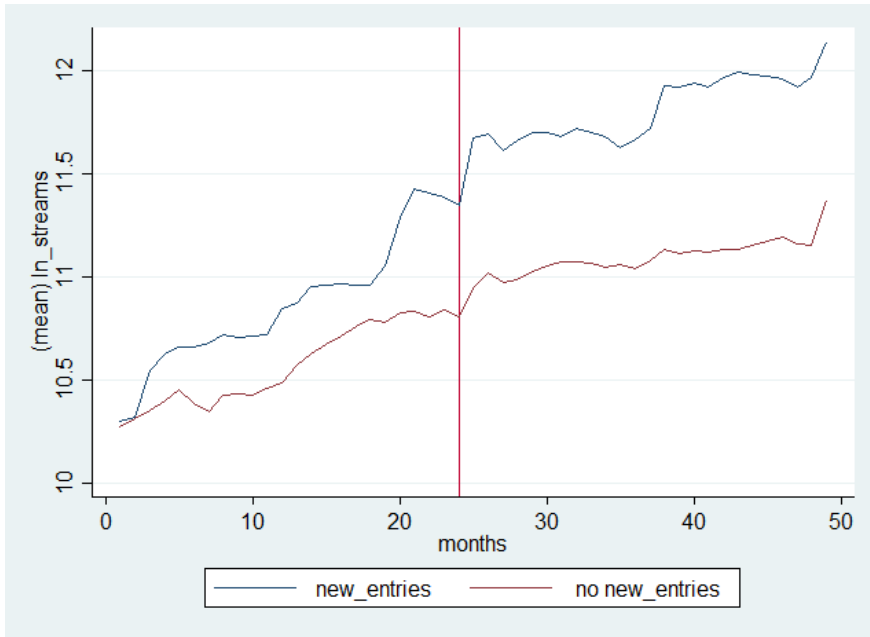


Figure 3. Spotify streams over time for new-entry artists and no-new entry artists.

Tables

Table 1. Descriptive statistics

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

Notes: Authors' calculations

Table 2. Spotify Steams by subgroups

	N	Year 2019		Year 2020		% Change
		Mean	Median	Mean	Median	Mean
<i>Male artists</i>						
TikTok = No	158	186606	32013	200446	37223	7.4 %
TikTok = Yes	95	906061	257621	1085998	359528	19.8 %
All Male artists	253	459346	57537	535029	74762	16.4 %
<i>European artists</i>						
TikTok = No	142	192935	31150	198344	131944	2.8 %
TikTok = Yes	82	690142	34606	853123	209830	23.6 %
All European artists	224	373949	53638	434226	66873	16.1 %
<i>New Entries</i>						
TikTok = No	19	212213	81919	230441	89148	8.5 %
TikTok = Yes	51	1347418	539383	1479805	742645	9.8 %
All New Entries	70	1039291	309842	1140692	390567	9.7%

Source: Data drawn from Songstats platform.

Table 3. Difference-in-difference models of Spotify streams.

	Common treatment effect				Ranked treatment effect		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
After	0.529*** (0.008)	0.537*** (0.008)	1.204*** (0.010)	1.241*** (0.009)	0.496*** (0.006)	0.510*** (0.007)	1.221*** (0.009)
Treatment	1.925*** (0.009)	1.932*** (0.010)	1.701*** (0.009)	0.967*** (0.008)	0.887*** (0.006)	0.938*** (0.007)	0.858*** (0.007)
After x Treatment	0.042*** (0.013)	0.046*** (0.012)	0.050*** (0.011)	0.051*** (0.010)			
After x Ranked					0.386*** (0.015)	0.359*** (0.015)	0.199*** (0.014)
Ranked in Dj Mag list 2020					0.799*** (0.015)	0.783*** (0.016)	0.818*** (0.015)
Male Artists		1.060*** (0.009)	0.685*** (0.009)	0.441*** (0.009)		0.750*** (0.008)	0.456*** (0.009)
Age		0.004*** (0.003)	0.008*** (0.003)	0.016*** (0.003)		0.018*** (0.003)	0.014*** (0.003)
Cons	9.736*** (0.008)	8.732*** (0.015)	9.756*** (0.030)	8.227*** (0.027)	9.303*** (0.007)	7.979*** (0.015)	8.382*** (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. 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 [1]	No [2]	Yes [3]	No [4]	Yes [5]	No [6]
After	1.298*** (0.017)	0.596*** (0.007)	1.165*** (0.010)	1.511*** (0.019)	1.714*** (0.017)	0.572*** (0.007)
Treatment	0.640*** (0.021)	1.069*** (0.010)	0.961*** (0.010)	1.202*** (0.021)	1.076*** (0.032)	1.027*** (0.009)
After x Treatment	0.296*** (0.016)	0.015* (0.011)	0.174*** (0.011)	-0.282*** (0.019)	0.388*** (0.017)	0.015* (0.010)
Male Artists			0.668*** (0.010)	-0.326*** (0.023)	-2.292*** (0.081)	0.517*** (0.010)
Age	-0.010*** (0.002)	0.022*** (0.002)	0.020*** (0.003)	0.002** (0.001)	-0.014*** (0.001)	0.015*** (0.003)
Cons	8.650*** (0.064)	8.787*** (0.019)	8.324*** (0.029)	6.999*** (0.075)	13.948*** (0.055)	8.632*** (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. 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.