The Influence of YouTube Videos on Song Popularity

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Abstract

YouTube creators often criticize major music labels for blocking their videos due to copyright infringement, stating that the music labels would benefit from the extra exposure that the artists receive from having their songs featured in YouTube videos. One of these creators is Rick Beato, whose series 'What Makes This Song Great' features songs from major labels. Using Google Trends data in a difference-in-difference approach, it indeed appears that 'What Makes This Song Great' significantly increases song popularity on YouTube. Major labels would therefore benefit from allowing Beato to continue making his YouTube series without interference, since increased song popularity likely results in more Spotify streams and album sales.

Introduction

In his YouTube series 'What Makes This Song Great?', producer Rick Beato analyzes (mostly 20th century) songs to find out what makes them great. However, major music labels have taken down some of his videos due to copyright infringement. Beato argues that his videos bring a new wave of interest to these songs from new or recurring listeners, since most of the songs are 20th century songs that do not receive a lot of playtime on the radio anymore. There are several examples in recent years that seem to support this claim. In October of 2020, Nathan Apodaca uploaded a video of himself lipsyncing to Fleetwood Mac's 'Dreams' while riding a skateboard and sipping on cranberry juice. His video went viral, which resulted in 'Dreams' re-entering the charts after earning over 16 million streams in a single week (Garvey, 2020). In August of that same year, Phil Collins' 'In The Air Tonight' experienced a 1100% increase in sales over two days compared to the two days prior thanks to a viral video in which YouTubers Tim and Fred Williams reacted to the song after hearing it for the first time (Moore, 2020). I would like to find out if the release of a 'What Makes This Song Great?' video on YouTube significantly increases the popularity metric for the song in question on YouTube, according to Google Trends. If Beato is right, major music labels have a financial incentive to allow Beato to make videos about their music instead of blocking the videos for copyright infringement.

Related Work

The influence of social media videos on song popularity has received little attention in the academic literature. However, as social media becomes a bigger part of our lives, researchers dedicate more of their time and resources studying its effects on society. In 2018, Park et al. published their research on the influence of user engagement on YouTube resulting from user-generated content versus company-generated content on music sales. They found that user engagement of user-generated content had a greater impact on music sales than user engagement of company-generated content. In addition, they found that the user engagement resulting from user-generated content influences music sales positively and significantly. Since Rick Beato's 'What Makes This Song Great' is not sponsored by music labels, we can categorize it as user-generated content on YouTube. Dhar and Chang (2009) investigated whether user-generated content from MySpace provided any predictive value for music sales. They found that blogpost chatter is a predictor of music sales, however they were not able to establish a causal relationship with their findings. These findings help to form the main hypothesis of this research project if we assume that music sales are a reflection of music popularity:

H1: Rick Beato's 'What Makes This Song Great' series has a positive effect on the popularity of the songs.

Dewan and Ramprasad (2009) also investigated the relationship between blog buzz and music sales, finding a significant bi-directional relationship between the two, meaning that music sales also influence blog posts. Since 'What Makes This Song Great' does not cover a song's sales, the relationship is not bi-directional.

Industry Background

In the music industry, music labels often own the rights to a song. When a song is played on the radio, the music label will earn a commission which they use to pay the artists, the studios and the marketing of their music. Whenever someone uses music without paying the label, they are infringing copyright laws. On YouTube, music labels have the option to demonitize videos, take them down completely, or file a copyright strike. After three copyright strikes, a YouTube channel is removed. Many YouTube creators have critized YouTube for allowing music labels too much power over the platform, one of which is Rick Beato. Their reasoning is that the music labels benefit much more from allowing YouTube creators to use their music, since the songs are shared to a large and diverse audience that may have never heard of the music before.

Data

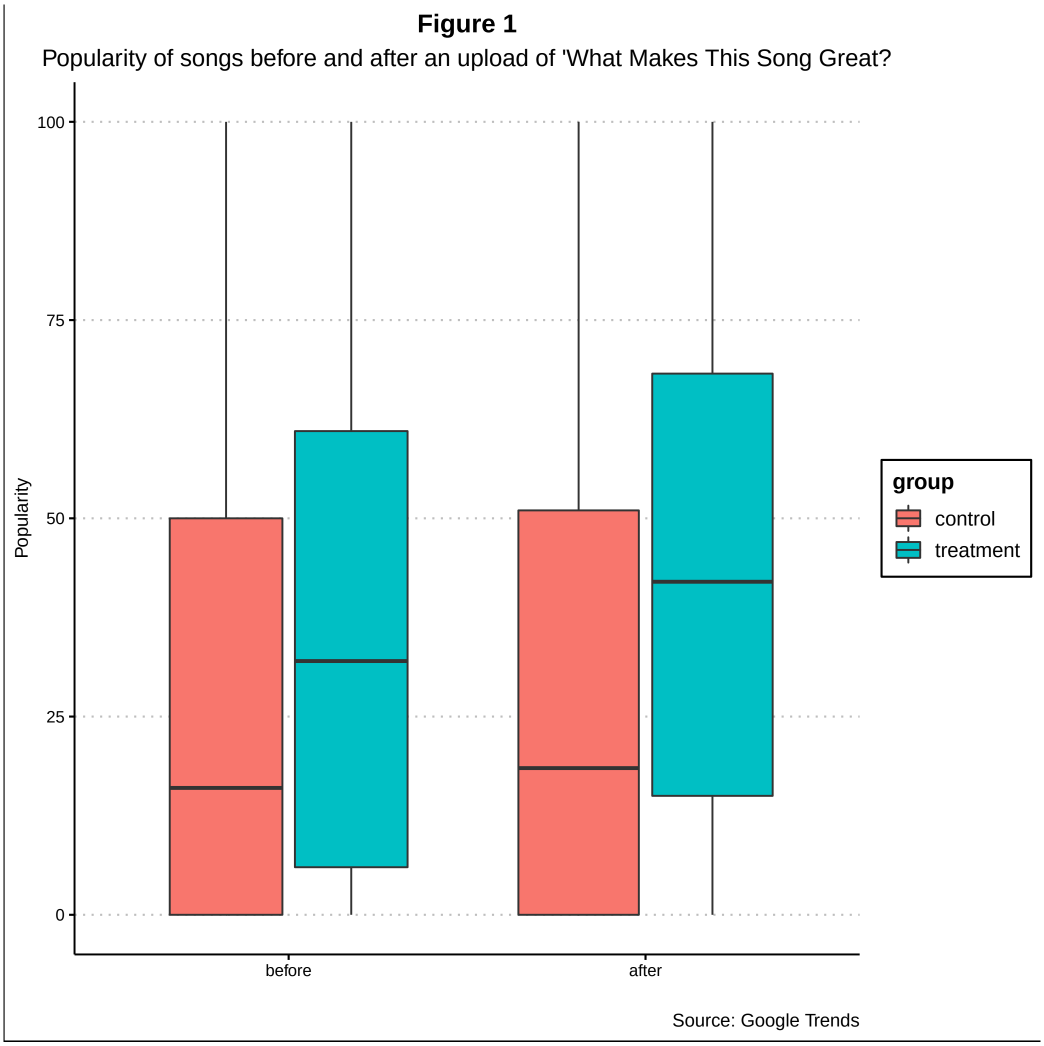
Originally I wanted to see what effect Rick Beato's videos had on song sales, YouTube views or Spotify streams. However, this data is notoriously difficult to obtain. Therefore I decided to obtain popularity metrics using Google Trends. Google Trends returns the popularity of specified search queries in a given period. The popularity metric is normalized for easier comparison, meaning that in each given period, the popularity metric will range from 0 to 100, always including 0 and 100. This can bias the results, since a minor increase in popularity may appear as a massive spike if search volume is low. Therefore I collect popularity metrics of pairs of songs. A given pair consists of a song in the treatment group (a song that was featured in 'What Makes This Song Great') and a song in the control group. In order to create the control group, I had to find out songs that were similar in every single way, except that they have not (yet) been featured in an episode of 'What Makes This Song Great'. In other words, I had to find more songs that Rick Beato thinks are 'great'. Rick Beato has done over a hundred episodes of 'What Makes This Song Great' and asking him for another hundred that seemed pointless. Therefore I decided to use Spotify's playlist algorithm, which recommends the user new songs based on the existing songs in a playlist. After I made a playlist of the treatment group, I added the songs that Spotify recommended to a new playlist since adding them to the same playlist could bias results. Since the algorithm tends to recommend songs from the same artist, I included only a limited number of songs per artist such that the maximum number of songs a single artist had in the control group and the treatment group combined was three. The reason for the number three was that an artist was featured a maximum of three times in 'What Makes This Song Great'. The dataset contains 103 rows with the song/artist, 15 days of Google Trends data per song (one week surrounding an upload of 'What Makes This Song Great'), the pair number (denoting what song the song was paired up with in Google Trends), and whether the song belongs to the control group or the treatment group.

Data Collection

I used the R package 'gtrendsR' to download my data. For each pair of songs, I downloaded 15 days worth of data (one week surrounding an episode). The data comes from worldwide search queries, including low search volume since all data is valuable. Furthermore, the search queries are based on YouTube search queries only. It can be argued that one searches for a song for its lyrics or other purposes, while searching for a song on YouTube only has one purpose: you want to hear the song. This choice seemed logical given my research question.

Data Processing

The boxplots below have been constructed using the popularity scores of 103 pairs of songs, before and after an episode of 'What Makes This Song Great' is uploaded. From the boxplots we can see that the average popularity score is higher after the release of an episode of 'What Makes This Song Great', but only in the treatment group. Remember that the control group was not featured in an episode of 'What Makes This Song Great'. This suggests that Rick Beato brings a new wave of interest to songs with his YouTube series. However, based on these boxplots alone we cannot make this claim and we will need to discover the relationship between 'What Makes This Song Great' and song popularity further.

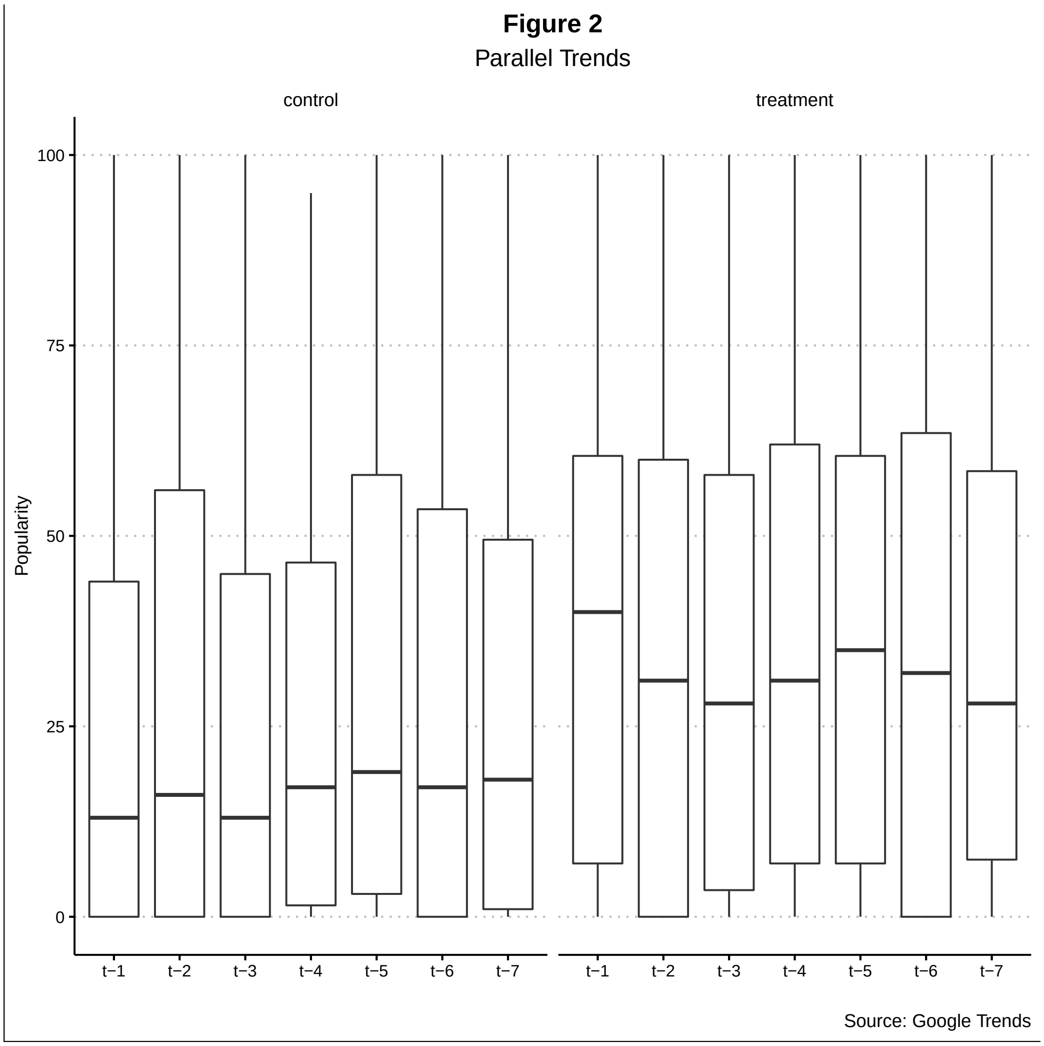


Methodology

Experimental research with random allocation of participants to control and treatment groups is the best way to obtain causal knowledge. However, as is the case here, this is not always possible. The difference-in-differences approach is a good way to get close to causal knowledge, however, when all we have is past data. The difference-in-differences approach helps to account for confounds that influence the relationship between 'What Makes This Song Great' and song popularity. Using the method discussed in the 'Data' section, I created a control group to be used here. The formula below conceptualizes the OLS regression used, where the dichotomous variables ‘After’ and ‘Treated’ are 1 for the after-treatment period and the treatment group respectively.

$$Popularity_it = \beta_0 + \beta_1 After_t + \beta_2 Treated_i + \delta After_t * Treated_i + \varepsilon_i t$$

In Figure 2 below, we can see that the trends before treatment seem about parallel for both the control and treatment groups.



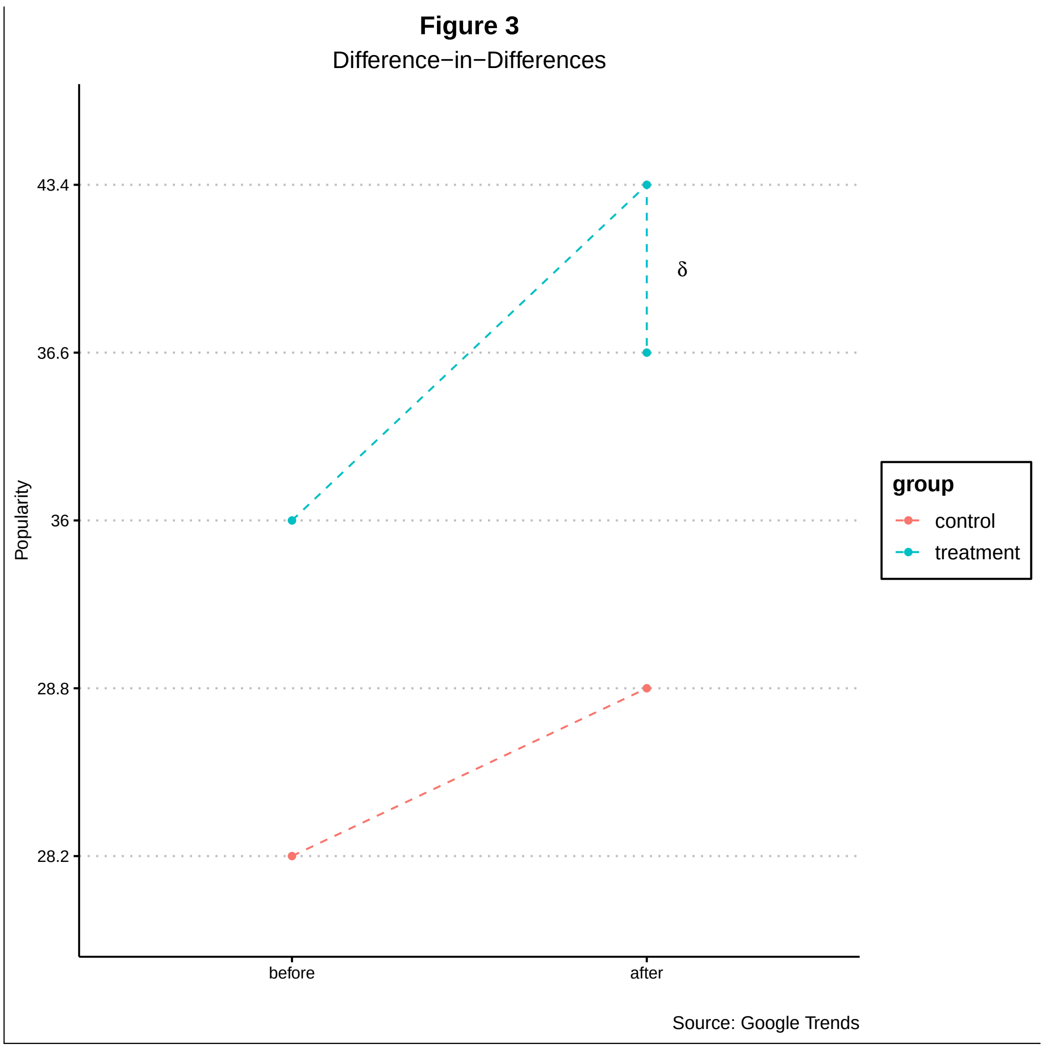
Results

Using the difference-in-differences approach, we obtain an average treatment effect estimate of 6.818 (se = 2.207, alpha = 0.002, 95% CI = {2.490, 11.146}). This signals that ‘What Makes This Song Great’ indeed significantly increases song popularity by about 6.8 points in Google Trends on average, meaning that when Rick Beato features a song in an episode of ‘What Makes This Song Great’ it will receive 6.8% more search queries on YouTube compared to all other search queries on YouTube. With an alpha of 0.002, there is about a 0.2% chance that we would have found these results (or a more extreme version) if we assumed that ‘What Makes This Song Great’ does not influence song popularity. This probability is low enough to reject this null hypothesis. The hypothesis of this research project is therefore not rejected.

Table 1: Difference-in-differences Regression

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	28.2149792	1.139900	24.7521488	0.0000000	25.979939	30.450019
group	7.8349515	1.612062	4.8602039	0.0000012	4.674128	10.995775
time	0.5811373	1.560873	0.3723157	0.7096834	-2.479317	3.641592
group:time	6.8179612	2.207407	3.0886739	0.0020284	2.489825	11.146097

The difference-in-differences graph can be seen below, where the average popularity scores of the control and treatment groups before and after treatment are plotted. We can see the difference-in-differences estimator denoted by delta which visualizes the 6.8 point increase in popularity. Without the treatment, the treatment group would have received an average popularity score of 36.6 after an increase similar to the control group.



Conclusion

Using a difference-in-difference approach with an artificial control group created by the music recommendation algorithm of Spotify, I investigated whether Rick Beato's 'What Makes This Song Great' series on

YouTube significantly increases the popularity of the songs featured in the episode. As hypothesized, the YouTube series indeed has a significant positive impact on song popularity. This is likely due to the fact that people (re)discover these songs and proceed to listen to them more often. However, the difference-in-difference approach remains a method to obtain an estimate of causality (albeit one of the better ones). The approach is still quite new and it is still subject to a lot of research. Therefore, we should be careful making conclusions about the larger population, such as the effect of YouTube videos in general on song popularity.

Managerial Relevance

Since we have quite a good reason to believe that Rick Beato's YouTube series 'What Makes This Song Great' increases song popularity, music labels would do well to allow Beato to continue making his videos without interference. The boost in popularity is likely due to a new wave of interest coming from Beato's audience after they (re)discovered the music featured in 'What Makes This Song Great'. This boost in popularity will likely also be visible in other song performance metrics, such as Spotify streams and album sales. However, this needs to be tested for it to be certain.

Future Directions of Research

This research project has a few limitations. For one, its external validity is not very strong. This could be addressed by designing similar studies around other YouTube videos, such as song covers which are another popular phenomenon on YouTube. To improve internal validity, it would benefit this research project to be replicated identically. Given the random nature of the Spotify algorithm used to create the control group, identical replication could result in different results. Google Trends also appears to be slightly inconsistent with its results, likely due to the larger variance among queries associated with lower search volume.

Word Count

Number of Words: 2153

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