Marketing Letters (2018) 29:485–499
https://doi.org/10.1007/s11002-018-9476-3

The *featuring* phenomenon in music: how combining artists of different genres increases a song's popularity

Andrea Ordanini[1] **· Joseph C. Nunes**[2] **· Anastasia Nanni**[1]

Published online: 17 December 2018

Abstract

The appearance of songs including *featured* artists on Billboard's Hot 100 music charts has increased exponentially in the past two decades. This particular type of creative collaboration involves one artist integrating another artist's contribution, either instrumentally or vocally, into their work and publicizing it with a "featuring" credit. According to broad literature in sociology on categorical boundaries, artists who deviate from existing genres are expected to be penalized for violating collective expectations and norms. We find songs *featuring* other artists actually have a greater likelihood of making it into the top 10 than songs not featuring other artists. Additionally, consistent with theorizing about congruency in the co-branding literature, we observe that the greater the difference (cultural distance) between the genres of the artists involved, the more likely the song is to reach the top of the charts. We argue that by combining the expertise of specialists in each genre, as well as comingling audiences while still maintaining each collaborator's original positioning, artists who feature artists from other genres are able to produce more successful songs.

Keywords Music · Genre · Category boundaries · Hot 100 · Featuring · Artist · Co-branding

Andrea Ordanini is a BNP Paribas Professor of Marketing and Service Analytics at Bocconi University. Joseph C. Nunes is a holder of the Joseph A. DeBell Endowed Professorship in Business Administration and Professor of Marketing at University of Southern California. Anastasia Nanni is Ph.D. student in Marketing at Bocconi University.

✉ Andrea Ordanini
andrea.ordanini@unibocconi.it

Joseph C. Nunes
jnunes@marshall.usc.edu

Anastasia Nanni
anastasia.nanni@unibocconi.it

1 Bocconi University, Via Rontgen 1, 20136 Milan, Italy

2 Marshall School of Business, HOH 604, University of Southern California, 3670 Trousdale Pkwy, Los Angeles, CA 90089-0443, USA

1 Introduction

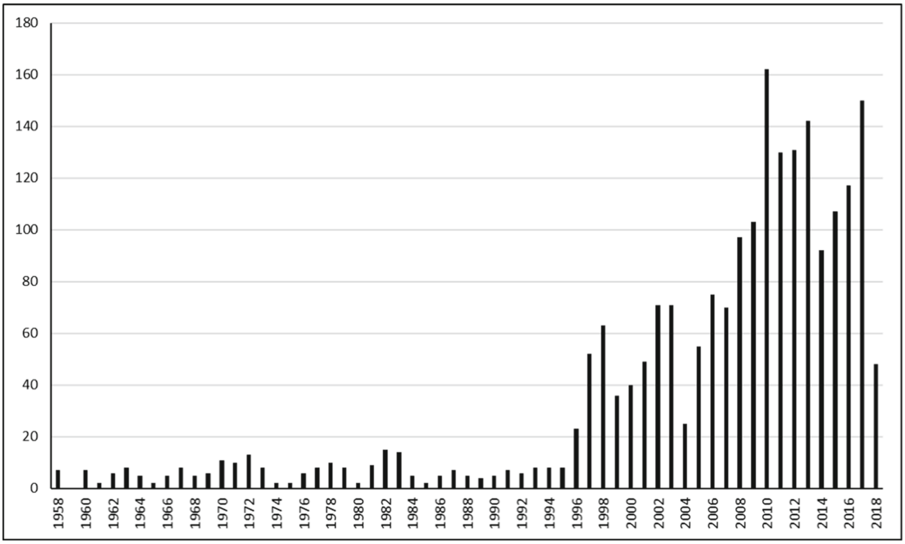
The appearance of songs on the music charts *featuring* other artists has increased exponentially in the past two decades (see Fig. 1). This particular type of creative collaboration involves one artist integrating another artist's contribution, either instrumentally or vocally, into their work and publicizing it with a "*featuring*" credit (e.g., "The Motto" by Drake featuring Lil Wayne). Performers who appear on Billboard's *Hot 100* as featured artists also frequently appear as solo artists (e.g., "How to Love" by Lil Wayne) and host artists who feature other artists (e.g., "Mirror" by Lil Wayne featuring Bruno Mars).[1] In other words, a *featuring* collaboration reflects a deliberate decision by two artists to combine their talents to create a conspicuously hybridized product.

Historically, the use of the word "featuring" started becoming common in the 1980s as a result of the collaborative nature of the hip-hop culture (Rose 1994). For years, songs featuring other artists rarely made it into the mainstream, that is, until July 1990 when "She Ain't Worth It," a song by pop artist Glenn Medeiros featuring Bobbie Brown rapping climbed to no. 1 on Billboard's *Hot 100* music chart. This combination of pop and rap reportedly established the commercial potency of creative collaborations *across* genres in an industry accustomed to marketing products *within* genre (Molanphy 2015). By 1996, the use of the word "featuring" to market creative collaborations in the music industry—both *across* and *within* genres—had skyrocketed.

Yet collaborations *across* versus *within* genres are fundamentally different. When collaborations stay within a genre (e.g., "No Love" by Eminem featuring Lil Wayne), the song is more likely to conform to conventional genre codes (e.g., hip-hop/rap). When genres are crossed ("The Monster" by Eminem featuring Rihanna), categorical boundaries are traversed as the final product combines elements characteristic of different genres (Goldberg et al. 2016; Hannan 2010; Murray 2010). According to a broad literature in sociology on categorical boundaries, artists who deviate from existing genres are expected to be penalized for violating collective expectations and category norms (Hannan 2010; Kovács and Hannan 2015; Mattsson et al. 2010).

In this manuscript, we investigate whether artists' collaborations *across* versus *within* genre systematically lead to different levels of success. We do so within the music industry, which is big business and attracts millions of customers every year (Ward et al. 2014), by examining the *featuring* phenomenon's effect on how songs perform on the charts. While a burgeoning literature on "multiple category membership" suggests transgressing categorical boundaries results in negative consequences (for a review, see Hannan 2010), based on work on co-branding, we take an opposing view. We predict specific factors associated with featuring collaborations can facilitate the success of songs combining artists from different genres, helping them outperform songs featuring collaborations within a single genre. First, for featuring collaborations, there are at least two distinct producers (artists) who combine their respective expertise. Much of the prior work on crossing genre boundaries has focused on a single producer (artist) attempting to span genres. As composite concepts, *featuring* collaborations may be

[1] As of February 2017, Lil Wayne had accumulated the most Billboard *Hot 100* appearances among solo artists, appearing 86 times as a featured artist, and 47 times alone or featuring another artist. Drake had appeared 50 times as a featured artist and 82 times alone or featuring another artist. Of course, some artists' appearances are more skewed; Ray Charles appeared on the charts 74 times, but only two times as a featured artist. In contrast, 31 of T-Pain's 46 appearances on the *Hot 100* have been as a featured artist.



Note: Data for 2018 runs only through April 21.

Fig. 1 Number of songs with featuring credits on Billboard's *Hot 100* by year

viewed and valued as a combined set of interrelated competencies (Murphy 1988), much like co-branded innovations (Park et al. 1996).

Second, a featuring collaboration is typically short term (often a single song—83% of songs with featured artists since 1996 are unique combinations of artists). This allows each artist to maintain his or her own positioning within their respective genre. Hence, artists can leverage their distinct brands to entice audiences with less risk of diluting their own brand. By bringing together omnivores (Peterson 1992), those who like variety and listen to different genres of music, and loyalists, those dedicated to one or the other genre, hybrid songs can increase the potential audience size significantly. They should help make *featuring* collaborations more successful.

In terms of success, we rely on a song's overall popularity, reflected by its performance on the music charts. Specifically, we focus on entering the top 10 of Billboard's *Hot 100* as an indicator of extraordinary success. Previous literature has established that the commercial success of songs on the *Hot 100* is not linear; the distribution is highly skewed and follows a J-shaped "power law-like" curve such that it drops steeply after the 10th position (Haampland 2017; Hesbacher et al. 1982). While top 10 songs on the charts are different in terms of their success, we utilize alternative and complementary measures of chart success and the results replicate.

Critically, when featuring collaborations include artists from different genres, we do not consider all outcomes the same. Instead, we take into account the degree of difference or "distance" between the artists' genres. For example, hip-hop/rap is typically considered a genre that is closer to R&B/soul than country (Lena and Peterson 2008). Hence, a rapper featuring an R&B singer ("Dilemma" by Nelly featuring Kelly Rowland) is qualitatively different than a rapper featuring a country artist (e.g., "Over and Over" by Nelly featuring Tim McGraw). This allows us to determine whether the "type" of genre spanning artists engage in, based on the distance between genres, matters.

2 Literature review

2.1 Co-branding and brand alliances

Co-branding, also referred to as brand alliance, is the public pairing of two or more independent brands (e.g., the Citibank AAdvantage card). Co-branding leverages the strength of a collaboration whenever the positive associations of the partner (constituent) brands transfer to the newly formed co-brand (composite brand). Washburn et al. (2000) find empirical support for the benefit of co-branding; consumers rated co-branded products more positively than either individual brand regardless of whether the original brands were perceived as having high or low brand equity. The fundamental belief is that "… because brand names are valuable assets, they may be combined with other brand names to form a synergistic alliance in which the sum is greater than the parts" (Rao and Ruekert 1994, 87). Purely, from a brand signaling perspective, two brand names may provide greater assurance of product quality than one alone (Wernerfelt 1988).

2.1.1 Ingredient branding

A related stream of research looks at ingredient branding in which one or more key attributes of one brand are incorporated into another brand (e.g., Ben and Jerry's Heath Bar Crunch ice cream). Much of this work (see Park et al. 1996) has focused on combining the attributes of a brand in one category (Godiva's chocolate taste) with attributes of a brand in another category (Slim Fast diet aid's calories) to offer a new product in yet another category (cake mix). Work by Desai and Keller (2002), however, examines what happens when an established ingredient brand is brought into the host brand's category. They find that when a new, dissimilar attribute is introduced (e.g., Dayquil cough relief liquid introduced in Life Savers candy), a co-branded ingredient leads to more favorable evaluations. A featuring collaboration is likely to be considered an example of ingredient branding when the output from the artists are highly integrated and perceived as functioning together; although, it might be considered an example of component branding when each artist's contribution is distinguishable and perceived as separable by consumers (Newmeyer et al. 2018). In either event, the literature on co-branding and branding alliances suggests collaborating brands are set up for success, particularly when from dissimilar categories. Yet not all co-branded collaborations are created equal and issues of congruency matter.

2.1.2 Brand congruency

Research by Lanseng and Olsen (2012) finds brand concept consistency is important in consumers' evaluations of brand alliances, and extra mental effort is required when finding the fit between brands focused on experiences. Especially relevant is work by Walchli (2007) that finds moderately incongruent brand pairs (specifically, Business Week/The Wall Street Journal for a new publication) can have significant upside potential compared to highly congruent (Business Week/Fortune) and highly incongruent (Business Week/People) brand pairs. These findings suggest that as incongruity (genre distance) increases up to a point, collaborations across brands (artists) are likely to be more successful. This leads to the first hypothesis tested in this research, which posits a positive, nonmonotonic (concave) effect of distance on chart success:

> H1: As genre distance (incongruence) between the host and featured artist increases, the likelihood of making the top 10 (success of the collaboration) will increase, albeit at a decreasing rate

2.2 Category (genre) boundary strength

Research in sociology explains the labeling of popular music by genre as an "aesthetic classification system" that attempts to categorize "the way that the work of artists is divided up both in the heads and habits of consumers" (DiMaggio 1987, 441). In other words, genre functions as shorthand for a collection of conventions. An audience member is likely to categorize artists based on observing some minimum set of core features, what Hannan et al. (2007) label the "test code" for membership. When collaborating across genres, artists "contest genre specific codes and audience expectations by introducing stylistic and other elements that deviate from existing, normative styles and forms" (Mattsson et al. 2010, 1356).

2.2.1 Fuzzy versus crisp boundaries

The relative willingness of a genre's adherents to accept deviations is commonly referred to as *boundary strength*. Adherents to genres with stronger boundaries penalize deviations more than genres with weaker boundaries (Negro et al. 2011). Deviations become more acceptable as boundaries become *fuzzier*, and genre as a signaling device grows increasingly unimportant to audiences. The boundary strength for pop music, for example, is known for being particularly weak, such that, compared to other genres, fans are far more tolerant of artists who deviate from norms (Lena and Peterson 2008). In contrast, rap and hip-hop is known for having much stronger, or *crisp*, boundaries (Negus 1998). Further, research by van Venrooij (2009) finds pop–rock is one of the most general labels for songs while hip-hop/rap and R&B/soul occupy a much more "niche aesthetic space." Expected differences in boundary strength leads to the second hypothesis tested in this research.

> H2: The positive effect of genre distance (incongruence) between the host and featured artist will be moderated by the boundary strength of the host's genre

3 Data and measures

3.1 Data collection

Our analysis is based on data from Billboard's *Hot 100* music charts. Billboard is the preeminent source for assessing which songs of any genre are the most popular in the marketplace at any point in time (Bradlow and Fader 2001). The original data were downloaded from the Ultimate Music Database (*umdbmusic.com*) and were supplemented and validated using other sources (e.g., iTunes, Wikipedia). The data include all 1909 songs with a *featured* artist that appeared on the *Hot 100* between January 1, 1996 and April 21, 2018. We chose January 1, 1996 as the starting date because this was when songs featuring other artists began appearing on the chart regularly (i.e., exceeding 5% of yearly entries). To avoid right censoring issues in the analysis, we only consider songs no longer on the chart during the last week of this time frame.

Every song in our sample has at least one host and one guest, the most frequent configuration by far (78.8% of songs). However, not every song has just one host and just one guest. Of the 1909 songs in our sample, 1875 songs have one host, 31 have two hosts, and three have three hosts. In terms of guests, 1532 songs have one guest, 280 songs have two guests, 66 songs have three guests, 25 songs have four guests, five songs have five guests, and one song has six guests. Whenever more than one artist (host or guest) were present, genre was determined by whichever artist was credited first.

3.2 Dependent variables

The primary dependent variable in our analysis is *Top10*, a dichotomous measure that takes the value "1" if the song entered the top 10 positions on the *Hot 100* and "0" otherwise. Recall song performance declines steeply until the 10th position, diminishing smoothly afterwards from the 11th position onward (Hesbacher et al. 1982; Haampland 2017). Compared to alternative measures of success, using entry into the top 10 in the presence of such a skewed distribution helps alleviate sample selection issues introduced by considering only those songs that entered the chart. We check the robustness of results using a variety of alternative metrics intended to capture the intensity of chart success, including *Top40*, *Peak Rank*, *Entry Rank*, as well as complementary measures of popularity, such as *Stay* on the chart, the number of weeks a song remained on the *Hot 100* regardless of its position.

3.2.1 Collaboration aids success

In our dataset, the average likelihood of entering the *top 10* by a song with a featured artist is 18.4%, significantly greater than the 13.9% likelihood for songs that do not include a featured artist (18.4% > 13.9%; $\chi^2_{(1)} = 24.1$; $p < .01$). By including a featured artist, within or across genres, a song is more likely to achieve extraordinary commercial success. The central question of this research, recall, is whether this kind of success (entering the top 10) depends on whether artists collaborate within genre or across genres.

Additionally, in our dataset, we observe a song featuring another artist will *Stay* on the *Hot 100* chart 13.3 weeks, on average, with a standard deviation of approximately 10 weeks. This is not significantly longer than songs without featured artists, which stay an average of 13.4 weeks. While simply including a featured artist does not extend a song's time on the *Hot 100* significantly, we are interested in whether the specific type of featuring collaboration does.

3.3 Independent variable—genre distance

The primary independent variable in our analysis is *Distance*, a variable that reflects the extent to which a featuring act represents a boundary spanning cultural phenomenon

(Goldberg et al. 2016). This measure operates at the genre level and captures the extent to which artists who collaborate on featuring songs belong to closer versus more distant genres. We collected information about musical genres of the artists using classifications provided by Apple's iTunes application.

The *Distance* measure we constructed is an established metric used widely throughout the sociological literature on consumption (Hannan 2010; Kovács and Hannan 2015) and popular in the broader literature on network analysis (Hanneman and Riddle 2005; Crandall et al. 2008). We built it as follows. If the genre of the host (featuring) artist and the guest (featured) artist are the same, the distance is 0. If the genres differ, we calculate the distance using a modified version of Jaccard's similarity categorization measure, which assumes a negative exponential relationship between similarity and distance (Shepard 1987). Specifically, Jaccard's similarity measure is the ratio of the number of times two different specific categories (two genres) are both present to the number of times either one or the other is present alone. In our case, for each specific pair of genres (e.g., hip-hop/rap and R&B/soul), the numerator reflects the total number of songs in which either the host (guest) belongs to one genre and the guest (host) belongs to the other genre. The denominator reflects the number of songs within each genre in which the host and guest belong to the same genre. The ratio therefore reflects the extent to which two genres co-occur in featuring collaborations. Formally, the similarity measure D between genres a and b is calculated as follows:

$$D(a,b) = -\left[\ln\frac{|a\cap b|}{|a\cup b|}\right] \div \gamma$$

Taking a value of 0.5 for the γ parameter according to the Shepard's law (Goldberg et al. 2016), the distance measure has a mean of 1.2 in our population with a standard deviation of 1.6. Figure 2 shows the calculated *Distance* for each pair of genres as well as the frequency of those pairings in the data. Rock and dance, along with hip-hop/rap and R&B/soul,[2] emerge as the two pairs of closest genres (although they differ widely in frequency). Country and hip-hop/rap, along with Latin and hip-hop/rap, emerge as the two pairs of most distant genres. Hip-hop/rap and R&B/soul, along with hip-hop/rap and pop, were the two most frequent collaborations in the data by far and are not as distant as dance and hip-hop/rap or rock and hip-hop/rap.

Note the order of genres in pairs in Fig. 2 is irrelevant; the labels do not specify which genre is the host versus the guest, but only that there is a collaboration across the two genres. It is important to reemphasize that measuring distance using collaboration co-occurrence is an established approach to measuring the similarity/distance in cultural goods (Bourdieu 1993) and artistic classification systems (DiMaggio 1987). Moreover, our Jaccard scores based on co-occurrence portray a picture of genre distance that is similar to those obtained using other criteria such as instrumentation, technique, mentality/ideology, sound, place, and/or time (see MusicMap.info, a website devoted to providing a genealogy of popular music genres). This provides reassurance regarding the credibility of our measurement instrument.

[2] On iTunes, hip-hop/rap form a single genre as do R&B/soul.

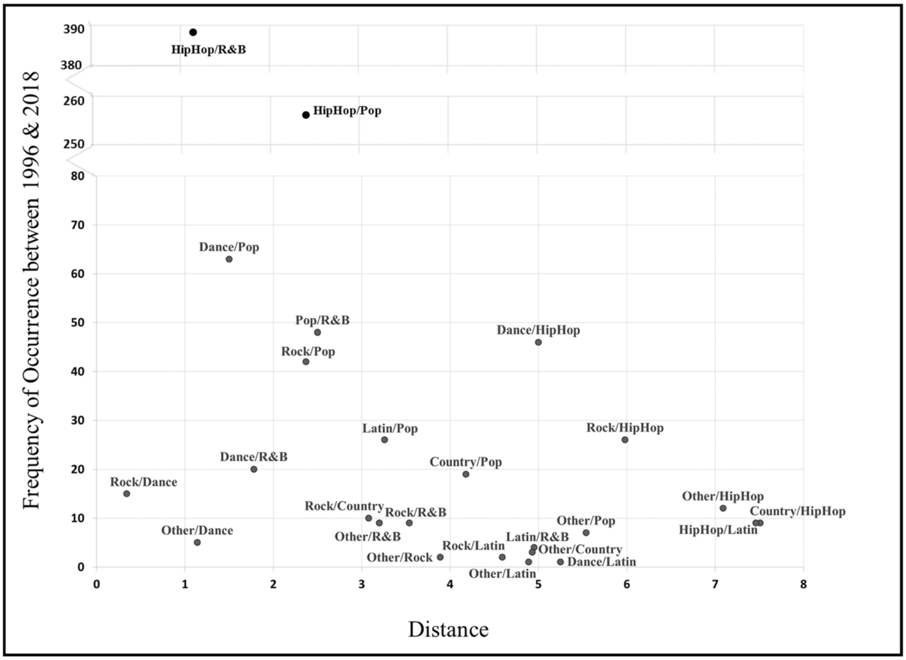


Fig. 2 Frequency of featuring collaborations based on distance between genres

3.4 Potential moderator—genre

In addition to our distance measure, we include *Genre* of the host, because it can affect chart performance (Askin and Mauskapf 2017), but, more importantly, as stated in Hypothesis 2, it is expected to moderate the effect of distance. In other words, the same distance between genres can be more (less) acceptable to audiences depending on whether the host's genre has weak (fuzzy) versus strong (crisp) boundaries (Hannan et al. 2007). The relative frequency of the genres of the host artists, collected using classifications provided by Apple's iTunes application, is unsurprising, with hip-hop/rap (54%), pop (19%), and R&B/soul (12%) being those most commonly involved in featuring collaborations.

3.5 Other covariates

Another variable likely to affect success on the charts and thus our dependent variable is the *Past Popularity* of the artists involved in the collaboration (Bradlow and Fader 2001). This variable, included as a covariate, is calculated by computing the sum of the number of times each artist involved (hosts and guests) reached the top 10 prior to the collaboration in question. Given these appearances preceded the collaboration in question, this variable is considered exogenous. Further, given the large number of zeroes and its right skewed distribution (skew = 1.7), we recoded the original *Past Popularity* variable creating an ordinal measure with three levels: 0 = no prior success (45%), 1 = average number of prior top 10 hits is less than five (44%), and 2 = average number of prior top 10 hits is greater than five (11%).

Given their potential impact on chart performance, we also collected information about the *Gender* of the artists and their *Nature*, whether the artists involved in the featuring collaboration were a soloist or a group (Bhattacharjee et al. 2007). These variables were not significant and thus omitted from the model.

4 Analysis

4.1 Probit model

Given the binary nature of *Top10* as our focal dependent variable, we began by estimating a Probit model with *Distance* as the focal predictor variable. We include *Distance* as in both linear and quadratic terms to allow us to investigate potential boundary effects as anticipated in Hypothesis 1. As covariates, we include *Past Popularity* and *Genre* of the host artist and also include yearly fixed effects to capture any extraordinary events that might have occurred during the time span of our dataset. Finally, because some artists appear more than once, we cluster the standard errors at the artist level.

5 Results

The results of the Probit model are presented in Table 1. The area under the ROC curve is 0.71, and the Hosmer and Lemenshow test ($\chi^2_{(8)} = 14.0$; $p > .05$) suggests the model fit is acceptable. More importantly, a Wald test indicates that the inclusion of the focal independent variable *Distance* provides a tangible improvement in the fit of the model ($\chi^2_{(2)} = 13.2$; $p < .01$). In other words, compared to a situation in which host and guest artists belong to the same genre (i.e., *Distance* = 0), some degree of distance (crossing genres) is always preferred by consumers.

5.1 Greater distance leads to greater success

The predicted probability of entering the *Top10*, fixing all of the covariates at their mean levels, is 13% when *Distance* is 0 and goes up to 19% for levels of *Distance* near the mean (1.25), which is the typical distance for songs featuring artists straddling hip-hop/rap and R&B/soul, as well as hip-hop/rap and pop. For levels of *Distance* that are twice the average value, which is more in line with songs featuring artists straddling pop and R&B/soul, the predicted probability of entering the top 10 climbs to 22%, lending support to Hypothesis 1.

5.2 The effect is curvilinear

Based on the regression parameters, we observe that *Distance* is positively related to the chance of entering the top 10 positions of the chart, but the effect diminishes slightly at higher distance levels as indicated by a significant negative curvilinear effect. This means consumers appear to reward artists who cross genres (i.e., collaborations that are incongruent), but as the distance gets greater, the positive effect tends to

Table 1 Probit regression results

	Coefficient	Standard error***	z	$p > \|z\|$
Distance	0.22	0.07	3.33	0.00
Distance_sq	− 0.03	0.01	− 2.46	0.01
Past popularity*				
1–5	0.31	0.08	3.95	0.00
> 5	0.19	0.13	1.51	0.13
Genre**				
Rock and alternative	0.44	0.21	2.09	0.04
Country	− 0.46	0.28	− 1.64	0.10
Dance and electronic	0.45	0.18	2.54	0.01
Hip-hop/rap	0.05	0.12	0.41	0.69
Latino	− 0.12	0.38	− 0.31	0.76
Pop	0.40	0.13	2.99	0.00
Other	Empty for perfect separation			
Years	Fixed effect			
Constant	− 0.97	0.31	− 3.13	0.00

$N = 1890$; pseudo-$R^2 = 0.084$; Wald $\chi^2_{(32)} = 144.5$; $p > \chi^2 = 0.00$

*0 = reference category

**R&B/soul = reference category

***Adjusted for 1711 clusters in artist

diminish, lending support to Hypothesis 1. The curvilinear effect is represented in Fig. 3, which plots the marginal effects according to distance.

5.3 The effect of the host genre

In line with Hypothesis 2, the positive effect of *Distance* is indeed moderated by the *Genre* of the host artist ($\chi^2_{(5)} = 142.6$; $p < .01$). By testing for the marginal effects of *Distance* at the individual genre level, we observe the distance effect on chart success is positive and highly pronounced for dance ($b = 0.29$; $p < .05$), pop ($b = 0.25$; $p < .01$), and rock ($b = 0.15$; $p < .10$) host genres, while it becomes less pronounced for hip-hop/rap ($b = 0.06$; $p < .01$). In contrast, the effect is not significant for R&B/soul ($b = 0.12$; *ns*) and Latino ($b = 0.17$; *ns*) and turns out to be negative for country ($b = -0.14$; $p < .05$).[3] Interestingly, a country artist who decides to feature another artist seems to hurt a song's chances of entering the top 10.

These results suggest the effect of distance varies by musical genre. Consistent with Hypothesis 2, when the featuring collaboration involves hosts from a genre with "fuzzy" or porous boundaries (i.e., having weaker category norms, Hannan et al. 2007), such as dance, pop, and rock, the positive effect of distance on chart success becomes more pronounced. Once we turn to genres with

[3] We report the linear components for simplicity; note the curvatures are as expected.

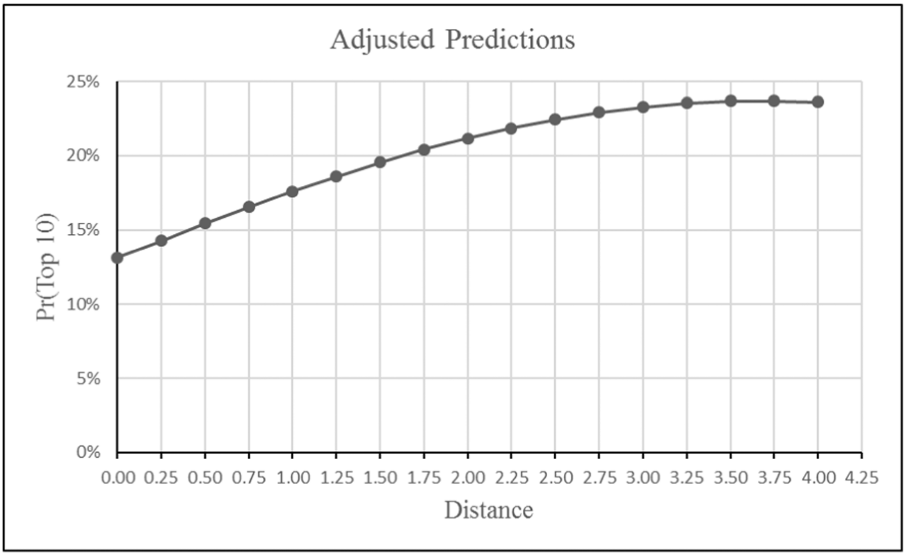


Fig. 3 Probability of entering the top 10 based on distance between genres

"crisper," or stronger category boundaries, such as country or hip-hop/rap, the effect of distance is attenuated or even reversed.

6 Robustness checks and extensions

6.1 Other measures of chart performance

While prior literature suggests the use of *Top10* as a binary variable appropriately captures success on the music chart (Haampland 2017), we replicate our estimation using *alternative* and *complementary* measures of performance. The first alternative measure we employ is the less stringent chance of entering the *top 40*, a cutoff that has represented a popularity threshold since emerging as a radio format in the 1950s. The results replicate; again, we observe a positive effect of *Distance* ($b = 0.12$; $p < .05$), as well as slight negative curvature ($b^2 = -0.02$; $p < .05$).

Next, we investigate the effect of distance on *Peak Rank*, an over-dispersed count variable reflecting the highest position attained by the song on the chart. Results from a negative binomial regression provide evidence that *Distance* positively (and linearly) affects chart performance ($b = 0.05$; $p < .05$). Finally, again using negative binomial regression, we tested whether *Distance* affects *Entry Rank*, an indicator of a song's popularity the first week it enters the *Hot 100*. In this case, the effect is directional without reaching statistical significance ($b = 0.01$; *ns*). Taken together, these analyses suggest the effect of *Distance* is robust across a variety of measures of success in terms of popularity on the charts.

A complementary measure of success is *Stay*, the number of weeks a song remains on the Hot 100, reflecting its sustainability in terms of chart success. Results from a negative binomial regression indicate that in terms of staying power, *Distance* again has a positive effect ($b = 0.09$), as well as slight negative curvature ($b^2 = -0.02$). When

Distance is 0, a featuring song stays on the chart for about 11.5 weeks. Then, as *Distance* reaches its mean level, average *Stay* increases by more than one week (12.9 weeks). This suggests *Distance* improves a featuring song's chart performance not only with respect to how high it climbs (intensity) but also with respect to how long it remains popular (sustainability).

6.2 Endogeneity threats

As a further robustness check, we examine the potential threat of endogeneity regarding our focal predictor, *Distance*. Endogeneity typically arises for one of three main reasons, simultaneity, measurement error, and omitted variables (Wooldridge 2010). First, we are confident simultaneity is not an issue as the decision to collaborate that gives rise to the *Distance* measure temporally precedes chart performance. Second, measurement error should not be an issue as *Distance* depends on a count of existing collaborations at the genre level and not self-reports. The only possible threat appears to come from omitted variables.

Recall that we include fixed effects of time and genre and a covariate for the artists' past popularity to help account for potential unobserved priors. In an additional effort to address the issue of endogeneity, we estimate an instrumental variable Probit model that includes linear and quadratic *Distance* terms as potentially endogenous predictors (Wooldridge 2010). Identification in this case requires at least two instruments. Our choice of instrumental variables was informed by prior research suggesting diversity in collaborations can affect creativity in different ways. On one hand, increasing diversity facilitates knowledge generation and therefore innovativeness; on the other hand, diversity makes coordination in the group more difficult, inhibiting innovative processes (Østergaard et al. 2011; Fernandes and Polzer 2015).

From the available set of covariates, we chose *Gender* of the host artist (mixed vs. male or female) and *Nature* of the guest artist (group vs. soloist) to reflect these two dimensions of diversity with opposite effects on creativity, which, in featuring, is reflected by the distance between artists involved in the collaboration. Accordingly, we expect that hosting a group (vs. a soloist) increases knowledge generation (Hülsheger et al. 2009), inspiring the host to seek greater distance across genres. On the negative side, a host comprised of mixed genders already provides substantial diversity (Bear and Woolley 2011), tempering any desire to further increase the distance between the host and guest artist.

Results from the instrumental variable model provide estimates consistent with those from the original model. Notably, the null hypothesis that *Distance* is exogenous cannot be rejected outright ($\chi^2_{(2)} = 6.0$; $p = .05$). While the proposed instruments for *Distance* and *Distance-squared* work in the expected direction, they are weak ($F = 10.2$ and $F = 7.1$, respectively). Faced with these results, and considering the limitations in terms of data available, we consider the original Probit model with fixed effects and covariates a good attempt in dealing with potential omitted variable bias (Rossi 2014).

7 Discussion

According to sociological work on cultural boundaries, a song that crosses genres should be at a disadvantage in terms of its reception from audiences (Hannan 2010). In contrast, work in marketing on co-branding suggests collaborations can benefit from incongruity (Walchli 2007). In this research, we find crossing categories by mixing genres has a significant positive effect in music. Songs that feature a guest artist from a different genre are more likely to enter the *top 10* of Billboard's *Hot 100*. More importantly, the greater the distance between the genres, the more likely the song is to achieve extraordinary success by making it into the *top 10*.

Why should *featuring* collaborations in music stand out? We believe these results can be justified by the circumstances; one artist *featuring* another artist's contribution is a distinct type of creative collaboration. Remember, the outcome of the featuring collaboration is between specialists from their respective genre. And, critically, both artists typically stay true to their form with the resulting song providing audiences less of a blend and more of a combination. Mariah Carey does not rap when featured by Jadakiss on "U Make Me Wanna." Rather, she croons like the R&B singer she is. Further, the featuring song is likely to attract Jadakiss fans, Mariah Carey fans, and fans of both, comingling loyalists as well as attracting those who already appreciate both artists.

Finally, we observe the effect of distance is not homogeneous across genres. It appears host artists from certain genres with what are considered weaker category boundaries can exploit the potential of a distant collaboration more easily than artists belonging to genres with stronger category boundaries. This means the benefits derived from a distant collaboration are not universal but depend on who is trying to exploit them. In this sense, it is not only "how far" you go that matters; rather, "where you start from" from also plays a role. Finally, knowing the distances between genres may change over time; future research may explore the dynamic effect of distance on success over time using a different approach.

7.1 Implications

While this work focuses on collaborations in music, we consider implications that extend outside of this domain. When brands (producers)—particularly in the arts—combine their creative and expressive expertise, they must be careful to communicate a few things to consumers. First, that each side plans on maintaining their positioning in their original area of expertise and that the collaboration is not a permanent future direction. Second, the combination is not a mish-mash, but the pieces or components combined are created by the appropriate party. In the case of featuring, one party (the host artist) takes primary responsibility for the outcome as well. Third, characteristics of those who implement the collaboration should be taken into consideration when evaluating the true potential of the joint offer; critically, belonging to a category with strong boundaries should preclude the search for distant partners.

In conclusion, we believe various institutions contribute to the compartmentalization of music, dividing artists into categories for their own purposes. Consider, for example, the National Academy of Recording Arts and Sciences, whose voting members have determined Grammy Award nominees and winners since its inception in 1958. They maintain very specific categories (genres) for the purpose of bestowing awards. But even the Academy recognizes the power of *featuring*. The practice has become so common that in 2002, the Academy began awarding a Grammy to the "Best Rap/Sung Collaboration" by artists who "do not normally perform together," further specifying that the "collaborative artist(s) should be recognized as a featured artist(s)." Recognizing cross-genre collaborations in this way shines a light on what appears to be an inevitable progression in creative collaboration that incorporates genre blending.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

Askin, N., & Mauskapf, M. (2017). What makes popular culture popular? Product features and optimal differentiation in music. *American Sociological Review, 82*(5), 910–944.

Bear, J. B., & Woolley, A. W. (2011). The role of gender in team collaboration and performance. *Interdisciplinary Science Reviews, 36*(2), 146–153.

Bhattacharjee, S., Gopal, R. D., Lertwachara, K., Marsden, J. R., & Telang, R. (2007). The effect of digital sharing technologies on music markets: a survival analysis of albums on ranking charts. *Management Science, 53*(9), 1359–1374.

Bourdieu, P. (1993). *The Field of Cultural Production: Essays on Art and Literature*. Cambridge, UK: Polity Press.

Bradlow, E. T., & Fader, P. S. (2001). A bayesian lifetime model for the "Hot 100" Billboard songs. *Journal of the American Statistical Association, 96*(454), 368–381.

Crandall, D., Cosley, D., Huttenlocher, D., Kleinberg, J., Suri, S. (2008). Feedback effects between similarity and social influence in online communities. Proceedings of the 14th ACM SIGKDD international conference on knowledge discovery and data mining, KDD '08 (pp. 160–168). New York: ACM.

Desai, K. K., & Keller, K. L. (2002). The effects of ingredient branding strategies on host brand extendibility. *Journal of Marketing, 66*, 73–96.

DiMaggio, P. (1987). Classification in art. *American Sociological Review, 52*(4), 440–455.

Fernandes, C.R., Polzer, J.T. (2015). Diversity in groups. In Scott, R., Kosslyn, S. (eds) *Emerging trends in the social and behavioral sciences*. New York: John Wiley & Sons.

Goldberg, A., Hannan, M. T., & Kovács, B. (2016). What does it mean to span cultural boundaries? Variety and atypicality in cultural consumption. *American Sociological Review, 81*(2), 215–241.

Haampland, O. (2017). Power laws and market shares: cumulative advantage and the Billboard Hot 100. *Journal of New Music Research, 46*(4), 356–380.

Hannan, M. T. (2010). Partiality of memberships in categories and audiences. *American Review of Sociology, 36*, 159–181.

Hannan, M. T., Pólos, L., & Carroll, G. R. (2007). *Logics of organization theory: audiences, codes, and ecologies*. Princeton: Princeton University Press.

Hanneman, R.A., Riddle, M. (2005). Introduction to social network methods (online at http://faculty.ucr.edu/~hanneman/nettext). Accessed 28 Jan 2018.

Hesbacher, P., Anderson, B., Snyderman, P., & Koppel, R. (1982). Record world and billboard charts compared: singles hits, 1970–1979. *Popular Music and Society, 8*, 101–112.

Hülsheger, U. R., Anderson, N., & Salgado, J. F. (2009). Team-level predictors of innovation at work: a comprehensive meta-analysis spanning three decades of research. *Journal of Applied Psychology, 94*(5), 1128–1145.

Kovács, B., & Hannan, M. T. (2015). The space of categories and the consequences of category spanning. *Sociological Science, 2*, 252–286.

Lanseng, E. J., & Olsen, L. E. (2012). Brand alliances: the role of brand concept consistency. *European Journal of Marketing, 46*(9), 1108–1126.

Lena, J. C., & Peterson, R. A. (2008). Classification as culture: types and trajectories of music genres. *American Sociological Review, 73*(5), 697–718.

Mattsson, J. T., Peltoniemi, M., & Parvinne, P. M. T. (2010). Genre-deviating artist entry: the role of authenticity and fuzziness. *Management Decision, 48*(9), 1355–1364.

Molanphy, C. (2015). Feat. don't fail me now: the rise of the featured rapper in pop music. Slate.com, Culturebox, Arts, Entertainment and More. Published July, 31, 2015 at http://www.slate.com/articles/arts/culturebox/2015/07/the_history_of_featured_rappers_and_other_featured_artists_in_pop_songs.html

Murphy, G. L. (1988). Comprehending complex concepts. *Cognitive Science, 12*(4), 529–562.

Murray, F. (2010). The oncomouse that roared: hybrid exchange strategies as a source of productive tension at the boundary of overlapping institutions. *American Journal of Sociology, 116*(2), 341–388.

Negro, G., Hannan, M. T., & Rao, H. (2011). Category reinterpretation and defection: modernism and tradition in Italian winemaking. *Organization Science, 22*(6), 1449–1463.

Negus, K. (1998). Cultural production and the corporation: musical genres and the strategic management of creativity in the US recording industry. *Media, Culture and Society, 20*(3), 359–379.

Newmeyer, C.E., Venkatesh, R., Ruth, J.A., Chatterjee, R. (2018). A typology of brand alliances and consumer awareness of brand alliance integration. *Marketing Letters, 29*(3), 275–289.

Østergaard, C. R., Timmermans, B., & Kristinsson, K. (2011). Does a different view create something new? The effect of employee diversity on innovation. *Research Policy, 40*, 500–509.

Park, C. W., Jun, S. Y., & Shocker, A. D. (1996). Composite branding alliances: an investigation of extension and feedback effects. *Journal of Marketing Research, 18*(2), 453–466.

Peterson, R. A. (1992). Understanding audience segmentation: from elite and mass to omnivore and univore. *Poetics, 21*, 243–258.

Rao, A. R., & Ruekert, R. W. (1994). Brand alliances as signals of product quality. *Sloan Management Review, 36*(2), 87–89.

Rose, T. (1994). *Black noise: rap music and black culture in contemporary America*. Hanover: University Press of New England.

Rossi, P. (2014). Even the rich can make themselves poor: a critical examination of the use of IV methods in marketing. *Marketing Science, 33*(5), 655–672.

Shepard, R.N. (1987). Toward a Universal Law of Generalization for Psychological Science. *Science, 237*(4820), 1317–1323.

van Venrooij, A. (2009). The aesthetic discourse space of popular music: 1985-86 and 2004-05. *Poetics, 37*, 315–332.

Walchli, S. B. (2007). The effects of between-partner congruity on consumer evaluation of co-branded products. *Psychology and Marketing, 24*(11), 947–973.

Ward, M. K., Goodman, J. K., & Irwin, J. R. (2014). The same old song: the power of familiarity in music choice. *Marketing Letters, 25*, 1–11.

Washburn, J. H., Till, B. D., & Priluck, R. (2000). Co-branding: brand equity and trial effects. *Journal of Consumer Marketing, 17*(7), 591–604.

Wernerfelt, B. (1988). Umbrella branding as a signal of new product quality: an example of signalling by posting a bond. *The Rand Journal of Economics, 19*(3), 458–466.

Wooldridge, J.M. (2010*). Econometric analysis of cross section and panel data*. 2nd edn. Cambridge, MA: MIT Press.