Platforms, Power, and Promotion: Evidence from Spotify Playlists*

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Abstract

Many online markets are dominated by a handful of platforms, raising concerns about the exercise of market power in the digital age. Spotify has emerged as the leading interactive music streaming platform, and we assess its power by measuring the impact of its promotion decisions - via platform-operated playlists - on the success of songs and artists. We employ discontinuity and instrumental variables approaches to identification and find large and significant effects of playlist inclusion on success. Our results provide direct evidence of a prominent platform's power and suggest a need for continued scrutiny of how platforms exercise their power.

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1 Introduction

From some combination of network effects and attractive functionality, a handful of online platforms have come to dominate, or nearly dominate, their respective markets in search advertising (Google), online retailing (Amazon), social networking (Facebook), among others. Against a backdrop of growing concentration, market power, and income inequality, concerns about platforms' exercise of power have become ubiquitous.[1] Some observers warn of a new era of "Internet monopoly," calling for heightened antitrust enforcement.[2] Political candidates are contemplating breaking up platform operators, and regulators as well as scholarly observers are discussing the adaption of the regulatory landscape to new issues raised by digital platforms.[3] The usual concern about market dominance is that firms with market power will harm consumers by charging high prices. While the major platforms do not charge consumers high prices - and in many cases do not charge consumers at all - dominant platforms warrant attention as they are sometimes alleged to affect the fortunes of their suppliers.[4]

Despite these concerns, we know very little about harms from dominant platforms nor, for that matter, whether these platforms have the power to influence public opinion or even the more mundane matter of product preferences.[5] While the power of platforms such as Google, Facebook, Amazon, and Apple (and others) to influence preferences and consumption decisions appears self-evident, careful analyses show that apparent effects can be deceptive. For example, Blake et al. (2015) demonstrate that being prominently displayed among Google's sponsored search results - despite being an avenue for voluminous traffic to an advertiser - can have little effect on consumer choices. And the new literature on advertising effectiveness pioneered by Lewis et al. (2015) points to various reasons - including activity bias and the endogeneity of ad targeting - why ads on major platforms could seem to have large effects even if they do not.

[1] Much of the recent concern about the exercise of market power can be traced to the literatures on markups (De Loecker and Eeckhout, 2018), anti-competitive acquisitions (Cunningham et al., 2018), and cross-ownership of firms by investors (Azar et al., 2018).

[2] For example the Open Markets Institute argues that "Online intermediaries have emerged as the railroad monopolies of the 21st century, controlling access to market and increasingly determining who wins and who loses in today's economy." See https://openmarketsinstitute.org/issues/tech-platforms/. George Soros has argued that the "fact that they are near-monopoly distributors makes them public utilities and should subject them to more stringent regulations, aimed at preserving competition, innovation, and fair and open universal access." See Porzecanski (2018).

[3] See, for instance, Senator Elizabeth Warren's proposal to break up big tech https://medium.com/@teamwarren/heres-how-we-can-break-up-big-tech-9ad9e0da324c. See also the report on Market Structure and Antitrust in Digital Platforms from the Stigler Center for the Study of the Economy and the State (https://research.chicagobooth.edu/-/media/research/stigler/pdfs/market-structure---report-as-of-15-may-2019.pdf) as well as the European Commission's report on Competition policy for the digital era (http://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf).

[4] See Ip (2018).

[5] Opportunistic behavior by platforms has been documented. See, for instance, Edelman (2011) and Zhu and Liu (2016).

Despite the ubiquity of current concern about platforms' power to influence behavior, actual evidence is scant. Remedying this deficit requires carefully designed and narrowly targeted studies of particular platforms and their features to measure the causal impact of platforms' discretionary choices on the behavior of consumers.

The platforms dominating the public debate are the "GAFAM" firms (Google, Amazon, Facebook, Apple, and Microsoft), which is not surprising given that these five firms have grown quickly to positions among the most valuable firms in the world. These firms also tend to be understandably secretive, making the study of the impact of their practices difficult. Some platform operators, however, afford sufficient transparency for targeted study of their features and corresponding impact on consumers. The contemporary recorded music industry provides one such context, as it is possible to link playlist inclusion decisions with daily song-level data on song streaming that Spotify makes public.

As recently as two decades ago, distribution and promotion of recorded music operated through two fragmented sets of gatekeepers in the U.S. Promotion operated through radio stations which, under then-binding regulations, remained largely independently owned until the Telecommunications Act of 1996.[6] Hence, numerous independent program directors decided which songs to play and therefore promote. Distribution occurred through record stores, which were also fragmented, allowing numerous distinct store buyers to determine what was available to consumers at the point of sale. It is a testament to the former retail fragmentation that Walmart's predigitization growth to 20 percent of the recorded music market prompted substantial consternation (Christman, 2002; Rousseau, 2003). Digitization has altered promotion and distribution substantially, fostering the creation of a few platforms that now collectively - and simultaneously - dominate both promotion and distribution. Platforms can therefore play important roles in determining song and artist success, including the determination of which songs and artists are discovered in the first place. In 2018, Spotify and Apple music together accounted for 55 percent of the global streaming subscription market, which itself has come to account for 55 percent of global recorded music revenue as both physical sales and permanent digital downloads contract.[7]

While not part of the GAFAM group that dominates public discussion, Spotify is an important downstream platform through which music, once produced, is promoted and distributed. With a catalogue consisting of over 35 million songs, promotion at Spotify mainly comes in the form

[6] See Berry and Waldfogel (2001).

[7] See the IFPI 2019 Global Music Report, `https://www.ifpi.org/downloads/GMR2019.pdf`. In the US, streaming accounted for 75% of the recorded music revenue in 2018.

of playlists, which function in two ways. First, playlists are potentially informative lists of songs that can simply promote user awareness of particular songs. Second, playlists are utilities for listening to music: a user who subscribes to a playlist can select it, then automatically play its songs in either rank or random order. Users opt into playlists by subscribing to them at no cost, and the most popular playlists have nearly 20 million subscribers. Playlists can take the form of personalized recommendations - like Spotify's Discover Weekly playlist or Pandora's song- or artist-seeded individual stations - but platforms can also promote songs via general, i.e. one-to-many, playlists. Some of these lists - like Spotify's Today's Top Hits - are curated using editorial discretion and are often used to promote songs and artists that are already widely known. Other curated lists - like Spotify's New Music Friday - are more specifically dedicated to the discovery of new songs and artists. Algorithmic playlists - like the Global Top 50 or the U.S. Viral 50 - are, on the other hand, based algorithmically on streaming charts rather than human curators.

While there is free entry in playlists at Spotify - anybody can create and share their own playlist which can then be followed by any other user - there is a high degree of concentration by list owner. Of the 25 most-followed playlists, 24 are maintained and curated by Spotify.[8] Playlists owned and curated by Spotify also cover more than 75 percent of the followers of the top 1,000 playlists at Spotify.[9] With Spotify dominating playlists at Spotify, it is clear that the platform is well-positioned to wield influence.

Against this backdrop, this paper measures the extent to which Spotify has the ability to influence users' listening decisions. First, we ask whether playlist inclusion affects the number of streams that songs receive. Second, we ask the related but distinct question of whether playlist inclusion decisions affect consumers' discovery of new songs and artists. These questions recall the traditional question of whether promotion on radio stimulates music sales, one that is empirically challenging to address because playlist and airplay decisions are endogenous: curators choose songs they expect will be popular. While data on platform decisions and consumer behavior are not directly available, we are able - with a bit of ingenuity - to assemble relevant metrics for measuring platform power in this context. In particular we are able to combine information on the songs that Spotify's human curators and algorithms choose for their most-followed playlists with daily streaming volumes on the top 200 songs by country. We then employ four empirical approaches to measure the impact of playlist inclusion on song

[8] All of the 25 most-followed playlists are owned by Spotify, but one of them is algorithmic rather than discretionary (the Global Top 50 playlist).

[9] Spotify's algorithmic playlists cover another 9.3 percent.

performance. (1) We use the discontinuous jumps in the number of songs' playlists followers when widely followed lists add a song. (2) For algorithmic playlists where we know the inclusion criterion, we compare streams of songs just making the list with songs just off the list to measure the impact of list inclusion on streams. (3) We exploit differential song rankings on equivalent (New Music Friday) playlists across countries to measure the impact of list rankings on product discovery and streams. (4) We develop an instrumental variables approach to explain cross-country differences in New Music Friday rankings based on home bias in New Music Friday lists, along with the size of domestic music markets. Larger markets have more domestic music, giving rise to worse ranks for foreign songs in larger markets. Finally, we also explore who benefits from Spotify playlists, i.e. the sorts of songs - according to label type and artist national origin - that are included on playlists.

Our results show that Spotify has substantial power to influence song success as well as consumption decisions. First, the major platform-operated playlists have large and significant causal impacts on streaming, so the platform has power to influence consumption decisions, even among songs and artists that are already widely known. Appearing on Today's Top Hits, a list with 18.5 million followers during the sample period, raises a song's eventual streams by almost 20 million, which is almost a quarter of the average value of streams for songs that make that playlist. Being on the Global Top 50 list raises a song's streams by about 3 million, or by about 3.3 percent of the average streams for songs that make the Global Top 50. Second, Spotify also has substantial effects on which new artists and songs become discovered. Being ranked #1 on the U.S. New Music Friday list raises a song's streams by about 14 million. Third, most of the benefit of the global lists accrues to US-origin major-label songs, while the New Music Friday lists have larger representation from domestic and independent-label music.

The fact that playlists have substantial impacts on song success should be of interest for both music industry participants and observers of platforms more generally. Growing concentration of power in the hands of online platforms can create a number of potential issues, including bias in their treatment of suppliers (Edelman, 2011; Zhu and Liu, 2016).[10] While Spotify is not a music producer, the major record labels have ownership stakes in Spotify. As of April, 2018, Sony BMG owned 5.7 percent, and Universal and Warner each owned 4 percent, although they

[10] In December of 2018, India modified its rules around foreign direct investment (FDI) in e-commerce, preventing foreign investors (like Amazon or Walmart) from controlling and marketing their own inventory on their e-commerce platforms and in so doing protect smaller sellers. https://www.reuters.com/article/us-india-ecommerce-explainer/explainer-what-are-indias-new-foreign-direct-investment-rules-for-e-commerce-idUSKCN1PP1Y2. In February 2019, Austria's competition authority started to investigate whether Amazon was exploiting its market dominance at the expense of other retailers on its platform. See https://www.reuters.com/article/us-austria-competition-amazon-com/amazon-faces-probe-into-treatment-of-sellers-in-austria-idUSKCN1Q315G.

have since reduced their holdings.[11] And while the goal of this paper is limited to measuring the extent of Spotify's power through its playlists, it has important antitrust implications in light of the potential evolution of the music industry. In September 2018, the New York Times reported that Spotify had been striking direct licensing deals with a small number of independent artists, potentially offering them an advantage on the platform - easier access to Spotify's own playlists among others - while bypassing major labels.[12] Given Spotify's power to influence consumption through its playlists, such deals might raise antitrust concerns. As concentration increases in streaming as well as other markets dominated by one or a few players, our results suggest a need for continued scrutiny of how platforms exercise their power.

This paper proceeds in 6 sections after the introduction. Section 2 provides background on the various types of playlists as well as their functions; and the section discusses the literature related to our study. Section 3 describes our data sources. Section 4 presents estimates of the effects of inclusion on Spotify's major global playlists on streams. Section 5 describes our various identification strategies for measuring the effects of the New Music Friday lists on product and artist discovery and discusses estimation results. We make no attempt in this paper to explore possible bias in playlist decisions, but section 6 descriptively explores the types of songs - by label type and national origin - that are included in various playlists. Section 7 concludes.

2 Background on Playlists

2.1 The Types and Functions of Playlists

Playlists have two broad functions. They are both potentially informative lists of songs, as well as utilities for playing the songs on those lists. Anyone is free to create and share playlists, and many individuals do so. For example, Napster co-founder and early Facebook investor Sean Parker maintains an influential list called "Hipster International," which is widely credited with making New Zealand-based artist Lorde into an international superstar.[13] In addition to independent individuals, various other kinds of entities maintain playlists. For example, the major record labels, Warner, Universal, and Sony, operate playlists through Digster, Topsify, and Filtr brands respectively.

[11] See Variety Staff (2018) and Christman (2018).

[12] See `https://www.nytimes.com/2018/09/06/business/media/spotify-music-industry-record-labels.html`.

[13] See Bertoni (2013).

Spotify itself maintains both curated and chart-based algorithmic general playlists, as well as playlists that are customized to each user. These different playlists work in different ways. Among the lists that are not tailored to individual users, lists vary along two dimensions: whether they are algorithmic or curated by humans and whether they are global or country-specific. These dimensions in turn determine the empirical strategy that we use to identify the causal effects of list inclusion.

Playlists like Today's Top Hits, RapCaviar, Baila Reggaeton, and Viva Latino are all global lists that are curated by Spotify employees, who choose songs for inclusion on the lists. These lists generally add songs that have been streamed on Spotify for some period of time and include songs and artists that are already widely known. These playlists are therefore likely to be used as utilities for listening to the songs that they include, rather than as sources of information revealing heretofore obscure songs or artists. Spotify tests songs on playlists with smaller followings, then promotes promising songs to the major global lists with wide followings. "By the time a song lands on Today's Top Hits or other equally popular sets, Spotify has so relentlessly tested it that it almost can't fail."[14] The day that a song appears on a particular playlist, the list's followers can see the song on a playlist to which they subscribe. Hence, the number of the song's followers rises by the number of playlist follower when the add occurs. Other playlists, too, can add the song at or around the same date, so the number of playlist followers that a song has can jump by more than the number of followers of the list in question.

The New Music Friday playlists are also curated by Spotify but are country-specific and are updated every Friday, when 50 new songs are added to the list for each country. Because songs are added to the New Music Friday list for only a week - and because the added songs are generally added when they are literally new to Spotify - these playlists bring new information in addition to functioning as utilities for music listening. Thus, the New Music Friday lists have the possibility of promoting the discovery of new songs and artists. The absence of streaming history for dates prior to the songs' inclusion on the lists makes it impossible to measure the impact of list inclusion using a before-and-after comparison of how streams change as the songs move to these lists.

Spotify has a widely-followed Global Top 50 list, which algorithmically includes the top 50 songs of the previous day according to streams. Spotify also maintains the corresponding Top 50 lists for each country, which are based on the country-specific streams from the previous day. Because the algorithm underlying these lists is transparent, one can compare streams of songs

[14] See https://www.wired.com/2017/05/secret-hit-making-power-spotify-playlist/.

just making the list to those just missing the list in order to identify the effect of inclusion on the Top 50 lists.

2.2 Playlist Concentration

Thousands of playlists are available to users at Spotify. While we will discuss data in detail below, we note here that we have obtained the names, owners, and number of playlists followers for the top 1,000 lists at Spotontrack.com, a website that tracks Spotify playlists. The top list is Today's Top Hits, a curated list maintained by Spotify with 18.5 million followers as of December 2017. The next-most followed list is the algorithmic Global Top 50, with 11.5 million followers. Next are RapCaviar with 8.6 million, Viva Latino with 6.9 million, and Baila Reggaeton with 6.3 million. A few things are noteworthy. First, all of the 25 most-followed playlists are maintained by Spotify, and all but one of them (Global Top 50) are curated and therefore discretionary rather than algorithmic. Second, the number of followers drops off fairly quickly, particularly after the top 25: The 200^{th} list has 166,000 followers. The 500^{th} has 43,000, and the 1000^{th} has under 11,000, fewer than one percent of the top list's followers.

By list owner, the concentration is large. Spotify's curated lists have over three quarters of the followers of the top 1,000 playlists; Spotify's algorithmic lists have another 9.3 percent. The lists operated by the major record labels, Filtr, Digster, and Topsify, have 3.1, 2.7, and 0.9 percent of the top 1000's cumulative followers. The remaining list owners have negligible shares. It is clear that Spotify dominates playlists at Spotify. If playlists influence listening choices, then Spotify's curated lists are well-positioned to wield influence.

2.3 Relationship to Existing Literature

There is a large theoretical literature on platforms (see Rysman, 2009 for a summary) and a growing body of theoretical work on platform incentives to bias (Hagiu and Jullien, 2011; Cornière and Taylor, 2014). While our goal is limited to measuring the extent of Spotify's power through its playlists, such power can have important implications regarding competition on the platform. In particular, it could generate incentives for Spotify to bias its playlists in favor of certain artists. From that perspective, this paper also naturally relates to the literature on the question of whether platforms are biased in their treatment of suppliers. Bourreau and Gaudin (2018) consider a streaming platform that carries content from various providers and study its incentives to steer consumers from one content provider to another and in so doing reduce their market power. The empirical work on this question is limited, and some examples include Edelman (2011) on whether Google biases its search results in favor of its own properties and Zhu and Liu (2016) on whether Amazon enters the markets for products established by its marketplace vendors.

Our question - how do playlists affect song success and artist discovery - also has antecedents in a number of existing literatures. While we are aware of no existing work on playlists per se, there is some work on music discovery at Spotify (Datta et al., 2017) and Deezer (Aguiar, 2017). Moreover, curated playlists contain critics' assessments, so studying the impact of playlists on subsequent streams resembles work like Reinstein and Snyder (2005) on the impact of critical assessments on movie box office revenue. Playlists are in some ways like radio stations, and playlist inclusion resembles a radio station's decision to air a song, so the study of playlist impacts on streaming resembles the question addressed in studies of the impact of airplay on recorded music sales (Liebowitz, 2004; Dertouzos, 2008; McBride, 2014). Algorithmic playlists are literally most-streamed lists, so measuring their impact on streams is very related to existing work on the impact of best-seller lists on sales and product variety (Sorensen, 2007; Carare, 2012). Salganik et al. (2006) find evidence that signals of popularity such as best-seller lists lead to a "self-fulfilling prophecy." Playlists also resemble advertising, and some of the empirical challenges in measuring their impact recalls the challenges described in the new literature on advertising effectiveness (see, e.g. Lewis et al., 2015). Finally, platform design can also affect creativity for cultural products (Wu and Zhu, 2018).

3 Data

The underlying data for this study come from three separate sources and consist of two distinct datasets. The first dataset includes streaming data at Spotify. In particular, we observe the daily top 200 songs on Spotify, by country, for 26 countries, during 2016 and 2017.[15] The 2017 country-specific streaming data are available directly from Spotify, which provides daily streaming totals for each of the top 200 songs by country, back to the start of 2017.[16] The 2016 streaming data are from Spotontrack.com, which tracks streams, playlists, and followers on Spotify.[17] The 2017 country-level streaming data contain 1,847,615 daily song observations

[15]We include these 26 countries because we can obtain the New Music Friday lists for these countries. See below.

[16]See https://spotifycharts.com/regional.

[17]See Seehttp://www.spotontrack.com.

and a total of 48,731 song-countries and 19,055 distinct tracks.[18] In addition to country-specific top 200 daily streams, we also have the daily global top 200 streams, which cover all countries where Spotify operates and include 1,764 distinct songs during 2017. Table 1 reports the total number of streams, by country, in the 2017 country-level data.

Our second dataset also comes from Spotontrack.com and corresponds to the songs that appear on various playlists, including their ranks and the dates the songs enter and leave the lists. We focus on the five most-followed Spotify-owned global playlists, as well as three country-specific Spotify-owned playlists. The global lists are the four global curated lists (Today's Top Hits, RapCaviar, Viva Latino, and Baila Reggaeton) and the algorithmic Global Top 50. The country-specific list is New Music Friday, which is available separately for each country. The New Music Friday playlists for 2017 include 52,851 distinct song-countries and 20,621 distinct songs (because many songs appear on multiple countries' recommendation lists). While we have New Music Friday playlists for all of 2017, our data on the global curated playlists begins at different dates during 2017, with the latest in May, 2017. Table 2 summarizes the information, with both the number of followers for the lists, as well as the dates we start observing the lists.

We also obtain song and artist characteristics for each song streaming in the country-level and global streaming sample in 2017, as well as for each song on the playlists we study. In particular, we observe the record label and the International Standard Recording Code (ISRC) for each song.[19] The ISRC code provides us with measures of the national origin of each song, as well as its release vintage.

The label identity allows us to create of measure of whether songs are released by major or independent record labels. We have a total of 6,577 distinct labels in our combined datasets, and no clear way of classifying them into major and independent. Using their names, however, we are able to identify some of the obvious major labels.[20] While this method guarantees that all the labels that we classify in the major category are indeed majors, some of the non-obvious majors may end up being identified as independent labels. Since the main goal of this classification is to make comparisons, for instance, between the major composition of different playlists, our measure nevertheless remains informative. We are also interested in separately

[18] Countries included in the sample are Brazil, Canada, Switzerland, Colombia, Germany, Denmark, Spain, Finland, France, Great Britain, Hong Kong, Indonesia, Iceland, Italy, Malaysia, Mexico, Netherlands, Norway, Philippines, Portugal, Sweden, Singapore, Turkey, Taiwan, and the United States.

[19] The ISRC is the internationally recognized identification tool for sound and music video recordings. See https://www.usisrc.org/.

[20] We classify as major any record label containing the following names: Asylum, Atlantic, Capitol, Epic, Interscope, Warner, Motown, Virgin, Parlophone, Republic, Big Machine, Sony, Polydor, Big Beat, Def Jam, MCA, Universal, Astralwerks, WM, Trinidad & Tobago, RCA, Columbia.

studying the new artists on the New Music Friday lists. To determine which artists are new among those whose songs are in the 2017 country-level streaming data, we start with artists whose songs are on the 2017 New Music Friday playlists, then remove the artists with songs observed streaming during the previous year 2016. For each of the remaining artists, we obtain recording release histories from Musicbrainz, an open music encyclopedia that collects music metadata and makes it available to the public.[21] Using these histories, we discard artists whose first release predates 2017. This leaves us with a set of 670 new artists whose songs appear on the New Music Friday playlists during 2017.

We use these underlying datasets to create our main analysis samples, which consist of the songs from a playlist, merged with the streaming data. With this sort of dataset we can do two broad things. For songs already appearing on the streaming charts when they appear on a playlist - from the global curated playlists - we can construct time series on their streaming, before and after their chart appearance. We also observe when the songs leave the chart, so we can also examine the evolution of their daily streaming before and after they leave the chart.

The second broad dataset, for the New Music Friday playlists, resembles the first, except that we lack any pre-listing streaming data. We link dates and ranks for appearances on a country's New Music Friday lists with subsequent daily appearances on the country's daily top 200 streaming chart. Because songs remain on the New Music Friday lists for 7 days, there is no variation in the timing of removal.

We use a different approach for the analysis of the impact of inclusion in the Global Top 50 algorithmic playlist. Because we observe the top 200 streaming songs in each day of our sample - and because the Global Top 50 playlist is based on the song's past streaming ranking - we can replicate the Global Top 50 playlist and additionally observe the level of streams for songs that would have been ranked 51^{st} and lower had the Global Top 50 list been longer. We can therefore pay particular attention to a possible discontinuity in streams around the 51^{st} ranked song. In empirically exploring the determinants of the Global Top 50, we noticed that playlist matched the previous day's streaming ranking for 133 days during 2017 and matched the streaming ranking of two days earlier for 218 days. We use only these 351 of 365 days in our estimation, where we know not only the Global Top 50 but also which songs would have been listed next had the Global Top 50 list been longer.

For calculating the effect of playlist inclusion on streaming, we will ultimately be interested in the time that songs spend on the playlists. Measuring this is complicated by two facts. First,

[21] See https://musicbrainz.org/.

songs can enter and leave the playlists more than once. This is rare, except for the Global Top 50, where songs can enter and leave the playlist according to the vagaries of the streaming charts. Songs on this list have an average of 1.38 spells. Table 2 describes the duration of the song spells on various Spotify lists in our data. For example, the mean spell on Today's Top Hits is 54.2 days, and the average number of spells per song is 1.004. The mean spell on RapCaviar is 39 days (with an average of 1.07 spells per song), and the mean spell for Viva Latino is 111 days (with 1.03 spells per song). A second complication arises from the fact that some songs are already on the list when our playlist data begin, and some are still on the lists as our data end, so our duration measures are censored. We can use censored regression to estimate the underlying mean spell length. Table 2 reports these, and as expected they are longer than the raw averages. Finally, we multiply the underlying mean spell lengths by the number of spells per song.

4 Effect of List Inclusion on Streams

This section examines the effects of the Spotify's largest global curated playlists, which tend to include already-established songs and artists, on the volumes of streaming experienced by included songs. We turn in Section 5 to effects of the New Music Friday playlists on the performance of new songs, or product discovery.

4.1 Effect of Inclusion on Global Playlists

Before turning to regression approaches, a simple look at some data is instructive. Figure 1 shows the evolution of playlist followers and U.S. daily streams for a song added to Today's Top Hits during 2017. The song "What Ifs" by Kane Brown was added to the Today's Top Hits playlist on October 5, 2017. On or about that date, the number of playlist followers for the song jumped from 11.6 to 29.2 million. The number of playlist followers then fluctuated around 30 million for about a month. On November 2, the song was removed from Today's Top Hits, and its number of followers fell from 30.8 million to just 10.8 million. In subsequent months the number of followers continued to generally decline, sometimes rapidly as particular playlists removed the song.

The large and discontinuous jumps in followers for the Kane Brown song above, which was added then removed from the most-followed playlist on Spotify, suggest a method for measuring the impact of playlist inclusion on streams for the global playlists. We can look at the streams in countries where the song was already observable among the streaming songs (among the top 200 daily songs for the country) prior to the song's inclusion on the list. We can then examine whether the streams change with the discontinuous change in followers.

The idea here borrows from the regression discontinuity approach (Lee and Lemieux, 2010). Our assumption here is that a song's underlying popularity evolves smoothly after release as people hear of the song, and some little-followed playlists add the song. But when a list with many followers adds the song, the song is "treated," and the number of users exposed to the song via playlists jumps discontinuously. Figure 1, which overlays U.S. daily streams against the number of the song's daily followers, provides much of the answer for this song. In June 2017, the song has nearly 200,000 daily streams, and the number rises steadily (around day of the week fluctuations) to October. On October 5, when the number of followers jumps from about 12 to nearly 30 million, the number of daily streams rises by roughly 100,000. Later, on November 2, when the number of followers falls by almost 20 million, the number of daily streams falls by about 100,000.

Approaching this systematically, we can pool song-countries and flexibly characterize streams around the event via the following model:

$$s_{ict} = \gamma_\tau + \mu_{ic} + \pi_d + \varepsilon_{ict} \tag{1}$$

Here, s_{ict} is a measure of streaming for song i in country c on day t, π_d is a day of the week effect, μ_{ic} is a country-specific song fixed effect, and ε_{ict} is an error term. Finally, τ refers to the days since the event (or until the event when $\tau < 0$). We can then plot the coefficients γ_τ against τ.

Before turning to estimates, we need to clarify the designation of the event day. We observe the date that a song enters a playlist, but we do not know what time the song entered. This creates some challenges in defining the last untreated and first treated days, i.e. the last full day in which the song is not on the playlist and the first day in which the song is on the playlist all day. Our data are updated every 24 hours, so the appearance of a song on a playlist on a particular day means that the song may have entered the list any time during the previous 24 hours. This in turn leaves two possibilities. One is that the song entered today, so that the apparent entry day is actually partially treated, while the day before its appearance was fully untreated. The second possibility is that the song entered the list the previous day. In that case, the entry day would be fully treated, while the previous day would be partially treated. We cannot distinguish these two cases. We can be confident, however, that two days before the entry day is fully untreated, while the day after the entry day is fully treated. Hence, our shortest window for effect estimation compares two days prior to the entry day to one day after. In our estimation below we set $\gamma_T = 0$ on the last definitely fully untreated day and $\tau = 3$ for the first definitely fully treated day. We define the drop window analogously.

The left panel of Figure 2 reports the results of this estimation for the event of addition to Today's Top Hits. A few things are clear. First, there is a pre-event trend: streams are rising when songs are added to the playlist, although streams fall on the last pre-treatment day. Second, while there is no apparent effect on the first potentially partially treated day (the day prior to the song's appearance on the list, with $\tau = 1$), streaming rises somewhat on the (potentially partially treated) entry day ($\tau = 2$) and substantially by the first fully treated day ($\tau = 3$). Streams continue to rise for two more days, then begin rising at a steady rate. The right panel of Figure 2 reports the analogous model for the removal events from Today's Top Hits.

We estimate the effect as the coefficient on the first fully treated day relative to the level of the last fully untreated day. (This may be conservative, as streams seem to be rising relative to trend for a few days after the add event). We use data from countries that differ substantially in size and therefore streaming volumes. To make the data comparable across countries, we normalize streams by the countries' annual total streams in our data. We then multiply these figures by a million to put them in convenient units. We refer to this measure as "normalized streams."

Table 3 reports effects of additions and removals from the four curated global playlists. We estimate that appearing on Today's Top Hits daily raises streams by 3.346 normalized streams (standard error=0.28). We estimate that removal from Today's Top Hits reduces normalized streams by 2.757 (0.09). What is the size of the benefit of being included among Today's Top Hits? Songs remain on Today's Top Hits for an average of 74.4 days (see Table 2). If we assume that the effect evolves linearly, then the average daily effect is 3.052, the average of the add and removal effects ($= \frac{3.346+2.757}{2}$). Today's Top Hits is a global list, so to calculate its effect on streams we multiply the average daily effect estimate by the average spell length of its songs, by the average spell per song entering the playlist, and by the global number of streams in millions. This is (3.052 streams per million) $\times$ (74.4 days) $\times$ (1.004 spells) $\times$ (85,047 million streams).[22] This yields 19.4 million additional streams, which - given our best estimate of Spotify's payments of \$3.97 per thousand streams - translates to \$77,016 in payments from Spotify alone.[23] See Table 4, which also presents estimates for the other global lists. These estimates vary between \$39,876 for RapCaviar and \$200,516 for Viva Latino. We defer further discussion of magnitudes until we discuss the effect of appearing on the Global Top 50 playlist.

4.2 Effect of the Global Top 50 Playlist

If we knew the algorithm underlying algorithmic lists, then we could use a discontinuity approach to measure the impact of list inclusion on streams, comparing songs that just made the list to those that just missed inclusion. We do not know the list algorithms generally, with the important exception of the most-played lists, such as the Global Top 50, which shows the top 50 songs according to the previous day's streams. Because we observe the streams for the top 200 songs each day, we know which song would have been listed as the Global Top 51^{st} through 200^{th} if the Global Top 50 list were longer, or if it were a Global Top N.[24] This allows us to ask whether the dropoff in streams is larger for the previous day's 51^{st} song than for songs at nearby ranks. The effect of list inclusion will then show up as a discontinuity in the relationship between streaming and the previous day's ranks between the ranks of 50 and 51.

To implement this flexibly, we estimate the relationship between the change in log streams across sequential ranks and the rank, with the following model, estimated on the global data:

$$\log\left(\frac{s_{rt}}{s_{r-1,t}}\right) = \theta_r + \varepsilon_{rt}, \tag{2}$$

where s_{rt} is global streams at rank r on day t, θ_r is an estimated parameter, and ε_{rt} is an error term. This delivers a sequence of coefficients θ_r showing the percent reduction in streams as we move from the $(r-1)^{th}$ ranked song to the r^{th} ranked song. If we plot these θ_r coefficients in the neighborhood of θ_{51}, is there a jump?

[22] While some songs appear more than once on Today's Top Hits, the songs included in the sample used in Table 3 only enter the list once. In the above calculations, we therefore assume that the effect of entering and exiting the playlist is the same for songs that would enter the playlist more than once.

[23] We obtain estimates of Spotify's per stream payouts from McIntyre (2017), Sanchez (2018), and Trichordist (2018).

[24] In our data, we observe that the Global Top 50 is based on either the streams from the previous day or from two days ago. The Global Top 50 playlist matched the previous day's streaming ranking for 133 days and the streaming ranking of two days earlier for 218 days during 2017. We therefore observe the songs that would have been ranked 51^{st} through 200^{th} for 351 days in 2017 (out of the 365).

Figure 3 reports the result of estimating equation (2) using the daily global top 200 Spotify streaming data. The decline in streams is roughly steady at just under 2 percent for ranks 40-50. The decline from 50 to 51 jumps to 6 percent, then returns to the roughly 2 percent for ranks 52-60, and the difference is large relative to the confidence interval. Thus, just making the list adds about 4 percent to streams, and a regression of $\log\left(\frac{s_{rt}}{s_{r-1,t}}\right)$ on rank and an indicator variable equal to one for the 51^{st} rank gives a coefficient of -.047 (standard error of .008).

How big is the overall effect of being on the Global Top 50? The average global streams for a song at the 50^{th} position on the Global Top 50 (and therefore ranked 50^{th} the previous day) is 1,242,513. Multiplying this by 0.047 gives 59,000 streams per day. The average duration on the Global Top 50 chart (correcting for censoring and the number of spells per song) is 51.24 days. If the effect of being on the list were the same across ranks - and therefore the same for each day spent on the list - then we can calculate the overall effect of appearing on the Global Top 50 as $(0.047) \times (1,242,513) \times (51.24) = 3,021,867$ streams. Songs on the Global Top 50 playlist have an average of 92.8 million global streams, suggesting that 3.3 percent of their streams arise from being on the Global Top 50 chart.

4.3 Magnitudes and Mechanical Effects

To gauge the size of the effect estimates, it is useful to compare them to the effects that would arise mechanically if streaming users spent all of their time using a playlist to which they had subscribed. Take Today's Top Hits, a playlist with 50 songs with 18.5 million followers during the sample period. If followers did all of their listening through the playlist and listened to all 50 songs per day, then entering the list would add 18.5 million daily streams to each song on the list. With a bit of detective work we can estimate that Spotify users listen to an average of roughly 12.5 songs per day. In 2016 Spotify reported paying \$1.813 billion to rights holders.[25] With our estimate of Spotify's average royalty of \$3.97 per thousand streams, this suggests 457 billion worldwide Spotify streams during 2016. Spotify reported 100 million active users during 2016.[26] Given 365 days in the year, this suggests that users listened to an average of 12.5 songs per day.

Applying this average listening propensity, if Today's Top Hits users spent their listening time only with the list, then daily streams for listed songs would rise by about 4.63 million $(=\frac{18.5}{(\frac{50}{12.5})})$ streams per day. Our econometric estimate of the daily streams effect of being added to Today's

[25]See https://www.statista.com/statistics/487332/spotify-royalty-payment-costs/.
[26]See https://www.statista.com/statistics/367739/spotify-global-mau/.

Top Hits is 259,531, which is 5.6 percent of the maximum mechanical effect (see Table 4). For the other global curated lists, the share varies between 9 and 12 percent.

5 New Music Friday Playlists and Product and Artist Discovery

We have documented large and significant impacts of Spotify's playlist decisions on the success of songs added to major global curated playlists. As reflected in the fact that those songs had streaming histories prior to their addition to playlists, the songs added to the major global playlists are widely known prior to their addition to those playlists. "Product discovery" is an elastic term. Even a song well known to some people must be "discovered" before being adopted by others. Hence, even the major global playlists promote discovery of songs and artists. That said, the promotion of new music stands as a potentially different sort of product discovery, at least in degree if not also in kind. Moreover, the promotion of music that is not only new but is also by artists who are themselves new to the market offers a greater degree of product discovery than the promotion of widely known or even new songs by known artists. With these distinctions in mind, we turn now to analyses of Spotify playlists that explicitly promote new music, the New Music Friday lists.

Each week, Spotify constructs a rank-ordered list of 50 new songs for each country in which it operates.[27] These New Music Friday lists differ across country, albeit with overlap, so that across our 26 countries, Spotify recommended an average of 397 distinct songs per week during 2017. Of these songs, about 17 percent became successful in the sense of appearing in at least one country's top 200. This dwarfs the unconditional success rate. Of the 934,265 songs entering Spotify in 2017, only 19,055, or 2 percent, entered the daily streaming top 200 in at least one of our sample countries. This, in turn, at least naively suggests a benefit of the New Music Friday lists in reducing the costs consumers face in discovering music.

Some of the New Music Friday recommendations are for songs by already-known and successful artists, with whom listeners are already acquainted. Other recommendations are for songs by new and previously unknown artists, raising the possibility that these lists help with artist discovery. Songs almost always arrive on the New Music Friday list the day they are released, so we cannot use the before and after approach employed for the global lists above. Instead,

[27] At times the New Music lists have included more than 50 songs. As we document below, effects are concentrated near the top of the lists.

we can ask how eventual streaming varies with songs' New Music Friday ranks. As a way to introduce our approach, we begin by showing the share of songs at each New Music Friday rank that ultimately appear in the recommended countries' top 200 daily streaming charts. Figure 4 summarizes these relationships for the top 20 recommended songs using all of the country-weeks in the sample.

Songs with better ranks on the New Music Friday playlists are more likely to appear on the daily Spotify top 200 streaming charts. Close to 85 percent of the songs ranked #1 on a country's New Music Friday lists appear on the country's streaming chart, as do over 80 percent of those ranked #2. The share charting declines monotonically in rank, reaching about 10 percent for songs ranked 20 (or, not shown, lower). We observe a similar relationship between recommendation rank and the share of songs appearing in the top 100, as well as in the top 50, 25, or 10 (not shown). In short, songs with top 10 recommendations have some chance of appearing in the top 200 or even the top 100, while songs recommended outside the top 20 are rather unlikely to achieve even the top 200.

Figure 4 shows that songs with higher-ranked recommendations tend to achieve higher streaming ranks. This is suggestive that high recommendation ranks matter for performance. But whether higher-ranked recommendations actually *cause* better streaming performance is another matter requiring different evidence. We offer two broad approaches below, using song fixed effects and using an instrument for the New Music Friday rank.

5.1 Song Fixed Effect Approach

The New Music Friday lists differ across countries, and this creates a possible empirical strategy for measuring the impact of New Music Friday ranks on success. Figure 5 provides an illustration of the cross-country variation in New Music Friday rankings, comparing the U.S. and Canadian New Music Friday lists released on December 10, 2017. The rankings are positively correlated, but they are substantially different. If we take the view that countries have similar tastes but are treated with different rankings, then we can measure the effects of New Music Friday rankings by comparing the streaming performance of the same songs in different countries where they have received different New Music Friday rankings.

Figure 6 shows the U.S.-Canada rank differential distribution for the entire year. Of the songs appearing on both lists, the mean and median differential is roughly zero, but there is variation. The question asked by this measurement approach is whether the songs ranked higher in, say, the U.S. than Canada perform systematically better in the U.S. than Canada. Using a binary measure of whether a song (eventually) appears in the country's daily top 200 streaming chart as the outcome, the song-specific differential can take one of three values: 1, 0, and -1. Figure 7 shows the relationship between the rank differential on the horizontal axis and the smoothed outcome measure. Songs with a better rank in the U.S. are more likely to make the Spotify streaming charts in the U.S. than Canada. This is preliminary evidence that differential New Music Friday rankings give rise to differential stream success.

To implement this approach for all countries via a regression, define D^{200}_{ic} to be a binary measure of whether song i appears among the daily top 200 streaming songs in country c at some point after entering the New Music Friday playlist. Next, define δ^r_{ic} as a dummy that is 1 when song i in country c is ranked r^{th} on the country's New Music Friday list.

As noted above in the discussion of Figure 4, a regression of D^{200}_{ic} on the δ^r_{ic} terms does not indicate the effect of rank on streaming. The unobserved quality of the song - to the econometrician - affects both rank and streams. Presumably, songs that are good will have both high placements on the list and high streaming. If we had a measure of each song's quality, then we could control for this directly, and then measure the impact of the New Music Friday ranks on streaming. While we do not observe song quality, we can include a song fixed effect to control for its quality, then ask whether the song is more likely to appear in the streaming charts in countries where it has a more favorable recommendation. That is, we can estimate

$$D^{200}_{ic} = \alpha^r \delta^r_{ic} + \mu_c + \eta_i + \varepsilon_{ic}. \tag{3}$$

In this setup η_i is the unobserved quality of song i. Begin with the assumption that songs have the same appeal in different countries, or that η_i is the same across countries. Then the coefficients α^r show how ultimate streaming success varies with position on the New Music Friday list. That is, α^r provides evidence on the causal impact of higher recommendation ranks.

Figure 8 reports the estimated parameters α^r (with α^{50} normalized to 0) from two specifications, with and without song fixed effects. The line labelled "OLS," from the specification without song fixed effects, echoes the "top 200" bars in Figure 4. The "Song Fixed Effects" line comes from a specification including song fixed effects, and the size of the effect of a top ranking is smaller with the song FE included. Songs with a number 1 rank are over 80 percentage points more likely to appear on the streaming charts than songs ranked 50^{th}. After including song fixed effects, this differential shrinks to just below 50 percentage points. This finding is consistent with the idea that some part of the raw relationship between ranks and streams arises because curators give favorable ranks to songs they expect consumers will like, rather than a causal impact of the New Music Friday playlist ranking on streams. The effect falls sharply with rank, to about 18 percentage points at rank 10 and to about 4 percentage points at rank 20. (We provide evidence on statistical significance in Table 5 below).

Even controlling for song quality with song fixed effects, two main threats to identification remain. The first is that countries have different tastes, in which case perceived song quality would differ across countries, and a single song fixed effect that is common across countries would not control for song quality. A second challenge is that country-specific New Music Friday lists will differ across countries for endogenous reasons. We explore these in turn.

The song fixed effects approach assumes that unobserved song quality is the same across places where the song receives different ranks. This puts some burden on places having similar preferences. We deal with this by grouping countries with a common language, with an English-speaking group consisting of the US, Canada, and Great Britain and a Spanish-speaking group consisting of Spain, Mexico, and Colombia. We can verify the similarity of these countries' musical tastes, based on Spotify listening. Using the 2017 streaming data to create a vector for each country with the share of streams for each artist, we see that the correlations between linguistically similar countries' vectors are among the highest. The correlation for the US and Canada is 0.95, and the correlation for Mexico and Spain is 0.93. We then re-estimate (3) using only similar countries.

Rather than report a proliferation of figures, we summarize our results by estimating (3) with three rank dummy variables (ranks 1-5, ranks 6-10, and ranks 11-30) rather than 49. Table 5 reports these results, starting with OLS and the baseline song fixed effects approaches in columns (1) and (2). Columns (3) and (4) report specifications using English (US, Canada, and Great Britain) and Spanish-language (Spain, Mexico, and Colombia) country groups, respectively, and results are quite similar to the baseline.[28] Effects for ranks 1-5 are large, effects for ranks 6-10 are smaller but significant, and effects for ranks 11-30 are small and insignificant.

This still leaves a concern that ranks are endogenously different across countries. Perhaps the most salient concern arises from domestic music, which one might expect to be both better-ranked on its home-county New Music Friday list, as well as better-performing on its domestic streaming chart but not because the better ranking causes the better performance. The New Music Friday lists have elevated ranks for domestic music: on average, domestic music makes up

[28] We also obtain very similar results using only the US and Canada, and Spain and Mexico, respectively.

15 percent more of the New Music Friday listings at home than abroad. To avoid this problem, we re-estimate the model excluding domestic music. Results, in column (5) of Table 5, are very similar to the baseline results.

5.2 New Songs and Artists

While all of the songs entering the New Music Friday lists are new, many are by established artists. While the popularization of a new song, even if by an established artist, requires product discovery on the part of curators and consumers, ascertaining whether the New Music Friday list can promote discovery of works by new artists is of separate interest. In order to study artist discovery we would like to estimate the New Music Friday effect separately for artists who are not already widely known to consumers. To this end we re-estimate the model including only songs by less-well-known artists. Column (6) of Table 5 includes only independent-label artists without streams in the 2016 data, and results are similar. Column (7) includes only the demonstrably new artists, those who not only have no streams in 2016 but whose first recording appears in 2017. This reduces the sample size sharply, to 2,221. Still, results remain quite similar, although standard errors rise. Column (8) uses only the new artists and excludes domestic music. Results are again quite similar. Finally, column (9) uses new independent artists, again with similar results. This evidence suggests that the New Music Friday playlists aid in the discovery of new artists.

5.3 Instrumental Variables Approach

Even with domestic music excluded, one can be concerned that the differential rankings of, say, French songs in the US and Germany may endogenously reflect differential curatorial expectations about tastes in the two countries. To get around this we would require a source of variation in the New Music Friday rank of particular songs across countries that is unrelated to the appeal of the song.

Home bias, along with different-sized home markets, gives us a possible strategy. Suppose there is home bias in the New Music Friday lists, so that a disproportionate share of the songs on the New Music Friday lists are domestic in each country. Suppose further that because of differences in market size, there are different amounts of domestic music in each market. Then non-domestic music would receive worse ranks in larger markets, simply because it was more likely to be pushed down the ranking by domestic music. For our purpose, this would give us a reason why particular songs would achieve different New Music Friday ranks in different countries that is unrelated to the appeal of the song in the two countries.

To explore this strategy, we use the total Spotify streams (among the top 200) as a measure of market size for each country. Using only the non-domestic songs, we then run a first-stage regression of the songs' New Music Friday ranks on song fixed effects and the music market size variable (total streams in the country). The coefficient on the market size variable indicates whether a given song has a worse (higher) rank in a country with a larger market, and the coefficient is large and significant (see Table 6).

We then implement this directly in a regression of our streaming measure (whether a song appears in the top 200 on song fixed effects as well as its New Music Friday rank, instrumenting the rank with the market size measure. We have only one instrument, so we can only use one measure of New Music Friday rank.

Column (1) of Table 6 reports OLS regressions of the streaming measure on the New Music Friday rank (divided by 10) without fixed effects. The resulting coefficient reflects both the determinants of ranks and their effects. Column (2) then includes song fixed effects, and - as in our earlier exercises - the coefficient on rank falls by roughly half. Column (3) reports the first stage regressions of the New Music Friday rank (divided by 10) on song fixed effects as well as market size, estimated with robust standard errors. The market size measure is positively and significantly related to rank, indicating that non-domestic songs have worse (higher) ranks in countries with larger music markets. Column (4) continues to include song fixed effects and also instruments the rank measures using market size. Robust standard errors are reported. Coefficients are similar to the song FE estimates, although standard errors are much larger, and the coefficients are slightly smaller in absolute value. We take the similarity of the IV estimates to the FE estimates, along with the similarity of the results from the country FE approach, to indicate that our basic estimates do not arise from endogenous New Music Friday ranks.

One might still be concerned that the instrument - destination market size - is correlated with preference for particular origin countries. For example, Germany is a large destination market, and its consumers might have an elevated preference for music from other German-speaking countries. In that case, the instrument would not simply give rise to variation in songs' New Music Friday ranks. Rather, it could be correlated with preferences. We explore this within the IV approach by excluding not just domestic music (as above) but also all imported music from countries sharing a language with the destination country. Columns (5) and (6) report the resulting first and second stage regressions, and results are essentially unchanged. We address one additional concern. It is possible that destination countries differ in the competitiveness provided by their domestic repertoire and therefore the success of imports as a whole. Under this interpretation, a song's higher New Music Friday rank in a smaller destination market would endogenously reflect the destination market's higher preference for the song, along with all imported songs. We can deal with this concern by including a destination country fixed effect, which allows each country to have systematically different preferences for imported music. We cannot implement this approach with our instrument, as our instrument varies only across destination countries. Still, because the various IV strategies give results similar to the basic OLS approach with song fixed effects, we use this as a baseline. And when we add country fixed effects to the OLS with song fixed effects baseline in column (7), the basic result is virtually unchanged. We conclude that New Music Friday ranks have a causal impact on streaming and that the song fixed effects approach provides reasonable quantitative estimate of its impact.

5.4 Effects over Time

Songs remain on the New Music Friday lists for only seven days. To the extent that listeners use the New Music Friday playlists as a utility for playing recommended songs, we would expect a clear effect during the week that songs remain on the list. Effects could continue past the time on the list, for example via the information communicated by list inclusion. Here we explore whether New Music Friday effects are persistent. We adapt the estimation framework of equation (3) slightly to estimate effects over time. Define $D^{200}_{ic\tau}$ as a binary measure that is 1 if song i appears in the streaming top 200 in country c τ days after appearance on country c's New Music Friday list:

$$D^{200}_{ic\tau} = \alpha^r_\tau \delta^r_{ic} + \mu_c + \eta_i + \varepsilon_{ic\tau}. \tag{4}$$

Then the parameter α^r_τ indicates the additional propensity to be among the top 200 streaming songs τ days after being added to the list.

Figures 9 and 10 reports three sets of estimates for different groups of ranks. Figure 9 covers only the first 14 days after the appearance of the New Music Friday list. The leftmost figure shows how the effect of appearing in the top 5 varies across days since appearance. The center figure repeats the analysis for songs ranked 6-10, and the rightmost left figure reports it for songs ranked 11-30.

As Figure 9 shows, there are large and immediate effects of songs appearing on the New Music Friday lists. These effects rise for the first four days, then decline. There is no sharp decline after day 7, when the songs leave the lists. And indeed, as Figure 10 shows, the effects persist for 100 days after appearance on the list, indicating that the effects of the New Music Friday lists are not merely mechanical. In short, there are large, persistent, and significant effects for songs in the top 5 and large but smaller effects for songs ranked 6-10. Effects for songs ranked 11-30 are small.

5.5 Aggregate Effects on Streams

We are interested in impacts of list inclusion on the total number of streams. We can construct measures of country-level streams for each song, subject to the caveat that we only observe streams when a song is among the daily top 200. Hence, our measure understates streaming, particularly for lower-ranked songs that are more commonly outside the top 200.

Figure 11 aggregates the effect over time, reporting the aggregate result by rank. A number 1 ranking adds about 550 normalized streams (corresponding to about 14,000,000 additional streams for a song ranked #1 on the U.S. chart). A song ranked #5 gets over 80 additional normalized streams, or about 2.1 million additional U.S. streams for a #5 ranking on the U.S. New Music Friday playlist. The effects peak within a few days after appearance on the New Music Friday list.

With our estimate of Spotify's royalty payment of $3.97 per thousand streams, the benefit of being ranked #1 on the U.S. New Music Friday playlist is worth $55,315, including only the direct benefits arising from Spotify payments.

6 Which Types of Songs Do Spotify Playlists Promote?

Rights holders in the independent record label community have long lamented their limited access to radio airplay (Thomson, 2009). Even in the streaming era, with its relaxed distribution bottlenecks, concerns remain. Moreover, cultural policies of many countries promote domestic music. While we do not attempt any measure of bias in this study, it is nevertheless interesting to descriptively explore which sorts of songs, by label type and national origin, are available and commonly streamed at Spotify. Further, which sorts of songs appear on the global curated and the country-specific New Music Friday playlists?

As Table 7 shows, among the 19,055 songs that we observe streaming in the 2017 country-specific sample, just under half (measured by either listings or distinct songs) are from independent record labels. The independent share of streams, however, is much smaller, at just over a quarter. U.S. origin songs make up a quarter of listings and songs in the country-level sample but account for 59 percent of streams. Domestic songs make up just over a quarter of listings, distinct songs, and streams in the country-level data on average.

The song sample made up of the global daily top 200 includes only 1,764 songs. Of these, independent songs account for a quarter of the tracks and just under a fifth of streams. U.S. origin songs account for 68 percent of these tracks and 71 percent of streams.

How about the playlists? Independent-label songs account for well under half of the listings and distinct songs at the global curated lists, while US-origin tracks account for roughly three quarters or more of the listings and songs, as well as streams, appearing on the global curated lists.

The New Music Friday lists have different coverage. First, they include greater independent music representation, just over half of the tracks overall. Second, they include less US-origin representation, accounting for roughly a third of listings and songs. Finally, domestic music makes up just under a fifth of the New Music Friday listings and songs. Given the large number of origin countries in the world, this average reflects a substantial amount of home bias. On average, origin repertoires make up 15 percentage points more of the New Music Friday lists in their home countries, relative to their origin shares outside of the home country.

7 Conclusion

Concerns about the exercise of market power by online platforms have grown substantially, to the point of generating debates over the suitability of current antitrust enforcement in the digital age. Despite these concerns, the empirical evidence regarding the causal impact of platforms' choices on the behavior of consumers is scant. The recorded music industry provides an opportunity for empirically documenting platform power: digitization altered promotion and distribution substantially, fostering the creation of platforms that collectively and simultaneously dominate both promotion and distribution. Streaming has emerged as an important channel for music consumption, and Spotify is the most prominent platform, with a higher market share than was held by retailers or radio stations in the digital era. Moreover, we are able to observe both platform promotion decisions - songs' inclusion on playlists - as well as measures of song success.

Relying on data from Spotify, this paper explores whether the platform has the ability to influence users' listening choices through its playlists, one of the most important channels to promote recorded music online. With all of the 25 most-followed playlists being maintained by Spotify, and with over 75 percent of the top 1,000 playlists' followers belonging to Spotify's curated lists, Spotify is clearly well-positioned to wield influence. We find clear evidence that Spotify has power to influence consumption decisions and document large and statistically significant effects of appearing on Spotify's general playlists. The major global playlists raise streams for prominent songs substantially. Getting on Today's Top Hits is worth almost 20 million additional streams, which translates to about $77,000 in additional revenue from Spotify alone. Playlists also affect the success of new songs and new artists. Getting on the top of the New Music Friday playlist in the U.S. is worth roughly 14 million streams ($55,315). Making the Global Top 50 chart raises streams by about 59,000 per day, or by about 3 million overall. Playlists have important impacts on which songs are heavily streamed. The major global lists tend to promote major-label and US-origin music, while the New Music Friday lists provide heavier coverage of independent and domestic music.

The fact that playlists have substantial impacts on song success should be of interest for music industry participants as well as observers of platforms more generally. Growing concentration in the streaming market, as well as other markets dominated by one or a few players, may create a need for scrutiny of how platforms exercise their power.

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A Figures and Tables

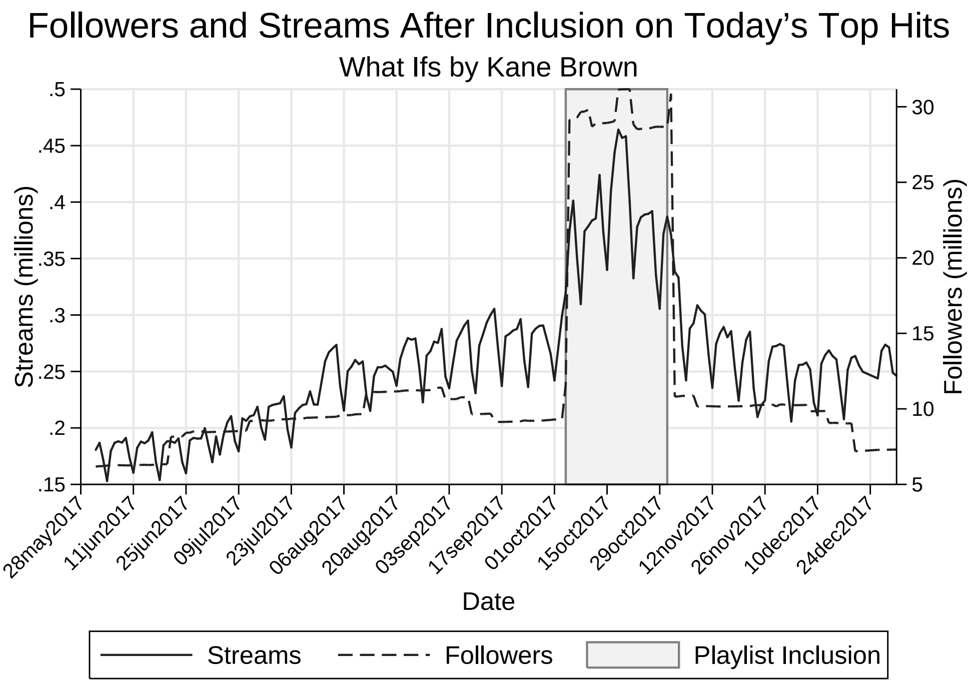

Figure 1: Daily Followers and US Streams for a Song added to Today's Top Hits.

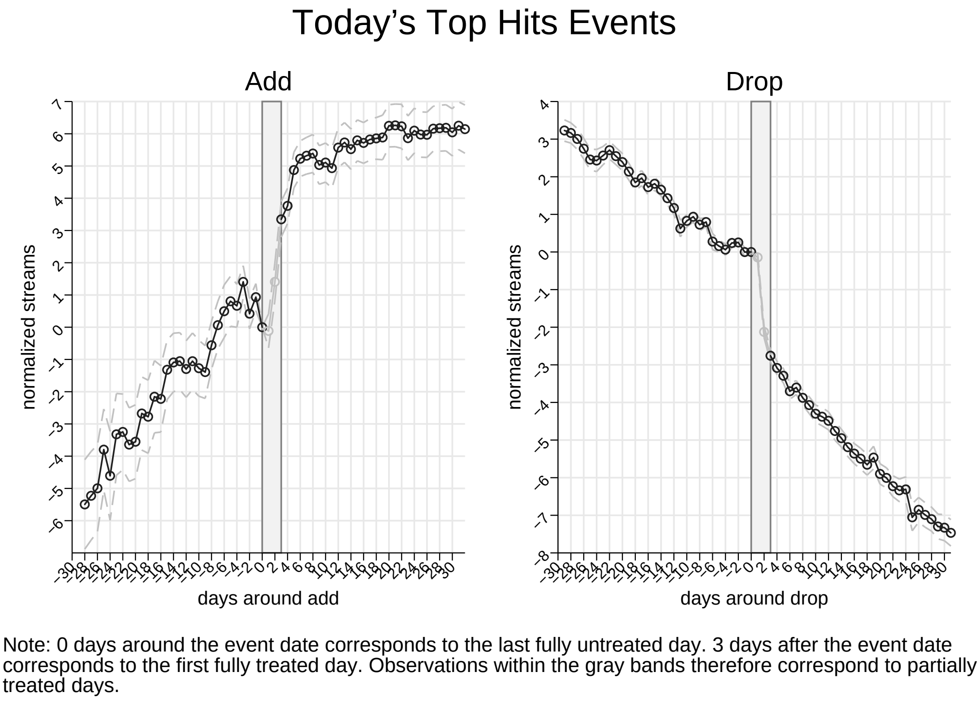

Figure 2: Normalized streams before and after add and removal events at Today's Top Hits.

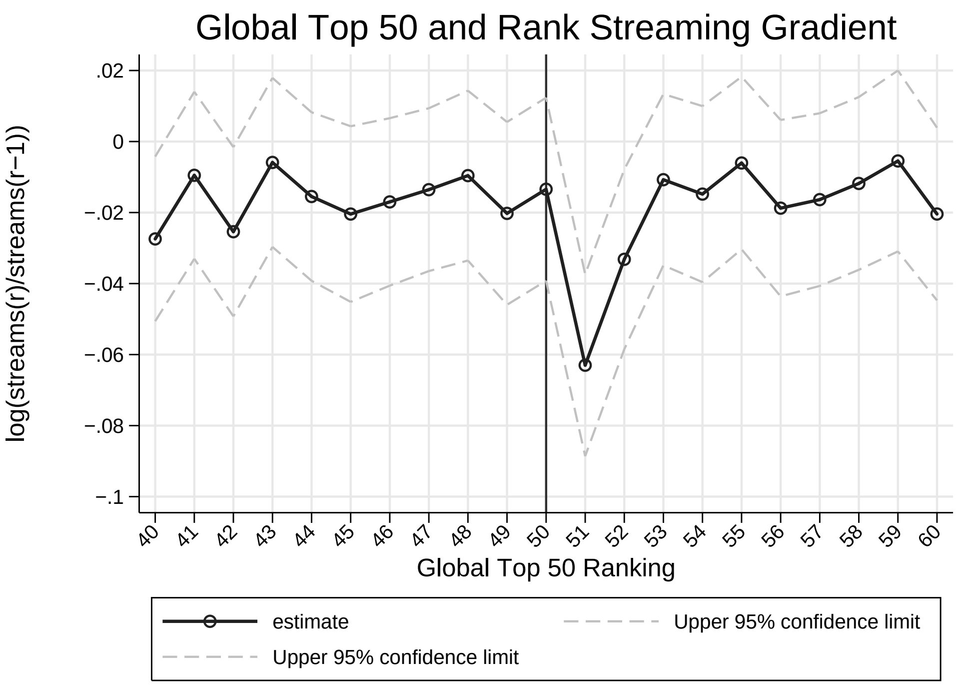

Figure 3:

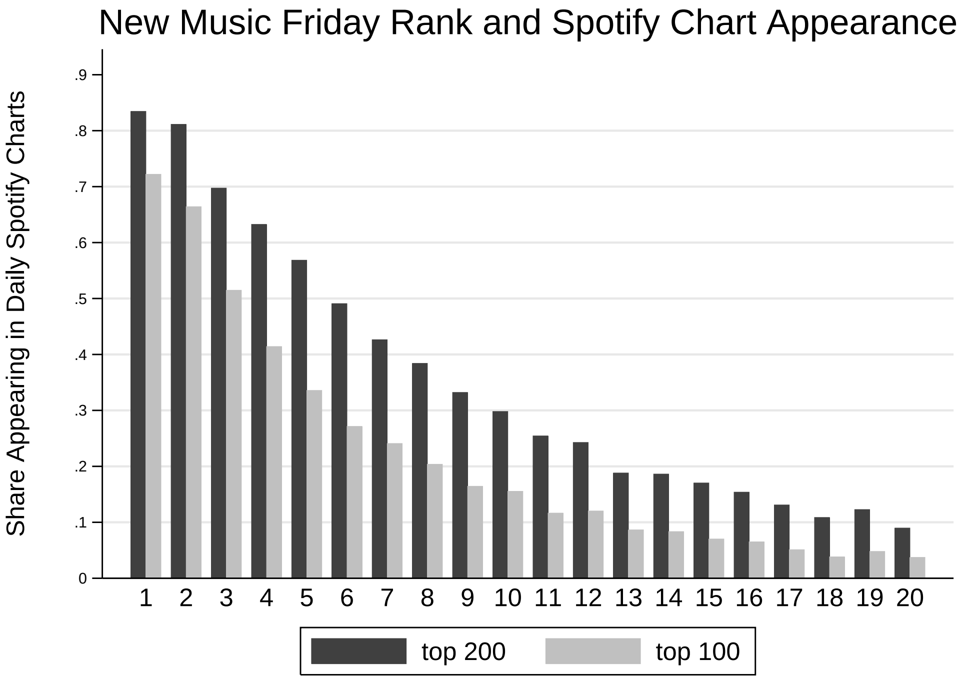

Figure 4: New Music Friday Ranking and Spotify Chart Appearance.

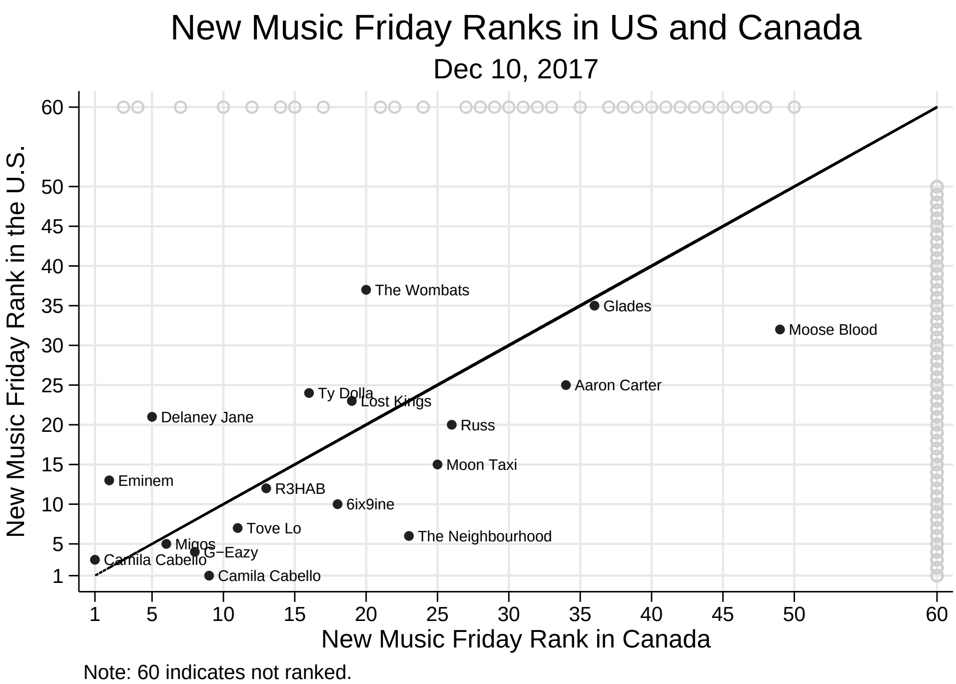

Figure 5: New Music Friday Ranks in US and Canada.

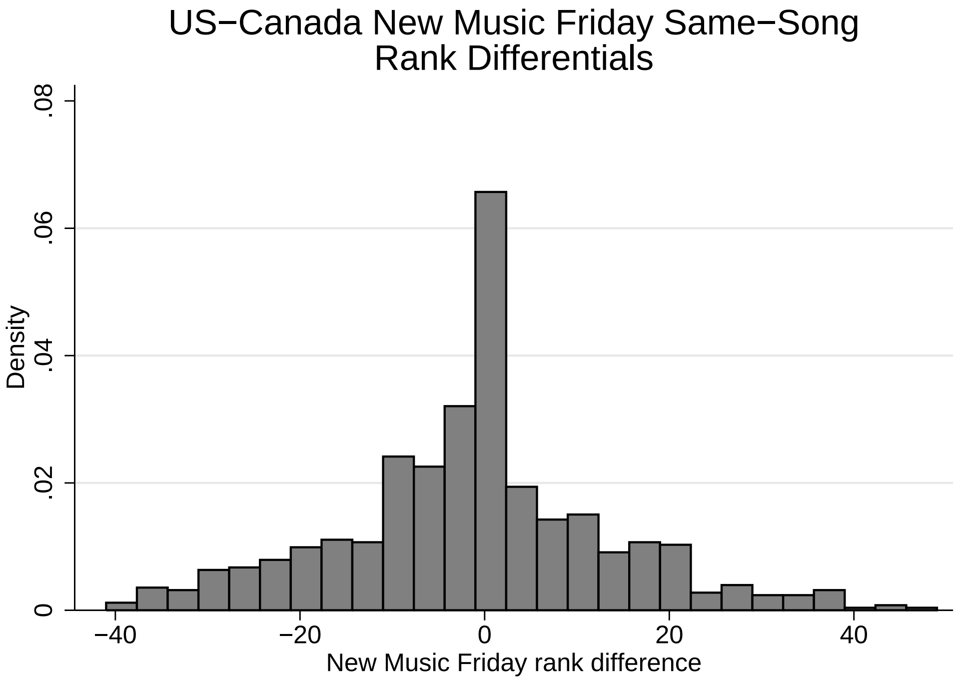

Figure 6: New Music Friday Rank Differentials for US and Canada.

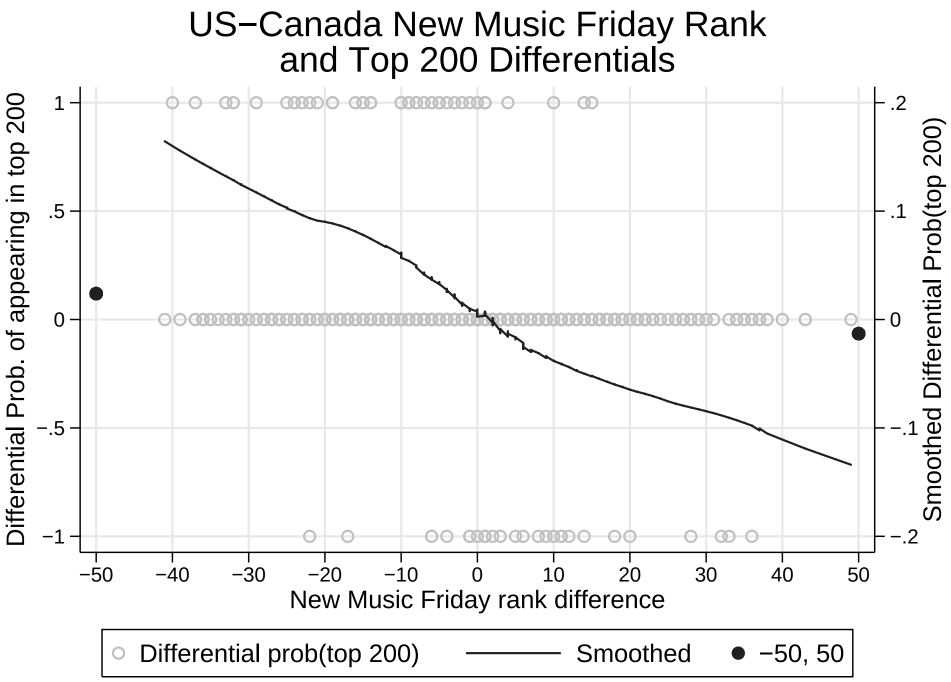

Figure 7: US-Canada New Music Friday Rank Differentials and Probability of Appearing in Top 200.

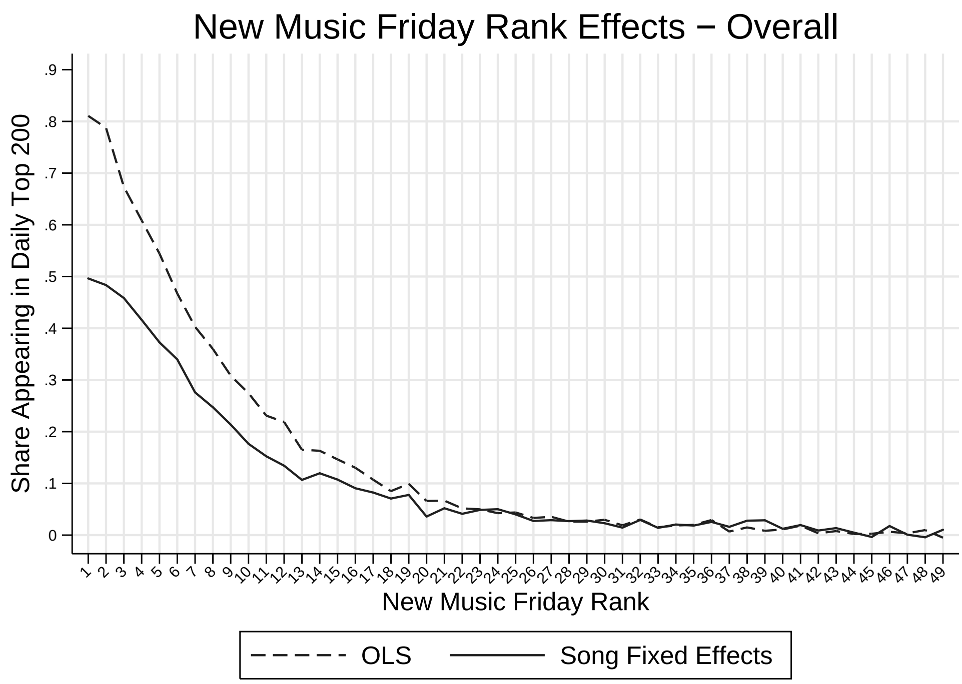

Figure 8: Effect of Appearing in New Music Friday on Top 200 Streaming Chart Appearance.

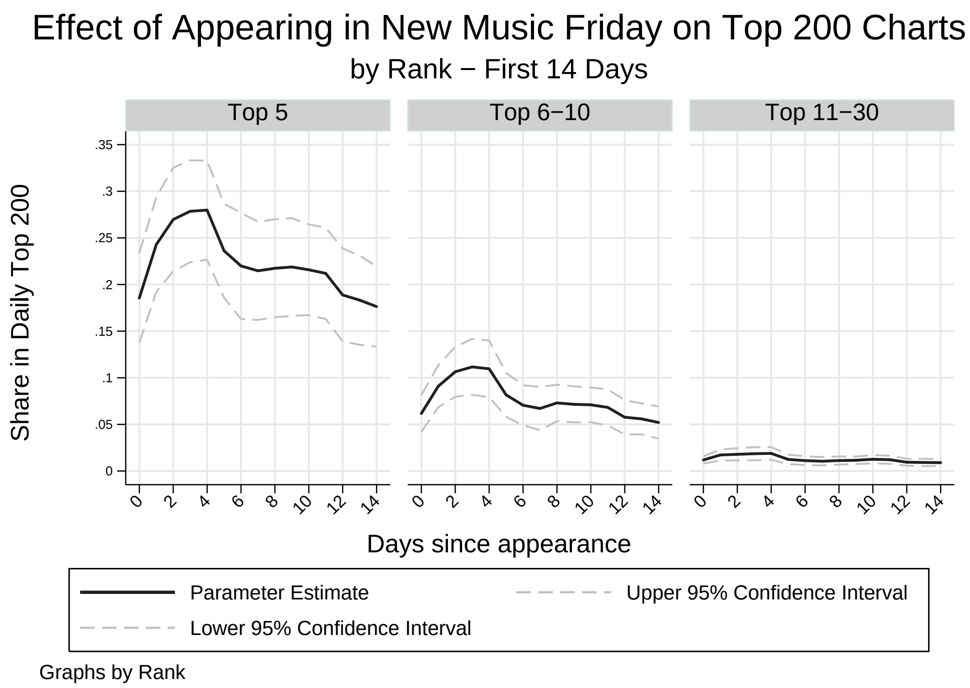

Figure 9: Effect Over Time of Appearing in New Music Friday - First 14 Days.

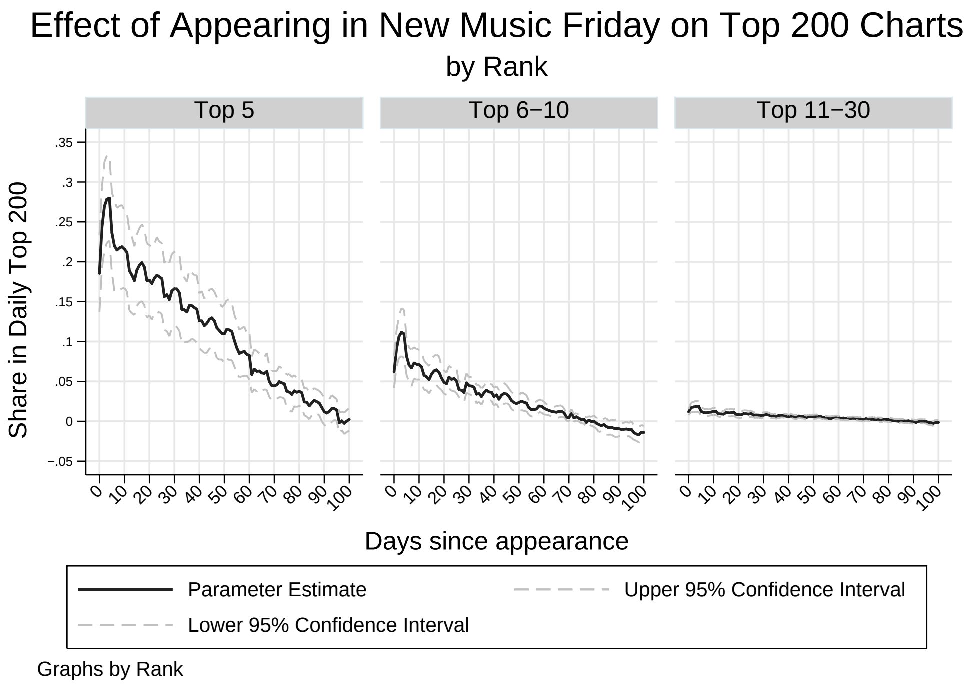

Figure 10: Effect Over Time of Appearing in New Music Friday.

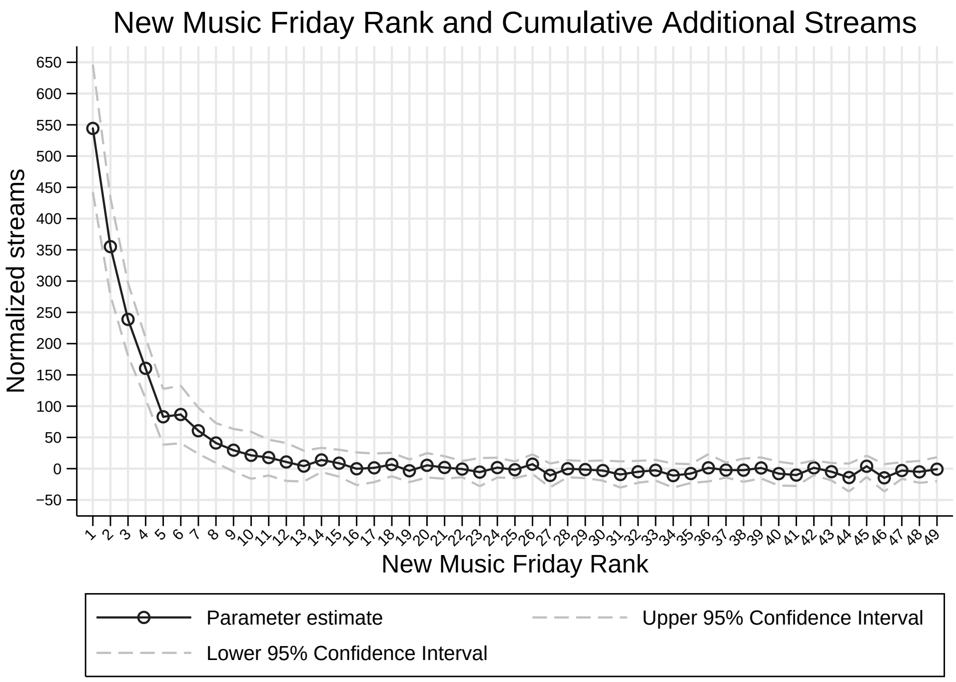

Figure 11: Effect of Appearing in New Music Friday on Normalized Streams.

Table 1: Total Sample Streams during 2017.[†]

Country	Streams
Brazil	6,663.5
Canada	3,107.3
Switzerland	475.0
Colombia	815.8
Germany	5,931.7
Denmark	1,486.5
Spain	3,671.8
Finland	1,223.8
France	3,060.8
Great Britain	7,018.6
Hong Kong	289.8
Indonesia	1,253.4
Iceland	79.4
Italy	2,322.6
Mexico	6,186.0
Malaysia	637.4
Netherlands	3,390.9
Norway	1,967.5
Philippines	3,253.6
Poland	764.4
Portugal	431.6
Sweden	3,316.2
Singapore	744.5
Turkey	899.2
Taiwan	435.8
United States	25,620.5
Total	85,047.3

[†] All figures are expressed in millions of streams.

Table 2: Playlists Characteristics.[†]

Playlist Name	Start	Nb. of Songs	Songs not Streaming	Listings	Followers (millions)	Mean Spell Duration	Adjusted Mean Spell Duration	Mean Spell Per Song	Median Streams	Mean Streams
Today's Top Hits	5/3/17	226	26	12,152	18.5	54.2	74.4	1.004	29.9	86.0
Global Top 50	1/1/17	434	0	18,250	11.5	30.2	37.1	1.383	37.5	92.8
RapCaviar	3/3/17	458	165	15,242	8.6	39.1	49.8	1.074	6.1	34.3
Viva Latino	5/3/17	111	13	12,158	6.9	111.0	227.9	1.027	36.1	58.6
Baila Reggaeton	4/16/17	141	21	12,980	6.3	96.9	181.8	1.000	7.8	38.5
New Music Friday	1/1/17	20,621		52,851	6.4					

[†] Note: Streaming volumes and durations refer to songs that we observe streaming at some point during the 2017 sample period, across all 26 sample countries. For the Global Top 50 playlist, streaming volumes and durations refer to songs that are included in the final estimation sample as explained in the text. Adjusted mean spell durations are derived from a censored regression of spell duration on a constant. Songs already on the list at the start of the respective playlists sample, or still on the list at the end, are treated as censored. New Music Friday followers are across 26 countries. Followers as of December 31, 2017.

Table 3: Effect Estimates - Normalized Streams.[†]

	Today's Top Hits		RapCaviar		Viva Latino		Baila Reggaeton	
	(add) Coef./s.e.	(drop) Coef./s.e.	(add) Coef./s.e.	(drop) Coef./s.e.	(add) Coef./s.e.	(drop) Coef./s.e.	(add) Coef./s.e.	(drop) Coef./s.e.
Add	3.346***		3.047***		3.211***		2.152**	
	(0.28)		(0.60)		(0.75)		(1.03)	
Drop		-2.757***		-1.371***		-1.863***		-1.390**
		(0.09)		(0.15)		(0.37)		(0.66)
R^2	0.901	0.944	0.862	0.804	0.791	0.763	0.901	0.859
No. of Obs.	65650	85961	28896	35622	9807	13123	8428	11635

[†] The dependent variable is the total normalized streams defined as daily song streams in a country divided by the (country's total 2017 streams/1,000,000). The sample includes song-country observations that fall within a 30 day window around the add (drop) date. For the add specifications, the table reports the coefficient on an indicator variable equal to 1 one day after inclusion on the list, as explained in the text. For the drop specifications, the table reports the coefficient on an indicator variable equal to 1 two days after exclusion from the list, as explained in the text. All specifications include song-country fixed effects and day of the week fixed effects. Standard errors are clustered on the song-country level and are in parenthesis.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 4: Per-Song Value of Appearance on Global Lists.†

Playlist	Worldwide Daily Streams	Worldwide Overall Streams	Daily Low	Daily High	Overall Low	Overall High	Maximum Mechanical Daily Effect	List Usage as a percent of Listening
Today's Top Hits	259,532	19,399,550	1,557	2,180	116,397	162,956	2,594,627	10.00%
RapCaviar	187,862	10,044,227	1,127	1,578	60,265	84,372	1,197,496	15.69%
Viva Latino	215,777	50,507,751	1,295	1,813	303,047	424,265	972,487	22.19%
Baila Reggaeton	150,615	27,384,199	904	1,265	164,305	230,027	882,922	17.06%

† The Worldwide Daily Streams column corresponds to the average daily effect (calculated as the average of the add and removal effects estimated in Table 3) times the total number of global streams in 2017 (85,047 million streams, see Table 1). The figures in the Worldwide Overall Streams column are obtained by multiplying the worldwide daily streams by the average spell length and by the number of spells per song. The daily (overall) low columns correspond to the worldwide daily (overall) streams multiplied by the lower bound on the Spotify payment per stream ($0.006). The daily (overall) high columns correspond to the worldwide daily (overall) streams multiplied by the upper bound on the Spotify payment per stream ($0.0084). The maximum mechanical effect is calculated as explained in the text.

Table 5: New Music Friday Rank Effects.†

	(1) OLS	(2) Song FE	(3) US,GB CA	(4) CO,ES MX	(5) No Domestic	(6) Indie w/o '16 streams	(7) New Artist	(8) New Artist No Domestic	(9) New Indie Artist
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
NM Rank: 1-5	0.674***	0.401***	0.396***	0.266***	0.349***	0.329***	0.459***	0.384***	0.334***
	(0.05)	(0.03)	(0.06)	(0.07)	(0.03)	(0.06)	(0.09)	(0.12)	(0.09)
NM Rank: 6-10	0.351***	0.221***	0.240***	0.093**	0.194***	0.140***	0.145***	0.129**	0.169**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.07)
NM Rank: 11-30	0.080***	0.048***	0.036	0.001	0.043***	0.020***	0.015	0.022*	0.001
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Song Fixed Effects	✗	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.349	0.763	0.917	0.904	0.728	0.709	0.729	0.644	0.707
No. of Obs.	46184	46184	6373	5033	37507	19259	2221	1745	1528

† The dependent variable is an indicator for whether a song appears in the daily top 200 Spotify streaming charts. All specifications include country fixed effects. Standard errors are clustered at the rank level and reported in parenthesis. The sample includes only the weekly top 50 New Music Friday recommendations, as the lists usually but do not always include 50 songs.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 6: IV Approach to New Music Friday Rank Effects.†

	(1) OLS Coef./s.e.	(2) SongFE Coef./s.e.	(3) FirstStage Coef./s.e.	(4) IV Coef./s.e.	(5) FirstStage Coef./s.e.	(6) IV Coef./s.e.	(7) SongFE Coef./s.e.
Log(Country streams)			0.056***		0.048***		
			(0.006)		(0.006)		
(New Music Friday Rank)/10	-0.116***	-0.057***		-0.048**		-0.069**	-0.060***
	(0.001)	(0.002)		(0.023)		(0.033)	(0.002)
Constant	0.446***						
	(0.005)						
Song Fixed Effects	✗	✓	✓	✓	✓	✓	✓
Country Fixed Effects	✗	✗	✗	✗	✗	✗	✓
R^2	0.214	0.054		0.052		0.054	0.152
F-Stat excluded instrument			102.609		56.177		
P-value			0.000		0.000		
No. of Obs.	37507	37418	30885	30885	24192	24192	37418

† In columns (1), (2), (4), (6), and (7), the dependent variable is an indicator equal to 1 if a song appears in the Top 200 Spotify streaming charts. For columns (3) and (5) the dependent variable is the New Music Friday rank (divided by 10). All regressions exclude domestic songs. Columns (5) and (6) additionally exclude all imported music from countries sharing a language with the destination country. Robust standard errors are reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 7: Characteristics of Streamed and Playlisted Songs.[†]

	Country Streaming Data	Global Streaming Data	Today's Top Hits	Rap Caviar	Viva Latino	Baila Reggaeton	New Music Friday
Indie percentage of Listings	46.6%	21.9%	25.6%	28.7%	28.2%	41.2%	53.3%
Indie percentage of Songs	47.5%	24.1%	24.3%	33.8%	31.3%	43.3%	65.2%
Indie percentage of Streams	27.4%	19.0%	22.2%	17.9%	14.7%	15.0%	-
US percentage of Listings	26.1%	72.5%	71.3%	96.6%	78.0%	78.7%	37.7%
US percentage of Songs	25.5%	71.1%	72.1%	95.4%	74.1%	76.6%	29.9%
US percentage of Streams	59.2%	71.2%	72.9%	98.3%	82.8%	81.9%	-
Domestic percentage of Listings	27.0%	-	-	-	-	-	18.0%
Domestic percentage of Songs	25.0%	-	-	-	-	-	18.0%
Domestic percentage of Streams	25.2%	-	-	-	-	-	-

[†] For the country streaming data and the New Music Friday data, the domestic percentages reported correspond to the average of the country-specific shares of domestic songs (as well as listings and streams).