How Independent Is Independent Music?
Artists, Recordings, and Label Promotion on Spotify

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Abstract

Three months after Spotify let artists pitch songs directly to its playlist editors in 2018, more than 10,000 artists had gained their first editorial placement. But royalties follow recordings, not artists, and an artist who self-releases one song can release the next through a label. The authors ask how much of the music promoted for independent artists is independently released. They link 2016–2019 placements on Spotify's editorial and major-label playlists to follower counts, 2026 catalog credits, and later releases. Spotify's own playlists supply over nine-tenths of self-releasing artists' potential playlist audience. Yet after pitching opened, the catalog classifies only about half of these artists' editorial placements as self-released, and one fifth on the majors' playlists. Among artists featured on both, the gap comes almost entirely from how often each is featured. The majors' playlists also predict an artist's next major label: of 70 self-releasing artists they featured who released with a major within a year, 54.3% released with the playlist's owner, against 31.8% expected from the mix of firms, a pattern that predates direct pitching. Classifying placements by artist rather than recording thus overstates self-released placements about twofold on Spotify's playlists and fivefold on the majors'.

Keywords: platforms; creator economy; promotion; intermediation; music streaming

Streaming platforms now let artists reach listeners without a record deal. In July 2018, for example, Spotify opened its playlist editors to direct pitches from artists, labels, and their teams, and by late October more than 67,000 artists and labels had used the new route (Spotify 2018a, 2018c). Spotify reported the result in numbers of artists: more than 10,000 had obtained their first editorial placement. Yet an artist can release one recording independently and another through a label. Spotify pays each recording's royalties through the licensor that delivered it, usually a label or distributor, which then pays the artist under their agreement (Spotify n.d.). A platform that promotes independent artists may therefore still be promoting label-released recordings.

Prey (2020) notes that roughly 70% of Spotify's revenue goes to rights holders and argues that Spotify must therefore reduce its reliance on them. Aguiar, Waldfogel, and Zeijen (2024) show that Spotify expanded its testing and promotion of newly released independent music, and they report that the share of its royalties paid to independent labels outside the Merlin network doubled from 13% to 26% between 2017 and 2023 (p. 24). Their category includes independent labels, whereas our self-release measure covers only recognized DIY distributors and labels named after the artist. Wlömert, Papies, and van Heerde (2025) show that a playlist's effect on streams differs between playlists curated by the platform, by the artist's own label, and by third parties, and is larger for songs from independent labels. To our knowledge, however, no study compares an artist's release category with the credits on the recordings selected for that artist, or follows promoted artists to the firms that later release their music. We therefore ask two questions. First, when a platform promotes independent artists, how much of the music it promotes is independently released? Second, does promotion on a label-operated playlist predict which major later releases the artist's music?

Spotify's editors run one set of playlists, and the three major labels run another: Sony's Filtr, Universal's Digster, and Warner's Topsify (Prey 2020, pp. 2–3). We call a song's addition to a playlist a placement. We link placements on 2,353 editorial and 3,203 label playlists from January 2016 through March 2019 to historical follower counts, to each artist's release history, to the label credited on each placed recording, and to the artist's later releases. An artist is self-releasing when do-it-yourself (DIY) distributors or labels named after the artist form the most common category of the artist's releases before July 2018 (artist-level independence). A recording is self-released when its own credit names such a distributor or label and no major

label (release-level independence). We take recording credits from a catalog collected in 2026 and test how later changes in credits affect our conclusions.

We find a large gap between artist-level and release-level independence: curators often feature label-credited recordings by artists classified as self-releasing. Spotify's own playlists supply over nine-tenths of the potential audience attached to these artists' placements, measured by playlist followers. The majors' playlists account for about a third of these artists' placements but only 6% to 7% of their follower-weighted reach (Figure 1). Yet later credits classify only about half of these artists' post-opening placements on Spotify's playlists as self-released (49.6%), and one fifth of their placements on the majors' playlists (20.2%). Classifying these placements by artist rather than by recording would thus overstate self-released placements about twofold on Spotify's playlists and fivefold on the majors'. Among the 1,094 artists featured on both kinds of playlist, differences in how often each artist appears account for 15.5 of the 16.8-point gap, and differences in each artist's mix of self-released recordings for only 1.4 points. Indeed, for 528 of these artists, the 2026 catalog credits none of the placed recordings as self-released.

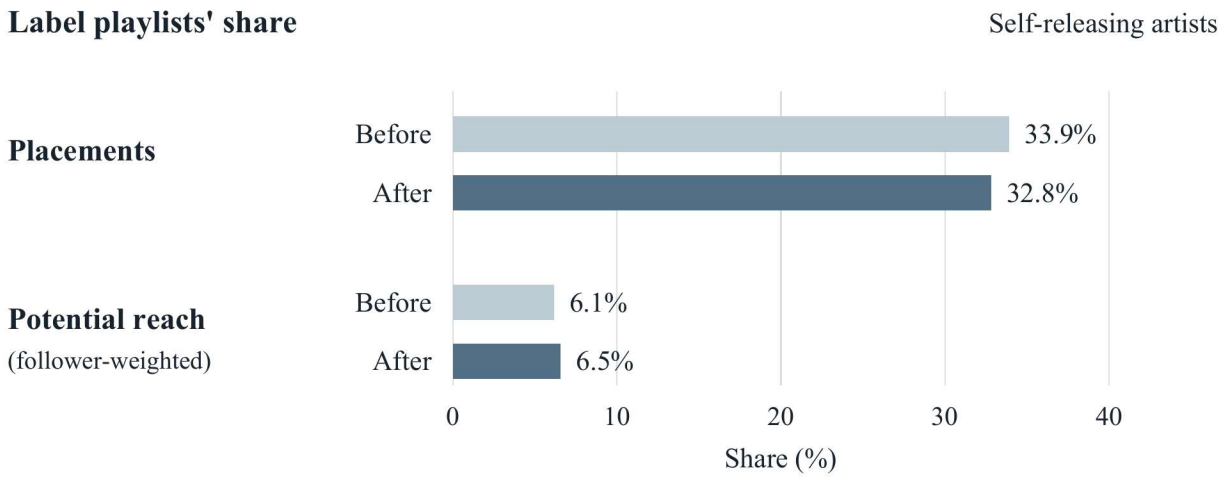

Figure 1**. Label playlists supply a larger share of placements than of potential reach.** *Notes.* Both measures use the same follower-matched placements of baseline self-releasing artists. Before: April 2017–June 2018; after: August 2018–March 25, 2019. Follower weights measure potential reach, counting overlapping audiences again. Table W34 reports a longer window; Table W40 reports the aligned comparison.

We also find that label promotion predicts the firm behind an artist's next major-label release. Among 70 self-releasing artists who had no recorded major release when follow-up

began, were placed on a major's playlist after the opening, and then released with a major within a year, 54.3% released with the major that ran the playlist, against 31.8% expected from the mix of firms: an excess of 22.5 percentage points (one-sided $p < .001$). The match holds after we remove cases whose placed recording carries a major credit in the later catalog, cases linked to Universal's Spinnup distribution service, and repeats of the placed recording (48.3% against 33.8%, $p = .009$). It also appears among artists placed between August 2017 and February 2018, before direct pitching opened (63.2% against 31.1%). Hence, the major that promotes an artist is, disproportionately, the major that later releases the artist's music.

Finally, we examine how the balance between the two kinds of playlist changed around the opening. Compared with April 2017 to June 2018, self-releasing artists' monthly placements after the opening were about 70% higher on both kinds of playlist, whereas major-label artists moved toward Spotify's playlists. The allocation model compares each artist's editorial placements with the same artist's label placements. That ratio fell 36.1% for self-releasing artists relative to major-label artists. This relative shift began in early 2018, before direct pitching opened.

This research makes three contributions. First, we measure the gap between the independence of the artists a platform promotes and that of the recordings it promotes. To our knowledge, this is the first study to compare, for the same placements, an artist's release category with the credits on the recordings selected for that artist. Aguiar, Waldfogel, and Zeijen (2024) document Spotify's growing promotion of independent music by classifying songs by label and weighting playlist slots by followers. Linking each selected recording to the artist's release history shows how far an artist-based count misstates the music a platform promotes. Second, we show where the difference between the two kinds of playlist arises. Among artists featured on both, how often each artist appears accounts for most of the gap, so two channels can feature the same artists yet promote very different mixes of self-released and label-credited music. This finding puts repeated selection, not recruitment alone, at the center of how platforms create the right mix of creators, a question Peres et al. (2024) pose for creator-economy research. Third, we show that promotion on a label-operated playlist predicts which major later releases the promoted artist's music, beyond the firms' overall frequencies and after screens for earlier relationships and repeated recordings. Research on intermediation explains why intermediaries keep their value after direct access opens (Mallen 1973; Chircu and Kauffman 2000; Stanton and Thomas 2016).

Our evidence places such a relationship inside the platform itself: a label's promotion is tied to its own later releases.

For a platform seeking more self-released music, recruitment is only the first decision. It must also decide which artists receive repeated placements and which of their recordings it features, and it should track which firms its promoted artists work with next. For labels, the results show that their playlists supply a small share of these artists' potential reach but predict which major releases the artist's music next. The next section reviews research on platform promotion and intermediaries. We then develop our argument, describe the data and methods, and present the results before discussing implications for platforms, labels, and artists.

Platform Promotion and Intermediaries

Access, Selection, and Creator Incentives

Platforms choose both who can seek promotion and what receives it. Boudreau (2010) distinguishes granting access from relinquishing control and shows that these choices have different consequences for innovation. Hagiu and Wright (2015) study how control over interactions shapes the choice between platform and more integrated forms of organization. In 2018, Spotify opened a common submission route but kept the decision about which songs to feature. Artists gained a way to ask for consideration, but the value of that opportunity still depended on which songs the editors chose and how many listeners their playlists reached.

Platforms selectively promote complements to raise the value of their ecosystems (Rietveld, Schilling, and Bellavitis 2019). Revenue sharing, recommendation systems, and entry costs also shape creator participation and production (Bhargava 2022; Qian and Jain 2024; Zhu, Shi, and Banerjee 2026). We compare the recording credits attached to placements of artists in the same self-releasing category.

A placement is also worth more when the playlist reaches more listeners. Aguiar and Waldfogel (2021) show that prominent Spotify playlist placements affect listening. Pachali and Datta (2025) find that featuring a playlist on Spotify's search page and adding a track by a major-label superstar both raise its followers. Wlömert, Papies, and van Heerde (2025) document variation in playlist effectiveness associated with popularity, prior exposure, song–playlist fit, and the curator. Their comparison of playlists curated by the artist's own label concerns effects on listening, whereas our owner comparison follows artists forward to a later major-label release.

We pair placement counts with historical follower values to distinguish the number of selections from potential reach. We do not observe listening.

Why Direct Access Leaves a Role for Intermediaries

A direct submission route lets creators seek consideration without an intermediary's introduction. An intermediary is a business that helps creators reach audiences or commercial partners; a record label can perform that role while also supplying music. Channel theory distinguishes these firms from the functions they perform (Mallen 1973; Coughlan et al. 2006). Electronic-commerce research explains how direct routes coexist with continuing intermediation (Sarkar, Butler, and Steinfield 1995; Chircu and Kauffman 2000). Direct-channel models examine changes in relationships between manufacturers and retailers (Chiang, Chhajed, and Hess 2003; Arya, Mittendorf, and Sappington 2007). Here, labels supply recordings and run playlists inside a platform that promotes artists itself. We examine whether labels remain involved in the recordings Spotify promotes, and in artists' later releases, once artists can pitch to its editors directly.

In an online labor market where employers can contract directly with workers, agencies help inexperienced workers obtain jobs (Stanton and Thomas 2016). Peukert and Reimers (2022) find that digitization improves publishers' ability to predict commercial success, especially among publishers investing more in analytics. We test whether the major that promotes an artist is also the major behind the artist's next major-label release. An owner match can reflect a relationship already underway, recruitment, or shared tastes, and its timing can separate some of these accounts.

Record labels also have different reasons to direct attention toward particular work. Hagiu and Jullien (2011) show that an intermediary's revenue model influences how it routes users among sellers. De Cornière and Taylor (2019) show that the welfare consequences of biased intermediation depend on selling firms' responses and the alignment between their returns and consumer benefits. A label can feature a song to earn returns on its recording, attract listeners to its playlist, or support an existing or prospective release partnership. Hence a label may feature a rival's recording when the song improves its playlist or builds a relationship with the artist.

Commercial Relationships Within Platforms

Spotify and the major labels depend on each other: the labels supply much of the music listeners want, and Spotify supplies distribution and promotion. A platform benefits from

attractive work supplied by other firms, even as it can compete with those firms for business (Jacobides, Cennamo, and Gawer 2018; Zhu and Liu 2018). Labels can distribute across services or withhold music from one. Cheng, Ofek, and Yoganarasimhan (2026) study UMG music's removal from TikTok and document heterogeneous effects on music demand. Winkler et al. (2026) find that the withdrawal lowered Spotify demand for UMG's titles, with losses concentrated among viral songs and compounded by reduced inclusion on Spotify's curated playlists. Schauerte et al. (2024) examine how launching a direct digital offering affects consumers' use of incumbent services. We examine how labels that supply recordings also promote artists through playlists on the same platform.

Spotify research places relationships with record labels at the center of recommendation and promotion. Aguiar, Waldfogel, and Waldfogel (2021) document favoritism toward independent-label music on New Music Friday relative to subsequent performance. Bourreau and Gaudin (2022) model how royalty differences affect recommendations. Prey (2020) examines how playlists mediate Spotify's music, advertising, and finance markets and describes its reciprocal dependence on record labels.

Aguiar, Waldfogel, and Zeijen (2024, October version) provide the closest empirical comparison. They classify songs through recording affiliations and measure promotion with follower-weighted playlist slots. They also document Spotify's growing testing and promotion of independent music and compare platform-operated with major-operated playlists. We link artists' release categories to the recordings selected and to later major-label releases. For self-releasing artists featured on both types of playlists, we separate differences in the recordings chosen for each artist from differences in how often each artist appears. Web Appendix A distinguishes the studies' outcomes.

How Direct Access and Label Promotion Fit Together

The literature identifies several services that can sustain a label's role after direct access opens. A label can help an artist reach listeners and can also finance, distribute, or plan a release. Whether label services substitute for Spotify's promotion or complement it depends on the artist's alternatives and on what the label earns.

Audience Services and Commercial Support

Better platform promotion can reduce the value of a label's audience service. Suppose editorial and label placements independently reach the same pool of listeners. If repeated

exposure adds no benefit and returns to new listeners diminish, more editorial reach reduces the value of another label placement. Holding service options and contract terms fixed, the artist has less reason to obtain additional label promotion. By contrast, a larger audience opportunity can increase the value of release planning, distribution, or financing that helps the artist use it. Better platform promotion can thus strengthen an artist's position and still leave a reason to sign with a label.

Placement counts record selections, follower weights measure potential reach, and duration records time available for discovery. Listening data would show how many people use those opportunities. Recording credits name the label or distributor on the selected work, and later releases show which major becomes the artist's release partner. These records can show a commercial relationship even when the promoting playlist has few followers.

Why Labels Select Artists Outside Their Established Roster

A label has commercial reasons to select music beyond its established roster. An affiliated recording can generate direct returns. An appealing song can attract or retain listeners to the playlist. Selection can also accompany an existing artist-development relationship or a prospective release partnership. Each of these returns must beat the value of featuring some other song.

An artist classified as self-releasing can have recordings with several different label credits. For example, an artist who releases two singles through a DIY distributor and a third through a Sony imprint is classified as self-releasing, yet placements of the third single carry a major's credit. A playlist can therefore feature more self-releasing artists without selecting more self-released music. Among artists appearing on both types of playlists, we separate two reasons for a difference in the music selected. The playlists can choose different recordings by the same artist, or they can feature some of these artists more often than others. If the first difference is small, the aggregate gap mainly reflects which artists receive more placements.

It does not identify the curator's motive. Playlist fit, expected demand, existing services, and prospective partnerships can all influence whom a curator features and how often. The 2026 catalog names the firm on each recording but not when that firm became involved.

We test whether an artist's later major release matches the major that ran the earlier playlist more often than expected from the mix of firms. Prior services, artist development, recruitment, and shared market or genre specialization can all produce an owner-specific pattern. We use

timing and recording identifiers to separate cases close to placement or involving the same work. Dated contracts would establish whether the relationship began before, during, or after promotion.

The transition rate measures the share of promoted artists who later release with any major. Owner matching asks whether that major is the one that operated the earlier playlist, among cases with an identifiable owner. A label can promote many artists while developing or maintaining commercial relationships with a smaller subset. If label promotion reflects firm-specific relationships, later releases should match the promoting owner more often than the mix of owners and later majors predicts. This prediction does not require most promoted artists to release with that owner. Neither comparison requires the July opening to have created these relationships.

Outside Options and the Comparison Across Artist Groups

Better opportunities without a label (an improved outside option) can let an artist negotiate better terms while continuing to work with it. Conversely, fewer partnerships can reflect weaker opportunities. The number of artist–label relationships alone therefore cannot tell us whether artists gained. Our records link label-run promotion to the firms listed on selected recordings and on artists' later releases. Web Appendix K formalizes the outside-option argument and the demand for promotional services, showing why those links alone do not determine whether creator bargaining power rises or falls.

We ask whether the balance between Spotify and label placements changed differently for the two artist groups. We track both playlist types because an artist's placements can grow on Spotify's playlists and on the labels' at the same time. We show the raw paths from April 2017, when editorial coverage becomes substantial, alongside a model of each artist's monthly placements.

Empirical Setting and Data

Direct Pitching and the Promotional Channels

Spotify changed access to editorial consideration on July 19, 2018. Its new tool in Spotify for Artists and Spotify Analytics let artists, labels, and their teams select one unreleased song and provide information to editors (Spotify 2018a). Editors retained the selection decision. Before the tool, promoters used personal contact with curators alongside digital information. Bonini and

Gandini's interviews, conducted from October 2017 through April 2018, document those contacts (2019, p. 4).

The submission route attracted substantial early use. By late October, Spotify reported that more than 67,000 artists and labels had pitched and more than 10,000 artists had received their first editorial placement (Spotify 2018c). The report combines artists and labels without separating release affiliations. Pitching at least seven days before release also placed a song in followers' Release Radar. We study placements on curated playlists and observe neither pitches nor Release Radar placements.

Direct pitching accompanied other initiatives. Spotify's direct-licensing negotiations with selected artists were reported in June, and Spotify announced and expanded an invitation-only upload beta in September (Karp 2018; Spotify 2018b). Figure 2 shows the study window around the pitching launch. We omit July and end on March 25, 2019, before the personalization announcement (Spotify 2019). We call additions to Spotify's curated lists editorial placements and additions to Filtr, Digster, and Topsify label placements.

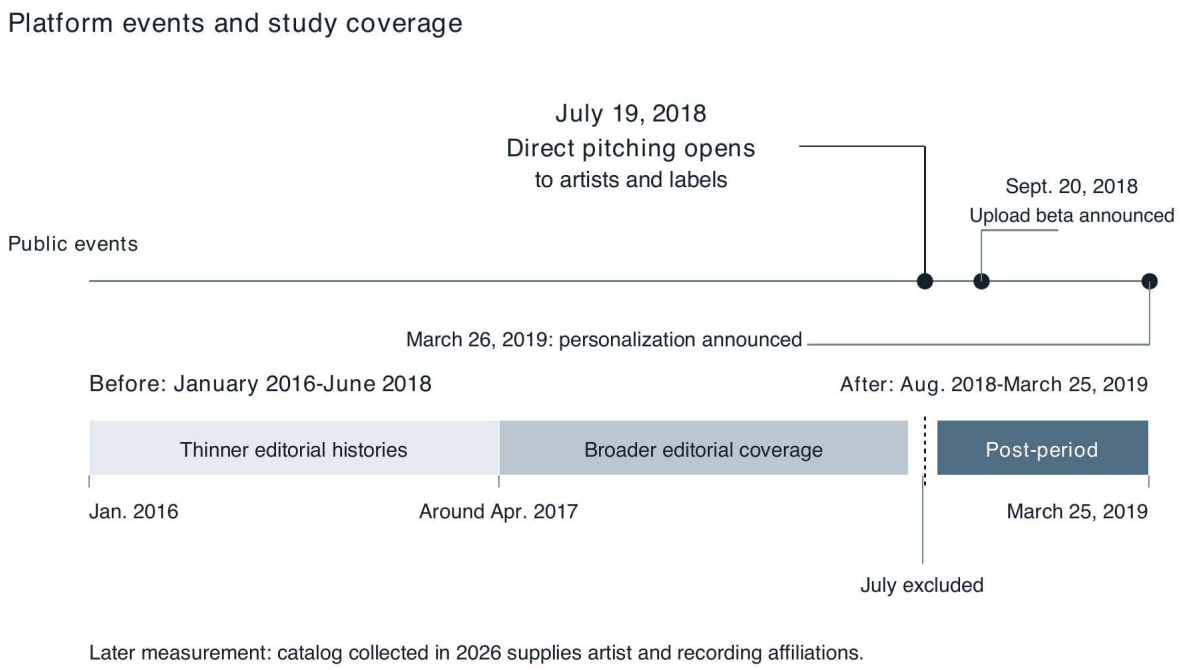

Figure 2**. Direct pitching and the periods observed.** *Notes.* Dates locate public announcements and the analysis window. Broad editorial coverage begins around April 2017; earlier histories are thinner. July is excluded, and observations end March 25, 2019. The later catalog dates affiliation measurement, not the start of a label relationship. Figure W7 gives the additional initiative chronology.

Histories and Coverage

Table 1 lists the records we link and what each measures. The playlist roster contains lists tracked before the opening. Some histories reconstruct additions that preceded tracking; substantial editorial coverage supplies roughly fifteen pre-opening months. We exclude a large restamping batch dated August 16, 2018, because its recorded dates often do not identify the true additions. We check the allocation estimates by starting each playlist at its coverage onset and by dropping playlists touched by the batch.

We construct the allocation panel around each artist's recorded monthly activity. An artist with additions on one channel and none on the other receives a zero for the latter channel in that month. Among the input artists, 2,422 of 12,205 self-releasing artists and 6,885 of 11,759 major-label artists appear on both channels. The model thus compares observed placement histories, including months with activity on only one channel. Tables W2, W19, and W29 document

construction and support; placement chances for artists absent from these histories require a broader population.

Table 1. Records and samples used in the study

Records	Coverage	Observation	What the records reveal
Playlist histories	January 2016–March 25, 2019; July 2018 omitted	Song addition to a playlist	Curator selections, placement duration, and entry position
Historical followers	1,216,411 matched additions	Followers at addition	Potential reach on the same placement sample
Release catalog	Collected in 2026	Artist and recording	Artist release category and affiliation of the work selected
Subsequent releases	Three August–February cohorts; 365-day follow-up	Artist–cohort	Later major-label release and its match to the playlist owner

Notes. The roster contains 2,353 editorial and 3,203 label playlists. The baseline input has 84,280 artists with pre-opening release histories; the count estimator retains 51,271 artists and 584,912 artist–channel–month cells. Follower matches cover 1,216,411 of 1,498,112 baseline additions. The matched recording comparison uses the baseline cohort; broader recording and relationship descriptives also include later-first-release artists. Relationship cohorts begin in 2016, 2017, and 2018. Tables W2, W19, W23, and W29 give construction and coverage.

Our placement comparison covers only playlists tracked before the opening. Another 344 playlists were first tracked after the opening, and their membership histories were never collected. Table W28 describes their available follower histories. A first recorded date marks the start of observed coverage rather than necessarily the launch of a playlist.

Artist Categories and Recording Credits

The baseline cohort is the group of artists with releases preceding the opening. We assign each artist the most common release category and hold it fixed: major-label, self-releasing, or Other. Major-label includes Sony, Universal, Warner, and their imprints. Self-releasing includes recognized DIY distributors and artist-name labels. Other contains the remaining non-empty

label names and is not a verified independent-label category. For artists whose first recorded release follows July 31, 2018, the broader sample uses their first release year to assign a category. We use this broader sample for supplementary recording descriptions and eligible relationship cohorts. The main recording comparison uses the same baseline placements as the audience comparison.

An artist category summarizes a release history that can include several affiliations. The dictionary-certain check retains artists whose category is supported by label names the dictionary recognizes. It does not require every release to have the same affiliation. Consider Spinnup. The dictionary classifies the service as self-releasing, while Universal operated it for unsigned artists (Vivendi 2017, p. 65). An artist can therefore use a DIY release route within a major-owned service network.

The catalog collected in 2026 supports two classifications. Artist affiliation summarizes the artist's release history. Recording affiliation uses the label or distributor name listed for the particular work placed; we call that name its recording credit. Reissues or transfers can change the credit after placement. We compare artist categories with these individual recording credits and test how alternative assumptions about the timing of major credits change the historical interpretation. Web Appendix B and Web Appendix F give the classification rules.

Audience and Subsequent Releases

We match the latest follower value on or before an addition within thirty days. Every match is dated the addition day, so zero- and ninety-day rules give the same sample. The source does not flag interpolation. Unmatched additions precede the list's own follower history, while every retained post-opening addition has a match.

Each addition records one selection. Weighting that addition by its matched follower value measures the potential audience attached to it, counting repeated audiences again. These sums are distinct from listening and unique users. Removal dates and entry positions measure how long a song remains and where it enters the list. We report followers, duration, and entry position separately.

Release histories link an artist's placement to the label on a later release. We identify the first observed major-classified release after follow-up begins and compare its major with the earlier playlist owner, meaning the major group that operates the playlist. The release date records publication rather than a signing. Track IDs and International Standard Recording Codes

(ISRCs) identify cases in which the starting placements and later major-classified releases contain the same recording. We then check whether the owner match extends beyond repeated releases of the same work.

Empirical Strategy

The first comparison asks whether playlists feature self-released recordings when they promote artists classified as self-releasing. The audience, recording, and allocation comparisons use artists with pre-opening releases. The release-partner cohorts also admit eligible artists whose first recorded release comes later.

Comparing Reach and Recording Affiliation

We calculate each group's label share twice on the same follower-matched placements: once by counting additions and once by summing their historical followers. Both calculations use the same placements; only their weights differ. Headline descriptives begin in April 2017; the appendix reports the longer series and the full estimation windows.

For recording affiliation, the unit is the selected addition. Label-playlist recordings are classified as the owner's single major, a rival major, multiple majors, self-released, residual Other, or unclassified. Spotify placements use the same taxonomy without the owner–rival distinction. A multi-major credit can include the playlist owner. The primary rule gives any recognized major credit precedence over a self-release credit. We also report an inclusive rule that counts every recording carrying a recognized self-release credit. Neither rule dates the credit.

We compare recordings selected for baseline artists whose placements have historical follower counts, using both counts and follower weights. We then restrict the comparison to artists appearing on both types of playlists in the same period: the common-artist sample. Each artist's weight is the artist's share of placements on that channel, or of summed followers in the weighted analysis. The channels can differ in how often they feature the same artists and in each artist's mix of self-released recordings. We separate these components using a symmetric decomposition. The within-artist component compares each artist's self-released recording share across channels, using average channel weights. The between-artist-weight component holds each artist's average recording share fixed and compares the weights. Their sum equals the gap in the common-artist sample. Equation W5 states the identity; Table W37 reports the components.

Following Release Partners

To follow subsequent release partners, we form cohorts of artists classified as self-releasing with no recorded major release when follow-up begins. Within the cohort window, the index is the first label placement for label-placed artists, the first editorial placement for editorial-only artists, or the first release for active artists placed on neither channel. We track the first major-classified release within 365 days. Label-placed artists may also have editorial placements.

The original release-history rule gives self-release credits precedence in mixed self/major releases. We retain its transition rates and reproduce its owner comparison, then apply a consistent any-major rule to both eligibility and the later outcome. That harmonization removes artists with an earlier or same-day mixed major credit and adds later outcomes recognized by the same rule. The owner comparison then treats mixed credits the same way the recording comparison does.

Among attributable cases, we compare the earlier playlist owner with the later release major. Random reassignment preserves the frequencies of owners and later majors while breaking their pairing. We calculate exact expected match rates and enumerate the one-sided permutation distribution for the main harmonized comparisons. The appendix also reports the simulation-based results and the any-parent rule used for multi-parent outcomes in the small 2016 cohort.

The recording screen compares all index-day tracks with all major-classified main-credit releases in the following year using track IDs and ISRCs. Additional screens remove cases whose index recording carries a major credit in the later catalog or whose catalog contains a Spinnup release dated on or before placement. These screens flag possible earlier relationships but do not date a services agreement. We report each screen against its own benchmark and distinguish it from the available genre and market checks.

The Within-Artist Allocation Comparison

We next ask whether self-releasing artists' balance between Spotify and label playlists changed differently from that of major-label artists around the opening. The triple difference compares the two channels within each artist's monthly activity, then compares that change across artist groups. Major-label artists provide a benchmark on the same playlists, allowing us to account for proportional channel growth shared across groups. Major-label artists also gained the submission route. The model therefore compares two groups exposed to the opening.

Let y_{ist} count additions for artist i, playlist type s, and month t. Let S_i identify self-releasing artists, O_i the Other group, E_s editorial playlists, and P_t months after the omitted July. We estimate by Poisson pseudo-maximum likelihood:

$$\mathbb{E}[y_{ist} \mid X] = \exp\{\beta S_i E_s P_t + \gamma O_i E_s P_t + \alpha_{is} + \lambda_{it} + \delta_{st}\}. \quad (1)$$

Artist-by-type effects α_{is} absorb an artist's persistent tendency to appear on one channel. Artist-by-month effects λ_{it} absorb changes common to the artist's two placement outcomes. Type-by-month effects δ_{st} absorb proportional channel growth shared across affiliation groups. Thus a broad editorial expansion can increase both groups' placements while leaving the relative comparison unchanged.

We report $100[\exp(\beta) - 1]$, the percentage change in self-releasing artists' editorial-to-label ratio relative to majors. A negative value means their ratio rose less, or fell more, than the benchmark ratio. Both groups can gain editorial placements. The Other interaction supplies a second benchmark.

The model accommodates zero counts without adding a constant. We independently reproduce its coefficients through the equivalent profiled objective and vary the weight of prolific placement histories. Web Appendix H provides the derivation and support accounting. For the audience specification, we replace the count with summed historical followers per artist–type–month, divided by 1,000. We first fit counts on that exact matched sample, separating a sample change from the effect of follower weighting.

Timing and Inference

The average before–after comparison leaves the timing of the change open. The event study estimates that same placement comparison separately over time. We keep the main sample and fixed effects, separate self-releasing and Other interactions, monthly bins in early 2018, and June as the reference. This reveals the spring path instead of folding it into a broad pre-period average. A causal interpretation rests on parallel paths: absent the opening, the two groups' editorial-to-label ratios would have changed at the same proportional rate (Olden and Møen 2022). Tests of the earlier coefficients assess that assumption against the observed pre-period movement. The post-period average and the static coefficient summarize different time comparisons.

We assess timing with pre-period tests, earlier fake dates, and specified trend scenarios. Measurement checks address coverage and affiliation separately. Artist-clustered standard errors allow within-artist dependence; additional covariances allow contemporaneous dependence by

group–month or channel–month. A separate monthly aggregate contrast uses Newey–West errors. These standard errors do not fully capture shocks that persist over time for one artist group on one channel (Conley and Taber 2011). Tables W13–W15 report the complete timing and inference results, which determine how we interpret the relative allocation estimate.

Results

Spotify Supplies Most of the Potential Reach

Spotify supplies most of the potential reach in self-releasing artists' observed placements. Label playlists' follower-weighted share remains near 6%–7% before and after the opening (Figure 1), despite their much larger share of placements. Table W34 reports all groups.

Potential reach expands on both channels. From the April 2017–June 2018 baseline to the post-opening period, self-releasing artists' monthly summed follower values rise from 429 million to 763 million on editorial playlists and from 28 million to 53 million on label playlists. Repeated and overlapping audiences remain in these sums. Spotify's share of these artists' potential reach thus stayed near 94% while the total grew by almost 80% (Table W40).

Major-label artists' weighted label share falls from 14.7% to 12.3%, while self-releasing artists' share edges up from 6.1% to 6.5%. Relative to major-label artists, self-releasing artists therefore receive a larger share of their follower-weighted placements on label playlists. Figure W8 shows the longer monthly paths; the conditional model in the "Editorial Growth and the Relative Allocation Change" section adjusts for artist and monthly differences.

The channels also offer different lengths of availability. Using the full January 2016–June 2018 pre-period, self-releasing artists' label placements last a median of 92 days before the opening and 62 days afterward, compared with 33 and 21 days on editorial lists. At 180 days, 78.2% of their post-opening label placements have ended, versus 88.9% of editorial placements. Label lists combine smaller potential audiences with longer recorded availability. Table W24 reports duration and entry position.

Self-Releasing Artists and the Recordings That Get Featured

An artist's category does not tell us whether the promoted recording is self-released. In the matched sample of self-releasing artists, self-released recordings account for 49.6% of post-opening editorial placements and 20.2% of label placements, using later credits (Table 2). Follower weights give 43.0% versus 19.7%. We separate differences in the recordings selected for each artist from differences in how often each artist appears.

Table 2. Labels on selected recordings and how often artists appear

Panel A: Self-released recording share after the opening

Matched baseline placements	Editorial	Label	Gap, percentage points
Equal weight per addition	49.6%	20.2%	29.4
Weight by playlist followers	43.0%	19.7%	23.3

Panel B: Decomposition among artists appearing on both channels

Weighting of additions	Pooled gap	Within artists	Between artist weights
Equal weight per addition	16.8	1.4	15.5
Weight by playlist followers	11.1	1.9	9.1

Notes. August 2018–March 25, 2019. Panel A uses 21,361 editorial and 10,419 label additions by baseline self-releasing artists with historical follower matches. The recording classifier gives recognized major credits precedence over self-release credits. Credits were collected in 2026. Panel B restricts both channels to the same 1,094 artists, contributing 9,593 editorial and 8,990 label additions. Entries are percentage points, rounded independently. The symmetric decomposition separates within-artist recording shares from the relative placement weights assigned to those artists. It describes Panel B's restricted population, not Panel A's full gap. Tables W36–W37 give population and classification checks.

The comparison narrows to 1,094 artists featured on both playlist types, who supply 58.5% of matched self-releasing additions after the opening. Their count-based gap is 16.8 points. The average difference in self-release shares within the same artist accounts for 1.4 points; different shares of placements assigned to those artists account for 15.5 points. Giving every artist equal weight yields a 1.3-point gap. Among these artists, the channels differ mainly in whom they feature more often. The dominant difference is repeated selection of particular artists, rather than the average recording mix chosen for a given artist. The small within-artist component does not mean both channels choose the same songs: of the 1,094 artists, 139 have a higher self-release share on editorial playlists, 111 have a higher share on label playlists, and 844 have equal shares (Table W37).

For 528 of these 1,094 artists, none of their placed recordings on either channel is classified as self-released in the later catalog. In other words, many artists classified as self-releasing were promoted with recordings that the 2026 catalog credits to labels.

Classification choices affect the size of the gap. Counting all recordings with a recognized self-release credit, including mixed major/self credits, raises the matched post shares to 56.5% on Spotify and 38.1% on label playlists. Their ordering remains, and follower weighting gives 52.5% versus 36.3%. The broader sample yields the same ordering (Table W36). The contrast survives the treatment of mixed credits, although its magnitude changes substantially.

Comparing April 2017–June 2018 with the post-opening period, the share carrying a recognized major credit falls from 49.6% to 45.5% on Spotify and from 80.1% to 70.1% on label playlists. On label playlists, self-classified recordings rise from 1.4% to 1.7%, while residual Other credits rise from 17.9% to 27.5%. Most of the shift therefore lies in label names whose ownership is not established by this classification. Those credits must be identified before we can count the firms involved (Table W40).

A major credit recorded in 2026 may have been added after the playlist placement. Reassigning every currently major-credited placement of a self-releasing artist to self-release at placement, while holding other credits fixed, gives post shares of 71.5% on Spotify and 78.9% on label playlists in the broader sample. This scenario reverses the channel ordering. Restricting reassignment to catalog rows whose observed dated editions all follow placement gives 54.5% and 23.4%, but that narrower scenario assumes older-dated credits were already valid. A recording can retain its original release date after a label transfer. The credit gap in the 2026 catalog is clear, but its direction at the time of placement depends on when the major credits became valid (Table W36).

The Promoting Owner and the Later Release Partner

Among promoted artists with a later major-label release, the release major matches the earlier playlist owner more often than the mix of firms predicts. Under consistent any-major rules for eligibility and later releases, 38 of 70 post-opening cases match the earlier playlist owner: 54.3%, against 31.8% expected from the observed mix of owners and later majors, an excess of 22.5 percentage points (Table 3). The exact one-sided permutation p-value is below .001. Hence, among artists who later release with a major, label promotion predicts which major.

Table 3. Earlier playlist owners and later release majors

Cohort and affiliation rule	Cases	Matches	Observed	Expected	p
2018, original rule	85	52	61.2%	30.8%	< .001
2018, consistent any-major rule	70	38	54.3%	31.8%	< .001
2018, consistent rule, repeated recordings excluded	62	30	48.4%	32.9%	.004
2018, consistent rule, joint screens	58	28	48.3%	33.8%	.009
2017, consistent any-major rule	38	24	63.2%	31.1%	< .001

Notes. Cohorts run from August through the following February, with 365-day release follow-up. Cases have an attributable earlier owner and a later major-classified release. Expectations preserve each row's owner and later-major frequencies. The consistent rule treats any major credit as major for eligibility and outcomes. Joint screens set aside index recordings with a major credit in the later catalog, catalog Spinnup releases dated on or before placement, and observed recording repeats. The p column gives exact one-sided permutation probabilities (Table W38). The 2017 follow-up partly crosses July 2018. Tables W38–W39 give earlier cohorts, case flows, owner breakdowns, and inference.

Removing observed repeats of the placed recording leaves 30 matches among 62 harmonized cases. The joint screens leave 28 among 58, a 14.5-point excess over that sample's benchmark. No observed recording repeat remains in that last group. Matching therefore extends beyond the original classification rule and the repeated appearance of the same recording. The smaller owner-specific samples have less precision; the appendix reports them separately.

Spinnup explains little of the match. Five of the original 85 cases have a catalog Spinnup release dated on or before placement; three match the owner. Removing those cases leaves 49/80 matches against 31.0% expected. Among Universal's original 21 cases, 13 have an index recording that carries a major credit in the later catalog, and all 13 match. Dated credits for these recordings would show whether Universal was already the label at placement.

Earlier cohorts show that owner matching was already present. Consistent affiliation rules give 24/38 matches in the 2017 cohort, against 31.1% expected. The smaller original 2016 cohort gives 11/18, against 37.7%, with its full follow-up ending before direct pitching. Tables W7 and

W38 distinguish the original and harmonized samples. Owner matching therefore predates direct pitching: the 2017 cohort was placed before the opening, and the 2016 cohort was followed entirely before it.

Genre or market specialization could also produce such matching. Checks using known pre-index playlist genre give 30/58 matches against 30.4% expected; known playlist market gives 25/49 against 30.2%. However, 37 of the 58 genre cases and 30 of the 49 market cases fall in a pooled sparse category. These tests compare owners within broad groups and leave differences within the pooled category uncontrolled. Both samples come from the original 85 cases, not the harmonized 70 or jointly screened 58 (Table W39). The owner association survives these available proxy checks, while finer specialization remains unresolved.

The owner match concerns a minority of promoted artists. Under the original eligibility rule, 8.39% of label-placed artists have a first observed major release within a year, compared with 1.74% of editorial-only artists and .99% of active unplaced artists (Table W33). More than 91% of eligible label-placed artists do not make that transition. Owner matching describes the smaller group with a subsequent major release, within a much larger population without one.

Editorial Growth and the Relative Allocation Change

Next, we trace how the mix of editorial and label placements changed. Figure 3 shows the raw monthly paths.

From April 2017–June 2018 to the post-opening period, self-releasing artists' editorial additions rise from 1,662 to 2,896 a month and their label additions from 792 to 1,341. The increases are 74.2% and 69.2%, leaving their label share nearly unchanged at 32.3% and 31.6%. Major-label artists' editorial additions rise from 8,558 to 9,931 while label additions fall from 15,039 to 12,664. Their label share falls from 63.7% to 56.0% (Figure 3). These broader raw series include later-first-release artists; Figure 1 uses the follower-matched baseline cohort.

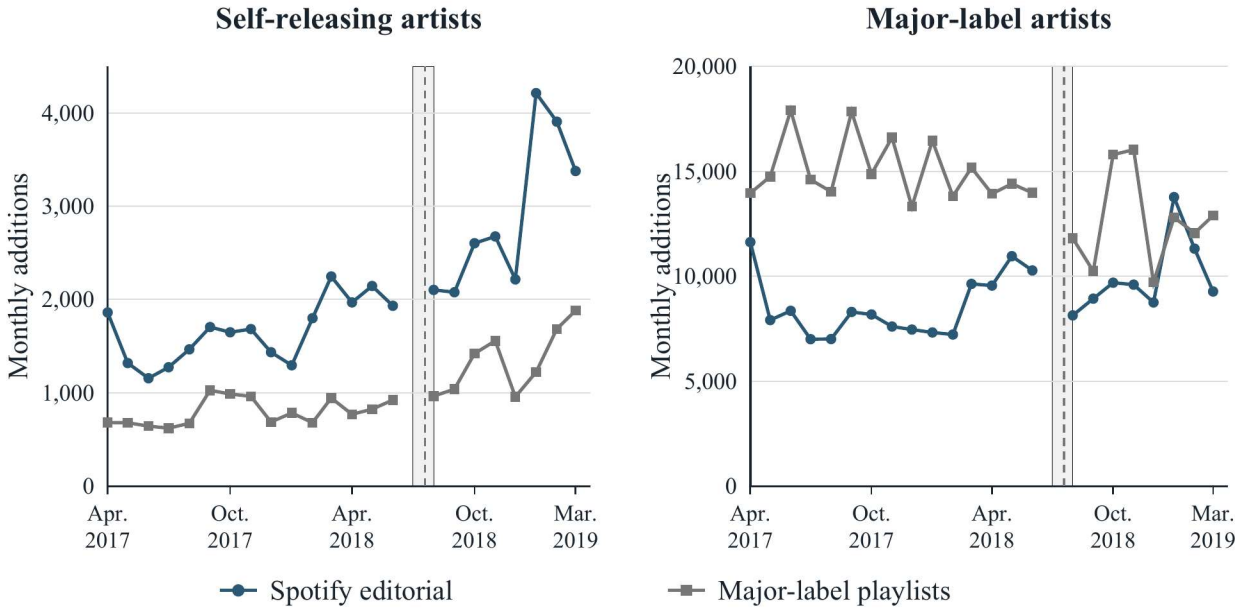

Figure 3**. Monthly additions to editorial and label playlists.** *Notes.* The two panels trace the broader classified sample from April 2017, with separate vertical scales. July 2018 is omitted; March 2019 ends on March 25. Table W40 reports aligned period means, and Table W31 reports full-window summaries and age-specific estimates. The allocation model uses its full estimation window. Figure W8 supplies follower-weighted paths.

The within-artist model separates this comparison from persistent artist differences, changes in monthly activity, and channel growth shared across groups. Its coefficient is −.448, equivalent to a 36.1% decline in self-releasing artists' editorial-to-label ratio relative to majors (Table 4). The transformed 95% interval is −44.6% to −26.4%. The decline relative to the residual Other group is 29.8%. The negative comparison coexists with self-releasing artists' growth on both channels: their gains relative to majors are larger on label playlists.

Table 4**. Within-artist allocation across promotional channels**

Outcome and sample	**Self versus Major**	**Other versus Major**	**Self minus Other**
Counts, baseline	−.448 (.072)	−.095 (.027)	−.353 (.072)
Counts, follower-matched	−.470 (.073)	−.086 (.026)	−.384 (.074)
Followers, same matched sample	−.556 (.090)	−.075 (.044)	−.480 (.092)

Notes. Poisson pseudo-maximum-likelihood estimates of Equation 1; artist-clustered standard errors in parentheses. The baseline fit uses 584,912 cells and 51,271 artist clusters. Both matched fits use 450,510 cells and 44,447 clusters. The follower outcome sums followers per addition, divided by 1,000. Self denotes baseline self-releasing artists; Major is the reference. A negative coefficient means their editorial-to-label ratio changed less favorably than the reference ratio. Timing is shown in Figure 4.

Follower weighting strengthens the negative estimate, from −.470 for matched counts to −.556. Self-releasing artists' follower-weighted label share changes little, while major-label artists' share falls. The difference between those movements drives the negative relative comparison. Explaining their larger shift requires submission, release-planning, and editorial-decision records.

The negative pattern survives an established-major benchmark, owner-specific samples, coverage-onset and never-batch restrictions, and dictionary-certain affiliation (Tables W5, W20, and W22). Separate count fits are near zero below 10,000 followers and negative in the two middle bands; the largest band is not estimable. Table W23 estimates the bands separately and does not test whether their coefficients differ.

The recent-release estimate implies a 41.2% relative decline for recordings with a recorded age of ninety days or less at placement, compared with 19.9% for catalog recordings older than 180 days (Table W31). These estimates come from separate fits, without a joint contrast. All eight recent-release post-period coefficients are negative (Figure W2). Release age dates publication relative to placement; it does not establish use of the pitching tool.

Across both channels and the full observation window, the most active tenth of the 12,205 baseline self-releasing artists accounts for 63.6% of their additions (Table W21). With outcomes this concentrated, the Poisson estimate gives more weight to the most active artists, and estimators that weight observations differently answer different questions (Winkler et al. 2026). Weighting by the inverse of each artist's total additions preserves the negative pattern: −.879 (CR0 standard error .081). Replacing label playlists with six chart playlists instead gives a positive, imprecise coefficient on a different sample, +.551 (.364).

Restricting placements to self-classified recordings changes the outcome while keeping artist categories fixed. The Self–Major coefficient is −1.058 (standard error .570), and the Self–Other contrast is −.029 (.195). These estimates are imprecise (Table W25).

The Change Spans the Opening

The static coefficient compares averages on either side of July. Figure 4 shows how that comparison develops month by month, locating a transition that begins before direct pitching. The self-releasing–major balance peaks in February 2018 and declines through June. Tests reject equality of the early-2018 coefficients to the June reference ($p = .007$) and of all pre-period coefficients to that reference ($p = .004$). Starting each playlist's history at coverage onset also rejects the early-2018 comparison ($p = .004$). The spring decline remains when histories begin at each playlist's coverage onset.

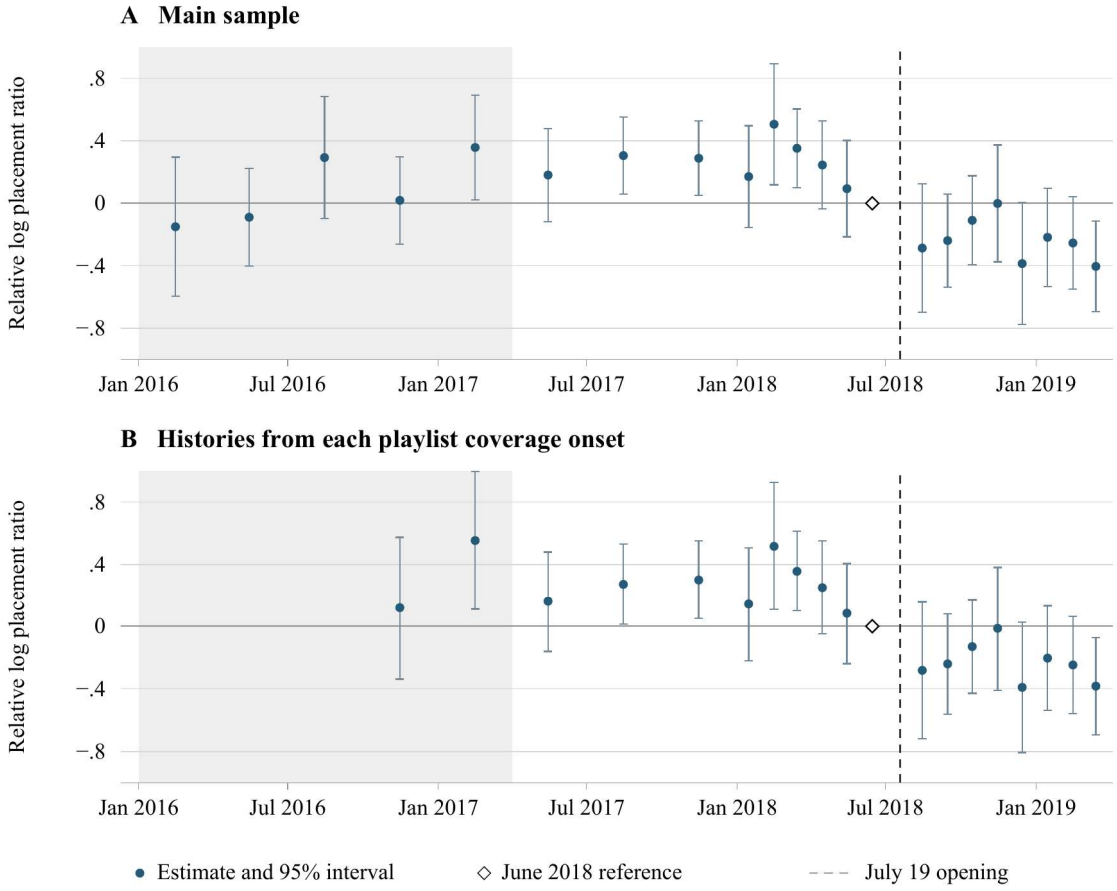

Figure 4. Relative allocation before and after the opening. *Notes.* Self–Major event-study coefficients with June 2018 as reference and separate Other interactions. Panel A uses the main sample; Panel B starts each playlist at coverage onset. Bars show artist-clustered 95% intervals. The diamond is June's normalized zero. Pre-2018 bins are quarterly; later bins are monthly. July is omitted. Shading identifies the thin early editorial coverage. Table W13 gives coefficients and tests.

The lower relative placement balance continues after the opening. All eight post-period estimates lie below June; their average is −.24, with standard error .15 and a 95% interval of [−.53, .06]. The interval includes zero. The before–after coefficient combines the spring decline with the lower ratio observed after July. It measures a transition spanning the opening; the July launch does not isolate its beginning. Both the June licensing report and July pitching announcement follow the February peak, so their public dates do not separate the contributions of those initiatives.

Earlier fake dates describe an opposite path. All seventeen estimates are positive, as is the dedicated July 2017 estimate, +.125 ($p = .179$). They reinforce the importance of the changing pre-period path rather than validate parallel trends. Linear-trend and aggregate monthly analyses depend on the extrapolation window and unit of observation (Tables W14–W15).

The placement histories show why growth in direct promotion is not enough to characterize an artist's relationship with labels. Self-releasing artists gained placements on both channels, while the major-label benchmark moved further toward Spotify. The recording comparison asks what music those placements featured, and the owner comparison asks which major appeared on a later release. Together, they describe the opportunities artists received and the commercial relationships around those opportunities.

Artists, Labels, and Platform Strategy

Choosing Whose Work Audiences Encounter

Spotify expanded opportunities for self-releasing artists while continuing to promote music released through the major labels. Its own playlists supply most of the potential reach attached to these artists' placements, yet the 2026 credits and later releases show substantial label involvement. For a platform seeking more self-released music, the next decision is which artists receive repeated promotion and which of their recordings appear in those placements.

Among artists featured on both playlist types, most of the gap in self-released music comes from how often particular artists appear. Featuring more work by artists whose selected recordings are mostly self-released would change the mix through placement frequency. Selecting more self-released recordings by the same artists would change it through recording choice.

Decisions for Platforms, Labels, and Creators

A platform pursuing that objective should report two separate outcomes: the artists it features and the self-released recordings it selects. Repeated placements need their own weight, because one artist with many placements can change the mix far more than several artists featured once. Our common-artist comparison shows that this weighting accounts for most of the observed channel gap. A platform can use the same comparison to locate which repeated selections drive its release mix before testing changes to those selections. Dated credits establish the relevant release affiliation, and audience responses show whether a proposed change also serves listeners.

Label playlists carry fewer followers, yet the major that runs a playlist is disproportionately the major on the artist's later release, even after screens for earlier relationships and repeated recordings. A label might provide audience development, financing, or release support. Those services and their terms determine what the relationship adds for the artist and the platform. Owner matching is consistent with each of these services, and only dated agreements can distinguish recruitment from support already underway.

For labels, playlists matter for more than audience size: they offer longer recorded availability and predict subsequent release partners. Labels evaluating their playlists should therefore weigh the release relationships of the artists they feature alongside follower reach. For artists, direct pitching adds a route to consideration. Deciding whether to work with a label still turns on the listeners it reaches, the services it provides, and the terms it offers. Better opportunities without a label can improve an artist's terms within a continuing partnership.

Applications Beyond Music

The argument applies where creators can participate directly and professional firms also release or promote their work. YouTube's creator networks offer audience development and sales services (YouTube n.d.). Amazon provides advertising for self-published and traditionally published books (Amazon n.d.). Steam supplies publishing and marketing tools for developers and publishers (Valve n.d.). On each, a creator who publishes independently can also work with a publisher, so counting creators does not show which work gets promoted or which firms release or promote it.

The same comparison applies to authors, video creators, and game developers. It requires records that link each creator to the particular book, video, or game featured, to the firm releasing or promoting it, and to the dates of those relationships. With such records, a platform

can test whether repeated promotion concentrates opportunities among creators whose work involves those firms. The Spotify percentages are specific to this setting, but the distinction between admitting creators and choosing whose work to feature applies wherever a platform makes both decisions.

Conclusion

This research asked how much of the music a platform promotes for independent artists is independently released. On Spotify, by the credits in a 2026 catalog, the answer is about half on the platform's own playlists and one fifth on the majors' playlists, even though Spotify's playlists supply over nine-tenths of the potential audience attached to these artists' placements. For artists featured on both kinds of playlist, the gap comes almost entirely from how often each artist is featured. In addition, the major that promotes an artist is disproportionately the major that later releases the artist's music, and this match also holds for artists placed before direct pitching opened.

Hence, independent participation and independently released promotion are different outcomes. Classifying placements by artist rather than by recording would overstate the self-released music a platform promotes about twofold on its own playlists and fivefold on the majors'. A platform that wants more independently released music must therefore manage whose work receives repeated placements, not only whom it recruits. The majors' playlists, in turn, carry little of these artists' potential reach, yet the major that runs a playlist is disproportionately the one that later releases the artist.

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