Virus Shook the Streaming Star:
Estimating the COVID-19 Impact on Music Consumption

Jaeung Sim
PhD Candidate
College of Business
Korea Advanced Institute of Science and Technology (KAIST)
jaeung@kaist.ac.kr

Daegon Cho *(corresponding author)*
Ewon Assistant Professor
College of Business
Korea Advanced Institute of Science and Technology (KAIST)
daegon.cho@kaist.ac.kr

Youngdeok Hwang
Assistant Professor
Paul H. Chook Department of Information Systems and Statistics
City University of New York
youngdeok.hwang@baruch.cuny.edu

Rahul Telang
Trustee Professor of Information Systems
H. John Heinz III College
Carnegie Mellon University
rtelang@andrew.cmu.edu

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Abstract

Many have speculated that the recent outbreak of COVID-19 has led to a surge in the use of online streaming services. However, this assumption has not been closely examined for music streaming services, the consumption patterns of which can be different from video streaming services. To provide insights into this question, we analyze Spotify's streaming data for weekly top 200 songs for two years in 60 countries between June 2018 and May 2020, along with varying lockdown policies and detailed daily mobility information from Google. Empirical evidence shows that the COVID-19 outbreak significantly reduced music streaming consumption in many countries. We also find that countries with larger mobility decreases saw more notable downturns in streaming during the pandemic. Further, we reveal that the mobility effect was attributable to the complementarity of music consumption to other activities and likely to be transient rather than irreversible. Alternative mechanisms, such as unobservable Spotify-specific factors, a demand shift from top-selling songs to niche music, and supply-side effects, did not explain the decline in music consumption.

Keywords: digital distribution, lockdown restrictions, music streaming, pandemic, Spotify

1. Introduction

The spread of the novel coronavirus (COVID-19) has had an unprecedented impact on public health—1.6 million people have died from COVID-19 worldwide as of December 14th, 2020 (European Centre for Disease Prevention and Control 2020). To limit the spread of the outbreak, governments have enacted various social distancing policies, such as reducing transportation, halting nonessential activities, and issuing shelter-in-place orders. The pandemic has impacted the economy as well. The sudden downturn caused by COVID-19 has affected almost every aspect of economic endeavors on both demand and supply sides (Bonaccorsi et al. 2020). Many industries have been adjusting to the new norms, and every component of their value chains—from production and distribution channels to consumers—has been shaken.

Although COVID-19 has exposed many players to risk, it has not posed a threat to all. Amid the market meltdown, many anticipated that digital streaming services would see a surge in demand since many people have been forced to stay at home and work remotely (Forbes 2020a, Nielsen 2020). During this time, people may spend more time online via their digital devices, which may increase media content consumption. As theaters have remained closed, consumers are likely to turn to video content at home. In this regard, COVID-19 shutdowns have accelerated the transition toward the on-demand streaming services away from ownership-based models.[1] In line with this growth, Netflix's and Spotify's shares were up 32.2% and 27.1%, respectively, from the beginning of the year through May 21, 2020, whereas S&P 500's dropped 9.5% over the same period.[2]

While it has been reported that people's increased time at home has significantly benefited visual forms of entertainment (e.g., live video streaming), audio consumption went in the opposite direction.[3] A possible reason for this disparity is that music is often consumed as a complement to other activities rather than a standalone entertainment. For instance, music can serve as a source of distraction while in traffic—almost 29% of all music consumption takes place in the car (Nielsen 2017). Similarly, music listening during work or while doing chores

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[1] Even before the pandemic, consumers had started shifting toward music subscription services over individual purchases (Li et al. 2020). The music industry was one of the first to be noticeably affected by this trend and has served as a compelling example of the post-ownership economy. By using music streaming services, users can replace a traditional music collection with a virtual playlist, listen to unlimited music, and conveniently discover new music (Datta et al. 2017; Aguiar and Waldfogel 2018). Such services became the main driver of the market after a 15-year consecutive decline since 1999. By 2019, global streaming revenue had grown by 22.9%, to $11.4 billion, and accounted for more than half (56.1%) of global recorded music revenue for the first time (IFPI 2020).

[2] These are computed by stock prices of each company on the given days, obtained from Yahoo! Finance.

[3] Many outlets focused on the surge in Spotify's paid subscribers and higher podcast uploads (e.g., Financial Times 2020, The Los Angeles Times 2020), while some pointed out the declining number of streaming counts in a few countries (e.g., Forbes 2020b, VoxEurop 2020). In particular, VoxEurop (2020) wrote, "[T]hose confined and working from home have more time to watch, listen and read. Music services should benefit from this, but the data suggests the opposite," implying that it might be unexpected to investors and field experts.

accounted for a combined total of about 30% of all consumption (Nielsen 2015), and 54% of consumers listened to music while commuting (IFPI 2018).

This evidence suggests that the adverse impact on such music-friendly activities will likely be reflected in lower music consumption levels. This is because music is less intrusive than other media forms and has complementary properties; that is, the pandemic might reduce music consumption by restricting travel and cutting down the music-friendly activities. This hypothesis can only be substantiated if various socioeconomic aspects and pandemic-related policies are thoroughly studied together. To gain insights into the impact of the pandemic on streaming music consumption, we combine and analyze music streaming data, COVID-19 statistics, policy measures from the government, as well as mobility data from major tech companies, broken by countries.

Specifically, we analyze Spotify's streaming data for weekly top 200 songs for two years in 60 countries. Our assumption-free statistical test and model-based inference reveal that in more than two-thirds of countries that enforced lockdown, music streaming volume significantly decreased after the lockdowns took effect. On average, music consumption decreased by 12.5 percent after WHO's pandemic declaration on Mar 11, 2020. Analyzing the Spotify streaming data together with people's mobility patterns suggests that reduced commuting time is strongly correlated to the decline in music consumption. Our analysis of movement patterns also shows that the downturn in music consumption was more noticeable in countries where time spent on commuting and movement drastically plummeted.

Our additional analysis further confirms how the complementarity of music listening led to the demand decline during the pandemic. We find that video-based music consumption via YouTube went up when the COVID-19 cases are high, lockdown policies are restrictive, and more time spent at home, which suggests that such music streaming did not decrease when it is not complementary to other activities. Besides, we find that music consumption was more affected by commuting than general mobility. Importantly, a noticeable rebound of music consumption in countries with temporary ease of COVID-19 implies that such effects are transient rather than irreversible. We also provide evidence that our findings were very unlikely to be driven by the consumers shifting toward a niche market or unobservable Spotify-specific factors. We also observe that popular artists did not significantly change their music release decisions during the pandemic, suggesting that the supply level of popular artists has not driven the reduced music consumption.

Our study makes several important contributions. To the best of our knowledge, this study provides the first empirical evidence of the impact of the COVID-19 on digital streaming consumption in a global context. First, despite the common expectation that the pandemic would universally benefit online media platforms, we show that it has adversely impacted music streaming services. Our study highlights that music consumption can decline due to its complementary nature. Second, our discussion on the pandemic and digital consumption implies that the substantially changing media consumption environment can put streaming music in a fiercer competition against other media forms, e.g., visual media offering more dynamic and vivid experiences to consumers (Kumar and Tan 2015). These findings demonstrate the significance of contextual preference in media consumption.

2. Data

To examine the impact of COVID-19 on music consumption, we use Spotify's weekly streaming data for the top 200 weekly music charts during 104 consecutive weeks between June 2018 and May 2020 across 60 countries listed in Table A1 in the online appendix. Spotify is the world's largest subscription music streaming service with 96 million paid subscribers and 74 million free users, offering unlimited free streaming with advertisements, as well as paid premium services (The Telegraph, 2020). The weekly streaming volume of a song refers to the number of times it was played by legitimate paid-for or free service users each week. We aggregate weekly streaming counts of the top 200 songs for each country, and built the country-week level for 104 weeks of 60 countries, for a total of 6,240 observations.

We combine music consumption data with COVID-19 case statistics from the European Centre for Disease Prevention and Control (ECDC). ECDC provides daily updated panel data of COVID-19 cases and deaths by country, except Hong Kong.[4] To make these statistics comparable across countries, we calculate the number of COVID-19 cases and deaths per million people using national population data from the World Bank. We utilize data on enforced social distancing measures by the governments from the Oxford COVID-19 Government Response Tracker (Petherick et al. 2020). The data contain various government responses to COVID-19, such as shelter-in-place orders at the country-day level. 59 out of 60 countries in the Spotify dataset are matched to such enforcement data. Lastly, we use country-day-level data on individuals' time allocation changes (for activities) since the COVID-19 outbreak from Google's COVID-19 Community Mobility Reports (Google LLC 2020). The data report daily percentage changes in the number of visits by place category (e.g., transit stations, workplaces, and residential) with respect to the baseline average of visits on the corresponding day of the week during the five-week pre-pandemic reference period (for more details, see Online Appendix A). Table 1 presents variable descriptions and summary statistics.

[4] We supplement the data with COVID-19 statistics released by the Government of the Hong Kong Special Administrative Region.

[Table 1 about here.]

Figure 1 presents streaming trends by country during our research period. The blue (yellow) line indicates the weekly streaming volume when no (one or more) government restriction was in effect, according to the Oxford COVID-19 Government Response Tracker. Although we observe downward shifts in demand after restrictions, such fluctuations might be attributed to market trends and seasonality, while overall trends and seasonality substantially vary across countries. To statistically assess whether such shifts could have occurred without the COVID-19 outbreak, we conduct a distribution-free statistical test using simple A/B testing and empirical reference distributions (Box et al. 2005, pp. 68-71). We find that music streaming volume significantly decreased after the lockdowns took effect in more than two-thirds of countries that enforced lockdown (see Online Appendix C).

[Figure 1 about here.]

3. Econometric Analysis and Results

3.1. Impact of COVID-19 Outbreak on Music Consumption

To account for the growth and seasonality of the streaming demand, we compare weekly streams of each week with those of a comparable week a year ago in each country (e.g., Chen et al. 2020, Fang et al. 2020). This approach allows us to comprehensively capture various components of the COVID-19 effect—such as individuals' preventive efforts to avoid exposure to the virus, as long as the parallel pre-trend assumption is satisfied (Fang et al. 2020).

Figure 2 illustrates this procedure. We divide our research period into two one-year-long periods. The first year spans 52 weeks from June 1st, 2018 to May 30th, 2019. The second year covers the following 52 weeks from May 31st, 2019 to May 28th, 2020. The first week of the first year (from June 1st to June 7th in 2018) corresponds to the first week of the second year (from May 31st to June 6th in 2019). By subtracting the earlier streams from the later ones, we examine whether and to what extent the difference between the two years widened after WHO declared the outbreak a pandemic on March 11th, 2020.

[Figure 2 about here.]

Figure 3 presents the streaming trends in the first year and the second year at the global level. We observe that the trends were sufficiently parallel between the two years before the pandemic declaration. However, after the declaration, the two trends began to part drastically; in April and May 2020, the second year's trend deviated from the parallel line by approximately 0.4 billion streams per week. We formally test this assumption by estimating the relative time model that leverages leads and lags of the treatment (Autor 2003, Burtch et al. 2018) and find that such differences were unlikely to appear without the COVID-19 outbreak (see Online Appendix C).

[Figure 3 about here.]

To quantify the differences, we employed a difference-in-differences (DID) approach that leverages observations in the first year as a control group and those in the second year as a treated group. This can be expressed as:

$$\ln\left(Streams_{ijt}\right) = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_t \delta_t + \varepsilon_{ijt}, \qquad (1)$$

$$\ln\left(Streams_{ijt}\right) = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt}, \qquad (2)$$

where i=1, …, n indexes countries; j=1, 2 indexes the two-year period; t=1, …, 52 indexes the week of the year. $Streams_{ijt}$ is weekly total streaming counts of the top 200 charts in country i, year j, and week t; $Treated_j$ indicates 1 if $j = 2$ (the treatment year), 0 otherwise (the control year); $After_t$ indicates 1 if week of the year t is later than March 11th, corresponding to the pandemic declaration date, 0 otherwise; α_i is a set of country fixed effects; δ_t is a week-of-the-year dummy variable; $\alpha_i \cdot \gamma_j$ is the product of country dummy and period dummy; $\alpha_i \cdot \delta_t$ is the product of country dummy and week-of-the-year dummy; ε_{ijt} is an error term clustered at the country level to take account of autocorrelation in the data (Bertrand et al. 2004).

β_3 captures the impact of the COVID-19 outbreak on streaming demand. In Equation (1), $\sum_t \delta_t$ controls for week-of-the-year fixed effects. In Equation (2), $\sum_i \sum_j \alpha_i \cdot \gamma_j$ captures country-specific period fixed effects that controls for heterogeneous annual growth of demand. $\sum_i \sum_t \alpha_i \cdot \delta_t$ captures country-specific week-of-the-year fixed effects that reflect heterogeneous seasonality, and cancels out $\sum_t \delta_t$ which picks up common week-of-the-year fixed effects.

As seen from the results in Table 2, the coefficients of $Treated_j \cdot After_t$ are negative and significant, and the magnitudes of these coefficients remain unchanged across models. These results suggest that streaming demand decreased by 12.5% after the pandemic declaration. The results are also qualitatively consistent across sample selection criteria (e.g., continents and rank ranges) and functional forms (e.g., count models and disaggregated country-rank level data) (see Online Appendix C).

[Table 2 about here.]

Although the pandemic declaration is a useful indicator of the COVID-19 outbreak, it does not reflect heterogeneity in the timing and severity of COVID-19 across countries. Furthermore, one might raise a concern that the decline in streaming might be attributable to a common trend in Spotify demand. To address this concern, we use the country-specific number of confirmed cases and deaths as independent variables and include a set of common time fixed effects that absorb any Spotify-specific demand shock. The results show that 1,000 COVID-19 cases per million people each week were associated with a 14.4% decline in streaming consumption, supporting the validity of our findings (see Table C4 in the online appendix).

3.2. Lockdown Restrictions, Movement, and Music Consumption

During the pandemic, media consumption contexts may dramatically change as commuting and traveling are restricted. Specifically, government responses to the COVID-19 outbreak, such as shelter-in-place orders, can reduce time spent on transportation. This could discourage the consumption of streaming music. To explore this hypothesis, we obtain information on various types of government policies from the Oxford COVID-19 Government Response Tracker (Petherick et al. 2020). The data specify eight types of containment and closure policies, and the details are provided in Table A2 in the online appendix. We observe that a substantial number of countries did not enforce restrictions on public transport, shelter-in-place, and internal movement, and many countries released these restrictions over time. We leverage this variation to estimate the following model:

$$\ln\left(Streams_{ijt}\right) = \alpha_i + \tau \cdot Restriction_{ijt} + \theta_1 \cdot Cases_{ijt} + \theta_2 \cdot Deaths_{ijt} + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \sum_j \sum_t \gamma_j \cdot \delta_t + \varepsilon_{ijt}, \qquad (3)$$

where $Restriction_{ijt}$ indicates 1 if country *i* enforced a lockdown policy in period *j* and week of the year *t*; $Cases_{ijt}$ and $Deaths_{ijt}$ control for the weekly number of confirmed COVID-19 cases and deaths per million people in each country, respectively; $\sum_j \sum_t \gamma_j \cdot \delta_t$ is a set of common time fixed effects that absorb Spotify-specific demand shocks.

Table 3 shows the estimates for each restriction type. Most policies significantly decreased streaming demand, except for schools' closings and limits on private gatherings. These results indicate that restricted movement seemed to notably contribute to this demand shrinkage. We find qualitatively similar results when we use ordinal measures of government restrictions and include/exclude COVID-19 cases and deaths (see Tables C5-C7 in the online appendix).

[Table 3 about here.]

To dive deeper into how one of the complementary activities, namely mobility, affected streaming demand, we combined the previous dataset with country-specific data on time allocation changes from Google's COVID-19 Community Mobility Reports (Google LLC 2020). Figure 4 depicts the changes in time spent on the residence and streaming demand from the reference period in the data (between January 3rd and February 6th in 2020). It is clearly seen that residential time surged during the pandemic, and the rise in residential time accompanied a drop in streaming demand in most countries.

[Figure 4 about here.]

Motivated by these exploratory findings, we quantify how much the reshaped mobility patterns were associated with streaming demand using the following model:

$$\ln(Streams_{it}) = \alpha_i + \pi \cdot \Delta Time_{it} + \tau \cdot Restriction_{it} + \theta_1 \cdot Cases_{it} + \theta_2 \cdot Deaths_{it} + \sum_t \delta_t + \varepsilon_{it}, \qquad (4)$$

where $\Delta Time_{it}$ indicates the percentage changes in time allocation to a certain place category compared with those of the five-week reference period between January and February in 2020; other variables are equivalent to those defined in Equation (4). Since Google's data began in February 2020, we do not include country-specific growth and seasonality terms.

The estimated results are reported in Table 4. We find that the more time spent on outdoor activities (e.g., grocery/pharmacy, parks, and transit stations) was positively related to music consumption. In contrast, more residential time had a negative relationship with music consumption. Specifically, a 10% increase in residential time accompanied an 8.1% decline in demand for music streaming. In addition, we find consistent results by using Apple's COVID-19 Mobility Trends Reports (see Table C8 in the online appendix).

[Table 4 about here.]

4. Discussions

4.1. Additional Insights on Mobility and Music Consumption

We have discussed that decreased time spent moving to different locations (e.g., commuting to work, driving to restaurants) during the pandemic led to a decline in music consumption, as music listening is often non-intrusive and complementary to such activities. If this argument is true, such declines will not happen in the consumption of other media forms. To see this, we examine how video-based music consumption at YouTube has been affected by the pandemic by using the data from Soundcharts' API (see Online Appendix B). We find that video consumption for music is positively associated with the severity of COVID-19, lockdown policies, and time spent at home. In contrast, it is negatively associated with time spent on outdoor activities. This suggests that the decline in music streaming was indeed attributable to the audio-based nature and its complementarity with mobile activities.

Complementarity of music may also vary across mobility contexts; for instance, commuting—during which people are under a high level of stress (Ghose et al. 2019)—may motivate individuals to listen to music to relieve stress. To better understand the role of heterogeneous complementarity, we investigate whether music consumption was more influenced by commuting than general mobility. For this, we consider two approaches. First, we examine how the decrease in music consumption is associated with commuting time in European countries (see Online Appendix B). We observe that the estimated decline was more pronounced in countries with longer commuting time. Second, we investigate contingent effects of COVID-19 on top 200 streaming in Spotify by day of the week. We find that the effect was more prominent on weekdays than weekends, and this pattern was consistent with time allocation changes in workplaces and residences than those of transit stations. These results may imply that music tends to be more complementary to stressful situations as it helps relieve stress (Oldham et al. 1995).

It is also important to check whether such influences are transient or irreversible. If the decline in streaming volume is transient, we would see that the demand returns to pre-COVID levels as restrictions are lifted. We find that the temporary ease of COVID-19 during late April and May 2020 led to a noticeable rebound of consumption in countries with a decrease in confirmed cases, in line with Spotify's statement (TechCrunch 2020). Likewise, we find that the reduction in residential time was highly associated with the recovery of the streaming volume (see Online Appendix B). Despite this observation, the recent resurgence of cases might lead to a '*new normal*' that sets working from home and social distancing as a norm for the foreseeable future. As such, less commuting and more working from home will persist for a while, which will keep the music streaming demand at a low level until regaining normalcy.

4.2. Alternative Explanations and Robustness Checks

It is imperative to conduct an extensive set of robustness checks to rule out alternative explanations as we are examining complex social phenomena. We briefly provide results in this section as summarized in Table 5, with the full details provided in Online Appendix C. First, we test whether the functional form of our model drives our findings. We thus conduct a nonparametric test and fit a Poisson regression model, showing consistent results. Second, we examine the possibility that outliers might have driven the main effects by conducting subgroup analysis by continent or range of the rank position. We observe significant declines across different continents and rank positions. Third, we formally test if the parallel pre-trend assumption is violated by estimating a relative time model (Autor 2003, Burtch et al. 2018) and find supporting evidence of our identification assumption.

[Table 5 about here.]

Fourth, we examine the possibility that our findings were solely caused by the unobservable Spotify-specific factors that were not related to the pandemic. To assess this, we first thoroughly review Spotify's updating posts during the research period and find no abnormal difference in service updates and promotions that could induce a noticeable drop in streaming in the period after the pandemic. We also collect nationwide music streaming data of weekly top 400 songs in South Korea, where Spotify had not launched yet but is one of the largest music markets in the world. We observe that music streaming dropped by 12.0% after its initial surge in the number of cases and restrictive measures that followed. The magnitude of the estimated coefficient from South Korea data is consistent with our main finding from Spotify data, suggesting that Spotify-specific factors did not drive the plummeting demand for streaming music during the pandemic.

Fifth, since our main analysis covers weekly top 200 songs, one may ask whether the observed decline reflects an internal shift from popular songs to lesser-known ones such as chill or instrumental music (Spotify 2020), rather than a reduction in total consumption. Although our main estimates are highly comparable to the decline in year-over-year growth rates in Spotify's revenue, it may not be suitable to draw a conclusion directly from comparing the revenues and consumption.[5] We also provide back-of-the-envelope calculations on how significantly consumers should increase consumption of songs below the top 200 to compensate for the decline in top 200 consumption in Online Appendix C, but this still does not answer whether the internal shift occurred or not. To directly examine the possibility of demand shift, we obtain panel data of the daily number of followers from 1,500 playlists with over 75,000 unique songs.[6] Our main findings suggest that the growth of playlist followers was significantly decelerated after the COVID-19 outbreak. Moreover, we find no evidence that instrumental, contextual, and other types of music playlists experienced significant follower gains that could compensate for the loss of popular music. Our analyses of playlist followers are still implicative because the number of followers is not identical to active listeners.

Sixth, we examine the possibility that supply-side dynamics might affect music consumption. Using data collected from Spotify's API, we reveal that top-tier artists have not significantly reduced new songs' release measured by the number of new albums and tracks.

Seventh, we check if newly released songs were less successful during the pandemic by comparing songs' chart entrance and rank positions. We find that there is a tendency that fewer newly released songs made to the top 200 charts, and they landed lower in the chart, which

[5] Based on the publicized information obtained from Spotify's financial reports, we find that Spotify's year-over-year revenue growth rates decreased by 10.4 to 17.6 percentage points during the first three quarters of 2020, which are comparable to our main estimate—a 12.5 percent decline after the WHO's pandemic declaration. However, such results should be interpreted with caution because revenues are also related to subscription fees and advertisers' willingness to spend.

[6] The source of data is Soundcharts, a subscription-based music data provider. Since we rely on the top 500 playlists on October 22, 2020, for each of three provider types (Spotify, major providers, and third parties), our results might have been affected by selecting survivors. However, it is worth noting that this selection is likely to induce upward bias, shifting the results toward an increase in playlist followers after the COVID-19 outbreak. Thus, the observed deceleration of increase in playlist followers can be considered as conservative outcomes.

suggests that new releases were less successful during the pandemic.

5. Implications, Limitations, and Future Research

Spotify's recent financial reports indicate that the firm's revenues of the first three quarters of 2020 were 5.712 billion EUR. If the year-over-year growth rate maintained as in the same period of 2019, the revenue would be 6.404 billion EUR, suggesting that Spotify has lost about 692 million EUR in the first three quarters of 2020 with the pandemic outbreak. This financial outcome is consistent with our main findings. Our study further demonstrates that the pandemic-led decline is commonplace across countries, and possible impacts other than COVID-19 would be limited. More importantly, our research reveals that the notable shift of music demand is associated with consumers' behavioral patterns, particularly restricted mobility. When the pandemic is more widespread, people are more likely to stay at home. Our study shows that this behavioral shift has led to the reduction of music consumption.

Encountering this decline, digital music platforms may need to consider new strategic approaches to boost fans' engagement during and after the pandemic, which has already been happening lately. For example, Spotify introduced a new group session feature in May 2020, "Listening Together," with which users can share their own playlists and podcasts and simultaneously listen with other people. Also, enhanced video features that allow real-time interactions between artists and listeners can be considered, which Spotify also introduced in July 2020. Offering such video podcasts and live concerts features exclusively to premium users would increase consumers' willingness to pay for the premium subscription, which could compensate for the recent decline in revenue per premium user. Platforms can also consider closer collaboration with artists and music labels to compete with the online video platform to retain current users and attract more new subscribers.

Music labels and artists may counteract this decrease by reconsidering new album release timelines and promotion strategies. For instance, they might reallocate more promotion budgets to online video channels. With COVID-19, it is critical to recouping the lost revenues from live concerts, a major revenue source for artists in recent years. Thus, they may need to find alternative channels to connect with their audience and fans to generate revenues and maintain a close relationship with them for the post-COVID era. Popular artists can consider virtual live-streamed concert events under the new reality of life with social distancing. For example, in a recently held pay-per-view online concert, BTS, a popular K-pop superstar, drew nearly 760,000 viewers worldwide and generated $20 million in ticket sales in June 2020. The success led them to hold an additional two-day live-streamed concert in October that attracted nearly 1 million viewers from 191 countries (Music Business Worldwide 2020).

Our study provokes three main questions that could pave the way for future research. First, our study only looked at the top 200 songs on the chart in each country. There is a possibility that the consumption of songs beyond the ranking chart can be affected differently, which provides a meaningful avenue for future research. Although Spotify's financial reports, playlist analysis, and many other results also suggested the overall decline in music consumption, the magnitudes of such decline might have substantially varied across artists. For example, the top 10 songs were most affected among the weekly top 200 songs (see Table C3 in the online appendix). This might imply that the consumption in Spotify became more evenly distributed among musicians during the pandemic than it was before. Future research may provide more profound insights from revealing the uneven effects of COVID-19 on artists and underlying mechanisms.

Second, despite the extensive efforts to explore underlying mechanisms, there still exists a gap toward a more comprehensive understanding of all potential drivers of this phenomenon. Hence, future studies should be directed toward exploring additional factors affecting music consumption during the pandemic. For instance, fewer new releases' successes can be attributable to different causes: canceling live events, promotion changes, or shift in the demand side. Future research should investigate why new releases had less success during the pandemic than they did before. Likewise, the impacts of COVID-19 on various public mental health issues, such as high loneliness rates (Groarke et al. 2020), could be examined as potential drivers of the pandemic-induced decline in music streaming.

Third, future research should evaluate the effectiveness of firm interventions to mitigate the decline of music consumption—some of which we have suggested but could not directly examine. For instance, although Spotify's year-to-year revenue continued to decline in the third quarter of 2020, their recent efforts might have regained some listeners. It is also interesting to examine how artists' different actions led to varying outcomes, as some artists might have benefited from the pandemic. Relatedly, our research period is limited to three months from the pandemic declaration. Future research might benefit from investigating how firms should respond to the changes from the gradual rebound in mobility as we slowly recover from the pandemic.

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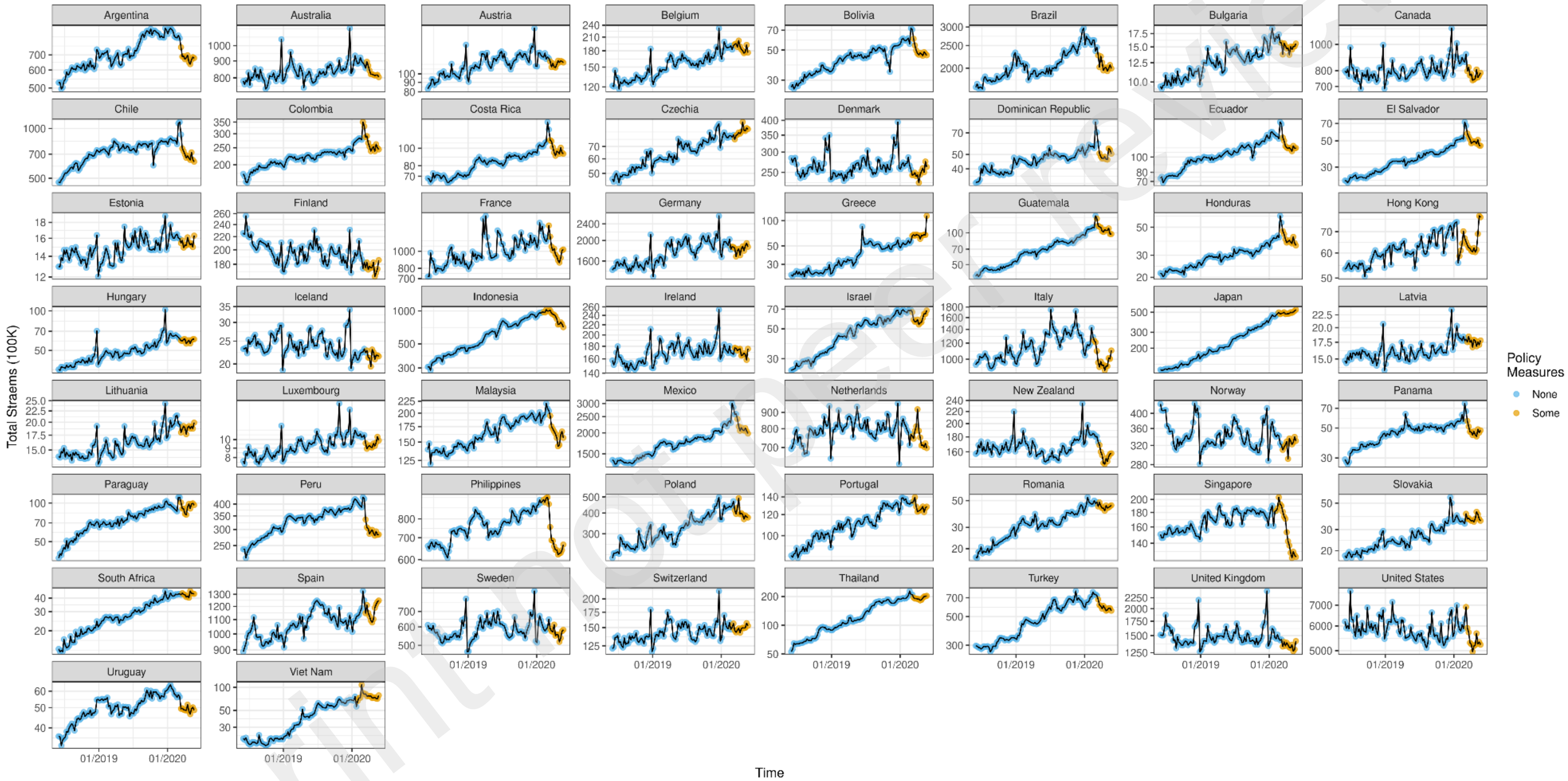
Figures and Tables

Figure 1. Music Streaming Trends by Country



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

Figure 2. Research Period and Econometric Setting

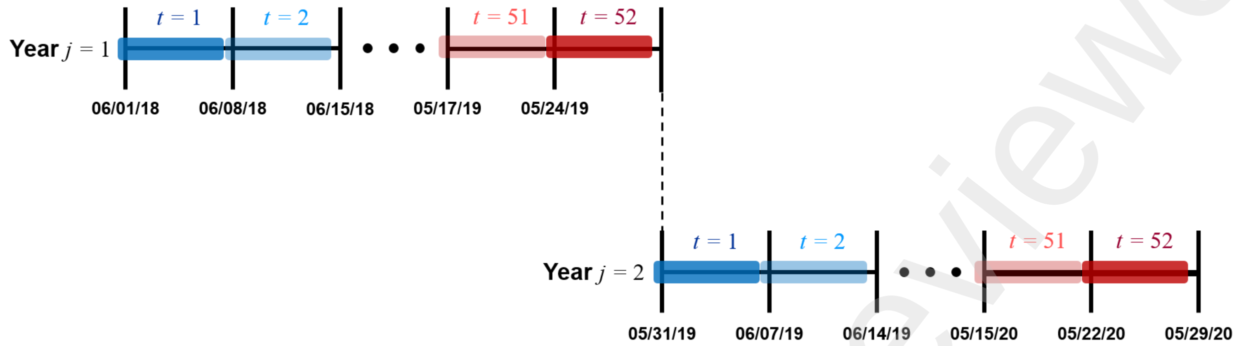


Figure 3. Global Streaming Trends by Research Year

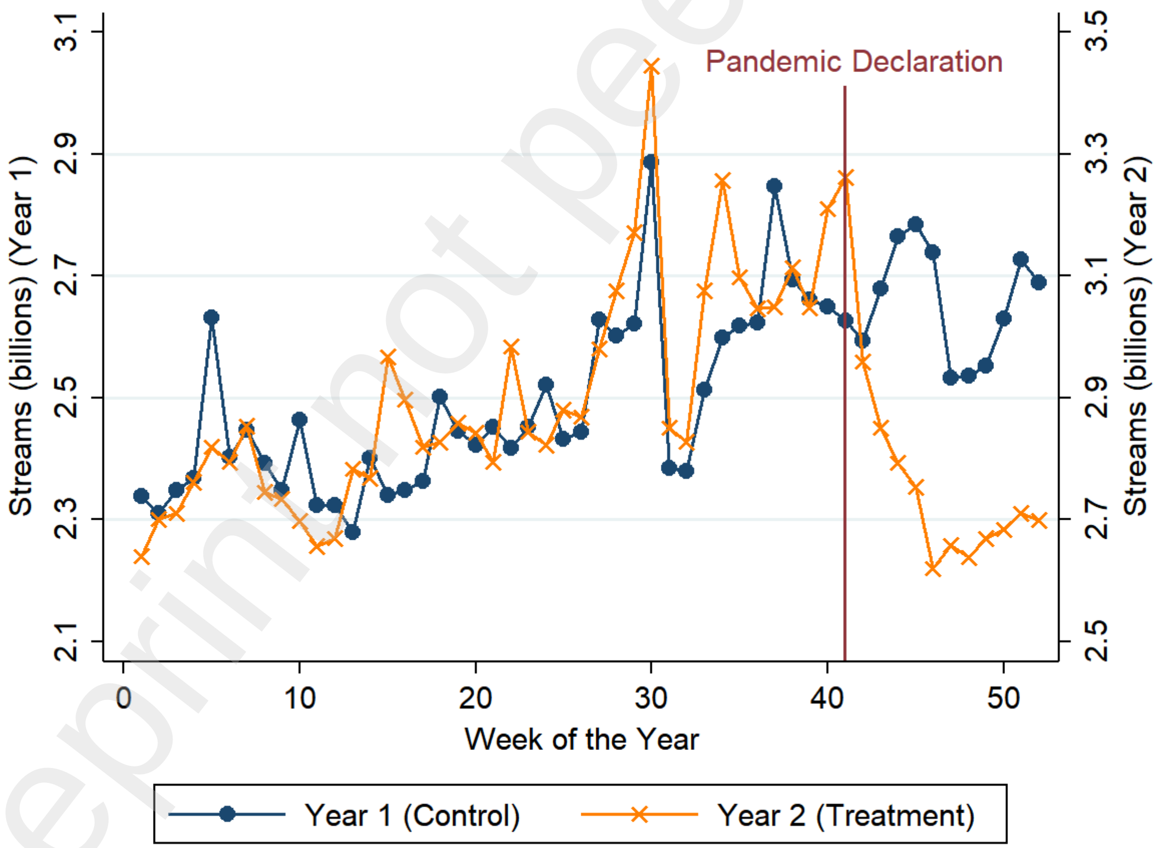
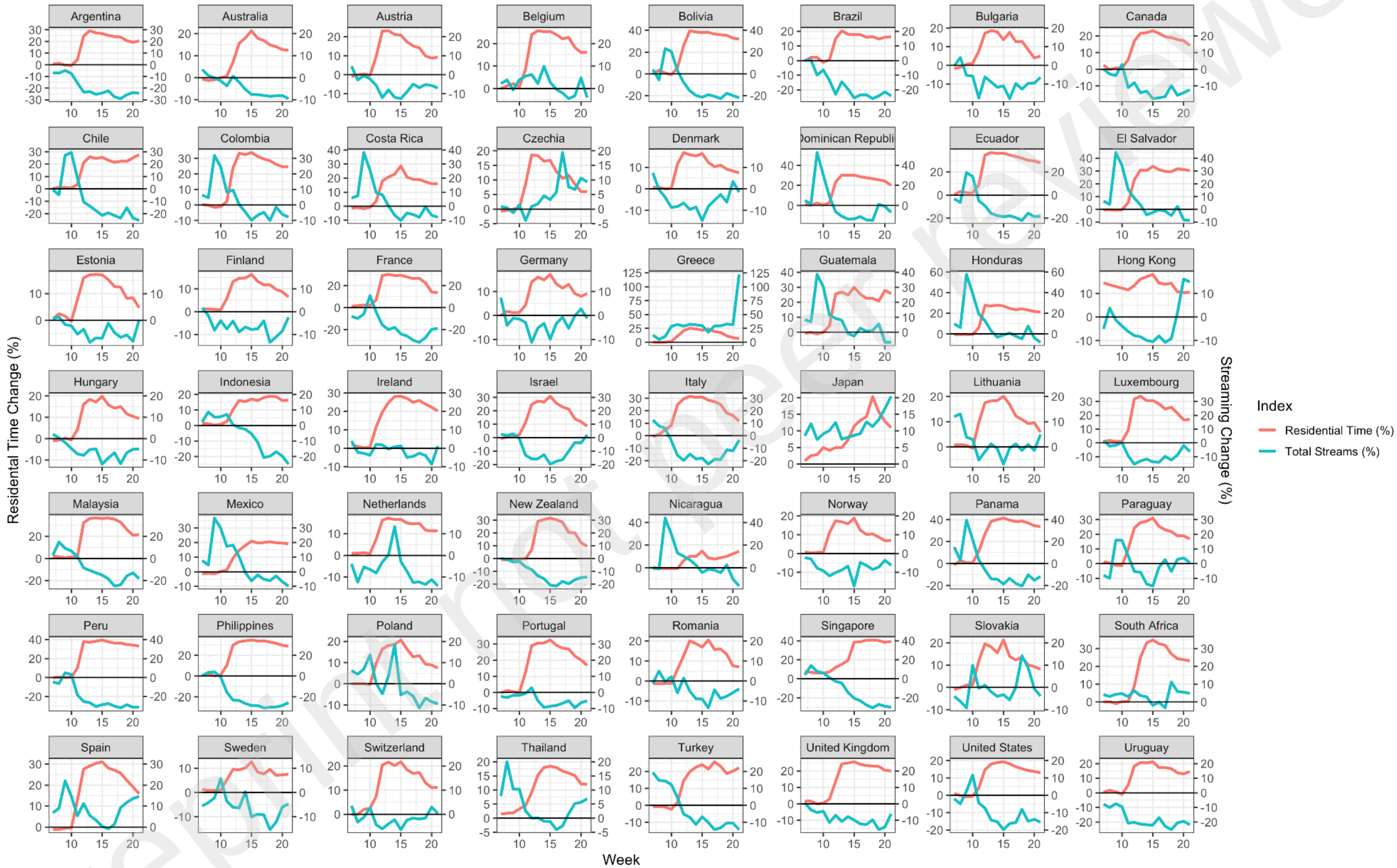


Figure 4. Residential Time and Streaming Change by Country



Notes. Residential time change and streaming change are the ratios of value in the current week to that in the reference period (January 3rd – February 6th, 2020).

Table 1. Variable Description and Summary Statistics

Variables	Description	Obs.	Mean	Std. Dev.	Min.	Max.
Streams	Total streaming counts of weekly top 200 songs	6,240	4.49e+07	8.64e+07	697,435	7.77e+08
Treated	1 if a year is the treated year (i.e., year 2), 0 otherwise (i.e., year 1)	6,240	0.500	0.500	0	1
After	1 if a week of the year is later than March 11, 2019 (March 11, 2020) for the control year (the treated year), and 0 otherwise	6,240	0.231	0.421	0	1
COVID-19 cases	Number of newly confirmed COVID-19 cases (per million people)	6,240	16.34	91.92	0	1,847
COVID-19 deaths	Number of newly confirmed COVID-19 deaths (per million people)	6,240	0.976	6.940	0	169.8

Table 2. Effects of COVID-19 Pandemic Outbreak on Demand for Streaming Music

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

Notes. Standard errors, in parentheses, are robust and clustered at the country level.
*p<0.10; **p<0.05; ***p<0.01.

Table 3. Effects of Government Restrictions on Demand for Streaming Music

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Government Restrictions (Binary)								
Schools	-0.0185							
	(0.0243)							
Workplaces		-0.0624**						
		(0.0243)						
Public Events			-0.0897***					
			(0.0206)					
Private Gatherings				-0.00959				
				(0.0452)				
Public Transport					-0.0709**			
					(0.0300)			
Shelter-in-Place Orders						-0.0795***		
						(0.0248)		
Internal Movement b/w Cities/Regions							-0.0842***	
							(0.0220)	
International Travel								-0.0348**
								(0.0158)
COVID-19 Statistics (per million people)								
Cases (Current Week)	-0.000152**	-0.000140**	-0.000147**	-0.000153**	-0.000153**	-0.000126**	-0.000136**	-0.000158**
	(5.93e-05)	(5.93e-05)	(5.88e-05)	(5.99e-05)	(5.90e-05)	(5.31e-05)	(5.26e-05)	(5.97e-05)
Deaths (Current Week)	0.000430	0.000373	0.000452	0.000437	0.000367	0.000520	0.000234	0.000489
	(0.000951)	(0.000955)	(0.000950)	(0.000949)	(0.000934)	(0.000900)	(0.000903)	(0.000951)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Countries	59	59	59	59	59	59	59	59
Observations	6,136	6,136	6,136	6,136	6,136	6,136	6,136	6,136
Within R-squared	0.950	0.951	0.951	0.950	0.951	0.952	0.952	0.951

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01. In this analysis, Malta was excluded due to a lack of relevant data in the Oxford COVID-19 Government Response Tracker.

Table 4. Time Allocation Changes and Demand for Streaming Music

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)	(6)
Difference in time spent on (%)						
Retail/Recreation	0.00216***					
	(0.000426)					
Grocery/Pharmacy		0.00293***				
		(0.000461)				
Parks			0.00132***			
			(0.000203)			
Transit Stations				0.00299***		
				(0.000509)		
Workplaces					0.00330***	
					(0.000502)	
Residence						-0.00849***
						(0.00114)
Government restrictions controls	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 statistics controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of countries	58	58	58	58	58	58
Observations	870	870	870	870	870	870
Within R-squared	0.522	0.553	0.550	0.543	0.547	0.577

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01. Malta was excluded in this analysis due to a lack of relevant data in the Oxford COVID-19 Government Response Tracker. Iceland was excluded from Google's dataset.

Table 5. Summary of Additional Analyses

Question	Analysis	Result	Location
	Additional Analysis of Mobility and Music Consumption		
Does the complementary nature of audio consumption matter?	• Analysis of video consumption for music in YouTube	• Video-based music consumption increased (decreased) with the severity of COVID-19, lockdown policies, and time spent on outdoor activities (residence).	Table B1 – Table B3
When is the complementarity more influential?	• Analysis of heterogeneous commuting time among European countries	• The decline was more significant in countries with longer commuting time.	Table B4 – Table B5
	• Contingent effects on music streaming and time allocation by day of week	• The effect was more prominent on weekdays than weekends and more consistent with effects on time spent on workplaces and residence than that on transit.	Table B6 – Table B7
Will the decline in music consumption last?	• Analysis of the temporary ease of COVID-19 during April and May 2020	• A rebound in countries with decreasing cases • The reduction in residential time was highly associated with the recovery of streaming volume.	Figure B2 – Figure B3
	Alternative Explanations and Robustness Checks		
Does using a specific functional form drive our results?	• A distribution-free statistical test using empirical reference distributions	• Two-thirds of countries experienced an unprecedented decline after the pandemic.	Figure C2
	• Poisson regressions	• Consistent with main results	Table C2
Do outliers drive our results?	• Subgroup analysis by continent	• The decline was consistent across continents.	Table C1
	• Subgroup analysis by rank position	• The decline was consistent across rank positions.	Table C3
Is the parallel pre-trend assumption violated?	• Estimating the relative time model with leads and lags of the treatment	• Streaming differences are mostly indistinguishable across weeks-of-year before the pandemic declaration.	Figure C3
Are Spotify-specific unobservables responsible for the findings?	• Estimating a model with the number of confirmed cases and deaths and common time fixed effects	• 1,000 COVID-19 cases per million in each week were associated with a 14.4% decline in streaming consumption	Table C4
	• Analysis of Spotify's updates	• No distinct updates after the pandemic declaration	Table C9
	• Analysis of the Korean market	• Music streaming decreased in the absence of Spotify.	Table C15
Does demand shift from superstars to underdogs explain the results?	• Follower trends of 1.5K playlists (top 500 for each provider type) in Spotify	• Significant deceleration of the number of followers after the pandemic and no evidence of demand shift	Table C15 – Table C16
Is the supply-side effect responsible for the decline?	• Analysis of music releases of recently successful artists in Spotify	• No evidence that popular artists reduced new music releases significantly	Table C18
Is the decline attributable to the promotion of new releases?	• Analysis of chart entrance and rank positions of newly-released songs	• Fewer newly-released songs appeared on the top 200 charts, and their rank positions were lower. • This effect was more prominent among superstars.	Table C19 – Table C20

Online Appendix A. Details of Data and Analysis

A1. List of Countries

Table A1. List of Countries Examined in This Study

Continents	Countries
Asia	Hong Kong, Indonesia, Israel, Japan, Malaysia, Philippines, Singapore, Thailand, Turkey, Vietnam
Europe	Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland^, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta+, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Switzerland, United Kingdom
North America	Canada, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, United States
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay
Oceania	Australia, New Zealand
Africa	South Africa

Notes. +Malta was excluded in the analysis of government restrictions due to lack of relevant data in the Oxford Covid-19 Government Response Tracker. ^Iceland was excluded in Google's COVID-19 Community Mobility Reports.

A2. Details of Government Restrictions and Mobility Data

Lockdown Measurements

The Oxford COVID-19 Government Response Tracker (Petherick et al. 2020) provides country-day-level data on eight types of containment and closure policies: the closings of schools and universities, closing of workplaces, cancellation of public events, limits on private gatherings, closing of public transport, shelter-in-place orders, restrictions on internal movement between cities and regions, and restrictions on international travel. 59 out of 60 countries in the Spotify dataset are matched to the lockdown enforcement data (Malta are not matched). The measurements are described in **Table A2**, their summary statistics are reported in **Table A3**, and their correlation matrix is reported in **Table A4**. Although policies may be highly correlated with each other, there exists a considerable variation among countries. For instance, a substantial number of countries did not enforce restrictions on public transport, shelter-in-place, and internal movement even after the pandemic declaration, and many countries released these restrictions over time.

Mobility Changes

Google's COVID-19 Community Mobility Reports (Google LLC 2020) provides information on daily percentage changes in the number of visits by place category compared with the corresponding day of the week during the 5-week period between January 3 and February 6 in 2020. The data cover six categories of place, such as retail & recreation, grocery & pharmacy, parks, transit stations, workplaces, and residence. The data began on February 15, 2020, and therefore, the number of country-week observations is 855 for 57 countries. The summary statistics of time allocation changes are reported in **Table A5**, and the correlation matrix of these variables is shown in **Table A6**.

Table A2. Definition of Government Restrictions

Restriction Type	Description	Ordinal Code	Binary Variable
Schools	Record closings of schools and universities	0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, e.g., just high school, or just public schools) 3 - require closing all levels	1 if ordinal code >= 2; 0 otherwise
Workplaces	Record closings of workplaces	0 - no measures 1 - recommend closing (or recommend work from home) 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (e.g., grocery stores, doctors)	1 if ordinal code >= 2; 0 otherwise
Public Events	Record cancelling public events	0 - no measures 1 - recommend cancelling 2 - require cancelling	1 if ordinal code >= 2; 0 otherwise
Private Gatherings	Record limits on private gatherings	0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less	1 if ordinal code >= 1; 0 otherwise
Public Transport	Record closing of public transport	0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it)	1 if ordinal code >= 2; 0 otherwise

Table A2. Definition of Government Restrictions (Continued)

Shelter-in-Place Orders	Record orders to "shelter-in-place" and otherwise confined to the home	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc.)	1 if ordinal code >= 2; 0 otherwise
Movement b/w Cities/Regions	Record restrictions on internal movement between cities/regions	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place	1 if ordinal code >= 2; 0 otherwise
International Travel	Record restrictions on international travel Note: this records policy for foreign travelers, not citizens	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure	1 if ordinal code >= 2; 0 otherwise

Notes. Details are available at Codebook for the Oxford Covid-19 Government Response Tracker (retrieved from https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md, accessed on November 22, 2020). We define binary variables as 1 if a government enforces a restriction, and 0 otherwise.

Table A3. Summary Statistics of Government Restrictions

Mean (1: Yes; 0: No)	Sample Period (N)		
Government restrictions	All Period (N=6,316)	Before Pandemic (N=5,428)	After Pandemic (N=708)
Schools	0.109	0.005	0.910
Workplaces	0.093	0.001	0.795
Public Events	0.107	0.003	0.904
Private Gatherings	0.100	0.001	0.862
Public Transport	0.023	0.000	0.196
Shelter-in-Place Orders	0.060	0.000	0.517
Movement b/w Cities/Regions	0.070	0.001	0.600
International Travel	0.122	0.020	0.911

Table A4. Correlation Matrix of Government Restrictions (N=6,136)

Government restrictions	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Schools	–						
(2) Workplaces	0.8933	–					
(3) Public Events	0.9342	0.8934	–				
(4) Private Gatherings	0.8994	0.9018	0.9262	–			
(5) Public Transport	0.4348	0.4715	0.4393	0.4379	–		
(6) Shelter-in-Place Orders	0.7193	0.7555	0.7288	0.7271	0.5197	–	
(7) Movement b/w Cities/Regions	0.7748	0.7944	0.7869	0.7662	0.5410	0.8008	–
(8) International Travel	0.8705	0.8167	0.8573	0.8308	0.4043	0.6429	0.7010

Table A5. Summary Statistics of Time Allocation Changes (N=885)

Place time spent on (difference %)	Mean	Std. Dev.	Min.	Max.
Retail/Recreation	-39.16	29.74	-91.29	12.57
Grocery/Pharmacy	-16.67	20.70	-77.14	26.57
Parks	-14.79	39.89	-92.57	135.9
Transit Stations	-40.10	28.33	-86.71	10.43
Workplaces	-30.78	24.83	-78.57	16.71
Residence	14.53	11.19	-2.286	41.57

Table A6. Correlation Matrix of Time Allocation Changes (N=885)

Place time spent on (difference %)		(1)	(2)	(3)	(4)	(5)
(1)	Retail/Recreation	–				
(2)	Grocery/Pharmacy	0.8671	–			
(3)	Parks	0.6178	0.6960	–		
(4)	Transit Stations	0.9585	0.8541	0.5604	–	
(5)	Workplaces	0.9411	0.8421	0.4754	0.9509	–
(6)	Residence	-0.9441	-0.8886	-0.6547	-0.9490	-0.9455

Online Appendix B. Additional Analysis of Mobility and Music Consumption

B1. Music Consumption in YouTube

We show that music consumption through audio streaming services has significantly declined since the COVID-19 outbreak. However, it is still not clear whether the decline was attributable to the complementarity nature of music. To further investigate the mechanism, we examine how video-based music consumption, which requires attention and far less complementary to other activities like driving, is affected by the outbreak.

To answer this question, we obtain YouTube music streaming data via Soundchart's API. We query all artists who appeared on Spotify's weekly charts during our research period, which allow us to have 1,008 artists in total. We collect those artists' monthly view counts on YouTube and the viewers' country-level geographic data from July 2018 to October 2020.[7] This enables

[7] Soundcharts tracked YouTube view counts each week and calculated monthly views on a rolling monthly basis. In our bootstrap-based test, we utilize the entire dataset for sufficient power of analysis. In the econometric analysis, we only use the last-observed rolling monthly views each month and discard data observed on days earlier than the 24th of each month.

us to examine the heterogeneity of change in streaming demand across countries.

Given that the possibility that artist-specific demand shocks could contribute to such abnormal increases in YouTube view counts, such as releases of new albums or social media activities, the artist-level data is unlikely to satisfy the parallel pre-trend assumption. Therefore, we focus on between-countries and within-artists variations by employing econometric models with extensive fixed effects. First, we estimate the relationship between the severity of COVID-19 and YouTube views across countries by estimating the following equation:

$$\ln\left(Streams_{ijkt}\right) = \sum_i \sum_k \alpha_i \cdot \phi_k + \theta_1 \cdot Cases_{ijt} + \theta_2 \cdot Deaths_{ijt} + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \sum_k \sum_j \sum_t \phi_k \cdot \gamma_j \cdot \delta_t + \varepsilon_{ijkt}, \qquad \text{(B1)}$$

where *i* indexes countries; *j* indexes the two-year period; *k* indexes artists; *t* indexes the week of the year; ϕ_k denotes a set of artist dummy variables; ε_{ijkt} is an error term clustered at the artist-country level; and other variables are identically defined as Equation (3). In this specification, $\sum_i \sum_k \alpha_i \cdot \phi_k$ picks up artist-country-specific fixed effects, controlling for country-specific popularity of each artist. $\sum_i \sum_j \alpha_i \cdot \gamma_j$ and $\sum_i \sum_t \alpha_i \cdot \delta_t$ control for country-specific growth and seasonality, respectively. $\sum_k \sum_j \sum_t \phi_k \cdot \gamma_j \cdot \delta_t$ captures artist-month-year fixed effects, allowing us to control for any artists- and YouTube-specific demand shocks.

To investigate how lockdown restrictions and mobility affected video consumption for music listening, we estimated the following equations:

$$\ln\left(Streams_{ijkt}\right) = \sum_i \sum_k \alpha_i \cdot \phi_k + \tau \cdot Restriction_{ijt} + \theta_1 \cdot Cases_{ijt} + \theta_2 \cdot Deaths_{ijt} + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \sum_k \sum_j \sum_t \phi_k \cdot \gamma_j \cdot \delta_t + \varepsilon_{ijkt}, \qquad \text{(B2)}$$

$$\ln(Streams_{ikt}) = \sum_i \sum_k \alpha_i \cdot \phi_k + \pi \cdot \Delta Time_{it} + \tau \cdot Restriction_{it} + \theta_1 \cdot Cases_{it} + \theta_2 \cdot Deaths_{it} + \sum_k \sum_t \phi_k \cdot \delta_t + \varepsilon_{ikt}, \qquad \text{(B3)}$$

where $Restriction_{ijt}$ indicates 1 if country *i* enforced a lockdown policy in year *j* and week of the year *t*; $\Delta Time_{ijt}$ indicates the percentage changes in time allocation to a specific place category compared with those of the reference period; other variables are equivalent to those defined in Equation B1. Note that we do not include the index of the two-year period *j* because Google's mobility data began in February 2020.

Table B1 reports the estimates of Equation B1, suggesting that the increase in YouTube demand was more prominent in countries with a larger number of COVID-19 cases. In **Table B2**, we find that video-based music streaming is positively associated with the implementation of lockdown policies. Lastly, we present the estimates of Equation B3 in **Table B3** and find that time spent on outdoor activities (e.g., grocery/pharmacy, parks, and transit stations) were negatively related to music consumption on YouTube. In contrast, residential time had a positive relationship with YouTube music streaming. Specifically, a 10% increase in residential time accompanied a 5.3% increase in demand for video-based music streaming. These results confirm our argument that the decreased music streaming was attributable to the audio-based consumption form.

Table B1. COVID-19 Statistics and Demand for Video-streamed Music

DV = ln(YouTube Streams)	(1)	(2)	(3)
COVID-19 Statistics (Current Week)			
Cases (per million people)	9.95e-06***		6.40e-06**
	(2.33e-06)		(3.04e-06)
Deaths (per million people)		0.000146***	8.66e-05**
		(3.19e-05)	(4.17e-05)
Artist-country FE	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes
Country-specific month-of-the-year FE	Yes	Yes	Yes
Common month FE	Yes	Yes	Yes
No. of Artists	1,008	1,008	1,008
No. of countries	57	57	57
Observations	778,941	778,941	778,941

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01.

Table B2. Effects of Government Restrictions on Demand for Video-streamed Music

DV = ln(YouTube Streams)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Government Restrictions (Binary)								
Schools	0.0449***							
	(0.00322)							
Workplaces		0.0229***						
		(0.00327)						
Public Events			0.0607***					
			(0.00335)					
Private Gatherings				0.0169***				
				(0.00535)				
Public Transport					0.0166***			
					(0.00449)			
Shelter-in-Place Orders						0.0270***		
						(0.00320)		
Internal Movement b/w Cities/Regions							0.0409***	
							(0.00280)	
International Travel								-0.00563
								(0.00410)
COVID-19 Statistics (per million people)								
Cases (Current Week)	7.48e-07**	4.56e-07	1.04e-06***	8.30e-07**	8.07e-07**	8.42e-07**	3.00e-07	9.21e-07**
	(3.66e-07)	(3.71e-07)	(3.65e-07)	(3.65e-07)	(3.65e-07)	(3.65e-07)	(3.67e-07)	(3.65e-07)
Deaths (Current Week)	0.000191***	0.000241***	0.000210***	0.000244***	0.000241***	0.000206***	0.000219***	0.000247***
	(1.57e-05)	(1.58e-05)	(1.58e-05)	(1.59e-05)	(1.57e-05)	(1.60e-05)	(1.58e-05)	(1.58e-05)
Artist-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-month-of-the-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Artist-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Artists	1,007	1,007	1,007	1,007	1,007	1,007	1,007	1,007
No. of Countries	57	57	57	57	57	57	57	57
Observations	956,591	956,591	956,591	956,591	956,591	956,591	956,591	956,591

Notes. Standard errors, in parentheses, are robust and clustered at the artist-country level. *p<0.10; **p<0.05; ***p<0.01.

Table B3. Time Allocation Changes and Demand for Video-streamed Music

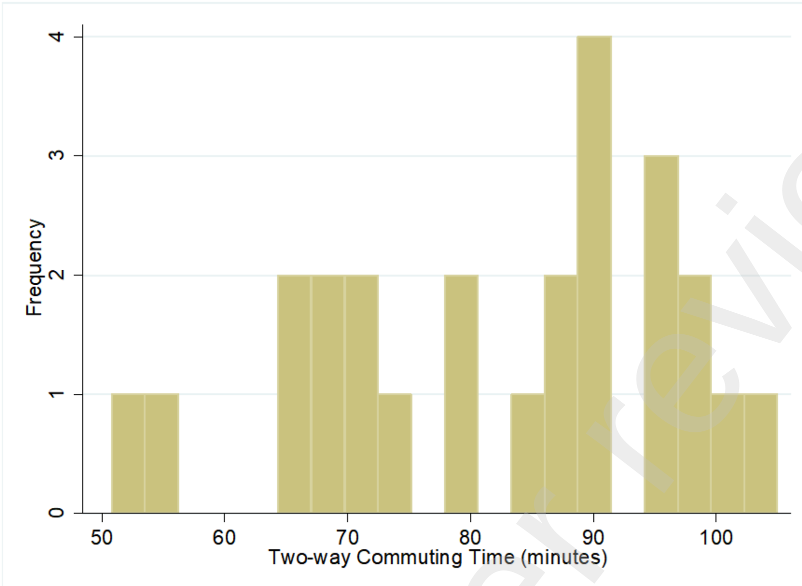
DV = ln(YouTube Streams)	(1)	(2)	(3)	(4)	(5)	(6)
Difference in time spent on (%)						
Retail/Recreation	-0.00211***					
	(8.29e-05)					
Grocery/Pharmacy		-0.00124***				
		(9.39e-05)				
Parks			-0.00065***			
			(2.34e-05)			
Transit Stations				-0.00223***		
				(8.97e-05)		
Workplaces					-0.00073***	
					(9.95e-05)	
Residence						0.00517***
						(0.000207)
Government restrictions controls	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 statistics controls	Yes	Yes	Yes	Yes	Yes	Yes
Artist-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Artist-month FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of artists	1,002	1,002	1,002	1,002	1,002	1,002
No. of countries	56	56	56	56	56	56
Observations	360,522	360,522	360,522	360,522	360,522	360,522
R-squared	0.988	0.988	0.988	0.988	0.988	0.988

Notes. Standard errors are robust and clustered at the artist-country level. *p < 0.10; **p < 0.05; ***p < 0.01. The panel is unbalanced, and 6 artists not observed in 2020 are dropped in this analysis.

B2. Heterogeneity by Commuting

To analyze how the effects of COVID-19 varied depending on commuting time, we use a data set on commuting time in European countries (Eurostat 2019, Giménez-Nadal 2020). This data set has been updated in a five-year interval, and the most recent data were measured in 2015. Therefore, this is more reliable than other data sources such as OECD Family Database, wherein commuting time was measured in different years across countries and outdated by ten or more years (OECD 2016). In each year, European residents between 15 and 65 years of age were asked a question of “In total, how many minutes per day do you usually spend traveling from home to work and back?” and the distribution of average commuting time in our sample is illustrated in **Figure B1**.

Figure B1. Distribution of Commuting Time among European Countries



To formally assess how commuting time moderated the influences of COVID-19, we estimated the following regression model:

$$\ln\left(Streams_{ijt}\right) = \alpha_i + \beta_1 \cdot Treated_j \cdot After_t + \beta_2 \cdot Treated_j \cdot After_t \cdot Z_i + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt}, \qquad \text{(B4)}$$

where Z_i is a set of indicators denoting the relative level of commuting time in country i, and other variables are identically defined as Equation (2).

We first divide countries into two groups based on the median level of commuting time in our sample countries and reported the estimates in **Table B4**. We observe that the estimated effect was larger for countries with longer commuting time (-10.2%) than those with shorter commuting time (-8.2%). The interaction term in Column (3) was statistically insignificant, possibly because average commuting time was operationalized as static within each country. We also divide the countries based on the quartiles of commuting time and estimated Equation E1 (**Table B5**). We find that the decline in streaming was significant only among countries with relatively long commuting time.

Table B4. COVID-19 Outbreak and Music Streaming by Commuting Time

DV = ln(Streams)	(1)	(2)	(3)
Commuting Time	Below Median	Above Median	All
Treated x After	-0.0859**	-0.108***	-0.0859**
	(0.0349)	(0.0295)	(0.0341)
Treated x After x Above Median			-0.0225
			(0.0447)
Country FE	Yes	Yes	Yes
Week-of-the-year FE	Absorbed	Absorbed	Absorbed
Country-specific growth FE	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes
No. of Countries	12	13	25
Observations	1,248	1,352	2,600

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01.

Table B5. COVID-19 Outbreak and Music Streaming by Commuting Time: Quartiles

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)
Commuting Time	Q1 (Bottom)	Q2	Q3	Q4 (Top)	All
Treated x After	-0.0787	-0.0930*	-0.140*	-0.0815**	-0.0787
	(0.0621)	(0.0383)	(0.0567)	(0.0260)	(0.0579)
Treated x After x Q2					-0.0143
					(0.0680)
Treated x After x Q3					-0.0609
					(0.0784)
Treated x After x Q4					-0.00279
					(0.0629)
Country FE	Yes	Yes	Yes	Yes	Yes
Week-of-the-year FE	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes
Country-specific w-of-the-year FE	Yes	Yes	Yes	Yes	Yes
No. of Countries	6	6	6	7	25
Observations	624	624	624	728	2,600

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01.

B3. Heterogeneity by Day of Week

Given that commuting is mostly concentrated on weekdays compared to weekends, the effects of COVID-19 on music consumption could be highly contingent across days of the week. To explore this possibility, we analyze daily top 200 streaming data of Spotify using the following model:

$$\ln(Streams_{ijkt}) = \alpha_i + R_k + D_t + \beta_1 \cdot Treated_j \cdot After_t + \beta_2 \cdot Treated_j \cdot After_t \cdot D_t + + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt}, \qquad \text{(B5)}$$

where *i* indexes countries; *j* indexes the two-year period; *k* indexes rank positions within each chart; *t* indexes the week of the year; R_k is a set of rank fixed effects; D_t is a set of day-of-the-week indicators on day *t*; other variables are identically defined as Equation (2). Note that we do not aggregate streams of all songs at the country-day level because Spotify charts have systematically omitted songs consumed less than 1,000 times. Thus, unlike the weekly dataset, numerous observations ranked higher than or equal to the top 200th position were systematically missed. For this reason, we instead maintain the country-rank-day level of data and controlled rank fixed effects.

The estimates of Equation B5 are reported in **Table B6**. According to the estimates in Column (4), music streaming decreased more significantly on weekdays (-13.0%) than weekends (-11.7%). In Column (5), we observed that the effect was significantly larger on Friday (-13.9%) when people have stayed home, particularly less before the pandemic, and smaller on Sunday (-10.6%) when people have stayed home longer than other days. These results provide suggestive evidence that reduced mobility is closely associated with the decline in streaming consumption.[8]

To understand the mechanism more deeply, we investigate which mobility types explain this heterogeneity better by utilizing Google's COVID-19 Community Mobility Reports (Google LLC 2020). The data report daily percentage changes in the number of visits by place category such as transit stations, workplaces, and residential. Using this information, we assess how the changes in time allocation varied across days of the week and compare the results with the heterogeneous effects on music consumption.

[8] The insignificant interaction on Saturday might be attributable to 1) a relatively small effect on Monday than Tuesday and Friday, and 2) more active mobility on Saturday compared to Sunday.

Table B6. Effects of COVID-19 Pandemic Outbreak on Streaming Music by Day of Week

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)
Sample	All days	Weekdays	Weekends	All days	All days
Treated x After	-0.135***	-0.137***	-0.129***	-0.139***	-0.138***
	(0.0151)	(0.0151)	(0.0159)	(0.0152)	(0.0149)
Treated x After x Weekends				0.0144***	
				(0.00449)	
Treated x After x Tuesday					-0.00665**
					(0.00287)
Treated x After x Wednesday					0.00976***
					(0.00352)
Treated x After x Thursday					0.00608
					(0.00439)
Treated x After x Friday					-0.0118**
					(0.00492)
Treated x After x Saturday					0.00259
					(0.00662)
Treated x After x Sunday					0.0257***
					(0.00523)
Rank FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Week-of-the-year FE	Yes	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes	Yes
No. of Countries	60	60	60	60	60
Observations	7,728,775	5,540,232	2,188,543	7,728,775	7,728,775

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01.

To quantify the differences, we estimate the following regression model:

$$\Delta Time_{it} = \alpha_i + D_t + \beta_1 \cdot After_t + \beta_2 \cdot After_t \cdot D_t + \varepsilon_{it}, \qquad \text{(D6)}$$

where $\Delta Time_{it}$ is the percentage change of time allocation for each place category, and other variables are identically defined as Equation D5. Since Google's data began in February 2020, we do not include country-specific growth and seasonality controls.

Table B7 presents the results. As expected, time spent on transit stations and workplaces (residence) substantially decreased (increased) after the COVID-19 outbreak. Notably, the effect on transit stations was amplified on weekends, while the effects on workplaces and residences were attenuated on weekends. For workplaces and residences, the effects were amplified (reduced) on Friday (Saturday and Sunday), in concert with music streaming demand. These results imply that streaming changes are more consistent with the changes in time spent on workplaces and residences than general transportation, indicating that reduced commuting seems to explain a significant portion of the COVID-19 impact on music streaming demand.

Table B7. Effects of COVID-19 Pandemic Outbreak on Time Allocation by Day of Week

DV = Differences in Time Allocation (%)	(1) Transit	(2) Workplaces	(3) Residence	(4) Transit	(5) Workplaces	(6) Residence
After	-51.29***	-45.33***	19.37***	-52.11***	-44.96***	19.15***
	(1.881)	(1.824)	(0.964)	(1.908)	(2.019)	(0.956)
After x Weekends	-3.311***	12.24***	-4.649***			
	(0.707)	(1.055)	(0.380)			
After x Tuesday				0.808*	0.165	-0.227
				(0.425)	(0.792)	(0.195)
After x Wednesday				3.355***	1.713*	-0.808***
				(0.580)	(1.023)	(0.240)
After x Thursday				2.059***	0.124	-0.221
				(0.517)	(1.002)	(0.225)
After x Friday				-2.000***	-4.140***	2.561***
				(0.506)	(0.932)	(0.261)
After x Saturday				-1.021	10.44***	-3.302***
				(0.850)	(1.443)	(0.454)
After x Sunday				-3.968***	13.30***	-5.560***
				(0.859)	(1.561)	(0.461)
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Countries	57	57	57	57	57	57
Observations	5,918	5,918	5,918	5,918	5,918	5,918

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01. Three countries are excluded in the Google's dataset.

B4. Will the Decline in Music Consumption Last?

If the reduction in streaming were transient, we would observe a recovery in demand in countries where individuals' movement restricted by COVID-19 was relatively quickly normalized. To explore this possibility, we divide the 12-week-long post-pandemic declaration period in our dataset into two windows: The first half consisting of the first six weeks and the second half of the remaining six weeks. Then, we calculate the ratios of the number of COVID-19 cases and streaming volume in the first half to those in the second half. Using these ratios, we plot the differences between the two windows in **Figure B2**. We observe a clear negative relationship between COVID-19 cases and the streaming volume. Likewise, we calculate the ratios of residential time and streaming volume in the first half to those in the second half and plot these outcomes in **Figure B3**. Notably, we observe that streaming demand began to rebound in countries with an increase in movement.

Figure B2. COVID-19 Contagion Trend and Streaming Change by Country

Notes. The first half indicates the first six weeks during the post-pandemic period, while the second half indicates the last six weeks in that period.

Figure B3. Residential Time Trend and Streaming Change by Country

Notes. The first half indicates the first six weeks during the post-pandemic period, while the second half indicates the last six weeks in that period.

Online Appendix C. Alternative Explanations and Robustness Checks

C1. Distribution-free Statistical Analysis

Our distribution-free analysis is based on simple A/B testing using empirical reference distributions (Box et al. 2005, pp. 68-71). Given a series of observations, this analysis examines how often differences at least as great as the difference during the treatment period had occurred in the past. Suppose that a researcher obtained 190 pre-treatment and 10 post-treatment observations. The first pre-treatment difference is obtained by subtracting the average calculated from batches 1 to 10 from the average of batches 11 to 20. This calculation is repeated using the average of batches 2 to 11 and that of batches 12 to 21 and so on. In this way, the researcher will obtain 180 pre-treatment moving differences of successive groups of 10 observations. The difference during the treatment period is calculated by subtracting the average of batches 181-190 from that of batches 191 to 200. If the post-treatment difference was -1,200 and 3 of 180 pre-treatment differences were numerically smaller (negative and larger absolute value), the probability that the decline as great as the difference during the treatment would be 3/180 = 0.017. In other words, in relation to this reference set, the observed difference was statistically significant at the 0.017 level of probability.

In our context, we determined how often a drop as great as that we observed from COVID-19 had occurred in the past. To do so, we calculated a moving difference across averages of two subsequent groups with a size of the number of weeks since a government restriction and compared past differences with the latest one.[9] We provide a hypothetical example wherein we obtained 190 pre-lockdown 10 weeks of post-lockdown observations (**Figure C1**). As described above, the reference distribution consists of 180 pre-treatment moving differences (from Δ_1 to Δ_{180}). The post-COVID streaming difference is calculated by subtracting the average of weeks 181 to 190 from that of weeks 191 and 200 (Δ_{181}). Then, the *p*-value of the A/B testing is calculated by the following formula:

[9] The government restriction indicates whether one of the restrictions on schools, workplaces, public events, private gatherings, public transport, shelter-in-place orders, and internal movement between cities and regions was enforced or not. We did not include a restriction on international travels as it began too early and weakly relevant to domestic movements. For countries without restrictions, we considered the moment of the pandemic declaration instead as the treatment.

$$p = \sum_{k=1}^{180} 1(\Delta_k \leq \Delta_{181}) / 180$$

where k indexes the order of moving differences. This can be generalized as:

$$p = \sum_{k=1}^{L-2l} 1(\Delta_k \leq \Delta_{L-2l+1}) / (L - 2l)$$

where L is the length of the whole research period, and l is the length of the treatment period. To ensure sufficient statistical power, we used all available Spotify charts. Since the entry of Spotify varied across countries, L also varies across countries. Similarly, countries have different lengths of l as they adopted lockdown policies in different weeks.

In **Figure C2**, the red vertical line indicates the change we saw during the lockdown restrictions, whereas the histogram shows the reference distribution or past changes. We can say that the countries with the red vertical line placed on the far left saw significant declines. This model-free test suggests that the decline was more severe than 95% of past observed changes in 34 among 58 countries and more so than 90% of past changes in 40 countries, analogous to the p-value less than 0.05 and 0.1 in typical statistical tests, respectively.

Figure C1. Example of Moving Differences
(Entire Period = 200 weeks, Post-lockdown Period = 10 weeks)

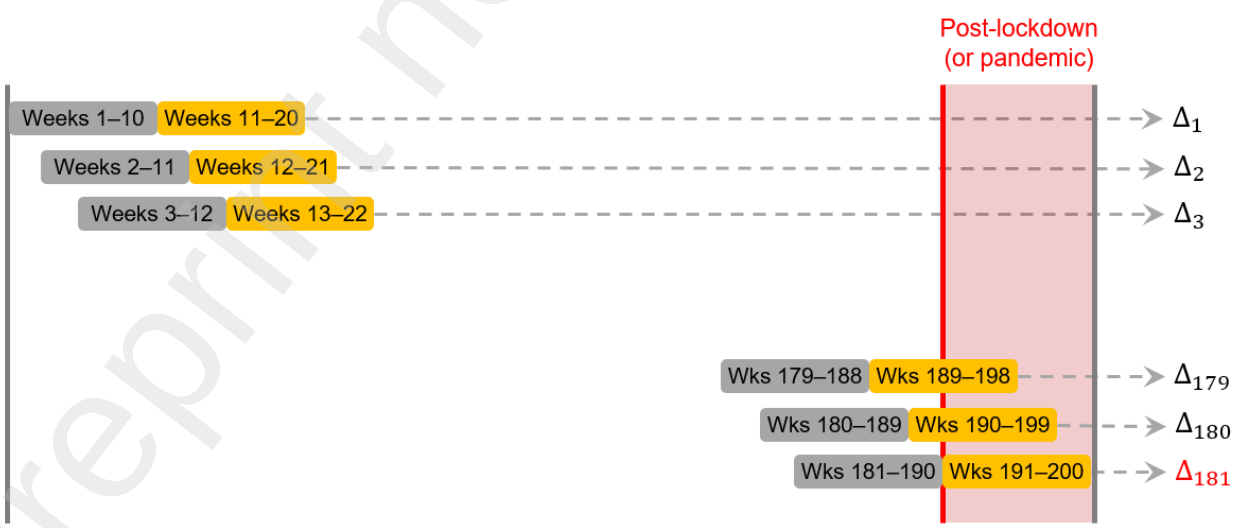
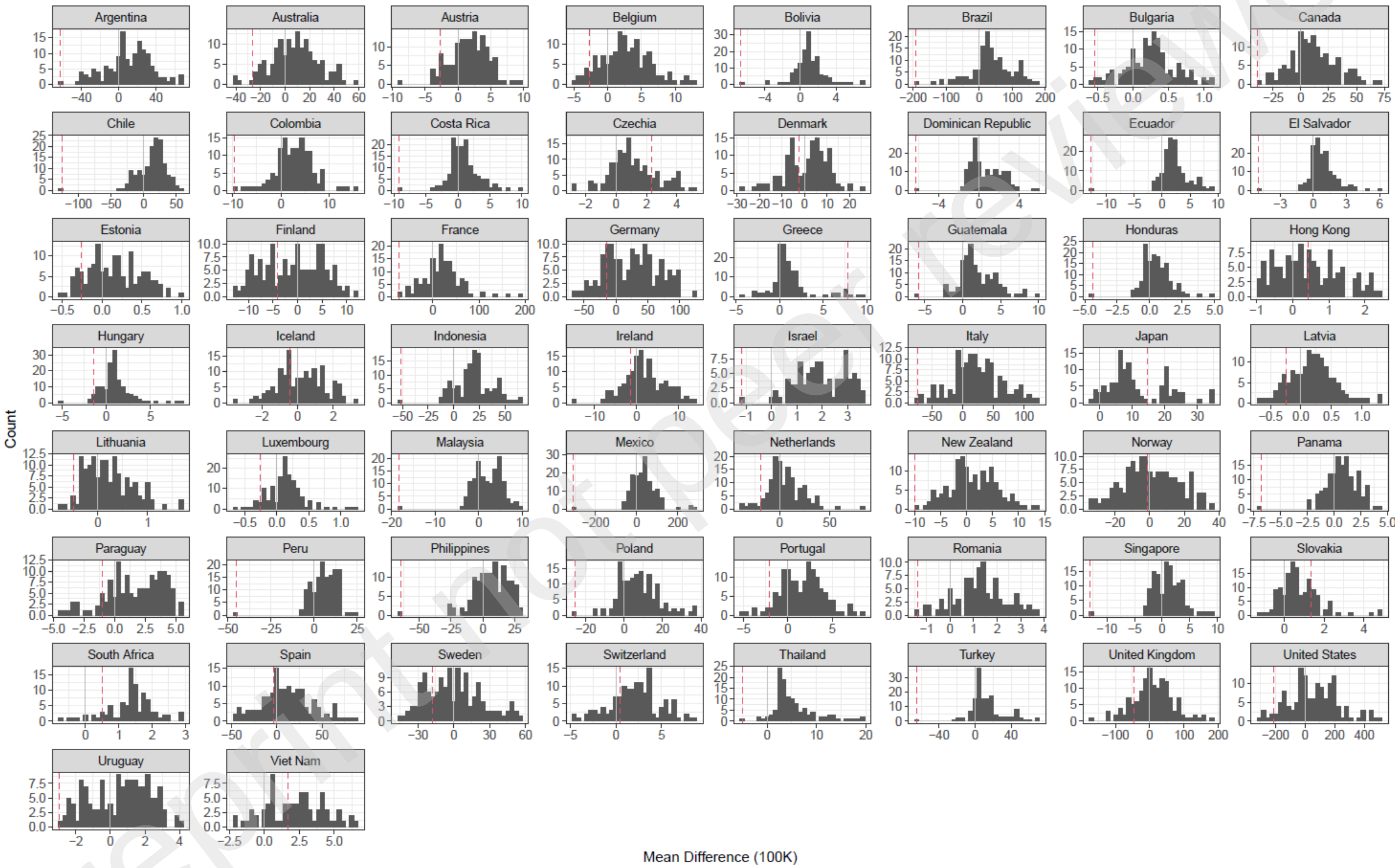


Figure C2. Assumption-free Testing of Music Consumption by Country



Notes. The red vertical line indicates the change in streams, and the gray vertical line indicates zero on the x-axis.

C2. Sensitivity Tests for Regression Estimates

To check whether the small number of abnormal countries drove our findings, we divide the sample countries by continent and re-estimate our main specification. The results in **Table C1** show that the decline after the pandemic declaration was statistically significant across all of the four continents (Asia, Europe, North America, and South America), while the magnitudes were heterogeneous.

To investigate the sensitivity to model selection, we adopt the following approaches. First, we estimate a Poisson regression model to account for the functional form of streaming volume. The results in **Table C2** indicate that the use of a count variable yielded similar results. Second, and importantly, using aggregated streaming counts imposes higher weights on popular songs. Although it is not unreasonable, one may wonder about unweighted impacts on songs, as they inform about whether the majority of songs experienced a decline in streaming, whereas the aggregated estimate provides insights on the market size. To do this, we estimate the following specification:

$$\ln\left(Streams_{ijkt}\right) = \alpha_i + R_k + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \varepsilon_{ijt}, \quad \text{(C1)}$$

where *k* indexes rank on chart *ijt*; R_k is a set of rank fixed effects; other variables are identically defined as Equation (1). This specification treats each rank position with equal weight, allowing researchers to observe unweighted impacts.

The results reported in **Table C3** show that the country-rank level estimate is negative and statistically significant, showing that the vast majority of songs in the top 100 charts experienced a substantial drop in demand (Column 1). Besides, we find that the top 10 tracks experienced the largest drop in demand; however, the other ranges also presented a 10% or more demand drop as well, suggesting that our findings were unlikely to be driven by selecting specific ranges of songs.

Table C1. Effects of Pandemic on Demand for Streaming Music by Continent

DV = ln(Streams)	(1)	(2)	(3)	(4)
Continent	Asia	Europe	North America	South America
Treated x After	-0.261***	-0.0947***	-0.0777**	-0.208***
	(0.0475)	(0.0201)	(0.0324)	(0.0368)
Country FE	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes
No. of countries	10	28	10	9
Observations	1,040	2,912	1,040	936

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01. Africa and Oceania are not considered in the subgroup analysis because each continent includes only one or two countries.

Table C2. Poisson Regression with Fixed Effects

DV = Streams	(1)	(2)	(3)
Treated x After	-0.112***	-0.112***	-0.125***
	(0.0346)	(0.0346)	(0.0118)
Country FE	Yes	Yes	Yes
Week-of-the-year FE	No	Yes	Absorbed
Country-specific growth FE	No	No	Yes
Country-specific week-of-the-year FE	No	No	Yes
No. of countries	60	60	60
Observations	6,240	6,240	6,240

Notes. Robust standard errors are in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

Table C3. Country-rank-level Estimates

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)
Rank Positions	All	Top 10	Top 11-50	Top 51-100	Top 101-200
Treated x After	-0.121***	-0.204***	-0.108***	-0.110***	-0.124***
	(0.0144)	(0.0273)	(0.0195)	(0.0150)	(0.0126)
Rank FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
No. of countries	60	60	60	60	60
Observations	1,248,000	62,400	249,600	312,000	624,000

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01.

Table C4. COVID-19 Cases, Deaths, and Demand for Streaming Music

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)
COVID-19 Cases (per million people)					
Current Week	-0.000153**				
	(6.03e-05)				
Current + Last Week		-7.95e-05**			
		(3.32e-05)			
Current + Last 2 Weeks			-5.24e-05**		
			(2.48e-05)		
Current + Last 4 Weeks				-2.86e-05	
				(1.82e-05)	
Cumulative					-1.21e-05
					(1.33e-05)
COVID-19 Deaths (per million people)					
Current Week	0.000339				
	(0.000960)				
Current + Last Week		0.000247			
		(0.000476)			
Current + Last 2 Weeks			0.000189		
			(0.000324)		
Current + Last 4 Weeks				0.000121	
				(0.000208)	
Cumulative					6.52e-05
					(0.000140)
Country FE	Yes	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes	Yes	Yes
No. of countries	60	60	60	60	60
Observations	6,240	6,240	6,240	6,240	6,240
Within R-squared	0.949	0.949	0.949	0.948	0.948

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01.

Although the pandemic declaration is a helpful indicator of the COVID-19 outbreak, it does not reflect heterogeneity in the timing and severity of COVID-19 across countries. Furthermore, one might raise a concern that the decline in streaming might be attributable to a common trend in Spotify demand. We use the number of confirmed cases and deaths to measure the temporal severity of COVID-19 and examine whether and how the decline in streaming demand varied across countries depending on the severity. The estimated model is as:

$$\ln\left(Streams_{ijt}\right) = \alpha_i + \theta_1 \cdot Cases_{ijt} + \theta_2 \cdot Deaths_{ijt} + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \sum_j \sum_t \gamma_j \cdot \delta_t + \varepsilon_{ijt}, \qquad \text{(C2)}$$

where $\gamma_j \cdot \delta_t$ is the product of a period dummy and a week-of-the-year dummy; $Cases_{ijt}$ and $Deaths_{ijt}$ are the number of confirmed COVID-19 cases and deaths per million people in country *i*, period *j*, and week of the year *t*, respectively. $\sum_j \sum_t \gamma_j \cdot \delta_t$ is a set of common time fixed effects that absorb any Spotify-specific demand shock, and consequently, the term $Treated_j \cdot After_t$ is dropped.

Table C4 shows the results. We observe that the number of COVID-19 cases was negatively and significantly associated with streaming consumption, which is greater for relatively recent cases. The result in Column (1) suggests that 1,000 COVID-19 cases per million people each week were associated with the 14.4% decline in streaming consumption.

We also check the robustness of how government restrictions affected music streaming. Firstly, we estimate a model that excludes COVID-19 cases and deaths. **Table C5** reports the results. Except for slight variations in the magnitudes, we do not observe significant differences from the main results. Secondly, we adopt ordinal measures of government restrictions. The estimates are reported in **Table C6** and **Table C7**. Again, we find qualitatively consistent results, suggesting that our findings are unlikely to be driven by not accounting for the degree of restrictions.

Table C5. Effects of Government Restrictions on Demand for Streaming Music (without COVID-19 Cases/Deaths Controls)

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Government Restrictions (Binary)								
Schools	-0.0275							
	(0.0262)							
Workplaces		-0.0731***						
		(0.0253)						
Public Events			-0.0957***					
			(0.0225)					
Private Gatherings				-0.0190				
				(0.0473)				
Public Transport					-0.0700**			
					(0.0307)			
Shelter-in-Place Orders						-0.0894***		
						(0.0258)		
Movement b/w Cities/Regions							-0.0887***	
							(0.0225)	
International Travel								-0.0318*
								(0.0173)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific w-of-the-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Global week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of countries	59	59	59	59	59	59	59	59
Observations	6,136	6,136	6,136	6,136	6,136	6,136	6,136	6,136

Notes. Standard errors are robust and clustered at the country level. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. Malta was excluded in the analysis due to a lack of relevant data in the Oxford Covid-19 Government Response Tracker.

Table C6. Effects of Government Restrictions on Demand for Streaming Music Using Ordinal Independent Variables (with COVID-19 Cases/Deaths Controls)

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Government Restrictions (Ordinal)								
Schools	-0.0130							
	(0.00925)							
Workplaces		-0.0380***						
		(0.0102)						
Public Events			-0.0425***					
			(0.0111)					
Private Gatherings				-0.00555				
				(0.0117)				
Public Transport					-0.0435***			
					(0.0160)			
Shelter-in-Place Orders						-0.0475***		
						(0.0150)		
Internal Movement b/w Cities/Regions							-0.0536***	
							(0.0118)	
International Travel								-0.0110*
								(0.00560)
COVID-19 Statistics (per million people)								
Cases (Current Week)	-0.000149**	-0.000135**	-0.000149**	-0.000150**	-0.000150**	-0.000133**	-0.000139***	-0.000163***
	(5.82e-05)	(5.71e-05)	(5.94e-05)	(6.02e-05)	(5.65e-05)	(5.12e-05)	(5.09e-05)	(6.07e-05)
Deaths (Current Week)	0.000389	0.000527	0.000449	0.000449	0.000393	0.000479	0.000383	0.000483
	(0.000942)	(0.000922)	(0.000953)	(0.000942)	(0.000887)	(0.000877)	(0.000883)	(0.000980)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of countries	59	59	59	59	59	59	59	59
Observations	6,136	6,136	6,136	6,136	6,136	6,136	6,136	6,136

Notes. Standard errors are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01. Malta was excluded in the analysis due to a lack of relevant data in the Oxford Covid-19 Government Response Tracker. Government restrictions are operationalized as ordinal variables.

Table C7. Effects of Government Restrictions on Demand for Streaming Music Using Ordinal Independent Variables (without COVID-19 Cases/Deaths Controls)

DV = ln(Streams)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Government Restrictions (Ordinal)								
Schools	-0.0153							
	(0.00948)							
Workplaces		-0.0431***						
		(0.0106)						
Public Events			-0.0455***					
			(0.0120)					
Private Gatherings				-0.00951				
				(0.0122)				
Public Transport					-0.0444***			
					(0.0166)			
Shelter-in-Place Orders						-0.0522***		
						(0.0158)		
Internal Movement b/w Cities/Regions							-0.0570***	
							(0.0124)	
International Travel								-0.00755
								(0.00636)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-the-year FE	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Country-specific growth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific week-of-the-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of countries	59	59	59	59	59	59	59	59
Observations	6,136	6,136	6,136	6,136	6,136	6,136	6,136	6,136

Notes. Standard errors are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01. Malta was excluded in the analysis due to a lack of relevant data in the Oxford Covid-19 Government Response Tracker. Government restrictions are operationalized as ordinal variables.

Table C8. Apple's Mobility Measure and Streaming: Two-way Fixed Effects Model

DV = ln(Streams)	(1)	(2)	(3)
Difference in route requests (%)			
Driving	0.00124***		
	(0.000443)		
Transit		0.000894*	
		(0.000457)	
Walking			0.000724**
			(0.000340)
COVID-19 Statistics (per million)			
Cases (Current week)	-8.32e-05*	-9.44e-05	
	(4.36e-05)	(5.86e-05)	
Deaths (Current week)	0.000623	0.000756	3.01e-05
	(0.000554)	(0.000621)	(0.000469)
Country FE	Yes	Yes	Yes
Common week FE	Yes	Yes	Yes
No. of countries	48	26	48
Observations	960	520	960

Notes. Standard errors are robust and clustered at the country level. *p < 0.10; **p < 0.05; ***p < 0.01.

To further examine the robustness of our findings, we replaced Google's data with Apple's Mobility Trends Reports retrieved from https://covid19.apple.com/mobility. The data contain post-COVID mobility trends, a relative volume of directions requests compared to a baseline volume on January 13th, 2020, for each country or city. The direction requests are categorized as 'driving,' 'transit,' or 'walking,' denoting transportation types of the requests. According to Apple's description, the relative volume has increased in many regions since January 13th, consistent with normal, seasonal usage of Apple Maps. We estimate the following two-way fixed effects model:

$$\ln(Streams_{it}) = \alpha_i + \pi \cdot Request_{it} + \theta_1 \cdot Cases_{it} + \theta_2 \cdot Deaths_{it} + \sum_t \delta_t + \varepsilon_{it}, \text{(C4)}$$

where $Request_{it}$ indicates the routing request index; other variables are equivalent to those defined in Equation (4). The estimated results in **Table C8** suggest that requests for driving, transit, and walking were positively associated with streaming demand. In conclusion, our main findings are consistent across different mobility data sources in terms of services and measurements.

C3. Parallel Trend Assumption

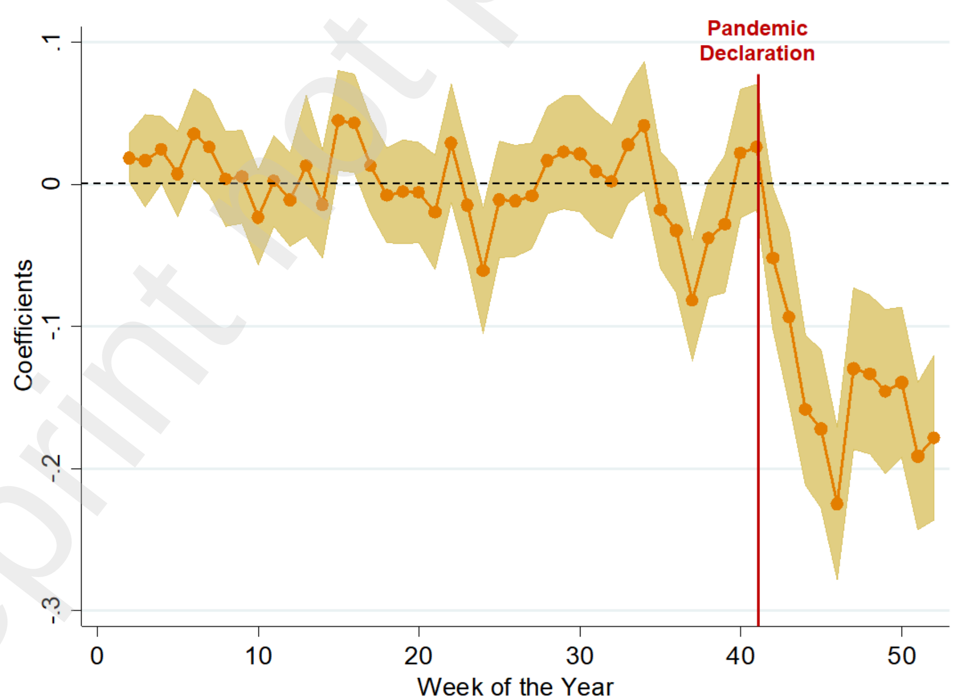
Since our work relies on the parallel trend assumption, as prior studies did (e.g., Fang et al. 2020), we formally test this assumption by estimating the relative time model that leverages leads and lags of the treatment (Autor 2003, Burtch et al. 2018):

$$\ln(Streams_{ijt}) = \alpha_i + \sum_t Treated_j \cdot \delta_t + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt}, \quad \text{(C3)}$$

where all variables are identically defined as Equation (2). In this model, $Treated_j \cdot \delta_t$ quantifies the extent to which the streaming differences between the treatment year and the control year varied across weeks of the year.

Figure C3 presents the estimates of $Treated_j \cdot \delta_t$. We find that the streaming differences across weeks are mostly indistinguishable before the pandemic declaration. We observe a temporary decline in streams during February 2020, which could be attributed to the earlier outbreak of COVID-19 in Asia and Europe. After the pandemic declaration, the streaming demand rapidly dropped significantly. These results indicate that streaming trends would be sufficiently parallel between two years without COVID-19.

Figure C3. Estimates of Relative Time Model



Notes. The orange dots indicate the coefficients of Equation C3. The yellow area indicates a 95% confidence interval of each coefficient.

C4. Analysis of Spotify's Updates

Findings

To check whether the drastic changes in Spotify's products or policies induced the demand drop, we thoroughly review the updates of Spotify during the research period. We obtain the complete list of Spotify's posts from the "What's New" section—posting the "latest updates, from partnerships to products to podcasts"—on Spotify's announcement page.[10] We review each announcement and categorize them into 17 types, such as "Podcast," "Playlist," and "Price Promotion." To deliver our findings effectively, we first present our results and then report the description of types. The complete lists of the announcements are available in the online supplementary material.

Table C9 presents the differences in the number of Spotify's announcements by type between the two consecutive years. This table was constructed by subtracting the number of announcements in the control year (**Table C10**) from the number in the treatment year (**Table C11**) for each month of the research year. We found that Spotify announced more about podcasts, price promotion, and service improvement, while they reduced campaigns and music events (e.g., live concerts and awards). We claim that these changes were unlikely to have driven the global decline in music consumption. First, there had been variations in campaigns and music events even before the pandemic, but they did not lead to a long-term dramatic increase or decline in streaming consumption. Second, more content, price promotion, and service improvement were very unlikely to damage the demand. Rather, they may need to be interpreted as Spotify's attempts to recover the reduced demand during the pandemic.

[10] Retrieved from https://newsroom.spotify.com/category/whats-new/ on November 2nd, 2020.

Table C9. Differences in Spotify's Announcements between Control and Treatment Years

Calendar Month (Control Year)	2018-06	2018-07	2018-08	2018-09	2018-10	2018-11	2018-12	2019-01	2019-02	2019-03	2019-04	2019-05
Calendar Month (Treatment Year)	2019-06	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12	2020-01	2020-02	2020-03	2020-04	2020-05
The Month of Research Year	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Podcast	2	3	-1	2	2	0	-2	4	6	2	6	4
Playlist	-1	2	0	0	0	-1	-2	-3	-1	1	0	0
Campaign	1	-2	0	-3	-4	-1	-2	0	0	-2	-1	1
Music Event	0	1	0	0	2	0	2	0	2	-2	0	-1
News	1	0	-1	1	-1	0	2	0	0	0	-2	-1
Digital Partnership	1	0	0	1	-3	1	1	0	1	-1	0	0
Price Promotion	0	0	0	1	1	-1	1	0	0	1	0	1
Service Improvement	1	0	1	-1	-1	0	0	0	0	1	0	1
New Service	0	1	0	0	1	0	0	0	0	1	0	0
Partnership	1	0	0	1	0	0	0	0	0	0	0	0
Supplier Support	0	0	0	0	-2	-1	0	0	0	0	0	-1
Tips	0	0	1	1	0	1	0	0	0	0	0	0
Video	1	1	0	0	-1	0	0	0	0	0	0	0
Management	-1	0	-1	0	0	0	0	0	0	0	0	0
New Market	0	0	0	0	0	0	0	0	-1	0	0	0
Audio Book	0	0	0	0	0	0	0	0	0	0	0	1
Total	6	6	-1	3	-6	-2	0	1	7	1	3	5

Table C10. Number of Spotify's Announcements by Category in Control Year

Calendar Month	2018-06	2018-07	2018-08	2018-09	2018-10	2018-11	2018-12	2019-01	2019-02	2019-03	2019-04	2019-05
The Month of Research Year	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Podcast	1		2	3	4	1	3	2	2	2		
Playlist	2			1	2	4	2	3	2		1	1
Campaign		2	1	3	4	2	2		1	2	1	1
Music Event	2		2	1	1	2		1		2		1
News	2		1		1		1				2	2
Digital Partnership		1			3	1				1		
Price Promotion			1			1						
Service Improvement				1	2							
New Service												
Partnership										1		
Supplier Support					2	1						1
Tips												
Video					1							
Management	1		1									
New Market									1			
Audio Book												
Total	8	3	8	9	20	12	8	6	6	8	4	6

Table C11. Number of Spotify's Announcements by Category in Treatment Year

Calendar Month	2019-06	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12	2020-01	2020-02	2020-03	2020-04	2020-05
The Month of Research Year	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Podcast	3	3	1	5	6	1	1	6	8	4	6	4
Playlist	1	2		1	2	3			1	1	1	1
Campaign	1		1			1			1			2
Music Event	2	1	2	1	3	2	2	1	2			
News	3			1			3					1
Digital Partnership	1	1		1		2	1		1			
Price Promotion			1	1	1		1			1		1
Service Improvement	1		1		1					1		1
New Service		1			1					1		
Partnership	1			1						1		
Supplier Support												
Tips			1	1		1						
Video	1	1										
Management												
New Market												
Audio Book												1
Total	14	9	7	12	14	10	8	7	13	9	7	11

Types of Spotify's Updates

Lists of announcement types:

- Podcast: Spotify's announcements on its podcasts are categorized as 'podcast.'
- Playlist: Advertisements on new or existing playlists are assigned to 'playlist.'
- Campaign: This indicates Spotify's campaigns promoting specific groups, topics, or actions, such as "Listening Together." Supports for underrepresented producers also belong to this category.
- Music event: Music-related events such as concerts and awards fall in this category.
- News: This indicates miscellaneous news on Spotify or artists without promoting specific podcasts or playlists.
- Digital partnership: We assign this category to posts on partnership with tech firms, covering interactions with mobile devices, smart speakers, and new payment methods.
- Price promotion: Any form of monetary benefit is categorized as 'price promotion'. This also includes promoting gift cards and providing free Google Home Mini.

- Service improvement: It denotes improvements in current services, for instance, playlist sharing features and enhanced search systems.
- New service: This indicates announcements on brand new services, such as Spotify Lite, and video podcasts. Incremental changes do not fall into this category.
- Partnership: This type is assigned to posts announcing a partnership with large content-providing firms, such as Hulu. This does not include a partnership with a single musician or podcaster.
- Supplier support: This indicates posts on new services and functions that help podcasters or content providers to create and manage their content effectively, for example, the new platform for podcasters. Spotify's efforts to help underrepresented producers were categorized as 'campaign' instead of 'supplier support.'
- Tips: Tips indicate posts that informed how to use service functions that had already existed in the platform.
- Video: This type is assigned when Spotify notified their new video clips posted on other platforms, unlike podcasts.
- Management: It denotes managerial issues, such as the appointment of a new chief content officer.
- New market: This indicates posts announcing Spotify's entry into new markets (e.g., India, Russia, and Croatia).
- Audio book: The post announcing the introduction of the Harry Potter series to Spotify is uniquely categorized as 'audio book.' We distinguished audio-book content from other podcasts because audio books can be considered as an innovative form of e-books rather than the extension of radio content (e.g., Hong and Lee 2017).

C5. Streaming Demand in the Korean Market

To further alleviate the Spotify-specific unobservable factors, we collect additional music streaming data in South Korea, where Spotify did not launch in the territory due to the local players' dominance in the country during the research period. According to the most recent annual report by the International Federation of the Phonographic Industry (IFPI) in 2019, South Korea was ranked sixth place in the global music market. More importantly, the COVID-19 had been widespread and prevalent in the country earlier this year, which provides a suitable setting to validate the pandemic effect on music consumption.

We obtain nationwide streaming data of weekly top 400 songs from the Korea Music Content Industry Association between June 2018 and May 2020. The ranking and streaming counts are constructed based on online streaming data assembled by major record labels and digital music distributors in South Korea, who account for over 95% of music sales (Cho et al. 2019).

In this analysis, we employed an alternative exogenous shock in mid-February wherein COVID-19 began to spread dramatically in Daegu, the third-largest official metropolitan area in South Korea (The New York Times 2020). **Figure C4** presents the streaming trends between June 2018 and May 2020. We observe that the streaming trend in the current year began to further part from the trend in the previous year, possibly due to the earlier outbreak in the neighborhood, China, and corresponding social distancing measures. Therefore, we focus on the marginal effect of the domestic shock, a relatively conservative estimate of the COVID-19 impact on music streaming, by controlling for potential unobserved shocks at the beginning of 2020 and the first outbreak of a confirmed COVID-19 case. The estimated models are as:

$$\ln\left(Streams_{jt}\right) = \alpha + \beta_1 \cdot Treated_j + \beta_2 \cdot Treated_j \cdot Beginning\ \ of\ \ 2020_t + \beta_3 \cdot Treated_j \cdot Domestic\ \ First\ \ Case_t + \beta_4 \cdot Treated_j \cdot Domestic\ \ Shock_t + \sum_t \delta_t + \varepsilon_{jt}, \qquad \text{(C5)}$$

$$\ln\left(Streams_{jt}\right) = \alpha + \beta_1 \cdot Treated_j + \theta_1 \cdot Cases_{jt} + \theta_2 \cdot Deaths_{jt} + \sum_t \delta_t + \varepsilon_{jt}, \qquad \text{(C6)}$$

where *j* indexes the two-year period; *t* indexes the week of the year; $Beginning\ \ of\ \ 2020_t$ indicates 1 for weeks in 2020, 0 otherwise; $Domestic\ \ First\ \ Case_t$ indicates whether weeks include or later than January 20, 2020 when the first domestic case was confirmed, 0 otherwise; $Domestic\ \ Shock_t$ indicates whether weeks include or later than February 18, 2020 when the first Shincheonji church case was confirmed in Daegu; $Cases_{jt}$ and $Deaths_{jt}$ are the number of confirmed COVID-19 cases and deaths per million people; other variables are identically defined as Equation (2).

The notable differences of these models from our main specification are twofold. First, the index for countries is omitted due to examining a single country. Second, we focus on the marginal impact of the sudden domestic shock in Daegu instead of the overall difference between the two consecutive years. For this, we control for potential confounding effects of the aforementioned events observed in **Figure C4**.

The estimated results are shown in **Table C12**. After controlling for potential confounding effects at the beginning of 2020 and the first confirmed case, the streaming demand decreased by 12.0%

after the sudden domestic shock in Daegu. The significant coefficient of the number of deaths further confirms that the recent streaming decline in South Korea was attributable to the COVID-19 outbreak. These results imply that our main findings still hold in the market, where Spotify does not serve, supporting our argument.

Figure C4. Streaming Trends in the Korean Market by Research Year

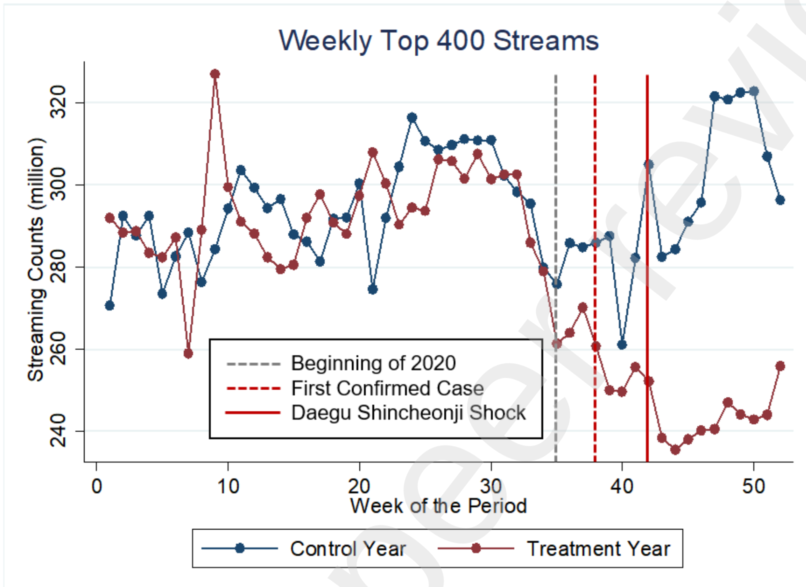


Table C12. COVID-19 Outbreak and Demand for Streaming Music in South Korea

DV: ln(Streams)	(1)	(2)
Treated	-0.00373	-0.0250**
	(0.00878)	(0.00949)
Beginning of 2020	-0.0583***	
	(0.0115)	
Domestic First Case	-0.0320	
	(0.0192)	
Domestic Shock	-0.128***	
	(0.0230)	
COVID-19 Statistics		
Cases (per million)		0.000270
		(0.000580)
Deaths (per million)		-0.391***
		(0.0386)
Week-of-the-year FE	Yes	Yes
Observations	104	104
R-squared	0.907	0.844

Notes. Robust standard errors are in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01.

C6. Revenue Implications

We provide back-of-the-envelope calculations on how significantly consumers should increase consumption of songs below the top 200 to compensate for the decline in top 200 consumption. First, we calculate the changes in Spotify's revenue growth rates. To do so, we collect monthly active users and revenue information by service type—i.e., premium and ad-supported services from Spotify's quarterly financial reports.[11] We find that Spotify's total revenue growth rates decreased by 10.4 to 17.6 percentage points, highly comparable to our main estimate—a 12.5 percent decline after the WHO's pandemic declaration.[12]

Second, we quantify how much the Spotify Top 200 represents total music consumption on Spotify to consider a scenario wherein the pandemic affects a revenue per stream. We assume that streaming revenue is equivalent to Spotify's average payment to right holders per stream and use 2.54 USD (per thousand streams) as a lower bound and 8.4 USD (per thousand streams) as an upper bound (Aguiar and Waldfogel 2018). In the first quarter of 2020, the total streaming count of weekly top 200 songs for each of the 60 countries in this study is approximately 39.6 billion, and the corresponding revenue is about 100.6 – 332.6 million USD. According to Spotify's financial reports, the total revenue of Spotify was 1,848 million EUR or 2,033 USD (by assuming that 1 EUR = 1.1 USD) in that period. Based on this calculation, the estimated proportion of weekly top 200 streams is about 5.4 – 18.0%.

Let us postulate that the overall revenue decline is 14%, and the consumption proportion of the top 200 is 12%. If a revenue per stream were constant throughout the research period, consumption of songs below the top 200 would decrease by 14.2%. Even when we assume that a revenue per stream decreased by 10%, non-rankers will experience a 3.3% decline in consumption. Thus, we conclude that the consumption shift from popular songs to lesser-known ones unlikely occurred without a dramatic drop in revenue per consumption.

[11] The reports are available at https://investors.spotify.com/financials/default.aspx. Notice that Spotify's fiscal quarters correspond to calendar quarters. For instance, Spotify's first, second, and third fiscal quarter of 2020 ends March 31, June 30, and September 30, 2020, respectively. Detailed calculations are available upon request.

[12] Note that both premium and ad-supported revenues showed significant declines in year-over-year growth rates.

C7. Analysis of Playlist Followers in Spotify

To assess whether our results were driven by the consumption shift from top-selling songs to relatively niche music, we analyze archival data on the number of playlist followers purchased from Soundcharts by which detailed daily playlist-level statistics are provided through its own APIs. Playlist analysis is worthwhile for several reasons. First, playlists are known as the preferable way of listening to music that two-thirds of Spotify listening time is spent on Spotify- or user-generated playlists (Business of Apps 2020). Second, a small fraction of songs in the playlists in our sample is overlapped with bestselling songs on the top charts (4.41% of total unique songs). Third, our playlists offer diverse and wide facets of the music, such as genres and popularities of songs and artists (75K unique songs and 1.2B non-unique followers in total). Therefore, we can effectively explore the popularity trends of various music beyond top-selling lists.

In order to track the previous number of playlist followers, we rely on the proprietary API provided by Soundcharts. As the platform has tracked the daily number of followers and tracklists of playlists, we are able to pick up how the popularity of playlists has changed. To construct panel data of playlist followers, we obtain the list of top 500 playlists on October 22, 2020, for each of the three provider types: Spotify, major providers, and third parties. Our results might have been affected by selecting survivors, such that the effects of COVID-19 are likely to be biased upward. It is worth mentioning that shifting the estimates toward an increase in playlist followers after the COVID-19 outbreak is likely to yield relatively conservative results regarding our hypothesis. Thus, if the estimated differences are negative and significant in the current sample, we may expect that playlists not listed on this ranking chart experienced more drastic decreases in the number of playlist followers.

The number of followers was highly uneven across playlists in our sample. For instance, Today's Top Hits—the largest playlist—has followers twice as much as those of the third-largest playlist, "RapCaviar" (26,902,159 vs. 13,437,991). Despite this popularity gap, we find that 'top labeled' playlists—including the word 'top' in their names—occupied only 7.9% among our playlist sample, as summarized in **Table C13**. To ensure whether these playlists indeed covered less popular songs, we check the overlap between top-labeled playlists and the others. **Table C14** shows that top-labeled playlists contain only 4.41% of the total unique songs listed on our playlists, indicating that our dataset covers substantially various music beyond top-listed songs.

Table C13. Statistics on Top 500 Playlists for Spotify, Major Providers, and Third Parties

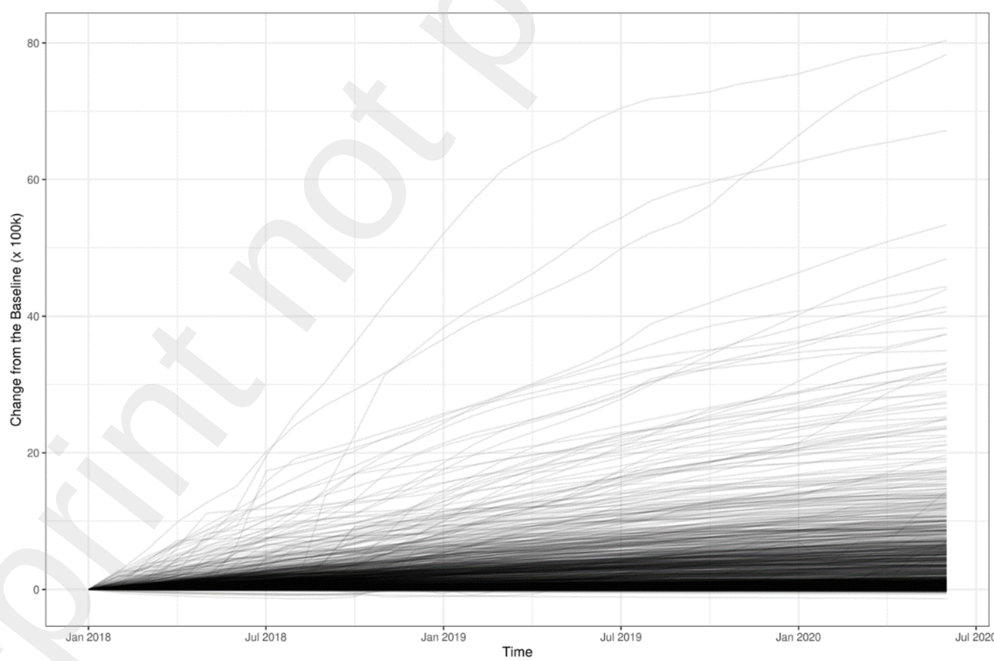
Variables	All playlists	Top-labeled playlists	Proportion (%)
Unique playlists	1,500	84	5.60%
Non-unique songs	172,003	9,585	5.57%
Non-unique followers	1,183,402,224	93,828,010	7.93%

Table C14. Statistics on Track Composition of Playlists

Variables	All playlists	Top-labeled playlists	Proportion (%)
Unique playlists	1,325	67	5.06%
Unique songs	75,082	4,306	5.74%
Non-unique songs	155,220	6,851	4.41%
Non-unique followers	1,158,206,408	91,336,552	7.89%

Note. In Table 1.2, we only consider playlists of which track lists on October 22, 2020 are available in the Soundcharts' API, thus we omit 175 playlists.

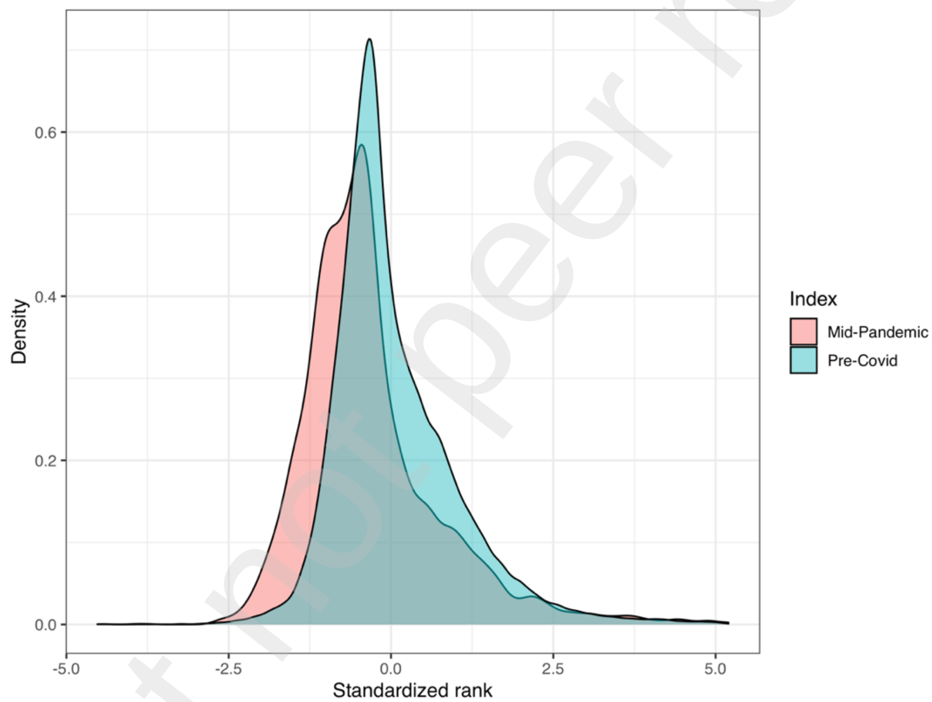
Figure C5. Playlist Followers Trends from January 2018



Note. We took the monthly average number of followers for each playlist.

Based on the list of playlists, we construct daily panel data from January 2018. In **Figure C5**, we present the changes in the number of followers for each playlist since January 2018. We observe that the number of followers increased continuously for most of the playlists, while the growth tended to be decelerated. To assess whether the growth was particularly slowed down after the COVID-19 outbreak, we compare the monthly increases in followers before the pandemic with those during the pandemic period. **Figure C6** shows the standardized monthly differences in the number of followers. It is clearly shown that the follower increases were significantly smaller during the pandemic than in the pre-COVID period.

Figure C6. Standardized Monthly Differences in Playlist Followers



To quantify how much the number of followers dropped after the pandemic, we estimate a regression model similar to our main specification as:

$$\ln\left(Followers_{ijt}\right) = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_t \delta_t + \varepsilon_{ijt}, \tag{C7}$$

where *i* indexes playlists; *j* indexes the two-year period; *t* indexes the day of the year. $Followers_{ijt}$ is the cumulative number of playlist followers; $Treated_j$ indicates 1 if *j* = 2 (the treated period), 0 otherwise; $After_t$ indicates 1 if week of the year *t* is later than March 11th (i.e., the pandemic declaration) in year j, 0 otherwise; α_i is a set of playlist fixed effects; $\sum_t \delta_t$ controls for day-of-the-year fixed effects; ε_{ijt} is an error term clustered at the playlist level to take account of autocorrelation in the data (Bertrand et al. 2004). β_3 indicates the difference in streaming demand after the COVID-19 outbreak.

Table C15. COVID-19 Pandemic Outbreak and Number of Playlist Followers

Playlist Types	β_3	No. of Playlists	Observations	R-squared
All Types	-0.0559***	1,327	970,037	0.969
Popular	-0.0509**	215	157,165	0.961
Top	-0.0984*	79	57,749	0.950
Chart	-0.0949	6	4,386	0.921
Hit	-0.0425	157	114,767	0.954
Hot	-0.0506	15	10,965	0.995
Popular Genres	-0.00271	173	126,463	0.957
Pop	-0.0697**	54	39,474	0.966
Rock	-0.138***	46	33,626	0.967
Dance	0.181	43	31,433	0.923
Hip Hop	0.0127	35	25,585	0.983
Instrumental	-0.122***	46	33,626	0.971
Classic	-0.102***	34	24,854	0.980
Piano	-0.0296	4	2,924	0.999
Drum/Bass	-0.252	8	5,848	0.815
Contextual	0.0127	82	59,942	0.967
Chill	0.0600	41	29,971	0.961
Workout/Gym	0.137	29	21,199	0.957
Car/Driving	-0.279*	9	6,579	0.937
Sleep	-0.0113	5	3,655	0.996
Emotional	-0.0613*	17	12,427	0.986
Mood	0.0258	5	3,655	0.995
Happy	-0.0546	8	5,848	0.994
Sad	-0.115	6	4,386	0.954
Latin	-0.0411***	24	17,544	0.991
Acoustic	-0.0780**	18	13,158	0.975
Nostalgia+	-0.0593	49	35,819	0.981
Others	-0.0634***	798	583,338	0.970

Notes. *p < 0.10; **p < 0.05; ***p < 0.01. Playlist fixed effects and day-of-the-year fixed effects are included. +Nostalgia includes the following keywords: 60s, 70s, 80s, 90s, and 00s.

Table C15 presents the estimate for all playlists and the results of subgroup analysis by playlist type. The first row suggests that the increase in playlist followers decreased by 5.4% on average after the pandemic declaration. Then, we examine the heterogeneity across playlist types. Specifically, we define five major types following insights from academic literature and industry experts. For instance, it has been suggested that music consumption has recently shifted from popular music to instrumental and chill music (Spotify 2020). In addition, music listening has also been suggested as highly contextual (Corrigall and Schellenberg 2015). Thus, we define playlist categories '*popular charts*' consisting of playlists with popularity-related keywords ('top,' 'chart,' 'hit,' and 'hot'), '*popular genres*' including playlists with relevant keywords ('pop,' 'rock,' 'dance,' 'hip hop'), '*instrumental*' type consisting of playlists with keywords, 'classic,' 'piano,' 'drum' and/or 'bass,' and '*contextual*' type including playlists with keywords, 'chill,' 'workout' and/or 'gym,' 'car' and/or 'driving,' and 'sleep.' Moreover, we consider the '*emotional*' category that consists of playlists with 'mood,' 'happy,' and 'sad,' as music listeners prefer mood-congruent music choices (Lee et al. 2013). As expected, we observe a significant reduction in new followers among popular playlists. Interestingly, we find a larger decline in the number of new followers among instrumental and emotional playlist types, contrary to our expectation. Contextual playlists did not experience an acceleration of new followers, either.

We also analyze the number of playlist followers at a more specific keyword level. The main insights from the analysis are as follow:

- Instrumental music, particularly classic and drum/bass music, experienced a significant deceleration of playlist followers during the pandemic.
- Chill music playlists did not experience a significant increase in followers, which is comparable to the relative drop in top music playlists.
- We found no convincing evidence of heterogeneous effects on playlist followers across mood types.
- Nostalgic playlists did not attract more followers during the pandemic.
- Playlists that were not categorized into the aforementioned types experienced a significant decrease in new followers on average.

To further examine the robustness of our findings, we consider an alternative definition of playlists for popular music. Specifically, we postulate that playlists with a large number of followers represent popular music. Then, we examine whether or not the decline in the number of followers was occurred only among playlists for popular music by conducting a subgroup analysis based on follower rank. **Table C16** shows the results. We find that, although the magnitudes are higher for popular playlists, the negative impacts are economically and statistically significant among less popular playlists as well. Considering the potential upward bias from selecting survivors, particularly among relatively low ranked playlists, we conclude that the negative coefficients substantially support the overall decline in music streaming.

In sum, these results suggest that the growth of playlist followers was decelerated after the COVID-19 pandemic outbreak. And the instrumental, contextual, and other types of music playlists did not seem to attract a particularly larger audience that could compensate for the consumption loss of top-listed songs. However, the results should be interpreted with caution as followers are not the same as active listeners. Our playlist follower analysis does not capture the COVID-19 impact on existing followers.

Table C16. COVID-19 Pandemic Outbreak and Number of Playlist Followers

Playlist Rank	β_3	No. of Playlists	Observations	R-squared
Top 10 or above	-0.136**	10	7,310	0.935
Top 50 or above	-0.103***	48	35,088	0.924
Top 100 or above	-0.132***	93	67,983	0.848
Top 200 or above	-0.119***	192	140,352	0.894
Top 500 or above	-0.0978***	469	342,839	0.939
Below Top 10	-0.0553***	1,317	962,727	0.967
Below Top 50	-0.0542***	1,279	934,949	0.963
Below Top 100	-0.0502***	1,234	902,054	0.961
Below Top 200	-0.0453***	1,135	829,685	0.952
Below Top 500	-0.0330***	858	627,198	0.911

Notes. *p < 0.10; **p < 0.05; ***p < 0.01. Playlist fixed effects and day-of-the-year fixed effects are included. Playlists that were not observed at the beginning of the research period are excluded in the analysis.

C8. Analysis of Music Releases in Spotify

To explore the music supply changes, we examine new releases of top-tier artists in Spotify.[13]

[13] Practically, we had to focus on selected artists because Spotify's API does not allow access to the complete catalog by restricting entities per query.

Considering that popular artists are more influential than lesser-known artists, their release decisions have a significant impact on music demand, particularly among the top 200 songs. To operationalize top artists, we focused on recently successful artists who were listed on weekly top 10 songs within the past 12 or 24 months. By defining the popularity based on the rolling cutoff of recent chart positions, we can reflect the dynamic nature of popularity and allow scalable coding of numerous artists from 60 different countries.

Figure C7 shows the trends of new releases of recently-successful artists by years.[14] We observe that the number of new releases increased over the years in terms of artists, albums, and songs. However, this could be systematically associated with the number of artists listed on ranking charts, reflecting the composition of the previous charts. To address this issue, we divide the statistics by the total number of artists ranked weekly top 10 at least once during the period. Three graphs on the bottom suggest that musicians released new albums and songs as usual.

To formally test artists' decisions, we construct a panel dataset at the artist-month level. **Table C17** presents summary statistics of dependent variables by superstar criterion. Based on the first criterion, which defines superstars as artists who were listed on weekly top 10 songs within the past 12 months, 1,573 artists were observed during the research period and released 11,507 albums and 32,341 tracks in total. Using this dataset, we estimated the following regression model:

$$y_{ijt} = f(\alpha + \beta_1 \cdot Treated_j + \beta_2 \cdot Treated_j \cdot After_t + \delta_t), \qquad \text{(C8)}$$

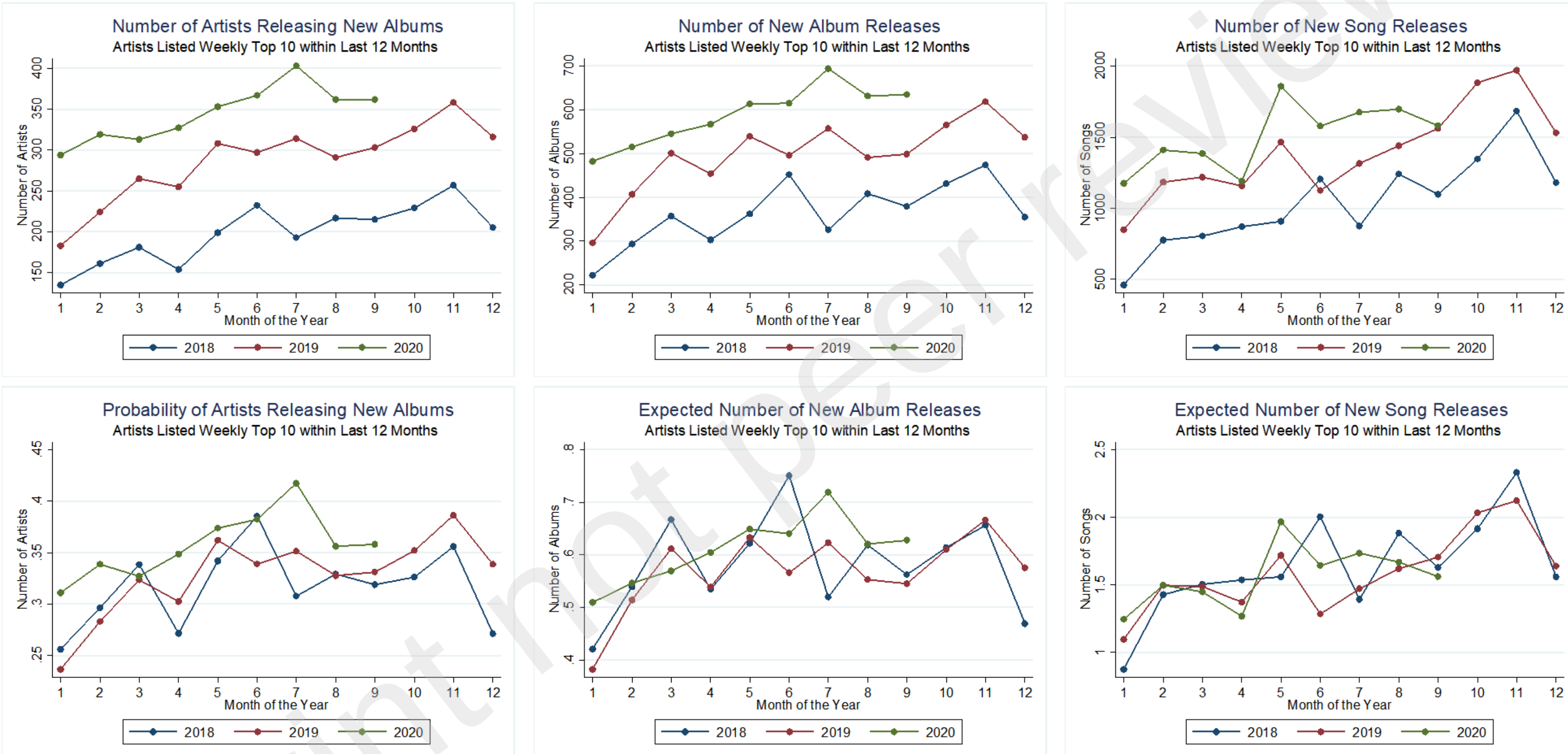
where y_{it} is a dependent variable, α is a constant, δ_t is a series of month of year fixed effects, $f(\cdot)$ is a functional form of the estimation model, and other variables are identically defined as Equation (2). To estimate the likelihood of music release, we use a logistic regression.[15] To account for over-dispersion of the number of albums and the number of songs, we adopt a negative binomial model.

[14] *1(Release = Yes)* is defined as whether or not an artist released music in each month, *Number of Albums* is defined as the number of albums (including singles) that an artist released in each month, and *Number of Songs* is the sum of the number of tracks included in newly released albums in each month. Evidently, the following inequality holds:

$$1(\text{Release = Yes}) \leq \text{Number of Albums} \leq \text{Number of Songs}.$$

[15] We do not consider a hazard model given that an artist may serially release multiple albums during a short period.

Figure C7. Music Supply Trends of Recently Successful Artists in Spotify



Contrary to recent attention to delayed music releases (Musically 2020), the estimated results in **Table C18** provide no evidence that artists reduced new music releases significantly. This finding could be associated with the increase in time spent at home, which facilitates music production (Rolling Stone 2020) or attempts to keep people's attention in the presence of more distractions (The Washington Post 2020).

Table C17. Summary Statistics of Dependent Variables

Dependent Variable	Mean	Std. Dev.	Total
Ranked weekly top 10 within 12 months (1,573 artists, 19,904 observations)			
1(Release = Yes)	0.331290	0.470689	6,594
Number of Albums	0.578125	1.171959	11,507
Number of Songs	1.624849	6.300182	32,341
Ranked weekly top 10 within 24 months (1,665 artists, 26,375 observations)			
1(Release = Yes)	0.320265	0.466587	8,447
Number of Albums	0.573384	1.256993	15,123
Number of Songs	1.593896	6.508102	42,039

Table C18. COVID-19 Outbreak and Recently Successful Artists' Decision to Release Music

Superstar Criterion	Ranked weekly top 10 within 12 months		
Functional Form	Logit	Negative Binomial	
Dependent Variable	(1) 1(Release = Yes)	(2) Number of Albums	(3) Number of Songs
Treated	0.141***	0.0332	-0.0353
	(0.0359)	(0.0344)	(0.0654)
Treated x After	-0.0488	-0.0106	0.0462
	(0.0681)	(0.0667)	(0.112)
Month of the year FE	Yes	Yes	Yes
No. of artists	1,573	1,573	1,573
Observations	19,904	19,904	19,904
Superstar Criterion	Ranked weekly top 10 within 24 months		
Functional Form	Logit	Negative Binomial	
Artists	(1) 1(Release = Yes)	(2) Number of Albums	(3) Number of Songs
Treated	0.0824***	0.0287	-0.0599
	(0.0317)	(0.0324)	(0.0609)
Treated x After	-0.0452	-0.0282	0.0588
	(0.0594)	(0.0606)	(0.104)
Month of the year FE	Yes	Yes	Yes
No. of artists	1,665	1,665	1,665
Observations	26,375	26,375	26,375

Notes. Robust standard errors are in parentheses. *p<0.10; **p<0.05; ***p<0.01.

C9. Promotion of New Releases

We also examine how the success of newly released songs by superstars changed after the COVID-19 outbreak. Especially, we concentrate on the relative performance of the new releases on the charts, compared with existing songs. As discussed above, we find no evidence that recently successful musicians reduced new music releases significantly. Therefore, if the pandemic affected all songs similarly, a similar number of songs would appear on the top 200 charts and be ranked in similar positions. Conversely, if the pandemic affected newly released songs differently, we would observe different numbers or positions of chart-ranked songs. We estimated the following econometric model:

$$y_{ijt} = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt}, \qquad \text{(C9)}$$

where y_{ijt} indicates either the number of new songs on top 200 charts or rank position on top 200 charts; other variables are identically defined as Equation (2). The number of new songs was examined at the country-week level, while ranked positions were analyzed at the song-week level among newly released songs listed on top 200 charts.

Table C19 reports the estimates for the number of new songs on the top 200 charts. We find that after the pandemic declaration, the number of new songs on the top 200 charts decreased by 5.9 tracks. The effect was more salient among recently successful artists. New songs of top artists on top 200 charts decreased by 5.0 tracks, while those of other artists reduced by 0.9 tracks only. The results of ranked positions are reported in **Table C20**. We find that new songs were ranked lower (numerically larger) on the charts by 20 positions after the COVID-19 outbreak, indicating that new releases were significantly less promoted than pre-existing music. It is worth noting that our findings were unlikely to be driven by reduced releases of top artists, given the little difference in their new releases during the pandemic.

Table C19. COVID-19 Outbreak and Number of Newly Released Songs on Top 200 Charts

Dependent Variable	Number of new songs on top 200 charts		
Superstar Criterion	Ranked weekly top 10 within 12 months		
New Song Criterion	Released in the current week		
Artists	(1) All	(2) Superstars	(3) Non-stars
Treated x After	-5.929***	-5.006***	-0.923***
	(0.490)	(0.370)	(0.345)
No. of Countries	60	60	60
Observations	6,240	6,240	6,240
R-squared	0.721	0.677	0.661
New Song Criterion	Released within 1 week from the current week		
Artists	(1) All	(2) Superstars	(3) Non-stars
Treated x After	-5.528***	-4.825***	-0.703
	(0.654)	(0.516)	(0.435)
No. of Countries	60	60	60
Observations	6,240	6,240	6,240
R-squared	0.744	0.685	0.701

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01. Country fixed effects, country-specific growth fixed effects and country-specific week-of-the-year fixed effects are included.

Table C20. COVID-19 Outbreak and Ranked Positions of New Songs on Top 200 Charts

Dependent Variable	Ranked Position on Top 200 Charts		
Superstar Criterion	Ranked weekly top 10 within 12 months		
New Song Criterion	Released in the current week		
Artists	(1) All	(2) Superstars	(3) Non-stars
Treated x After	20.02***	17.36***	17.05***
	(2.529)	(2.746)	(4.294)
Observations	85,481	58,698	26,643
R-squared	0.077	0.108	0.168
New Song Criterion	Released within 1 week from the current week		
Artists	(1) All	(2) Superstars	(3) Non-stars
Treated x After	14.87***	13.18***	10.82***
	(2.024)	(2.444)	(2.908)
Observations	123,611	84,062	39,510
R-squared	0.054	0.078	0.117

Notes. Standard errors, in parentheses, are robust and clustered at the country level. *p<0.10; **p<0.05; ***p<0.01. Country fixed effects, country-specific growth fixed effects and country-specific week-of-the-year fixed effects are included.

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