Spotify Playlists as a Medium for Publicizing Songs? Evidence from a Regression Discontinuity Approach.

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Abstract

This paper examines the interplay between the Spotify 'Viral 50 - Global' and 'Top 50 - Global' playlists, two daily playlists Spotify publishes containing the 50 most viral and 50 most streamed songs of the day, respectively. As Spotify also publishes Viral Global and Top Global charts containing the 100 most viral and 200 most streamed songs every day, this opens up the possibility to exploiting the discontinuity at the 50th rank in either playlist for an RD design. Concretely, we assess whether the inclusion of a song in one of two playlists improves the song's probability of entering the other chart within 30 days, and whether inclusion of a song in one of two playlists improves the song's best ranking on the other chart within 30 days. We explore the former question using linear, quadratic, linear probit, quadratic probit, local linear regression, and local randomization models. We approach the second question using a Tobit Type-I model, due to the right-censoring of ranks present in both charts. We do not find robustly significant treatment effects in either of our designs. One implication of these results is that the exposure of the Viral playlist - which is usually more easily penetrable for smaller artists - does not appear to lead to significant popularity gains of songs.

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1 Introduction

With the advent of music streaming services, the landscape of music discovery mediums changed. Music streaming services allow users to stream music on their mobile devices and computers, and beyond providing users with music, they also offer different ways of discovering music. Those ways include algorithmic curation, a process personalized to each user, which streamlines content to those users (Rader and Gray, 2015) and, more relevant to our research, what we call in this paper standardized playlists. Audio streaming services construct standard playlists in many ways, often delivering users various playlist options. Spotify, the most popular audio streaming service worldwide, offers subscribers, among others, the 'Top 50 Global' playlist. This playlist consists of the most-streamed[1] songs worldwide within the platform from the previous day. They also provide users with the 'Viral 50 Global' playlist, which uses an undisclosed combination of user sharing analytics across various platforms, like blogs and social media, recent rises in plays, and the number of discoveries for a track to create a list of ranked songs[2]. Like algorithmic curation, standard playlists also shape user music consumption behaviour (Aguiar and Waldfogel, 2018). Indeed, the 'Top 50 Global' playlist alone has over 16.7 million followers[3]. Considering the multitude of standardized playlist offerings available within Spotify, most with millions of followers, it is not far-fetched to assume that millions of Spotify users rely on those standardized playlists every day for discovering and consuming music. Accordingly, understanding the extent of the ability of those playlists to influence music consumption choices provides us with insights into the overall power of those audio streaming platforms.

Understanding how powerful internet service companies are, including audio streaming services, has become a top priority for antitrust authorities. All investigations of potential breaches of competition law begin with establishing that the undertaking in question has the power to transgress the law in the first place. For example, in proving abuse of market power, competition authorities must first establish that the undertaking has a dominant position (QC and Padilla, 2020). Due to the features of internet service markets, like extensive network externalities and infinite economies of scale, telltale indicators of market power, such as revenue-based market shares, are not applicable within those markets (Schweitzer and Welker, 2019). Hence, researching alternative, market-specific indicators may assist in antitrust investigations. In the audio streaming market, this could be the ability of standardized playlists to influence music consumption.

In this paper, we use different methodological approaches to understand the power of Spotify playlists. We employ all methodological approaches to two scenarios. First, we analyse whether exposure through the Viral 50 playlist may propel songs into mainstream popularity in terms of streams. Moreover, we study whether inclusion in the Top 50 playlist may lead to more sharing of a track on other digital platforms and, in turn, more stream volume for said track.

For all methodological approaches and both scenarios, we exploit the built-in discontinuity in Spotify charts. Since only the top 50 songs in each chart show up in their corresponding playlist, we may apply a regression discontinuity approach where the running variable is the rank of a song in a given chart. The cutoff point is then the 50th rank.

We divide our approaches into parametric, non-parametric and Tobit models. In parametric ones, the dependent variable is, for a given chart, a binary indicator equal to 1 when a song in a given chart appeared in the other chart within 30 days of debuting in the former chart. The treatment effect is, then, the result of the RD analysis with the 50th rank as the threshold. For the parametric approach, we estimate eight models. These include first-order linear, second-order linear, linear probit, and quadratic probit, all of which we estimate with and without covariates. One of those covariates is a binary indicator equal to 1 when the track appeared on the other chart within 30 days of debuting in a given chart. The other is a binary variable equal to 1 when the song is a collaboration between artists.

[1]See https://artists.spotify.com/en/help/article/how-we-count-streams

[2]See https://artists.spotify.com/help/article/how-viral-charts-work

[3]The only way to access the number of users a playlist has is through the Spotify app. At the time we wrote this section, the indicated number was the number of followers.

We use a first-order linear specification since it is the most basic approach. Besides, we opt for second-order linear specification to control for quadratic effects. Finally, we consider probit models since linear probability models may result in fitted values higher than 1 and lower than 0. For all models, we use White standard errors to account for heteroskedasticity.

Beyond parametric approaches, we also regard non-parametric ones since they are less sensitive to model specification. We consider both local linear regression and local randomisation design, as the latter works better when the running variable is discrete (which is the case with the rank of a song in both charts). We also consider Tobit models, with and without covariates, as they allow for more variation in the dependent variable. For those models, the dependent variable is the right-censored observed best rank of a song on a given chart within 30 days of debuting in the other chart. The treatment effect is, then, the effect of belonging to a given playlist on a track's best rank in the other chart.

For all methodological approaches, we apply various validity and robustness checks. For both scenarios, we find no robustly significant effects. This lack of significance is most evident in the first scenario, i.e. the effect of inclusion in the Viral 50 playlist on the probability of a song being on the Top Global chart within 30 days, as most models reject discontinuities for almost all bandwidths. Meanwhile, it is less clear for the other scenario, i.e. the effect of inclusion in the Global 50 playlist on the probability of a song being on the Viral Global chart within 30 days. Local linear regressions and second-order linear models suggest a treatment effect significantly different from zero for large bandwidths. However, we do not consider this convincing evidence as, for small bandwidths, the quadratic linear models and local randomisation give insignificant results.

2 Literature Review

Research linking exposure through music discovery mediums and the success of songs in the form of music sales exists. Radio setlists, for instance, like Spotify playlists, select and expose new music to listeners, and research on the connection between radio airplay and sales is extensive. Bandookwala (2010), as an example, assess the impact of radio airplay on digital music sales in New Zealand and finds a significant positive relationship between radio play and predicted sales. He attributes this relationship to the exposure effect, which dictates that people unconsciously tend to develop preferences for things simply because of familiarity. Similarly to Bandookwala, Dertouzos and Garber (2006) studies how radio airplay of music relates to the sales of albums and digital tracks by analysing the 99 largest broadcasting markets in the United States. Likewise, he finds a positive and statistically significant relationship. Studies that relate exposure through music discovery mediums and success in the form of streams, unlike those relating music discovery mediums and sales, are scarce. The only available paper to our knowledge is Aguiar and Waldfogel (2018), which, similarly to our paper, addresses the relation between the number of Spotify streams and product discovery through Spotify playlists.

Aguiar and Waldfogel (2018) analyse the effect of Spotify playlists on music discovery and the promotion of music through four distinct approaches. In one of those approaches, Aguiar and Waldfogel examine how inclusion in the New Music Friday playlist affects a song's probability of success in terms of streams by exploiting the heterogeneity across country-specific New Music Friday playlists. They additionally allow heterogeneity across rankings in the New Music Friday playlist. Beyond this base method, they further use an instrumental variable approach to correct possible endogeneity. Overall, they find that streams sharply increase for songs included in the New Music Friday playlist because of this inclusion. For example, they conclude that a track ranked 5 in the New Music Friday playlist gets, on average, an additional 2.1 million streams for this ranking alone.

Given that Aguiar and Waldfogel (2018) analyse the relationship between different playlists and how this relationship affects music success in terms of streaming, their analysis is similar to ours on the impact of inclusion in the Global Viral playlist on a song's probability of being on the Top Global chart within 30 days. Note, however, that they investigate the Good Friday playlist, which music critics curate and for which an extended list like the Viral Global chart for the Viral 50 playlist is not available. Accordingly, Aguiar and Waldfogel (2018) could not exploit the built-in discontinuity of the Global Viral chart (i.e. only the top 50 songs making it into the Viral Global 50 playlist) as we could. Instead, they resorted to individual fixed effects and a possibly endogenous instrumental variable for the estimation. Conversely, we could exploit the discontinuity and, thus, apply the well-established RDD approach.

In another approach, Aguiar and Waldfogel (2018) exploit the Spotify Daily Top Global Chart discontinuity (i.e. only the top 50 songs making into the Top Global 50 playlists). Using this discontinuity as a running variable, they apply an RDD approach, analysing whether a dropoff in streams is higher for the previous day's 51st song than for songs at nearby ranks. Using the average global streams for a track at the 50th rank in the Top Global 50 playlists, the value of the average treatment effect, and the average duration of a song in the Top Global 50 playlist, they then estimate that, on average, 3.3% of streams strictly follow from the inclusion in the playlist.

As Aguiar and Waldfogel (2018) do, we exploit the built-in discontinuity in the Top Global chart to apply an RDD approach in one of our analyses. Unlike them, however, we don't strictly focus on the Top Global playlist and chart. Instead, we relate the Top Global Chart to the Top Viral chart, analysing the impact of inclusion on the Top Global playlist on the probability of a song appearing in the Viral chart after some time. Again, we believe one of the explanations for the positive effect Aguiar and Waldfogel find is music discovery through the Top Global playlists increasing music sharing and, thus, total streams. If that is the case, we should observe songs performing better in the Viral 50 chart after debuting on the Top Global chart. Our analysis tests for that, and thus, one can view our work as a continuation of Aguiar and Waldfogel's work.

Studying the connection between the "virality" of a song and a song's success in terms of music streams is relevant since social media has become a central music sharing and discovery medium. TikTok, for example, is currently one of the largest social media platforms and is best known for music and dance-oriented videos (Bhandari and Bimo, 2020). According to TikTok themselves, 75% of American users use the platform to discover new music. Considering that TikTok has one billion active users and that sharing is one of the components behind the Viral 50 Global playlist algorithm, "virality" is most likely a foremost factor in determining the success of a song in terms of Spotify streams. Nevertheless, while research on new media and music sales in the music industry context has been explored by, for instance, Dewan and Ramaprasad (2014), there is currently no research linking new media services like Tiktok and the number of streams in audio streaming services.

Finally, another consideration for our analyses appears to be whether or not a song is a collaboration between different artists. McKenzie et al. (2021) analyse the relationship between music features and demand, finding that tracks featuring other artists outperform those without features in terms of streams. While they do not entirely reject the possibility that music collaborations may increase the quality of a song, they do believe that the promotion across different fanbases is most likely the primary reason for this increase in demand. Likewise, Deshmane and Martinez-de Albeniz (2020) study the effect of collaborative projects on career trajectories. Through a difference-in-difference analysis, they compare artists that released a song with a music feature to similar artists that released a track in the same week without features. Similar to McKenzie et al.'s findings, they conclude that artists that released a collaboration track increased their future streams by 6.6%, which follows from an increase of 27.5% in streams for the featured release and 5.1% for future releases.

3 Data

We conduct our research on two datasets we construct from the daily Top Songs and the daily Viral Songs charts, available in the Spotify Charts database[4]. Respectively, the Daily Top Songs Global and Daily Viral Songs Global contain a ranking of the previous day's 200 most streamed and 100 most viral songs. Again, the top 50 songs of each chart appear, ranked, on their corresponding playlists. Our sample

[4]See https://charts.spotify.com/charts/overview/global

period is from January 1st, 2017, through March 3rd, 2022. Both datasets include global data instead of country-specific data.

Because of the large amount of available data, we opted for a simple cross-sectional analysis. Thus, we modified the Spotify data, only including each track once and setting this track's corresponding rank to the rank of when it first appeared in its respective chart. Our revised datasets for each chart then contained, for each song, its title, its unique identifier, its rank, and the date of the first appearance on its corresponding chart.

Using the variables mentioned above and for both charts, we further constructed multiple binary variables. Firstly, we created a binary variable equal to 1 in case the track appeared on the other chart within 30 days of first entering the chart. In other words, if, within 30 days of showing up on the Top chart, the song entered the Viral chart, the variable value for that track would be 1. We use a 30-day ahead window since the effects of playlist inclusion most likely are not instantaneous. Besides, we also created a binary variable which, for each chart, is 1 when the song appeared on the other chart before (or on the same day) entering said chart. Alternatively, for a Top chart song, the variable would be equal to 1 if it appeared on the Viral chart before entering the Top chart. Finally, we also included a binary variable equal to 1 if the song is a collaboration between artists. Note that Spotify considers a band or group of musicians as a single artist.

Beyond the binary variables above, we also constructed a discrete variable that identifies the best rank on the other chart within 30 days of a track entering a given chart. In other words, if within 30 days of a song entering the Top chart, it appears on the Viral chart, then the variable value would be the minimum rank of the track on the Viral chart throughout the 30 days. An extensive explanation of how we construct all the variables we use in our analysis, including song-specific examples, is available in Appendix A.

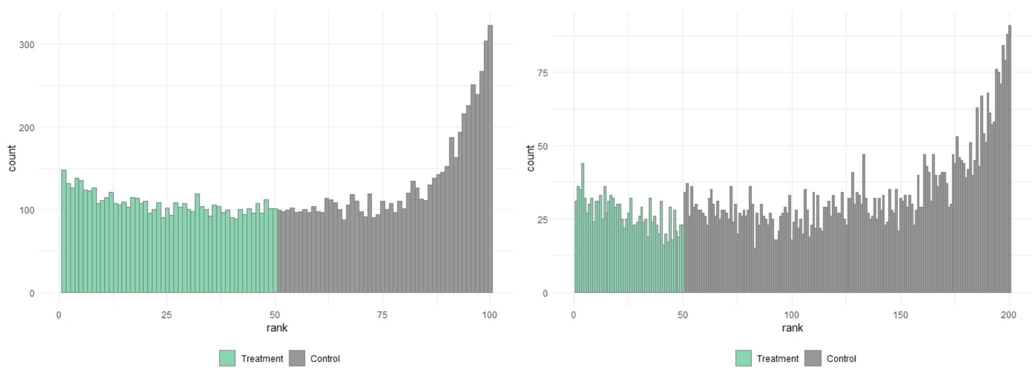
Our modified Viral chart and Top chart databases have 12,133 and 6,536 unique songs (observations). In Table 1, we display various summary statistics for both those databases. Moreover, in Figure 1, we display histograms of the frequencies of each rank for first-time appearances of songs in the Viral and Top charts, respectively.

In the considered period, only 3.4% of new Viral chart songs that had never been in the Top chart before appeared in the Top chart within 30 days of debuting on the Viral chart. This suggests that the effect of inclusion in the Viral 50 playlist on later inclusion in the Top chart cannot be high in magnitude. The reverse figure is much higher - 46% of new Top 50 songs that had never been in the Viral before appeared in the Viral chart within 30 days, whereas the percentage is 30.5 for Top 51-200 songs. Mostly, this follows from the Viral chart containing many songs by relatively unknown artists. Meanwhile, songs in the Top chart are mostly well-known songs by established artists, which tend to get much exposure.

Interestingly, it also appears that songs that jump from one chart to another tend to do better in the second chart than the average second chart debutant. For example, the average Top debut rank is 113.8, and 79.9 for songs that entered the Viral in the previous 30 days. Likewise, whereas the average Viral chart rank of a track first debuting in the Viral is 55.4, the average Viral chart rank of a song first entering the Viral within 30 days of debuting in the Top is 35.6.

Table 1: Summary statistics

Daily Viral Songs Global	
Inside the Viral 50 Playlist	*Value*
% of Viral 50 songs that were in the Top chart before first entering the Viral 50	26.3
% of Viral 50 songs that were in the Top chart within 30 days of first entering the Viral 50	23.8
% of Viral 50 songs that were not in the Top chart before first entering the Viral chart but that were in the Top chart within 30 days of entering the Viral chart	3.4
Outside the Viral 50 Playlist	*Value*
% of Viral 51-100 songs that were in the Top chart within 30 days of first entering the Viral 51-100	12.2
% of Viral 51-100 songs that were in the Top chart before first entering the Viral 51-100	14.5
% of Viral 51-100 songs that were not in the Top chart before entering the Viral 51-100 but that were in the Top chart within 30 days of entering the Viral 51-100	3.4
Viral Global Chart	*Value*
Average viral rank of a song upon first entering the Viral chart	55.4
Average best attained Top chart rank of a Viral chart song, conditional on the song having entered the Top chart within 30 days of entering the Viral chart	79.9
Daily Top Songs Global	
Inside the Top 50 Playlist	*Value*
% of Top 50 songs that were in the Viral chart before first entering the Top 50	2.4
% of Top 50 songs that were in the Viral chart within 30 days of first entering the Top 50	48.0
% of Top 50 songs that were not in the Viral chart before first entering the Top chart but that were in the Viral chart within 30 days of first entering the Top chart	46.0
Outside the Top 50 Playlist	*Value*
% of Top 51-200 songs that were in the Viral chart within 30 days of first entering the Top 51-200	42.5
% of Top 51-200 songs that were in the Viral chart before first entering the Top 51-200	14.6
% of Top 51-200 songs that were not in the Viral chart before entering the Top chart but that were in the Viral chart within 30 days of first entering the Top chart	30.5
Global Top chart	*Value*
Average top rank of a song upon first entering the Top chart	113.8
Average best attained Viral chart rank of a Top chart song, conditional on having entered the Viral chart within 30 days of entering the Top chart	35.6



(a) Viral chart (b) Top chart

Figure 1: Histogram for the debuting rank of songs in the charts

4 Methodology

4.1 Parametric models

To assess how exposure through the Viral 50 playlist affects the general popularity of songs, we compare the probability of a track appearing in the Top chart upon entering the Viral 50 playlist to that of songs that do not make it into the Viral 50 playlist. Since the top 50 songs in the Viral chart appear in the Viral 50 playlist, and there are 100 songs ranked in the Viral chart, we may interpret the 50th rank as a cutoff point. Moreover, artists do not know a priori what is necessary to make it into the Viral 50 playlist, given that it depends on the performance of other songs. Besides, Spotify's algorithm for constructing the Viral chart is unknown, making it even harder for artists to manipulate their ranking. Refer to Section 4.5 and 5.1 for details. We may then use the discontinuous change in the treatment to analyse the effect of including a song in the Viral 50 playlist on the probability of inclusion in the Top chart, with songs barely not included in the Viral 50 playlist, as counterfactuals for songs that narrowly meet the cutoff.

In this framework, we have a running variable (the rank of the song in the Viral chart), a cut off (the 50th rank), and a treatment rule that assigns tracks to the treatment group based on a hard-thresholding rule (songs with a rank $\leq$ 50 belonging to the treatment group). Therefore, our experiment meets the fundamental requirements for a Sharp regression discontinuity design.

We allocate observations with running variable scores above the cutoff as belonging to the treatment group, and so we take the negative rank as the running variable:

$$D_i = \begin{cases} 0 & \text{if } x_i < c \\ 1 & \text{if } x_i \geq c, \end{cases} \tag{1}$$

where c = -50, x_i is the negative of the rank (rank as defined in Section 3) of song i in the Viral chart. Observations with a rank $\geq$ -50, then, receive the treatment. Working with the negative rank does not change the treatment effect. Besides, for simplicity, we display the positive rank in figures.

At first, we consider a first-order parametric approach to estimation using RDD as, conventionally, this is the basic approach:

$$y_i = \alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c) + \epsilon_i. \tag{2}$$

In Equation 2, y_i is a binary variable that equals 1 when track i appeared on the Top chart within 30 days of debuting on the Viral chart. Moreover, β_1, β_2 and τ are parameters, with τ being the average treatment effect of exposure (through the Viral 50 playlist) on the probability of appearing in the Top chart within 30 days. Finally, ϵ is the error term, which we assume follows an i.i.d Normal distribution.

For the model in Equation 2, we may interpret the fitted values as the probability of a song, of a given rank, being in the Top chart within 30 days of entering the Viral chart. Again, our goal is to analyse the effect of exposure in the Viral 50 playlist on a song's general popularity. However, in this setup, a track may be present in the Top chart before ever debuting in the Viral chart. Thus, we introduce in the model a covariate for songs that appeared in the Top chart before or on the same day they did in the Viral chart. Likewise, we introduce a covariate for collaborations as, as we explain in Section 2, they pool fans from different fandoms and, accordingly, are likely to be more popular:

$$y_i = \alpha + \tau D_i + \beta_1(x_i - c) + +\beta_2 D_i(x_i - c) + \beta_3 z_{1i} + \beta_4 z_{2i} + \epsilon_i. \tag{3}$$

In the specification in Equation 3, z_{1i} corresponds to a binary variable which equals 1 when song i appeared on the Top chart before entering the Viral chart. Further, z_{2i} is a binary variable equal to 1 if song i is a collaboration between artists. A detailed explanation of those variables is available in Section 3.

Note that we do not include covariates to control for confounding but do it to improve efficiency, as, under RDD assumptions, the regression estimates are already unbiased and consistent. In addition, covariates should be continuous at the cutoff point, as it would otherwise be impossible to attribute the discontinuity in the dependent variable to the running variable (Imbens and Lemieux, 2008). Both covariates we use are continuous around the 50th rank of the Viral chart, and a detailed explanation of how we test for that is available in Sections 4.5 and 5.1.

In addition to the linear model, we further evaluate quadratic models with and without covariates to control for second-order polynomials:

$$y_i = \alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c) + \beta_3(x_i - c)^2 + \beta_4 D_i(x_i - c)^2 + \epsilon_i \text{ and} \tag{4}$$

$$y_i = \alpha + \tau D_i + \beta_1(x_i - c) + \tau D_i + \beta_2 D_i(x_i - c) + \beta_3(x_i - c)^2 + \beta_4 D_i(x_i - c)^2 + \beta_5 z_{1i} + \beta_6 z_{2i} + \epsilon_i. \tag{5}$$

We do not consider higher-order polynomials as Gelman and Imbens (2019) find that controlling for global high-order polynomials in RD analysis leads to noisy estimates, sensitivity to the polynomial degree and poor coverage of confidence intervals.

Given that the errors in linear probability models are heteroskedastic, we use White standard errors for all models. When using linear probability models, fitted values may still be larger than 1 and smaller than 0, which is impossible to correct. Accordingly, we further use Maximum Likelihood to estimate a linear probit model with and without covariates, where Φ represents the cumulative density function of a Normal distribution:

$$P[y_i = 1] = \Phi(\alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c)) \text{ and} \tag{6}$$

$$P[y_i = 1] = \Phi(\alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c) + \beta_3 z_{1i} + \beta_4 z_{2i}). \tag{7}$$

Mirroring our analysis for linear models, we also estimate quadratic probit models with and without covariates:

$$P[y_i = 1] = \Phi(\alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c) + \beta_3(x_i - c)^2 + \beta_4 D_i(x_i - c)^2) \text{ and} \tag{8}$$

$$P[y_i = 1] = \Phi(\alpha + \tau D_i + \beta_1(x_i - c) + \beta_2 D_i(x_i - c) + \beta_3(x_i - c)^2 + \beta_4 D_i(x_i - c)^2 + \beta_5 z_{1i} + \beta_6 z_{2i}). \tag{9}$$

4.2 Non-Parametric models

4.2.1 Local linear regression

Parametric regression discontinuity designs are often sensitive to model specification. Hence, we also use a local linear regression approach. While more robust, one should not see this method as a 'superior model' but as a complement to the previous models. Although a kernel regression approach with local constant fits would also be possible, such an approach has boundary bias issues which are undesirable in an RD setting (Tibshirani and Wasserman, 2013). Therefore, one should usually use local linear regression designs instead for RD studies (Hahn et al., 2001).

In a data-driven local linear regression discontinuity design, we estimate a local linear regression on each side of the cutoff. We use the Imbens-Kalyanaraman bandwidth algorithm to select the bandwidth for estimating the local linear regressions in a first step. We opt for this algorithm because it is asymptotically optimal under squared error loss (Imbens and Kalyanaraman, 2012). In addition, we compute weights using a triangular kernel, which is known to be optimal in this setting (Lee and Lemieux, 2010). Using these weights and the Imbens-Kalyanaraman bandwidth, we estimate a two-sided local linear regression model around the cutoff so that the discontinuity that arises is the estimated average treatment effect.

Concretely, this involves estimating the following local linear regression equation:

$$y_i = \alpha + \tau D_i + \beta_l(x_i - c) + (\beta_r - \beta_l)(x_i - c)D_i + \epsilon_i, \tag{10}$$

where the ranks x_i are chosen only in the Imbens-Kalyanaraman bandwidth h around the threshold c, i.e. $x_i \in [c - h, c + h]$. As we use a triangular rather than rectangular kernel for the estimation, this regression is estimated as follows:

$$(\hat{\alpha}, \hat{\tau}, \hat{\beta}_l, \hat{\beta}_r) = \underset{(\alpha,\tau,\beta_l,\beta_r)}{\operatorname{argmin}} \sum_{n=1}^{N} (y_i - \alpha - \tau D_i - \beta_l (x_i - c) - (\beta_r - \beta_l)(x_i - c)D_i)^2 K(|x_i - c|/h), \tag{11}$$

where, in our case, $K(\cdot)$ denotes the triangular kernel function.

While local polynomials of an order higher than one are also possible, introducing higher orders would involve more noise in our estimates, especially given that the dataset contains few mass points near the threshold. Since in a sufficiently small bandwidth around the cutoff point, a weighted linear fit is usually a good approximation, we do not consider local polynomials of a higher order; for a more detailed discussion on (the choice of) local polynomials, see, for example, Cattaneo et al. (2019).

4.2.2 Local randomisation design

One of the underlying assumptions of the local linear regression approach is that the running variable is continuous, i.e. takes values in an infinite set. In this approach, each mass point is equivalent to a single observation. Hence, using local linear regressions in settings with few mass points brings complications similar to using small datasets. In our setting, we use the rank of a song in the Viral chart as the running variable, which only takes 100 distinct values, with relatively few mass points near the cutoff. Accordingly, employing a local linear regression approach may, in our setting, result in poor performance.

A more suitable alternative to the local linear regression approach is the local randomisation technique (Cattaneo et al., 2019). This approach makes explicit the foundation underlying all regression discontinuity analyses: that assignment of the running variable in a narrow window around the cutoff is random. For this to make sense, two central assumptions must hold for our case, namely:

A1: The distribution of a song's rank within a window around the cutoff point of 50 may not depend on the potential outcome and must be the same for all songs within that window.

A2: Within a window around the cutoff, the potential outcome depends exclusively on whether a song belongs to the viral playlist and not directly on the rank of said song.

For a small enough window, the first assumption is reasonable in our context. For example, songs around the 50th rank in the top chart are separated by only a few thousand daily streams out of the 1,000,000+ that they receive. We may, then, interpret variations in rank around this threshold as 'almost random'. Likewise, the second assumption is also plausible for a small enough window. While the potential outcome may directly depend on the rank of the song for ranks lower than 50, the effect is likely limited when only songs close to the 50th rank are under consideration. It is, for instance, unlikely that a track listed at rank #49 on a playlist will perform significantly worse than a song at rank #48, simply by the difference in rank alone.

We expect songs with very low ranks to differ significantly from those with very high ones. Hence, it is implausible that a song's rank is 'essentially randomly assigned' over the whole range of the running variable. To select the window size, we use a data-driven procedure that utilizes a binary variable equal to 1 when the song is a collaboration as a predetermined covariate. This procedure uses the covariate to determine a window size in which the collaboration status is uncorrelated with the rank of a song. Uncorrelation within a small window paired with correlation within a larger window suggests that song ranks within the small windows are randomly assigned. Since the procedure relies on the chosen covariate correlating with the running variable, we must still justify why the collaboration status correlates with the rank of a song. In this case, we expect tracks published in collaboration to correlate positively with the debuting rank in the Viral chart as collaborations pool fans from different fanbases. This pooling should translate into higher popularity.

We calculate the resulting estimated average treatment effect with a difference in means approach. A detailed technical outline of the calculation of the window size and the derivation of p-values for this method is available in Cattaneo et al. (2019).

4.3 The effect of playlist inclusion on attained rank

The methods outlined above all utilize a binary dependent variable. Although a straightforward approach, it severely limits the variation in our data, resulting in high standard errors. An alternative way to model our data, and the possible regression discontinuity design, is by not merely looking at whether a song made it into the Top chart but by considering a song's specific rank within the Top chart. This results in much higher variation in the dependent variable – for example, there are two hundred ranks in the Top chart. A complication with this approach is that Spotify only discloses the 200 most streamed songs on the Top chart. In other words, our observations are right-censored.

To deal with this right-censoring while still using the available and precise ranking data, we employ a censored regression discontinuity design, as in, for example, Black et al. (2007). In this approach, we assign to a song its specific best rank in the Top chart (as defined in the Section 3 as the debuting rank) when available, and the upper limit in the Top chart plus 1 when undisclosed. Since the dependent variable is the best rank within 30 days in the Top chart, the upper limit plus 1 is 201. As the process that determines whether or not a song makes it into a chart is the same process that determines the rank of a track on said chart, conditional on having made it on there, we resort to a Tobit type-I model. Our model, therefore, looks as follows:

$$Y_i = \begin{cases} y_i^*, & \text{if } y_i^* < y_U \\ y_U, & \text{if } y_i^* \geq y_U. \end{cases} \tag{12}$$

In our case, Y_i represents the observed best rank on the Top chart within 30 days of debuting in the Viral chart. y_i^* denotes the latent best rank in the Top chart within 30 days of debuting in the Viral chart, and y_U is 201. We model our latent variable y_i^* in the same way as in Section 5.2. For the linear model, we thus have,

$$y_i^* = \alpha + \tau D_i + \beta_1(x_i - c) + \beta_2(x_i - c)D_i + \epsilon_i \tag{13}$$

and for the quadratic model we have,

$$y_i^* = \alpha + \tau D_i + \beta_1(x_i - c) + \beta_2(x_i - c)D_i + \beta_3(x_i - c)^2 + \beta_4 D_i(x_i - c)^2 + \epsilon_i. \tag{14}$$

Here x_i denotes the (negative) rank of the song in the Viral chart. c again denotes the threshold and D_i, as usual, denotes the treatment - that is, $D_i = (x_i \geq -50)$. Our effect of interest, therefore, is τ. In this case, this represents the effect of the discontinuity at rank 50 on the *latent* best rank variable, which represents the effect of belonging to the Viral 50 playlist on a track's best rank in the Top chart.

For a detailed discussion on the workings of the Type-I Tobit regression model, we refer the reader to, for instance, McDonald and Moffitt (1980) or Amemiya (1984).

4.4 The effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

Beyond the previously described scenario, we further study how belonging to the Top playlist may contribute to a song becoming even more popular. To achieve that, we compare the probability of a track appearing in the Viral chart upon entering the Top 50 playlist to that of songs that do not make it into the Top 50 playlist. As is the case for the Viral chart, only the top 50 songs in the Top chart make it into the Top 50 playlist, and we may again interpret the rank as the running variable with the 50th rank as the cutoff point. The treatment rule is also the same as before, with songs with a rank $\geq$ -50 belonging to the treatment group.

We use the same methodology described in sections 4.1, 4.2 and 4.3 since the running variable, cutoff and treatment rule are the same. Note, however, that the running variable is now the rank in the Top chart. Besides, the dependent variable is now a binary indicator for whether a song appeared in the Viral chart within 30 days of debuting in the Top chart. At last, we include a covariate for songs present in the Top chart before debuting on the Viral chart instead of the other way around. An explanation of the validity of the rank in the Top chart as a running variable is available in the sections 4.5 and 5.1. Briefly, when looking at the histogram, it appears there appears to be sorting, but the Frandsen (2017) test suggests no sorting.

For the effect of chart inclusion on attained rank, the upper limit plus one also changes from 201 to 101. In addition, the dependent variable is the latent best rank in the Viral chart within 30 days of debuting in the Top chart. Finally, the running variable is the debuting rank (as defined in Section 3) of a song on the Top chart.

4.5 Design validity

In order to test whether our regression discontinuity design meets the necessary assumptions, we perform a range of tests and checks. The first assumption we assess is that of no sorting around the threshold. If artists could intentionally sort around the cutoff, that could cause selection bias and invalidate our results. In order to examine possible sorting in our data, we utilize both the sorting test proposed in McCrary (2008) as well as the sorting test proposed in Frandsen (2017). These tests both assess whether the distribution of ranks around the cutoff point is smooth, but the former test has several issues with discrete running variables such as ours, and so the latter test is more reliable for our design. The null hypothesis of both tests is the absence of sorting around the threshold.

In addition, we assess whether our covariates are balanced at the cutoff. This serves the same purpose as the sorting tests performed above - if there is a notable and significant discontinuity in the covariates around the cutoff, that provides some evidence that there is selection bias in our data. Concretely, for each chart, we perform linear, linear probit, quadratic, and quadratic probit RDDs on both of our covariates with the rank in the considered chart as the running variable. If all specifications find a signifiant discontinuity at the cutoff of 50, that provides strong evidence of intentional sorting or other forms of selection bias.

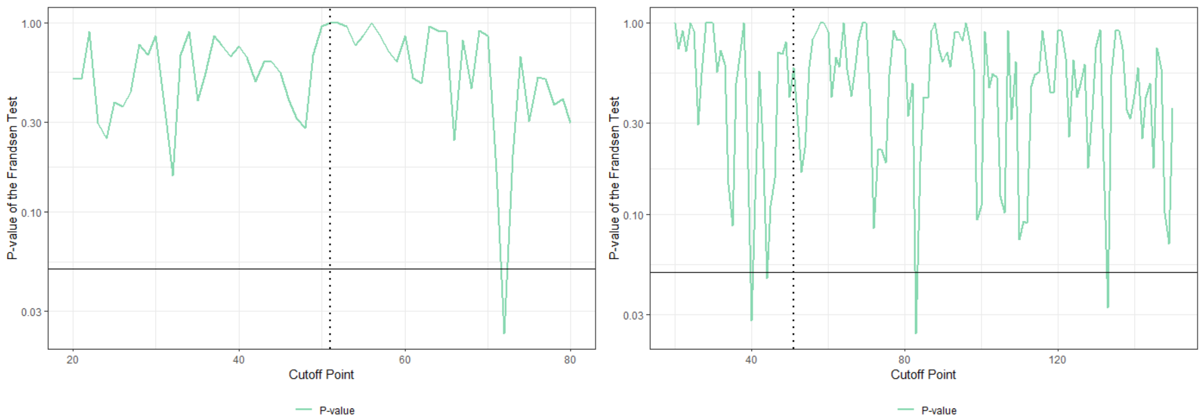
5 Results

5.1 Design validity

As a first visual assessment of possible sorting in our data, we consider the two histograms displaying the frequency of each rank for both charts in Figure 1. For the Viral dataset, the distribution of ranks looks near identical before and after the cut-off point, suggesting that there are no sorting concerns there. On the other hand, there are signs of sorting in the Top dataset, but they display a form of sorting opposite to what would be expected in the presence of intentional manipulation: around the cutoff, there are fewer songs inside the playlist than outside of it.

To formally test for sorting, we perform a McCrary test in both distributions, where we find a p value of 1.161×10^{-3} for the Viral data and 6.720×10^{-8} for the Top data. Thus, the McCrary test rejects the null hypothesis of no sorting around the threshold for both datasets. However, as the McCrary test assumes the running variable to be continuous, there are concerns about the validity of this test. Figure 15 in Appendix C.1 plots the McCrary test results for many different cutoff points, which suggests that while the Top data has potential sorting issues, the Viral data does not.

We repeat the same process using the test proposed by Frandsen (2017) for sorting in a discrete running variable. Using this test, we find quite different results: For the Viral data the Frandsen p value is 1.000 and for the Top data it is 0.584, indicating that there is no significant evidence of sorting in either dataset. Similarly to the McCrary test, we perform a range of placebo tests for the Frandsen test. The p values of those tests are available in Figure 2. The plot lends some support to the nonexistence of sorting around the threshold.



(a) Viral data

(b) Top data

Figure 2: Frandsen test p values for a range of placebo cutoff points; values beneath the horizontal line are significant at the 5% level

Taking the aforementioned checks and tests into account, there clearly does not appear to be sorting in the Viral dataset. Evidence for the Top dataset is more ambiguous, with both the histogram and McCrary test providing evidence for the existence of sorting, whereas the Frandsen test disputes this. In any case, as the supposed sorting is the other way around from what would be expected with intentional sorting, we do not believe possible sorting detected at this point poses a danger to the validity of our design. Rather, it is more likely that such a discontinuity at the threshold is caused by the boost that songs in the Top 50 playlist get to their stream counts. As a result of this, it is more difficult for a new song to enter the Top 50 than it is to enter the Top 51-200, which can explain a larger number of songs debuting in the 51-60 than the 41-50 range.

As discussed in the methodology, we also assess whether there are discontinuities in our used covariates at the threshold for both charts. These covariates are (i) a binary variable for whether or not a song was released in collaboration, and (ii) a binary variable for whether or not the song had appeared on the other chart before debuting on the considered chart. The results of our covariate RDDs for the Viral data can be found in Table 10 and the results of our covariate RDDs for the Top data can be found in Table 11, both in Appendix C.2. Again, we find no issues in the Viral data. Our results for the Top data are ambiguous - the quadratic probit and linear models reject the nonexistence of a discontinuity at the threshold for the 'Appeared Before' covariate, whereas the linear probit and quadratic models do not. Although this is cause for some concern, the discontinuity is not robust to model specification, and so does not provide strong evidence for the existence of a bias at the cutoff.

5.2 The effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart

Table 2 displays the regression results of the linear and quadratic discontinuity models with the rank of the song in the Viral chart as the running variable and the regressand being whether the song appears in the Top chart within 30 days. For the linear, quadratic, linear probit, and quadratic probit models, (1) denotes the model without any covariates and (2) denotes the model with the two covariates. Both first and second order linear regressions are plotted in Figure 3[5], albeit without covariates. The same holds for the probit regressions plotted in Figure 4.

Notably, the linear first-order regression suggests a negative treatment effect for both the model with

[5]'Top200' and 'Viral100' in the axes titles refer to the Global Top and Global Viral charts, respectively. We use the same notation in the rest of the figures

covariates and the one without them. However, this likely follows from poor extrapolation of the linear fit. Indeed, the treatment effect shrinks almost to zero in the quadratic linear model, especially when considering the model with covariates.

While the quadratic regression suggests no effect whatsoever of the quadratic term, in practice, this term has a relatively large influence on the fit of the regression line. The squared rank value becomes high in the right tail, with its values reaching 10,000. This is evident in Figure 3(b), as we can see a large curvature left of the threshold.

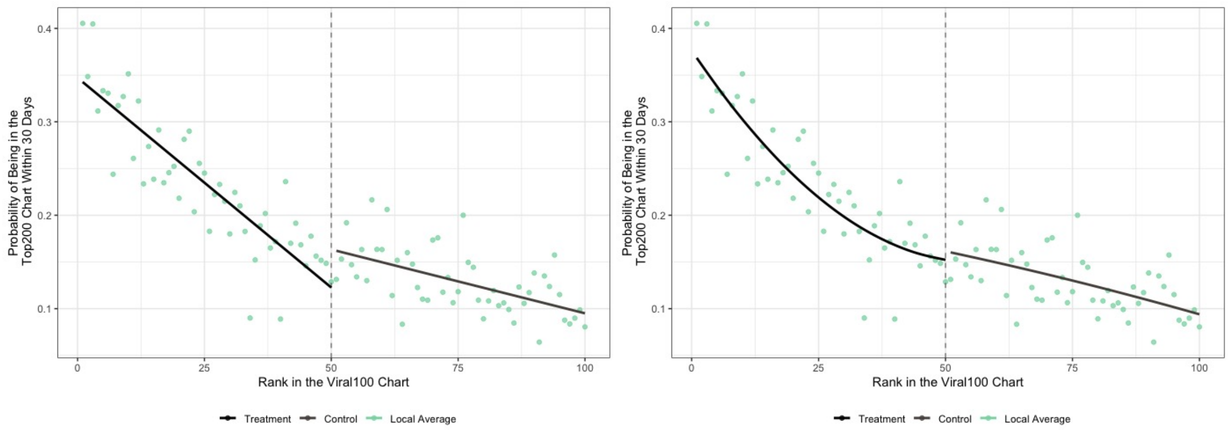
The probit models yield results very similar to those of the linear models. Although the coefficients differ due to the functional form of probit models, the inferred treatment effects in the probit models are roughly equal to the estimated treatment effects in the linear model.

Table 2: Discontinuity regressions results for the effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart

	Linear		Quadratic		Linear Probit		Quadratic Probit	
Variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$I_{ViralRank \leq 50}$	-0.041***	-0.025**	-0.009	0.001	-0.141**	-0.134*	-0.046	-0.001
	(0.014)	(0.010)	(0.021)	(0.015)	(0.059)	(0.075)	(0.089)	(0.114)
$Rank$	-0.001***	0.000	-0.001	0.000	-0.007***	-0.001	-0.004	0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)	(0.008)
$I_{ViralRank \leq 50} \times Rank$	-0.003***	-0.002***	0.000	0.000	-0.008***	-0.012***	-0.002	-0.002
	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)	(0.008)	(0.010)
$Rank^2$	—	—	0.000	0.000	—	—	0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
$I_{ViralRank \leq 50} \times Rank^2$	—	—	0.000	0.000	—	—	0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
collaboration	—	0.022***	—	0.022***	—	0.142***	—	0.144***
		(0.005)		(0.005)		(0.035)		(0.035)
$appeared\_before$	—	0.653***	—	0.653***	—	2.234***	—	2.235***
		(0.010)		(0.010)		(0.036)		(0.036)
constant	0.163***	0.025***	0.161***	0.021**	-0.970***	-1.867***	-0.991***	-1.888***
	(0.010)	(0.007)	(0.015)	(0.011)	(0.042)	(0.058)	(0.065)	(0.087)

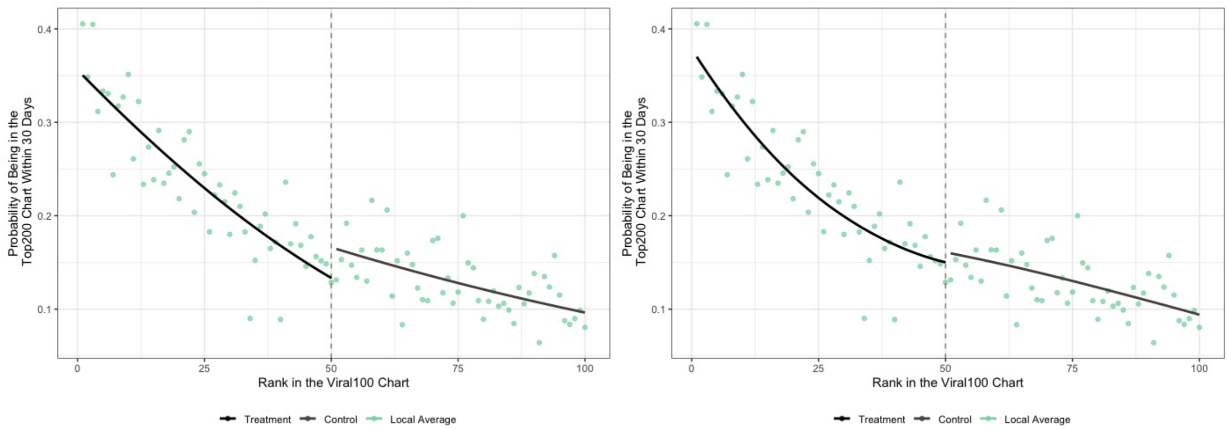
Note. White standard errors are denoted in parentheses. *** denotes a p value below 0.01, ** denotes a p value below 0.05, * denotes a p value below 0.10.

Note. (1) excl. covariates (2) incl. covariates



(a) Linear model (b) Quadratic model

Figure 3: Polynomial discontinuity regressions plots for the effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart



(a) Linear Probit model (b) Quadratic Probit model

Figure 4: Probit discontinuity regressions plots for the effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart

We display the results of the local linear regression in Table 3. The associated IK bandwidth is 2.655 - as our running variable is discrete, this bandwidth implies that we only consider songs with ranks between, and including, 48 and 53. The table suggests that the estimated discontinuity is close to zero for the model with and without covariates.

Table 3: Results for the local linear regression of being included in the Viral 50 playlist on the probability of being in the Top chart

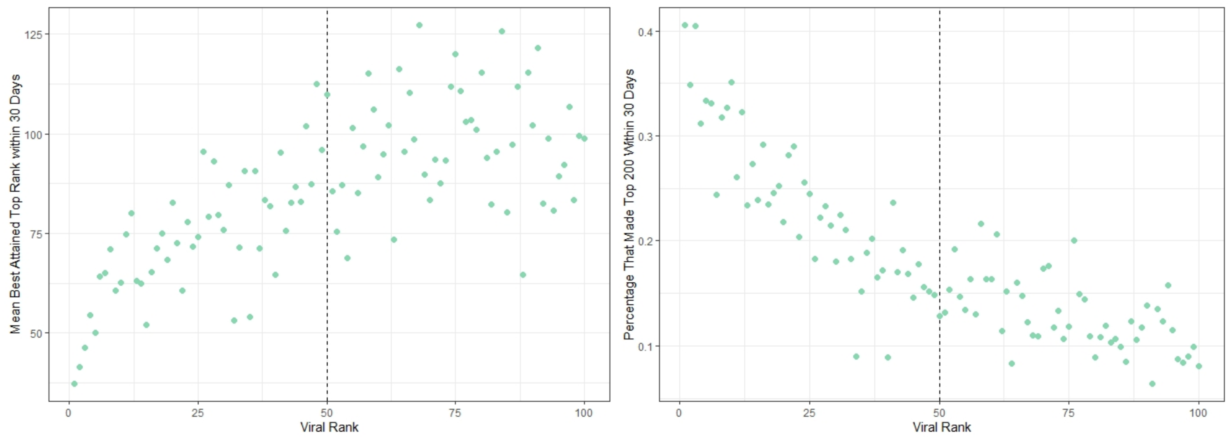
	Local linear regression	
Variables	(1)	(2)
$I_{ViralRank \leq 50}$	0.004	0.061
	(0.053)	(0.039)
$ViralRank$	0.025	0.049
	(0.035)	(0.025)
$I_{ViralRank \leq 50} \times ViralRank$	-0.041	-0.061*
	(0.033)	(0.025)
$collaboration$	—	-0.002
		(0.021)
$appeared\_before$	—	0.621**
		(0.027)
$Constant$	0.121	0.033
	(0.037)	(0.028)
$IKBandwidth$	2.655	2.655

Note. White standard errors are denoted in parentheses. ** denotes a p value below 0.01, * denotes a p value below 0.05
Note. (1) excl. covariates (2) incl. covariates

The local randomization approach yields a similar result to the local linear regression. Based on the covariate-test for window selection, we select a window of [41;60] so that we only use songs with a rank within that interval for the estimation. Accordingly, this window size implies a sample of 997 observations to the left of the cutoff point and 992 to the right. We find that the probability of a song in the treatment group being on the Top chart within 30 days of entering the Viral chart is 16.6%. Meanwhile, for songs in the control group it is 15.9%. Then, the difference of means between the treatment and control group yields an estimated treatment effect of 0.007. Therefore, the local randomization RD approach also rejects that inclusion in the Viral 50 playlist affects the probability of a song appearing in the Top chart within 30 days of its debut in the Viral playlist.

Finally, we consider the results for the Tobit models. Figure 5 displays, per rank, (a) the mean best rank in the Top chart a song in the Viral chart achieved, conditional on having made the top chart within 30 days, and (b) the percentage of songs that made the top chart within 30 days. Visual inspection of these graphs does not reveal any discontinuity in the data around the cutoff of 50. Nevertheless, the Tobit detects changes in sample means and sample probabilities simultaneously, so we must check the coefficient estimates before drawing any conclusions.

Table 4 displays the results for both the linear and quadratic Tobit models. Only one of the four models presented in the table indicates a significant treatment effect - namely, the linear model without any covariates. In addition, this treatment effect has the opposite sign than should be expected, suggesting that inclusion in the Viral 50 playlist decreases a song's performance on the Top chart. As this effect does not persist when covariates or quadratic terms are included, we conclude that the significant estimate found by the base linear model is spurious in nature. As such, these findings do not provide convincing evidence for the presence of a discontinuity at the threshold. For a visual summary of models (1) and (2), we refer the reader to Figure 16 in Appendix C.3.



(a) Sample means (b) Sample probabilities

Figure 5: (a) Mean best attained Top chart rank within 30 days per Viral chart rank, conditional on having made the Top chart within the same period, (b) Percentage of songs that made the Top chart within 30 days per Viral chart rank

Table 4: Results for the Type-I Tobit regressions for the effect of Viral 50 playlist inclusion on attained rank in the Top chart

	Linear		Quadratic	
Variables	(1)	(2)	(1)	(2)
$I_{ViralRank \leq 50}$	26.271**	12.227	10.104	2.485
	(10.7)	(7.733)	(16.280)	(11.814)
$ViralRank$	1.225***	-0.044	1.110	0.298
	(0.237)	(0.170)	(1.052)	(0.760)
$I_{ViralRank \leq 50} \times Rank$	1.762***	1.677***	0.151	-0.098
	(0.334)	(0.238)	(1.426)	(1.023)
$ViralRank^2$	—	—	0.002	-0.006
			(0.019)	(0.014)
$I_{ViralRank \leq 50} \times ViralRank^2$	—	—	-0.035	-0.021
			(0.026)	(0.019)
$collaboration$	—	-11.552***	—	-11.592**
		(3.554)		(3.551)
$appeared\_before$	—	-254.397***	—	-254.269***
		(3.889)		(3.886)
$Constant$	383.773***	411.450***	384.678**	408.179***
	(7.732)	(6.236)	(12.052)	(9.171)

Note. White Standard errors are denoted in parentheses. *** denotes a p value below 0.01, ** denotes a p value below 0.05, * denotes a p value below 0.10

Note. (1) excl. covariates (2) incl. covariates

5.3 The effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

Table 5 displays the results of the linear and quadratic discontinuity models. In addition, Table 5 also contains the probit estimation results. Both linear regressions are plotted in Figure 6. The probit regressions are plotted in Figure 7.

In this case, the linear model does not reject the null hypothesis of a zero treatment effect, for neither the base case nor when we include covariates. The quadratic model does reject this null hypothesis, suggesting a positive treatment effect of 0.111 in the base regression and 0.121 when including covariates. The associated implication is that being included in the Top 50 playlist increases a song's probability of making the viral 100 within thirty days by roughly 11 or 12%, dependent on the model specification (with or without covariates).

Once again, the probit models yield similar results to their linear counterparts. We can see this in the near-identical predictions produced by the models, as displayed in Figures 6 and 7. The linear probit model yields insignificant results, while the quadratic probit model yields significant results only when incorporating covariates. Although the probit results are not directly interpretable, especially when including covariates, this model suggests a treatment effect of making the Top 50 on the probability of appearance in the Viral chart of roughly 11%, an estimate very close to the result of the linear quadratic model.

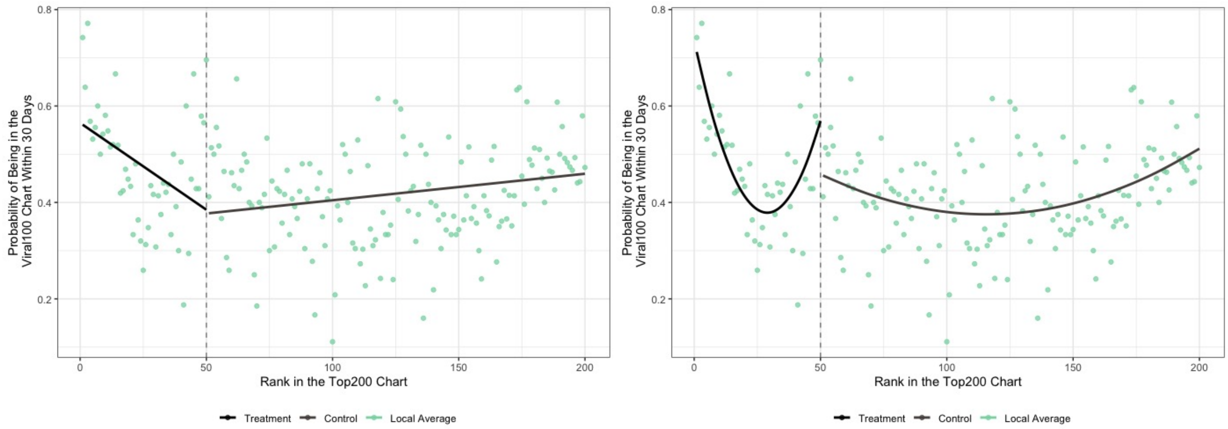
The fact that the significance and even direction of these results depend on the exact specification employed - that is, first- versus second-order models - is concerning. While the quadratic models are more flexible and, as such, more accurate in general than the linear models, it is likely that these models still suffer from misspecification. Therefore, we should not take these results at face value - various robustness checks are presented in Section 5.4.

Table 5: Discontinuity regressions results for the effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

	Linear		Quadratic		Linear Probit		Quadratic Probit	
Variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$I_{TopRank \leq 50}$	0.008	-0.026	0.111***	0.121***	0.022	-0.093	0.283*	0.325***
	(0.032)	(0.031)	(0.047)	(0.046)	(0.083)	(0.075)	(0.120)	(0.120)
$Rank$	0.001***	-0.001***	-0.003***	-0.001	0.001***	-0.002	-0.006***	-0.003
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
$I_{TopRank \leq 50} \times Rank$	-0.004***	-0.004***	0.021***	0.018***	-0.010***	-0.009***	0.053***	0.047***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.010)	(0.010)
$Rank^2$	—	—	0.000	0.000	—	—	0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
$I_{TopRank \leq 50} \times Rank^2$	—	—	0.000	0.000	—	—	0.001***	0.001***
			(0.000)	(0.000)			(0.000)	(0.000)
$collaboration$	—	0.098***	—	0.098***	—	0.266***	—	0.265***
		(0.014)		(0.014)		(0.035)		(0.039)
$appeared\_before$	—	0.484***	—	0.479***	—	1.358***	—	1.347***
		(0.016)		(0.016)		(0.036)		(0.059)
$constant$	0.377***	0.378***	0.459**	0.397***	-0.312***	-0.310***	-0.104*	-0.265***
	(0.015)	(0.015)	(0.022)	(0.022)	(0.057)	(0.057)	(0.057)	(0.059)

Note. White standard errors are denoted in parentheses. *** denotes a p value below 0.01, ** denotes a p value below 0.05, * denotes a p value below 0.10.

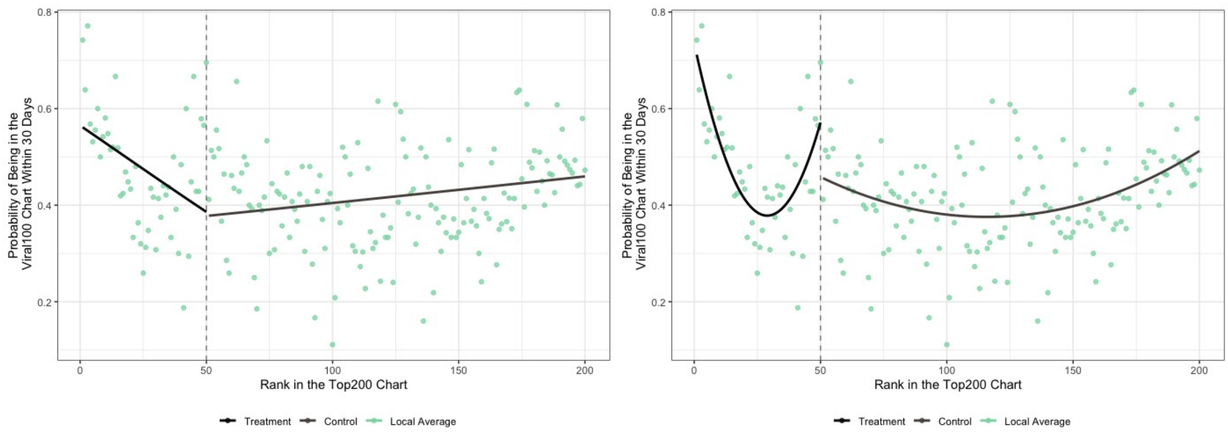
Note. (1) excl. covariates (2) incl. covariates



(a) Linear model

(b) Quadratic model

Figure 6: Polynomial discontinuity regressions plots for the effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart



(a) Linear Probit model

(b) Quadratic Probit model

Figure 7: Probit discontinuity regressions plots for the effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

For the local linear regression, the results are available in Table 6 below. The IK bandwidth for this setting is 3.653, so we only consider songs with a Top chart rank between, and including, 47 and 54. Interestingly, the local linear regression yields a large and highly significant discontinuity estimate, with an estimated value of roughly 0.3. The model, therefore, suggests that inclusion in the Top 50 playlist increases a song's probability of being in the Viral chart within a month by over 30% compared to songs that do not make into the playlist - a very substantial increase.

Table 6: Results for the local linear regression of being included in the Top 50 playlist on the probability of being in the Viral chart

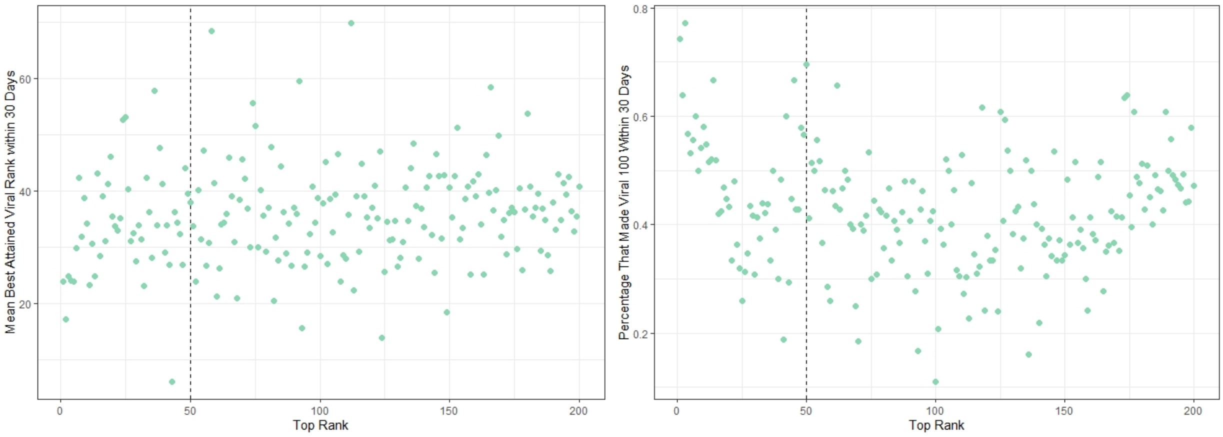
	Local linear regression	
Variables	(1)	(2)
$I_{TopRank \leq 50}$	0.323**	0.305**
	(0.123)	(0.118)
$TopRank$	0.055	0.065
	(0.054)	(0.052)
$I_{TopRank \leq 50} \times ViralRank$	0.022	-0.003
	(0.066)	(0.063)
$collaboration$	—	0.269**
		(0.072)
$appeared\_before$	—	0.422**
		(0.123)
$Constant$	0.721**	0.590**
	(0.100)	(0.095)
$IKBandwidth$	3.653	3.653

Note. White Standard errors are denoted in parentheses. ** denotes a p value below 0.01, * denotes a p value below 0.05

Note. (1) excl. covariates (2) incl. covariates

As discussed in the methodology, however, the validity of the local linear regression in our setting is dubious. Indeed, utilizing the local randomization approach yields much smaller estimates than the local linear regression method. In the local randomization approach, we once again use a window of [41;60] based on the covariate testing procedure. Effectively, this yields a sample of 214 observations for the treatment group and 301 for the control group. The sample probability of being in the Viral chart within 30 days for the treatment side of the sample is 0.495, whereas it is 0.439 for the control side. Thus, the difference-in-means estimate for the treatment effect is equal to 0.057. The associated finite sample p value equals 0.216, meaning that the local randomization approach - in contrast to the local linear regression approach - does not reject the null hypothesis of no treatment effect.

Finally, we analyse the Tobit models. Figure 8 displays (a) the mean best rank in the Viral chart a song in the Top chart achieved, conditional on having made the Viral chart within 30 days, and (b) the percentage of songs that made the Viral chart within 30 days. Again, there does not appear to be an evident discontinuity at the cutoff. Table 7 provides the results for the linear and quadratic Type-I Tobit regression models for this data. As before, the linear model differs quite drastically from the quadratic model, yielding no discontinuity at the threshold. The quadratic model suggests a significant negative discontinuity of around 18.5 ranks. Note that the inclusion of covariates does not substantially change this estimate. This result suggests that inclusion in the Top chart playlist sizably boosts a song's Viral ranking. A plot visualizing the results of this regression can be found in Figure 17 in Appendix C.3.



(a) Sample means

(b) Sample probabilities

Figure 8: (a) Mean best attained Viral chart rank within 30 days per Top chart rank, conditional on having made the Viral chart within the same period, (b) Percentage of songs that made the Viral chart within 30 days per Top chart rank

Table 7: Results of the Type-I Tobit regressions for The effect of Top 50 playlist inclusion on attained rank in the Viral chart

	Linear		Quadratic	
Variables	(1)	(2)	(1)	(2)
$I_{TopRank \leq 50}$	-0.014	8.078	-18.445**	-18.763**
	(5.371)	(4.973)	(7.774)	(7.220)
$TopRank$	-0.082**	0.123**	0.418***	0.201**
	(0.025)	(0.025)	(0.108)	(0.101)
$I_{TopRank \leq 50} \times Rank$	0.745**	0.609**	-3.509**	-2.891**
	(0.157)	(0.146)	(0.625)	(0.580)
$TopRank^2$	—	—	-0.003**	0.000
			(0.001)	(0.001)
$I_{TopRank \leq 50} \times ViralRank^2$	—	—	-0.071**	-0.067**
			(0.012)	(0.011)
$collaboration$	—	-14.721**	—	-14.649*
		(2.254)		(2.247)
$appeared\_before$	—	-75.156**	—	-74.371**
		(2.967)		(2.987)
$Constant$	116.207**	112.260**	102.732**	109.992**
	(2.547)	(2.410)	(3.732)	(3.537)

Note. White standard errors are denoted in parentheses. *** denotes a p value below 0.01, ** denotes a p value below 0.05, * denotes a p value below 0.10.

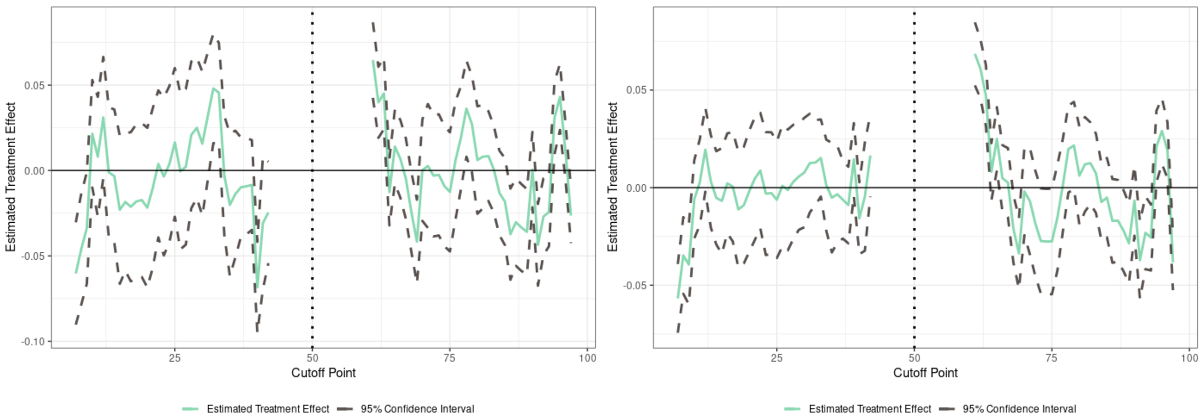
Note. (1) excl. covariates (2) incl. covariates

5.4 Robustness

5.4.1 The effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart

As suggested in Lee and Lemieux (2010), we check the robustness of our linear, quadratic, linear probit, quadratic probit, and linear and quadratic tobit models by assessing the estimated treatment effect when restricting the bandwidth to a range of values around the threshold. Additionally to these checks, we perform a series of placebo tests as proposed by Valentim et al. (2021).

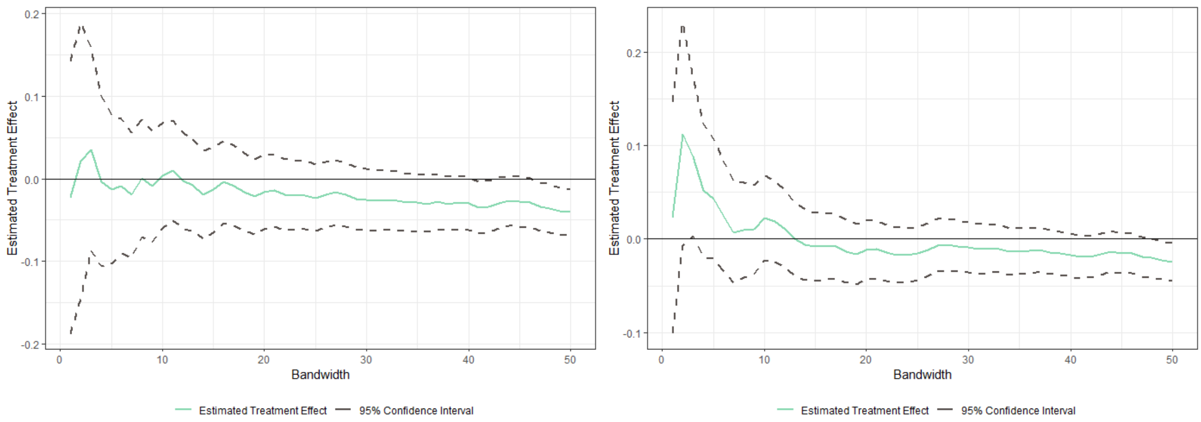
As discussed earlier in this section, we found a statistically significant effect for being on the Viral 50 playlist on a song's probability of being in the Top chart in the linear model. We perform a range of placebo tests for this model, the results of which are shown in Figure 9(a) (for the quadratic model, see Figure 21(a)). There we see that the effect is insignificant for the majority of placebo cutoffs in both models, which lends support to the significant result. However, the bandwidth selection shows a different story. Looking at the graph in Figure 10(a), we see that the effect is not statistically significant up until a bandwidth of around 45, and the magnitude of the estimated effect rises as the bandwidth grows. This indicates that the found effect is driven by songs far away from the cutoff. The estimates of the probit linear model behave similarly; see Figure 19(a) in Appendix D.1, whereas the bandwidth plot for the quadratic model in Figure 18(a) reveals no significant discontinuity at any choice of bandwidth.



(a) Without covariates

(b) With covariates

Figure 9: The treatment effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart in a linear model for a range of placebo cutoff values



(a) Without covariates

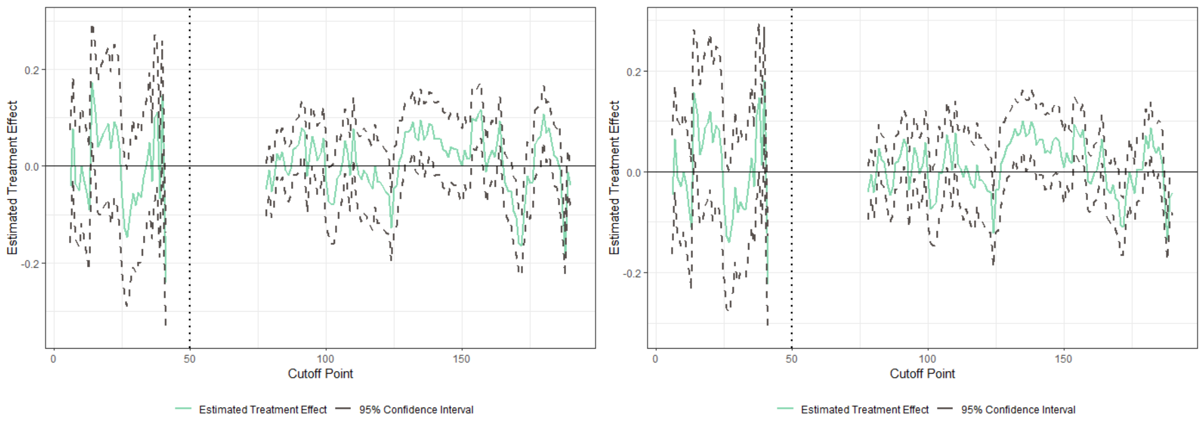
(b) With covariates

Figure 10: The treatment effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart in a linear model for a range of bandwidth window sizes

With the inclusion of two covariates, the previously found effect becomes smaller but still significant. Plotting a graph of placebos in Figure 9(b) shows that this effect does not hold for most other cutoff points (the same holds in the quadratic model in Figure 21(b)). Just like the case without covariates, this lends support to the significance of the treatment effect. However, looking at the bandwidth graph of the linear model in Figure 10(b), we see that significance is only achieved for bandwidths that encompass almost the entire dataset. See Figure 18(b) in Appendix D.1. for the quadratic bandwidth plot, which again presents insignificant estimates for almost all bandwidth choices. Taking into consideration the aforementioned results, as well as the insignificant results produced by the local linear regression and local randomization approaches, we find that the discovered effect of the inclusion in the Viral playlist on the probability of being in the Top chart is not robust.

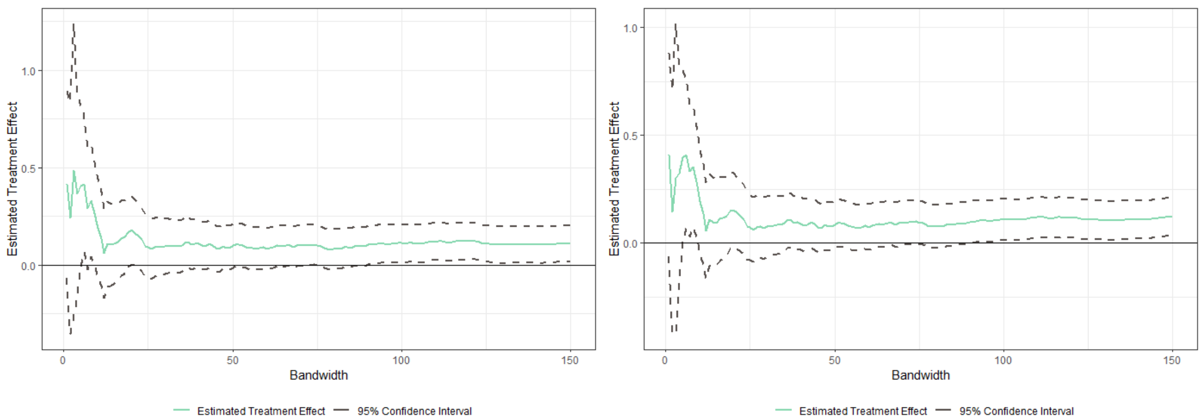
5.4.2 The effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

When considering the effect of Top 50 inclusion on the probability of being in the Viral 100, it is the quadratic model that yields a statistically significant discontinuity at the threshold. Figure 11(a) displays placebo tests for a range of cutoffs in the quadratic model, a small number of which yield significant estimates. The bandwidth plot in Figure 12(a) shows that the estimated effect is not significantly different from zero for small bandwidths, and only consistently starts to yield a significant value when the bandwidth exceeds 100. This indicates that the quadratic model's significant treatment effect is sensitive to precise model specification and partially driven by data points far from the cutoff point.



(a) Without covariates (b) With covariates

Figure 11: The estimated treatment effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart in a linear model for a range of placebo cutoff values



(a) Without covariates (b) With covariates

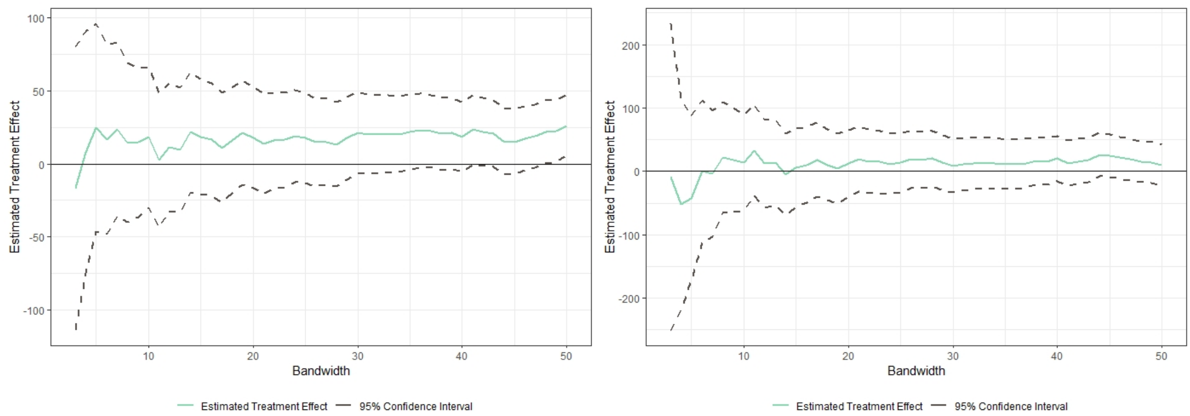
Figure 12: The estimated treatment effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart in a linear model for a range of bandwidth window sizes

The inclusion of covariates in our robustness checks do not change our results by much. The placebo results in Figure 11(b) are extremely similar to those of the model without covariates. The bandwidth plot in Figure 12(b) is equally similar to the model absent covariates. As such, the same conclusions hold: the model's significant treatment effect is driven to some extent by data far away from the cutpoint. As such, and taking once more into consideration also the insignificant results produced by the local randomization technique, we conclude that the detected significant treatment effects of Top 50 inclusion on the probability to be in the Viral chart is not robust to changes in specification.

5.4.3 The effect of Viral 50 playlist inclusion on attained rank in the Top chart

Figure 13 displays the Type-I Tobit-estimated effect of inclusion in the Viral 50 on the best latent Top rank within 30 days for different bandwidths, where covariates are not included in the regression. Notably, the linear model only yields a significant treatment estimate when including almost the entire sample.

This result suggests that the identified treatment effect is possibly driven by data far away from the threshold of 50, and, therefore, that the effect we find is not robust to changes in specification. The quadratic model is insignificant for all bandwidths, providing some evidence that the explored effect does not exist. Figure 22 in Appendix D.1. contains similar results with the inclusion of the two covariates, and even displays insignificant results for both the linear as well as the quadratic model at every bandwidth.



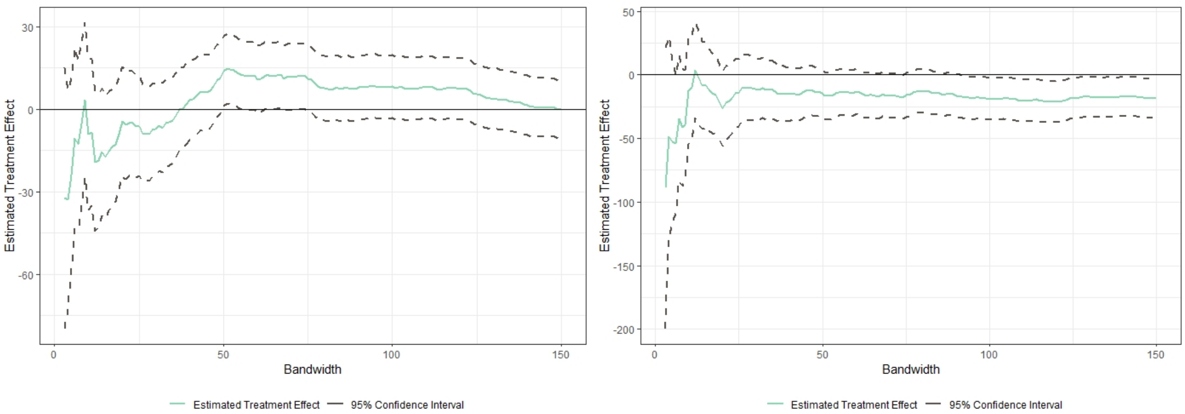
(a) Linear

(b) Quadratic

Figure 13: The estimated effect of Viral 50 inclusion on the latent Top rank for the linear and quadratic Tobit models and different bandwidth sizes with 95% confidence intervals.

5.4.4 The effect of Top 50 playlist inclusion on attained rank in the Viral chart

Moving on to the opposite effect - namely that of inclusion in the Top 50 on the best latent Viral rank within 30 days, Figure 14 displays the Tobit Type-I estimated effect size for different bandwidths. Once again, we did not include covariates in the estimation for this figure. Notably, the linear model yields insignificant results for almost all bandwidths, whereas the quadratic Tobit model only suggests significant results once the bandwidth approaches 100. This result again indicates that the effect we find effect follows from points farther away from the cutoff, and so this result is also not robust to changes in precise model specification. Figure 25 in Appendix D.2 shows that these findings do not change when including covariates.



(a) Linear

(b) Quadratic

Figure 14: The estimated effect of Top 50 inclusion on the latent Viral rank for the linear and quadratic Tobit models and different bandwidth sizes with 95% confidence intervals.

6 Discussion

In this paper, we primarily analysed the effect of (i) the effect of the inclusion of a song in the Spotify Viral 50 playlist on the probability of said song appearing in the Spotify Top chart within 30 days of debuting in the Viral 50 playlist and (ii) the effect of the inclusion of a song in the Spotify Top 50 playlist on the probability of entering the Spotify Viral chart within 30 days of entering the Top 50 playlist.

As only songs with a rank below 50 show up in the respective playlist and because the Top chart and Viral chart contain 200 and 100 tracks each, the border between the 50th and 51st ranks presents a natural threshold for a Sharp regression discontinuity design analysis, which we exploited for our analyses. We used different approaches, including linear and quadratic global polynomials, probit models, local linear regression and local randomisation.

None of the methods we used provided evidence for a significant effect of inclusion in the Viral 50 playlist on the probability of a song being on the Top chart. The linear polynomial and probit models yielded a significant negative estimated effect, but this significance only persists when taking large bandwidths around the 50th rank threshold. In including quadratic terms in the global regression models, the estimated discontinuity shrinks to zero and loses statistical significance. Moreover, the local linear regression fails to reject no discontinuity, similar to the local randomisation approach. Together, these results imply no significant treatment effect, which is not wholly surprising as the number of Viral 50 playlist users is small, with less than 1.8 million followers. Consequently, targeting the Viral 50 - a much more attainable goal than e.g. entering the Top 50 - by focusing on more song shares does not appear to be a productive strategy to boost song popularity.

The existence of the opposite effect, namely of Top 50 inclusion on the probability of being in the Viral chart, is less clear. The linear polynomial and probit models do not reject the absence of a discontinuity, while their quadratic counterparts suggest a boost in the probability of entering the Viral chart of roughly 11%. This effect, however, is sensitive to changes in model bandwidth as the effect we estimate is insignificant for most bandwidths smaller than 90. Furthermore, the local linear regression provides evidence for a significant positive effect of over 0.3 when using a bandwidth of 3.7 around the cutoff. Conversely, the local randomisation method yields an insignificant treatment effect, using a bandwidth of size 10. As the running variables we use in this paper are discrete - taking only values in the integers between 1 and 200, at most - the local linear regression setup is of dubious validity. As only that method yields a significant effect, we conclude there is no compelling evidence for a discontinuity also for this dataset. We find this result somewhat surprising given the popularity of the Top 50 playlist (over 18 million followers). This result implies that a boosted number of shares, following playlist exposure, is not one of the mechanisms through which inclusion in the Top playlist raises a song's popularity.

Finally, we employed a Tobit Type-I model to investigate (i) whether inclusion in the Viral 50 playlist significantly boosts a song's (latent) best attained Top chart rank within 30 days of debuting in the Viral 50 playlist, and (ii) whether inclusion in the Top 50 playlist significantly boosts a song's (latent) best attained Viral chart rank within 30 days of debuting on the Top 50 playlist. In line with expectations based on earlier results, the Tobit model suggests no existence of a Viral 50 inclusion effect on a song's latent best attained Top chart rank. This insignificance persists even when including quadratic terms and covariates and for any bandwidth size. The opposite effect - that of Top 50 inclusion on a song's latent best attained Viral rank - is insignificant in the linear Tobit model but significantly positive in the quadratic Tobit model. In turn, this suggests a ranking improvement of roughly 18 to 19 spots. This result persists when including covariates and losing significance for most bandwidths smaller than 100. This indicates that the significant result is - at least partially - driven by data far from the threshold. As such, we found no strong evidence for the existence of either effect.

Our study has several limitations that other researchers can address in future research. For one, our paper only considered the song's debuting rank in a chart. Although this simplifies our analysis and protects it against autocorrelation concerns, it also has several implications for our data. It is, for example, difficult for songs of non-established artists to immediately break the Top 50 playlist. Conventionally, those songs enter the Top chart and slowly rise into the top 50; such tracks might, therefore, be underrepresented in small windows around the threshold of 50 in both charts. A similar analysis with panel data methods could simultaneously massively increase the sample size and yield a more balanced sample. Additionally, songs may debut at, for instance, rank 51, and the next day may break the top 50 and stay there for the remainder of the month. In turn, their running variable score would be 51 but their corresponding dependent variable would be largely driven by their time in the Top 50. This introduces extra noise, which we could reduce by considering all observations.

Additionally, all of our analyses used a 30-day window to construct dependent variables. However, no heuristic or formal proof that justifies this choice exists - as such, repeating a similar analysis but including dependent variables, which one would construct using differently-sized windows would most likely provide more reliable results. Finally, as Spotify charts also publishes the same Viral and Top chart data partitioned per country, one could pursue similar analyses to ours, exploring heterogeneity across countries and cross-country effects.

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Appendix

A Data dictionary

Table 8: Data Dictionary

Variable	Data Type	Description	Example
rank	integer	The rank of the song in the Viral 100 (Top 200) chart.	5
uri	string	The unique Spotify song identifier	spotify:track:4pdPtRcBmOSQDlJ3Fk945m
artist	string	The unique Spotify song artist. Can be a single artist, a band or a group.	The Weeknd, Daft Punk
title	string	The title of the song	I Feel It Coming
date	date	The earliest date the song appeared in the Viral 100 (Top 200) chart	24/02/2020
below50_1	binary	Equals 1 if the rank is inbetween 1-50, i.e. the song is included in the playlists.	0
within_a_month	binary	Equals 1 if the song shows up within 30 days in the other chart, 0 otherwise.	1
appeared_before	binary	Equals 1 if the song shows up on the other chart before entering the chart.	1
best_rank	integer	The best rank on the other chart within 30 days of a track entering a given chart. Equals "NA" if not found.	40
collaboration	binary	Equals 1 if the song is a collaboration between artists.	1

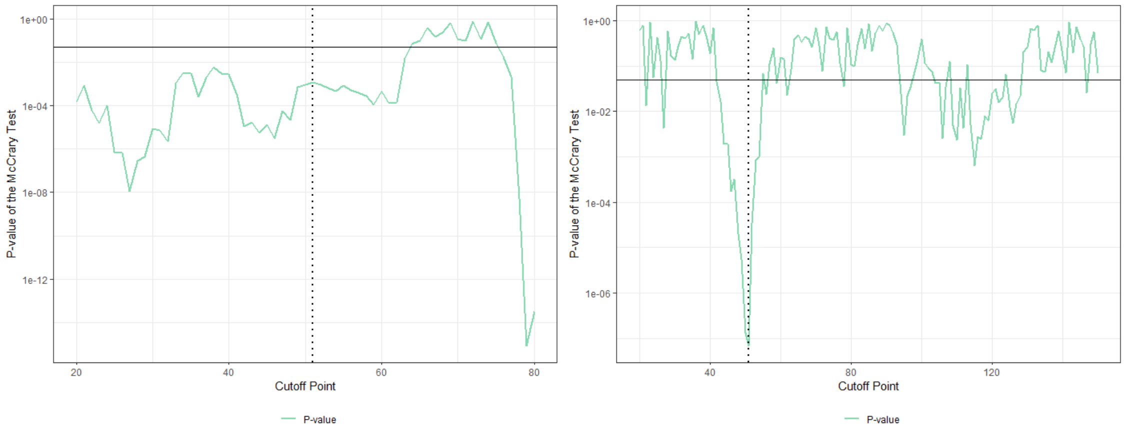
B Summary statistics

Table 9: Partitioned summary statistics for the songs in the Viral chart and Top charts for the 2017-2022 period.

Global Viral Chart		
Inside the Viral 50 Playlist	Collaborations	Non-Collaborations
% of Viral 50 songs that were in the Top chart before first entering the Viral 50	33.365	21.622
% of Viral 50 songs that were in the Top chart within 30 days of entering the Viral 50	30.740	19.287
% of Viral 50 songs that first entered the Top chart within 30 days of first entering the Viral 50	3.608	3.194
Outside the Viral 50 Playlist	Collaborations	Non-Collaborations
% of Viral 51-100 songs that were in the Top chart within 30 days of entering the Viral 51-100	16.765	13.055
% of Viral 51-100 songs that were in the Top chart before first entering the Viral 51-100	14.258	10.955
% of Viral 51-100 songs that first entered the Top chart within 30 days of first entering the Viral 51-100	3.682	3.222
Global Viral Chart	Collaborations	Non-Collaborations
Average viral rank of a song upon first entering the Viral chart	54.292	56.026
Average best attained Top chart rank of a Viral chart song in the first 30 days after entering the Viral chart, conditional on having entered the Top chart within 30 days of entering the Viral chart	79.579	80.098
Global Top Chart		
Inside the Top 50 Playlist	Collaborations	Non-Collaborations
% of Top 50 songs that were in the Viral chart before first entering the Top 50	3.571	2.089
% of Top 50 songs that were in the Viral chart within 30 days of entering the Top 50	59.127	45.504
% of Top 50 songs that first entered the Viral chart within 30 days of first entering the Top 50	56.349	43.597
Outside the Top 50 Playlist	Collaborations	Non-Collaborations
% of Top 51-200 songs that were in the Viral chart before first entering the Top 51-200	15.764	14.158
% of Top 51-200 songs that were in the Viral chart within 30 days of entering the Top 51-200	49.602	40.234
% of Top 51-200 songs that first entered the Viral chart within 30 days of first entering the Top 51-200	36.624	28.520
Global Top Chart	Collaborations	Non-Collaborations
Average top rank of a song upon first entering the Top chart	121.051	111.590
Average best attained Viral chart rank of a Top chart song in the first 30 days after entering the Top chart, conditional on having entered the Viral chart within 30 days of entering the Top chart	36.585	35.176

C Results

C.1 McCrary tests



(a) Viral on Top

(b) Top on Viral

Figure 15: The p value of the McCrary test for a range of placebo cutoff points for both the Viral and Top datasets, where values under the horizontal line show significance at the 95% confidence interval.

C.2 Covariate continuity

Table 10: Results for the discontinuity regressions for the effect of being in the Viral 50 playlist on share of songs which were collaborations and share of songs which had appeared on the Top chart before

	Collaboration				Appeared Before			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$I_{ViralRank \leq 50}$	0.024	-0.050	0.060	-0.065	-0.024	-0.014	-0.082	-0.053
	(0.019)	(0.029)	(0.045)	(0.066)	(0.015)	(0.023)	(0.056)	(0.084)
$ViralRank$	-0.001***	-0.004***	-0.001	-0.008	-0.002***	0.002	-0.008	-0.007
	(0.000)	(0.002)	(0.001)	(0.004)	(0.000)	(0.001)	(0.001)	(0.005)
$I_{ViralRank \leq 50} \times Rank$	0.001	0.003	0.012***	0.010*	0.002***	0.000	-0.003	0.002
	(0.001)	(0.003)	(0.002)	(0.006)	(0.000)	(0.002)	(0.002)	(0.007)
$ViralRank^2$	—	0.000	—	0.000	—	0.000	—	0.000
		(0.000)		(0.000)		(0.000)		(0.000)
$I_{ViralRank \leq 50} \times Rank^2$	—	0.000	—	0.000	—	0.000	—	0.000
		(0.000)		(0.000)		(0.000)		(0.000)
$constant$	0.417***	0.441***	-0.671****	-0.616***	0.198***	0.200***	-0.834***	-0.843***
	(0.013)	(0.021)	(0.030)	(0.045)	(0.010)	(0.016)	(0.040)	(0.062)

Note. White standard errors are denoted in parentheses. *** denotes a p value below 0.001, ** denotes a p value below 0.01, * denotes a p value below 0.05.

Note. (1) linear (2) quadratic (3) linear probit (4) quadratic probit

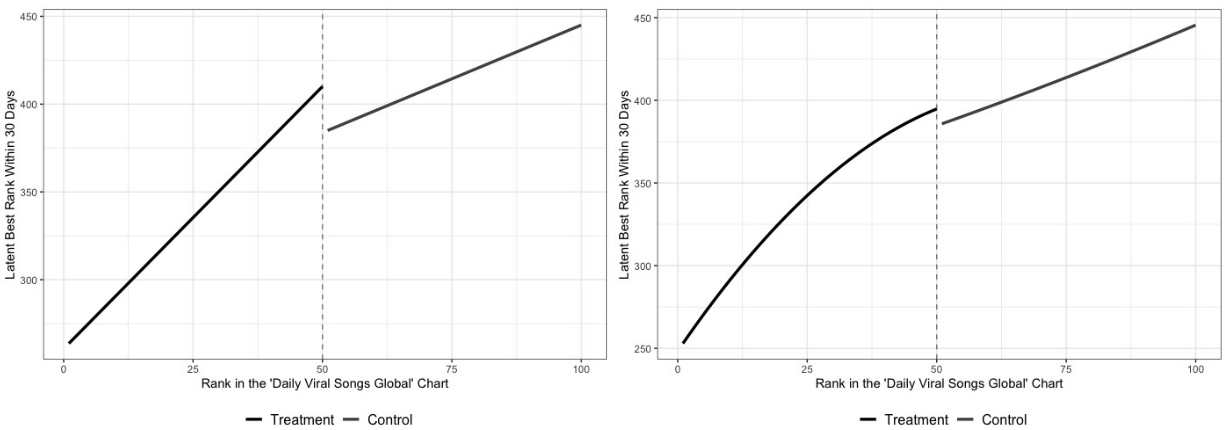
Table 11: Results for the discontinuity regressions of the effect of being in the Top 50 on share of songs which were collaborations and share of songs which had appeared on the Viral 100 before.

	Collaboration				Appeared Before			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$I_{TopRank \leq 50}$	-0.005	-0.020	0.060	-0.065	0.080***	-0.017	-0.069	0.447***
	(0.006)	(0.041)	(0.045)	(0.066)	(0.013)	(0.021)	(0.081)	(0.126)
$TopRank$	0.001	-0.002**	-0.001	-0.008**	0.002***	-0.002***	0.000	0.029***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.000)	(0.000)	(0.002)	(0.008)
$I_{TopRank \leq 50} \times Rank$	-0.004***	0.003	0.012***	0.010	-0.002***	0.005***	0.006	0.016
	(0.001)	(0.003)	(0.002)	(0.006)	(0.000)	(0.002)	(0.003)	(0.012)
$TopRank^2$	—	0.000	—	0.000	—	0.000	—	0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
$I_{TopRank \leq 50} \times Rank^2$	—	0.000	—	0.000	—	0.000	—	0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
$constant$	0.253***	0.272***	-0.671***	-0.616***	-0.046***	0.073***	-1.752***	-1.994***
	(0.004)	(0.019)	(0.030)	(0.045)	(0.007)	(0.010)	(0.046)	(0.092)

Note. White standard errors are denoted in parentheses. *** denotes a p value below 0.001, ** denotes a p value below 0.01, * denotes a p value below 0.05.

Note. (1) linear (2) quadratic (3) linear probit (4) quadratic probit

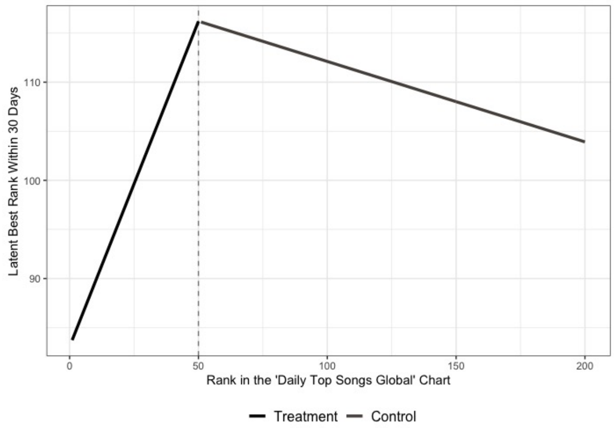
C.3 Tobit model



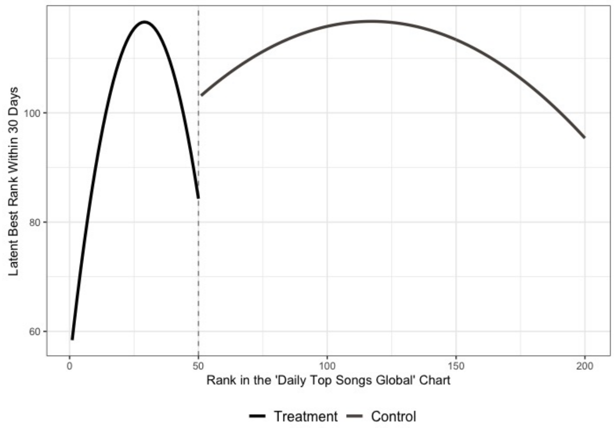
(a) Linear model

(b) Quadratic model

Figure 16: The effect of inclusion in the Viral chart on the best latent Top rank within a month.



(a) Linear model

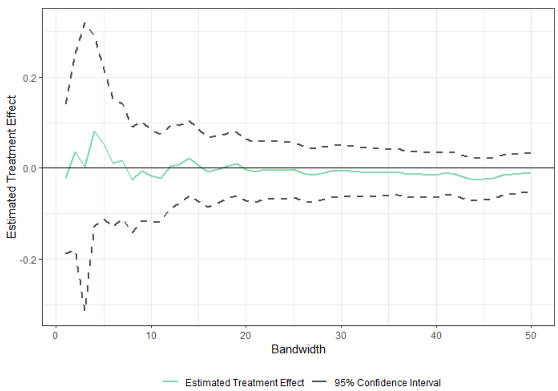


(b) Quadratic model

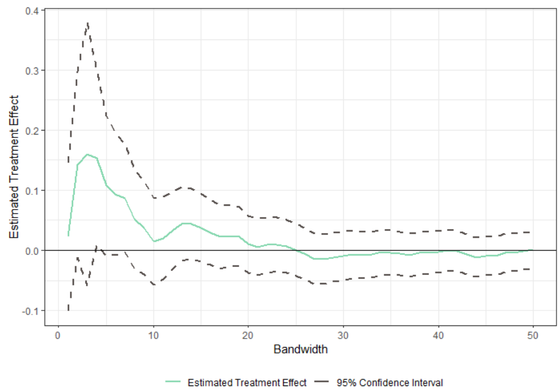
Figure 17: The effect of inclusion in the Top chart on the best latent Viral rank within a month.

D Robustness

D.1 The effect of Viral 50 playlist inclusion on the probability of a song being on the Top chart

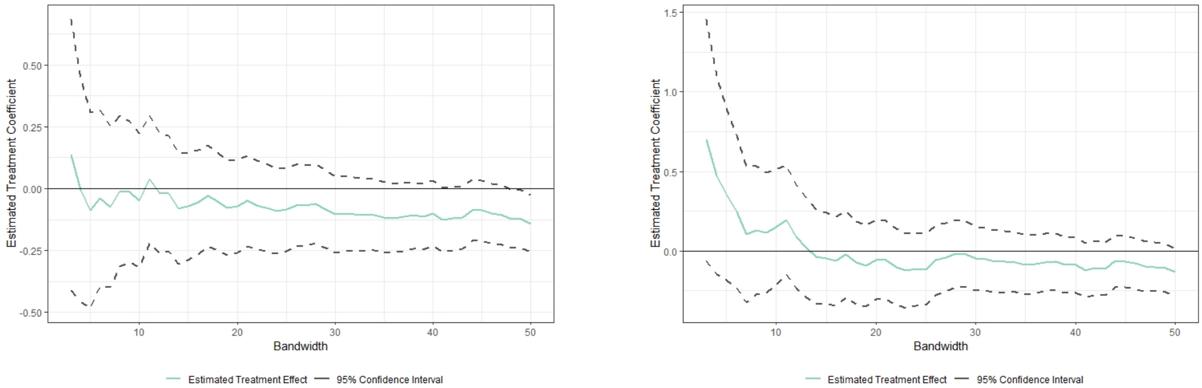


(a) Without covariates



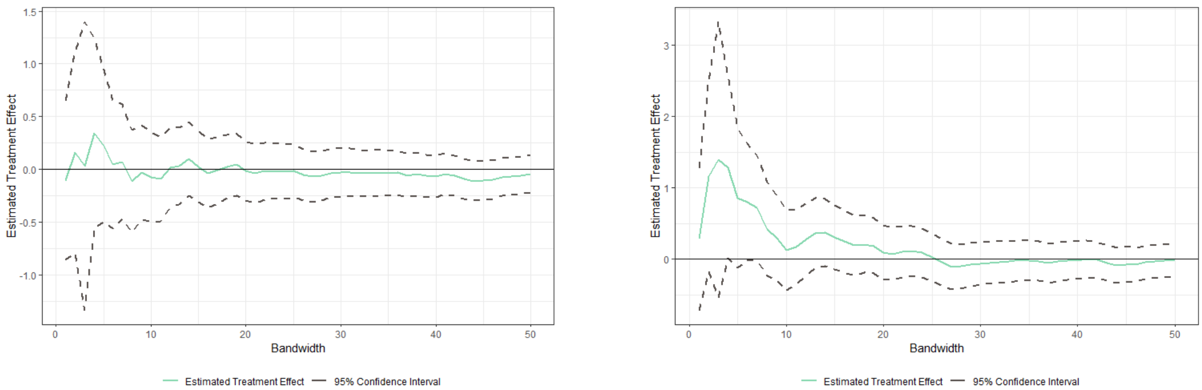
(b) With covariates

Figure 18: The estimated treatment effect in the quadratic model for different bandwidths using White standard errors at the 95% confidence interval.



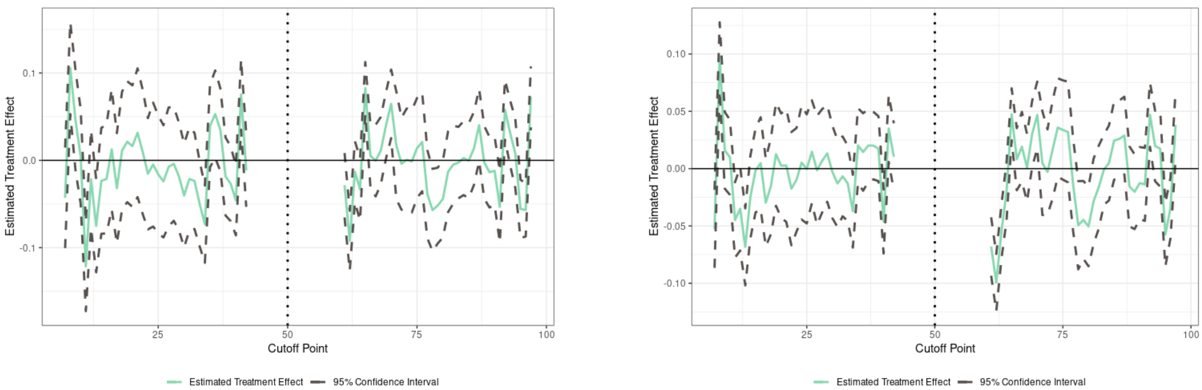
(a) Without covariates (b) With covariates

Figure 19: The estimated treatment effect in the probit linear models for different bandwidths using White standard errors with 95% confidence intervals.



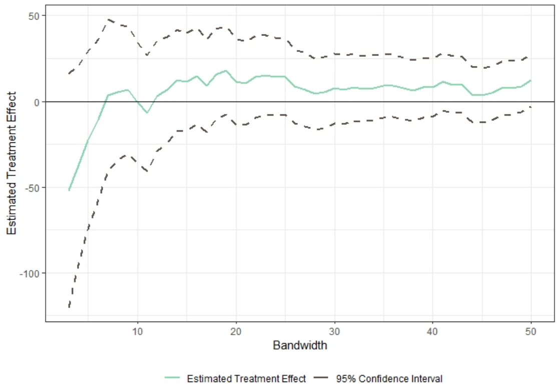
(a) Without covariates (b) With covariates

Figure 20: The estimated treatment effect in the probit quadratic models for different bandwidths using White standard errors with 95% confidence intervals.

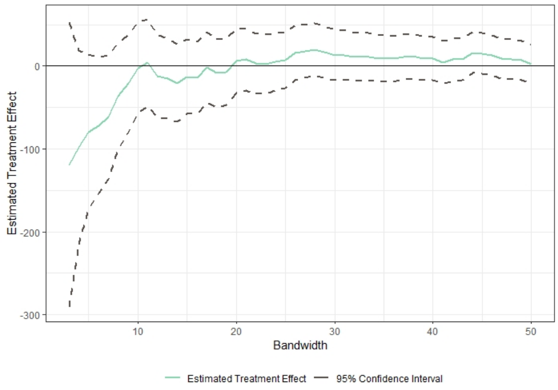


(a) Without covariates (b) With covariates

Figure 21: The estimated treatment effect in the quadratic model for a different range of placebo values using White standard errors at the 95% confidence interval.



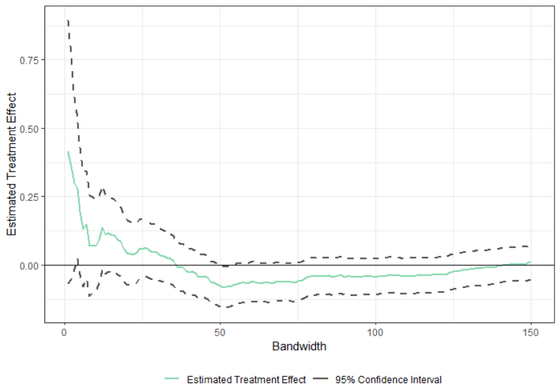
(a) Linear



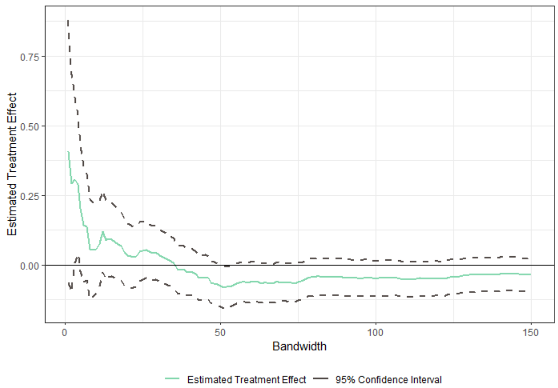
(b) Quadratic

Figure 22: The estimated effect of Viral 50 inclusion on the latent Top rank for the linear and quadratic Tobit models with the inclusion of covariates and different bandwidth sizes with 95% confidence intervals.

D.2 The effect of Top 50 playlist inclusion on the probability of a song being on the Viral chart

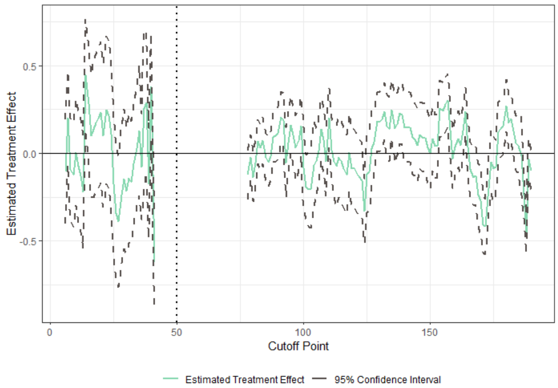


(a) Without covariates

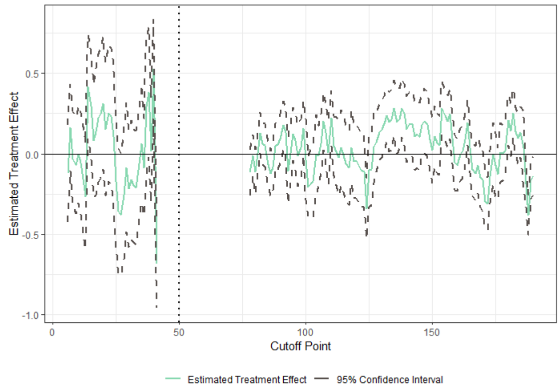


(b) With covariates

Figure 23: The estimated treatment effect in the linear model for different bandwidths using White standard errors at the 95% confidence interval.

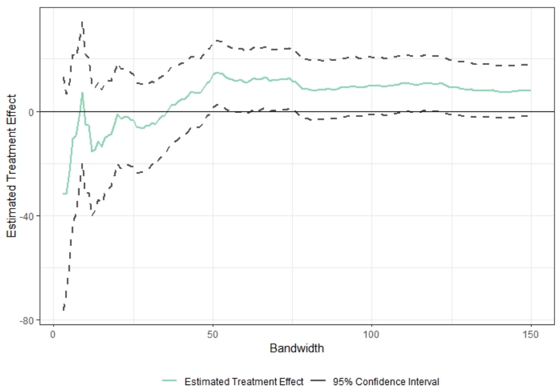


(a) Without covariates

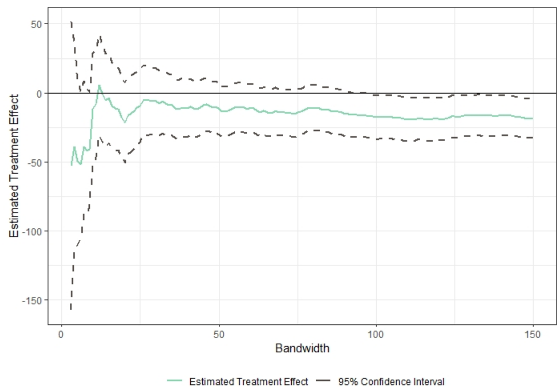


(b) With covariates

Figure 24: The estimated treatment effect in the probit linear model for a different range of placebo values using White standard errors at the 95% confidence interval.

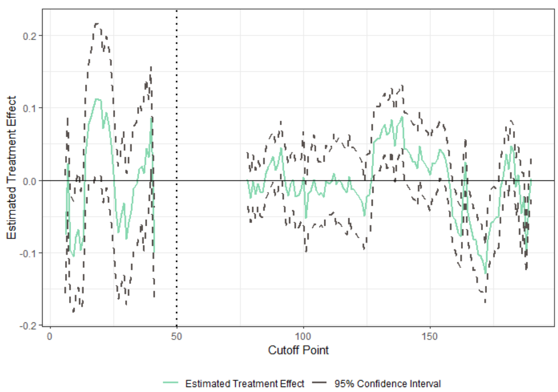


(a) Linear

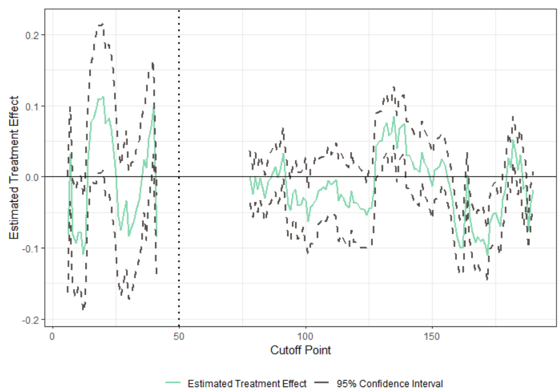


(b) Quadratic

Figure 25: The estimated effect of Top 50 inclusion on the latent Viral rank for the linear and quadratic Tobit models with the inclusion of covariates and different bandwidth sizes with 95% confidence intervals.

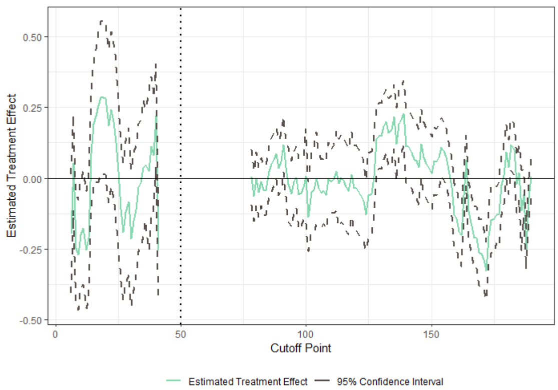


(a) Without covariates

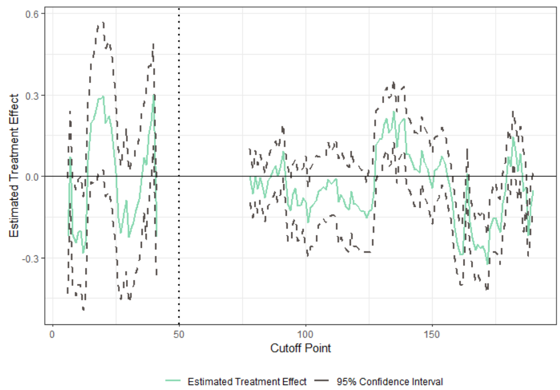


(b) With covariates

Figure 26: The estimated treatment effect in the linear model for a different range of placebo values using White standard errors at the 95% confidence interval.



(a) Without covariates



(b) With covariates

Figure 27: The estimated treatment effect in the probit linear model for a different range of placebo values using White standard errors at the 95% confidence interval.