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PLATFORM POWER STRUGGLE:
SPOTIFY AND THE MAJOR RECORD LABELS

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ABSTRACT

Digitization has facilitated the emergence of large distribution platforms downstream from traditionally powerful suppliers. Digital platforms can carry many suppliers' products, test the products' consumer appeal, and choose which products to promote, potentially shifting power from the suppliers to the platforms. We study these forces in the recorded music industry, which was traditionally dominated by a few "major" record labels distributing their products through fragmented radio stations and retailers. Now, the majors receive most of their promotion and distribution through platforms like Spotify, which carry millions of songs from both major and "independent" suppliers. We study Spotify's use of playlists using data covering 2017-2020. First, Spotify used their expanded playlist capacity to test – and discover – proportionately more independent songs to promote on their playlists. Second, at least relative to major-label playlists, Spotify-operated playlists promoted new independent songs more than was indicated by their subsequent success. Third, placement on Spotify new-music playlists has a large causal impact on streams. The independent-label share of new-music promotion rose from 38 percent in late 2017 to 55 percent in early 2020, which helps to explain the reported decline in the share of Spotify royalty payments to major-label suppliers over the same period.

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1 Introduction

In many industries, concentrated suppliers are surrounded by a fringe of small-scale potential competitors. Because downstream retailers have traditionally been able to carry only a limited number of products, they have been reliant on well-known suppliers offering market-tested products. Since digitization, retailing has increasingly been undertaken by digital platforms, such as Amazon, Netflix, and Spotify, to name a few. These platforms differ fundamentally from traditional retailers in their capacities to stock, test, and promote products, with important possible implications for the balance of power between suppliers and distribution platforms. First, the lack of shelf-space constraints allows digital platforms to carry wide selections from numerous suppliers. Second, platforms' ability to gather information on consumer reactions to products may allow platforms to discover appealing alternatives from non-traditional suppliers. Third, platforms' ability to promote products may allow the platforms to steer consumers toward products the platform discovers, reducing the platform's costs and shifting power away from traditional suppliers.

The recorded music industry provides a leading test case for this kind of platform-supplier interaction. The upstream suppliers are dominated by the "major" record labels, three firms responsible for 80-90 percent of traditional music sales but a declining share of the new music released as the number of independent suppliers has proliferated. Downstream, two platforms – Spotify and Apple Music – play the roles formerly performed in the US by roughly 12,000 radio stations and 8,000 record stores.[1] Spotify and the major record labels are dependent on one another, but their interests diverge. Streaming royalties are revenue to the record labels but costs to Spotify; and while streaming revenue has restored the labels to financial health, Spotify has struggled to achieve profitability, due at least in part to the royalty payments burden. Spotify's fortunes would be improved if it could either depress its payments to its traditional suppliers (i.e., depress major-label royalties), or steer users toward lower-cost music from non-major-label suppliers without substantially degrading the user experience.

The decades since digitization have brought a large increase in the amount of new music, mostly from independent record labels standing ready to substitute for major-label fare

[1] See https://www.encyclopedia.com/manufacturing/news-wires-white-papers-and-books/naics-451220-prerecorded-tape-compact-disc-and-record-stores and https://www.census.gov/data/datasets/1992/econ/cbp/1992-cpb.html.

(Waldfogel, 2017). Prior to digitization – when radio was the main distribution channel – independent or "indie" music had limited avenues for discovery or promotion. Digital platforms' capability to test thousands of songs, along with platforms' needs to control costs, may change this. For music platforms, playlists are an important tool for both experimentation – the platform's search for music which users might find appealing – and for platform promotion of these discoveries to users. Spotify, the major record labels, and other entities operate large numbers of playlists on the Spotify platform, with varying numbers of followers; and Spotify itself has recently added many new playlists. All of these playlists may allow Spotify to test a large share of the growing body of independent music and to discover appealing alternatives to higher-priced major-label fare.

This leads to this paper's three broad empirical questions – using music distribution as its context – about the ways in which digital platforms can use a fringe of potential suppliers to gain bargaining power with their traditional suppliers. First, does increased testing of new independent music on Spotify's growing array of playlists allow it to identify more independent-label music that users find appealing? Second, does Spotify spur substitution of independent for major-label music by promoting independent music more aggressively than it promotes major-label music? Third, is promotion on the Spotify platform – in particular, the decision to assign songs to playlists – consequential for songs' and suppliers' revenue? Putting it all together, does the growing independent share of music promoted on Spotify, driven by the mechanisms above, explain the declining share of revenue that Spotify reports paying to the major record labels?[2]

Our main evidence has four parts, beginning with some background facts about playlist use. By launching new playlists and attracting more followers to its playlists, Spotify has altered the platform to facilitate more extensive testing and promotion of newly-released independent music.[3] Between 2017 and 2020, the number of slots on new-music playlists in our sample grew from 115,000 to 237,000. The remainder of the evidence is the answers to the three questions articulated above. First, more extensive platform testing of independent music has facilitated the discovery of appealing alternatives to traditional major-label supplier fare. Using data on 519,810 new songs entering new-music playlists on Spotify between 2017

[2]We discuss the Spotify annual reports describing royalty payment trends in Section 4.3.

[3]Following the industry convention, music released in the past 18 months is referred to as "frontline" music. We use the terms "new-music" and "frontline" music interchangeably throughout the text. Correspondingly, we interchangeably refer to playlists that focus on frontline music as "new-music" and "frontline" playlists.

and 2020, along with information on their subsequent playlist placement and streaming success, we document that as the platform has tested proportionally more indie songs on its growing array of playlists, it has disproportionately discovered independent music that the platform promotes and which succeeds streaming on the platform. The particular songs Spotify chooses to test are endogenous, but we make use of the expanding number of testing slots on playlists as a source of exogenous variation in the numbers of indie and major songs tested. We find that additional major and indie song testing delivers additional songs that are promoted heavily on the platform (e.g., appearing on million-follower playlists) and succeed streaming (appear streaming among the daily global top 200). Among tested songs, the share of overall new-music playlist promotion – slots on playlists, weighted by playlist followers – allocated to indie music rose from 38 to 55 percent between 2017 and 2020.

Second, Spotify's growing promotion of independent-label songs appears to contain a pro-indie bias, at least relative to major-label promotion decisions. Using an outcome-based bias test, we find that both the playlists operated by Spotify itself as well as the playlists operated by other non-major-label curators promote independent music more aggressively than do major-label-operated playlists. Third, playlist inclusion decisions have substantial promotional power. We build on the discontinuity approach that Aguiar and Waldfogel (2021) used to study a handful of large Spotify playlists – which account for only 11 percent of the new-music playlist influence in the current sample – to measure the collective impact of the 3,267 most-followed new-music playlists; and we find that the assignment of an additional thousand followers to a song raises daily streams by 6.6. Placement on sample playlists, as a group, accounts for 16 percent of observed top 200 streams at the start of 2020, up from 12 percent in 2017. Hence, the growing assignment of playlist followers to independent music helps to explain the shift in royalty payments from major to independent suppliers reported by Spotify.[4] Moreover, Spotify has a substantial, and growing, amount of power.

The paper proceeds in five sections after the introduction. Section 2 provides background on the structure and recent history of the music industry, the role of playlists at music platforms, and the literatures to which this paper contributes. Section 3 presents the streaming and playlist data used in the study and provides detailed descriptive facts. Section 4 reports our main results on the effect of more extensive testing on the discovery of appealing low-

[4] See Spotify's yearly SEC filings available at https://investors.spotify.com/financials/default.aspx.

cost music, possible pro-independent bias in promotion on the platform, and the impact of playlist promotion on song and supplier success. Section 5 discusses the aggregate impact of playlist promotion on streaming and puts the results into perspective with a comparison of the evolving role of major record labels on the Spotify platform with their continued dominance of terrestrial radio airplay. Section 6 concludes.

2 Background

This section addresses three topics. First, we discuss both the recent history of recorded music and the relationship between Spotify and the majors. Second, we discuss the role of playlists in product discovery and promotion at Spotify. Third, we place our study in the context of relevant existing research.

2.1 The music industry environment

Prior to 2000, the recorded music industry consisted largely of four, and later three, "major" record labels (Universal Music Group, Sony Music Entertainment, and Warner Music Group) responsible collectively for the vast majority of music sales but a minority of new releases. These suppliers promoted and distributed their products through fragmented radio broadcasting and retail industries.[5] The majors released a relatively small number of carefully curated works entailing substantial investment, and they had considerable control over which music listeners encountered, mostly on radio.[6] Alongside the majors were a large number of independent record labels releasing music receiving little promotional exposure and a modest share of sales.

Digitization has transformed the structure of the music industry, in three ways. First, Napster's introduction – and associated piracy – caused recorded music revenue to fall sharply. US revenue fell from $23 billion in 1999 to $7.4 billion in 2014.[7] Revenues and profits of the

[5]In 1990, the major recorded labels accounted for about 93 percent of the sales of recorded music. See https://www.nytimes.com/1990/03/19/arts/when-the-business-of-music-becomes-even-bigger.html.

[6]See Boehlert (2001) on payments for airplay. See Teague (2012) for discussions of major label control: "From their monopoly over CD sales to their litigious battle against file sharing, the major record labels have a long history of trying to maintain a chokehold on music distribution." See https://www.ifpi.org/our-industry/investing-in-music/ for information on major-label investment in music.

[7]See https://www.riaa.com/u-s-sales-database/. Figures are in 2021 dollars.

record labels fell in Napster's wake. Individual firms' financial results confirm this: Warner Music Group's net income was negative in 6 of the 7 years between 2005 and 2011.[8]

Second, while digitization's first manifestation – piracy – threatened revenue, content creation did not diminish. Instead, digitally-induced cost reductions – for production, distribution, and promotion – ushered in an explosion of creative content, largely from outside the major record labels (Waldfogel, 2018; Benner and Waldfogel, 2016).

Third, digitization facilitated the creation of music distribution platforms, which has in turn had two separate effects: (1) By attracting both users and suppliers to a few major platforms, platform operators – chiefly Spotify and Apple Music – now account for most of the retail market. To launch an appealing service, a platform needed to carry wide repertoires of music.[9] Spotify created such a streaming music offering in 2006. After much cajoling, founder Daniel Ek convinced all of the major record labels to distribute their content on the platform. The major record labels took ownership stakes and advance payments, and they negotiated royalty rates that helped to reverse the fortunes of the recorded music industry.[10] (2) Bundled sales of music subscriptions now generate additional revenue and profit. After its establishment, Spotify's revenues grew sharply, from 98 million euros in 2010 to 11.4 billion in 2021 and to 14.3 billion in 2023; and payments from interactive streamers to labels began to bring substantial revenue relief to labels starting in 2010. This accelerated sharply between 2014 and 2021 as overall revenue derived from paid streaming rose from $0.8 billion to $9.5 billion and outstripped reductions in physical revenue.[11] Although total revenue from other sources fell, the increases from paid interactive streaming more than compensated, raising total US music industry revenue in 2021 to a level not seen since 2008.

Despite the expanded revenue to recorded music, frictions have divided the major labels and

[8]See, for example, Rob and Waldfogel (2006); Zentner (2006). According to Warner Music Group, the recorded music industry had been "unstable" since 1999 and had "contracted considerably, which has adversely affected our operating results." Moreover, the "industry-wide decline" was due "primarily to digital piracy." See p. 40, https://investors.wmg.com/static-files/186045a1-e5e7-4339-8c20-315b2fbcaeb7.

[9]In its Web V decision the Copyright Royalty Board wrote, "[when] the interactive market was proffered as a benchmark market in Web IV (as in the present proceeding), the Judges performed the same inquiry for that market, concluding that interactive licensees likewise "must have" access to the repertoires of each Major in order to survive commercially." See https://www.federalregister.gov/documents/2021/10/27/2021-20621/determination-of-rates-and-terms-for-digital-performance-of-sound-recordings-and-making-of-ephemeral.

[10]See https://www.theguardian.com/music/musicblog/2009/aug/17/major-labels-spotify and https://www.theverge.com/2015/5/19/8621581/sony-music-spotify-contract.

[11]This measure from RIAA US data, includes revenues from "limited tier paid subscriptions" and "paid subscriptions."

Spotify. The rebound in recorded music revenue from bundled subscription services restored the major record labels' profitability. With the exception of 2020 at Warner, both Warner Music Group and Universal Music Group have been profitable since 2018. Spotify, on the other hand, has been mostly unprofitable and reports incurring "significant costs to license content," noting that if they cannot "successfully earn revenue at a rate that exceeds the operational costs, including royalty and other licensing expenses . . . [they] will not be able to achieve or sustain profitability."[12] The conflict between major labels and Spotify is salient to industry participants. Despite the restoration of their profitability, the majors object to their music facing competition on the platforms and to the platform's substitution of lower-cost music for major-label fare. The CEO of Universal Music has expressed concern about "a vast and unnavigable number of tracks flooding the platforms" as well as consumers being guided to music that "is less expensive for the platform to license."[13]

Music from different suppliers differs in cost and, potentially, in its appeal to users. Despite the confidentiality of licensing deals, independent-label music is widely understood – as the Universal CEO's comments reflect – to be less costly to the distribution platforms.[14] A platform could therefore directly reduce its costs by steering its users to independent-label music, but only if the platform discovered indie music sufficiently appealing not to degrade the user experience. A few features of the Spotify environment make this plausible. First – and this is the main mechanism in this study – the platform has the ability to test thousands of indie songs to find those most appealing to consumers.

Second, while a platform might not be able to operate indefinitely without a major label's content, an experiment conducted by Pandora during the Web IV proceeding showed that Pandora could "steer toward or away from each major record company's music without causing a significant negative reaction from Pandora's listeners."[15] Third, platform steering on Spotify only changes a song that the user is served by default. Unlike "non-interactive"

[12]Spotify 2021 Annual Report, p. 10. See https://s29.q4cdn.com/175625835/files/doc_financials/2021/AR/2021-Spotify-AR.pdf.

[13]See https://www.billboard.com/pro/lucian-grainge-umg-full-staff-memo-2023-read-message/

[14]This is supported by the assertion that "[r]oyalty rates differ from stream to stream because some record labels negotiate better terms than others." (See https://www.billboard.com/pro/music-streaming-royalty-payments-explained-song-profits/.) It is further supported by the claim that royalty rates are "likely higher for artists on major labels and other industry companies who have unique deals with the streaming giant." (See https://www.hypebot.com/hypebot/2020/08/calculating-spotifys-per-stream-payout-harder-than-you-might-guess.html).

[15]See page F-1 of https://www.crb.gov/rate/14-CRB-0001-WR/statements/Pandora/Tab_15_Shapiro_WDT_Appendix_F_PUBLIC_pdf.pdf.

services like Pandora, where users do not control the particular songs they can hear, Spotify is "interactive." Its users can skip any song and, moreover, can choose any particular song. Hence, the effects of steering on Spotify have less potential to degrade the user experience than on a non-interactive service (or offline radio). Thus, it is possible that Spotify could pursue a strategy of steering usage away from traditional suppliers' music.

2.2 Digital platform tools for experimentation and promotion

Digital platforms have some inherent capabilities that traditional retailers lack, and these capabilities may give the platforms power in their supplier relationships. First, digital platforms lack shelf constraints and can carry indefinitely many products. Rather than being limited to small numbers of well-known brands, or popular products, digital platforms can carry millions of books, the products from thousands of clothing manufacturers, or millions of songs from many different suppliers. Second, by monitoring sales or usage, digital platforms can in effect experiment with products from the large number of potential suppliers they can carry. At some platforms – such as Google and Amazon – the relevant tool for controlling experimentation is a search function. At others, it is product page recommendations. At music platforms, playlists are a major tool.

Playlists are curated lists of songs and also utilities for listening to music, and have two important and distinct functions for Spotify as the platform owner. First, they are tools for experimentation in the service of discovering appealing music. The lists deliver songs to users, and the platform can learn from the users' responses, for example from user song skips or likes. Moreover, Spotify itself, as well as the major record labels and others, operate a wide range of new-music playlists, ranging from Today's Top Hits, with an average of 27 million daily followers at the end of 2020, to many other playlists with far fewer followers.[16]

In the pre-digital world, songs were largely "tested" by playing them on the radio.[17] Testing songs was costly, in the sense that all of a station's listeners were exposed to a song each time it was aired. In contrast to "linear" radio broadcasting services, digital music platforms operate myriad playlists, each of which functions like a traditional radio station but serves

[16]For example, our sample contains 394 lists with fewer than 100,000 followers, and 256 lists with fewer than 50,000 followers, during 2017.

[17]For an account of expensive pre-digital song testing, see https://www.worldradiohistory.com/research_callout.htm.

only a fraction of the platform's user base. A user served a song on Spotify can skip the song, switch to another playlist, or choose any particular song on the platform, none of which entail leaving the platform. Radio listeners served an unappealing song, by contrast, are likely to tune away to another broadcaster's service. In addition, Spotify is able to observe user reactions to songs that users encounter on both Spotify-curated playlists as well as other (third-party) curators' playlists. In short, testing is less costly on Spotify than on radio.

It is well known that the quality (i.e., consumer appeal) of creative products is unpredictable at product launch (Caves, 2000). The substantial increase in the number of independent-label songs whose creation and release were made possible by digitization – what Aguiar and Waldfogel (2018) describe as the "random long tail" – present a trove of potentially valuable songs that playlist testing might allow the platform to discover. If the platform could discover appealing music among the large number of independent-label releases, the platform could use these discoveries to serve users with lower-cost fare. That is, once a song demonstrates its promise, the platform can feature it on widely-followed lists; and playlists can fulfill their second function, as tools for promoting music broadly to users. More than in traditional retailing, platforms have the ability to promote their discoveries, by featuring the products on the platform's promotional channels. For Spotify, this means including discovered songs on widely-followed playlists. The exploration of these mechanisms – and the platform's use of them in its interaction with its traditional suppliers – is the subject of this paper.

We note that the mechanisms that we study are one of a variety of ways that Spotify exposes users to music. Users can request songs, artists, or albums directly, or ask for algorithmic recommendations based on such starting points. Spotify also provides specific algorithmic playlists customized to users (such as "Discover Weekly") and based on streaming trends (such as "Viral 50"). We study only curated general (same for each user) playlists, and we note that algorithmic recommendations are another potential channel for Spotify to learn about song potential and promote them. This has the important implication that Spotify's full influence on consumption exceeds what we can measure in this study.

2.3 Prior research and our contribution

We argue that digital platforms can use the ability to carry many products, along with other measurement capabilities, to test and discover valuable new products to promote and distribute. While we believe our argument is novel, the mechanisms we study are related to various literatures in economics, strategy, and information systems.

First, this is related to the "long tail" literature demonstrating that digital retailing raises consumer welfare by offering wider choice than was traditionally possible (Brynjolfsson et al., 2003). The difference here is that the wide array of products at the firm offers not just product variety for consumers but also a firm-level strategic tool for experimentation. Our study of the use of playlists for experimentation provides a clear mechanism for the welfare gains from the "random long tail" in Aguiar and Waldfogel (2018). Our argument that digital platforms may substitute for the testing or "vetting" role of concentrated upstream suppliers is related to the Greve and Song (2017) observation that readers' ability to share ratings and reviews reduces the power of publishers.

Second, this work is related to large literatures on platform curation and its effect on the user experience (Rietveld et al., 2019, 2021; Elfenbein et al., 2015; Hui et al., 2016; Aguiar and Waldfogel, 2021). Recommendation tools have also been analyzed theoretically as means of reducing platform costs and enhancing bargaining power with suppliers (Bourreau and Gaudin, 2022). Our paper also addresses platform substitution toward less expensive inputs, but focuses on the platform's actions to discover valuable songs among the less expensive independent music.

Third, this work touches on a few strands of related literatures in strategy on interactions between platforms and their suppliers. One of these strands looks at the conflict between suppliers and platforms when platforms themselves become sellers, which has received both theoretical (Hagiu et al., 2022) and empirical attention (Zhu and Liu, 2018; Zhu, 2019). We study a situation where a platform owner has an interest in competitive outcomes of suppliers, but does not compete directly.[18] Another strand, more closely related to the present work, considers the choice of which suppliers - and products - to promote (Rietveld

[18] While Spotify has "quietly struck direct licensing deals with a small number of independent artists," the platform has not become a record label. See https://www.nytimes.com/2018/09/06/business/media/spotify-music-industry-record-labels.html.

et al., 2019; Agarwal et al., 2023).[19] That literature concludes that more work is needed on bargaining with suppliers.[20] Our paper takes up this call, studying a suite of behaviors the platform undertakes to control the costs arising from its interactions with its biggest suppliers. We provide evidence of the evolving relations between concentrated and powerful suppliers and an increasingly powerful platform as it develops capabilities to learn about the appeal of complements and steer users' listening behavior. In doing so, we advance the literature by studying platform environments with some very large, rather than simply fragmented, suppliers.[21]

Finally, we note some relevant studies that share our focus on music streaming or Spotify in particular. Datta et al. (2018) show that streaming music (as opposed to owning it) leads to more and more diverse music consumption. Pachali and Datta (2024) document how Spotify uses its platform design to shape which operators' playlists are visible to users. Of particular relevance is their observation that in 2019, Spotify rearranged the user interface in a way that increased the visibility of its own playlists at the expense of playlists operated by the majors. Aguiar and Waldfogel (2021) estimate the streaming effects of songs being included in the four largest human-curated Spotify playlists as well as the New Music Friday lists for 22 countries, whose followers collectively account for 11 percent of the follower-weighted playlists in this sample. In Section 4.3, we measure the impact of the the 3,267 top new-music playlists and we show both that general playlists have large impacts on streaming success and that our estimation approach is robust. Aguiar et al. (2021) document pro-independent bias in Spotify's curation patterns for New Music Friday playlists. Our bias analysis in Section 4.2 applies a similar outcome-based logic to all of Spotify's new-music playlists.

3 Data and descriptive facts

We have information on Spotify streaming and playlists, which we combine to create three broad datasets for this study. First, we have information on the daily song-level streams for

[19] See also Jiang et al. (2011), which presents a theoretical model in which the platform learns which products to carry.

[20] See also Rietveld and Schilling (2021) for a specific call for research on platforms' actions affecting their "bargaining power vis-a-vis complementors."

[21] A variety of studies examine contexts in which powerful platforms interact with fragmented suppliers. See, for example, Rietveld and Eggers (2018) and Cennamo and Santaló (2019) on game consoles, Kapoor and Agarwal (2017) and Wen and Zhu (2019) on smartphone app stores, and Gawer and Henderson (2007) on Intel as a development platform.

the global top 200 songs on Spotify during 2017-2020.[22] The second source of information covers new-music, or "frontline," playlists.[23] For each of 3,267 new-music playlists at Spotify during 2017-2020, we have the daily number of followers for the playlist, the playlist curator type (Spotify, a major record label, or other), and the list of songs on the playlist each day. The "other" playlists are operated by various third parties, and many are independent record labels. We discuss this further at Section 4.2 below. We arrive at the 3,267 new-music playlists as follows: We begin with the 15,000 most followed playlists on Spotify on November 2020; and we retain the 4,335 frontline playlists as defined by Chartmetric. Of these, we retain the 3,267 lists that operate at any time between the second quarter of 2017 and the first quarter of 2020.[24] They range from Today's Top Hits, with 27 million followers at the end of 2020, to playlists with 22,000 followers at the end of 2020.[25] We create these datasets for the period between the second quarter of 2017 and the first quarter of 2020. The start date is determined by the onset of playlist data availability, and the end date omits the COVID-19 pandemic period from the study, when music listening patterns temporarily changed (Sim et al., 2022). We combine these data to create three analysis datasets that we describe in detail below. Much of the analysis is based on comparison of major-label and independent-label music. We determine whether each song is on a major record label based on Discogs' mappings of labels to parent companies.[26]

3.1 Growing playlist testing capacity

The first dataset covers playlists. For each of the 3,267 new-music playlists, we observe their curator type (Spotify, a major record label, or other), the daily number of songs on the list by type (indie vs major), the playlist's daily number of followers, and when the playlist was

[22]These data come from charts.spotify.com and kworb.net.

[23]See chartmetric.com. As noted in footnote 3, we refer to frontline and new-music playlists interchangeably. On these playlists, over 75 percent of tracks are less than 18 months old.

[24]We omit the algorithmic Spotify Charts lists such as the Global Top 50 as well as other chart-based lists.

[25]Many playlists were created during our study period, and thus had fewer than 22,000 followers for much of this period.

[26]We classify a label as a part of Warner Music Group if the label's name contains "Warner" or any of the other Warner subsidiary label names listed at https://www.discogs.com/label/2345-Warner-Music-Group. We classify a label as part of Universal Music Group if the label name contains "Universal" or a Universal subsidiary listed at https://www.discogs.com/label/38404-Universal-Music-Group. Finally, we classify a label as part of Sony if its name contains "Sony" or any of the Sony subsidiary labels listed at https://www.discogs.com/label/25487-Sony-Music. We also rely on Hannes Datta's musicMetadata classifier (see https://github.com/hannesdatta/musicMetadata) as well as extensive manual classification.

established. The dataset includes a total of 566,243 distinct songs from all sample playlists. Table 1 summarizes the data. The period 2017-2020 brought two major developments in the Spotify playlist landscape. First, Spotify launched a large number of new-music playlists. Second, Spotify's playlists attracted additional followers while the playlists operated by the major record labels stagnated.

For each playlist operator type and year, Table 1 reports two measures of playlist capacity, the yearend numbers of new-music playlists and the collective number of song slots on the playlists. The table also reports the daily number of followers at yearend as a measure of promotional capacity. Spotify dominates promotional capacity, with roughly 80 percent of the aggregate new-music playlist followers the entire period. For example, at the end of 2017, Spotify-curated playlists account for 282 million of the 354 million total daily followers. While the numbers of major-label playlists, slots, and followers, are roughly stable, the numbers of Spotify and other playlists grow substantially, although the other playlists continue to account for a small fraction of promotional capacity. The number of Spotify-curated playlists grows from 778 to 1,225, and the number of slots on these playlists grows from 42,165 to 90,588. Slots on other playlists grow similarly. The growing number of slots on new-music playlists on the Spotify platform provides the increased capacity for the song testing that we explore below.

3.2 Tested songs, promotion, and success

Second, we create a song-level dataset for tracking the testing, promotion, and success of the songs entering the new-music playlist sample. We define a song as being "tested" (or "born") during our sample period when we observe it being included for the first time in one of the 3,267 playlists. Out of the 566,243 distinct songs appearing across all playlists, 519,810 songs are born during our sample period.

The first pattern evident in these data is the disproportionate allocation of increased testing capacity to independent-label music. As Figure 1 shows, the number of major-label songs tested per week remains stable at under 1,000 over the whole sample period, while the number of independent-label songs tested rises from nearly 2,000 in early 2017 to 4,000 by the end of the sample period. This pattern – of growing testing of indie songs – appears on both playlists curated by Spotify and on other curators' lists. By contrast, major-label-operated lists test mainly major-label songs, although testing of indie songs on major-label lists rises slightly during the sample. The growing indie share of songs tested on Spotify and other lists is perhaps not surprising, given the growing number of non-major-label releases. Moreover, the rising indie testing on other lists may stem from indie-label operation of some of those lists. The stable indie share on major-label lists, by contrast, recalls the major labels' efforts to maintain control of radio promotion (Boehlert, 2001; Teague, 2012).

Table 2 shows the promotion and success outcomes for major-label and independent songs. Of the 519,820 tested songs in the sample, 409,335 (78.8 percent) are from independent labels. Of the 409,335 indie songs entering the new-music playlist sample, a very small share – 0.14 percent – succeed streaming, in the sense of appearing in the top 200 within a year of birth. Major-label songs entering the playlist sample are more successful: 2.09 percent stream in the top 200. According to their propensity to appear in the daily top 200, major-label sample songs are 14.5 times more successful than indie songs. Major-label songs are similarly more successful according to total observed streaming: The major-label songs have 21.3 times more observed streams than the independent songs.

The relative streaming success of major songs (14-21 times more than independent songs) provides a benchmark for evaluating the relative promotional treatment that the three types of playlist operators give to major and independent songs. Table 2 shows the shares of independent and major-label songs reaching playlists with different numbers of followers on lists operated by the three types of operators. The last column shows the relative tendency for major vs independent songs to reach any playlist follower echelon. Major-label songs are 9 (13) times more likely to reach lists of at least 100K (500K) followers operated by major record labels. That is, the relative promotion of major songs by major-label-operators is similar to the eventual relative streaming success of major songs on the platform.

By contrast, major-label songs are far less likely – just 1.6 - 2.6 times more, as opposed to 13 times more likely – to reach lists of at least 100K or 500K followers operated by Spotify or other operators. This suggests that non-major-label playlist operators promote major-label songs less than the songs' subsequent success warrants. By extension, it suggests that non-major-label operators have a pro-independent bias in their promotion, or at least that there is a differential in pro-independent bias between major-label-operated playlists and the two other curators'. We present direct tests in Section 4.2.

3.3 Playlist inclusion and streaming

The third analysis dataset is a daily panel containing the songs we observe streaming on Spotify on the days when those songs appear among the global top 200 Spotify charts. For our sample period, which runs from the second quarter of 2017 to the first quarter of 2020, the streaming data include 3,489 distinct songs, of which 3,410 also appear in the new-music playlist sample.[27] For each song j in the sample, we observe its global streams on day t, which we term s_{jt}, as well as the sum of the number of playlist followers across all of the sample playlists on which it is included on day t, which we denote F_{jt} and refer to as "song followers." For example, if on day t song j were on two lists, one with 1 million followers and another with 0.5 million followers, F_{jt} would equal 1.5 million.

As Table 3 shows, of 3,410 songs we observe streaming, 2,762 are from major labels, while the other 648 are independent. Overall, the songs observed streaming have an average of 1.16 million daily streams and an average of 24.17 million daily followers, with the vast majority of these followers from Spotify-operated lists. Average daily streams are similar for major and independent songs, which is perhaps not surprising given that these are the selected sample of successful songs appearing among the daily top 200 streaming songs.

The streaming sample's 3,410 songs account for a small share of the 519,820 songs entering the new-music playlist sample. With a bit of detective work, we can infer that the top 200 streams account for about ten percent of overall streams on Spotify.[28]

4 Empirical results

This section presents empirical results based on analyses of the three datasets described above. We begin, in Section 4.1, with our exploration of whether more extensive testing of

[27] Of the 79 songs that appear in the global top 200 charts but do not appear in the new-music playlist sample, 25 are catalog songs that were released before 2013. Songs that appear streaming but not playlisted include yearly resurfacing Christmas songs and songs receiving exposure due to off-platform events.

[28] Spotify reportedly paid \$5 billion in royalties in 2020, when they were also reported to have been paying an average of \$3 to \$5 per thousand streams. See https://www.forbes.com/sites/marisadellatto/2022/03/24/spotify-says-it-paid-7-billion-in-royalties-in-2021-amid-claims-of-low-pay-from-artists/ and https://dittomusic.com/en/blog/how-much-does-spotify-pay-per-stream. The \$5 royalty rate, along with the \$5 billion payout implies one trillion streams on Spotify. During full-year 2020, the sum of daily top 200 streams comes to 93 billion streams. Hence, the top 200 accounted for just 9.3 percent of streams assuming the \$5 royalty rate and less under the \$3 royalty rate.

independent music on playlists led to the discovery of additional independent-label music of value to Spotify consumers (and greater promotion of independent music on playlists). Section 4.2 explores whether Spotify applies its promotional capacity in a way that reflects bias in favor of independent-label music. Section 4.3 demonstrates that Spotify's promotion choices are consequential by measuring the impact of the assignment of playlist followers on streaming success.

4.1 Deeper experimentation, discovery, and promotion

By early 2020, the new-music playlists at Spotify were testing about 700 major-label songs and nearly 4,000 independent-label songs per week, with the indie count having doubled since 2017, and the major count stable (see Figure 1). Did the more extensive testing of independent music deliver, first, more independent songs that the platform chose to promote on widely-followed playlists and, second, more independent songs that achieved substantial streaming success? Because the platform has the capacity to learn both from the songs it chooses for its own playlists as well as the lists operated by other curators, we conduct empirical exercises using tested songs on all playlists.

We employ a sequence of promotion and success measures: a) whether a song reaches a playlist with at least one million followers, b) the log of one plus the cumulative playlist followers assigned to a song in the year after its first appearance on a new-music playlist, c) whether the song streams in the daily top 200 in the year after its first appearance on a new-music playlist, and d) the log of one plus the song's total streams when it appears among the daily top 200 during the first year. There is an important measurement distinction between the promotional variables (based on playlist followers) and the success variables (based on top-200 streams). We observe followers for all sample songs and all days, while we observe streams only for songs that appear in the top 200 and only for the days when they appear among the top 200.

To explore whether deeper testing generates heavier promotion or more success, we make comparisons across birth dates, asking how the number of, say, independent or major songs born on day t affects the number of those songs achieving the promotion or success measures above. In particular, we estimate

$$D_t^m = \psi_0^m + \psi^m N_t^m + \psi_2^m t + \varepsilon_t^m \tag{1}$$

and

$$D_t^i = \psi_0^i + \psi^i N_t^i + \psi_2^i t + \varepsilon_t^i \tag{2}$$

where i indicates independent and m indicates major label songs, N_t^m, for example, is the number of major-label songs born on day t, and D_t^m is the number of major-label songs born on t attaining one of the outcome measures above. Then, pending a suitable approach to causal inference, ψ^i and ψ^m would show the effect of testing an additional song of each type on the number of songs discovered.

Table 4 shows OLS regressions. All coefficients are positive and significant, indicating that additional testing yields additional promotable and successful songs, for both independent and major-label song testing. For example, the indie coefficient of 32.49 in the first column indicates that the testing of an additional 1000 independent songs delivers an additional 32.49 songs that appear on a Spotify playlist with one million or more followers within a year of birth. The analogous coefficients for major-label testing are generally much higher, indicating systematically greater promise for major-label songs. Positive and significant indie-label coefficients are important here: Given the relative growth in the testing of indie music, positive ψ^i coefficients guarantee a rising indie share for the outcome.

While the OLS results are plausible, one can be concerned that the numbers of songs of each type tested in a week is endogenous. Perhaps the curators test more major-label songs in particular weeks precisely because they have higher expectations about the major-label songs released that day. This would pose a challenge to the interpretation that additional testing causes more discovery. As discussed above, the growing number of playlists, and slots on playlists, enables more testing and is unrelated to day-to-day variation in song quality. We can use the variation in the *capacity* for testing as an instrument for the number of songs actually tested. Using this instrument mitigates the challenge of day-specific endogeneity of N_t^m and N_t^i.

Table 4 reports results. The last column reports the first-stage, and the instrument works: Growing capacity drives growing testing for both major and, especially, independent music. The independent coefficients are positive and strongly significant for promotional outcomes and at least marginally significant for streaming outcomes. It is important to remember that we only observe streams among the top 200 and not total streams. As mentioned above, the observed streams account for about ten percent of total Spotify streams, so these streams provide an incomplete picture of total streaming. Hence, we must look directly at the mechanism linking playlist followers to streams for more complete evidence of whether the more extensive indie testing promotes growing indie streaming success. Section 4.3 explores the impact of playlist followers on streams.

4.2 Do the different curators promote indie music differently?

The foregoing results in Table 4 show that extensive indie experimentation on Spotify and other-operated playlists leads both to more independent music discovery and greater independent music promotion. While growing independent shares of promoted and successful songs may be natural consequences of more extensive independent music testing, they may also reflect differential attitudes toward independent music held by major-label, Spotify, and other playlist curators.

As Aguiar and Waldfogel (2021) document in the context of New Music Friday lists, a decision to promote a song reflects the platform's enthusiasm for the song and also likely exerts a causal impact on the song's success.[29] For the new-music lists generally, too, curators need to decide how much promotion to grant each song upon entry (on the day when first tested), as well as in the first year of the songs' lives; and there is strong evidence that assignment of promotional resources reflects curators' (accurate) predictions about song prospects. Songs assigned more playlist followers, either initially or in their first year, are more likely to succeed streaming. The left panel of Figure 2 shows the relationship between deciles of initial (first-day) allocation of playlist followers and the share of songs that succeed, measured by log first-year streams. The right panel divides songs by deciles of total first-year promotion. Both figures show clear positive relationships between promotion and success. While some part of the relationship in the right panel reflects the causal impact of promotion on success, much of the relationship reflects curators' allocation of more promotional resources to songs they expect to do better.

[29]Note that "New Music Friday" playlists are a small subset of new-music lists, accounting for just one percent of the playlist followers in our sample.

Given the clear predictive relationship between first-year followers and streaming success, we can infer curators' beliefs about songs' prospect from their allocation of promotional resources to songs. We use a variant of the Aguiar et al. (2021) approach to testing for independent-label bias on the New Music Friday lists: We test for bias in the assignment of promotional resources by asking whether the relationship between assigned followers and eventual success differs between major and independent music. If major songs are more likely to succeed, conditional on the promotion that curators give them, then we can infer that curators gave major songs fewer playlist followers than their success prospects warranted.

Figure 3 shows the respective relationships between curator-assigned followers and success measures for indie vs major music. The upper-left panel examines all playlists combined and shows that at any decile of assigned followers, major-label songs experience more streaming success. A very similar pattern emerges for Spotify-operated as well as other-operated lists. The pattern for major-label-operated lists is quite different, however. One would not expect an anti-major-label bias on major-label-operated playlists; and there is very little difference in realized success of indie vs major label songs, conditional on followers that major labels assign.

The difference between the major-label curators and the two other types (Spotify and "others") has a few possible interpretations. First, Spotify and others may be biased in favor of independent music. Unlike Spotify itself, the others lack the platform's cost-based reason for bias, although we note that many of the other playlists are operated by independent labels.[30] To the extent that other and major-operated lists reflect independent and major label biases, respectively, the similarity of Spotify playlist promotion to the others would demonstrate a pro-indie bias.

A second possible interpretation is that what we identify as "bias" reflects some unobserved determinant of success that is common across playlist curators, conditional on exposure. Under this weaker interpretation, it is nevertheless of interest that the differential success of major vs independent music, conditional on promotion, is *smaller* for major-label-operated lists. At a minimum, this indicates that the allocation of promotion on the platform differs

[30]For example, the operator of one of the most-followed "other" lists, Fruits Music, describes itself "the biggest independent streaming record label in the world." See https://www.fruitsmusic.com/. Other labels among the top other playlists include Loudkult (https://loudkult.com/), Trap Nation (operator of label Lowly Palace, https://en.wikipedia.org/wiki/Trap_Nation), and Soave (https://www.soaverecords.com/).

from what would arise in an environment, like radio prior to digitization, in which the major labels retained substantial control over promotion (Boehlert, 2001; Teague, 2012).

Streaming does not just reflect songs' inherent appeal. Rather, it also reflects the extent of promotion a song receives. Hence, the eventual success measures are contaminated by intervening promotion. Yet, this creates a bias that leads our test to understate the extent of pro-indie bias. The additional promotion given for independent music should deliver greater independent music success, all things equal. Yet, we find greater major success, conditional on heavier promotion of independent music. This is consistent with relative pro-indie bias in both Spotify and other playlist curators' allocation of promotional resources.

Regression tests reinforce the findings in Figure 3. We run variants of the following regression using the cross section of songs entering new-music playlists on the platform:

$$y_j = \kappa \delta_j^{major} + f(F_j^{1y}) + \epsilon_j^m, \tag{3}$$

where y_j measures the performance of song j on the Spotify charts, δ_j^{major} is an indicator for major-label songs, and $f(F_j^{1y})$ represents a function of the first-year followers assigned to song j: $\ln(F_j^{1y})$ and deciles of F_j^{1y}. We rely on two distinct measure of song performance, y_j. First, we use an indicator equal to one if song j appears in the Spotify top 200 charts within a year after testing. Second, we use the logarithm of the total observed streams accumulated within a year after testing. We estimate the models separately by playlist operator as well as overall.

The top panel of Table 5 presents the results of estimating (3) when relying on an indicator for whether the song reaches the top 200 charts as a dependent variable. Specification (1) relies on all lists and controls for the logarithm of the assigned followers during the first year after testing, while specification (2) controls for the deciles of the distribution of followers assigned. The major-label coefficient is positive and significant in both specifications. The remaining columns report similar specifications separately by curator type. All specifications show pro-indie bias, while the coefficient for major-operated lists is about a third as large as the coefficient for Spotify-operated lists and roughly a sixth as large as the coefficient for others playlists. The bottom panel of the table relies on log streams within a year of testing as a measure of song performance and shows similar results. As indicated in Appendix Table

A1, controlling for playlist birth followers – as opposed to cumulated followers after testing – leads to similar results.

The evidence in Figure 3 and Table 5 shows that promotion by Spotify and other-operated playlists gives a bigger boost to independent music, relative to major labels. Hence, it appears that the platform does two distinct things to lessen its reliance on major-label music. First, by testing more indie music on its growing array of playlists, the platform discovers more high-appeal indie music. Second, the platform appears to depress use of major-label music further by promoting independent music more assertively.

The net result of more extensive testing of independent music, along with a possible promotional bias in its favor, gives rise to a growing share of promotional resources on new-music playlists allocated to independent music. As reported in Figure 4, the share of cumulative new-music playlist followers allocated to indie songs among the sample of 519,820 tested songs increases from 38 percent in 2017 to about 55 percent in 2020.

4.3 The impact of playlists on streams

It is clear from the foregoing sections that playlists on Spotify devote a growing share of their promotional power to independent music. Whether this explains the evolving share of royalty payments made to different suppliers depends on whether the playlist follower assignments causally influence streams.

We are interested in estimating the relationship between song streaming (s_{jt}) and the number of song followers (F_{jt}, the total followers of lists containing song j on day t). The challenge in estimating this relationship is that F_{jt} is endogenous, in two senses. First, songs are non-randomly chosen for inclusion on playlists. Hence, in a cross section, more popular songs would be placed on playlists with more followers. This would give rise to a positive relationship between s_{jt} and F_{jt} apart from the causal impact of F_{jt} on s_{jt}. Of course, we have panel data, so we can include a song fixed effect and identify the effect of F_{jt} on s_{jt} from the change in s_{jt} with a change in F_{jt}. Second, even with this amendment one can be concerned that a song whose popularity is growing would both experience increases in streams and growth in its playlist follower measure. While we implement the song fixed effects approach in Appendix B, we are concerned that temporal variation in songs' popularity will induce a positive relationship between F_{jt} and s_{jt} that could overstate the causal impact of F_{jt} on s_{jt}.

A more promising approach, in our view, makes use of significant jumps in the follower measure (F_{jt}) across days, when a song is added to one or more playlists with large followings. This approach builds on the approach in Aguiar and Waldfogel (2021), which examined the jumps in streams surrounding the addition of songs to particular highly-followed playlists individually. Rather than using the discontinuities in followers associated with a small number of particular lists, we here use jumps in the overall measure F_{jt}, which aggregates the followers from different playlists.

To this end, define:

ΔF_{jt} = the change in followers for song j on day t and

$D_{jt} = 1$ on the day that a jump occurs. For example, $D_{jt} = 1$ if $\Delta F_{jt} \geq 250,000$.

We can then estimate

$$s_{jt} = \sum_{\tau=-10}^{10} \alpha_\tau (D_{jt} \Delta F_{j,t+\tau}) + \mu_j + \psi_{jt}^a + \lambda_t + \epsilon_{jt}, \tag{4}$$

where α_τ are coefficients on leads and lags on the jump day variables, τ refers to days until, or since, the jump event, and the ψ_{jt}^a terms are song age fixed effects, where age = t - song release date. The term λ_t is a date fixed effect, and ϵ_{jt} is an idiosyncratic error. We restrict our sample to the 21 days surrounding the jump events. Because a song can experience multiple jumps within the sample period, the term μ_j is not only a song fixed effect but rather a song-spell fixed effect. Estimating equation (4) requires us to choose threshold values for ΔF_{jt} in order to define jumps. We employ jump thresholds of 100,000+ followers ($\Delta F_{jt} \geq 100,000$), 250,000+ followers, 500,000+ followers, and 1,000,000+ followers.[31]

Before presenting the estimates, the designation of event dates merits clarification. We obtain a discontinuity estimate of the effect of adding followers by subtracting the α coefficient for the last fully untreated day (the last full day before a song experiences a jump in followers) from the first fully treated day (the first full day on which the song has the additional

[31]Our sample includes 125 lists with 1 million or more followers, 277 with 500,000 or more, 524 with 250,000 or more, and 1,069 with 100,000 or more.

followers). While our data allow us to observe the date on which a particular song experiences a jump in followers, we do not know the exact time of the jump. This creates a challenge in defining the last untreated, and the first treated, days to be used to identify the effect of interest. Our data are updated every 24 hours, so observing a jump in followers on a particular day means that the jump could have happened any time during the previous 24 hours. This leaves two possibilities. The first one is that the song experienced the jump on the current day, so that the apparent jump day is in fact partially treated, while the day before the jump was fully untreated. The second possibility is that the song experienced a jump in followers the previous day. In that case, the jump day would be fully treated, while the previous day would be partially treated. While we cannot distinguish these two cases, we can be confident that two days before the jump date is fully untreated, and that the day after the jump day is fully treated. Our shortest window for effect estimation therefore compares two days prior the jump day to one day after. In our estimates below, we set $\alpha_\tau = 0$ on the last fully untreated day ($\tau = -2$), and we treat $\tau = 1$ as the first fully treated day. We estimate the effect of a positive jump in followers as α_1, and we refer to this coefficient as α in the reminder of the text. We define the drop window analogously.

Figures 5a and 5b report the α coefficients surrounding adds and drops, using $\Delta F_{jt} = 250,000$ as a threshold. We measure followers in thousands, so that the coefficient α may be interpreted as the effect of a one thousand follower change on daily streams. We can draw a few conclusions from the figures. First, the measured effects of followers coincide well to the timing of the jumps. Streams are rising slowly as a follower jump occurs, then streams rise at the add date. Second, adding followers raises daily streams by about 6.6 streams per thousand followers, and the effect of losing followers at drop dates is similar in size.

Table 6 presents the results of estimating equation (4) using alternative jump thresholds ΔF_{jt}. Columns (3) and (4) report the coefficients that rely on jump events of $\Delta F_{jt} \geq 250,000$ and therefore correspond to Figures 5a and 5b, respectively. We compute the effect of playlist followers on daily streams by averaging the add and drop effects. For instance, relying on a jump threshold of 250,000 followers implies an average daily effect of $\frac{6.629+6.609}{2} = 6.62$ streams for each additional thousand playlist followers. The remainder of the table employs alternative jump thresholds. Columns (1) and (2) use $\Delta F_{jt} \geq 100,000$. Columns (5) and (6) use 500,000+ followers, and the last two columns rely use 1,000,000+ followers. The estimated impact of playlist followers on daily streams is similar across the various jump thresholds.

We observe only the top 200 songs by day, and we can implement the approach only for songs observed both before and after the jump. We have two broad strategies for exploring the consequence of observing only the daily top 200 songs, which we explore in Appendix B. We impute the missing observations for songs whose streams are observed only before or after a jump. These imputation approaches should in principle bound the estimates, and we find a range of 4.15 to 8.17 corresponding to our baseline estimate of 6.62. Appendix B also shows that α is constant over time and that it does not differ in statistically significant way across list curator types. In what follows we use the no-imputation approach from the top-200 analyses and rely on jumps of 250,000 followers as our main estimates.

The evidence in Figures 5a and 5b and Table 6 shows that followers affect streams for the top streaming songs overall. Because most of the playlist followers we observe in the playlist sample are not assigned to songs that eventually stream in the top 200, it is important for our argument that followers affect streams similarly 1) for streams outside the daily top 200, and 2) for both major and independent music. We explore these in turn. We cannot directly measure the streaming impacts on songs outside the top 200, but we can explore how our estimate of α varies across different streaming cutoffs. Table 7 provides estimates of α using the top 50, top 100, and top 150 daily streamers, for comparison with our baseline estimates that use the top 200. Using the top 50, $\hat{\alpha} = 5.96$, while $\hat{\alpha} = 6.95$ using either the top 100 or the top 150. These are similar to our baseline estimate of 6.62. The effect of followers on streams does not decay as one moves down the streaming distribution, and we take this as evidence that the allocation of followers to music streaming outside of the top 200 drives its streaming success.

Our argument that growing allocation of playlist followers to indie music drives a growing indie royalty share requires that the effect of followers on streams operate for indie as well as major songs. Accordingly, we estimate the effect of followers on streams separately for independent and major-label songs; and as Figure 6 shows, the effect is as large for independent music. As reported in Table 8, comparing the first fully treated to the last untreated days – and averaging the add and drop effects – the overall indie effect is 8, while the major effect is 6.52, and we cannot reject the hypothesis that they are equal. Together, these results indicate that the growing independent testing and resulting promotion drives a growing share of streams and revenue to independent-label suppliers.

As noted above in Section 4.2, the independent song share of new-music playlist promotion rises from 38 to 55 percent over the sample period. If all listening on the platform were driven directly by new-music playlists – and if indie and major songs received identical payments per stream – then we would expect the share of royalties paid to indies to rise from 38 to 55 percent. In reality, streams are not driven only by new-music playlists; and payments per stream are understood to be smaller for independent music. Some listening arises directly from user choice of songs. Other listening is driven by personalized playlists such as Discover Weekly. Still, according to Spotify annual reports, between 2017 and 2023, the share of Spotify's royalty payments going to independent record labels outside of Merlin (a collection of independent labels) doubled from 13 to 26 percent.[32] The mechanism we document in the paper explains some of this pattern, although we cannot measure the precise share that it explains.

5 Discussion

5.1 Aggregate new-music playlist impacts

How much power do the new-music playlists have, in the aggregate, to explain streaming patterns? Our jump estimate of α, along with information on the followers (F_{jt}) and streams (s_{jt}), allows measurement of the share of streams causally attributable to playlist inclusion decisions. The share of song j's streams on day t that are causally attributable to playlist inclusion is given by:

$$\text{share}_{jt} = \frac{\alpha \times F_{jt}}{s_{jt}}.$$

We rely on the estimate of α that we obtained by relying on jumps of 250,000+ followers and based on the non-imputation approach ($\alpha = 6.62$). The share of streams attributable to playlist inclusion decisions rises from 12 percent in 2017 to 16 percent at the start of 2020.

[32]See Spotify's yearly SEC filings available at https://investors.spotify.com/financials/default.aspx and https://www.musicbusinessworldwide.com/major-record-companies-and-merlin-spotify/. See https://en.wikipedia.org/wiki/Merlin_Network for a description of the Merlin network.

The increase in the share of streams attributable to these playlists indicates that users are overall making more use of playlists over time at the expense of other ways of listening to music on Spotify, which is consistent with the rapid growth in playlist followers in Table 1.[33] Because Spotify-operated lists have about 80 percent of followers, Spotify accounts for about 80 percent of the influence caused by new-music lists. While major-label lists predominantly include major-label songs, Spotify playlists deliver more streams to major-label songs than do major-label playlists. We take the results to mean that Spotify has a large, and growing, amount of power over its suppliers and on what succeeds on the platform.

5.2 Comparing the majors' roles on Spotify and radio

We have documented that Spotify's testing and promotion of independent music has elevated its use on the platform. One comparison arises from the actual evolution of the independent-label shares of promotion and streaming relative to what would have arisen if the platform had not facilitated expanded testing of indie music. A comparison of developments on the platform with a traditional promotional venue – terrestrial radio in the US – is also potentially instructive. Between 2017 and 2020 – as the major shares of streaming fell on Spotify – the major-label share of airplay on US radio remained constant at roughly 90 percent of top 100 songs.[34]

We speculate that the contrast between radio and the experience on the platform has two causes. First, we suspect that major labels have closer traditional ties to radio stations.[35] We conjecture that if the major labels dominated the playlist environment at Spotify, then the independent share of promotion and streaming would rise less.

Second, as suggested in Section 2.2, experimentation is more costly on radio. Radio program directors could easily know about indie discoveries on Spotify. Why, then, does radio continue to rely so heavily on major-label music? We can think of a few possible explanations. First, major-label music may indeed be "better" than independent music; but unlike Spotify, radio stations do not incur lower costs if they substitute indie for major music. Hence, radio stations can choose the higher-cost option without cost penalty. Given the relatively high

[33]We obtain nearly identical estimates based on the ratios of sums of α-weighted follower to streams.

[34]See Appendix Figure A1. These data are obtained from kworb.net.

[35]See Boehlert (2001), documenting arrangements by which record labels paid for the inclusion of their songs on radio.

quality indie music that is discovered on Spotify, the degradation in the quality of the service from substituting independent for major-label music may be small, as the benefits in lower costs may exceed the costs from lower-quality music. The Pandora experiment discussed in Section 2.1 suggests that substitution away from a streaming service would be small. A second, and complementary, possibility is that the linear nature of radio broadcasting makes it more costly to play less appealing, or less familiar, music on a radio station than on a digital music platform. All of a station's current listeners are subjected to any song that the station airs. Users of streaming services, by contrast, can skip ahead to avoid a song, or simply choose a playlist or a song they wish to hear. Independent music, even if less familiar, may be better suited to the Spotify environment, in which users can choose among many listening options on Spotify without changing providers, as on radio.

The comparison with radio, along with the main evidence in the paper, indicate that the various features of digital platforms that we have emphasized (the ability to test many products and promote those with promise) has shifted power from away from traditional suppliers.

6 Conclusion

While streaming has restored the recorded music industry to profitability, Spotify's royalty payment obligations have kept their profits low. This study documents Spotify's use of playlists to steer usage – and revenue – away from major-label suppliers to control costs and enhance bargaining power as Spotify has grown more powerful. First, Spotify has come to control the playlist environment on the platform, both by adding playlists and by dominating playlist followers. This increase in control provides Spotify with substantial capacity to test and promote songs. Second, Spotify has used its expanded capacity to test a growing number of independent-label songs, and we document a causal impact of greater independent testing on the discovery of proportionally more independent songs that receive heavy promotion and streaming success. Third, Spotify appears to promote independent-label music more than its subsequent success warrants. Fourth, using a large number of new-music playlists, we document that the placement of songs on Spotify playlists has a causal impact on streaming. Hence, the shift in promotion toward independent music explains a decline in the share of royalty payments going to major-label suppliers.

Our findings provide important contributions to the platforms literature. First, we provide evidence about the evolving power relationship between a platform owner and concentrated suppliers. This relationship is not simply a function of relative size and dominance within segments: we document the actions that a platform owner takes to increase its bargaining power vis-a-vis suppliers. Second, we document testing and promotion as distinct but complementary purposes of Spotify's curation activities, and we show how Spotify invests in these capabilities. This contributes to the literature on selective engagement with – and promotion of – complements. Third and related, our findings contribute to our understanding of value creation in platform environments. It is well known that distribution platforms can carry longer tails of complements (products); we show how the potential success of such complements depends on the choices made by the platform owner – and conversely, how a platform owners' actions can allow it to deliver similarly valuable products to users at lower cost to the platform. Fourth, we contribute to the discussion surrounding the exercise of power by platform owners. We show how a platform owner's competition with complementors over promotion channels (i.e., playlists) can be a source of power in relationships with suppliers. Finally, while we study the music industry, the forces we document are generic to digital platforms, which can carry and test many products and chose which to promote, with implications for platform bargaining with its suppliers. While the study takes the interaction between a platform and its suppliers in the recorded music industry as its context, the mechanisms that we study can arise whenever digital platforms have access to a fringe of potential alternatives to their traditionally powerful suppliers.

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Figures and Tables

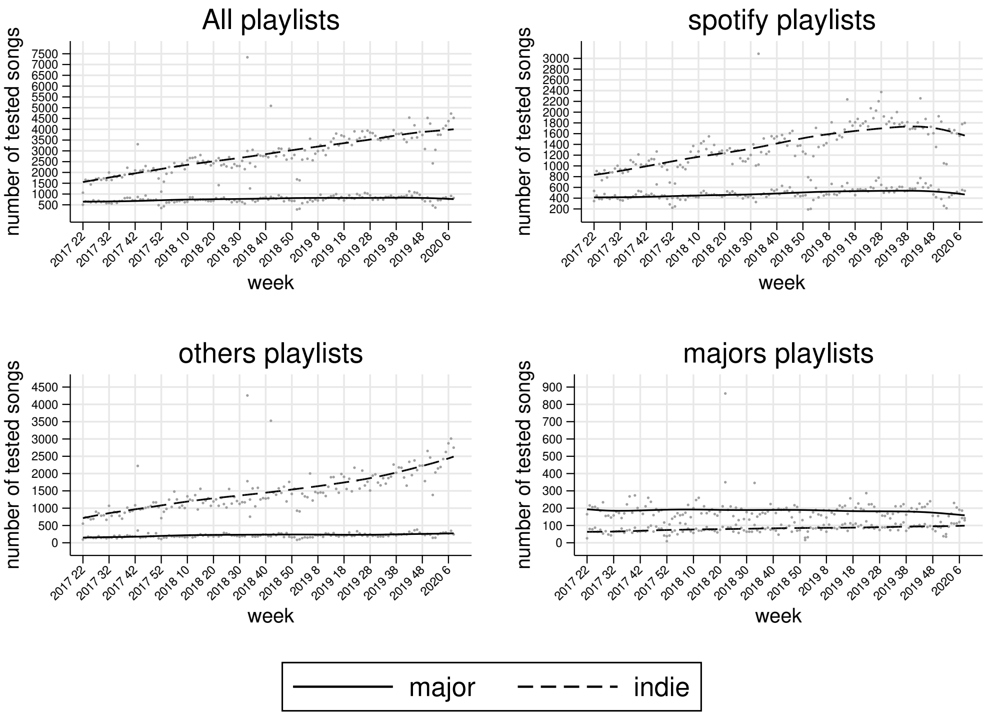


Figure 1: Major and indie song testing

Note: The panels show smoothed patterns of the numbers of indie and major songs tested (first added to new-music playlists) each week. The upper left combines all playlist curators. The remaining three panels cover lists operated by Spotify, other curators, and major record labels.

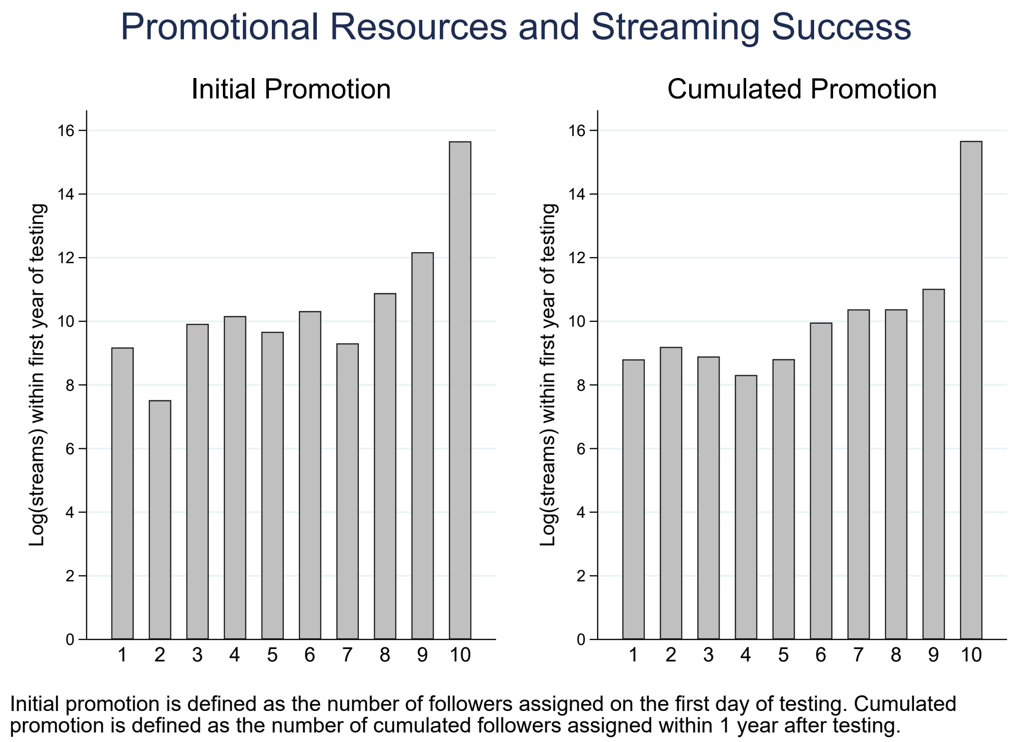


Figure 2: Promotional Resources and Streaming Success.

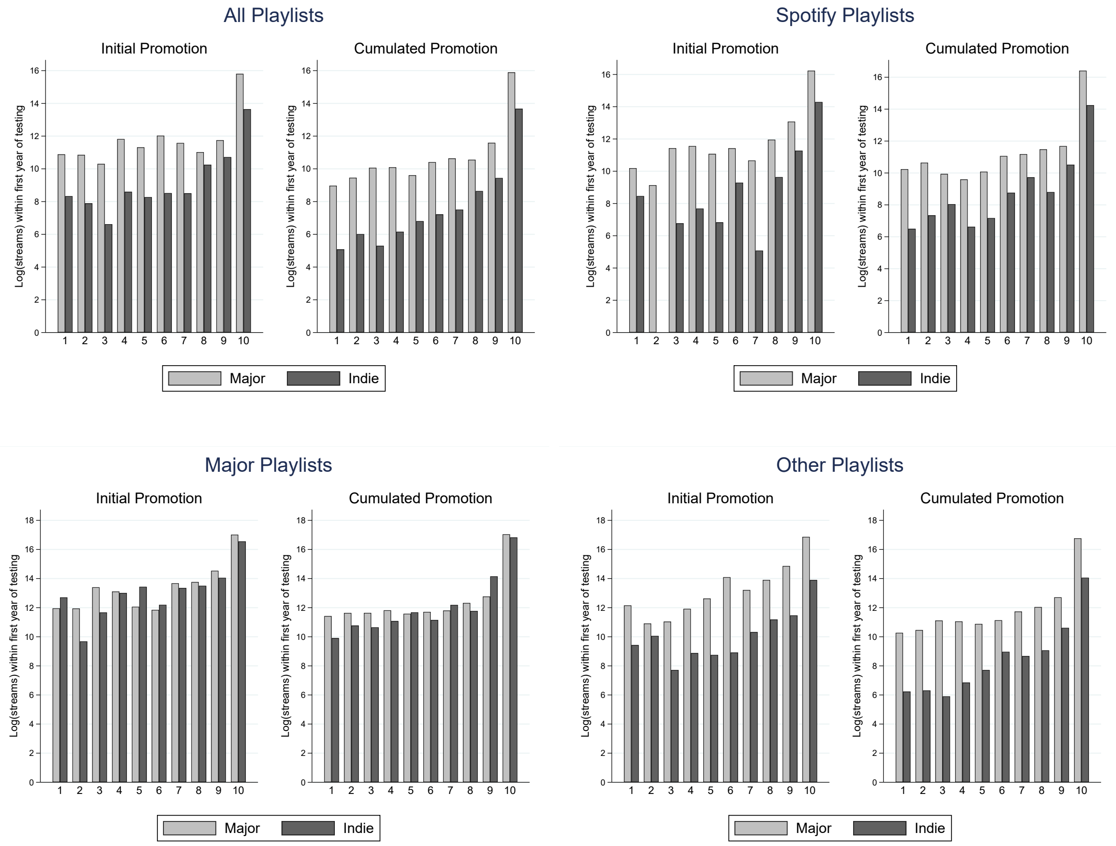


Figure 3: Outcome based test for bias, by curator type.

Note: The figures show major vs indie song streaming success across deciles of songs according to initial or first year promotion. Initial promotion is defined as the number of followers assigned on the first day of testing. Cumulated promotion is defined as the number of cumulated followers assigned within 1 year after testing. The upper left panel includes All playlists, the upper right only considers Spotify-operated lists, the bottom left is major-label lists, and the bottom right includes playlists operated by other curators.

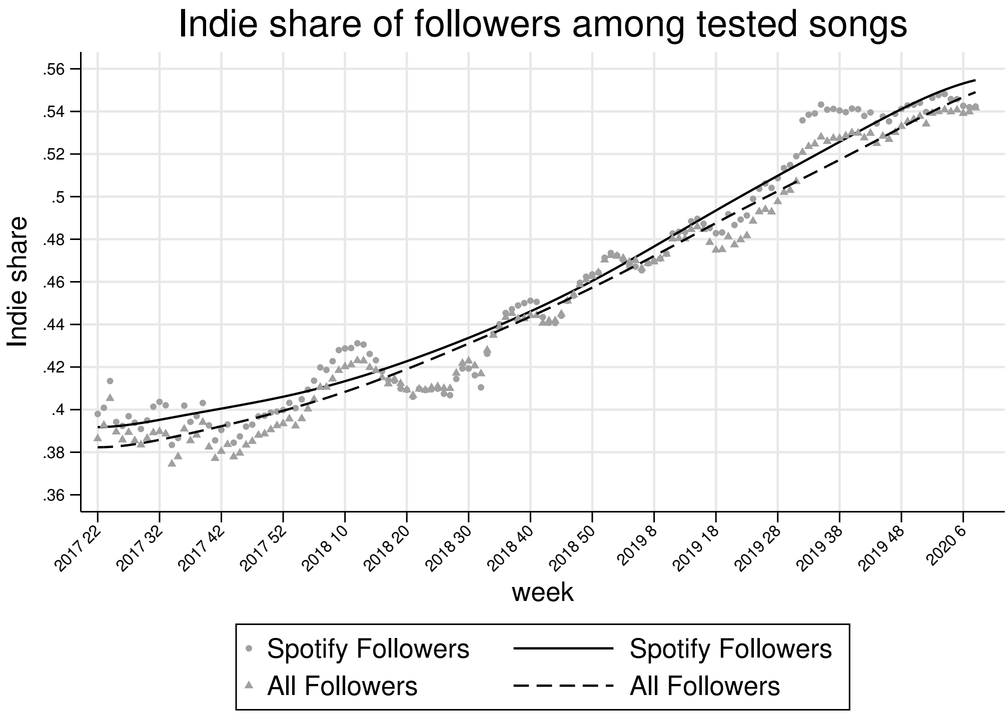
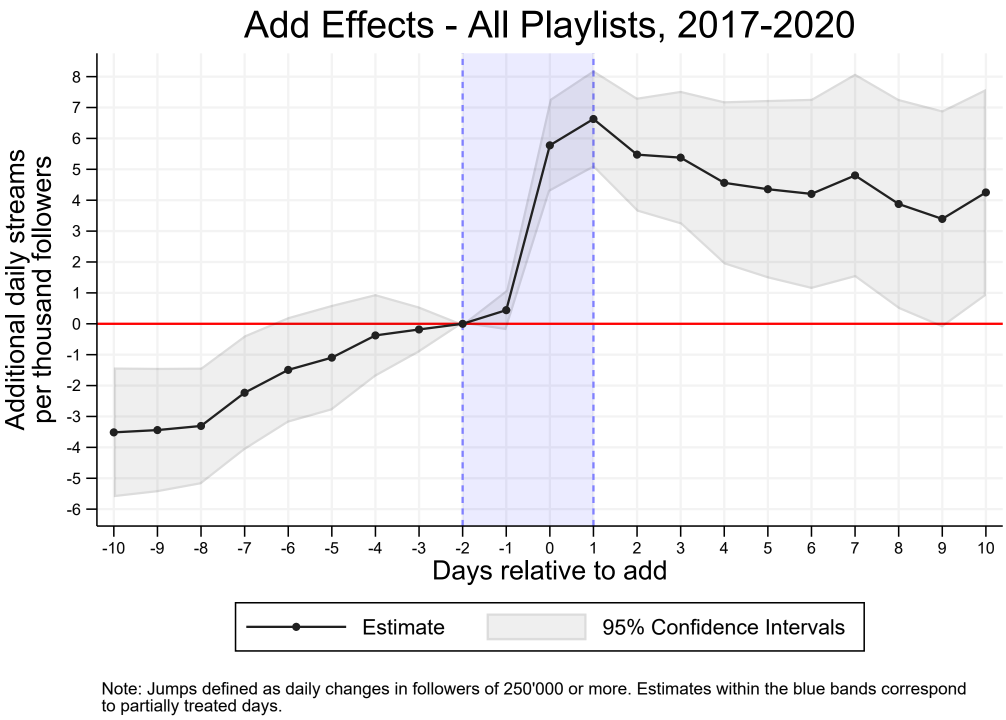
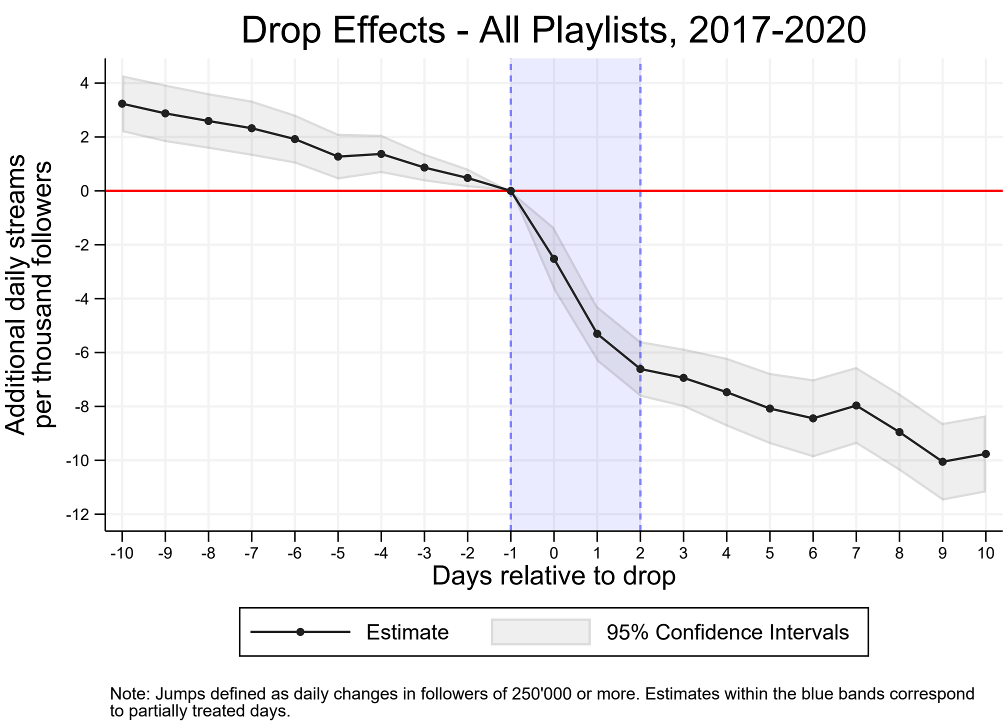


Figure 4: Indie Share of Followers among Tested Songs.

Note: The solid and dashed lines show smoothed patterns of the indie share of followers assigned among tested songs each week. The solid line considers followers from Spotify-operated playlists only, and the dashed line combines followers from all playlist curators.



(a) Add Effects on Streams.



(b) Drop Effects on Streams.

Figure 5: Add and Drop Effects on Streams.

Note: The figures show the coefficients from regressions of streams on indicators for days until, and since, a 250,000 follower jump in daily song followers. The top panel is for upward jumps in song followers; the bottom panel is for downward jumps.

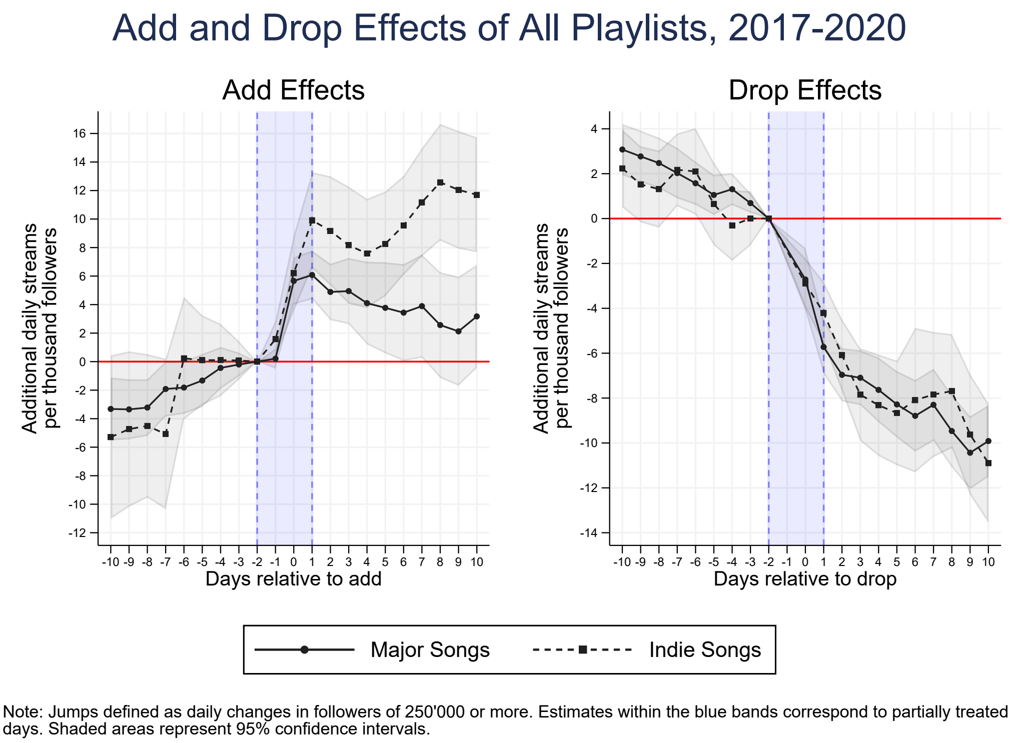


Figure 6: Add and Drop Effects on Streams, by song type.

Note: The figures show the coefficients from regressions of streams on indicators for days until, and since, a 250,000 follower jump in daily song followers. The left panel is for upward jumps in song followers; the right panel is for downward jumps.

Table 1: Descriptive Statistics: Playlists. †

	Year			
	2017	2018	2019	2020
All Playlists Combined				
Number of playlists	1,850	2,353	3,076	3,259
Total number of slots	114,869	172,462	232,960	236,543
Total number of followers	353,523,605	497,109,545	652,895,377	683,231,265
By Playlist Operator				
Spotify				
Number of playlists	778	1,018	1,210	1,225
Total number of slots	42,165	62,813	94,324	90,588
Total number of followers	281,544,788	403,553,926	523,006,800	539,125,855
Majors				
Number of playlists	461	478	497	496
Total number of slots	26,242	32,821	35,211	34,572
Total number of followers	44,508,718	48,688,869	52,841,769	53,937,285
Others				
Number of playlists	611	857	1,369	1,538
Total number of slots	46,462	76,828	103,425	111,383
Total number of followers	27,470,099	44,866,750	77,046,808	90,168,125

† The table describes the new music playlist sample. The first entry shows the number of distinct playlists from each operator type as of yearend or on the last day on which playlists are observed during that year. The second entry shows the number of song slots on the playlists. The third slot shows the number of playlist followers, summed across lists at yearend. Entries for 2020 use the sample end date rather than yearend 2020.

Table 2: Descriptive Statistics: Tested Songs.[†]

	Indie Songs ($N = 409,335$)	Major songs ($N = 110,475$)	Ratio: $\frac{\text{Major}}{\text{Indie}}$
% making the Spotify Top 200 within a year	0.14	2.09	14.48
Cumulated observed streams within a year	69516.19	1483290.00	21.34
Playlist Operator			
All Playlists Combined			
Followers assigned at birth	0.30	1.10	3.70
% included in a 100K playlist within a year	17.51	34.53	1.97
% included in a 500K playlist within a year	7.52	18.90	2.51
% included in a 1M playlist within a year	3.65	11.80	3.23
Cumulated followers assigned within a year	35.67	139.11	3.90
Spotify Playlists			
Followers assigned at birth	0.24	0.92	3.80
% included in a 100K playlist within a year	13.37	28.96	2.17
% included in a 500K playlist within a year	6.92	17.89	2.59
% included in a 1M playlist within a year	3.38	11.68	3.45
Cumulated followers assigned within a year	27.81	105.70	3.80
Majors Playlists			
Followers assigned at birth	0.01	0.13	17.10
% included in a 100K playlist within a year	1.63	15.27	9.34
% included in a 500K playlist within a year	0.26	3.36	13.12
% included in a 1M playlist within a year	0.00	0.00	-
Cumulated followers assigned within a year	1.25	21.85	17.44
Others Playlists			
Followers assigned at birth	0.05	0.05	1.10
% included in a 100K playlist within a year	9.56	22.03	2.31
% included in a 500K playlist within a year	0.69	1.16	1.66
% included in a 1M playlist within a year	0.35	0.48	1.35
Cumulated followers assigned within a year	6.61	11.57	1.75

[†] The table describes the 519,820 songs born into the playlist sample. Follower measures are in millions. Followers at birth are the playlist followers assigned to a song on its first day of appearance in the playlist sample. Cumulated first-year followers are the sum of daily followers, across day and playlists, that each song receives. The figures in the last comlumn correspond to the ratio of the corresponding figures in the first two columns.

Table 3: Descriptive Statistics: Song Streams and Followers.†

	Mean	Std. Dev.	Min	Max	N
All Songs (N=3,410)					
Streams	1.16	0.81	0.38	12.03	196,270
All Playlist Followers	24.17	21.50	0.00	129.65	196,270
Spotify Followers	19.61	18.35	0.00	108.39	196,270
Majors Followers	2.89	2.72	0.00	17.32	196,270
Others Followers	1.68	1.67	0.00	10.69	196,270
Indie Songs (N=648)					
Streams	1.09	0.68	0.38	10.42	27,934
All Playlist Followers	22.29	18.95	0.00	97.52	27,934
Spotify Followers	18.63	16.52	0.00	89.05	27,934
Majors Followers	1.84	2.14	0.00	13.41	27,934
Others Followers	1.82	1.78	0.00	8.11	27,934
Major Songs (N=2,762)					
Streams	1.17	0.83	0.38	12.03	168,336
All Playlist Followers	24.49	21.88	0.00	129.65	168,336
Spotify Followers	19.77	18.63	0.00	108.39	168,336
Majors Followers	3.06	2.77	0.00	17.32	168,336
Others Followers	1.66	1.65	0.00	10.69	168,336

† All figures represent average daily values and are expressed in millions. Streams are daily global Spotify streams for top-200 songs. Playlist followers for each song are the sum of the numbers of playlist followers for the playlists that include the song on the day.

Table 4: Experimentation and Discovery. All Playlists.[†]

Sample: Major-label Songs

Dependent Variable:	# Songs Making ≥ 1M Playlist		Log(Cumulated Followers)		# Songs Making Charts		Log(Cumulated Streams)		
	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(first) Coef./s.e.
Number of Tested Songs	103.911***	88.885***	9.722***	11.859***	17.693***	14.660*	34.653***	45.973***	
	(27.15)	(31.32)	(2.88)	(3.89)	(4.82)	(7.62)	(10.56)	(16.89)	
Number of Slots									2.642***
									(0.64)
Day of Testing	0.004***	0.005***	0.001**	0.000*	-0.000	-0.000	-0.002**	-0.002**	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.465	-	0.353	-	0.358	-	0.247	-	
F-stat excl. instruments									16.842
p-value									0.000
Number of Obs.	1000	1000	1000	1000	1000	1000	1000	1000	1000

Sample: Indie-label Songs

Dependent Variable:	# Songs Making ≥ 1M Playlist		Cumulated Followers		# Songs Making Charts		Cumulated Streams		
	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(OLS) Coef./s.e.	(IV) Coef./s.e.	(first) Coef./s.e.
Number of Tested Songs	31.977***	28.110***	2.622***	2.959***	1.182***	1.913*	7.933***	8.597*	
	(3.75)	(7.49)	(0.29)	(0.63)	(0.24)	(1.04)	(1.15)	(4.65)	
Number of Slots									9.376***
									(1.95)
Day of Testing	0.002	0.004	0.000***	0.000	-0.000	-0.000	-0.002*	-0.002	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.452	-	0.485	-	0.085	-	0.133	-	
F-stat excl. instruments									23.101
p-value									0.000
Number of Obs.	1000	1000	1000	1000	1000	1000	1000	1000	1000

[†] The top (bottom) panel of the table reports estimates for the sample of major-label (indie-label) songs. Both samples only include tested songs, i.e. songs that we observe being placed on a playlist for the first time within our sample period. The (IV) specifications use the number of playlist spots aggregated across lists to instrument the number of tested songs. The first two columns use the number of songs tested on day t that appear on a Spotify-operated playlist with a list 1 million followers within a year of t as the dependent variable. The third and fourth columns use the cumulated number of followers assigned to songs tested on day t within a year of t as the dependent variable. The fifth and sixth columns use the number of songs tested on day t that appear in the Spotify top 200 daily charts within a year of t as the dependent variable. The seventh and eight columns use the cumulated number of streams obtained by songs tested on day t within a year of t as the dependent variable. The number of tested songs is measured in thousands and the number of slots is measured in milions. The number of streams is measured in millions, and the number of cumulated followers is measured in billions. Robust standard errors are reported in parenthesis.

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5: Outcome-based Test for Bias in Promotion based on Cumulated Followers..[†]

Dependent Variable: Reaching Top 200 Charts

	All Lists		Spotify Lists		Others Lists		Major Lists	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Major Song	0.015***	0.015***	0.017***	0.019***	0.020***	0.037***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(assigned followers)	0.005***		0.001***		0.001***		0.002***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Follower deciles Fixed Effects	✗	✓	✗	✓	✗	✓	✗	✓
R^2	0.037	0.041	0.022	0.063	0.028	0.065	0.039	0.122
Number of Observations	519810	519258	519810	291410	519810	291868	519810	73257

Dependent Variable: Log(streams)

	All Lists		Spotify Lists		Others Lists		Major Lists	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Major Song	0.241***	0.241***	0.274***	0.309***	0.325***	0.592***	0.090***	0.093***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)
Log(assigned followers)	0.081***		0.012***		0.018***		0.038***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Follower deciles Fixed Effects	✗	✓	✗	✓	✗	✓	✗	✓
R^2	0.038	0.041	0.022	0.064	0.028	0.067	0.040	0.131
Number of Observations	519810	519258	519810	291410	519810	291868	519810	73257

[†] The assigned followers correspond to the operator-specific number of cumulated followers assigned within one year of testing. Specifications (2), (4), (6), and (8) control for deciles of the cumulated followers distribution. Robust standard errors are reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 6: Playlist Inclusion Estimates, by Jump Size.†

Jump Size:	100K		250K		500k		1M	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Add	6.277***		6.629***		7.359***		8.324***	
	(0.891)		(0.805)		(0.983)		(1.017)	
Drop		-6.475***		-6.609***		-5.982***		-6.108***
		(0.569)		(0.527)		(0.682)		(0.580)
Effect per Thousand Follower		6.376		6.619		6.671		7.216
R^2	0.989	0.991	0.989	0.991	0.988	0.989	0.987	0.988
No. of Tracks	1571	1586	1458	1505	1405	1434	1305	1322
No. of Observations	112400	126559	97436	122222	83306	112199	66095	93220

† All specifications include song-spell fixed effects, day fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 7: Playlist Inclusion Estimates, by Streaming Subsample.†

Streaming Subsample:	Top 200		Top 150		Top 100		Top 50	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Add	6.629***		6.978***		6.903***		5.396***	
	(0.805)		(0.942)		(1.142)		(1.694)	
Drop		-6.609***		-6.924***		-6.999***		-6.523***
		(0.527)		(0.621)		(0.788)		(1.147)
Effect per Thousand Follower		6.619		6.951		6.951		5.959
R^2	0.989	0.991	0.989	0.991	0.989	0.990	0.987	0.988
No. of Tracks	1458	1505	1184	1226	884	917	522	538
No. of Observations	97436	122222	78795	96179	56106	66305	29938	33882

† Jumps defined as daily changes in followers of 250'000 or more. All specifications include song-spell fixed effects, day fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 8: Effect Of Playlist Inclusion Estimates - All Playlists Combined. †

	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.
Add	6.629***			
	(0.805)			
Drop		-6.609***		
		(0.527)		
Add × Major Song			6.078***	
			(0.871)	
Add × Indie Song			9.917***	
			(1.718)	
Drop × Major Song				-6.961***
				(0.604)
Drop × Indie Song				-6.088***
				(0.819)
Effect per Follower		6.619		-
Effect per Follower Indie		-		8.002
Effect per Follower Major		-		6.519
F-test: Indie vs Major Effect			4.07	0.73
P-value			0.044	0.394
R^2	0.989	0.991	0.989	0.991
No. of Tracks	1458	1505	1458	1505
No. of Observations	97436	122222	97436	122222

† Jumps defined as daily changes in followers of 250'000 or more. All specifications include song-spell fixed effects, day fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Appendix A: additional tables and figures

This appendix contains supplemental tables and figures referred to in the text.

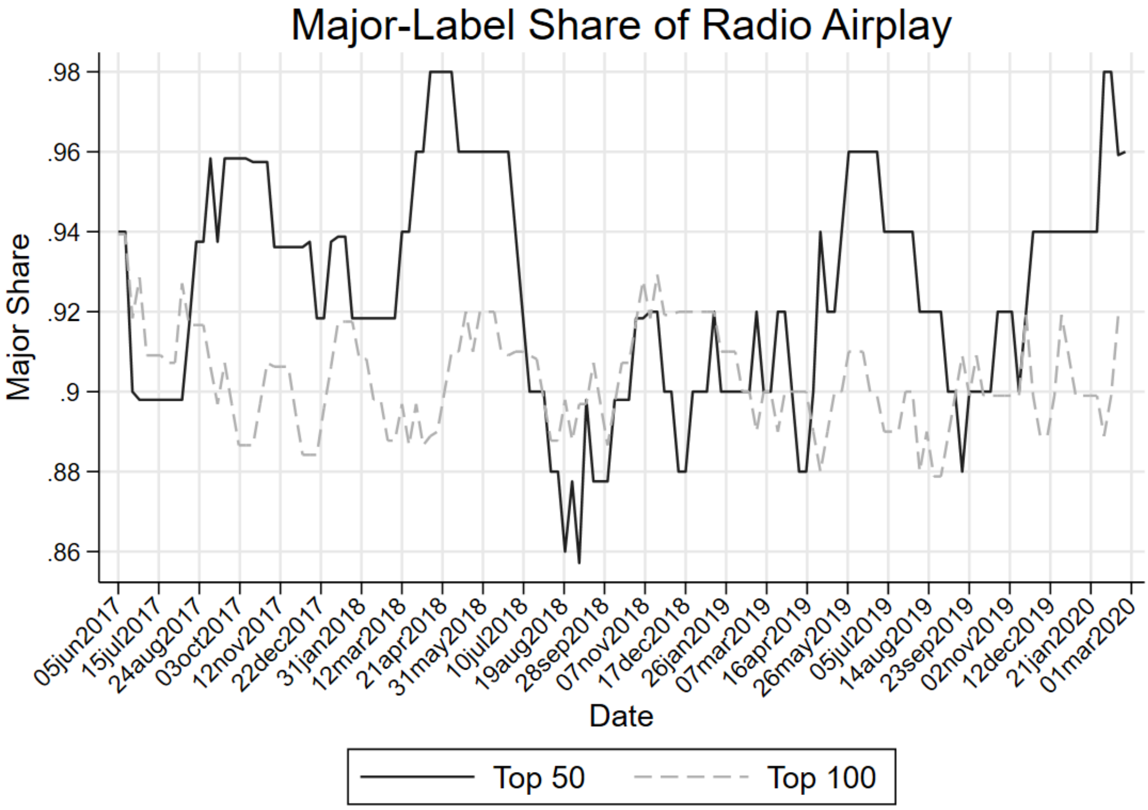


Figure A1: Major-Label Share of Radio Airplay. We obtaining weekly "Billboard Radio Songs Estimates" from kworb.net. We extract the first artist for each entry, and use our association of artists to labels to arrive at the major shares.

Table A1: Outcome-based Test for Bias in Promotion based on Birth Followers.†

Dependent Variable: Reaching Top 200 Charts

	All Lists		Spotify Lists		Others Lists		Major Lists	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Major Song	0.017***	0.015***	0.017***	0.017***	0.021***	0.046***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(birth followers)	0.003***		0.001***		0.001***		0.003***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Follower deciles Fixed Effects	✗	✓	✗	✓	✗	✓	✗	✓
R^2	0.026	0.039	0.020	0.064	0.027	0.066	0.036	0.130
Number of Observations	519810	498347	519810	270899	519810	250216	519810	60254

Dependent Variable: Log(streams)

	All Lists		Spotify Lists		Others Lists		Major Lists	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.	(7) Coef./s.e.	(8) Coef./s.e.
Major Song	0.271***	0.238***	0.279***	0.269***	0.334***	0.739***	0.110***	0.117***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
Log(birth followers)	0.045***		0.013***		0.024***		0.052***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Follower deciles Fixed Effects	✗	✓	✗	✓	✗	✓	✗	✓
R^2	0.026	0.040	0.020	0.064	0.027	0.067	0.037	0.136
Number of Observations	519810	498347	519810	270899	519810	250216	519810	60254

† The birth followers correspond to the operator-specific number of followers assigned at birth, i.e. the number of combined followers of the playlists on which the song was added for the first time. Specifications (2), (4), (6), and (8) control for deciles of the birth followers distribution. Robust standard errors are reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Appendix B: Robustness checks surrounding the estimation of α

Imputation and the top-200 cutoff

For songs observed after the jump but not before, we can use two additional approaches that should bound the true value. When we don't observe a song streaming on a day, its streams are between 0 and the minimum streaming value we observe for that day (s_{jt} for the song ranked 200). Hence, we estimate models that rely on samples where missing streaming values are imputed with these two extremes.

Table B1 reports estimates of α for add and drop effects using the 250,000 jump-size threshold and the three imputation approaches, along with the baseline estimate from columns (3) and (4) of Table 6 from the main text. Columns (3) and (4) impute using the daily minimum, while columns (5) and (6) impute with zero. Given our expectation that estimates imputing with zero would provide upper bounds while estimates using the daily minimum values would provide lower bounds, the estimates appear reasonable. No imputation gives an estimate of 6.6, which lies between the estimate of 4.2 for minima and the estimate of 8.2 when relying on the zero imputation.

Does α vary by playlist type or over time?

Our playlist measure F_{jt} can be disaggregated by type of playlist: $F_{jt} = \sum_c F^c_{jt}$, where c is the curator type (Spotify, major label, other). We can include each curator type separately and test whether effects are statistically discernibly different.

Table B2 reports the estimates that rely on jumps of 250,000 followers for the three various types of lists. Spotify-operated playlists show a positive and significant effect of playlist add while major-operated playlists and lists operated by other entities present insignificant add effects. However, as indicated by the F-tests displayed at the bottom of the table, we fail to reject that the effects of Spotify-operated, major-operated, and other playlists are the same. We interpret these results as evidence that different types of playlists do not have discernibly different effects on streams.

Playlists and their followers grew quickly over the time period we study, so we ask whether the per-follower impact of playlists on streams varies over time by re-estimating the basic model separately by month. As Figure B1 shows, the resulting coefficient estimates are stable over time.[36] Hence, we use a single coefficient to measure the per-follower impact of playlists on streams.

Fixed effects approach

Despite our concerns about the fixed effects approach, we implement it for comparison, estimating a variant of model 4 in the main paper, where flexible leads and lags of α are replaced by a single coefficient, and we also include song-spell-specific time trends:

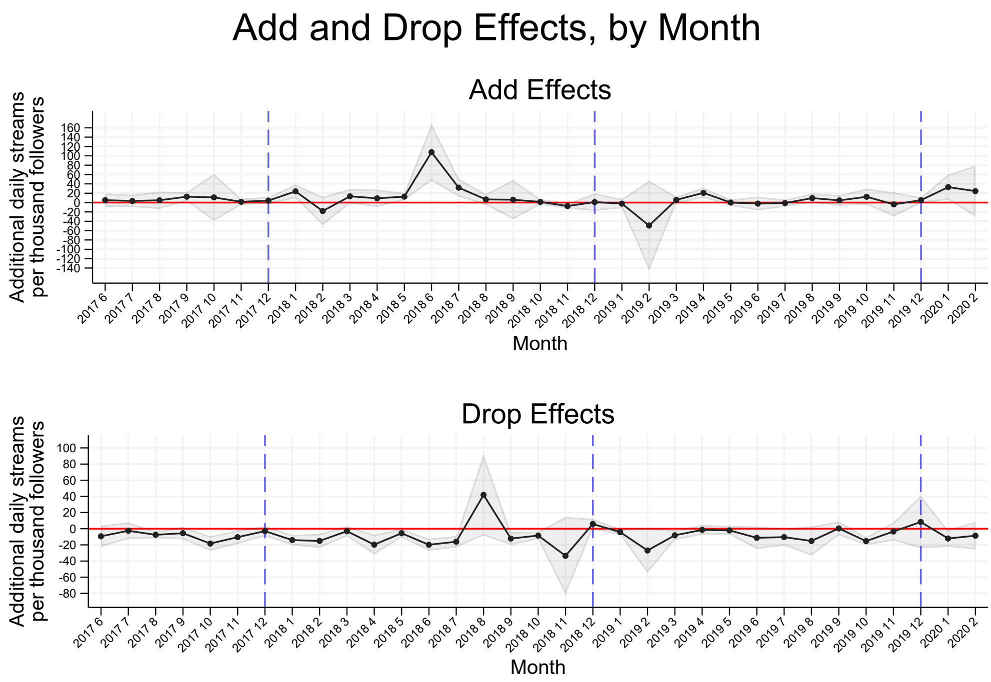
$$s_{jt} = \alpha F_{jt} + \mu_j + \lambda_t + \psi^a_{jt} + \theta t_j + \epsilon_{tj},$$

where variables are otherwise defined as above. Table B3 presents the FE estimates of the parameter α. Columns (1)-(3) use the entire data set. Column (1) includes no song-specific time trends, yielding an estimate of 29.95. Including linear and also quadratic song-specific time trends, in columns (2) and (3), reduces the estimate somewhat, to 26.97 and to 21.63. Columns (4)-(6) repeat the exercise using only the observations up to 10 days before, and 10 days after, a 250,000+ jump in followers. Estimate magnitudes are quite similar. As before, the estimates from the fixed effects approach are roughly three times larger than the jump estimates.

Figures 5a and 5b in the main paper suggest the reason why fixed effects produce larger estimates. Streams are rising as positive jumps approach, and streams are falling as negative

[36] A regression of the monthly coefficients on a time trend shows no statistically significant differences, indicating that the effects remain stable over time.

jumps approach. This leads the fixed effects approach to over-attribute the generally rising and falling pattern to the changes in followers. The inclusion of track-specific time trends helps but cannot solve the problem. This leads us to view the jump approach as more reliable than the fixed effects approach.



Note: Jumps defined as daily changes in followers of 250'000 or more. Gray area represent 95% confidence bands.

Figure B1: Add and Drop Effects on Streams, by Month.

Table B1: Effect Of Playlist Inclusion Estimates - All Playlists Combined - Imputed Streams. †

Impute missing streams:	No		Daily Minimums		Zero	
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(4) Coef./s.e.	(5) Coef./s.e.	(6) Coef./s.e.
Add	6.629***		4.176***		8.452***	
	(0.805)		(0.540)		(0.871)	
Drop		-6.609***		-4.115***		-7.889***
		(0.527)		(0.323)		(0.469)
Effect per Follower		6.619		4.146		8.171
R^2	0.989	0.991	0.988	0.991	0.984	0.985
No. of Tracks	1458	1505	1458	1505	1458	1505
No. of Observations	97436	122222	250921	347969	250921	347969

† Jumps defined as daily changes in followers of 250'000 or more. All specifications include song-spell fixed effects, day fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table B2: Effect Estimates - By Playlists †

	(1) Coef./s.e.	(2) Coef./s.e.
Add Spotify	5.665***	
	(0.935)	
Add Majors	1.842	
	(15.019)	
Add Others	-16.984	
	(25.049)	
Drop Spotify		-5.983***
		(0.730)
Drop Majors		-14.954
		(11.605)
Drop Others		-6.962
		(17.720)
Effect per Thousand Spotify Followers		5.824
Effect per Thousand Majors Followers		8.398
Effect per Thousand Others Followers		-5.011
F-test: Joint significance 3 coeffs	12.32	21.62
P-value	0.000	0.000
F-test: Difference between Spotify and Majors	0.06	0.60
P-value	0.800	0.438
F-test: Difference between Spotify and Others	0.81	0.00
P-value	0.367	0.956
R^2	0.984	0.988
No. of Observations	99636	124738
No. of Tracks	1471	1513

† Jumps defined as daily changes in followers of 250'000 or more. All specifications include song-spell fixed effects, day-of-the-week fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table B3: Fixed Effect Estimates. †

	Full Sample			20 days around 250K Jump		
	(1)	(2)	(3)	(4)	(5)	(6)
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Followers (in thousands)	29.999***	27.002***	21.661***	29.289***	26.336***	20.569***
	(1.080)	(1.069)	(1.066)	(1.076)	(1.012)	(0.949)
Track-specific linear trend	✗	✓	✓	✗	✓	✓
Track-specific quadratic trend	✗	✗	✓	✗	✗	✓
R^2	0.805	0.887	0.925	0.808	0.891	0.930
No. of Tracks	2646	2646	2646	2193	2193	2193
No. of Observations	190731	190731	190731	162766	162766	162766

† Columns (1)-(3) use full sample. Columns (4)-(6) use 20 days around jumps of 250K. All specifications include song fixed effects, day fixed effects, as well as song age fixed effects. Standard errors are clustered at the song level and reported in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.