Friends in High Places: Demand Spillovers and Competition on Digital Platforms

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Abstract

Competitor entry or expansion generates opposing effects of substitution and market expansion. The unique characteristics of digital platforms, indirect network effects and streamlined search and discovery, may amplify the market expansion effect and facilitate demand spillovers across providers or goods that compete in other settings. Using the Spotify music streaming platform as an empirical setting, I consider when demand shocks to a competitor generate positive spillovers to providers on a digital platform. I find that, on average, increases in competitor demand have a positive effect on provider performance. However, the effect differs greatly based on competitor popularity. Demand shocks to popular competitors benefit providers, while those to niche competitors do not. Demand spillovers are largely driven by discovery by new or irregular consumers and are not solely created by platform recommendation systems. These results generate insight on how digital platforms alter how firms compete and who they compete with.

Keywords: platforms, competition, spillovers, digital markets

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Introduction

Digital platforms are two-sided online "hubs", connecting consumers with providers competing "on top" of the platform, enabling greater exchange but fundamentally changing the organization of markets (e.g., Cennamo 2019, Gawer 2009, McIntyre and Srinivasan 2017). As digital platforms encroach into more industries, they offer unique challenges and opportunities to the provider firms operating in such ecosystems. As part of this process, provider firms must reassess how best to compete with their peers in the platform marketplace. Prior literature suggests that interactions across providers on digital platforms can be both complementary and competitive (Boudreau 2011, Boudreau and Jeppesen 2015, Venkatraman and Lee 2004), suggesting that traditional conceptions of competition may be challenged in such markets.

In traditional markets, expansion or growth by competitors is generally associated with substitution and profit erosion (e.g., Porter 1979). However, two-sided markets, such as digital platform markets, are characterized by indirect network effects, meaning that expansion or activity by competitors or peers on a digital platform may "grow the pie", increase consumption within the market, and potentially benefit other providers (e.g., Katz and Shapiro 1985, Rochet and Tirole 2003). The presence of indirect network effects, combined with tools that facilitate low-cost consumer search and discovery (Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012), may result in a market that is more likely to feature demand spillovers across firms or goods that compete with or substitute for each other in other settings.

On digital platforms, entry, product launch, or promotion by a competitor may draw awareness or consumption to a product market area on the platform, and the reduced cost of consumer search and discovery may then facilitate the transfer of attention from one provider to another. This may be especially likely in platform contexts where consumers value variety and consume goods and services from multiple providers on a platform (e.g., consumers may listen to many songs on an online streaming service, order from many restaurants on a food delivery service), and platforms enable such behavior by lowering the cost of additional consumption once on the platform. A priori, it is unclear when demand spillovers across peers may outweigh the negative effects of substitution or crowding within digital platform markets.

In this research, I integrate extant literature on demand spillovers and on competition on digital platforms to develop a theoretical framework that considers how provider characteristics alters the balance between these opposing effects. Prior literature studying localized demand spillovers suggests that more successful or popular firms are able to generate larger positive spillovers than their peers because they command more attention and have a larger existing consumer base (e.g., Alcácer and Chung 2007, Chung and Kalnins 2001, Shaver and Flyer 2000). Building on this work, I consider whether digital platforms create a form of "digital localization" and whether successful or popular providers generate larger positive spillovers than their less popular peers in this setting. If that is the case, expansion by successful and popular providers may be more beneficial to their peers than expansion by niche providers in some digital platform settings.

Using the digital music streaming industry as a setting, I investigate the effect of competitor demand expansion, defined as an increase in competitor demand, on provider performance in a digital platform market. To do so, I use data from Spotify, the world's largest music streaming platform. Spotify provides an excellent context for this research as a) users typically consume many different goods on the platform; b) users face low switching costs across providers on the platform (i.e., it is near costless for users to listen to music from different artists); and c) Spotify utilizes recommendation and search tools to facilitate discovery. Together, these characteristics provide a setting that is particularly likely to facilitate demand spillovers across providers on the platform. I examine how the release of an album by a highly similar peer (and the subsequent increase in peer consumption on Spotify) affects focal provider performance. To address concerns related to endogeneity, I also investigate whether the results are robust to a truly exogenous demand shock – the sudden death of a competitor, as the death of an artist prompts a temporary increase in artist popularity due to death-related publicity (Brandes et al. 2016).

The music industry has been traditionally been characterized by imperfect substitution across similar artists (Black and Greer 1986, Mixon and Ressler 2000, Throsby 1994) and there is evidence that product releases by similar peers can harm performance in other cultural goods industries with short product life cycles, such as the gaming or film industry (Calantone et al. 2010, Engelstätter and Ward 2018). However, in this setting, I find that on average, the count of unique listeners and streaming popularity on Spotify *increases* when a highly similar competitor releases an album. Underlying this main effect is significant heterogeneity depending on competitor popularity. Album release by a niche competitor has a negative effect on provider performance, as such competitors are unable to stimulate sufficient market expansion to outweigh the effects of consumer switching. On the other hand, album release by a popular competitor has a positive effect on focal artist performance, as popular providers generate large demand spillovers to overcome any effect of substitution. Using the sudden death of a competitor as a demand shock, I find consistent evidence that demand shocks to popular competitors generate larger positive demand spillovers than those to niche competitors. These results suggest that providers on some digital platforms may face more intense head-to-head competition from niche providers than from superstars.

I explore the role of consumer discovery or re-discovery in driving demand spillovers. The effects on performance are largely, but not entirely, driven by new or irregular consumers, highlighting that demand shocks to popular providers can stimulate significant consumer activity and broaden similar providers' reach to consumers. Platform recommendation systems also appear to amplify demand spillovers across peers, showing that such tools play a role in creating these spillovers, though do not appear to solely or primarily drive the documented results. Beyond platform recommendation systems, it appears that the centralized nature of the marketplace and the lower marginal cost of consumption may stimulate independent consumer choice to consume other similar offerings once on the platform.

In additional analyses, I show that such market dynamics have important implications for the strategies deployed by firms competing on the platform. Despite literature which suggests that firms benefit from releasing products at different times from their competitors (Calantone et al. 2010, Engelstätter and Ward 2018, Krider and Weinberg 1998), I find that the launching a product at the same time as a popular competitor can increase the performance benefits from product launch. On the other hand, releasing at the same time as a medium or low popularity competitor appears to attenuate performance increases experienced from product launch release. Further, I show that the positive spillovers from competitor demand expansion on the Spotify platform manifest not only on Spotify, but also on another digital platform. Competitor album release on Spotify improves provider performance on YouTube, accounting for competitor and provider activity on YouTube. This result raises questions regarding how the competitive dynamics imposed on firms competing in a given platform market translates to other settings.

Through this work, I contribute to a nascent literature that studies the balance between substitution and demand spillovers within digital platform settings (Cao et al. 2018, Haviv et al. 2019, Reshef 2019). Integrating theory from literature studying agglomeration economies (Alcácer and Chung 2007, Chung and Kalnins 2001, Porter 1998), I show that expansion by popular competitors may actually be more beneficial than expansion by niche competitors in digital platform markets and present evidence that such platforms may create a form of digital industry localization. These findings extend literature that considers the effect of star providers on platforms (Binken and Stremersch 2009, Hogendorn and Yuen 2009, Rietveld and Eggers 2018) to consider the effect of star providers on other providers operating on the platform. By presenting evidence that providers may not find themselves in head-to-head competition with their superstar peers, the findings suggest that platforms may not just alter how providers compete (e.g., Boudreau 2011, Kapoor and Agarwal 2017, Miric et al. 2019, Rietveld and Eggers 2018), but also *who* they compete with.

In addition, this research has practical implications for digital platform companies and providers. Conventional wisdom suggests that platforms should aggressively pursue providers, as a growing number of providers increases consumer demand (Boudreau and Jeppesen 2015, Gawer and Cusumano 2002, Schilling 2002). However, such strategies may run into difficulties as providers may prefer to join platforms with less intense competition (Venkatraman and Lee 2004). This research's findings suggest that, in some digital platform settings, providers need not be as concerned with competition from large or popular competitors because the negative effects of substitution may be counteracted by positive demand spillovers. In these settings, what is good for the platform may also be good for the providers competing on the platform.

In the following section, I review existing literature on competition in platform markets. I then discuss the data and methodology before presenting results and discussing their implications.

Competition and Platform Markets

Competitor Expansion and Incumbent Performance

In traditional industrial organization theory, expansion or activity by peer firms is thought to increase industry competition and erode profits (Porter 1979). Early theoretical literature in strategy highlights the importance of entry and mobility barriers to exclude competition, increase market power, and improve incumbent performance (Caves and Porter 1977, Porter 1979). Empirical evidence has supported this theoretical view. Expansion by competitors decreases product prices (Bergman and Rudholm 2003), and incumbent firms' revenues (Singh et al. 2006) and profitability (Galbraith and Stiles 1983). Similarly, activity by rivals reduces firm profitability across a variety of industries (Chen and Miller 1994, Schmidt 1997, Young et al. 1996).

However, in some cases, peer expansion or activity can improve incumbent performance. Increases in competitor demand may result in a positive spillover driven by consumer awareness, attention, and knowledge of a product market category (Feldman and Lynch 1988, Hendricks and Sorensen 2009, Liu et al. 2014, Shapiro 2017). For example, Shapiro (2017) shows that branded advertising for anti-depressants increases sales of rival anti-depressants. Competitor expansion may expand market volume and variety, increasing opportunities for firm growth (Mahajan et al. 1993, Shen and Xiao 2014). In cases where such attention-based spillovers exist, spillovers are larger for similar or proximal competitors (Janakiraman et al. 2009, Roehm and Tybout 2006). However, these spillovers come at the cost of price competition and switching, and the net effect of competitor expansion on firms within the market depends on the strength of these competing forces (Thomadsen 2012).

The magnitude and direction of countervailing competing and complementary effects are often determined by characteristics of market participants, suggesting that firms do not just experience these effects, but also create them (Shaver and Flyer 2000). Studying agglomeration economies, Shaver and Flyer (2000) argue that firms with lower-quality resources benefit the most from spillovers generated by industry localization, as they reap benefits from competitors while offering little to others. In contrast, firms with higher-quality resources, generate positive spillovers but gain little from their peers (Shaver and Flyer 2000). This argument appears consistent with empirical evidence studying industry localization. For example, in the hospitality industry, branded chains and larger hotels generate the largest spillovers but gain the least, while independent and smaller hotels create the smallest spillovers but gain the most (Chung and Kalnins 2001, Kalnins and Chung 2004). Similarly, in high tech industries, less technologically advanced firms favor locations with high levels of industrial agglomeration because they are better able to reap spillover benefits from co-located peers, while more advanced firms avoid such locations to limit the potential cost of outward spillovers (Alcácer and Chung 2007).

Competition in Digital Platform Markets

Two-sided digital platforms dramatically alter value creation in markets by increasing the range of goods and services that sellers can offer buyers, expanding the range of buyers sellers can reach, and decreasing search costs associated with matching buyers and sellers (Lanzolla et al. 2020). By increasing the variety of goods and services offered while simultaneously lowering search costs for consumers, digital platforms enable better matching between consumers and products (Afuah and Tucci 2001, Lanzolla et al. 2020). The centralized marketplace, in conjunction with platform recommendation and search tools, dramatically reduces the cost of discovery and increases total per-consumer consumption and the variety of products consumed

(Datta et al. 2017). As a result, platforms have dramatically increased value creation in many industries (Lanzolla et al. 2020).

In the creation of such marketplaces, digital platforms change the nature of competition for firms and goods competing on them. The virtually unlimited "shelf space" available on digital platforms means that providers may not compete directly with similarly positioned offerings, however, the vast number of providers can also lead to congestion, impaired consumer decision-making, and particularly intense competition (Anderson 2006, Boudreau 2011). Such marketplaces may produce new "winners" or "losers." For example, in digital platform settings, because of the wide product variety and search and recommendation tools that facilitate consumer discovery, "niche" offerings are more likely to find a substantial audience and thrive (e.g., Brynjolfsson et al. 2006, 2011, Oestreicher-Singer and Sundararajan 2012, Zhang 2018).

Two-sided digital platforms, are also characterized by network externalities, meaning that the value of the platform increases with the number of users (Rochet and Tirole 2003). Such network externalities may be generated through a direct effect (i.e., same-side network externalities), where actors on one side of a platform obtain increased utility through links with other actors on the same side of the platform (e.g., telephone or social media networks), or in an indirect effect (i.e., cross-side network externalities) , where a larger number of actors on one side of the platform makes the platform more attractive to actors on the other side (Cennamo and Santalo 2013, Katz and Shapiro 1994). Platform markets are characterized by indirect network effects, as an increasing number of providers increases the overall attractiveness of the platform and may stimulate consumer activity (Farrell and Saloner 1985, Katz and Shapiro 1985).

Given the large number of competing providers and the presence of indirect network effects, there are reasons to believe that competition on digital platforms may be more or less intense than in traditional markets (Boudreau 2011). Indeed, platforms foster both complementary and competitive interactions across providers. For example, in some platform settings, providers prefer to join platforms with fewer competitors (Venkatraman and Lee 2004), however, in other platform settings, network effects attract sellers to join an already crowded platform (Tucker and Zhang 2010), and in some cases, there is concurrent evidence of positive network effects and competitive crowding (Zhu and Liu 2018). When platform owners enter the complementors' product spaces, introducing an imposing and large competitor to existing providers, empirical evidence presents evidence of demand expansion and substitution depending on provider and market characteristics (Zhu 2019). In some cases, platform owner entry into the complementor space expands the market and generates positive spillovers to competing providers (Cennamo et al. 2018, Foerderer et al. 2018, Li and Agarwal 2016), while in other settings, it crowds out incumbent providers (Edelman and Lai 2016, Wen and Zhu 2019).

The nature of the competitive dynamics in a platform marketplace and the extent to which interactions across providers are complementary vs. competitive is influenced by the characteristics of or strategies deployed by the platform itself. Platforms "regulate" access to and interactions on the marketplace (Boudreau and Hagiu 2009), and accordingly, different platform attributes or choices may result in very different implications for providers.

An important consideration in determining how competitive or complementary relationships between providers on a platform is the nature of the goods or services offered on the platform. Some platforms offer goods or services purchased infrequently by users and are more perfectly substitutable. For example, the platform Zillow allows potential homebuyers to find houses for sale and connects users with real estate agents representing such properties. For most individuals, the purchase of one home eliminates the need for another. Such platforms feature more competitive relationships across providers on the platform as offerings due to the higher degree of substitutability across products. Other platforms facilitate regular consumption by users across many imperfectly substitutable providers. For example, DoorDash connects individuals with restaurants that they can order take-out or delivery from. Purchase of a meal from a restaurant on a given day does not necessarily eliminate demand for take-out or delivery on the following day. In these platforms, goods and services are not pure substitutes and consumers appreciate variety.

In addition, another factor that may determine the extent to which providers on a platform experience complementary (vs. competitive) dynamics with peers is the extent to which the platform lowers the cost of marginal consumption. For example, a platform's use of advertising revenue models or membership-based business models lowers the marginal cost of additional consumption and expands total consumption in an industry (Datta et al. 2017, Hagiu 2009). Consider the Apple Music platform, which charges users a monthly subscription fee to listen to an unlimited amount of content on the platform. Compared to Apple's other digital media platform, iTunes, which charges a per-unit price for content, Apple Music does not require payment for additional consumption. Such a business model encourages further consumption and exploration lowering switching costs across providers (and the marginal cost of additional consumption once on the platform), blunting head-to-head competition. Similarly, other platform strategies may encourage additional consumption on the platform. For example, platforms deploying search or recommendation tools lower consumer search costs, and accordingly, the marginal cost of consumption (e.g., Aguiar and Waldfogel 2018b, Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012).

Demand Spillovers in Digital Platform Markets

Platform settings where relationships between peers are not strictly competitive may give rise to complementary relationships between providers. The presence of indirect network effects (Farrell and Saloner 1985, Katz and Shapiro 1994) and the reduced cost of consumer search, discovery, and consumption (Brynjolfsson et al. 2011, Hagiu 2009, Oestreicher-Singer and Sundararajan 2012) may make digital platform markets particularly well-suited to generating demand spillovers across peers. Activity or expansion by peers on the platform may stimulate greater consumption on the platform, and low-cost search and discovery may facilitate the spillover of demand from one provider to another. This can result in an environment where activity or expansion by competitors is beneficial for other providers on the platform (Cao et al. 2018, Haviv et al. 2020, Reshef 2019).

Such demand spillovers could be generated in a number of different ways. Provider activity may create demand spillovers at the intensive margin (i.e., by increasing consumption by existing consumers) or at the extensive margin (i.e., by drawing novel or irregular consumers to the platform) (Cennamo and Santalo 2013, Haviv et al. 2020, Katz and Shapiro 1994). Demand expansion may occur across the platform or may be "localized", redirecting the attention of consumers from one product market space on the platform to another (Carmi et al. 2017, Oestreicher-Singer and Sundararajan 2012). If demand spillovers are localized, they would be larger for more proximal peers and substitution or crowding may occur across (rather than within) product categories. In any case, platform recommendation tools may play a role by steering consumers from one good or provider to similar others (Carmi et al. 2017, Oestreicher-Singer and Sundararajan 2012).

Given the tension between competitive and complementary dynamics between providers on digital platforms, a small but growing body of research has attempted to examine how the competing effects of substitution and demand expansion created by peer expansion or activity affects provider performance in platform settings. Such work has established that competitor demand expansion can generate positive spillovers for providers across a variety of platform settings (Carmi et al. 2017, Haviv et al. 2020, Reshef 2019). However, while we know that competitive and complementary dynamics can exist in digital settings, we lack a nuanced understanding of when and under what conditions such positive spillovers overcome the negative effects of substitution.

To help answer these questions, I draw from a broader strategy literature on demand spillovers to build theory regarding when we may expect competitor expansion to generate positive effects on providers. I consider the moderating role of provider and competitor characteristics on the balance between demand spillovers and competition. Different providers impose different spillovers on their competitors, as such spillovers are not just experienced by firms but are also created by them (Shaver and Flyer 2000). Drawing on prior work on agglomeration economies (Alcácer and Chung 2007, Chung and Kalnins 2001, Kalnins and Chung 2004), I consider the role of provider popularity in determining the balance between spillovers and substitution in digital platform marketplaces.

The net effect of competitor activity on a digital platform depends on the size of the positive demand spillover as well as any negative effects from substitution. The demand spillover is a function of a) the awareness or attention a competitor brings to the platform or a product market area of the platform upon expansion or activity; and b) the likelihood that a consumer subsequently transfers their attention and consumption from the competitor to another provider.

In contrast, the substitution effect is a function of a) the consumption that the provider would have attracted absent competitor activity; and b) the likelihood that a consumer would switch from the focal provider to the competitor because of competitor activity.

There is reason to believe that the likelihood that a consumer transfers consumption from one provider to another may be either lower or higher for popular vs. niche providers. Attention-based spillovers are most valuable when consumers lack information or are uncertain about the quality of a product (Hendricks and Sorensen 2009), and niche providers are particularly reliant on digital platforms to disseminate product information (Brynjolfsson et al. 2011, Gans 2012). Accordingly, it is possible that consumers may be more likely to switch towards niche providers to explore or discover providers that they know little about. On the other hand, popular providers have the benefit of familiarity and brand awareness can influence user engagement on platforms (Langaro et al. 2018). Platforms may also be inclined to promote popular providers to induce or reward loyalty (Rietveld et al. 2019).

While it is unclear how provider popularity affects the likelihood that consumption transfers from one provider to another, it is directly related to the amount of consumption a provider attracts. Popular providers attract more attention and have a larger dedicated consumer base and thus are likely to both generate larger demand spillovers and experience more substitution upon competitor expansion or activity. In contrast, niche providers relying upon a small set of dedicated consumers are likely to stimulate fewer demand spillovers and face smaller potential losses in consumption when a competitor expands. Accordingly, the net effect of competitor expansion or activity is likely a function of provider and competitor popularity. Popular providers are most likely to generate the largest spillovers for similar peers, and niche providers are most likely to benefit from them.

I investigate when and under what conditions demand spillovers may overcome the effects of substitution on a digital platform. I then investigate the mechanisms underlying such spillovers by considering whether they are driven by new or irregular consumers and the role of the platform in directing consumer attention across providers. By considering the trade-off between spillovers and competition in a digital market and investigating the mechanisms underlying these effects, I generate insights on competition and consumption on digital platforms.

In the following section, I review the empirical setting, before discussing data and methodology, presenting results, and discussing their implications.

Empirical Setting: Spotify and the Music Industry

I use the digital music streaming industry as an empirical setting using data from the Spotify music streaming platform. Spotify was developed as a platform in 2006 in Stockholm, Sweden by Daniel Ek and Martin Lorentzon to provide an alternative to the growing prevalence of piracy in the music industry and is currently the world's largest digital music streaming platform (Lidsky 2018). The company provides an audio streaming platform that connects content from record labels, media companies, and artists to consumers. Following ten years of rapid growth after launch, Spotify pursued an initial public offering at a valuation of over $25 billion (Parsons 2018, Wang 2018). As of 2020, Spotify is the world's most popular audio streaming platform, with 124 million active subscribers and 271 million monthly active users across 79 countries (Spotify 2020).

Spotify employs a "freemium" business model: most basic features are free to consumers with advertisements, while premium features, such as offline and commercial-free listening, are available through paid subscriptions. Through either the free or premium subscription, consumers do not pay for additional consumption, but rather have a membership that allows them to stream an unlimited amount of content. The proportion of streams that an artist has compared to the total number of eligible streams on the platform determines the share of revenue that each artist receives, and approximately 70 percent of Spotify's revenues are returned back to music producers (Meyers 2020). Based on this model, recent estimates suggest that the rights holder to a song earns between $0.0060 to $0.0084 per stream on the Spotify platform (Livni 2018). In addition, beyond any monetary benefits from streams on the Spotify platform itself, greater performance on the platform has benefits in other settings, increasing music downloads, attracting new followers, drawing attention to tours and concerts, and increasing revenues on other services (e.g., Aguiar and Martens 2016, Aguiar and Waldfogel 2018a, Andrews 2019, Constine 2012, Dewenter et al. 2012).

This empirical setting has several features that makes it attractive for this research. The music industry is a particularly apt setting to study this research question, as prior literature has noted that the creation of digital markets in the music industry has altered how firms compete for attention (Essling et al. 2017). As the world's leading digital music streaming platform, Spotify provides a setting with meaningful economic consequences to study the effect of competitor expansion on provider performance. The platform hosts nearly the entire population of popular artists, providing ample opportunity for spillovers through artist discovery and ensuring that each provider is likely to face some level of competitive pressure from peers.

In addition, Spotify is a platform that may be particularly likely to feature the demand spillovers discussed in this paper. Consumers are likely to listen to music from a variety of different providers on the artist, as providers and goods are not perfect substitutes. Spotify also features a freemium business model which does not require individuals to pay for additional consumption, creating low switching costs across providers and encouraging consumers to consume a variety of goods on the platform. While such features may inform how we interpret the findings and generalizability of this research (discussed in more detail following the presentation of the results), they make the setting particularly suitable to understand when and under what conditions increases in competitor demand may generate spillovers for providers in a digital platform setting.

In the following section, I outline the data and empirical strategy before presenting results.

Data and Methodology

Data

The data for this project primarily are sourced from Chartmetric, a music data analytics startup. Chartmetric is a data analytics platform that collects and organizes a variety of information regarding artists and their performance. The company positions itself as an "end-to-end music market analytics" provider for record labels, performing artists, managers, and distributers (Chartmetric 2020). Chartmetric tracks over 1.3 million artists on social media growth, performance across a variety of digital metrics, and placement on current and historical charts.

The sample consists of the top 10,000 artists on Chartmetric's platform ranked by Spotify followers at the time of data collection in October 2019. Of these 10,000 artists, I remove observations from three artist profiles that consist of aggregate categories or playlists ("Various Artists", "Ultra Music", and "Top Playlists"). For each artist in the sample, I collect daily data from the inception of Chartmetric's data collection March 23, 2016 through the end of September 2019, a sample of roughly two and a half years.[2]

For each artist, I collect information on performance on Spotify and other digital platforms (YouTube, Facebook, and Soundcloud); the dates on which an artist releases an album, single, compilation, or is featured on a song or album; and information regarding which artists Spotify classifies as related to the focal artist. For any artist that is included in the set of related artists but is not in the original set of focal artists, I collect information regarding the dates on which they release an album, single, compilation, or are featured on a song or album. For the analyses, I do not include any observations in which Chartmetric has constructed the data through interpolation.

The key dependent measures are measures of performance on the Spotify platform. I focus on two measures based on data availability – the count of Spotify listeners and Spotify's popularity measure for each artist on a given day. Spotify listeners is calculated as total of unique listeners that an artist has over the previous 28 days (Joven 2019). Spotify popularity is a measure (bounded between 0 and 100) constructed by Spotify to identify the current level of activity the artist has on the platform and is calculated using the number of streams that tracks released by the artist have received and how recently those streams have occurred (Spotify for Developers 2020). These different variables allow me to examine performance in different ways. The count of listeners captures a measure of the breadth of the artist's success on the Spotify platform and will allow me to identify when artists are able to reach new consumers, or at least consumers who have not listened to the artist within the last 28 days. Popularity captures a measure of the

[2] Chartmetric begins collecting different variables at different dates, so while I have some across this entire time period, I do not have continuous data for all variables across this entire timespan. I do not include interpolated data for missing variables.

depth of the artist's success on Spotify, as it primarily derives from stream counts and is not a function of the number of individuals listening to the artist. To account for skew in the data, I transform the count of listeners by taking the natural logarithm of the raw count.

Table 1 presents summary statistics of the main control and outcome variables used in the analyses.

Empirical Strategy

To examine the competitive dynamics in a platform marketplace, I examine how increased demand for a competitor affects artists on the Spotify platform. In the main analysis, I identify cases of increased demand for competitors using competitor product launches, in this case, album releases.

I rely upon Spotify's "Fans Also Like" categorization of related artists to determine the set of competing artists for each provider on the platform. This categorization is calculated using an algorithm that incorporates shared followers, musical similarity, and shared descriptions (Johnston 2019) and allows me to identify highly similar peers for each provider on the platform. Prior literature has argued that products in the recorded music industry serve as imperfect substitutes to each other (Alexander 1994, Black and Greer 1986, Mixon and Ressler 2000, Rosen 1981, Strobl and Tucker 2000), and there is evidence of substitution across similar artists for radio airplay, press coverage, top chart placement, album sales, and concert tickets (e.g., Blackburn 2004, Dertouzos 2008, Krueger 2005, Serpick 2007). As competition may be defined as "the pursuit of market position by firms that offer comparable products to a targeted set of customers" (Hoffmann et al. 2018, p. 3033), highly similar peers represent an appropriate competitive set. While Spotify provides up to twenty related artists for each artist on the platform, I focus on the top seven listed related artists to match the number of related artists most commonly displayed on an artist's page on Spotify.[3]

In many settings, identifying the impact of competitors' product launch decisions can be difficult because of the endogenous nature of the launch decision. Competitor launch decisions could relate to the focal firm's performance in a way that could bias the results. For example, if a competitor chose to launch a new product to stem previously strong performance from the focal firm, there may be pre-existing trends in the performance of the focal firm that may limit the ability to identify the impact of competitor product launch. Similarly, if competitors attempt to launch products when the focal firm is performing poorly, the same problem could exist.

In this setting, the assumption that must be met for identification is that the timing of album release is not systematically related to competitor performance on Spotify. I argue that, despite the endogenous nature of the launch decision, competitor album launch decisions are exogenous to focal artist performance on Spotify controlling for focal artist activity on the platform as well as date and artist fixed effects. Within the music industry, it is believed that the main factor determining the timing of release relies on the creative process for the artist (Hendricks and Sorensen 2009), which tends to be idiosyncratic and time-consuming. Album releases are usually planned well in advance, limiting the likelihood that release decisions are made based on short-term trends related to competitor performance (Alston 2018, Horsburgh 2020).

This identification strategy is equivalent to a difference-in-differences estimation with time-varying treatment. In this case, all artists undergo treatment at different time periods based on the related artist release times. This is a strength of the empirical strategy, as all sample artists are

[3] For an example of an artist's Spotify profile and the listing of the related artists, see *Figure 1*. Results are robust to using the top five or ten artists instead of the top seven and are presented in *Appendix Tables A6* and *A7*.

part of the treatment and control groups across time, eliminating the possibility that selection into treatment is driving the results. Because the effects of a related artist's album release may take time to manifest on the focal artist, I consider how focal artist performance is affected by related artist album release in the month following a related artist's release date.[4]

The key assumption in a difference-in-differences identification strategy is the parallel trends assumption, which requires that treated and control observations would have followed parallel paths over time if neither were treated (Abadie 2005). In later analyses, I test this assumption by examining whether and how related artist album releases coincide temporally with trends in focal artist performance. I find no evidence that related artist album releases correlate with any trends in focal artist performance on Spotify, suggesting that the parallel trends assumption is met.

I estimate regressions of the following form:

$$Y_{it} = \beta_1 Related\ Album\ Release_{it} + \beta_2 Focal\ Release_{it} + \beta_3 Focal\ FEs_i + \beta_4 Date\ FEs_t + \varepsilon \qquad (1)$$

In this equation, *i* indexes the focal artist and *t* indexes the date. *Y* refers to the dependent variables –the log of Spotify listeners and the Spotify popularity value of the artist on a given date. *Related Album Release* refers to an indicator variable that takes the value of 1 if at least one of the focal artist's set of top seven related artists released an album within the last thirty days. *Focal Release* refers to a vector of indicator variables that each take the value of 1 if the focal artist has released an album, single, or compilation, or they have been a featured on a release by another artist respectively in the last thirty days. These controls allow me to account for potentially confounding effects caused by focal artist activity. *Focal FEs* refer to the focal artist

[4] The data indicate that the positive effects of a focal artist's release on their own performance on the Spotify platform manifest within the first few days following album release, but I use a month to show how these results persist over time. Results are robust to considering longer (two months) and shorter (two week) time windows and are presented in *Appendix Tables A3* and *A4*.

fixed effects and *Date FEs* refer to the date fixed effects. These fixed effects allow me to purge out variation within artists and any account for any platform-wide shocks across time. Heteroskedasticity consistent standard errors are clustered at the focal artist level.

Despite the tests that I run, I cannot and do not claim that related artist album launch decision is truly exogenous. Thus, to further address concerns related to causality and broaden the scope of the analyses, I show that the results hold considering a truly exogenous demand shock to the focal artist by considering the sudden death of competing artists (Azoulay et al. 2010).

The death of an artist provides an immediate demand shock to their performance on due to an increase in death-related publicity (Brandes et al. 2016), and an artist's sudden death should be random with respect to their competitor's performance. To identify sudden and unexpected deaths, I follow Azoulay et al. (2010) and identify artists who died during the time period who were younger than sixty-seven at the time of their passing. I additionally require that the artists did not pass away following a prolonged public battle with a terminal illness to ensure that the death was truly sudden and unexpected. Using year-end lists of notable deaths from *Billboard Magazine* and the *New York Times*, I identify 55 individuals who meet these criteria during the sample time period, associated with 91 different Spotify artists.[5] Within the sample, I identify 186 artists that experience the sudden and premature death of a competitor, defined as one of the focal artist's top seven listed related artists. Because a small number of artists experience the sudden and premature death of a competitor multiple times in the sample, there are 190 instances

[5] Some individuals are members of multiple groups and thus are associated with multiple artists. For example, Chester Bennington, who passed away on July 20, 2017, was a member of Linkin Park, Dead by Sunrise, Stone Temple Pilots, and Grey Dze.

of “treatment.”[6] I use this treatment to consider how unexpected artist deaths affect the performance of competitors on the Spotify platform.

In the analysis using related artist album release, all sample artists are part of the treatment and control groups across time, eliminating the possibility that selection into treatment is driving the results. While this shock is plausibly random, because only certain artists undergo treatment, there may be concerns that underlying characteristics of treated artists bias estimates. To mitigate these concerns, I construct a matched sample of control artists for each treated artist that experiences the competitor death shock using coarsened exact matching (CEM) (Iacus et al. 2012). I match each treated artist to a control artist that does not experience a sudden death among any of its top twenty related artists and does not suddenly die during the sample. I require that control artists belong to the same genre as treated artists and be from the same country. I additionally match based on Spotify popularity and listeners the day before the premature death shock as well as growth in Spotify popularity and listeners over both the month and year prior to sudden death. Multiple control artists are matched to each treated artist following the CEM procedure, and I use the matching weights as provided by STATA’s CEM procedure in the analysis. Using this procedure, I am able to match 167 of the 190 instances of treatment (87.9%) to 2,663 control artists. I present results across the entire sample excluding focal artists who experience a sudden death as well as limited to the matched treatment and control artists.

This shock differs from related artist album release in a number of ways. Related artist album release represents competitor expansion driven by a product launch and is measured by activity on the Spotify platform itself. On the other hand, the death of an artist is not linked to product

[6] If the artist both experienced a sudden death and is a competitor of an artist that experienced a sudden death, they are removed from the sample. This happens in cases when individuals are associated with multiple groups.

launch or activity and affects all market settings. Because album release generates demand from a new product, it may generate different consumption patterns and habits by listeners. Album releases may be more likely to stimulate demand through individuals seeking out new music artist death, which may largely stimulate increased demand through nostalgia rather than music discovery. Further, given the smaller sample of sudden artist deaths, the coverage of treated focal artists and the ability to explore heterogeneity based on the popularity of related artist release is limited in the sudden artist death analysis. However, the exogenous nature of this demand shock should further address issues related to causality and shows that the effect is generalizable to other demand shocks beyond product launch.

Competitor Expansion: Related Artist Album Release

Main Effect

Table 2 presents the baseline results for the effects of related artist album release on focal artist performance on Spotify in Columns 1 and 2. Across both measures, related artist album release has a statistically strong, positive effect on performance on Spotify. Column 1 displays the results considering the log count of Spotify listeners and Column 2 displays the results considering Spotify popularity. The release of an album by a related artist increases the count of Spotify unique listeners by 0.7 percent and Spotify popularity by 0.113, equivalent to a 0.2 percent increase when scaling the coefficient estimate by the unconditional sample mean ($p < 0.01$ for both measures).[7] While statistically significant, these effect sizes are modest and meaningfully smaller than the increases in performance that an artist receives if they release an album or single themselves. Nevertheless, they represent increases in focal artist performance

[7] Effect sizes for logged dependent variables are calculated as e^{β}-1. For non-logged measures, percent changes are calculated as the coefficient estimate divided by the unconditional sample mean.

created through their competitor's action. This is an intriguing result. It appears to suggest that, on average, attention-based demand spillovers outweigh the effects of crowding and substitution in a digital platform market setting.

For the estimates presented above, the identification strategy relies on the assumption that the timing of a related artist album release is uncorrelated with factors that determine the outcome measures of interest, conditional on the controls. If I find that focal artists experience meaningful increases in performance on Spotify prior to the release of an album by a related artist, it suggests that any measured effect post-related artist album release may be confounded with a pre-release trend, potentially biasing the estimate of the treatment effect. However, if there is no pre-trend in the dependent measures, the main results are unlikely to be driven by the endogenous timing of a related artist release.

I investigate the presence of pre-trends using a relative time model. (Greenwood and Wattal 2017, Zhang 2018). The relative time model estimates the treatment effect for lags and leads relative to the time of treatment to estimate trends in the dependent measure during the pre-period and identify how the treatment effect develops over time (Autor 2003). I construct this model by replacing the indicator variable for related artist album release with a series of dummies indicating the distance in weeks between time *t* and the timing of treatment for a focal artist. I use the week prior to related artist album release as the omitted base time period. In cases where multiple related artists release within a one-month timespan, resulting in a date being both four weeks prior to and after a release, the date is included in the post period since it is considered treated. I visually present the results of this analysis in Figure 2.[8]

[8] Regression estimates underlying this figure are presented in *Appendix Table A1*.

Figure 2 shows that, for both dependent measures, there is no evidence of pre-existing time trends. Instead, effect sizes are not meaningfully different from zero during the pre-period, but sharply increase in the week of related artist album release. This suggests that the timing of related artist album release is exogenous to focal artist performance on the Spotify platform. Figure 2 also allows for the examination of the manifestation of the treatment effect across time. Panel A suggests that the positive effect of related artist album release on Spotify listeners emerges within the first week and continues to grow gradually over the first three weeks following album release before appearing to abate. This effect may manifest as steady and gradual growth because the count of listeners is calculated using a rolling 28-day window. Panel B shows that the positive effects of related artist album release on Spotify popularity emerges immediately following related artist album release and grows very slowly over the following weeks. Taken together, these figures suggest that the largest positive benefits following related artist album release are reaped quickly following the album release date.

Heterogeneity across Artists

While I have uncovered that the average effect of competitor album release on provider performance, as discussed above, it is possible that this average effect masks heterogeneity across providers. I first consider how the effect may differ based on focal provider popularity. Prior literature has established that niche providers often benefit the most from the reduced search costs and increased discovery in digital markets (e.g., Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012, Zhang 2018), and that attention-based spillovers are most valuable when consumers lack information or are uncertain about the quality of a product or a provider (Hendricks and Sorensen 2009). Further, niche providers attract less consumption to the market relative to their more popular peers and thus may face smaller potential losses in consumption due to substitution when a competitor expands. I investigate whether this is the case by examining how the effect of related artist album release differs based on focal artist popularity.

To do so, I split the sample based on the average Spotify popularity for each focal artist across the sample.[9] Because music popularity and performance exhibits significant skew (Hendricks and Sorensen 2009), I split the sample by classifying artists with an average Spotify popularity of greater than or equal to 70 as "High Popularity Artists" – this represents approximately the top ten percent of the distribution of artists based on average popularity (artists that could be considered "superstars"). I classify artists with an average Spotify popularity less than 70 and greater than or equal to 55 as "Medium Popularity Artists" – this roughly corresponds to artists with above median popularity who are not in the top decile. All other artists are classified as "Low Popularity Artists."

I consider the main specification considering the effect of related artist album release on focal artist Spotify performance across the three subsamples based on related artist popularity as outlined above. The results of this analysis are presented in Table 3. Columns 1 through 3 present the results considering the Spotify listeners as a dependent variable and columns 4 through 6 present the results considering Spotify popularity as a dependent variable. While I continue to find a positive effect of related artist album release on focal artist performance, effects appear larger for less popular artists. A related artist album release does not have a meaningful relationship with the count of Spotify listeners for high popularity artists but increases listeners by 0.5 percent for medium popularity artists ($p < 0.01$), and 0.7 percent for

[9] Because I use contemporaneous popularity as a dependent measure, I instead rely upon the average popularity across the sample to classify artists. This prevents artists from changing classifications across time (e.g., a high popularity artist remains a high popularity artist across the entire sample).

low popularity artists ($p = 0.017$). A similar pattern emerges considering Spotify popularity. Related artist album release increases Spotify popularity for high popularity artists by 0.055, equivalent to a 0.1 percent increase when scaling by the unconditional sample mean for high popularity artists ($p = 0.064$); by 0.037 for medium popularity artists, equivalent to a 0.1 percent increase when scaling by the unconditional sample mean for medium popularity artists ($p = 0.003$); and by 0.080 for low popularity artists, equivalent to a 0.2 percent increase when scaling by the unconditional sample mean for low popularity artists ($p < 0.01$). These results suggest that the positive spillover effects from competitor demand expansion outweighs the negative effects of competition for artists across the spectrum, though the effect sizes are slightly larger for less popular, niche artists.

I next consider how competitor popularity affects the size and magnitude of the effect of related artist album release on focal artist performance. More popular or well-endowed providers have larger consumer bases and command more consumer attention than their less popular counterparts, potentially allowing them to generate larger demand spillovers (Alcácer and Chung 2007, Kalnins and Chung 2004, Shaver and Flyer 2000). In this setting, increases in demand for more popular or well-endowed competitors may therefore be more beneficial than increases in demand for less popular, niche competitors. To investigate whether this is the case, I examine how the effect of competitor album release differs according to the popularity of an artist's competitor at the time of album release. I classify artists with an average Spotify popularity of greater than or equal to 70 at the time of album release as "High Popularity Artists", artists with an average Spotify popularity less than 70 and greater than or equal to 55 at the time of album release as "Medium Popularity Artists", and all other artists as "Low Popularity Artists."

The results of this analysis are presented in Table 4. For both dependent measures, a release by a high popularity related artist causes meaningful increases in performance on Spotify. An album release by a high popularity related artist increases the focal artist's count of Spotify listeners by 3.5 percent and Spotify popularity by 0.727, equivalent to 1.3 percent ($p < 0.01$ for both measures). An album release by a medium popularity artist also seems to have a positive effect on focal artist performance, but effect sizes are smaller. An album release by a medium popularity artist increases the focal artist's count of Spotify listeners by 0.8 percent and Spotify popularity by 0.204, equivalent to 0.4 percent ($p < 0.01$ for both measures). On the other hand, an album release by a low popularity artist appears to have a negative effect on focal artist performance on Spotify. An album release by a low popularity artist decreases the focal artist's count of Spotify listeners by 2.2 percent and Spotify popularity by 0.239, equivalent to 0.4 percent ($p < 0.01$ for both measures). These results are displayed graphically in Figure 3 and highlights the clear relationship between competitor popularity and the effects of competitor album release.

It is possible that these tests may obscure the true role that focal provider and competitor popularity play in determining the effect of competitor expansion because they do not consider the role of selection. Popular providers may be more likely to have other popular providers as similar peers and vice versa. If that is the case, my estimates may be confounding the effect of provider popularity with competitor popularity (or vice versa). To account for such bias and to investigate the interaction between provider and competitor popularity, I next consider the popularity of both the focal and related artist at the same time. As outlined above, the effects of competitor expansion appear to be the most positive for niche providers and when the competitor is popular. At the other end of the spectrum, we should expect that competitor expansion will be least beneficial when the focal provider is popular, and the competitor is a niche provider. I consider the heterogeneous effects of related artist album release by related artist popularity for subsamples based on average focal artist popularity across the time period of analysis. The results of this analysis are displayed in Table 5.

Columns 1-3 display the results considering Spotify listeners as a dependent variable. A release by a high popularity related artist increases the count of listeners by 1.4 percent for high popularity focal artists ($p = 0.014$), 4.6 percent for medium popularity focal artists ($p < 0.01$), and 8.9 percent for low popularity focal artists ($p = 0.033$). The release of an album by a medium popularity related artist appears to cause a marginally significant decrease of 0.9 percent for high popularity artists ($p = 0.099$), has no meaningful effect on Spotify listeners medium popularity focal artists, but causes an increase of 2.4 percent in listeners for low popularity focal artists ($p < 0.01$). The release of an album by a low popularity related artist does not have a meaningful effect on Spotify listeners for high popularity focal artists but decreases listeners by 1.8 percent for medium popularity artists and 2.2 percent for low popularity artists ($p < 0.01$ for both models).

Columns 4-6 display results considering the Spotify popularity as a dependent variable. The release of an album by a high popularity related artist increases Spotify popularity by 0.0369, 0.998, and 1.479 for high, medium, and low popularity artists respectively ($p < 0.01$ for all models). Relative to the sample mean for high, medium, and low popularity artists, this corresponds to a 0.5, 1.6, and 3.1 percent increase in popularity, respectively. The release of an album by a medium popularity related artist appears to have no meaningful effect on Spotify popularity for high popularity artists ($\beta = 0.055$; $p = 0.343$) but causes an increase of 0.157 in Spotify popularity for medium popularity artists and 0.375 for a low popularity artist ($p < 0.01$

for both models). Relative to the sample mean for medium and low popularity artists, this corresponds to a 0.3 and 0.8 percent increase in popularity, respectively. Again, the release of an album by a low popularity related artist seems to have negative consequences for the focal artist, decreasing Spotify popularity by 0.550 for high popularity artists, 0.284 for medium popularity artists, and-0.169 for low popularity artists ($p < 0.01$ for all models). Relative to the sample mean for high, medium, and low popularity artists, this corresponds to a 0.7, 0.5, and 0.3 percent decrease in popularity, respectively. The estimated effect of competitor album release by competitor and focal provider popularity is displayed graphically in Figure 4 and clearly shows that the effect of competitor album release is more positive for low popularity providers and for high popularity competitors.

Taken together, these results suggest that the effects of competitor expansion on focal actors in a platform marketplace varies greatly depending on the popularity of the competitor and focal provider. Less popular providers benefit more from attention-based spillovers created by competitor demand expansion, consistent with previous literature highlighting how reduced search costs and greater discovery benefits niche providers (e.g., Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012, Zhang 2018). Further, consistent with previous literature on agglomeration economics (e.g., Alcácer and Chung 2007, Chung and Kalnins 2001, Kalnins and Chung 2004), expansion by well-endowed, popular competitors generate larger demand spillovers relative to niche competitors and thus has a more positive effect on focal provider performance.

Mechanisms

I next explore the mechanisms underlying this result. As discussed above, within digital platform markets, increases in competitor demand can lead to demand spillovers through the extensive margin (i.e., increasing the number of consumers) or through the intensive margin (i.e., increasing the amount of consumption-per-consumer) (Carmi et al. 2017, Cennamo and Santalo 2013, Katz and Shapiro 1994, Oestreicher-Singer and Sundararajan 2012). Further, such spillovers may be a product of platform design tools that explicitly steer consumers from one good or provider to another or may be the result of independent consumer preferences and choices. In the following section, I first investigate whether and how discovery or re-discovery by new or irregular listeners drives attention-based demand spillovers and consider whether demand expansion following competitor album release is expansion across the entire market or localized within a product area. I then investigate the role of the platforms search and recommendation tools in creating and facilitating the documented spillovers.

Artist Discovery and Re-Discovery

I take advantage of differences in the two dependent variables to investigate whether the attention-based spillovers documented thus far are driven by discovery or re-discovery by new or irregular listeners (rather than increased consumption by existing consumers). I repeat the main analysis considering Spotify popularity as a dependent variable and controlling for the count of Spotify listeners. The count of Spotify listeners provides me with an indication of the breadth of consumption during a given time period, while Spotify popularity provide me with an indication of intensity or depth of consumption. The results outlined above suggest that both measures of performance increase following related artist album release. However, if the effect on the intensity measure (popularity) disappears when controlling for the count of Spotify listeners, it would suggest that the effect of the demand shock to a competitor on artist performance is driven by an increase in new or irregular consumers, rather than increased activity by regular consumers. The results of this analysis, considering the average effect of competitor album release as well as the effect of competitor album release by competitor popularity are presented in Table 6

In Column 1, controlling for the count of Spotify listeners, on average, I find a positive relationship between related artist album release and Spotify popularity, however, it is much smaller in magnitude than the estimates in Table 2 and is no longer statistically significant ($\beta = 0.003$; $p = 0.697$). In Column 2, showing the effect of competitor album release by competitor popularity controlling for the count of unique listeners, I find that the release of an album by a high popularity competitor increases Spotify popularity by 0.077, equivalent to 0.1 percent ($p < 0.01$), the release of an album by a medium popularity competitor increases Spotify popularity by a marginally significant 0.019, equivalent to 0.03 percent ($p = 0.057$), and the release of an album by a low popularity competitor decreases Spotify popularity by 0.059, equivalent to 0.1 percent ($p < 0.01$). These estimates all represent estimates that are meaningfully different and attenuated relative to the corresponding estimates obtained without controlling for the count of unique listeners in Table 4.

These results suggest that the effect of competitor album release is largely driven by artist discovery or re-discovery by new or irregular listeners. The release of an album increases consumption on Spotify by bringing new or infrequent consumers to the platform. These new or irregular consumers appear to create indirect network effects by then discovering or re-discovering competitors or related artists after they come to the platform. Prior literature has established that search and recommendation tools in digital markets greatly reduce the costs of search or discovery, enabling consumers to identify novel, and at times "niche," offerings that they are interested in but may have struggled to find in other settings (Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012). However, while discovery or re-discovery may explain much of the effect, there is some evidence that increases in competitor demand affects the consumption behavior of dedicated or existing consumers as well, suggesting that both channels play a role.

While the results thus far provide consistent evidence that competitor album release can stimulate an expansion in demand, it is unclear whether this demand expansion occurs across the entire platform or is more localized to a certain product market area. The ability to investigate this on a large scale is limited as I do not have data on consumption at the consumer-level. However, I attempt to conduct an exploratory analysis to investigate the limits of these attention-based spillovers and generate insight on whether they occur across the platform or are local in their nature. Focusing on the top ten artists by average popularity in the sample, I examine how album release by these star artists affects performance of all other sample artists. If the demand expansion I document is platform-wide, we would expect album releases by these superstar artists to on average have a positive effect on the performance of all other sample artists (because the most popular artists should generate the largest demand spillovers). The results of this analysis, presented in Table 7, are inconclusive. I find that, on average, the release of an album by a star artist has a negative but insignificant relationship with the count of Spotify listeners ($\beta = -0.037$; $p = 0.257$) and a positive but insignificant relationship with Spotify popularity ($\beta = 0.103$; $p = 0.562$) for all other artists on the platform.[10] While this does not appear to be consistent with demand expansion across the entire platform, it also does not show clear evidence of substitution across the platform, and the ability to make strong inferences is limited based on the small sample of treatment events. Further work must be done to untangle when

[10] I replicate this test looking at just within-genre effects. I find evidence that the release of an album by a star artist in the pop genre increases the count of unique listeners for other pop artists, however, I find no other meaningful relationship between the release of an album by a star artist and the count of unique listeners or Spotify popularity in the pop or hip hop and R&B genres (the genres making up the top ten artists in the sample).

increases in competitor demand result in localized increases in competitor demand vs. increases in demand across the entire platform.

Recommendation Tools and Platform Construction

Prior literature has established that search and recommendation tools in digital markets greatly reduce the costs of search or discovery, enabling consumers to identify novel offerings that they are interested in but may have struggled to find in other settings (Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012). As with many platforms, Spotify has its own search and recommendation tools that influence consumption patterns. For example, the promotion of certain artists or songs through placement on featured playlists can lead to a meaningful increases in consumption and discovery (Aguiar and Waldfogel 2018b). It is possible that Spotify's recommendation algorithms and user interface are the key drivers of discovery and re-discovery that create positive spillovers across competitors. For each artist on the platform, Spotify prominently displays the list of related artists on the focal artist's profile. In addition, Spotify offers an autoplay feature, such that listeners are automatically presented similar songs when they reach the end of an album, playlist, or selection of tracks (Spotify Autoplay 2020). To investigate the role of Spotify's recommendation systems in driving discovery and re-discovery, I conduct an analysis that takes advantage of the non-reciprocal nature of related artist relationships on the Spotify platform. For each artist in the sample, I consider the effect of competitor album releases separately for "reciprocal" and "non-reciprocal" related artists. Reciprocal related artists are the set of competitors for whom the focal artist is classified as a related artist; non-reciprocal related artists are the set of competitors for whom the focal artist is not classified as a related artist.

As an example, consider a hypothetical case with Artists A and B. Artist A is listed as one of Artist B's related artists, however, Artist B is not categorized by Spotify as one of Artist A's related artists. In this scenario, we know that Artist A and B are similar and related, however, there is nothing on Artist A's profile that directs you to Artist B.[11] This would be an example of a non-reciprocal relationship. Because of this, any effect of album release by Artist A on Artist B's performance on Spotify is less likely to be driven by the platform recommendation system or user interface. In such cases, Spotify does not directly steer listeners from the competitor to the focal artist, and accordingly, any effect I find should be primarily driven by demand expansion rather than platform recommendation systems.

I consider the average effect of related artist album release, as well as the effect of related artist album release by competitor popularity separately for reciprocal and non-reciprocal related artists. The results of this analysis are presented in Table 8. On average, the results seem to suggest that album releases by non-reciprocal competitors have larger effects on the focal provider Spotify performance than releases by reciprocal competitors (Columns 1, 3, 5, and 7). However, this result appears to be driven by the fact that non-reciprocal artists tend to be more popular than reciprocal artists, and a different story emerges when breaking the results down by popularity. Columns 2, 4, 6, and 8 show that, in general, the effects of competitor album release are more positive for high, medium, and low popularity competitor album releases for reciprocal relationships than non-reciprocal relationships.[12] This difference likely reflects the role of the platform's recommendation systems in facilitating discovery across artists. Nevertheless, even among non-reciprocal relationships, I find similar patterns albeit with attenuated coefficients.

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[11] *Appendix Figure A1* displays an example of such a non-reciprocal relationship considering the artists Drake and J. Cole.

[12] The one exception is considering the effect of low popularity competitor album release on the count of unique listeners, where estimates are similar.

These results seem to suggest that, while Spotify's recommendation system and user interface may contribute to the creation of demand spillovers, they do not solely or primarily drive the documented results.

Exogenous Demand Shock: Artist Death Analysis

The results presented above seem to suggest that, on average, within the Spotify market, attention-based demand spillovers seem to outweigh the effects of competitive crowding during competitor expansion. However, these results rely upon identification using the release of an album by a related artist, and despite the lack of pre-existing trends in the dependent measures, there may be a concern that the album release decision for related artists is endogenous with regards to focal artist performance on the Spotify platform. In an attempt to mitigate these concerns and to explore how this effect manifests using a different kind of demand expansion, I re-conduct the analyses using a truly exogenous demand shock – the sudden and unexpected death of an artist (e.g., Azoulay et al. 2010).

The timing of an artist's death should be random with respect to their competitor's performance. To ensure that this is the case, I only consider sudden and unexpected artist deaths, defined as the death of artists younger than sixty-seven (Azoulay et al. 2010) who did not pass away following a prolonged battle with a terminal illness. Using year-end lists of notable deaths from *Billboard Magazine* and the *New York Times*, I identify 55 individuals who meet this criterion during the sample, associated with 91 different Spotify artists.

In addition, death of an artist provides an immediate demand shock to their performance on due to an increase in death-related publicity (Brandes et al. 2016). I first verify this in the sample, by examining the relationship between sudden focal artist death and focal artist performance. The results of this analysis are presented in *Appendix Table A2* and show that, within the sample, that the sudden and unexpected death of an artist has a large, meaningful effect on the artist's performance on the Spotify platform, increasing the count of unique listeners by 35.7 percent and increases Spotify popularity by 3.870, equivalent to a 6.7 percent increase when scaled by the unconditional sample mean ($p < 0.01$ for both measures).

Having established that artist deaths create a large increase in performance on the Spotify platform, I re-conduct the main analysis and examine whether and how the sudden death of a related artist affects focal artist performance on Spotify. Consistent with the approach with related artist album releases, I consider an artist treated if a related artist has died within the last thirty days. I present the results across the entire sample excluding artists that experienced a sudden death as well as in a matched sample of treated and control artists constructed using a coarsened exact matching procedure. The results of this analysis are presented in Table 9.

In the full sample, I find that the death of a related artist has a positive but non-significant relationship with the count of Spotify listeners ($\beta = 0.022$; $p = 0.134$) and increases the focal artist's Spotify popularity by 0.439, equivalent to 0.8 percent ($p < 0.01$). In the matched sample, these patterns hold but with smaller magnitudes. The death of a related artist has an insignificant relationship with the count of unique listeners ($\beta = 0.014$; $p = 0.147$) but increases the focal artist's Spotify popularity by 0.286, equivalent to 0.5 percent ($p < 0.01$).

As demonstrated above, artist popularity appears to greatly influence the magnitude and direction of competitive spillovers in this setting, and accordingly, the popularity of artists that pass away suddenly during the time period could greatly influence the magnitude of the results. I consider how the popularity of a related artist moderates the effect of sudden related artist death. As before, I categorize related artist deaths based on the popularity of the related artist the day prior to their death. Given the smaller sample of artist deaths and the paucity of high popularity related artist deaths, I do not consider high, medium, and low popularity related artist deaths separately. Instead, I compare the effect of high and medium popularity related artist deaths together (Spotify popularity greater than or equal to 55 prior to artist death) relative to the effect of low popularity related artist death. The results of this analysis are presented in Table 10.

Just as with related artist album releases, I find evidence that the effect of sudden related artist death on focal artist performance on the Spotify platform differs greatly depending on the popularity of the related artist. In the full sample, the death of a high or medium popularity related artist increases the count of unique Spotify listeners by 4.4 percent ($p = 0.011$) and increases Spotify popularity by 0.671, equivalent to 1.2 percent ($p < 0.01$). On the other hand, the death of a low popularity related artist has no meaningful effect on the count of Spotify listeners ($\beta = 0.013$; $p = 0.978$) and a positive but statistically weak relationship with Spotify popularity ($\beta = 0.212$; $p = 0.128$). In the matched sample, a similar pattern holds with weaker results. Within this sample, the death of a high or medium popularity related artist does not have a meaningful relationship with the count of listeners ($\beta = 0.015$; $p = 0.332$) though the estimated effect is larger in magnitude than the death of a low popularity related artist ($\beta = 0.009$; $p = 0.524$). Further, the death of an above median popularity related artist increases focal artist Spotify popularity by a marginally significant 0.300, equivalent to 0.5 percent ($p = 0.073$), while the death of a low popularity related artist does not meaningfully affect focal artist Spotify popularity ($\beta = 0.156$; $p = 0.137$).

Relative to the results considering the effects of related artist album release, readers may question why the death of a low popularity related artist album release does not have a negative effect on focal artist performance. It is my belief that this is the result of how consumers may learn about the two different shocks. The size of any substitution effect is a function of a) the consumption that the focal provider attracts to the platform; and b) the likelihood that a consumer would switch from the focal provider. This likelihood of switching is a function of on-platform learning. It would require that consumers on the platform listening to a provider somehow have their attention drawn to a competitor. I believe that such on-platform learning is much likelier for album release than for artist death. When a provider releases an album, Spotify often will help disseminate information about product release by featuring the artist on users' Spotify feeds or placing the artist within promoted playlist. Spotify plays no such role in disseminating information regarding artist deaths, and alternatively, consumers are likely to learn about the death of an artist through channels such as social media or public press. Consumers are unlikely to learn about artist death once on-platform, and as a result, there may be little to no substitution effect.

These results also continue appear to show that the death of a related artist has weaker effects on the count of unique listeners than an album release by a related artist. This is perhaps not surprising given that the release of new music is more likely to stimulate consumption by listeners seeking to discover new music while the death of an artist may drive nostalgia-based consumption by dedicated listeners. To investigate whether this is the case, I consider the role of new or irregular listeners in generating the demand spillover associated with competitor death. I examine the relationship between related artist death and Spotify popularity controlling for the count of unique listeners. The results of this analysis are presented in Table 11.

I find that, on average, controlling for the count of unique listeners, the relationship between related artist death and Spotify popularity persists, suggesting that new music or artist discovery is not driving these spillovers. Controlling for the count of unique listeners, Columns 1 and 3 show that the sudden death of a related artist increases Spotify popularity by 0.191 in the full sample and 0.161 in the matched sample (equivalent to 0.3 percent in both cases; $p = 0.035$ and 0.037 respectively). Interestingly, Columns 2 and 4 show that, controlling for the count of unique listeners, there is no longer evidence in this setting that the death of high popularity competitors generates larger demand spillovers than the death of less popular competitors in either the full or matched sample. As highlighted above, this may be because the substitution effect is less relevant or due to characteristics of the treated artists. These findings show us that different shocks to competitors may stimulate different kinds of spillovers. In this case, while the release of an album may stimulate more exploratory listening and demand spillovers are largely driven by new or irregular listeners, the death of an artist may be more impactful in stimulating increased consumption among the existing consumer base.

Nevertheless, using two different kinds of demand shocks, I find evidence that increases in competitor demand can deliver positive spillovers to providers in a platform market. However, such positive spillovers appear to be larger when the competitor is popular or well-endowed. These results are in line with the literature on agglomeration economies that suggests that the benefits accrued from co-locating with a competitor are largest when the competitor possesses high quality benefits that can spillover (e.g., Alcácer and Chung 2007, Kalnins and Chung 2004, Shaver and Flyer 2000). The implication of this result is that, within markets where demand spillovers may be particularly likely to exist, such as digital platform markets, the presence of more powerful or well-endowed competitors may be more beneficial than the presence of niche competitors with less resources.

Additional Analyses

Contemporaneous Releases

Thus far, I have examined how the competitor demand expansion can affect the performance of a provider on a platform without considering the behavior or strategy of the focal provider themselves. In the following section, I consider the interaction between a provider's actions as well as their competitors in determining performance in a platform market. I examine product releases by the focal provider and consider how contemporaneous competitor demand expansion affects focal actor performance on the Spotify platform.

To do this, I conduct a modified version of the analysis using related artist album release as a form of competitor demand expansion. I interact the indicator variables for high, medium, and low popularity related artist album release with the indicator variable for focal artist album release. By examining the estimates of these interaction effects, I identify how a contemporaneous release moderates the effect of album release and how the moderation differs based on competitor album release. The results of this analysis are presented in Table 12.

Columns 1 and 2 suggest that, unsurprisingly, the release of an album generates large increases in focal artists' performance on Spotify, increasing the count of unique listeners by 11.0 percent and Spotify popularity by 1.295, equivalent to a 2.3 percent increase when scaling by the unconditional sample mean ($p < 0.01$ for both measures). However, the effect of an album release differs depending on whether a competitor releases an album at the same time. On average, releasing an album at the same time as a competitor attenuates the positive effects of album launch. Relative to launching an album in a "quiet" period for competitors, on average, releasing at the same time as a competitor decreasing the count of unique listeners by 2.2 percent ($p < 0.01$) and Spotify popularity by 0.107 equivalent to 0.2 percent ($p = 0.085$).[13]

Columns 3 and 4 show that underlying this average effect is significant heterogeneity based on competitor popularity. While on average, contemporaneous album releases may diminish performance increases upon album launch, the estimates suggest that releasing an album at the same time as a popular competitor does the opposite and magnifies the positive effects of album launch. Calculating the marginal effects across the interactions, I find that the release of an album at the same time as the release of a high popularity competitor increases the count of unique listeners by 18.7 percent and Spotify popularity by 2.063, equivalent to 3.6 percent ($p < 0.01$ for both measures).[14] In contrast, releasing an album at the same time as a medium or low popularity related artist results in much smaller increases in performance. The release of an album at the same time as a medium popularity competitor increases the count of unique listeners by 8.4 percent and Spotify popularity by 1.352, equivalent to 2.4 percent ($p < 0.01$ for both measures), and the release of an album at the same time as a low popularity competitor results in no meaningful increase in the count of unique listeners ($\beta = 0.010$; $p = 0.392$) and increases Spotify popularity by 0.533, equivalent to 0.9 percent ($p < 0.01$). These results relative to the main effect of focal artist album release are displayed graphically in Figure 5.

This is a striking result that has meaningful implications for product launch decisions in platform settings. It is generally thought that firms benefit from releasing products at different times from their competitors to avoid direct head-to-head competition (Calantone et al. 2010, Krider and

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[13] Effects calculated as the linear combination of the effect of related artist album release and the interaction of related artist album release and focal artist album release.
[14] Effects calculated as the linear combination of the effect of album release, related artist album release, and the interaction of the two.

Weinberg 1998). However, in this setting, I find that the launch of a project at the same time as a popular competitor can generate large positive effects. This is likely because the contemporaneous release by a popular competitor generates large indirect spillovers by discovery-oriented consumers. On the other hand, releasing at the same time as a medium or low popularity artist appears to attenuate increases in performance experienced from an album release, perhaps because such competitors do not generate sufficient spillovers to counteract the effects of substitution. Some of this effect may be driven by the peculiarities of the digital music streaming industry and Spotify's business model which combine to limit the marginal cost of additional consumption and create an environment that is particularly rife for spillovers. Further research is needed to evaluate in which platform settings such an effect may persist in. Nevertheless, this surprising result illustrates how the strategic considerations facing firms dramatically change within platform markets.

Cross-Platform Spillovers

Thus far, I have shown whether and under what conditions demand spillovers may outweigh the effects of crowding and substitution within the context of a digital platform. I next turn to examining whether such spillovers may manifest *across* platforms rather than just within them. Prior research establishes the presence of within-firm, cross-market spillovers, as an increase in awareness of a firm generated by joining an online retail platform can lead to positive spillovers for products offered by the firm in other market settings (Song et al. 2020). I extend this line of inquiry to consider whether such spillovers across market settings may be generated by an increase in demand or attention to a competitor. If this is the case, it would highlight the important effect of cross-competitor demand spillovers in digital platform markets by showing that such positive spillovers can affect multiple marketplaces rather than just the focal platform itself.

For this analysis, I consider whether and how the release of an album by a related artist on the Spotify platform affects performance on another digital platform, specifically the YouTube video streaming platform. I consider the count of YouTube channel views as the dependent variable. To ensure that any effects are not driven by competitor or focal artist activity on the YouTube platform, I control for information regarding YouTube video releases to examine whether competitor expansion on Spotify generates a positive spillover on YouTube, even accounting for focal artist and competitor activity on the platform. I first consider the main effect of competitor album release on Spotify on performance on YouTube and then examine how competitor popularity moderates this effect. The results of this analysis are presented in Table 13.

The results present evidence of cross-platform spillovers from competitor expansion. Column 1 shows that, even controlling for competitor and focal artist activity on YouTube, on average, a release by a related artist on Spotify increases the focal artist's count of YouTube channel views by 1.1 percent ($p < 0.01$). Again, however, this average effect differs greatly based on competitor popularity. Column 2 suggests that the positive spillovers of competitor album launch on YouTube performance are driven album releases by popular competitors. An album release by a high popularity competitor on Spotify increases the count of YouTube views by 4.4 percent ($p < 0.01$ for both measures), an album release by a medium popularity competitor has a positive but statistically weak relationship with the count of views ($\beta = 0.009$; $p = 0.116$), and an album release by a low popularity competitor on Spotify has a negative but statistically weak relationship with the count of views ($\beta = -0.013$; $p = 0.124$). In Column 3, I investigate what is driving this effect by considering the same model with the inclusion of a control for the count of

Spotify listeners. Following the inclusion of this control, I no longer find a meaningful relationship between competitor album release and the count of YouTube views. This result suggests that the increase in performance on YouTube is at least partially accounted for by increases in the count of new or irregular listeners on Spotify. Competitor album release appears to stimulate artist discovery or re-discovery on Spotify, and this increase in new or irregular listeners induces an increase in performance on YouTube as well.

These results provide more confidence that the main results are not being driven purely by consumers being directed to related artists solely through Spotify's related artist algorithms, as the effect manifests in other settings. Perhaps more surprisingly, this also appears to suggest that the indirect network effects and spillover benefits facilitated by digital platform markets do not just exist within a focal platform but also may manifest across other market settings as well. This is a potentially striking result, as it implies that the unique competitive dynamics of a platform may have trickle-down implications to other markets in which providers compete.

Robustness

I conduct a number of additional tests to examine the robustness of the findings considering the effect of related artist album release on focal artist performance on Spotify.

I consider whether results vary across genre by recreating Table 5, considering the effect of related artist album release by competitor popularity, across genre subsamples. The results, presented in *Appendix Table A3* suggests consistency across genres – releases by popular competitors have positive and sizable effects on focal artist performance, while releases by niche, low popularity artists decrease Spotify listeners and popularity. In *Appendix Table A4*, I show that results are robust to the inclusion of artist-specific time trends. In *Appendix Table A5*, I show that results are robust to considering the effect of related artist release on focal artist Spotify performance two weeks and two months after release (rather than a month as used in the main specifications). In *Appendix Table A6*, I show that results are robust to defining related artists using the top five and top ten related artists as provided by Spotify rather than the top seven related artists as used in the main specifications. Finally, in *Appendix Table A7*, I show that results are robust to considering single releases by related artists rather than album releases.

Platform Characteristics and Generalizability

It is natural to question whether and to what extent the results presented in this research generalize to other settings. As outlined above, certain platform settings may be more or less conducive to the demand spillovers described in this paper. In particular, digital platforms where buyers regularly purchase goods from a variety of providers and that ensure low switching costs through the design and business model employed are more likely to feature complementary interactions across providers. In digital platforms where buyers purchase goods infrequently and where the marginal cost of additional assumption is high, it is less likely that demand shocks to competitors will generate benefits to competitors.

As a setting, the Spotify digital platform exhibits characteristics that make complementary interactions across providers particularly likely. On Spotify, individuals typically listen to music from many artists on the platform, rather than just consuming infrequently from one provider. As in other creative industries, the popularity of a product decays relatively quickly, which can mean that substitution effects are more likely to be outweighed by market expansion effects upon product launch or competitor expansion (Cennamo et al. 2018). Consumers do not pay based on the amount they consume, and the marginal cost of additional consumption is only the time it takes to listen to the next song. In addition, through the use of recommendation systems and search tools, Spotify helps to direct consumers from one artist to similar peers. Given all of these characteristics, it is perhaps not surprising to find that demand shocks may exist on such a digital platform and readers may be left wondering what other platforms this effect may generalize to.

The findings of this research are most applicable to similar digital platforms that encourage repeat consumption across a variety of providers and are characterized by a low marginal cost for additional consumption. Platforms featuring these kinds of characteristics are certainly not uncommon (e.g., Netflix, YouTube, Twitter, Google Stadia) and they present a setting where substitution across goods is less prevalent as additional consumption is encouraged once on the platform and the platform is designed to help consumers search for and discover similar goods they may enjoy. Beyond such platforms, more work is needed to understand whether the demand spillovers documented in this research may exist in other settings, as platform design and governance can alter competitive dynamics and firm strategy for the providers competing on the platform (Boudreau and Hagiu 2009). Scholars can consider both how product (How frequently do consumers make purchases on the platform? How perfectly substitutable are products?) and platform characteristics moderate this effect (What kind of business model does the platform employ? Does the effect differ for nascent vs. mature platforms? How many consumers or providers are on the platform?).

While the magnitude and direction of the effect of competitor expansion may differ across different settings, I believe that this research provides theory that should generalize across other platform (and non-platform) settings. Consistent with prior literature in economics, management, and marketing, I present evidence suggesting that larger, more well-endowed peers generate larger demand spillovers. Demand shocks to more popular, powerful, or influential competitors should generate larger positive spillovers than those to less well-endowed competitors in any setting where demand spillovers exist, as more popular or successful competitors command more attention and awareness from consumers. The net effect of such demand shocks to competitors may differ based on the extent to which the setting features substitution across competing firms or providers.

Discussion

In this project, I examine how increases in competitor demand affect a provider's performance on the Spotify platform. I argue that digital platform markets facilitate demand spillovers across providers by fostering indirect network effects and facilitating consumer search and discovery. I find that, on average, positive demand spillovers outweigh the negative effects of substitution or crowding on the platform, however, the direction and magnitude of the effect differs greatly depending on the popularity of the competitor. Demand shocks to popular competitors have a net positive effect for artists, while demand shocks to niche competitors either negatively impact performance or have no meaningful effect. I show that the positive spillovers documented largely appear to be driven by artist discovery or re-discovery by new or irregular listeners, though there is some evidence that increases in consumption-per-consumer for existing customers play a role as well. Further, I show that the market dynamics have implications for provider strategy and may also have implications for provider performance in other markets. Taken together, these results provide us with a better understanding between the simultaneously complementary and competitive relationship between providers on a digital platform.

With this research, I contribute to a nascent literature that studies the balance between substitution and demand spillovers within digital platform settings (Cao et al. 2018, Haviv et al. 2019, Reshef 2019). By showing that providers may face more intense competition from niche peers vs. popular peers, I present evidence that digital platforms may not just alter how firms compete (e.g., Boudreau 2011, Kapoor and Agarwal 2017, Rietveld and Eggers 2018), but also *who* they compete with. I contribute to our understanding of competitive dynamics in digital platform settings and extend a body of literature on the effects of "stars" on platform markets (Binken and Stremersch 2009, Rietveld and Eggers 2018). In doing so, I build upon a literature examining demand spillovers linked to industry localization (e.g., Alcácer and Chung 2007, Chung and Kalnins 2001, Shaver and Flyer 2000), and in essence, show that platforms can create a form of digital localization.

Despite its contributions, this work has limitations that provide opportunity for further inquiry. Future research should examine how this effect manifests in platform settings where consumers pay-per-consumption and consider how the effect differs for competitor entry as well as other forms of competitor expansion. In addition, the dependent measures are based on artist performance on the Spotify platform, and, while I believe they are important metrics of artist success, I am unable to tie them directly to revenue or profit. Replicating this research in a setting where performance can be clearly linked to monetary outcomes would help to contextualize this effect and provide a sense of the economic magnitude of such spillovers. Further, the data I use for this project imposes an additional set of limitations on the findings. The sample is limited to the top 9,997 artists on Spotify based on follower count as of October 2019. As shown by the findings of this research, the characteristics of providers greatly affect the competitive dynamics in a platform context. By focusing on the artists with the most followers, I am unable to analyze the long tail of niche or less popular artists. Future work could further investigate competitive dynamics across providers for a broader range of actors. Finally, future work could investigate how such effects change over a platform's lifecycle. Network effects may be particularly strong when a platform is young and growing its consumer base rapidly and may be less important once a platform has a stable and dedicated set of customers. Accordingly, there is reason to believe that the relative strength of network effects vs. competitive crowding may change as a platform mature.

Digital platforms are becoming increasingly common, and firms across a variety of industry now find themselves participating in these markets to reach consumers. Such platforms alter the competitive landscape by changing the source and direction of complementarities (Jacobides et al. 2018), and pose new challenges and opportunities for the firms competing on them. While much work remains to be done to improve our understanding of the dynamics of these marketplaces, I believe that this research provides and important and meaningful contribution to the nascent and growing body of literature examining the nature of digital platform markets.

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Figure 1. Example of Spotify Interface. An example of the Spotify interface for an in-sample artist as of February 2020. Note the list of seven artists in the "Fans Also Like" column to the right. These artists comprise the set of related artists in the analysis.

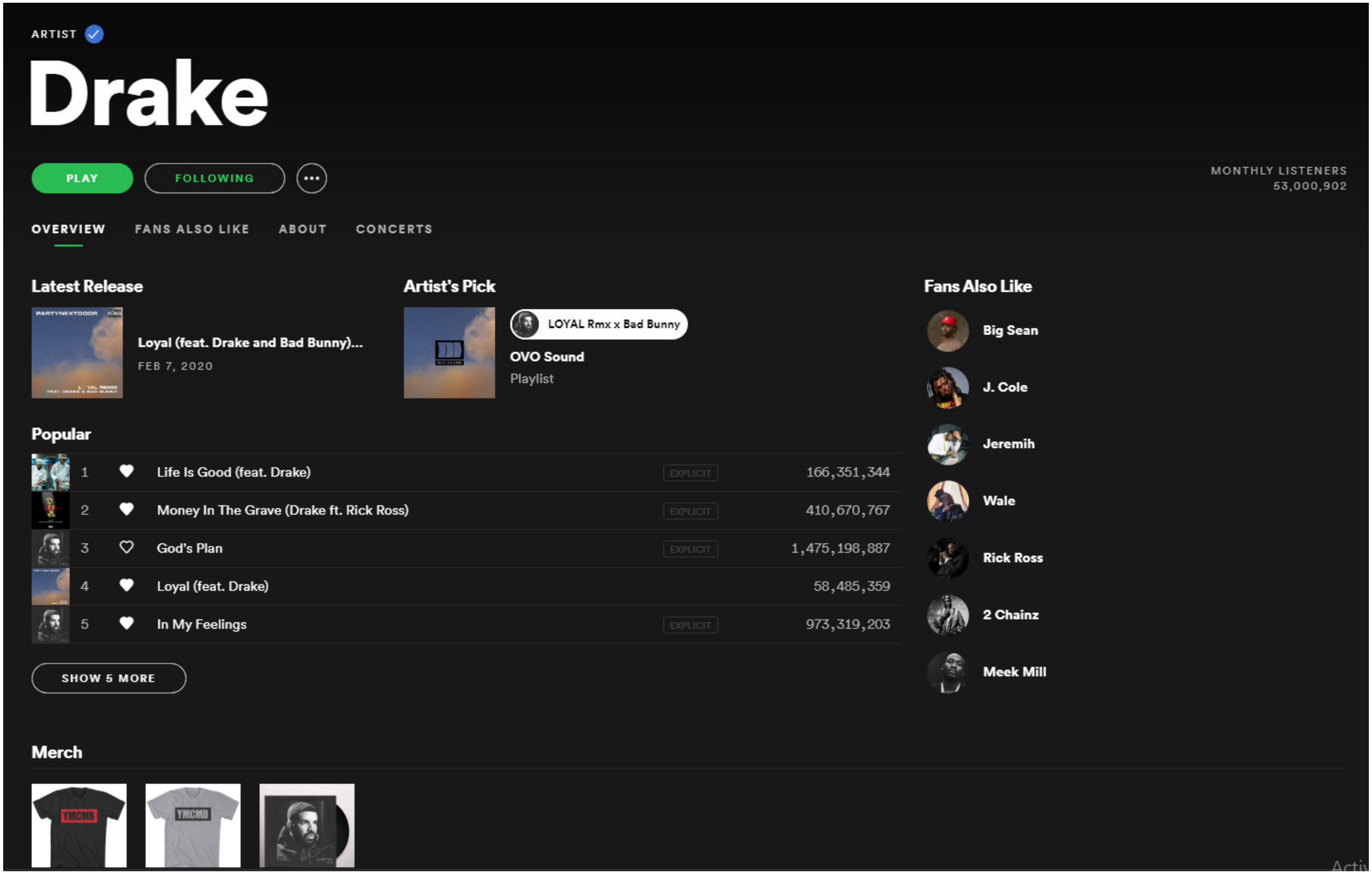
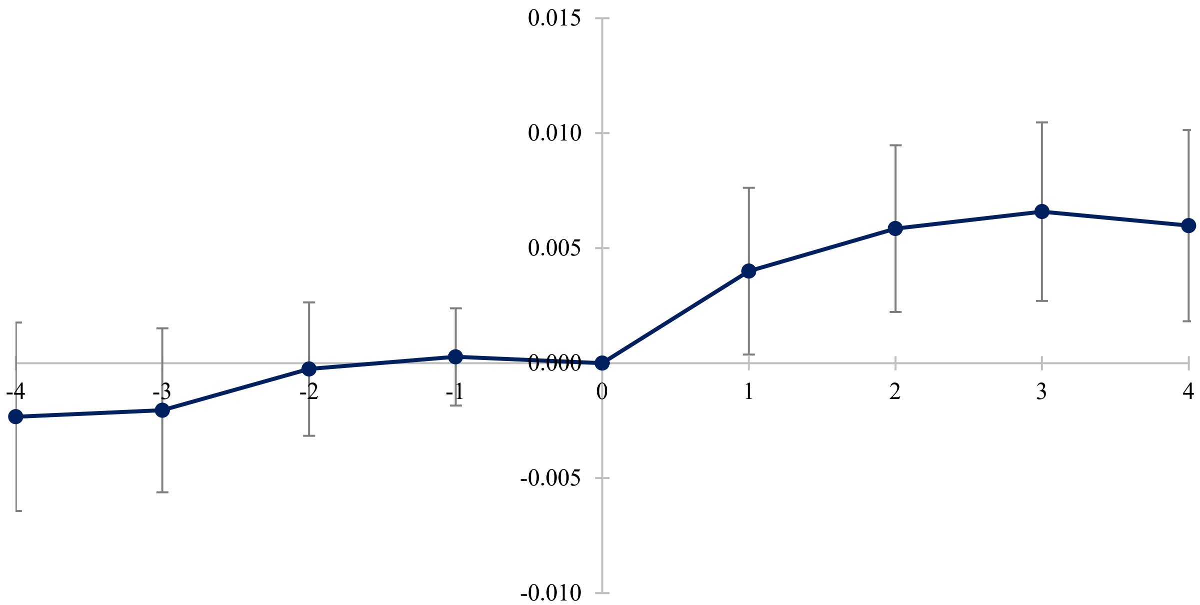


Figure 2. Temporal Effects of Related Artist Release on Focal Artist Spotify Performance.

The figure plots the estimated effect of related artist album release on Spotify listeners (Panel A), and Spotify popularity (Panel B) over the eight weeks pre- and post- related artist album release. The dots display coefficient estimates for the set of time trend dummies in the four weeks leading up to and after a related artist album release. The gray lines represent 95% confidence intervals for each coefficient estimate. The x-axis at $t = 0$ represents the week prior to related artist album release. The relative time effects are calculated using this week as a baseline. The results underlying this figure are displayed in *Appendix Table A1*.

Panel A. Spotify Listeners.



Panel B. Spotify Popularity.

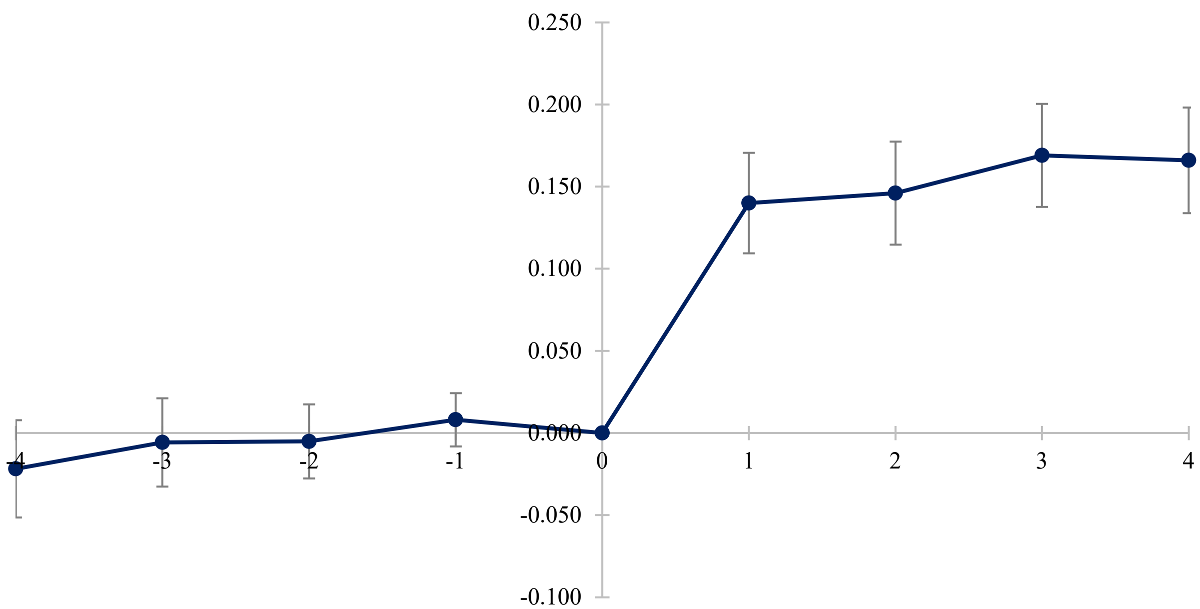


Figure 3. Effects of Related Artist Release by Related Artist Popularity.

The figure plots the estimated effect of related artist album release on Spotify listeners and Spotify popularity in the month following related artist album release. The columns display coefficient estimates for each dependent variable and the gray lines represent 95% confidence intervals for each coefficient estimate. The results underlying this figure are displayed in Table 4.

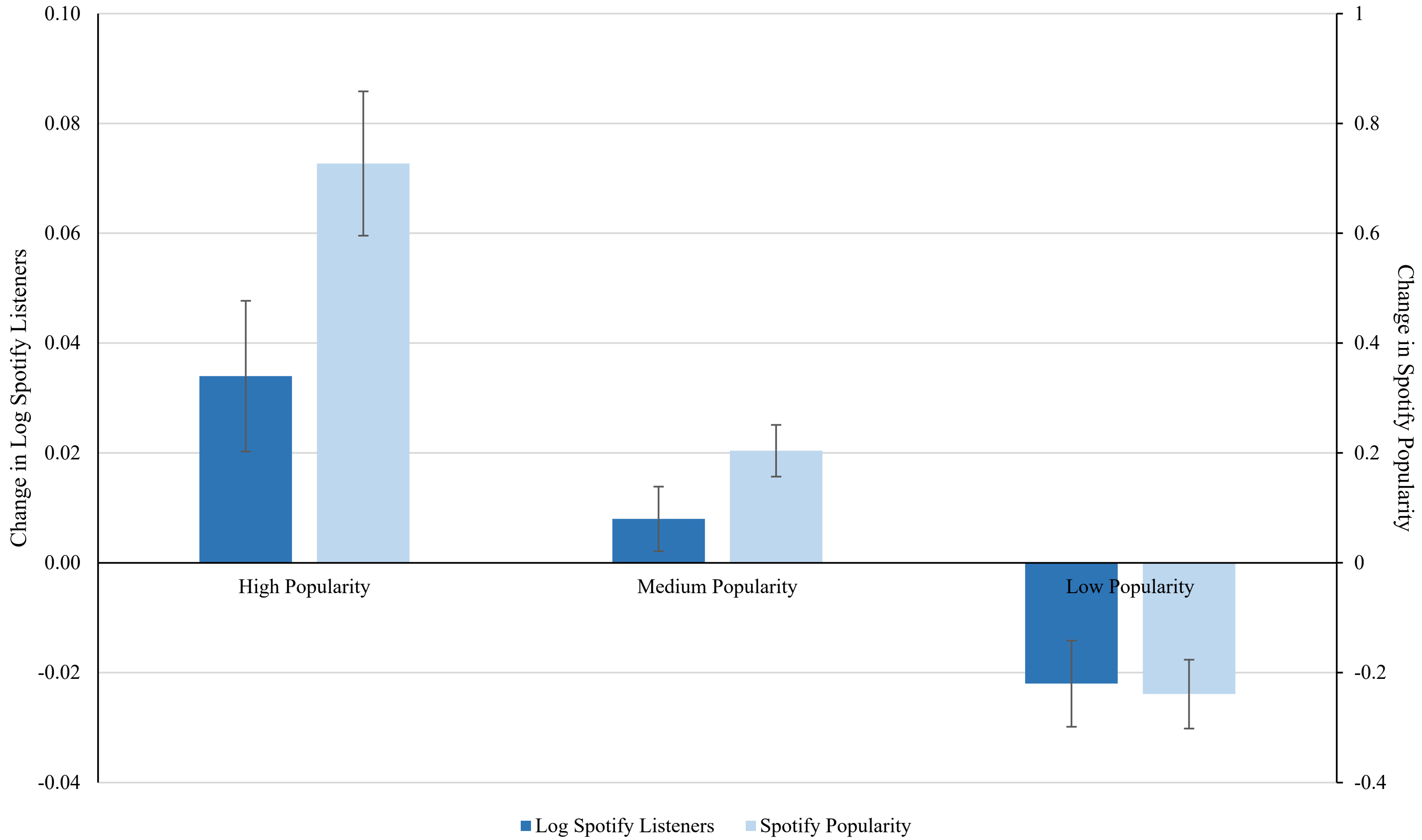


Figure 4. Effect of Related Artist Release on Spotify Popularity by Related and Focal Artist Popularity.

The figure plots the estimated effect of related artist album release on Spotify popularity in the month following related artist album release. The columns display coefficient estimates and the gray lines represent 95% confidence intervals for each coefficient estimate. The results underlying this figure are displayed in Table 5.

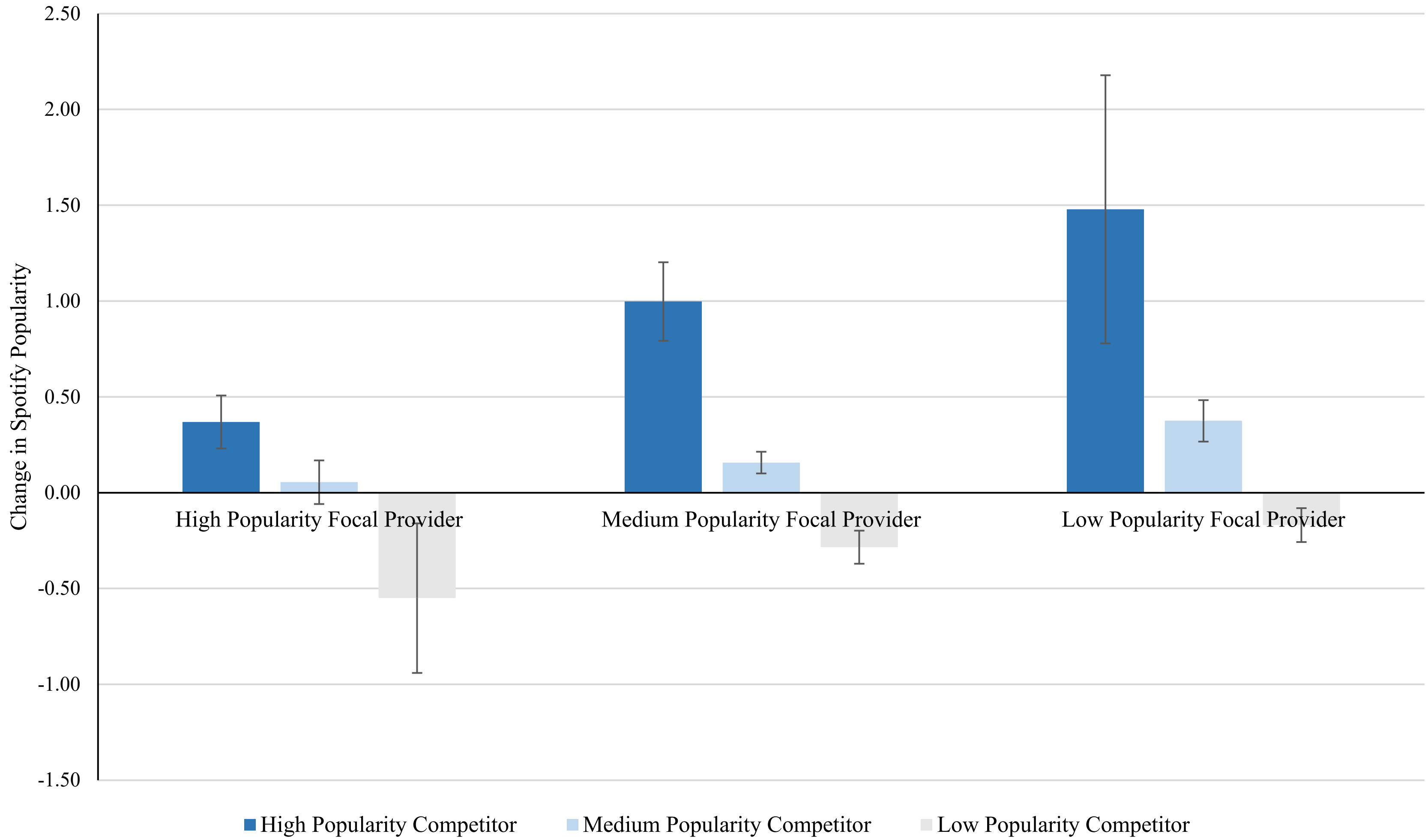


Figure 5. Effects of Focal and Related Artist Contemporaneous Album Release on Spotify Performance.

The figure plots the estimated marginal effect of an album release contemporaneous with an album release by a high, medium, or low popularity competitor on Spotify listeners and Spotify popularity. The columns display coefficient estimates for each dependent variable and the gray lines represent 95% confidence intervals for each coefficient estimate. The results underlying this figure are displayed in Table 10.

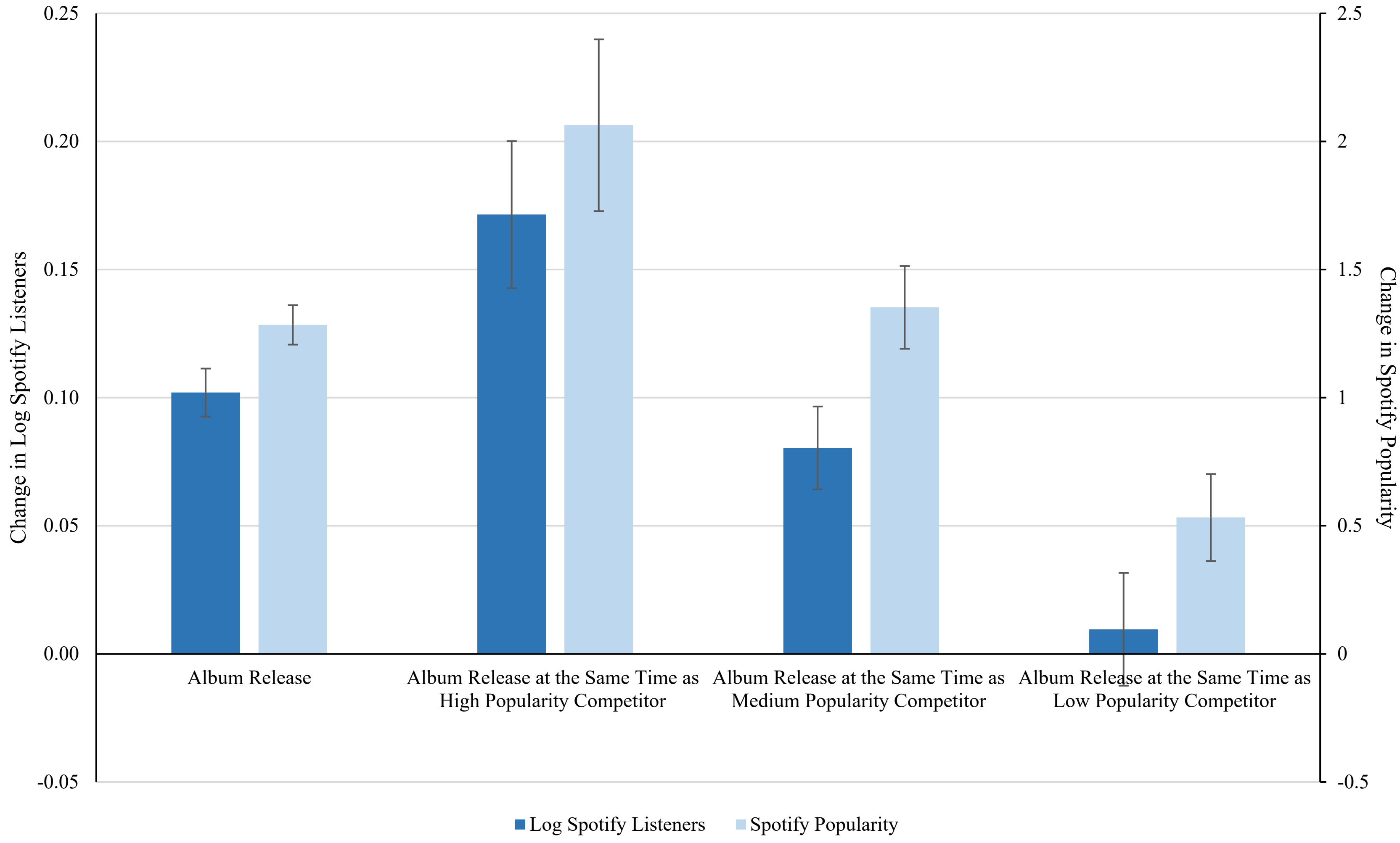


Table 1. Summary Statistics.

The table reports summary statistics for the artists in our sample. Data on age, employment, and sales are acquired through Chartmetric and cover the time period from March 23, 2016 to September 30, 2019.

Number of Artists		9,997
Panel A. Focal and Related Artist Releases		
Focal Artist Releases Album in the Last Month	mean	4.0%
	st.dev.	19.7%
Focal Artist Releases Single in the Last Month	mean	14.9%
	st.dev.	35.6%
Focal Artist Appears on Album or Single in the Last Month	mean	23.1%
	st.dev.	42.2%
Focal Artist Releases Compilation in the Last Month	mean	0.2%
	st.dev.	4.8%
Related Artist Releases Album in the Last Month	mean	19.1%
	st.dev.	39.3%
Panel B. Spotify Performance Metrics		
Spotify Popularity	mean	57.4
	median	57.0
	st.dev.	11.1
Spotify Listeners (in thousands)	mean	1,706.9
	median	586.9
	st.dev.	3,787.4
Panel C. Other Platform Performance Metrics		
YouTube Subscribers (in thousands)	mean	535.3
	median	60.1
	st.dev.	2,165.7
YouTube Views (in tens of millions)	mean	16.7
	median	1.3
	st.dev.	81.0

Table 2. Effect of Related Artist Release on Focal Artist Spotify Performance.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. In Column 3, I replicate Column 2 with the inclusion of a control for count of unique Spotify listeners. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity
Related Artist Released Album	0.007***	0.113***
	(0.002)	(0.016)
Log Spotify Listeners	0.094***	1.224***
	(0.004)	(0.036)
Focal Artist Released Album	0.094***	1.224***
	(0.004)	(0.036)
Focal Artist Released Single	0.059***	0.600***
	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.393***
	(0.002)	(0.024)
Focal Artist Released Compilation	-0.032	0.315**
	(0.031)	(0.143)
Artist Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	3,797,397	7,960,102
R-squared	95.2%	91.0%

Table 3. Effect of Related Artist Release on Focal Artist Spotify Performance by Focal Artist Popularity.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify considering the average popularity of the focal artist. High Popularity focal artists are those with an average Spotify popularity in the sample greater than or equal to 70, Medium Popularity focal artists have an average Spotify popularity in the sample greater than or equal to 55 and less than 70, and Low Popularity focal artists have an average Spotify popularity in the sample less than 55. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Spotify Listeners			Spotify Popularity		
	High Popularity Artists	Medium Popularity Artists	Low Popularity Artists	High Popularity Artists	Medium Popularity Artists	Low Popularity Artists
Related Artist Released Album	0.005	0.005***	0.007**	0.055*	0.037***	0.080***
	(0.003)	(0.002)	(0.003)	(0.029)	(0.012)	(0.022)
Focal Artist Released Album	0.086***	0.064***	0.067***	1.232***	0.806***	0.689***
	(0.007)	(0.004)	(0.010)	(0.054)	(0.028)	(0.058)
Focal Artist Released Single	0.042***	0.044***	0.059***	0.358***	0.267***	0.565***
	(0.004)	(0.002)	(0.005)	(0.038)	(0.018)	(0.038)
Focal Artist Appears on Album or Single	0.009**	0.008***	0.013***	0.297***	0.173***	0.189***
	(0.004)	(0.002)	(0.004)	(0.033)	(0.015)	(0.028)
Focal Artist Released Compilation	-0.001	-0.008	0.034	0.206**	0.178**	0.479
	(0.016)	(0.012)	(0.095)	(0.104)	(0.091)	(0.377)
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	535,333	1,842,792	1,419,208	1,026,921	3,734,180	3,198,900
R-squared	94.1%	92.9%	89.0%	87.5%	81.8%	80.9%

Table 4. Effect of Related Artist Release on Focal Artist Spotify Performance by Related Artist Popularity.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify considering the popularity of the related artist. High Popularity related artists are those with a Spotify popularity at time of release greater than or equal to 70, Medium Popularity related artists have a Spotify popularity at time of release greater than or equal to 55 and less than 70, and Low Popularity related artists have a Spotify popularity at time of release less than 55. Related artists for which daily popularity data is not collected are not included in this analysis. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity
High Popularity Related Artist Released Album	0.034***	0.727***
	(0.007)	(0.067)
Medium Popularity Related Artist Released Album	0.008***	0.204***
	(0.003)	(0.024)
Low Popularity Related Artist Released Album	-0.022***	-0.239***
	(0.004)	(0.032)
Focal Artist Released Album	0.094***	1.224***
	(0.004)	(0.036)
Focal Artist Released Single	0.059***	0.600***
	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.393***
	(0.002)	(0.024)
Focal Artist Released Compilation	-0.031	0.318**
	(0.031)	(0.142)
Artist Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	3,797,397	7,960,102
R-squared	95.2%	91.0%

Table 5. Effect of Related Artist Release on Focal Artist Spotify Performance by Focal and Related Artist Popularity

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify by focal and related artist popularity. High Popularity focal artists are those with an average Spotify popularity in the sample greater than or equal to 70, Medium Popularity focal artists have an average Spotify popularity in the sample greater than or equal to 55 and less than 70, and Low Popularity focal artists have an average Spotify popularity in the sample less than 55. High Popularity related artists are those with a Spotify popularity at time of release greater than or equal to 70, Medium Popularity related artists have a Spotify popularity at time of release greater than or equal to 55 and less than 70, and Low Popularity related artists have a Spotify popularity at time of release less than 55. Related artists for which daily popularity data is not collected are not included in this analysis. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Spotify Listeners			Spotify Popularity		
	High Popularity Artists	Medium Popularity Artists	Low Popularity Artists	High Popularity Artists	Medium Popularity Artists	Low Popularity Artists
High Popularity Related Artist Released Album	0.014**	0.046***	0.085**	0.369***	0.998***	1.479***
	(0.006)	(0.009)	(0.040)	(0.070)	(0.104)	(0.355)
Medium Popularity Related Artist Released Album	-0.009*	0.002	0.024***	0.055	0.157***	0.375***
	(0.005)	(0.003)	(0.007)	(0.058)	(0.029)	(0.055)
Low Popularity Related Artist Released Album	-0.020	-0.018***	-0.022***	-0.550***	-0.284***	-0.169***
	(0.013)	(0.004)	(0.005)	(0.198)	(0.044)	(0.045)
Focal Artist Released Album	0.109***	0.091***	0.094***	1.480***	1.222***	1.140***
	(0.008)	(0.005)	(0.009)	(0.087)	(0.047)	(0.065)
Focal Artist Released Single	0.051***	0.053***	0.073***	0.678***	0.477***	0.750***
	(0.006)	(0.003)	(0.006)	(0.070)	(0.037)	(0.051)
Focal Artist Appears on Album or Single	0.018***	0.014***	0.027***	0.565***	0.378***	0.365***
	(0.004)	(0.003)	(0.005)	(0.066)	(0.032)	(0.043)
Focal Artist Released Compilation	0.008	-0.019	-0.074	0.319*	0.314**	0.314
	(0.015)	(0.014)	(0.101)	(0.163)	(0.126)	(0.383)
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	429,057	1,785,267	1,583,070	852,641	3,707,128	3,400,326
R-squared	93.4%	89.3%	84.4%	77.5%	70.3%	74.7%

Table 6. Effect of Related Artist Release on Focal Artist Spotify Performance Controlling for Unique Listeners.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify controlling for the count of unique listeners on Spotify. This analysis is analogous to that contained in Table 2, Column 2 and Table 4, Column 2, except that it controls the count of Spotify listeners. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Spotify Popularity	(2) Spotify Popularity
Related Artist Released Album	0.003	
	(0.007)	
High Popularity Related Artist Released Album		0.077***
		(0.028)
Medium Popularity Related Artist Released Album		0.019*
		(0.010)
Low Popularity Related Artist Released Album		-0.059***
		(0.016)
Log Spotify Listeners	5.763***	5.762***
	(0.206)	(0.206)
Focal Artist Released Album	0.561***	0.561***
	(0.026)	(0.026)
Focal Artist Released Single	0.000	0.000
	(0.014)	(0.014)
Focal Artist Appears on Album or Single	0.112***	0.112***
	(0.009)	(0.009)
Focal Artist Released Compilation	0.012	0.014
	(0.061)	(0.061)
Artist Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	3,821,566	3,821,566
R-squared	98.8%	98.8%

Table 7. Effect of Top Ten Artist Release on Focal Artist Spotify Performance.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by any of the top ten artists in the sample by average Spotify popularity affects other artist's performance on Spotify. The effect is estimated as the interaction between an indicator that takes the value of 1 for non-top ten artists and an indicator that takes the value of 1 in the thirty days following a release by a top ten artist. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity
Top 10 Artist Released Album x Not Top 10 Artist	-0.037	0.103
	(0.032)	(0.177)
Focal Artist Released Album	0.094***	1.229***
	(0.004)	(0.036)
Focal Artist Released Single	0.059***	0.600***
	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.395***
	(0.002)	(0.024)
Focal Artist Released Compilation	-0.031	0.318**
	(0.031)	(0.143)
Artist Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	3,797,397	7,960,102
R-squared	95.2%	91.0%

Table 8. Effect of Reciprocal and Non-Reciprocal Related Artist Release on Focal Artist Spotify Performance.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. This analysis separately considers releases by "reciprocal" and "non-reciprocal" related artists. A reciprocal related artist is a related artist that both appears as a related artist for the focal artist, and also includes the focal artist among its list of top twenty related artists. A non-reciprocal related artist is listed as a related artist for the focal artist but does not contain the focal artist among its list of top twenty related artists. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reciprocal		Non-Reciprocal		Reciprocal		Non-Reciprocal	
	Log Spotify Listeners	Log Spotify Listeners	Log Spotify Listeners	Log Spotify Listeners	Spotify Popularity	Spotify Popularity	Spotify Popularity	Spotify Popularity
Related Artist Released Album	0.004*		0.008***		0.109***		0.110***	
	(0.002)		(0.002)		(0.022)		(0.021)	
High Popularity Related Artist Released Album		0.037***		0.034***		0.794***		0.544***
		(0.007)		(0.012)		(0.079)		(0.103)
Medium Popularity Related Artist Released Album		0.009***		0.005		0.252***		0.081**
		(0.003)		(0.005)		(0.028)		(0.041)
Low Popularity Related Artist Released Album		-0.023***		-0.021***		-0.216***		-0.292***
		(0.004)		(0.007)		(0.037)		(0.052)
Focal Artist Released Album	0.094***	0.094***	0.094***	0.094***	1.225***	1.224***	1.226***	1.228***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.036)	(0.036)	(0.036)	(0.036)
Focal Artist Released Single	0.059***	0.059***	0.059***	0.059***	0.600***	0.600***	0.600***	0.600***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.028)	(0.028)	(0.028)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.017***	0.017***	0.017***	0.394***	0.394***	0.394***	0.395***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.024)	(0.024)	(0.024)	(0.024)
Focal Artist Released Compilation	-0.031	-0.031	-0.032	-0.031	0.319**	0.316**	0.316**	0.318**
	(0.031)	(0.031)	(0.031)	(0.031)	(0.143)	(0.142)	(0.143)	(0.143)
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,797,397	3,797,397	3,797,397	3,797,397	7,960,102	7,960,102	7,960,102	7,960,102
R-squared	95.2%	95.2%	95.2%	95.2%	91.0%	91.0%	91.0%	91.0%

Table 9. Effect of Related Artist Sudden Death on Focal Artist Spotify Performance.

The table reports the results of estimating a modified version of equation (1) to examine how the death of a related artist affects the performance of a focal artist on Spotify. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated and if the focal artist experienced sudden death during the time period. The matched sample is constructed using a coarsened exact matching procedure described in the draft. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Full Sample (Excluding Sudden Deaths)		Matched Sample	
	Log Spotify Listeners	Spotify Popularity	Log Spotify Listeners	Spotify Popularity
Related Artist Death	0.022	0.439***	0.014	0.286***
	(0.015)	(0.126)	(0.010)	(0.110)
Focal Artist Released Album	0.094***	1.229***	0.125***	1.293***
	(0.004)	(0.036)	(0.012)	(0.116)
Focal Artist Released Single	0.060***	0.601***	0.050***	0.340***
	(0.003)	(0.028)	(0.008)	(0.091)
Focal Artist Appears on Album or Single	0.017***	0.396***	0.007	0.154***
	(0.002)	(0.024)	(0.007)	(0.058)
Focal Artist Released Compilation	-0.031	0.319**	-0.050**	0.305
	(0.031)	(0.143)	(0.023)	(0.254)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,779,378	7,921,723	1,133,369	2,388,814
R-squared	95.2%	91.0%	97.9%	95.3%

Table 10. Effect of Related Artist Sudden Death on Focal Artist Spotify Performance by Related Artist Popularity.

The table reports the results of estimating a modified version of equation (1) to examine how the death of a related artist affects the performance of a focal artist on Spotify considering the popularity of the related artist. High Popularity and Medium Popularity related artists are those with a Spotify popularity at time of release greater than or equal to 55 and less than 70, and Low Popularity related artists have a Spotify popularity at time of release less than 55. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated and if the focal artist experienced sudden death during the time period. The matched sample is constructed using a coarsened exact matching procedure described in the draft. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Full Sample (Excluding Sudden Deaths)		Matched Sample	
	Log Spotify Listeners	Spotify Popularity	Log Spotify Listeners	Spotify Popularity
High or Medium Popularity Related Artist Death	0.044**	0.671***	0.015	0.300*
	(0.017)	(0.188)	(0.016)	(0.167)
Low Popularity Related Artist Death	0.013	0.212	0.009	0.156
	(0.027)	(0.139)	(0.014)	(0.105)
Focal Artist Released Album	0.094***	1.229***	0.125***	1.293***
	(0.004)	(0.036)	(0.012)	(0.116)
Focal Artist Released Single	0.060***	0.601***	0.050***	0.340***
	(0.003)	(0.028)	(0.008)	(0.091)
Focal Artist Appears on Album or Single	0.017***	0.396***	0.007	0.154***
	(0.002)	(0.024)	(0.007)	(0.058)
Focal Artist Released Compilation	-0.031	0.319**	-0.050**	0.305
	(0.031)	(0.143)	(0.023)	(0.254)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,779,378	7,921,723	1,133,369	2,388,814
R-squared	95.2%	91.0%	97.9%	95.3%

Table 11. Effect of Related Artist Sudden Death on Focal Artist Spotify Performance Controlling for Count of Spotify Listeners.

The table reports the results of estimating a modified version of equation (1) to examine how the death of a related artist affects the performance of a focal artist on Spotify. This analysis is equivalent to the analysis conducted in Columns 2 and 4 of Tables 9 and 10 with the inclusion of a control for the log count of Spotify listeners. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Full Sample (Excluding Sudden Deaths)		Matched Sample	
	Spotify Popularity	Spotify Popularity	Spotify Popularity	Spotify Popularity
Related Artist Death	0.191**		0.161**	
	(0.091)		(0.077)	
High or Medium Popularity Related Artist Death		0.211**		0.100
		(0.096)		(0.075)
Low Popularity Related Artist Death		0.225		0.216
		(0.192)		(0.244)
Log Spotify Listeners	5.761***	5.761***	6.201***	6.202***
	(0.206)	(0.206)	(0.200)	(0.200)
Focal Artist Released Album	0.563***	0.563***	0.613***	0.612***
	(0.026)	(0.026)	(0.072)	(0.072)
Focal Artist Released Single	0.000	0.000	-0.102**	-0.102**
	(0.014)	(0.014)	(0.046)	(0.046)
Focal Artist Appears on Album or Single	0.112***	0.112***	0.006	0.006
	(0.009)	(0.009)	(0.040)	(0.040)
Focal Artist Released Compilation	0.012	0.012	0.163	0.163
	(0.061)	(0.061)	(0.105)	(0.105)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,803,426	3,803,426	1,140,163	1,140,163
R-squared	98.8%	98.8%	99.4%	99.4%

Table 12. Effects of Focal and Related Artist Contemporaneous Album Release on Focal Artist Spotify Performance.

The table reports the results of estimating a modified version equation (1) to examine how the effect of a release of an album by an artist is moderated by whether or not the release is contemporaneous with an album release by a high, medium, or low popularity related artist. High Popularity related artists are those with a Spotify popularity at time of release greater than or equal to 70, Medium Popularity related artists have a Spotify popularity at time of release greater than or equal to 55 and less than 70, and Low Popularity related artists have a Spotify popularity at time of release less than 55. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for all focal artist releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity	(3) Log Spotify Listeners	(4) Spotify Popularity
Focal Artist Released Album	0.104***	1.295***	0.102***	1.284***
	(0.005)	(0.041)	(0.005)	(0.039)
Related Artist Released Album	0.008***	0.124***		
	(0.002)	(0.017)		
High Popularity Related Artist Released Album			0.031***	0.722***
			(0.007)	(0.067)
Medium Popularity Related Artist Released Album			0.010***	0.212***
			(0.003)	(0.024)
Low Popularity Related Artist Released Album			-0.017***	-0.205***
			(0.004)	(0.033)
Focal Artist Released Album and…				
Related Artist Released Album	-0.030***	-0.231***		
	(0.007)	(0.063)		
High Popularity Related Artist Released Album			0.039***	0.058
			(0.015)	(0.167)
Medium Popularity Related Artist Released Album			-0.032***	-0.143*
			(0.009)	(0.085)
Low Popularity Related Artist Released Album			-0.075***	-0.547***
			(0.011)	(0.091)
Focal Artist Released Single	0.059***	0.600***	0.059***	0.600***
	(0.003)	(0.028)	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.393***	0.017***	0.393***
	(0.002)	(0.024)	(0.002)	(0.024)
Focal Artist Released Compilation	-0.031	0.316**	-0.030	0.318**
	(0.031)	(0.143)	(0.031)	(0.142)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,797,397	7,960,102	3,797,397	7,960,102
R-squared	95.2%	91.0%	95.2%	91.0%

Table 13. Effect of Related Artist Release on Focal Artist Performance on YouTube Controlling for Focal and Related Artist Activity on YouTube.

The table reports the results of estimating a modified version equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on other digital platforms. The dependent measures considered is YouTube views. Data on artist performance, related artists, and release dates come from Chartmetric. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In addition, all columns control for whether the focal and related artists have released videos on YouTube in the last month. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log YouTube Channel Views	(2) Log YouTube Channel Views	(3) Log YouTube Channel Views
Related Artist Released Album	0.011***		
	(0.004)		
High Popularity Related Artist Released Album		0.043***	-0.015
		(0.012)	(0.015)
Medium Popularity Related Artist Released Album		0.009	0.009
		(0.006)	(0.009)
Low Popularity Related Artist Released Album		-0.013	0.008
		(0.008)	(0.010)
Log Spotify Listeners			0.165***
			(0.031)
Focal Artist Released YouTube Video	0.016***	0.016***	0.045***
	(0.006)	(0.006)	(0.008)
Related Artist Released YouTube Video	0.011*	0.011*	0.001
	(0.006)	(0.006)	(0.009)
Artist Release Controls	Yes	Yes	Yes
Artist Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	3,824,821	3,880,972	3,824,821
R-squared	96.0%	94.8%	96.0%

Appendix

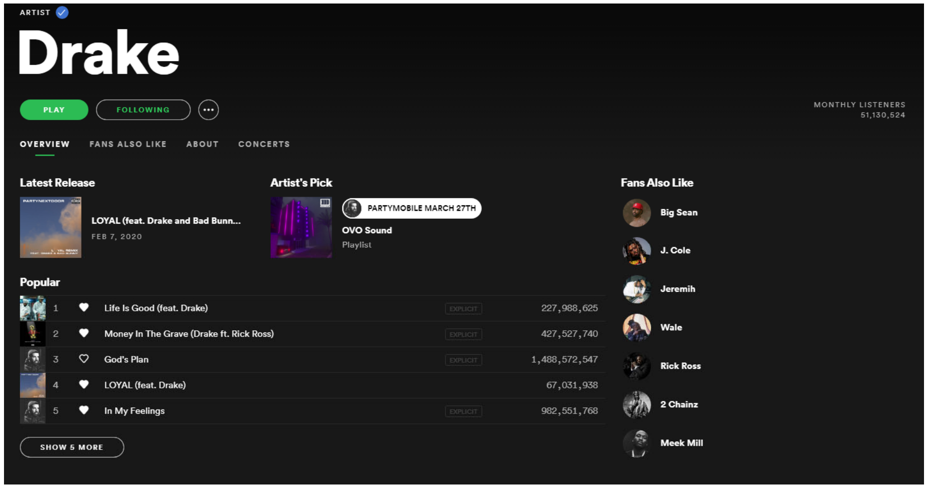
Friends in High Places: Indirect Network Effects and Competition on Platform Markets

Contents:

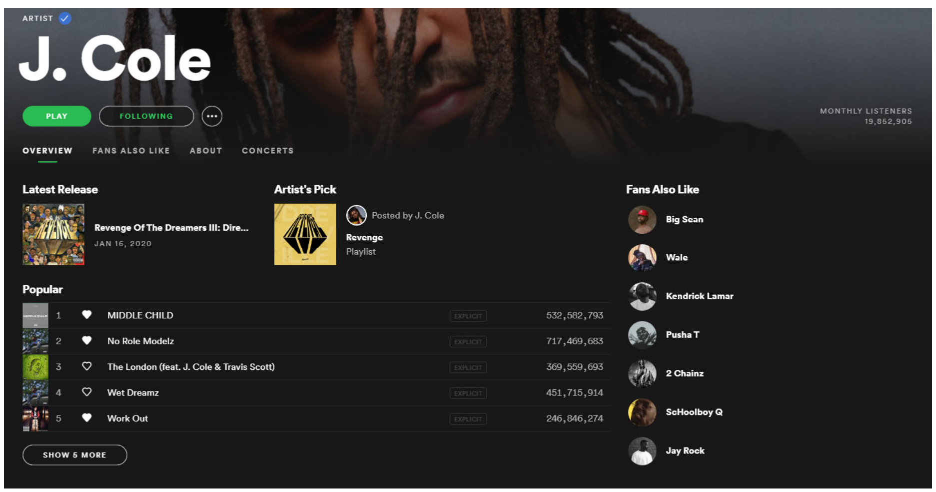
Appendix Figure A1. Example of a Non-Reciprocal Relationship.

This figure displays an example of a non-reciprocal relationship using the artists Drake and J. Cole. While J. Cole is listed as one of Drake's related artists, Drake is not listed among the set of J. Cole's related artists.

Panel A. Drake's Artist Profile



Panel B. J. Cole's Artist Profile



Appendix Table A1. Effect of Related Artist Release on Focal Artist Spotify Performance Over Time.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. In this specification, the indicator variable for related artist release is replaced with a series of indicators that designate the weeks pre- and post-the related artist album release. The week prior to related artist album release is considered the base week and is the excluded group. In cases where multiple related artists release within a two-month timespan, resulting in a date being both within eight weeks prior to and after a release, the date is included in the post period since it is considered treated. Results only display four weeks before or after release (longer time spans show insignificant trends). This model also controls for focal artist releases and artist and date fixed effects (not displayed in table). Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity
Eight Weeks Before Related Artist Album Release	0.001	-0.032
	(0.003)	(0.020)
Seven Weeks Before Related Artist Album Release	-0.001	-0.018
	(0.003)	(0.018)
Six Weeks Before Related Artist Album Release	-0.002	-0.003
	(0.002)	(0.017)
Five Weeks Before Related Artist Album Release	-0.002	-0.022
	(0.002)	(0.015)
Four Weeks Before Related Artist Album Release	-0.002	-0.006
	(0.002)	(0.014)
Three Weeks Before Related Artist Album Release	0.000	-0.005
	(0.001)	(0.012)
Two Weeks Before Related Artist Album Release	0.000	0.008
	(0.001)	(0.008)
The Week of Related Artist Album Release	0.004**	0.140***
	(0.002)	(0.016)
One Week After Related Artist Album Release	0.006***	0.146***
	(0.002)	(0.016)
Two Weeks After Related Artist Album Release	0.007***	0.169***
	(0.002)	(0.016)
Three Weeks After Related Artist Album Release	0.005**	0.166***
	(0.002)	(0.016)
Four Weeks After Related Artist Album Release	0.004*	0.173***
	(0.002)	(0.017)
Five Weeks After Related Artist Album Release	0.002	0.176***
	(0.002)	(0.017)
Six Weeks After Related Artist Album Release	0.002	0.184***
	(0.002)	(0.017)
Seven Weeks After Related Artist Album Release	0.003	0.187***
	(0.002)	(0.017)
Observations	1,809,764	3,756,281
R-squared	0.956	0.917

Appendix Table A2. Effect of Focal Artist Sudden Death on Focal Artist Spotify Performance.

The table reports the results of estimating a modified version of equation (1) to examine how the death of an artist affects the artist's performance on Spotify. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Spotify Popularity
Focal Artist Death	0.305***	3.870***
	(0.058)	(0.516)
Focal Artist Released Album	0.094***	1.229***
	(0.004)	(0.036)
Focal Artist Released Single	0.059***	0.600***
	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.395***
	(0.002)	(0.024)
Focal Artist Released Compilation	-0.031	0.318**
	(0.031)	(0.143)
Artist Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	3,797,397	7,960,102
R-squared	95.2%	91.0%

Appendix Table A3. Effect of Related Artist Release on Focal Artist Spotify Performance by Related Artist Popularity by Genre.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify considering the popularity of the related artist. This analysis is analogous to that contained in Table 5 except it is conducted across subsamples based on focal artist genre. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A. Spotify Listeners.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log Spotify Listeners	Rock	Pop	Electronic	Hip Hop & R&B	Country & Folk	Classical
High Popularity Related Artist Released Album	0.018***	0.024***	0.022	0.026**	0.018	0.044***
	(0.007)	(0.008)	(0.024)	(0.011)	(0.011)	(0.017)
Medium Popularity Related Artist Released Album	0.009***	0.011***	0.001	-0.002	0.014***	0.014*
	(0.003)	(0.004)	(0.008)	(0.005)	(0.005)	(0.008)
Low Popularity Related Artist Released Album	-0.013***	-0.022***	0.008	-0.032***	-0.032***	-0.020***
	(0.004)	(0.006)	(0.013)	(0.007)	(0.007)	(0.007)
Focal Artist Release Controls	Yes	Yes	Yes	Yes	Yes	Yes
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,217,955	1,802,271	202,692	961,827	411,338	262,819
R-squared	97.6%	95.4%	97.4%	95.7%	97.4%	97.0%

Panel B. Spotify Popularity.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Spotify Popularity	Rock	Pop	Electronic	Hip Hop & R&B	Country & Folk	Classical
High Popularity Related Artist Released Album	0.172***	0.569***	0.141	0.650***	0.328***	0.358***
	(0.058)	(0.087)	(0.174)	(0.103)	(0.110)	(0.119)
Medium Popularity Related Artist Released Album	0.082***	0.194***	0.025	0.312***	0.137***	0.074
	(0.026)	(0.033)	(0.071)	(0.050)	(0.046)	(0.053)
Low Popularity Related Artist Released Album	-0.095***	-0.215***	-0.068	-0.352***	-0.191***	-0.122**
	(0.032)	(0.052)	(0.115)	(0.079)	(0.051)	(0.050)
Focal Artist Release Controls	Yes	Yes	Yes	Yes	Yes	Yes
Artist Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592,709	3,793,385	417,930	1,990,881	873,850	571,070
R-squared	94.7%	92.4%	93.6%	89.5%	95.0%	95.9%

Appendix Table A4. Effect of Related Artist Release on Focal Artist Spotify Performance with Artist-Specific Time Trends.

The table reports the results of estimating a modified version of equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. This analysis is equivalent to those in Table 2 and Table 4 with the addition of artist-specific time trends. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Log Spotify Listeners	(3) Spotify Popularity	(4) Spotify Popularity
Related Artist Released Album	0.004***		0.062***	
	(0.001)		(0.013)	
High Popularity Related Artist Released Album		0.011**		0.601***
		(0.005)		(0.045)
Medium Popularity Related Artist Released Album		0.005**		0.237***
		(0.002)		(0.020)
Low Popularity Related Artist Released Album		-0.002		-0.338***
		(0.002)		(0.025)
Focal Artist Released Album	0.083***	0.084***	1.147***	1.145***
	(0.003)	(0.003)	(0.033)	(0.033)
Focal Artist Released Single	0.041***	0.041***	0.347***	0.347***
	(0.002)	(0.002)	(0.019)	(0.019)
Focal Artist Appears on Album or Single	0.011***	0.011***	0.351***	0.350***
	(0.001)	(0.001)	(0.017)	(0.017)
Focal Artist Released Compilation	-0.001	-0.001	0.230	0.232*
	(0.025)	(0.025)	(0.141)	(0.141)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Artist-Specific Time Trends	Yes	Yes	Yes	Yes
Observations	3,797,397	3,797,397	7,960,103	7,960,103
R-squared	97.8%	97.8%	93.9%	93.9%

Appendix Table A5. Effect of Related Artist Release on Focal Artist Spotify Performance Two Weeks or Two Months After Release.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. This analysis is equivalent to that in Table 2 except that it considers the effect of related artist release on focal artist performance in the two week or two-month window after album release rather than one-month window used in the main analysis. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Two Week Window		Two Month Window	
	Log Spotify Listeners	Spotify Popularity	Log Spotify Listeners	Spotify Popularity
Related Artist Released Album	0.006***	0.087***	0.007***	0.151***
	(0.002)	(0.015)	(0.002)	(0.019)
Focal Artist Released Album	0.067***	0.860***	0.098***	1.400***
	(0.004)	(0.035)	(0.004)	(0.037)
Focal Artist Released Single	0.024***	0.316***	0.091***	0.924***
	(0.002)	(0.026)	(0.003)	(0.031)
Focal Artist Appears on Album or Single	0.011***	0.277***	0.023***	0.518***
	(0.002)	(0.022)	(0.003)	(0.028)
Focal Artist Released Compilation	-0.029	0.309**	-0.028	0.307**
	(0.025)	(0.139)	(0.029)	(0.148)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,797,397	7,960,102	3,797,397	7,960,102
R-squared	95.2%	90.9%	95.3%	91.1%

Appendix Table A6. Effect of Related Artist Release on Focal Artist Spotify Performance for Top Five or Top Ten Related Artists.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. This analysis is equivalent to that in Table 2 except that it considers the effect of related artist release for the top five or top ten artists on Spotify's "Fans Also Like" category instead of the top seven artists used in the main analysis. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the five artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Top Five Related Artists		Top Ten Related Artists	
	Log Spotify Listeners	Spotify Popularity	Log Spotify Listeners	Spotify Popularity
Related Artist Released Album	0.006***	0.113***	0.006***	0.125***
	(0.002)	(0.018)	(0.002)	(0.015)
Focal Artist Released Album	0.094***	1.224***	0.094***	1.223***
	(0.004)	(0.036)	(0.004)	(0.036)
Focal Artist Released Single	0.059***	0.600***	0.059***	0.600***
	(0.003)	(0.028)	(0.003)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.393***	0.017***	0.392***
	(0.002)	(0.024)	(0.002)	(0.024)
Focal Artist Released Compilation	-0.032	0.316**	-0.032	0.314**
	(0.031)	(0.143)	(0.031)	(0.143)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,797,397	7,960,102	3,797,397	7,960,102
R-squared	95.2%	91.0%	95.2%	91.0%

Appendix Table A7. Effect of Related Artist Single Release on Focal Artist Spotify Performance.

The table reports the results of estimating equation (1) to examine how the release of an album by a related artist affects the performance of a focal artist on Spotify. Data on artist performance, related artists, and release dates come from Chartmetric and covers the time period from March 23, 2016 to September 30, 2019. All columns control for a focal artist's releases on a platform and include date and artist fixed effects. In this specification, the set of related artists are the seven artists that are the most similar to the focal artist according to Spotify's "Fans Also Like" categorization. For all album or track release variables, an artist is considered treated if the release occurred in the last thirty days. Observations are excluded in cases when the dependent variable is interpolated. Heteroskedasticity consistent standard errors clustered at the artist level are shown in parentheses underneath the coefficient estimates. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Log Spotify Listeners	(2) Log Spotify Listeners	(3) Spotify Popularity	(4) Spotify Popularity
Related Artist Released Album	0.005***		0.195***	
	(0.002)		(0.017)	
High Popularity Related Artist Released Album		0.051***		0.968***
		(0.008)		(0.072)
Medium Popularity Related Artist Released Album		0.014***		0.400***
		(0.003)		(0.028)
Low Popularity Related Artist Released Album		-0.034***		-0.332***
		(0.004)		(0.031)
Focal Artist Released Album	0.094***	0.094***	1.228***	1.227***
	(0.004)	(0.004)	(0.036)	(0.036)
Focal Artist Released Single	0.059***	0.059***	0.596***	0.589***
	(0.003)	(0.003)	(0.028)	(0.028)
Focal Artist Appears on Album or Single	0.017***	0.017***	0.392***	0.393***
	(0.002)	(0.002)	(0.024)	(0.024)
Focal Artist Released Compilation	-0.032	-0.030	0.316**	0.314**
	(0.031)	(0.031)	(0.143)	(0.143)
Artist Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,797,397	3,797,397	7,960,102	7,960,102
R-squared	95.2%	95.2%	91.0%	91.0%