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The Effect of The Covid-19 Pandemic on Music Streaming Patterns

Thum Chiean Tien
University of Warwick, United Kingdom

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Abstract

The Covid-19 pandemic has changed our lifestyles in many ways. One interesting way is the method we consume music, as live music events or shows were cancelled or postponed. Consumers shift to depending on remote music streaming as a coping mechanism or means of entertainment during the pandemic. However, it remains unclear how streaming consumption is affected based on music types in terms of language and genres, and if the change is motivated by a preference for local music. This paper explores these questions by analyzing musicians' revenue changes and Spotify streaming counts during the pandemic.

1 Introduction

The Covid-19 pandemic has brought about many changes to our lifestyles. The unforeseen cancellation and postponement of all live music events have prompted consumers to shift the way they consume music to digital streaming-based platforms (Sim et al., 2020). As more time is spent on digital devices during lockdown (Dinges, 2020), more opportunities to explore music streaming applications and new music presented themselves (Pereira da Silva, 2021; Váradi, 2021) as music became a huge coping mechanism for pandemic-related stress (Krause et al., 2021; Fink et al., 2021; Herrero et al., 2020).

Despite the increasing number of literature on pandemic-induced music consumption behaviors, the gap between understanding the changes brought forth based on the types of music exists. This paper investigates how the pandemic affects consumers' music streaming patterns and the types of music consumed. In particular, this study will analyze if there exists a preference for local music during lockdowns, which could provide them with more comfort by sounding 'closer to home' (HARMAN, 2020). Existing literature like Sim, Cho, Hwang and Telang (2020) demonstrated how mobility changes and the severity of covid cases decreased music streaming count in general but did not explore such effects based on the different types of music. This paper serves to fill the gap in understanding in the impact of the Covid-19 pandemic on this topic, which could be helpful to music producers to cater to consumers' tastes.

Using Billboard's annual compilation of highest-paid musicians' revenue composition in the US, this study examines the trend of artists falling off the chart when the pandemic started and explains the role of the pandemic in changing the music preference landscape. The second part of this research utilizes German Spotify streaming data extracted from Kework K. Kalusian's Spotify Chart Scraper through empirical examinations. The changes in streaming count of the different languages and genres of music consumed before and after the pandemic are evaluated. While a basic OLS regression suggests that the pandemic has a positive effect on streaming count, there is a disappearance of such effect in a more robust Difference-in-Differences model. The German Spotify data is consistent with the American Revenue data about an existing preference for local music during the pandemic. When both datasets are compared, it seems to suggest that a local music preference does exist, but it is not necessarily due to the pandemic.

2 Literature Review

Despite being a relatively recent phenomenon, there is extensive research on the effects of the pandemic on the music industry. While most literature studies music consumption statistics and demonstrates evidence of music being consumed more as a coping mechanism in lockdown, there is a lack of understanding of how the pandemic affects different types of music, specifically segmented based on languages and genres.

Carlson et al. (2021) have found a positive relationship between the pandemic and music streaming consumption through 107 online Likert Scale surveys, 42% of which have specifically indicated high musical engagement at the start of the outbreak. Fink et al. (2021) used a custom questionnaire to measure changes in musical engagement including changes in listening formats (Braun & Krause, 2020) and listening situations (Greb et al., 2018), in order to evaluate if the music was a substitute for social interaction in lockdown. Data collected between April and May 2020 in 6 European countries and New York state suggested a 51% increase in music streaming, and notably, 57% of respondents expressed special interest in new releases during the lockdown. However, Sim et al. (2020)'s Difference-in-Differences model spread across 2 years in 60 countries suggested a more robust framework and approach to the matter, and concluded that the pandemic had significantly reduced music streaming. The paper considered varying lockdown policies and mobility allowance information in the countries, inferring that reduced commuting time caused a decline in music consumption. An emphasis was put on studying music consumption as a complementary activity, filing a causal relationship between more mobility restrictions and less music streaming. Yet, this ignores the possibility of people listening to music outside commuting times or via non-streaming formats such as vinyl and radio as they work from home. Additionally, this paper assumes that the music release plans of mega artists remain unaffected by the pandemic, when in fact, popular artists like Lady Gaga and Sam Smith have postponed their album releases in 2020 (Dinges, 2020). Sim's paper did not explore the pandemic's impact on the types of music but briefly mentioned the declining number of genre-based playlist followers during the pandemic to highlight the decline in streaming. However, their approach aggregates data from all countries studied and is unable to reflect a specific shift in interest in local music or a specific genre or language, which this paper will explore.

The closest literature that evaluated the pandemic effect on different music types is Kalustian and Ruth's (2021) evaluation of Spotify streaming count based on audio features including loudness and danceability. The paper scrapped 3 months of daily Top 200 streamed songs in Germany, Austria and Switzerland between March and June 2020, and compared the statistical changes in streaming count according to the extracted mood-clusters represented by numerical audio features. Audio features in question include loudness, acousticness and danceability of music. The author used quantitative scores of these features to measure the effect of different kinds of music on listeners' experience in coping emotionally during the pandemic. In other words, if a song with a high loudness score receives higher streams during the pandemic, loudness is considered to help listeners in emotional coping. However, Spotify's accuracy in attaching numerical figures to subjective audio features and music quality remains skeptical. Rather than audio characteristics, Yeung (2020) categorized music into old and new releases to capture the pandemic effect on nostalgic music consumption. The paper uses a Difference-in-Differences method to evaluate the changes in streams with standard errors clustered in days, and conducted a placebo test to debunk the trend as an annual pattern. Yeung found that songs released 3 or more years before collection time received higher streams during the pandemic, especially about 60 days after the lockdown started.

This paper will build on Kalustian and Ruth's (2021) dataset of Spotify streams using a Difference-in-Differences approach similar to that of Yeung (2020) to investigate Sim et al (2020)'s claim of a decline in pandemic-induced music streaming and the effect based on music genres and language, which is not explored in existing literature. This paper will also explore the shift in preferences for local music during the pandemic.

3 Data: Sources and Analysis

3.1 American Musician Revenue: Descriptive Statistics

Two main datasets are used in this research project. First, Billboard's revenue breakdown reports of their Top-40 Money Makers in the United States from 2015 to 2020 are combined to provide insights into the change in revenue sources among top-paid musicians over the years. The compilation also offers the opportunity to study the composition of American musicians in the recurrence rate and new appearance rate of artists on the Top-40 list. Through the recurrence rate, I study artists that continuously make high revenues, and compare their main source of income, which observed a change as the pandemic hit. The rate of new appearances on the chart represents that year's shift in musical preferences, where a larger number of American artists among those who make the highest-paid list suggest a higher preference for local music.

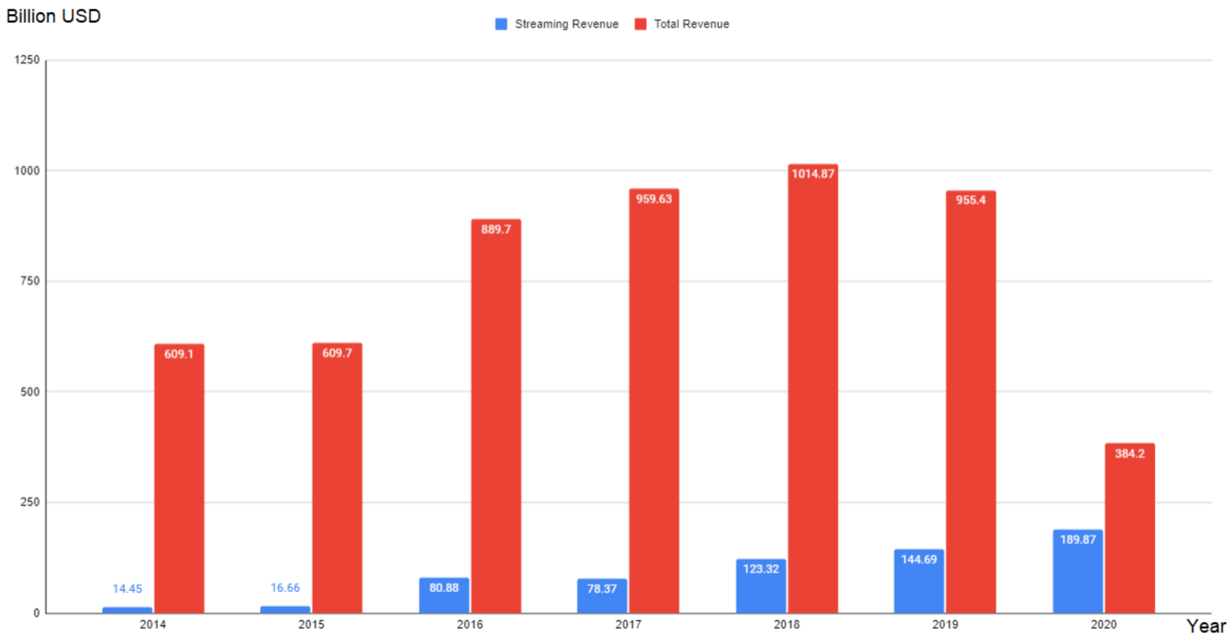

Figure 1 Streaming VS Total Revenue of Top-40 Highest Paid Musicians in the US

The proportion of musician revenue generated from streaming against total revenue (inclusive of sales, touring, streaming and publishing) grew rapidly in the US in the mid-2010s. Streaming revenue remains a small proportion over the years due to musicians' high dependency on touring as their biggest revenue source. With the Covid-19 pandemic in 2020 where most artists could not tour, the overall musicians' revenue had decreased by half. However, the aggregated streaming revenue increased, and took up almost 50% of the overall revenue, suggesting more music consumption through streaming compared to other formats.

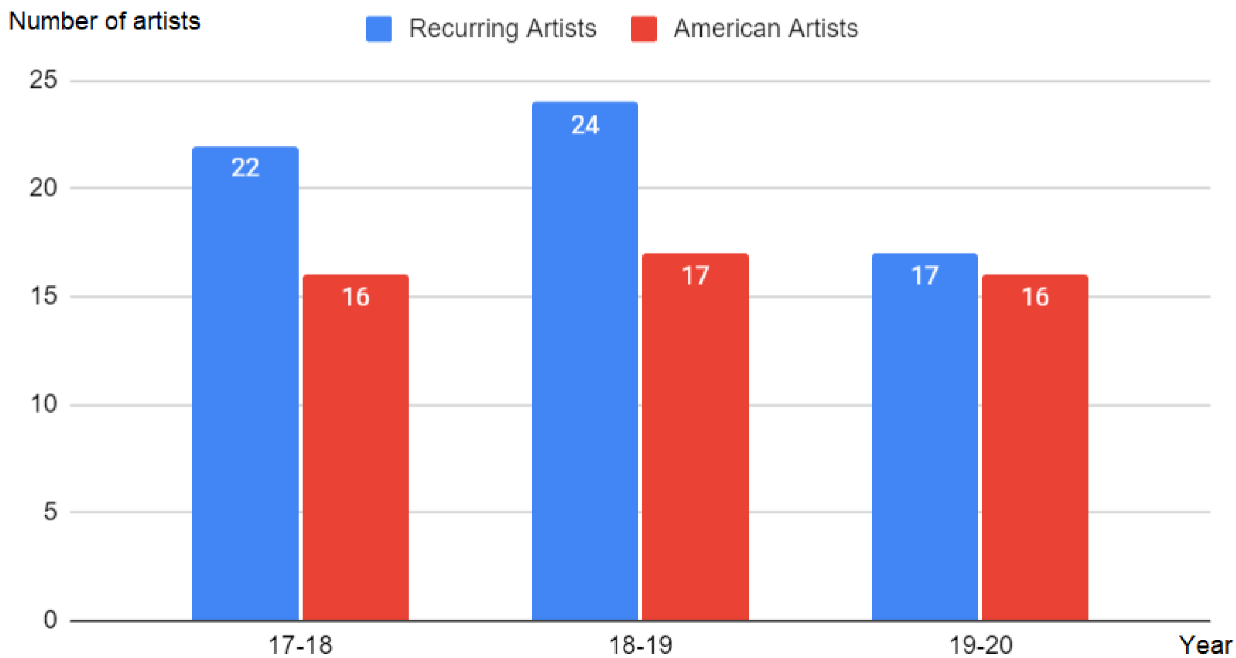

Figure 2 Recurrence Data on Billboard's Top Money Makers Chart

This chart demonstrates the number of artists that remain on the top-paid musicians chart two years in a row and the number of Americans amongst them. The number of artists that remained on the chart had reduced in 2020. A possible explanation is that with reduced touring capacity, only superstars including Taylor Swift, Ariana Grande and Travis Scott whose streaming popularity is massive could survive. In 2020, 16 out of 17 artists that remained the highest paid were Americans, which could suggest that more streaming of American artists' music took place during the pandemic, pointing to a preference for local music in lockdown.

3.1.1 The Taylor Swift case

Based on The Billboad (2020), the American singer-songwriter, Taylor Swift, has topped Billboard's Top-40 Money Makers Chart in 2015, 2018 and 2020. In 2015, her total revenue in the US was $73.5 billion. Touring itself made $61.7 billion while Swift's streaming revenue was only $0.564 billion. In 2018, a similar trend was observed. With a total of $99.6 billion under her belt, $90.5 billion came from touring while $5.67 billion was from streaming. Touring was her main source of revenue until the pandemic happened. In 2020, Swift registered an overall $23.8 billion but $0 came from touring while streaming across platforms made $10.6 billion. This case demonstrated an increased consumption of streaming during the pandemic, and the increased importance of American music in the US i.e., local music.

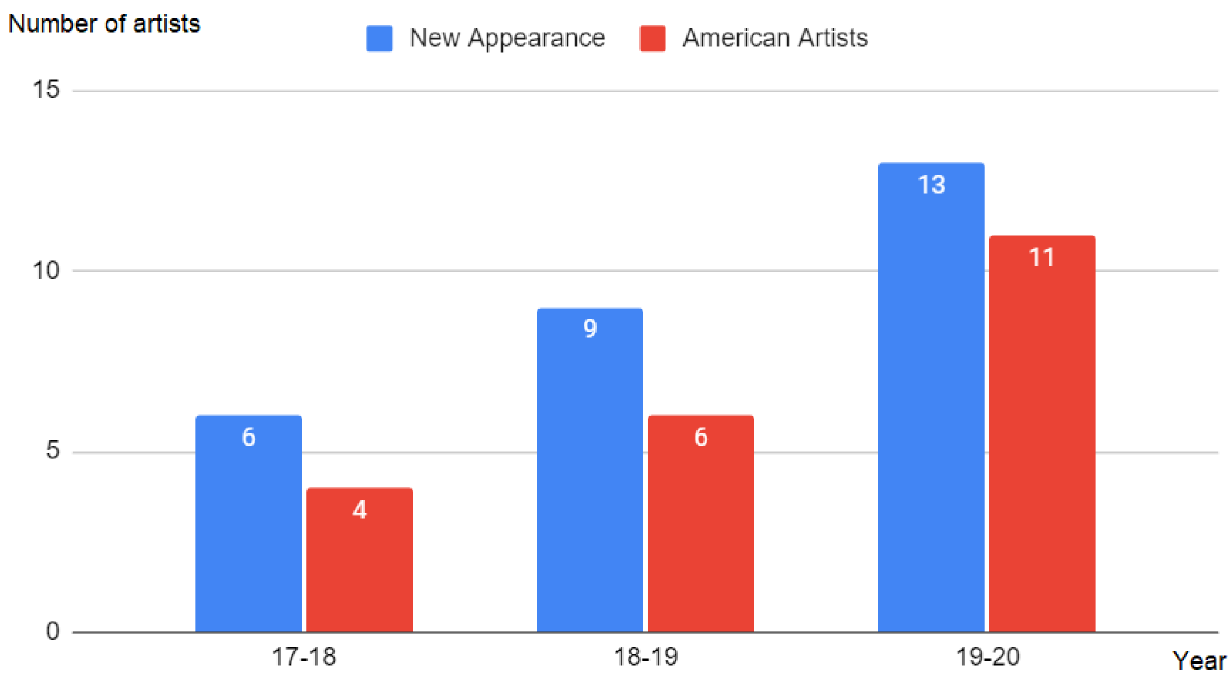

Figure 3 New Appearance on Billboard's Top Money Makers Chart

As the recurrence rate on the Highest Paid musician chart increased, new appearances of artists (who have never made the chart) increased. 2020 recorded the highest number of new appearances on the chart, with most of them being Americans, including Aventura, Tool and The Lumineers. However, these artists did not debut recently. For example, Tool is an American Rock band formed in 1990. It is observed that during the pandemic where streaming became the biggest revenue source for most artists, music of older local artists received streaming, suggesting a preference for local music subject to comfort through nostalgia (Yeung, 2020).

3.1.2 The Tool case

4 out of 5 of Tool's full-length albums were released between 1993 and 2006. The band has never appeared on the Top Money Makers chart during their active years, until 2020. They released an album in August 2019, alongside releasing their entire discography on all streaming platforms. These actions could have propelled their earnings the following year, with streaming becoming more significant due to the lack of touring opportunities.

However, the American Revenue data alone is insufficient in proving the preference for local music alongside an increase in music streaming during the pandemic. An empirical analysis is required to investigate the matter.

3.2 German Spotify Streams: An Empirical Model

Spotify is the largest music streaming site today with 406 million users worldwide, including 180 million subscribers (Spotify, 2022). The second dataset of this study is sourced from researcher Kework K. Kalusian's Spotify Chart Scraper, which collects details of the Top 200 streamed songs on the platform, including the artists' names and streaming count. 4 weeks' worth of daily German Spotify data were extracted across February and May in 2019 and 2020. External data including language, genre, and musician gender is added to run a Difference-in-Differences analysis on the changes in the streaming count based on music types as the pandemic took place. Data from 2018 was also extracted to be used in a placebo test, alongside the 2019 data.

The reason German Spotify data was used in this study is the country's natural segmentation of the music consumption market by languages. Scrapping the American Spotify data, consistent with the investigation of American musician revenue, would be possible but not worth being analyzed as the American market biases heavily towards English music which is in their main language used. Language cannot be used as a determinant for showing preference for local music. In other words, English songs by artists of different nationalities wouldn't strike too much of a difference to audiences in the US. However, in a German-speaking country, English songs and German songs are two completely different markets. (Larkey, 2000).

4 Method

The pandemic first started in Germany in March 2020 and was quickly followed by gradual restrictive policies and a national lockdown. The multiple cross-sectional data of the German Spotify streaming count collected is split into 4 different time groups consisting of 200 daily stream entries for one week each, according to the month and year they were collected, as shown in the tables below:

Table 1

Time Group	Date	Year 2020	Month=May
1	1-7 Feb 2019	0	0
2	1-7 May 2019	0	1
3	1-7 Feb 2020	1	0
4	1-7 May 2020	1	1

With the pandemic first taking place in March 2020, the month of February 2020 existing pre-pandemic is compared to May 2020, which exists post-pandemic in Germany. Yeung (2020) suggested that the pandemic effect peaked approximately 60 days into lockdown. As I considered the gradual school and kindergarten closures in Germany initiated in early March (Kampe et al., 2020) the start of 'lockdown', the 60-day period ended around early May 2020. May 2019 is made a counterfactual, where the pandemic did not take place despite being the month of May, as shown in the following table:

Table 2

	Control Group (MonthMay = 0)	Treatment Group (MonthMay = 1)	Counterfactual
Pre-2020	1	2	2
Post-2020	3	4	2+(3-1)

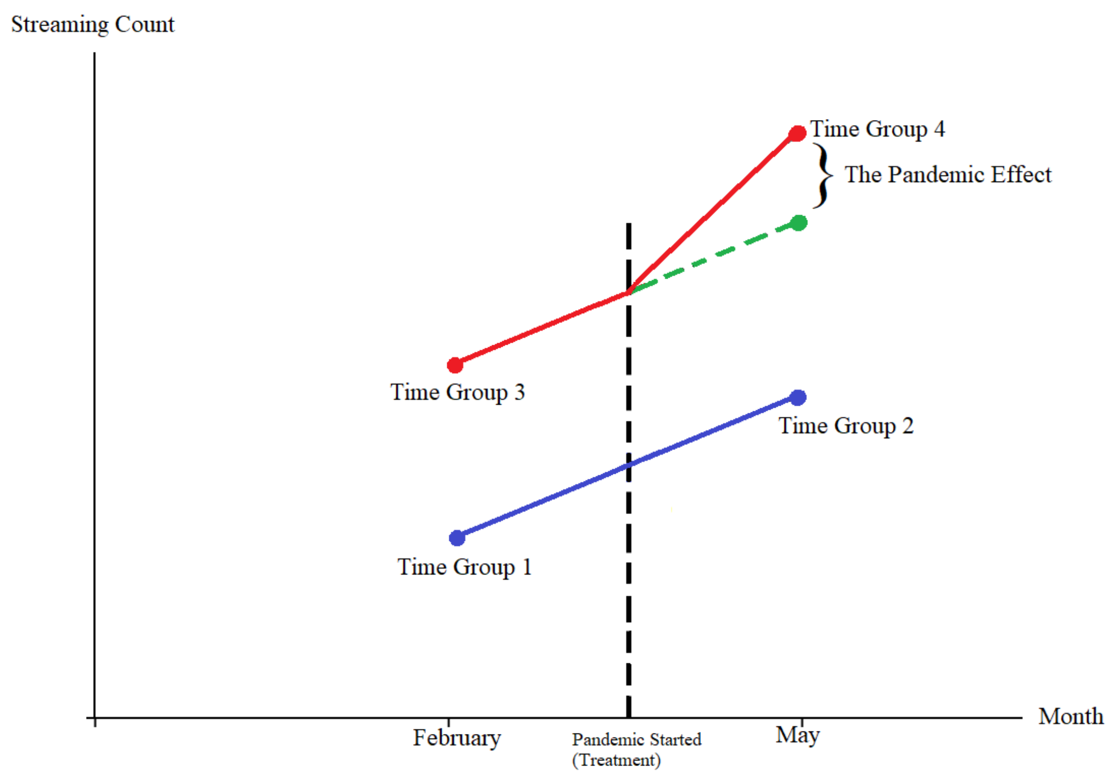

Figure 4 Graph Depicting the 4 Time Groups

Legend:

	Treatment Group Path
	Counterfactual Treatment Path
	Control Group Path

By subtracting the difference between Time Group 3 and 4 from the difference between Time Group 1 and 2, the pandemic effect is found in a Difference-in-Differences approach, based on a Parallel Trend Assumption:

$$DiD = (2\text{-}1) - (4\text{-}3)$$
$$= \text{Pandemic Effect}$$

The dependent variable, *streaming count,* in the model is treated with log functions. This is due to the unbalanced distributions of streaming counts across the data collected. The range of data collected is extremely large because typically a small number of 'super-hits' songs garner exceptionally high streams on and right after their release days. This causes the normal distribution to skew towards the left, as the majority of charted songs (outside the top 25th percentile) are a more stable streaming count that belongs in a similar range.

The following equations depict the main regressions used in the model, which first explores an OLS approach by listing the *pandemic* variable as a binary variable, depicting 1 for only data entries collected in May 2020 and 0 otherwise. The robustness of the model is then improved by replacing it with a *Year2020* variable, a *May* variable and the *Year2020*May* interaction term of *DiD* variable (henceforth known as *May2020*), used to investigate the pandemic effect:

OLS Equation:

$$\ln(\text{streaming count}) = \beta_0 + \beta_1 pandemic + \beta_2 gender + \beta_3 band + \sum^{6}_{i=4} \beta_i language + \sum^{10}_{i=7} \beta_i genre + \sum^{17}_{i=11} \beta_i day + \backslash\epsilon_i \tag{1}$$

DiD Equation:

$$\ln(\text{streaming count}) = \beta_0 + \beta_1 Year2020 + \beta_2 May + \beta_3 May2020 + \beta_4 gender + \beta_5 band + \sum^{8}_{i=6} \beta_i language + \sum^{12}_{i=9} \beta_i genre + \sum^{19}_{i=13} \beta_i day + \epsilon_i \tag{2}$$

Several control variables were used to investigate the effect of pandemic on the different types of music or the musicians studied:

Table 3 Control Variables

Variable	Label	Description	Category Value
gender	Being a male artist	Yes No	1 0
band	Being in a band	Yes No	1 0
language	Language of song	English German Other languages	1 2 3
genre	Genre of song	Pop Rap Rock Indie/Alternative	1 2 3 4
day	Day of the week	Monday Tuesday Wednesday Thursday Friday Saturday Sunday	1 2 3 4 5 6 7

These variables provide insights into understanding the public's general interest in music during the pandemic. *gender* shows whether male or female musicians tend to receive higher streams. *band* demonstrates if artists being in a band affects their streaming performance.

language is key to understanding the consumers' preference in music based on their languages. An assumption is made here that German songs are considered local music, to identify and separate local music from those which are not. This is due to the high collinearity between entries of the German language with a *Foreign* variable, which depicts the place of origin of the songs. The *Foreign* variable was considered to be included in this study but must be dropped. Next, *genre* is important in categorizing the types of music consumed and is essential in understanding the changes in music consumption behaviors. The data is categorized into 4 of the main, most popular genres based on OpenMic (2019)'s definitions of musical genres. *day* affects music consumption as consumers change their streaming consumption based on the day when new music is released.

5 Empirical Analysis & Discussions

The following table shows the OLS regression investigating how the binary variable *pandemic* affects ln(streaming count), alongside effects brought forth by other control variables. The model is treated based on Clustered Standard Errors by specific Song IDs attached to each charted song.

Table 4 OLS Regression Result (Clustered Standard Errors by Song IDs)

Variables	(1) Pandemic	(2) Gender	(3) Band	(4) Lan=2	(5) Lan=3	(6) Genre=2	(7) Genre=3	(8) Genre=4	(9) Day2	(10) Day3	(11) Day4	(12) Day5	(13) Day6	(14) Day7
l_streams	0.162***	-0.131**	-0.123**	0.060	-0.288***	0.063	-0.073	0.312***	0.007	-0.007	0.020**	0.200***	0.115***	-0.075***
	(0.040)	(0.060)	(0.053)	(0.043)	(0.094)	(0.047)	(0.100)	(0.113)	(0.005)	(0.009)	(0.009)	(0.009)	(0.008)	(0.010)

*** p<0.01 ** p<0.05 * p<0.1

Results show *Pandemic* has a positive effect of 0.162 on streaming count, the value is significant at p<0.01 with standard errors of only 0.040. The 95% confidence interval of this estimate is between 0.085 and 0.240, which preliminarily suggests a positive correlation between the pandemic and the streaming count by comparing the streaming count dated in May 2020 to entries of previous dates. However, the results suggest that songs in the German language contribute a positive effect of 0.06 on the streaming count compared to English songs. This could suggest an increase in streaming of German songs. For the *Lan=2* estimate, the 95% confidence interval is -0.024 and 0.145, suggesting the true estimate has a higher probability to be positive. However, songs of other languages bring forth a significant negative effect of -0.288 compared to English songs. We have sufficient evidence to prove that songs from other languages received fewer streams than English music in this case, which could be a sign of audiences returning to consume more music of mainstream languages during the pandemic.

In terms of genres, *Genre=4* has cotributed the largest positive effect on streaming count with a coefficient of 0.312 with 95% confidence intervals of 0.090 and 0.534. This genre is traditionally less popular (Blake, 2012), but the increase in time spent on mobile devices during lockdowns could lead to more discovery of independent musicians rather than just mainstream superstars. The significant coefficient of the *Pandemic* variable is considered plausible in this OLS study as 0.162 is relatively large. When compared to results of other variables like *Lan=2*, *Genre=2* and *Genre=3*, these variables have relatively smaller coefficients which are insignificant. For this contrast, we can suggest that these variables are not plausible as they have very little effect on the matter or there simply is difficulty in accurately capturing it. *Lan=3* and *Genre=4* have larger, more plausible values, which means the effects are better captured.

Additionally, it is observed that female or solo artists tend to get higher streams, relative to male artists or band musicians. This suggests the general taste in music in Germany or could suggest the lack of majorly popular bands, as opposed to the 1960s, 1990s or early 2010s when boy bands were especially prominent (Factinate, 2022). Factinate suggests that the late 2010s would achieve another peak in worldwide boy band popularity, but data shows otherwise, potentially meaning the effect takes time to show in streaming behavior or that the trend simply did not spread to Germany.

Another interesting observation is that Friday receives more streams compared to other days. It could be because it is the most common music release day, but the increase in streaming lasts only through Saturday. Higher-valued coefficients of the Day effect are significant, which could mean that the model has identified the variables with coefficients too small as implausible, thus considering them insignificant.

As the result of the main *pandemic* variable opposes what was proposed by Sim et al. (2020), a Difference-in-Differences method more similar to their approach is required to test the validity of these OLS results and to verify that of theirs.

Table 5 DiD Regression Result (Clustered Standard Errors by Song IDs)

Variables	(1) Year2020	(2) Month=May	(3) May2020	(4) Gender	(5) Band	(6) Lan=2	(7) Lan=3	(8) Genre=2	(9) Genre=3	(10) Genre=4	(11) Day2	(12) Day3	(13) Day4	(14) Day5	(15) Day6	(16) Day7
l_streams	0.158***	0.051	0.024	-0.122**	-0.132**	0.048	-0.270***	0.068	-0.057	0.329***	0.007	-0.007	0.020**	0.199***	0.115***	-0.075***
	(0.058)	(0.051)	(0.072)	(0.060)	(0.053)	(0.043)	(0.092)	(0.047)	(0.103)	(0.108)	(0.005)	(0.009)	(0.009)	(0.009)	(0.008)	(0.011)

*** p<0.01 ** p<0.05 * p<0.1

In a more robust Difference-in-Differences model, the pandemic effect (depicted by variable *May2020*) on streaming count turns insignificant. Results show a significant coefficient of 0.158 for the variable, *Year2020*, suggesting s positive year effect on streaming count; but the month is May and the Difference-in-Differences pandemic effect suggests insignificant influences. Variable *May2020* has a coefficient of 0.024, but the standard errors are close to 3 times larger, suggesting that the estimate might be far from the actual estimate. This goes against the results of the OLS regression, debunking the suggestion that the pandemic actually has a positive effect on streaming.

Other than that, consistent observations with OLS were made for the remaining variables. Notably, the *Lan=3* variable has a significant negative effect of -0.270 on the streaming count. In May 2020, songs in 'other languages' received fewer streams compared to English and German songs. The estimate has a 95% confidence interval of -0.450 and -0.090, confirming the estimate is negative. Despite having a positive coefficient of 0.048, *Lan=2* is insignificant. Thus, no sufficient evidence exists to suggest a preference for local German music. However, similar to *Genre=2* and *Genre=3*, their absolute coefficient values between 0.048 and 0.068 are implausible to be taken seriously or the actual effects are too small to be captured. The model managed to detect the small values regardless but rendered them insignificant. Additionally, the DiD model shows consistent results with the OLS model on the Day effect of streaming. Consumers start streaming more the day before new music is released, but such effect lasts only till Saturday, meaning they only stream more when anticipating new music and when the music is freshly released.

To understand how the streaming of music based on languages and genres is affected by the pandemic, the streams are isolated categorically and tested using the DiD method.

Equation:

$$ln(streamingcount*\underline{language1}) = \beta_0 + \beta_1 Year2020 + \beta_2 May + \beta_3 May2020 + \sum\nolimits^{9}_{i=4} \beta_i day + \epsilon_i \quad (3)$$

Table 6 Testing streams based on language and genre as outcome variables using DiD

Variables	(1) Year2020	(2) Month=May	(3) May2020	(4) Day2	(5) Day3	(6) Day4	(7) Day5	(8) Day6	(9) Day7
StreamLan1	0.253***	0.086***	-0.011	0.013	-0.013	0.013	0.192***	0.115***	-0.057
	(0.031)	(0.028)	(0.042)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
StreamLan2	0.056*	-0.007	0.079*	0.005	-0.001	0.026	0.203***	0.111***	-0.096**
	(0.032)	(0.032)	(0.042)	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)
StreamLan3	0.280***	0.327***	0.048	0.002	-0.021	0.005	0.154	0.116	-0.059
	(0.074)	(0.082)	(0.150)	(0.119)	(0.119)	(0.118)	(0.118)	(0.119)	(0.121)
StreamGen1	0.163***	0.010	0.017	0.004	-0.013	0.008	0.190***	0.113***	-0.090**
	(0.031)	(0.030)	(0.040)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
StreamGen2	0.189***	0.078***	0.017	0.010	-0.003	0.027	0.211***	0.118***	-0.066*
	(0.032)	(0.030)	(0.043)	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.041)
StreamGen3	-0.158	0.029	0.186	0.012	-0.030	0.021	0.197	0.084	-0.114
	(0.104)	(0.105)	(0.123)	(0.113)	(0.121)	(0.121)	(0.120)	(0.115)	(0.119)
StreamGen4	-0.172***	0.690***	0.401***	0.024	0.014	0.047	0.007	0.106	-0.088
	(0.056)	(0.096)	(0.150)	(0.179)	(0.175)	(0.178)	(0.189)	(0.171)	(0.171)

*** p<0.01 ** p<0.05 * p<0.1

Language: Songs in English and other languages are positively affected by the variables *Year2020* and *Month=May* but not the variable *May2020* (the pandemic effect). This suggests streaming for music in English and other languages increases over time with no evidence it is motivated by the pandemic. German songs show a positive correlation of 0.079 with *May2020*, which is during the pandemic, suggesting that the music in local language experiences increased the streaming as Covid hits. Evidence of preference for local music during the pandemic is thus present. In fact, the pandemic effect on all *StreamLan* variables has very small coefficients, which could suggest implausibility. However, comparing German to the other languages, its coefficient is much larger. *StreamLan2* has a clustered standard error of 0.042, which is more plausible than the other languages as its comparative size is smaller. Thus, it is still considered plausible, consistent with the model recognizing it as significant.

Genre: Results show that streams of Indie songs are positively affected by the pandemic by a significant coefficient of 0.401. The estimated effect of *May2020* on *StreamGen4* is much larger than other genres, with a 95% confidence interval of 0.102 and 0.700, confirming the positive effect of the pandemic on the streaming count of Indie/Alternative music. This is consistent with the previous models, suggesting that less popular music genres get discovered more during the pandemic, possibly due to increased use of music applications. Other genres do not demonstrate significant effects brought forth by the pandemic. Moreover, Pop, Rap and Indie music experiences positive *Year2020* effects, as the streaming count in 2020 is higher than in 2019. Amongst the genres, only Rap and Indie/Alternative music received higher streams in May as compared to data collected in February.

Day: For English, German, Pop and Rap songs, Friday sees the highest streaming count as it is the release day for new music in the country. The significant positive effect lasts until Saturday but becomes significantly negative on Sunday. These coefficients are plausible, especially Friday and Saturday as the values are much larger than the rest of the week. This further proves Germans' interest in new music peaks on release day but quickly plummets two days later.

With these terms being isolated based on characteristics, the coefficients could suggest a trend but are not sufficient to conclude that a preference for local music existed in the German market during the pandemic. Thus, interaction terms between the languages and May2020 are created and tested on.

Equation: $\ln(\text{streaming count}) = \alpha_0 + \alpha_1 Year2020 + \alpha_2 May + \beta_2\ \_ILan\_2 + \beta_3\ \_ILan\_3 +$

$$\gamma_1\ \_May2020\_1 + \text{Þ}_{21}\ \_ILanXMay2020\_2\_1 + \text{Þ}_{31}\ \_ILanXMay2020\_3\_1 + \epsilon_i \quad (4)$$

Table 7 Testing ln(streams) with interaction terms of languages and May2020, clustering standard errors by Song IDs

Variables	(1) Year2020	(2) May	(3) _ILan_2	(4) _ILan_3	(5) _IMay2020_1	(6) _ILanXMay2020_2_1	(7) _ILanXMay2020_3_1
l_streams	0.150***	0.051	0.100**	-0.272***	0.089	-0.110	0.247
	(0.058)	(0.052)	(0.044)	(0.091)	(0.083)	(0.078)	(0.293)

*** p<0.01 ** p<0.05 * p<0.1

Results show that without the pandemic, German-language songs have a positive significant effect of 0.1 on streaming count compared to English songs; music in other languages has a negative effect of -0.272 on streaming count. The coefficients suggest the increase in streaming of German songs is smaller than the decrease in streams of other languages, which is plausible in suggesting a preference in local music. When the pandemic is taken into consideration, the *May2020* variable has an insignificant positive coefficient of 0.089 on streaming count, consistent with the previous DiD model where the pandemic has no significant evidence in causing a positive effect on streaming count. The estimate has a 95% confidence interval of -0.073 and 0.251, the probability of the actual value being positive is higher. The interaction variable between German language and the pandemic also has an insignificant negative coefficient of -0.110 on streaming count, depicting the lack of evidence to prove that German songs received less streaming during the pandemic. This further establishes that no pandemic effect is present in music streaming consumption, but the preference for local music is present. The aforementioned trend in preference might be motivated by other factors, not necessarily the pandemic.

6 Robustness Check: Placebo Test

To test if the change in consumers' preferences, especially the preference for local music is an annual pattern, the study was tested with a placebo model, which assumes 2019 as the pandemic year, in comparison to 2018.

A Placebo DiD regression with clustered standard errors by Song IDs suggests a significant positive year and month effect. While the year effect is consistent, the latter was insignificant in the original model. The estimate of the variable *May2020* has also turned from insignificant positive to insignificant negative in this model. The previous model was unable to prove that a pandemic effect existed, the placebo suggests otherwise. We have little evidence to conclude that the pandemic effect does not exist. However, the reality of the pandemic being inexistent could mean the trend observed is motivated by streaming becoming more popular over time. As the original DiD model suggests a lack of influence by the pandemic, the conclusions drawn by Sim et al (2020) on less music consumption during the pandemic could be true. Alternatively, it could be due to a time lag of the pandemic effect, where a longer observation period is needed to detect any post-pandemic trends in streaming count.

To understand the changes in streaming of specific languages:

Table 8 Placebo: Testing ln(streams) with interaction terms of languages and DiD, clustering standard errors by Song IDs

Variables	(1) Year2019	(2) May	(3) _ILan_2	(4) _ILan_3	(5) _IMay2019_1	(6) _ILanXMay2019_2_1	(7) _ILanXMay2019_3_1
l_streams	0.256***	0.115**	-0.0004	-0.135	-0.114	0.106	0.034
	(0.053)	(0.051)	(0.043)	(0.109)	(0.079)	(0.085)	(0.224)

*** p<0.01 ** p<0.05 * p<0.1

Some key results to take note of are columns 3 and 4, where coefficients of *Lan=2* and *Lan=3* are negative when the pandemic did not exist. This could suggest relatively lower streaming of songs in German and other non-English languages in 2018, mostly due to the increase in popularity of English music over time, especially on international music streaming applications like Spotify. The absolute value of *Lan=2* of 0.0004 is extremely small and hard to capture by the model, thus the high standard errors and rendered insignificance. When interacting with the pandemic variable, *Lan=2* turns positive with a coefficient of 0.106, becoming relatively more plausible. However, the value remains insignificant, thus unable to prove a preference for German music in May 2019, in contrast to the original model suggesting a preference for German music in May 2020.

Additionally, the study of genres through a placebo test suggests Genre 1, 2 and 3 have significant positive coefficients for Year=2019 and May, but negative coefficients for the interaction terms May2019. This means the values are not particularly affected by the pandemic, which could be because there was not one in reality. Instead, Genre 4 has a significant positive coefficient in May 2019 but insignificant coefficients for the separate year and month variables, suggesting Indie/Alternative music experiences little general time effect as a less popular genre.

The Placebo provides substantial support proving the original model using the year 2020 as the treated year does not demonstrate any annual patterns, and that the streaming count changes in May 2020 did not happen by random.

7 Limitations

7.1 Study Time Period

Picking the best time period for this study is an issue. The pandemic effect may experience a time lag, or might just be a temporary shock. To study the most accurate trend, a longer time period might be needed to capture the pandemic effect. The periods of this dataset are chosen 60 days after the start of gradual cancellations of events and closure of schools in Germany starting the first week of March, not the official national lockdown, which only started on 22 March 2020.

7.2 Definition of Local Music

In this paper, the assumption of German-language songs are local music in Germany was made. However, the entire DACH region (Germany, Austria, Switzerland) consumes and produces songs in the German language. German-language songs might not fully represent an interest in local music despite using Spotify data from Germany only, since consumers are allowed to stream German-language songs produced in other countries. An attempt was made to add a control variable depicting foreign production, but it ends up with high collinearity with language, as most local songs are predominantly in the German language. Thus, this remains a limitation in this research.

7.3 Miscellaneous Streaming Services And Formats

This study uses data extracted from German Spotify. However, Spotify is not the only streaming service in Germany despite being the biggest music streaming platform in the market (Spotify, 2022) and the data should be representative of the market. Other formats including non-streaming-based music consumption like CDs and vinyl are not considered. This study is conducted to capture pure music streaming consumption, unlike Sim et al (2020)'s investigation of music complementarity in consumption with other activities.

8 Conclusion

Music consumption based on language and genres reflects personal utility maximization and might carry important signals to producers to allocate resources to create art that suits the general public's tastes.

The OLS model used in this paper suggests the pandemic has a significant positive effect of 0.162 on streaming count, but the effect disappears when tested on a DiD model. However, the data collected still observe non-annual patterns of increased music streaming in May 2020. Throughout the study, consistent results show female and solo artists have a higher streaming count in May 2020. The paper finds evidence that the time of May 2020 affects music streams based on genres and languages. Indie/Alternative songs have especially experienced the largest growth of 0.401 in streaming count in May 2020, suggesting that traditionally less popular genres get discovered during lockdown with increased use of music applications. Tests run on interaction terms between the pandemic and streams based on language suggest that German songs receive more streams relative to other languages. This concludes that the preference for local music is present in May 2020, which resonates with the American Revenue data about preference for local songs during the pandemic. However, as suggested by the DiD model, the pandemic effect is found insignificant. This means that the change in music consumption patterns in May 2020 might not be entirely due to the spread of Covid-19. The aforementioned trend in streaming might be motivated by other factors, not necessarily the pandemic.

This paper has successfully modelled Yeung (2020)'s Difference-in-Differences approach to investigate the changes in music streaming induced by the pandemic, especially the effects on genres and languages. With the presence of a pandemic effect inconclusive, this could resonate with Sim et al (2020)'s findings that the pandemic reduces music streaming, or suggest the need for a longer observation time to capture the impact of the pandemic. The findings of preference for local music could signal local music producers and musicians to continue making music despite the pandemic. However, the trend might be temporary over the first few months of lockdown when the most comfort is needed. As people get used to lockdowns, their music preferences might change over time. Thus, in a future extension of this research, improvements including considering a longer period of study, using more countries in the sample and allowing more musical genres with clearer definitions could provide clearer trend patterns.

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Appendix

4 main musical genre categories based on the definitions of musical genres listed by OpenMic UK (2019).

Genre	Definition
Pop	Pop music or popular music encompasses any music that is designed for the masses, or in other words, catered to mainstream radio audiences. Pop music often envelopes a variety of genes, including electronic, hip-hop, R&B and even Motown.
Rap	Rap is a music of rapid vocal delivery developed alongside hip-hop music and incorporates complex rhyme schemes.
Rock	Rock'n'roll music famously uses electric guitars, distorted amplification and snare and kick drum rhythms. Rock music evolves to combine with many other genres, giving birth to Country Rock, Pop Rock, Alternative Rock and more.
Indie/Alternative	Indie music is often created by 'independent' artists of the mainstream music scene. It usually blends with punk, rock and folk elements.