

The Effects of COVID-19 on Audio and Video Streaming from the Perspective of Spotify, YouTube, & TikTok

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ECON 4590: Advanced Data Analytics and Policy Evaluation

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Abstract

With the onset of the COVID-19 pandemic, the world as a whole saw a massive increase in the usage of social media and online entertainment platforms. The following paper looks to determine the approximate effects of the pandemic on audio and video-based entertainment platforms, specifically from the point of view of Spotify, TikTok, and YouTube. It will be shown that there was a statistically significant decrease in the usage of the Spotify streaming platform and statistically significant increase in the relative interest in TikTok and YouTube during the pandemic. These data analyses were based on those done by Jaeung Sim, Dr. Daegon Cho, Dr. Youngdeok Hwang, and Dr. Rahul Telang who have recently studied the same effects for Spotify (to a different degree).

Introduction

With the rise of the digital age of media, there was an overall net-negative on the global industry. With it came a rapid growth in digital-based sales and a plummet in total revenue. This resulted from the increased ease of pirating brought about by the Internet and sites like Napster and Lime Wire. From the early to late 2000's, there is a steady decrease in sales and total revenue in the music industry (see Figure 1). It was only with the advent of digital streaming (and improvements to piracy laws and countermeasures) that there started to be a revival in the industry. This paved the way for the change in the way that people consume entertainment through different forms of media. Previous studies have shown that the COVID-19 pandemic has had a negative overall effect on the music industry (gone into in detail in the Review of Literature section). The question brought up in this paper is whether that increase in revenue will be negatively affected by COVID-19 in the long run.

The consumers ability to pick and choose exactly what they are listening to and what they are buying has grown to be a more and more important factor. When the music industry was dominated by physical formats, the highest utility way of purchasing music was through full albums (highest "bang for your buck"). As was found by Lohse, Bellman, and Johnson (as well as in other reports), consumers will always choose the highest utility for the cost option. With the introduction of digital media that allowed consumers to purchase only the music they actually wanted, providing a new outlet of higher utility for the cost. This study will cover the shock to the music and video media industries by looking at the before, during, and after periods of the COVID-19 pandemic (as indicated by the World Health Organization). Specifically looking at how Spotify top 200 weekly charts total streams, Google searches for YouTube, and Google searches for TikTok were changed during the pandemic. This was done to try to find a correlation with the COVID-19 pandemic using both the official start date and also the weekly cases by country.

Review of Literature

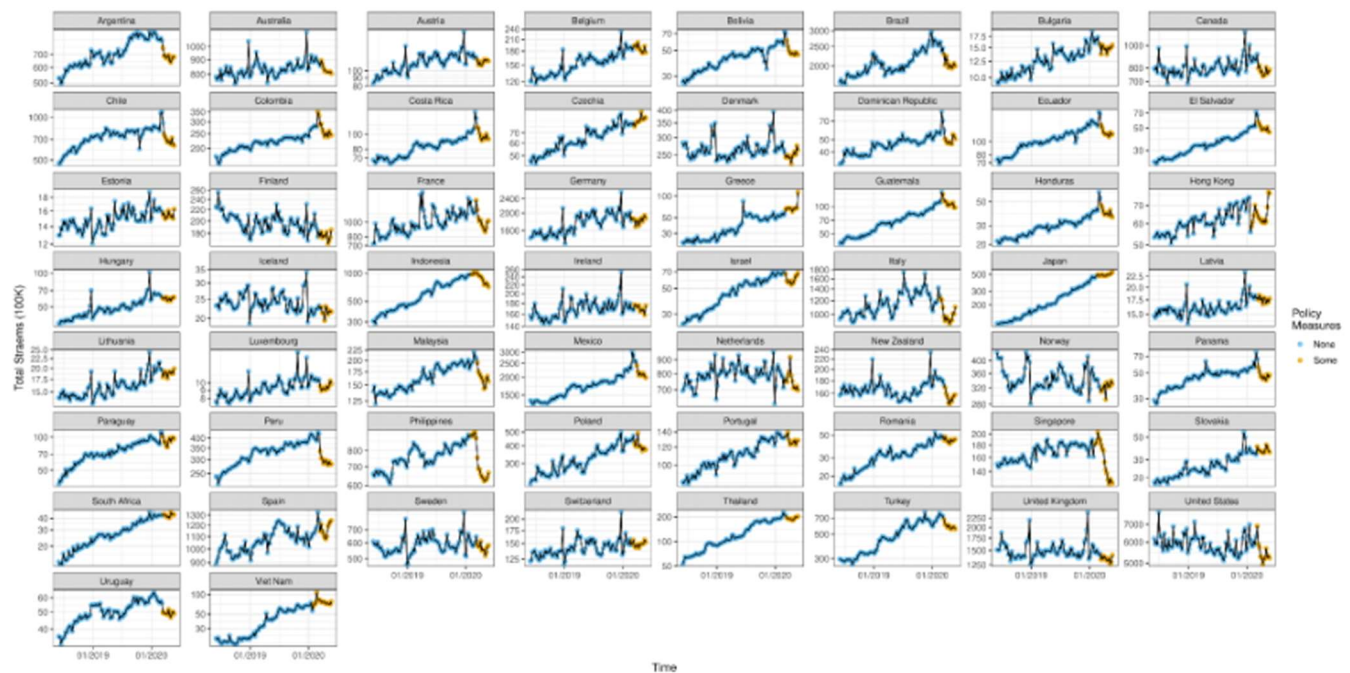
Seeing as the effects of COVID-19 are still quite present in the world and it is still a recent event, there are not many papers on the effects of the pandemic on the media industry in general. There is one notable paper published very recently in 2021 that is very relevant to this topic and will be used for comparison to this paper's outcomes. This paper, "Virus Shook the Streaming Star: Estimating the COVID-19 Impact on Music Consumption," looked closer at the taken for granted (at the time) assumption that the pandemic led to a surge in all online streaming services, specifically for music streaming (Sim, Cho, Hwang, & Telang, 2021). In addition to this paper, there are a number of papers that have been done on the streaming music industry over the past decade. While these papers look at very different topics, they provide important information about possible methods for analyzing this data and what data to use. They also indicate issues that should be considered for during analysis.

Estimating the COVID-19 Impact on Music Consumption – Sim, Cho, Hwang, & Telang

As a result of the COVID-19 virus and resultant worldwide pandemic, governments enacted social distancing, shelter-in-place orders, and general shutdown of non-essential workers. Due to the fact that many people were now stuck at home, the usage of entertainment media platforms surged. This resulted in a share growth for companies like Netflix and Spotify (32.2% and 27.1% respectively). While this share growth showed that these companies were doing better as a result of the pandemic, but it was shown in this paper that Spotify's usage actually went down during the pandemic. They made multiple proposals for why this may have occurred during the pandemic. One of the most logical and significant of these proposals was that audio entertainment took a massive hit to usage during the pandemic due to the fact that people were no longer commuting to and from work. They cited the Nielsen Corporation, a global marketing research firm, that found in 2017 that almost 29% of all music consumption take place in the car (Nielsen, 2017). Sim, Cho, Hwang, and Telang go on to use data involving Spotify weekly top 200 songs, COVID-19 statistics, policy measures from governments, and mobility data from major tech companies for 2 years in 60 countries.

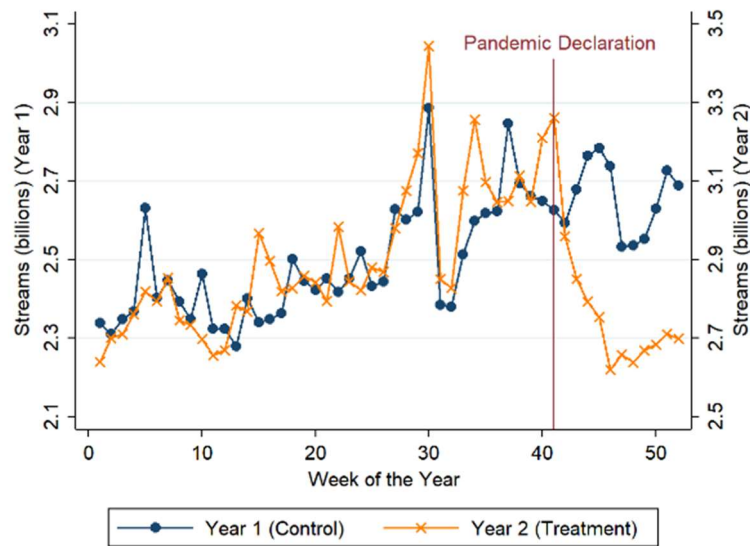
There results found that, on average, music consumption decreased by 12.5 percent after the official start of the pandemic (March 11, 2020, declared by the World Health Organization).

This paper takes a lot into account and uses a difference-in-difference approach to model the change between before and after the start of the pandemic. They do this using a simple dummy variable approach with two dummies: treated and after. *Treated* refers to whether the given year for the data was 2020 (pandemic year) or not. *After* refers to whether the given data was after the official start of the pandemic. They then go on to use an interaction term between these two variables which provides a regression estimate for the effects of the official start of the pandemic. This will be used in my study as well and will include another dummy variable term and interaction term that is the time after the global release of the COVID-19 vaccinations. This paper was done without including the effects of the vaccination and did not include data after the release of the vaccination. Literature Review Figures 1 & 2 show good visual representations of these findings.



Notes. The blue line indicates weekly streams with no government restriction, while the yellow line indicates weekly streams after at least one restriction.

Literature Review Figure 1 - Music Streaming Trends by Country (Sim, Cho, Hwang, & Telang, 2021)



Literature Review Figure 2 – Global Streaming Trends by Research Year (Sim, Cho, Hwang, & Telang, 2021)

***Note: Year 1 is from 6/1/2018 to 5/24/2019 and Year 2 is from 5/31/2019 to 5/29/2020*

Below, in Literature Review Figure 3, the regression results for this analysis can be seen. In all of their fixed effects regressions involving the treated, after, and interaction dummy variable terms they received a statistically significant and negative estimates across the models (-0.134 or -13.4% change in streams as a result of the pandemic). They went on to do many other analyses about possible other factors for why Spotify demand may have gone down, but these are the results that I will focus on in this paper (most important for comparison to my own data).

DV = ln(Streams)	(1)	(2)	(3)
Treated	0.283*** (0.0319)	0.283*** (0.0320)	Absorbed
After	0.142*** (0.0174)	Absorbed	Absorbed
Treated x After	-0.134*** (0.0169)	-0.134*** (0.0170)	-0.134*** (0.0169)
Country FE	Yes	Yes	Yes
Week-of-the-year FE	No	Yes	Absorbed
Country-specific growth FE	No	No	Yes
Country-specific week-of-the-year FE	No	No	Yes
No. of countries	60	60	60
Observations	6,240	6,240	6,240
Within R-squared	0.385	0.481	0.940

Notes. Standard errors, in parentheses, are robust and clustered at the country level.

*p<0.10; **p<0.05; ***p<0.01.

Literature Review Figure 3 - Effects of Pandemic on Demand for Streaming Music (Sim, Cho, Hwang, & Telang, 2021)

Sim, Cho, Hwang, and Telang also looked into possible other factors that may have skewed their results. This includes factors such as whether people began to diversify their music choices more during the pandemic and branch out to lesser-known artists (seeing as their data was only of the top 200 charts). They found that this was not the case and I have found in many places that the vast majority of streams (and sales) are dominated by a small percentage of the total artists in the industry. In 2020, it was found that the top 1 percent of artists accounted for 90 percent of all music streams (Smith, 2020). Another important note they made was that there was not a significant decrease in music released during the pandemic (based on tracks and albums released). Logically this actually makes sense because albums and new music take months (even years at times) to produce and release to the public. Consequently, anything that came out during the pandemic would have been well underway in production already. They did find that new music released during the pandemic tended to land lower on the top 200 charts on average.

This paper also includes data on Google's COVID-19 Community Mobility Reports which included data on time spent in residence. They also complemented this data with similar data collected by Apple's COVID-19 Mobility Trends Reports. This data, logically, showed a massive surge in residential time (time at home) and correlated with a drop in the number of streams in most countries. Unfortunately, this data will not be very useful for the study done in this paper due to the limited time that the data stretched over.

Another key point brought up by this paper (and something that came up in my own data) is that there are many music industry-specific factors that affect the Spotify data. Specifically, there are surges in Spotify usage during short stretches of a couple weeks due to factors such as popular artists releasing new albums. As of right now, the analyses done in this paper do not include adjustment or removal of these outliers (due to time constraints). This is definitely something that should be adjusted for in the future to check for validity of results. As of right now, I trust that they should not affect the overall outcome too much due to the length of these spikes in streams being very low.

The main shortcoming of this paper, in my opinion, is that the video-based entertainment consumption was limited to YouTube through the usage of Soundcharts' data collection API. While this is a widely used platform before and after the pandemic, they are missing a very

important contributor to the overall usage of video-based entertainment that gained attention during the pandemic, TikTok.

Other Influential Papers – Relatively Unrelated but Important

On-Demand Streaming Services and Music Industry Revenues – Wlömert & Papies

This paper looked at an industry-level perspective of the effects of music streaming on overall revenue (specifically in the German music industry). The data used in this paper was survey-based and looked at the usage of Spotify's free and paid platform models. Dr. Nils Wlömert and Dr. Dominik Papies' findings suggested that while the free-streaming model had an overall negative effect on total revenue, it was offset by the strong positive effect that the paid model had on revenue. They also observed that music streaming cannibalizes other music distribution channels (i.e. physical and digital downloads) and that the free-streaming model did have a correlation with pulling non-active members of the community back into the consumer pool. Additionally, this paper is helpful to my own study because it looked at the initial entrance of Spotify into the German music industry. Therefore, there methods of analyses should be helpful for looking at the effects resulted from the introduction of COVID-19 to the streaming and video entertainment industries.

The main takeaways that can be attributed to this paper, for my own analyses, are that the difference-in-difference approach was used to determine the effects of Spotify's enter into the German music market. Much like in the paper written by Sim, Cho, Hwang, and Telang, the use of a difference-in-difference approach was used to determine the effects of an event. The difference being that here they used survey data to see the effects of Spotify's entrance into the market over time. An example of this data can be seen in Literature Review Figure 4. This data is also much less instantaneous as can be seen in the data collected during the pandemic. The pandemic-related data almost always has a steep, dramatic change on a worldwide scale.

Streaming service adoption rates.

	t1	t2	t3	t4	t5	t6	t7	t8	t9
Absolute FSS ^a	4.7%	5.7%	9.2%	8.7%	8.1%	8.0%	10.0%	9.5%	9.8%
Cumulative FSS ^b	4.7%	8.0%	14.0%	16.7%	18.8%	20.5%	23.9%	25.7%	27.3%
Absolute PSS ^a	2.9%	2.9%	2.9%	2.8%	3.0%	3.6%	3.7%	4.0%	4.3%
Cumulative PSS ^b	2.9%	3.6%	4.2%	4.8%	5.3%	5.9%	6.5%	6.9%	7.3%

Notes. Percentages are based on all valid cases in our sample including the group of non-spenders and participants who adopted a FSS in the first survey (N = 2398).

^a Refers to the percentage of respondents that used the respective streaming service in a given period.

^b Refers to the cumulative share of respondents that used the respective streaming service at least once up to a given time period.

Literature Review Figure 4 - Streaming Service Adoption Rates by Survey Period (Wlömert & Papies, 2014)

Additionally, below is an example of the results of their findings. Here they use dummy variables, much like in the previous paper, to determine the effects of free and/or paid streaming adoption.

Estimation results.

Model	Model 1		Model 2	
	$\Delta \text{Log of monthly expenditures}$		$\Delta \text{Log of revenue per customer}$	
	Est. (se)	p (CI)	Est. (se)	p (CI)
$\Delta \text{FSS adoption } (\delta_1)$	-0.114 (0.049)	0.014 (-0.205/-0.023)	-0.022 (0.045)	0.624 (-0.110/0.066)
$\Delta \text{PSS adoption } (\delta_2)$	-0.274 (0.120)	0.023 (-0.510/-0.038)	0.430 (0.123)	0.004 (0.190/0.670)
$\Delta \text{FSS adoption} \times \text{expenditure level } (\beta_1)$			-0.076 (0.029)	0.010 (-0.133/-0.018)
$\Delta \text{PSS adoption} \times \text{expenditure level } (\beta_2)$			-0.043 (0.097)	0.660 (-0.232/0.147)
Time period fixed effects	Yes		Yes	
No. of respondents	2058		2224	
No. of observations	16,464		13,344	

Note: Difference-in-difference estimator.

Literature Review Figure 5 - Free vs Paid Model Estimation Results (Wlömert & Papies, 2014)

Other Takeaways from Literature

A commonality between all of the papers looking at audio and video streaming data was that it is better to look aggregate-level data. Many papers looked at both aggregate data and song/artist-level data and found that the song-level data often disagreed with the aggregate-level data due to omitted-variable bias that were dependent on specific songs becoming popular (i.e. so-called one-hit-wonders) (Aguilar & Waldfogel, 2017). This was considered for in my own analyses and aggregate-level data was always used (also because it is far easier to work with).

Data Analysis

Data was collected from a multitude of places for Spotify streaming usage, TikTok usage, YouTube usage, and COVID-19 cases and deaths. This data was all at a country level (with a total of 18 countries in the dataset) and weekly time intervals from January 6th, 2019 to March 20th, 2022 (168 weeks). It should be noted that the countries chosen were based off of countries with the highest Spotify usage (India was left out due to it being an outlier in terms of COVID cases).

Explanation of Data Units and Sources

It should be noted that many of the files were manually adjusted alongside the adjustments made within RStudio. The data attached with this paper is the final data used, but it should be noted that it would be relatively difficult to perfectly recreate the data.

Spotify Streams

This data came from the Spotify Top 200 Charts which has the weekly top 200 songs across the 18 countries chosen in the study. This data was adjusted to compile all streams for each song in a given week together. As a result, the data is formatted as the total number of streams in a given week in the top 200 songs, which represents Spotify as a whole well because that is the majority of all streams (Smith, 2020). This was also done to remove bias at a song and artist level and view the data from an aggregate level (as was done in many other papers using this dataset). The data was scraped from this website using a custom web-scraper script that will be given along with this paper (Spotify Corporation, 2022).

Relative Interest of TikTok and YouTube

This data was gotten from Google Trends data for searches made on Google for TikTok and YouTube respectively over a 5-year period, which was broken down to the 3 years that we have other data for (Google LLC, 2022). This data is given as a percentage at each week in comparison to the maximum value. In other words, each week is a proportion of the maximum (that may have happened at any given week) and the week with the maximum number of searches for YouTube or TikTok is represented as 100%. It should be noted that since the 5-year data was cut down, some of the max values are not present in the actual dataset (but that should not affect things). Every week is in reference to that maximum value as a percentage.

COVID-19: New Cases and New Deaths

This data was obtained from the World Health Organization and contained daily data for new COVID-19 cases and new deaths from COVID-19 across all countries. This data was then compiled into weekly data and adjusted to fit the full timeline that I have (adding 0's to the 2019 data for cases before WHO started documenting them). This data will represent the significance of the COVID-19 pandemic at different times in the dataset in each country.

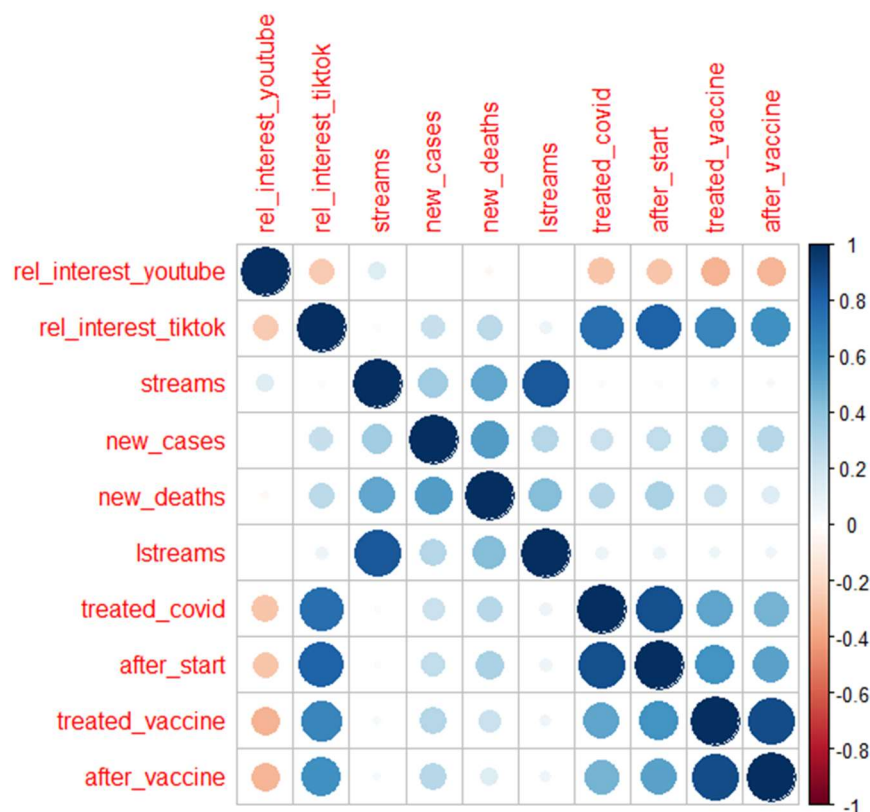
Dummy Variables – Start of Pandemic and Introduction of Vaccine

For a basic difference-in-difference approach, I used the same dummy variable approach as the Sim, Cho, Hwang, and Telang paper. This includes a dummy variable for the year before and years after the start of the pandemic and a dummy for the official start date of the pandemic (March 11th, 2020). From this I was able to compare to the estimates that they found in their paper. With this I created an interaction term to determine the effects of the pandemic on Spotify streams, TikTok searches, and YouTube searches.

Additionally, I also included a vaccination dummy variable to determine the effects of the COVID-19 vaccination on Spotify streams, YouTube Google searches, and TikTok Google searches. The vaccination dummy variable accounts for the time after March 1st, 2021. This was not the official release date for any specific vaccination but is a good average between when all the countries in the datasets started seeing real increases in vaccination amounts (it is also approximately a year after the official start of the pandemic). This data was retrieved from Our World in Data, a University of Oxford sponsored site and an example of the data can be seen in Figure 2 (Our World in Data, 2022).

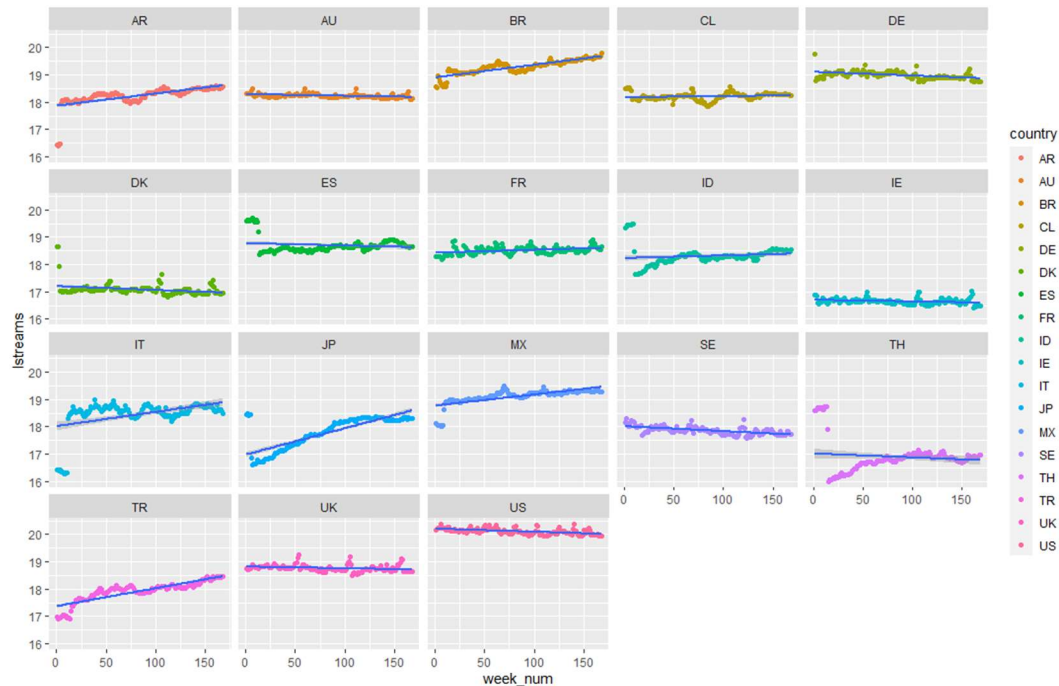
Regression Analyses

Initially, before starting with any regressions, the chosen variables were tested to see if there was any high multicollinearity present. The results of this can be seen in Data Analysis Figure 1 below and outside of the log(streams) and streams being close to 1 (which is expected) there are a couple points of interest to make. The first being that there is a high (near 1) value for the rel_interest_tiktok versus the dummy variables for the beginning of COVID. Looking into this further, from Data Analysis Figure 5 we can see that there is a surge in the Google search occurrence of TikTok during the same time as the start of the pandemic. There are 168 weeks in the dataset, of which week 63 contains the official WHO start of the pandemic (March 11th, 2020) and week 114 contains my chosen date for when the vaccine was (roughly) made public to the world as a whole. It can be seen that the massive surge in TikTok searches occurs at roughly the same time as the start of the pandemic. While it is logical to say that the pandemic was a key reason for the increase in Google searches, it's worth looking into.



Data Analysis Figure 1 - Multicollinearity Check

Data Analysis Figures 2, 5, and 6 show the log of Spotify streams, relative interest of TikTok, and relative interest of YouTube (relative interest being a percentage of the maximum Google search trends) versus week number.



Data Analysis Figure 2 - Log(Streams) vs Week Number (Pandemic start = 63)

The data above does not give a ton of help to determine the effects of the pandemic (starting week 63) on Spotify streams. In fact, it is difficult to determine if the pandemic had any effect on the overall Spotify streams. There are small noticeable decreases in the number of streams in each country around the start of the pandemic, which when graphed on a further aggregate level become more noticeable. Regression (1) in Data Analysis Figure 3 shows an attempt to recreate the data that Sim, Cho, Hwang, and Telang found in Literature Review Figure 2 but with data that goes further into the pandemic in Data Analysis Figure 4. Here we can see some interesting trends and make some observations.

As it can be seen in Data Analysis Figure 3, a statistically significant negative correlation between the pandemic and Spotify streams when using a fixed effects difference-in-difference model similar to the one used in Sim, Cho, Hwang, and Telang's paper. The estimate for the interaction term is also very close to what they got in their paper as well (15% decrease, versus 13.4%, after the start of the pandemic). This actually shows an even more negative effect on the

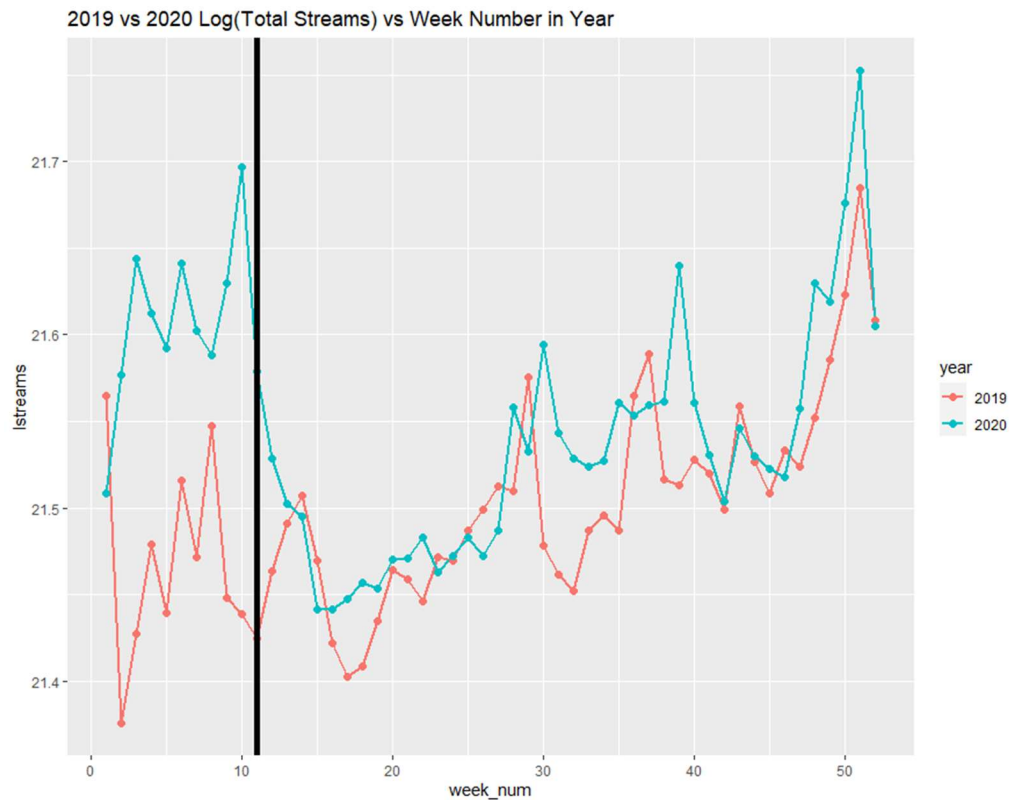
top 200 Spotify charts streams with the introduction of the pandemic than their paper. This is likely due to having more data further in to the pandemic than they had at their disposal.

	Dependent variable:					
	lstreams FE DiD Spotify (1)		rel_interest_tiktok FE DiD TikTok (2)		rel_interest_youtube FE DiD YouTube (3)	
treated_covid_limited	0.239*** (0.061)		0.168*** (0.019)		-0.062*** (0.014)	
after_start_limited	0.118*** (0.031)		0.047*** (0.006)		-0.024** (0.010)	
treated_covid_limited:after_start_limited	-0.150*** (0.031)		0.210*** (0.024)		0.033*** (0.010)	
Observations	1,872		1,872		1,872	
R2	0.125		0.766		0.106	
Adjusted R2	0.115		0.764		0.096	
Note:						*p<0.1; **p<0.05; ***p<0.01

Data Analysis Figure 3 – Data Analysis Estimates (Dummy Variable FE DiD Models)

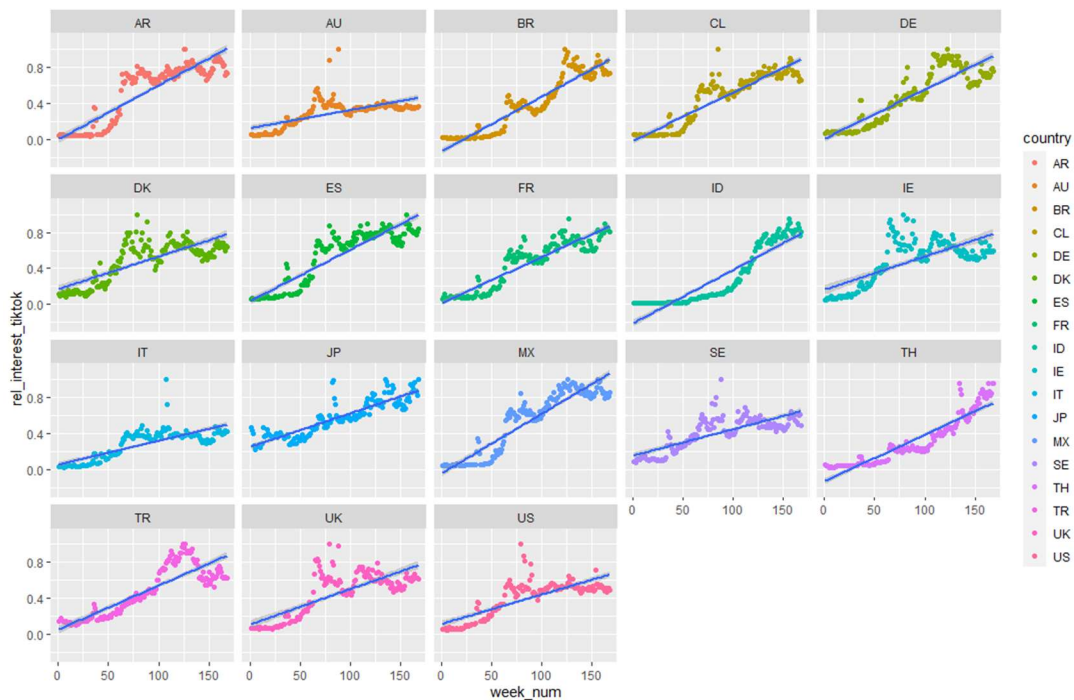
treated_covid_limited (dummy): 0 = 2019, 1 = 2020

after_start_limited (dummy): 0 = weeks before March 20th, 1 = weeks after March 20th (in both years)



Data Analysis Figure 4 – Log(Streams) vs Week Number in Year
After Black Line → WHO Start of Pandemic (Week After March 20th)

Another analysis that was looked into was the change in video-based media as a result of the COVID-19 pandemic. The thought here being that when people were stuck at home, they ended up consuming more video-based media rather than audio-based. The two sources of data looked at in this paper are TikTok and YouTube, of which both datasets can be seen graphically below in Data Analysis Figures 5 and 6. As it can be seen by Data Analysis Figure 5, there is a very apparent increase in the Google search activity for TikTok starting around the time of the pandemic. TikTok originally came out in 2017 (after changing names from it's true original launch in 2016 as a Chinese startup). It was not until the pandemic that this social media platform took off and gained popularity.

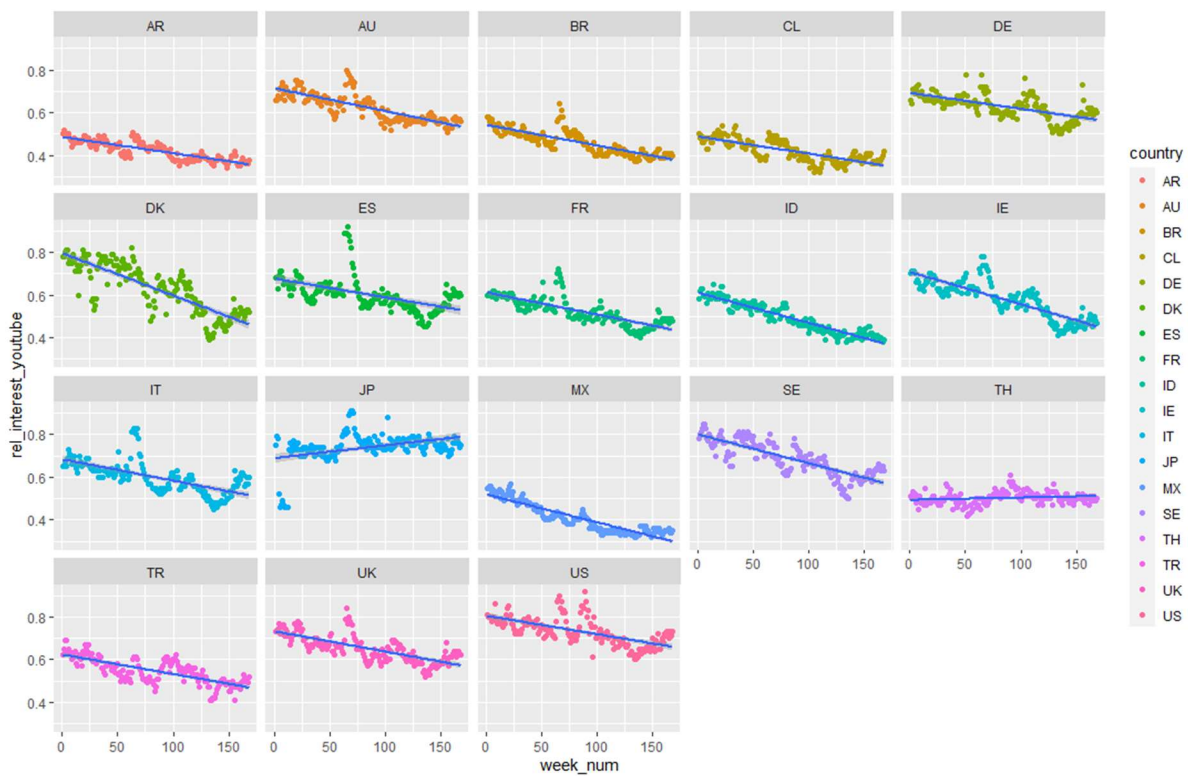


Data Analysis Figure 5 - Relative Interest (Google Searches) of TikTok vs Week Number (Pandemic start = 63)

Data analyses were done on both Google search data for TikTok and YouTube detailing the effects of the pandemic on their relative search interest using both a difference-in-difference approach and data for weekly COVID cases (by country). These models followed the same fixed effects dummy variable approach used for the Spotify top 200 charts model (using a treatment and “after_start” dummy variables). The results of these regressions were along the lines of what was predicted from viewing the data. These results can also be seen in Data Analysis Figure 3, which show positive and statistically significant correlations between the beginning of the

pandemic and the relative interest in TikTok and YouTube respectively (through Google Search Trends statistics). From these regressions, it can be seen that there is a very strong positive correlation for TikTok interest and the pandemic and a weak (but still significant) positive correlation between YouTube and the pandemic.

Regression (2) estimates a 21% increase in the average relative search interest for TikTok after the start of the pandemic across all countries in the dataset. It should be noted that there is still the possible issue of multicollinearity with regression (2), explained earlier in Data Analysis Figure 1. Currently there is no amazing solution to this but would be something worth coming back to in the future. Additionally, regression (3) estimates a 3.3% increase in the average relative search interest for YouTube after the start of the pandemic across all countries. Regression (3) also shows a decrease in the average relative search interest for YouTube over time in the non-interaction terms, which aligns with what is seen in Data Analysis Figure 6 below. There is also likely to be omitted variable bias in these regression estimates simply because the only variables being accounted for are dummies and country and time fixed effects. A possible omitted variable is the relative severity of the pandemic at different weeks.



Data Analysis Figure 6 - Relative Interest (Google Searches) of YouTube vs Week Number (Pandemic start = 63)

Additionally, another variable left out here that may have a significant effect is each countries government policies with respect to the COVID-19 pandemic. Below, in Data Analysis Figure 7, are the same regressions as before but with an additional lagged variable for the $\log(\text{new_cases})$. This is a log term for the previous week's new COVID cases at a country level. The idea of this term is to gauge the effect of how severe the pandemic is at different times of the pandemic (again, still with a fixed effects regression).

	Dependent variable:								
	rel_interest_tiktok			rel_interest_youtube			lstreams		
	FE	DiD	WHO	FE	DiD	YouTube	FE	DiD	Spotify
	(1)			(2)			(3)		
treated_covid_limited	0.165***			-0.061***			0.238***		
	(0.020)			(0.015)			(0.062)		
after_start_limited	0.055***			-0.025**			0.121***		
	(0.006)			(0.010)			(0.031)		
lag(lnew_cases)	0.009*			-0.001			-0.0003		
	(0.005)			(0.002)			(0.008)		
treated_covid_limited:after_start_limited	0.134***			0.045**			-0.151**		
	(0.047)			(0.018)			(0.075)		
observations	1,871			1,871			1,871		
R2	0.771			0.107			0.120		
Adjusted R2	0.769			0.097			0.110		
Note:									*p<0.1; **p<0.05; ***p<0.01

Data Analysis Figure 7 - Regressions with Added Lagged Log(Weekly New Cases) Term

The above results show that the added term for lagged weekly cases (per country) was not statistically significant for any of the regressions except for regression (1). This may be because many countries had many cases but still kept functioning relatively normally compared to others. In the future, it would be worth it to add some determinant for the governments' actions during the pandemic and whether they made major national level shutdowns.

Conclusions & Possible Future Work

From the data that has been collected as a part of this study, there is a clear correlation between the COVID-19 pandemic and the usage of both audio and video-based media (at least for Spotify, TikTok, and YouTube). It was found that on average across the 18 countries in this data that there was a 15% decrease in weekly streams on the Spotify top 200 charts; there was a 21% increase in the relative Google search trends for TikTok; and a 3.3% increase in the relative Google search trends for YouTube after the beginning of the pandemic. The data analysis for the Spotify top 200 charts also agreed with the analyses done by Sim, Cho, Hwang, and Telang in their very recent paper and added towards their results and data.

Looking towards what can be done with this data in the future, it would be interesting to incorporate analysis of a difference-in-difference regression for time before the global release of the COVID-19 vaccination and after the release. This could not be done in this paper both because there was not quite enough data yet and because I ran out of time. It would also be worth it to look into how to better use the WHO data for COVID cases and deaths over time (it can likely be incorporated better than I did). Additionally, in the study done by Sim, Cho, Hwang, and Telang, they looked at community mobility reports from Google and Apple as another determinant of the severity of COVID. Furthermore, this data would allow for analysis of how much commuting adds to the usage of audio-based media (and the decrease in use of video-based media). It would likely be worthwhile to look into other possible variables that could reduce the omitted variable bias that is likely present in the data as of right now.

Appendix – Figures

U.S. Recorded Music Revenues by Format

2000 to 2021, Format(s): All

Source: RIAA

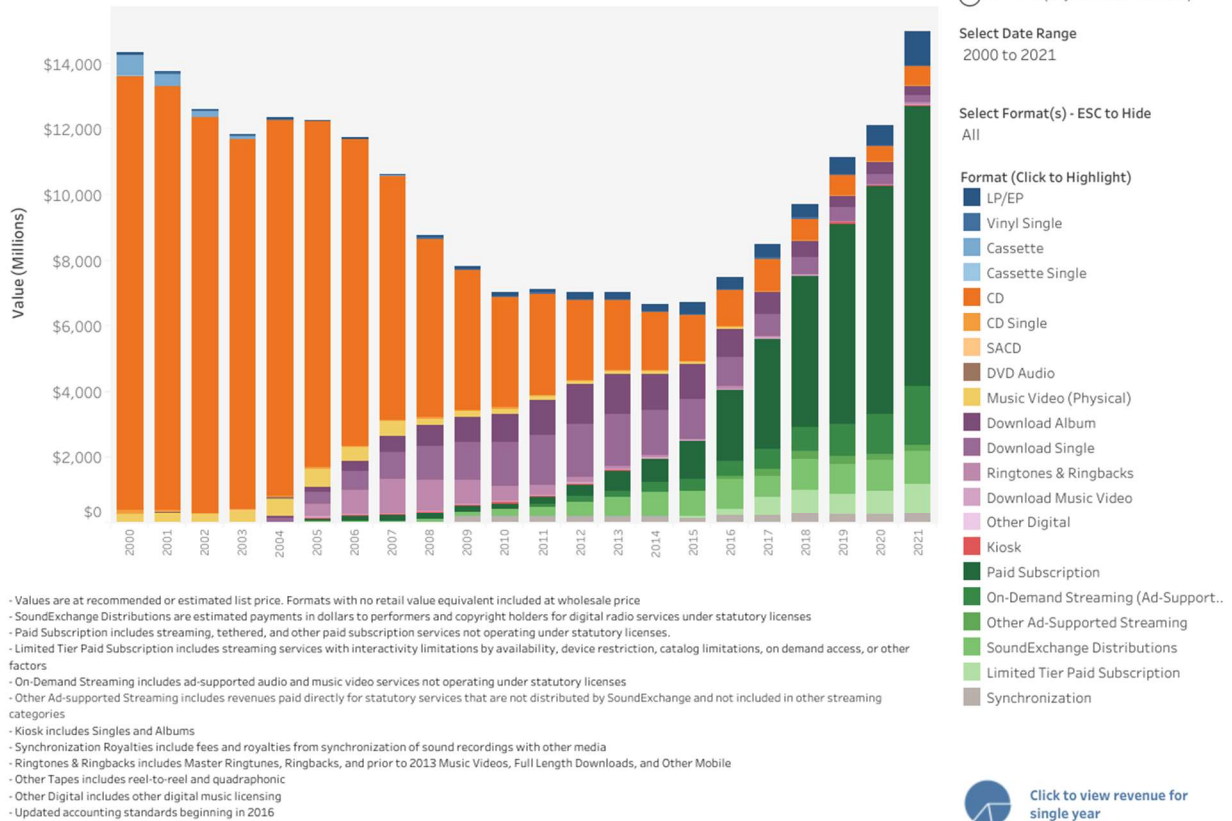
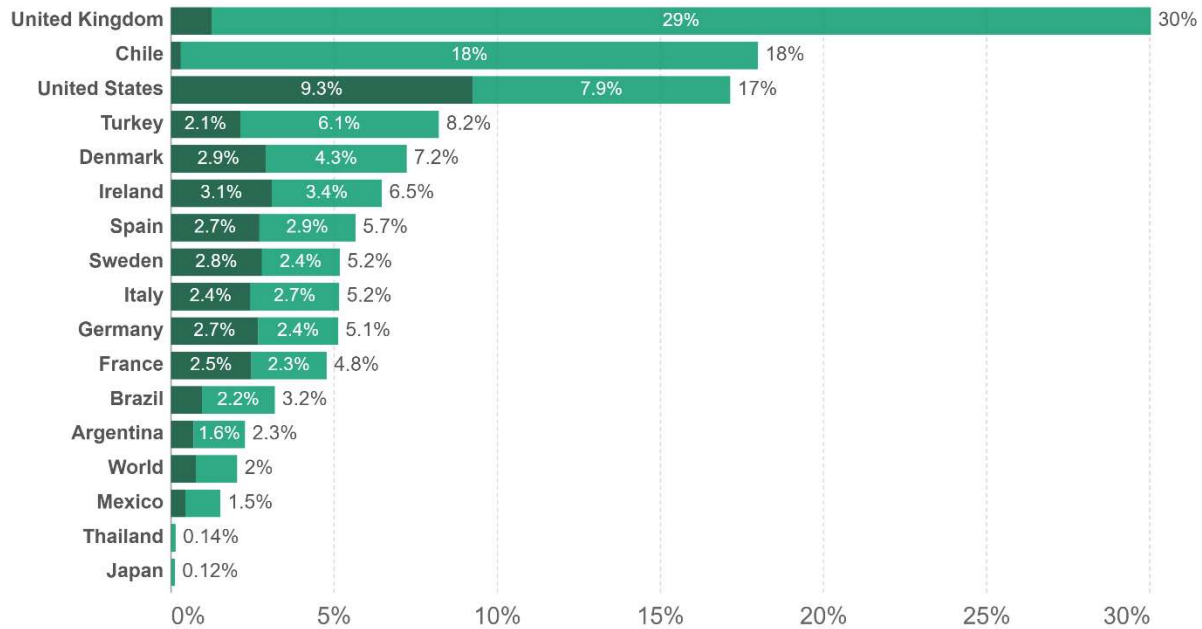


Figure 1 – RIAA US Recorded Music Revenues by Format (Recording Industry Association of America, 2022)

Share of people vaccinated against COVID-19, Mar 1, 2021

Our World
in Data

■ Share of people with a complete initial protocol ■ Share of people only partly vaccinated



Source: Official data collated by Our World in Data

Note: Alternative definitions of a full vaccination, e.g. having been infected with SARS-CoV-2 and having 1 dose of a 2-dose protocol, are ignored to maximize comparability between countries.

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Figure 2 – Our World in Data Example Data (Our World in Data, 2022)

Table 5. Summary of Additional Analyses

Question	Analysis	Result	Location
Additional Analysis of Mobility and Music Consumption			
Does the complementary nature of audio consumption matter?	<ul style="list-style-type: none"> Analysis of video consumption for music in YouTube 	<ul style="list-style-type: none"> Video-based music consumption increased (decreased) with the severity of COVID-19, lockdown policies, and time spent on outdoor activities (residence). 	Table B1 – Table B3
When is the complementarity more influential?	<ul style="list-style-type: none"> Analysis of heterogeneous commuting time among European countries Contingent effects on music streaming and time allocation by day of week 	<ul style="list-style-type: none"> The decline was more significant in countries with longer commuting time. The effect was more prominent on weekdays than weekends and more consistent with effects on time spent on workplaces and residence than that on transit. 	Table B4 – Table B5 Table B6 – Table B7
Will the decline in music consumption last?	<ul style="list-style-type: none"> Analysis of the temporary ease of COVID-19 during April and May 2020 	<ul style="list-style-type: none"> A rebound in countries with decreasing cases The reduction in residential time was highly associated with the recovery of streaming volume. 	Figure B2 – Figure B3
Alternative Explanations and Robustness Checks			
Does using a specific functional form drive our results?	<ul style="list-style-type: none"> A distribution-free statistical test using empirical reference distributions 	<ul style="list-style-type: none"> Two-thirds of countries experienced an unprecedented decline after the pandemic. 	Figure C2
Do outliers drive our results?	<ul style="list-style-type: none"> Poisson regressions Subgroup analysis by continent Subgroup analysis by rank position 	<ul style="list-style-type: none"> Consistent with main results The decline was consistent across continents. The decline was consistent across rank positions. 	Table C2 Table C1 Table C3
Is the parallel pre-trend assumption violated?	<ul style="list-style-type: none"> Estimating the relative time model with leads and lags of the treatment 	<ul style="list-style-type: none"> Streaming differences are mostly indistinguishable across weeks-of-year before the pandemic declaration. 	Figure C3
Are Spotify-specific unobservables responsible for the findings?	<ul style="list-style-type: none"> Estimating a model with the number of confirmed cases and deaths and common time fixed effects Analysis of Spotify's updates Analysis of the Korean market 	<ul style="list-style-type: none"> 1,000 COVID-19 cases per million in each week were associated with a 14.4% decline in streaming consumption No distinct updates after the pandemic declaration Music streaming decreased in the absence of Spotify. 	Table C4 Table C9 Table C15
Does demand shift from superstars to underdogs explain the results?	<ul style="list-style-type: none"> Follower trends of 1.5K playlists (top 500 for each provider type) in Spotify 	<ul style="list-style-type: none"> Significant deceleration of the number of followers after the pandemic and no evidence of demand shift 	Table C15 – Table C16
Is the supply-side effect responsible for the decline?	<ul style="list-style-type: none"> Analysis of music releases of recently successful artists in Spotify 	<ul style="list-style-type: none"> No evidence that popular artists reduced new music releases significantly 	Table C18
Is the decline attributable to the promotion of new releases?	<ul style="list-style-type: none"> Analysis of chart entrance and rank positions of newly-released songs 	<ul style="list-style-type: none"> Fewer newly-released songs appeared on the top 200 charts, and their rank positions were lower. This effect was more prominent among superstars. 	Table C19 – Table C20

Figure 3 - Summary of Additional Analyses (Sim, Cho, Hwang, & Telang, 2021)

References

- Aguiar, L., & Waldfogel, J. (2017). *As streaming reaches flood stage, does it stimulate*. Elsevier.
- Google LLC. (2022). *Google Trends*. Retrieved from trends.google.com:
<https://trends.google.com/trends/explore?date=today%205-y&geo=US&q=%2Fm%2F09jcv5>
- Lohse, G. L., Bellman, S., & Johnson, E. J. (2000). *Consumer buying behavior on the Internet: Findings from panel data*. John Wiley & Sons, Inc. and Direct Marketing Educational Foundation, Inc. Retrieved from
<https://www.sciencedirect.com/science/article/pii/S1094996800701964>
- Nielsen. (2017). *Nielsen Music U.S. Music 360 2017 Report Highlights*. Chicago: Nielsen Corporation.
- Our World in Data. (2022). *Share of people vaccinated against COVID-19, Mar 1, 2021*. Global Change Data Lab. Retrieved April 23, 2022, from
<https://ourworldindata.org/explorers/coronavirus-data-explorer?zoomToSelection=true&time=2021-03-01&facet=none&pickerSort=desc&pickerMetric=population&hideControls=true&Metric=People+vaccinated+%28by+dose%29&Interval=Cumulative&Relative+to+Population=true>
- Recording Industry Association of America. (2022, April). *RIAA.com*. Retrieved April 21, 2022
- Sim, J., Cho, D., Hwang, Y., & Telang, R. (2021). *Virus Shook the Streaming Star: Estimating the COVID-19 Impact on Music Consumption*. Institute for Operations Research and the Management Sciences. Retrieved from
<https://pubsonline.informs.org/doi/suppl/10.1287/mksc.2021.1321>
- Smith, D. (2020, September 10). *1% of Artists Generate 90% of All Music Streams, Latest Data Shows*. Retrieved from digitalmusicnews.com:
<https://www.digitalmusicnews.com/2020/09/10/music-streams-data/>
- Spotify Corporation. (2022, April 1). *Spotify Charts*. Retrieved from spotifycharts.com:
<https://spotifycharts.com/regional/us/weekly/latest>
- Wlömert, N., & Papies, D. (2014). *On-demand streaming services and music industry revenues — Insights from Spotify's market entry*. Elsevier. Retrieved from
<https://www.sciencedirect.com/science/article/abs/pii/S0167811615001226>