Embeddedness and the Production of Novelty in Music: A Multi-Dimensional Perspective

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ABSTRACT

Creativity and innovation are central to cultural production, but what makes certain producers more likely to innovate than others? We revisit the concept of embeddedness to evaluate how different dimensions of social structure affect the production of novelty in music. Using original data on over 10,000 unique artists and 115,000 songs recorded and released between 1960 and 1995, we estimate how musicians' social, cultural, organizational, and geographic embeddedness affects their propensity to create novel products. Results from a series of Relational Event Models (REM's) suggest that artists who are highly culturally and geographically connected are more likely to create novel songs, especially when they span multiple genres, are women, or are in the early stages of their careers. Surprisingly, variations in social and organizational embeddedness do not significantly influence this outcome. These findings produce new insights into the production of novelty in music, and encourage us to further examine the multiplexity of embeddedness and its role in organizing innovation.

Keywords: cultural production; embeddedness; innovation; music; networks

> "All music is collaboration. Even if you are a one-man band, writing and recording all the parts in your bedroom, you are collaborating with the ideas of your predecessors and your peers, both consciously and subconsciously..." (Matty Kuras, 2016)

INTRODUCTION

What makes certain actors more likely to produce novelty than others? While considerable research has been conducted on the successful diffusion of innovation and the link between innovation and performance, both for individuals (e.g., Uzzi et al. 2013) and organizations (e.g., Ahuja 2000; also see Berlyne 1971), less is known about the emergence of novelty itself, which serves as a critical first step in the process of innovation (Ruef 2002; Seidel and Greve 2016). Much of the established research on this topic focuses on how particular sets of economic actors are better able to innovate than others, highlighting individual creativity (Schumpeter 1942; Simonton 1984) or dynamic capabilities (Daneels 2002; Eisenhardt and Martin 2000). More recent scholarship, however, has emphasized the generative role of social structures in bringing about innovation, directing attention to the collaborative interactions in teams (Ruef 2010; Uzzi and Spiro 2005) and in social networks more generally (Burt 2004; Obstfeld 2005). The motivation and ability to create new things are shaped not only by individual characteristics, but by the connections between people and the relational structures in which they are embedded. Thus, we can understand the production of novelty as a process that is shaped by the social structures constituting organizations, institutions, and markets (Bourdieu 1993; Fligstein and Dauter 2007; White 1981, 2002).

Our goal in this paper is to revisit the concept of embeddedness to evaluate how different types of relationships between actors provide distinct resources—and generate distinct opportunities—for innovation. Empirical research on social networks has largely focused its attention on how direct and indirect social ties structure economic action (Burt 1992, 2005;

Granovetter 1985; Uzzi 1996, 1997), but we argue that there are other channels through which producers are consequentially connected and influenced. As the quote at the beginning of this paper suggests, the act of "collaboration" need not occur through direct contact or even conscious borrowing. Scholars have long recognized the multiplexity of networks (Emirbayer and Goodwin 1994; Pachucki and Breiger 2010; Padgett and Powell 2012; Zukin and DiMaggio 1990), yet our understanding of how different types of network embeddedness generate opportunities for innovation is limited.

Drawing on the production of culture perspective, the sociology of entrepreneurship, and the literature on social capital, we begin by developing a multi-dimensional framework to understand how cultural producers are embedded in their broader social environment. In our analyses, we measure and test the effect of four distinct types of embeddedness—social, cultural, organizational, and geographic—on the production of novelty in music. We are not the first to recognize multiple types of embeddedness and their roles in organizing social behavior (e.g., Zukin and DiMaggio 1990; Goldberg et al. 2016; Ruef 2002), but no one to our knowledge has generated a typology to understand how different dimensions of structural constraint independently shape innovation outcomes. To summarize: *social embeddedness* is defined by the system of collaborations between actors; *cultural embeddedness* is a function of an actor's position in a network defined by shared category membership; *organizational embeddedness* refers to an actor's connections with others through common organizational affiliation; and *geographic embeddedness* reflects a network position defined by physical proximity or co-location.[1] Note that, while social embeddedness assumes some kind of direct contact between

[1] It is worth pointing out that, unlike some previous treatments of cultural embeddedness (e.g., Goldberg et al. 2016; Ruef 2002), we view each of these dimensions as a type of "structural" embeddedness, in that they each reflect characteristics of the configuration of relations between actors. The distinction between dimensions is predicated on how the ties between actors are drawn, rather than the strength or weakness of the tie (see Moran 2005); or the more

actors, the other types define "relations" based on positional similarity or structural equivalence. Each of these dimensions generates a unique social structure that positions actors in different ways, shaping their propensity to create new products through channels that are not accounted for in current research.

To test whether and how these different dimensions of embeddedness shape the production of novelty, we use data on the global music industry, a context in which innovation is particularly important, but poorly understood (Negus 1992; Ratliff 2016). The dataset used for this analysis was constructed over the course of two years, and describes approximately10,000 unique artists and 115,000 songs recorded and released between 1960 and 1995. The scope and granularity of this data allow us to: 1) construct a measure of product novelty using algorithmically-derived features summarizing the sonic character of songs, and, and 2) calculate dynamic relational measures of artist embeddedness using information about band membership, genre attributions, record labels, and artist location. We then use these embeddedness measures, along with a host of artist-level attributes, to predict the relative "hazard" or likelihood of producing and releasing a novel song.

The rest of the paper is organized as follows. After providing an overview of the relevant theoretical and empirical research on the social origins of innovation, we unpack the concept of structural embeddedness. We then use extant theory to generate a series of hypotheses predicting how different types of producer embeddedness might affect the production of novelty. Most work in this area suggests that low levels of structural constraint provide advantages for the creation and performance of new ideas, products, and ventures (Burt 1992, 2004; de Vaan et al. 2015; Fleming, Mingo, and Chen 2007; Zaheer and Bell 2005). Yet while ample opportunities

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general cultural, organizational, or geographic context in which social networks exist (see Pachucki and Breiger 2010).

for brokerage may increase the likelihood for innovation, there is evidence suggesting that actors who are highly connected are more likely to create new products, due to increased levels of trust, legitimacy, and access to resources (Ahuja 2000). These findings typically focus on the *reception* of an innovation by a certain audience, and are thus most relevant in highly normative contexts (Cattani and Ferriani 2008; Rao et al. 2003; Walker, Kogut, and Shan 1997). In this paper, however, we argue that high levels of social connectedness in different contexts may also aid the production of novelty in music, where creativity and aesthetic innovation are core tenets of the organizational field (Becker 1982). Our findings partially support this prediction, suggesting that artists who are highly culturally and geographically embedded are in fact more likely to create novel products, especially when they span multiple genres. Variations in social and organizational embeddedness do not significantly affect this outcome. We conclude by elaborating on these results and by discussing their consequences for understanding how different types of embeddedness structure the "typology of the possible" to shape the production of novelty and innovation more generally (Padgett and Powell 2012: 3–4).

INNOVATION IN CULTURAL PRODUCTION

The "production of culture" perspective in sociology explicitly recognizes the integrated role of producers, institutions, and their environments in shaping symbolic and material culture (Hirsch 1972; Peterson 1990; Peterson and Anand 2004; Rubio 2012). The production of novelty is an important part of this process. For example, while Becker emphasizes the shared conventions that lend coherence to domains of cultural production, he also recognizes that "the limitations of conventional practice are not total. You can always do things differently if you are prepared to pay the price" (Becker 1982: 33). The "price" here refers to the possible costs associated with taking artistic risks and producing something that challenges the status quo, highlighting the performance implications of innovation in cultural markets. Relatedly, work on cultural entrepreneurship emphasizes the resources and strategies actors deploy to enhance the legitimacy of their new creations (Lounsbury and Glynn 2001). From this perspective, the production of novelty only becomes consequential when audiences recognize it as such (Burt 2004).

The study of innovation more generally has followed a similar trajectory, focusing largely on its adoption and diffusion rather than its emergence (Seidel and Greve 2016; for early exceptions see Ahuja 2000; Shan, Walker, and Kogut 1994). Indeed, most organizational research defines "innovation" as the successful adoption or valuation of some new product, practice, or venture (Damanpour 1991). In this paper, we focus instead on the process of emergence that leads to new and novel products. The production of novelty is an important first step in the innovation process, leading to new product lines, organizational forms, institutions, and markets (Padgett and Powell 2012). It also serves as an important signifier of creativity and competence in fields of cultural production, where "being innovative" is intrinsically valued by peer producers and critics. Consumers may be less inclined to value novelty for novelty's sake, but moderate levels of atypicality can help producers differentiate themselves from their competition and provide significant ecological advantages (Askin and Mauskapf 2016; Ruef 2000; Uzzi et al. 2013).

Extant research on the origins of innovation in organizations and markets highlights the role played by individual characteristics, group dynamics, and institutional environments. In the context of individuals, Dyer and colleagues argue that the ability to learn and internalize the skills of association, observation, and experimentation will enhance entrepreneurial efforts and make them more likely to succeed (Dyer, Gregersen, and Christensen 2011). Organizations can also develop these skills, acquiring dynamic capabilities that enable them to achieve some goal or outcome, such as producing and selling new products or building new markets (Daneels 2002; Eisenhardt and Martin 2000). Much of the research in this area, however, has emphasized the critical role of collaboration in the production of novelty. Through collaboration, individuals and organizations are able to access the diverse viewpoints, experiences, and resources necessary to generate innovative solutions to complex problems. This is the primary reason teams and small groups outperform individuals across so many different contexts, including entrepreneurial startups (Ruef 2010), the production of scientific knowledge (Uzzi et al. 2013), and Broadway musicals (Uzzi and Spiro 2005).

Relations, Networks, & Opportunities

Teams and groups may be more likely to innovate than individuals, but the fundamental unit behind this effect is that of the "relation" (Emirbayer 1997). The proliferation of network science has highlighted the relational nature of all kinds of social behavior, including creativity and innovation (e.g., Simonton 1984). Connections between people or organizations represent opportunities for collaboration, allowing diverse information to be shared and novel ideas to spread (Ruef 2002). However, this "network effect" is not limited to dyadic connections between actors (cf. Simmel, 1950). Indeed, the field of economic sociology is largely predicated on the idea that social relationships generate macro-level structures or markets that influence dynamics of production and consumption (Bourdieu 1993; Fligstein and Dauter 2007; White 1981, 2002). These structures typically reflect relationships between producers and consumers, or among producers themselves (the focus of this paper), shaping individual orientations toward entrepreneurship and innovation (Ruef and Lounsbury 2007).

STRUCTURAL EMBEDDEDNESS & THE PRODUCTION OF NOVELTY

As early as 1944, Polanyi argued that economic action was embedded in social structure. Granovetter (1985) and Zukin and DiMaggio (1990) developed this idea further, defining structural embeddedness as the "contextualization of economic exchange in patterns of ongoing interpersonal relations" (Zukin & DiMaggio 1990: 18). In this conception, economic transactions are shaped not only by the quality of relations themselves, but by the configuration of those relations and the way in which they position actors in the market (Moran 2005). Much of the subsequent empirical work on embeddedness has studied its effect on firm performance (e.g., Uzzi 1996, 1997), peer evaluation (e.g., Cattani, Ferriani, and Allison 2014), and knowledge transfer (e.g., Reagans and McEvily 2003; Wang 2015).[2] For example, Uzzi's work on the garment industry in New York City finds that firms engaged in embedded, rather than arms-length, relationships are more likely to survive and succeed. This advantage only holds up to a point, however; being too embedded—measured here by the presence of strong ties between producers—can derail economic performance by insulating firms from diverse sources of information that exist outside their network of direct contacts. In their study of the film industry, Cattani and colleagues (2014) find that producer embeddedness also affects how peers evaluate each other's work, although this effect does not extend to critic's evaluations.

Note that the work cited above has focused almost exclusively on the "social" dimension of structural embeddedness, where ties between actors are defined by direct collaboration or contact. Recent work on the multiplexity of networks, however, suggests that people are bound together by different kinds of relationships or connections (Boccaletti et al. 2014; Breiger and Puetz 2015; White, Powell, and Owen-Smith 2003). Not only are social networks historically

[2] We also recognize that there is a considerable stream of research studying how embeddedness affects innovation through the presence (or absence) of structural holes (e.g., Burt 1992, 2004, 2005); we review this work in the section titled **Social Embeddedness** below.

and culturally contingent (Emirbayer and Goodwin 1994; Pachucki and Breiger 2010), but different kinds of networks exist between actors (e.g., Padgett and Ansell 1993). Given the diversity of social life, it is not unreasonable to assume that actors are likely to have distinct positions in different kinds of networks, which in turn are likely to have independent effects on outcomes such as performance, reputation, and innovation (Heaney 2014). At the level of organizations and markets, Padgett and Powell (2012) argue that emergence is in essence a function of the coevolution of multiple networks. Yet our understanding of how different types of structural embeddedness affect innovation is limited.

To address this gap, we identify four types of embeddedness—social, cultural, organizational, and geographic—and develop predictions for how each influences the production of novelty. **Table 1** provides an overview of each type. It is worth pointing out that each of these dimensions is "structural," in so much as they each reflect systems of relations (i.e. ties) connecting actors (i.e. nodes). While direct social relationships may continue to play an important role in the production of novelty, it is not the only means by which cultural producers are connected to and influenced by one another. Different contexts define the content and boundaries of relevant social comparison in distinct ways, increasing the likelihood of influence through structural equivalence. We argue that exposure to the same context—whether it be defined culturally, organizationally, or geographically—will both increase the odds that producers cross paths, and provide a latent channel through which ideas and resources flow (cf., Podolny 2001).

--Insert Table 1 about here—

Importantly, we do not claim that these dimensions are exhaustive, or that they represent the most significant types of connectivity for all domains of social life. Nevertheless, extant research suggests that they comprise important contextual factors in fields of cultural production (Crossley 2009; de Vaan et al. 2015; Goldberg, Hannan, and Kovacs 2016; Kovacs and Hannan 2015; Lopes 1992; Peterson and Berger, 1971; Phillips 2011, 2013). Zukin and DiMaggio (1990) discuss cognitive, cultural, and political embeddedness in their book on structures of capital, but their focus remains on how these dimensions shape the logics of exchange. They also note that "the time is ripe…to begin to compare, classify, and develop analytic theories about varieties of informal social structures" (Zukin and DiMaggio 1990: 18), but few scholars have answered the call (for exceptions, see de Vaan et al. 2015; Goldberg et al. 2016; Ruef 2002).

Social Embeddedness

Social embeddedness refers to an actor's position in networks defined by direct social relations. This dimension is identical to Granovetter's conception of "structural" embeddedness, and thus constitutes the most well-theorized and empirically documented relationship with innovation. The networks in which actors are socially embedded are defined by direct interaction, which may occur regularly or irregularly. In the case of music, we operationalize this as an artist's connections to other artists via shared band membership.

In addition to some of the research cited above, other scholars have directly linked the concept of social embeddedness to creativity and innovation. Most of this research employs Burt's concept of "structural hole", which refers to a gap between two or more individuals in a network who have complementary sources of information (Burt 1992, 2004). The presence of structural holes is associated with low levels of social embeddedness or constraint, and generates opportunities that entrepreneurs and other actors can exploit through brokerage. Robust empirical findings support the argument that brokerage drives idea generation and reception, the creation of game-changing products, and innovation in firms through access to non-redundant information (Burt 2004; Cox, McDonald, Wang, and Hallen 2015; de Vaan et al. 2015; Fleming, Mingo, and Chen 2007; Zaheer and Bell 2005).

The body of work on structural holes clearly suggests that being embedded in a densely connected network of social ties hinders creativity. Actors with low levels of constraint are more likely to encounter diverse ideas and perspectives, which may aid them in their quest to innovate.[3] Despite the considerable evidence that social embeddedness dampens innovation efforts, however, other research makes a competing claim: namely, that being densely connected is positively associated with the production of novelty. This assertion stems from Coleman's (1990) work on network closure, which argues that being embedded provides actors with the social capital they need to challenge the status quo and engage in innovation (see also Burt 2005). Some empirical research supports this claim, finding that social embeddedness increases rates of successful innovation by generating trust, reducing opportunism, and facilitating the enforcement of norms (Ahuja 2000; Walker, Kogut, and Shan 1997; Tsai and Ghoshal 1998). This work suggests that the positive effects of embeddedness are strongest when measuring the evaluation of innovation, rather than the production of novelty per se, or in fields that are highly normative, such as gastronomy (Rao et al. 2003). In the context of music, we argue that high base rates of creativity, coupled with an explicit acceptance and expectation of innovation, make structural holes unnecessary to access non-redundant information. Given the diversity of ideas distributed among producers, those who are more centrally connected will be more likely to tap

[3] Our initial analysis uses an artist's degree centrality and density, rather than constraint, to measure embeddedness. We recognize the limitations of these measures, which fail to explicitly account for the tie structure of a focal actor's alters, but believe it allows for clearer interpretation of how producer connectivity affects the production of novelty. Degree is strongly negatively correlated with constraint in the data (~-0.80), meaning that those actors who are highly connected also tend to have greater access to structural holes. Supplementary analyses using constraint produce consistent results (models available upon request). We provide a more thorough rationale for using degree centrality in the **Data & Methods** section of this paper.

into new ideas, even if their sources are connected to each other. This compels us to make competing predictions:

H1b: *Cultural producers who are more centrally connected in networks defined by direct social relations will be less (or more) likely to produce novel products.*

Cultural Embeddedness

For the purposes of this paper, cultural embeddedness refers to an actor's position in networks defined by shared category membership. Alternative definitions have focused on the presence of trust (Ruef 2002) and linguistic similarity (Goldberg et al. 2016), but we follow Zukin and DiMaggio (1990), who emphasize the role of shared collective understandings in shaping social behavior (see also Vilhena et al. 2014). The "cultural" dimension of embeddedness refers to these collective understandings and the schematic classification structures that organize them (DiMaggio 1997). Unlike its social counterpart, cultural embeddedness is comprised of relations that reflect shared context and cultural similarity, rather than direct contact. Thus, our conception aligns closely with work on genres (Lena and Peterson 2008) and categories (Hsu and Hannan 2005), which act as important signifiers of meaning and community in music (Holt 2007). We operationalize this dimension as an artist's connections to other artists via shared genre membership.

To our knowledge, there has been no empirical research on the relationship between cultural embeddedness and innovation, so it is difficult to formulate a strong hypothesis a priori. Much of the early work on categories finds that spanning boundaries confuses audiences and hurts performance (Zuckerman 1999), but more recent findings suggest that such behavior can also increase access to diverse viewpoints and sources of information, much like brokerage (Hsu 2006). This and other work like it (e.g., Goldberg, Hannan, and Kovacs 2016) highlight the consequences of category (mis)fit for audience evaluation and consumption, but we can also apply these findings to producers, who engage in consumption throughout the cultural production process. As artists begin to create new work, they search the art worlds around them for inspiration, drawing on existing frameworks and features, and then recombining them to create something new (Becker 1982). Spanning categories or genres in new ways may provide opportunities for innovation, but engaging others who are culturally similar—e.g., those who share the same collective understandings or "world view"—provides producers with a blue print for innovation, granting them legitimacy and minimizing risk. To account for both forces, we predict:

H2: *Cultural producers who are more centrally connected in networks defined by shared category membership will be more likely to produce novel products, but only up to a point; being too embedded will negatively affect their likelihood of producing novel products.*

Organizational Embeddedness

Organizational embeddedness refers to an actor's position in networks defined by common organizational affiliation. This is different than the degree to which an actor is embedded *within* an organization (e.g., their position in intra-organizational networks, or the strength of their affiliation; see Ng and Feldman 2010). Instead, we conceive of organizational embeddedness as the degree to which an actor's organizational affiliation connects them to other actors in the same domain. Shared organizational affiliation may bring actors into direct contact with one another, but this is not necessary for a connection to exist. Simply being a part of the same organization provides them with shared culture, capabilities, and resources that tie them together, much like cultural embeddedness ties together actors of the same category. Furthermore, organizations are likely to have strategic emphases and resources in place that motivate their members' actions and production efforts in similar ways. In the context of music, we operationalize organizational embeddedness as an artist's connections to other artists via a shared record label.

The resource-based view of the firm provides a helpful framework to understand how organizations develop certain tendencies that are likely to be shared by its members, including the dynamic capability to innovate (Daneels 2002; Eisenhardt and Martin 2000). Members of the same organization develop strategies for creating and sharing knowledge (Walsh 1995), producing an "organizational advantage" that begets future performance and innovation gains (Nahpiet and Ghoshal 1998). Finally, organizational members develop shared culture (Schein 1990), producing stories and rituals that connect them through symbolic values and material practice (Lounsbury and Glynn 2001). In the music industry, record labels have developed different strategies to address changes in the technical and resource environment, leading to systematic variation in the creativity (e.g., Peterson and Berger 1971) and success (e.g., Benner and Waldfogel 2016) of their artists. For example, Lopes (1992) found that, in the 1970s and 1980s, major labels supported an open production environment that led to more diversity and innovation in musical production. To account for the role organizational affiliation might play in the production of novelty, we predict that:

H3: *Cultural producers who are more centrally connected in networks defined by shared organizational affiliation will be more likely to produce novel products.*

Geographic Embeddedness

The fourth dimension of embeddedness identified in this paper—geographic embeddedness—refers to an actor's position in networks defined by geographic proximity or co-location. This definition is designed to highlight the connections formed between musicians based in the same region or city, rather than the degree to which they are embedded in social networks that are geographically contingent. These connections may constitute explicit relationships or more latent associations based on shared context. Like the ties that define cultural and organizational embeddedness, actors that are physically proximate to one another are more likely to share resources, audiences, influences, and experiences, regardless of whether they have ever collaborated or met.

A growing stream of research on the geography of entrepreneurship has produced considerable evidence that certain regions are more "ripe" for entrepreneurial action than others, due to the presence of like-minded actors, community support systems, and accumulated resources (Cooper and Folta 2000; Lippmann and Aldrich 2016; Thornton and Flynn 2003). Moreover, geographic proximity can significantly affect the flow of information and resources that shape innovation, moderating the effect of intraorganizational networks (Funk 2014) and producing systematic variations in the capacity to innovate at local, regional, and national levels (Jian and Yongsheng 2009). In the music industry, geographically-defined networks of artists generate "scenes" that cultivate identities, audiences, and aesthetic or stylistic tendencies (Crossley 2009). Think of the importance of location for the development of particular music scenes like the Motown sound in Detroit, country music in Memphis, or reggae in Kingston, Jamaica. Relatedly, Phillips' (2011, 2013) study of jazz found that highly "disconnected" cities are more likely to release records that will be re-recorded in the future, but significantly less likely to produce original recordings. Drawing from this work, we predict that:

H4: *Cultural producers who are more centrally located in networks defined by geographic proximity will be more likely to produce novel products.*

DATA & METHODS

To model how different dimensions of embeddedness influence the production of novelty, we conduct a series of analyses using data on commercial recordings and recording artists in the global music industry. This context represents an ideal setting to study this phenomenon for several reasons. First, creativity and innovation play a central role in musical composition and production. Most musicians and critics consider novelty a preferred outcome of the creative process, as consumers value moderate levels of atypicality as a means to differentiate songs from one another (Askin and Mauskapf 2016). Second, musical production is an inherently collaborative process involving a range of different actors and interests (Becker 1982; Hirsch 1972; Negus 1992). Even in cases where a musical work is composed and recorded by a single artist (the most common mode of production in this dataset), this process incorporates the direct and indirect influences of other artists, past and present. Third, the music industry as an empirical setting is inherently relevant and interesting. With domestic wholesale and retail revenue surpassing $10 billion in 2014, and more than 50 million subscribers utilizing digital streaming services each month, music represents one of the largest fields of cultural production and consumption today (Friedlander 2014).

The data used in this paper comes from an original database describing over 20 million songs, albums, artists, and consumers, and was collected by scraping several digital data sources, including The Echo Nest (now owned by Spotify) and MusicBrainz. Although the database covers music released between ~1930 and 2015, we chose to limit our study to songs released between 1960 and 1995. Abbreviating the time horizon of the analysis allowed us to: (1) address incomplete data in the early years of the dataset (the LP was not developed until 1959, which is why data before then is so sparse), and (2) limit the computational requirements of the analysis, which would otherwise be prohibitive. For the years 1960–1995, we include all original recordings for which there is complete artist- and song-level information available. The resulting sample comprises 114,386 original songs produced by 10,434 artists across more than 20 countries, and is designed to represent as complete a picture as possible of the field of (commercial) music production during these years, though there is a bias toward Western popular music. For every song in the sample, data includes: day-level release dates; song-level sonic features (used to construct a novelty measure); artist demographics and attributes, including band membership, genre affiliations, record labels, and city/country of origin (used to construct embeddedness measures); and associated meta-data. Below, we summarize each of the measures used in the analysis, as well as the modeling procedure used to estimate results.

Song Novelty (Dependent Variable)

Work in psychology suggests that low-level features or descriptive attributes play an important role in shaping how actors interpret and make sense of products (Tversky 1977). In music, preferences are linked to a series of features that structure musical space, such as speed, repetition, sadness, and loudness (Greenberg et al, 2016; Ratliff 2016). While research recognizes that innovation occurs through the recombination of both features and labels (Pontikes and Hannan 2014), most empirical tests have used only labels to describe and compare products (for exceptions, see Cerulo 1988; Saleh et al. 2014).

Rather than focus on category blending or some other aspect of label recombination, we use data summarizing songs' constitutive features to construct a comparative measure of product novelty. All songs in the dataset are assigned a value for each of ten features, which were designed by The Echo Nest to describe a song's most important sonic characteristics. While these features necessarily distill the complexity of music into a handful of discrete summary statistics, and thus fail to capture what makes music "art", they are well suited for comparing songs to each other (Friberg et al. 2014; Mauch et al. 2015), and are used explicitly for that purpose by Spotify and other streaming services. These features include several standard musical attributes (e.g., "tempo," "mode," "key," "time signature"), as well as a series of algorithmically-derived measures that represent particular aural or emotive dimensions of music ("valence," "danceability," "acousticness," "energy," "liveness," "speechiness"). **Table 2** briefly describes each of the features used in the analysis.

---Insert Table 2 about here---

After normalizing all ten features and collapsing them into a single vector for each song, we use a cosine distance approach to calculate the similarity between relevant song-pairs' feature vectors (Katenka and Klaczyk 2012; Saleh et al. 2014). For each focal song x_n released at time t_n, we define the relevant set of song-pairs as those songs released *prior* to x_n. This allows us to account for the relative (dis)similarity between x_n and all songs that were released before it in our novelty measure. Each pairwise cosine similarity falls between 0 and 1, with 0 representing absolute dissimilarity and 1 representing absolute similarity across the ten-dimensional feature space. After calculating each of these pairwise similarities, we produce an average weighted (dis)similarity, or *Novelty Score*, for each focal song:

$$(1) \quad \frac{\frac{1}{\cos(x_n, x_1) * \log(t_n - t_1)} + \frac{1}{\cos(x_n, x_2) * \log(t_n - t_2)} + \cdots \frac{1}{\cos(x_n, x_{n-1}) * \log(t_n - t_{n-1})}}{n-1}$$

where $cos(x_n, x_1)$ represents the cosine similarity between focal song x_n and x_1, calculated for all songs in the relevant comparison set. The cosine similarity for each relevant song-pair is multiplied by $log(t_n - t_1)$, the log of the difference in release dates between songs x_n and x_1 in number of days.[4] This expression serves to weight the similarities of songs by their temporal

[4] Songs with identical release dates were randomly ordered and assigned a release-date difference of one day.

distance, such that songs released in close proximity to each other are weighted more heavily than those that are not. This accounts for the fact that the relative novelty for any given song is more likely to be defined in comparison to its "nearest neighbors," rather than the entire world of possible comparisons. Finally, we aggregate the inverse of each of these products, so that larger values represent more novel songs, and then normalize each value by dividing it by $n - 1$, or the total number of songs that have been released prior to x_n.

Social Embeddedness (Independent Variable)

To measure an artist's social embeddedness, we first construct the collaboration network between all active artists (individuals or bands) at the time of each release event, x_n. A tie between artists exists if they previously collaborated on a recording, or performed as members of the same band. We then count the number of collaboration ties for a focal artist at time t_n. The resulting value can be interpreted as the degree centrality for that artist (Freeman 1979).[5] Thus, artists high in degree are more centrally connected in the collaboration network, and likely to have recorded music with multiple bands. Because we recalculate this network for each release event, and only include producers who have entered the market, this statistic may change over time for a given artist.[6] For example, Eric Clapton's degree centrality in 1970 is markedly higher than it is in 1965, when he had only released recordings with The Yardbirds. Finally, while we

[5] The decision to measure embeddedness using degree centrality (coupled with density) rather than constraint was a conscious one, and reflects the complex nature of artist connections in this data, as well as the computational effort required to recalculate the collaboration network for each of the ~115,000 song releases. The structure of the aggregate collaboration network consists of a densely connected giant component surrounded by relatively isolated subcomponents. This structure makes it hard to interpret measures like constraint, which one would expect to be negatively correlated with degree centrality (this is exactly what we find; degree and constraint are correlated at -.80 in this data). Moreover, we do not weight the presence of collaborative ties by the frequency of collaboration (although we hope to do this in the future). Supplementary analyses using constraint produce consistent results, and suggest that artists who are high in degree centrality tend to be less constrained and have greater access to structural holes (models available upon request).

[6] The term "producer" here refers to the cultural producer or creator (e.g., the song writer/performer), rather than the technical producer or engineer per se. For the remainder of the paper, we use the terms "producer," "artist," and "musician" interchangeably.

do our best to account for all relevant collaborators in the production of a new song, we recognize that the data may be incomplete in certain cases.[7]

Cultural Embeddedness (Independent Variable)

To measure cultural embeddedness, we measure connections between artists based on genre overlap. The data we use for this task is drawn from The Echo Nest, and is more fine-grained and descriptive than traditional musicological conceptions of genre (cf., Lena 2012).[8] Individual artists are tagged with anywhere from 0 to 20 genre labels, with the distribution of genres per artist following a power law. Following existing research (e.g., Kovacs and Hannan 2015), we measure the cultural similarity between two artists by calculating their Jaccard coefficient,

$$J(x_n, x_1) = \frac{|x_n \cap x_1|}{|x_n \cup x_1|} \tag{1}$$

which represents the ratio of the number of genre categories affiliated with focal song x_n *and* x_1, to the number categorized as x_n *or* x_1. For example, if Eric Clapton is labeled as "rock," "blues," and "R&B," and George Harrison is labeled simply as "rock" and "R&B," their cultural similarity would be $\frac{|2|}{|3|} = 0.66$. To calculate an artist's cultural embeddedness at the time of a given song release, we average the pairwise similarities between a focal artist and all others who are simultaneously active in the network. This results in a value that falls between 0–1, representing the degree to which an artist is culturally similar to others at the time of a release.[9]

[7] Where possible, we try to isolate the original "cultural producer(s)" for each recording, identifying the individual(s) or group credited with the actual creation of a focal song. Many times this coincides with the performer(s) credited on a recording, but not always. When the data does not allow us to adjudicate between these actors and their role in the cultural production process, we impute the performer(s) as cultural producer(s).
[8] Genre labels were attributed post hoc through a machine-learned process that combines sonic characteristics and similarities, information scraped from the web, listener-generated tags, and other relevant cultural information.
[9] In the analysis that follows, this measure is multiplied by 100 for scaling purposes. Cultural embeddedness was also calculated using degree centrality and constraint, producing similar results.

Organizational Embeddedness (Independent Variable)

We use the record labels that represent artists to indicate organizational affiliation in the music industry, and measure organizational embeddedness by counting the number of connections between a focal artist and others who are represented by the same label. For the most part, musical artists operate outside of formal organizational boundaries, but record labels provide a critical source of human and financial capital through A&R departments, booking agents, and marketing and production teams. The scale of these resources may offer significant performance and innovation benefits, particularly for "major" label artists (Lopes 1992). Calculating their degree centrality through common organizational membership allows us to test how labels with larger and more connected artist rosters affect the creation of new products.

Geographic Embeddedness (Independent Variable)

To measure geographic embeddedness, we again use degree centrality, counting the number of ties between artists who are based out of the same city or country at the time of a release.[10] For example, an artist writing and recording music in the Seattle during the early 1990s—the height of the grunge scene—would likely be more centrally connected than a musician working in Boise, Idaho. As noted earlier, physical proximity to a community of like-minded individuals can have a significant effect on artist propensities for innovation. We measure geographic co-location at the city-level wherever possible, only using country-level connections in more remote regions of the world.[11] Artist-locations reflect "home base" rather than birth place and remain static over time, but we re-calculate geographically-defined connections at each release data to ensure only active users are included in degree centrality.

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[10] In the analyses that follow, all four embeddedness measures are represented as normalized z-scores to (1) account for the skewed nature of the distribution, and (2) allow for comparison across dimensions of embeddedness.

[11] In the future, we plan to calculate a continuous measure of geographic proximity using physical distance.

Additional Variables & Controls

In addition to measuring these different dimensions of embeddedness, we include a suite of song- and artist-level variables to account for potential confounds that may influence the production of novelty in music. These include: song's independent sonic features (e.g., those used to construct the novelty score outlined above), duration, and decade, which accounts for the changing nature of music production over time; dummy variables for groups, females, U.S.-based, and popular artists (=1 for those artists who have appeared on the *Billboard* Hot 100 Charts)[12]; and the number of genres spanned. To capture artists' *past* experience and propensity to create novel products, we also include (1) a variable measuring the number of days an artist has been active in the production network ("artist tenure"), (1) variables for the number of songs an artist has released in the past, both cumulatively and recently (2-year window), and (3) variables measuring the proportion of an artist's previous output deemed novel (again, both cumulatively and recently). **Table 3** includes descriptive statistics and simple correlations for each of these variables.

---Insert Table 3 about here---

Relational Event Modeling Approach

Before presenting results, we provide a brief explanation of the model estimation technique employed in this paper. Recently pioneered as a means of modeling the likelihood of discrete events over time, Relational Event Models (or "REM's") constitute a newly developed class of statistical models that allow scholars to predict social behaviors as a function of interrelated events that are located in specific temporal sequence (Butts 2008). These models have a series of

[12] The proportion of each of these in the data is as follows: ~50% groups/~50% individuals; ~80% male/~20% female; ~45% US-based/~20% UK-based/~35% other; ~44% popular/~56% not popular.

important advantages over more traditional panel regression methods, including: (1) they allow for fine-grained longitudinal analysis of specific "events"—here, the release of a new song—and their associated covariates; (2) they retain information about the exact sequence of events, rather than aggregating sequences across summary count measures or cross-sectional panels; (3) they include a randomly-generated risk set of "potential" events to enhance one's ability to make predictions based on observational data; and (4) their output can be interpreted as a Cox proportional hazard (e.g., conditional logistic regression) model, generating a likelihood-based understanding of predicted event outcomes. It is important to note that this last point requires REM's to predict dichotomous, rather than continuous, outcome variables (see Butts 2008). As discussed below, transforming a continuous variable into a discrete outcome sacrifices some precision, but it also increases the intuitive interpretation of results, which in this case will represent the proportional increase or decrease in relative likelihoods of producing a novel song (for a more complete description and explanation, see Quintane et al. 2014; Quintane and Carnabuci 2016).

The process by which we used the data described above to specify these models is as follows. First, we generated all of the statistics (e.g., dependent and independent variables) associated with each relational event—here, the release of a new song. To transform "song novelty" into a dichotomous outcome, we used the variable's original distribution to generate a threshold above which all songs are considered "very novel". The models presented below define this threshold at $2\,\sigma$ above the mean value of song novelty (e.g., Novelty Score > 0.241), thus predicting the relative likelihood of producing a song that is more novel than ~98% of all other songs (e.g., one of the ~2,500 most novel songs in this dataset).[13] Alternative specifications were

[13] This does not include the first 2,000 songs released in the dataset, which are left out of these models due to a lack of sufficient data to predict stable parameters.

estimated for 1 σ and 3 σ above mean song novelty, and results did not significantly change.[14] To predict the likelihood of producing a novel song, we then estimated a series of models using measures of producer's social, cultural, organizational, and geographic embeddedness, as well as the other artist- and song-level variable described above. Importantly, each of these measures was re-calculated for each song release to account for the continuous evolution of the surrounding social structure.

RESULTS

Our primary interest in this paper lies in the multi-dimensional effect of embeddedness on the production of novelty, but we begin by summarizing some of the other individual-level predictors of novelty included in these models. The results included in Models 1 and 2 support some of the existing research on drivers of innovation in cultural production (see **Table 4** for complete results). For example, teams and groups are more likely to produce successful innovations than individuals (Ruef 2010; Uzzi and Spiro 2005), and this effect is supported by the finding for "Individual" (reference = "Group") in Model 2. Solo artists are marginally less likely to produce novel songs than their multi-member counterparts, and this effect becomes more significant in later models, equating to nearly a 30% decrease in the likelihood of producing a novel song. Popular artists are also less likely to innovate than their peers. After appearing on the *Billboard* Hot 100 Charts, musicians are 17% less likely on average to record and release novel new songs, choosing instead to appeal to audience expectations and stick with the status quo. Finally, songs released between 1990–1995 are more likely to be novel than their predecessors, with the 1970s representing the least generative decade for musical innovations.

---Insert Table 4 about here---

[14] These results are available upon request.

In Model 3, we incorporate variables measuring an artist's past experience to assess the contingent nature of novelty creation. Although the linear term for "Artist Tenure" is not a significant predictor of product novelty, results suggest that the artists' past production efforts affect their propensity to generate novel products in the future. For example, the more songs that an artist has released over the course of his or her career, the less likely they are to produce something novel. This relationship reverses, however, when we measure *recent* artist production. Someone who experiences a 1 σ increase in productivity over the past two years is more than twice as likely to create a novel song. Moreover, we find that the propensity to create novel songs in the past makes artists more likely to create novel songs in the future, especially if their recent production history is marked by innovation. This result suggests that the capacity to produce novel products is imprinted over time, highlighting the way in which production outcomes are embedded in producer's personal histories (Lippmann and Aldrich 2016).

Model 4 includes several interesting results that require additional interpretation. First, artist tenure becomes a significant predictor of product novelty. Producers' propensity to innovate seems to decrease over time, echoing extant research on the relationship between age and innovation (Becker 1982; de Laat 2014; Ruef 2002; Stephan and Levin 1992). But when we include a quadratic term for tenure, we find that this relationship reverses, as artists near the end of their career start to become more likely to produce novelty again (see Jones 2010). This U-shaped finding suggests that, while young artists may be less constrained by the norms and expectations surrounding fields of cultural production, artists in the twilight of their careers have accrued sufficient social, political, and artistic capital to innovate without incurring the penalty assigned to producers in the middle of their careers.

Model 4 also includes our indicator for social embeddedness. Remember that this variable is designed to measure artists' connectedness to others through direct contact or collaboration. Following extant research on structural holes, network closure, and innovation, we made competing predictions about how social embeddedness might affect the propensity to produce novelty (cf., Burt 2005). Surprisingly, we find no support for either prediction—artists who collaborate with others and span multiple music groups are *not* more or less likely to release novel songs. Given all of the research on social embeddedness, this finding is certainly startling, but not inexplicable. Part of the reason that we sought to test different dimensions of embeddedness was to establish whether and how they generated different outcomes. In the context of musical production, this null result suggests that the degree to which artists are directly connected to each other may not be as consequential for innovation as previously thought. The channels through which producers access new and different information may instead be defined by other dimensions of connectedness.

In Model 5, we test the effect of these other dimensions. Social embeddedness continues to be an insignificant predictor of product innovation, as does organizational embeddedness. Although some research suggests that artist affiliations with certain record labels is linked to gains in performance and innovation (Lopes 1992; Peterson and Berger 1971), the connection between artists and labels is relatively weak, especially when compared to other professions. Part of the reason for this may be because the relationship between artists and labels is one of representation, rather than employment. Thus, sharing a position on a label's roster with other artists seems to not play a significant role in how likely you are to create novel music.

Although results from these models do not provide support for H1 or H3, we find robust support for H2 and H4. Specifically, artists who are more centrally connected in geographic space are much more likely to produce novel products. For every 1 σ increase in artists' geographic degree centrality, they experience a whopping 58.5% increase in the likelihood of creating a novel song. This is true even when controlling for US-based artists, who are more likely to be connected due to their disproportionate presence in the dataset. Artists who are culturally embedded are also more likely to produce innovations. An initial positive effect for this variable, which measures the degree to which producers are culturally similar to each other, suggests that a 1 σ increase in cultural embeddedness results in a 37.6% increase in artists' "risk" of creating novel products. Model 6 incorporates a quadratic term for cultural embeddedness, signaling a significant inverted U-shaped relationship between cultural similarity and innovation. As predicted, displaying moderate levels of cultural embeddedness allows artists to tap into the influence of others who are associated with some, but not all, of the same genre categories, encouraging them to incorporate new ideas while sharing common ground.

To develop a better understanding of when cultural embeddedness is an effective tool for the production of novelty, we analyzed its interactions with several artist-level characteristics—see **Table 5** for complete results.[15] In Model 7, we find a significant positive interaction between cultural embeddedness and the number of genres spanned by a given artist. The main effect of this variable was positive in Model 5, but the interaction suggests that this is only true for artists who exhibit high levels of cultural similarity. Put another way, the producers who are best positioned to take advantage of the diversity present across multiple genres are those who are highly culturally embedded. When it comes to producing novel products, those artists who span genres in a similar way to others are more likely to succeed. We also find a positive interaction effect between cultural embeddedness and artist gender. This result suggests that women are

[15] Although we did not have any *a priori* hypotheses concerning tradeoffs between different dimensions of embeddedness, we did try to interact them with each other as well (see for example Goldberg et al. 2016; Ng and Feldman 2010). None of these interaction effects were significant.

particularly likely to benefit from the structural advantages of cultural embeddedness, making them more likely than men to create novel musical products. One plausible explanation for this effect is that being culturally similar to others may erase some of the barriers women face in their efforts to produce novelty in fields of cultural production, empowering them to innovate, rather than play it safe. Finally, in Model 9, we calculated the interaction between cultural embeddedness and artist tenure. Although the effect here is not as strong, its significance suggests that cultural embeddedness is particularly helpful for artists at the beginning of their careers. Just like for women, or producers who span multiple genres, musicians who are just starting out receive additional benefit from being culturally embedded, as it provides them with a form of cultural capital that may encourage risk-taking and innovation.

---Insert Table 5 about here---

DISCUSSION & CONCLUSIONS

The findings presented in this paper provide compelling evidence that cultural production—and the production of novelty in particular—is shaped by the embeddedness of cultural producers, but not in the way previous theory suggests. Results suggest that producers who are centrally connected across genre categories and geographic contexts are significantly more likely to create novel products. Moreover, producers who are young, female, or span multiple genres benefit the most from being culturally embedded. By contrast, social and organizational embeddedness do little to explain the production of novelty within the music industry. This null result is particularly salient, as it reaffirms the motivation for reconceptualizing embeddedness as a multi-dimensional construct. Existing research has primarily focused on how direct social ties impact innovation and performance outcomes, but considering how actors might be connected to each other in other ways—through shared category membership, organizational affiliation, or geographic proximity—generates new avenues of research as it encourages us to think more deeply about how shared context can influence the production of novelty.

For example, cultural embeddedness operates through exposure to shared norms, values, and assumptions that transcend direct social interactions or collaborations. Artists who are members of the same category may be more likely to cross paths and collaborate; but even if they do not, they still share common ground and compete for audience attention. The same can be said for geographic embeddedness, which describes how actors immersed in the same musical scene or local community are likely to share resources, experiences, and audiences, whether or not they come into direct contact with each other. Moreover, being embedded in the same geographic or cultural context not only increases the propensity to share overlapping resources and influences; it also induces competition among co-located producers. Perhaps competition, rather than collaboration, is the real driver of innovation in this domain.

Taken together, these findings provide a more holistic perspective on how producer characteristics and networks generate competing "typologies of the possible," which in turn influence the production of novelty (Padgett and Powell 2012: 3–4). Nevertheless, our work has some important limitations that merit consideration. As with most empirical investigations relying on "big" data sources and methods, the conclusions drawn above are limited by the nature of the data. For example, the algorithmically-derived sonic features used to measure product novelty are inherently reductionist, and may not align perfectly with audience assessments of what is or isn't "novel." There are also limitations associated with the measurement of producer embeddedness. (e.g., we do not currently measure the relative strength [or weakness] of a given tie between actors. Collecting additional data and estimating new models that isolate within-artist variation will help resolve these issues in the future. This may also allow us to better address the possibility of a bidirectional relationship between producer embeddedness and product novelty, informing a stronger causal argument than is possible given the modeling strategy used in this paper.

To conclude, we would like to highlight several contributions this paper makes that have theoretical, methodological, and practical implications. First, conceiving of structural embeddedness as a multi-dimensional phenomenon recognizes the fact that information and influence flow not only through direct social relationships, but other relational structures that organize social life. It may not be surprising that cultural and geographic embeddedness play such an important role in the production of new music, but exactly which dimensions of embeddedness matter most, and in what ways, may be context dependent. Future research can unpack the relationships between these dimensions and test how they operate across different domains. Second, recognizing the multiplexity of embeddedness may have important consequences for the way entrepreneurs and the organizations that support them structure innovation. Rather than focusing on collaborative teams or social networks, they might identify other channels that simultaneously maximize information diversity and social cohesion. Finally, the data and methods used in this study present a host of exciting opportunities for empirical research on cultural production. Using computational and network methods like REM's to study large quantities of data that are rich in information about cultural content and social relations will continue to generate new insights into this process.

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TABLE 1

Types of Structural Embeddedness

Type of Embeddedness	Tie Defined By	Example
Social	Direct interpersonal collaboration	Connectedness to other artists via shared band membership
Cultural	Cultural similarity	Connectedness to other artists via shared genre affiliation
Organizational	Shared organizational affiliation	Connectedness to other artists via shared record label
Geographic	Geographical co-location	Connectedness to other artists via shared home city, region, or country

TABLE 2

Song-level Features

Features	Scale	Definition
Acousticness	0-1	Represents the likelihood that the song was recorded solely by acoustic means (as opposed to more electronic/electric means)
Danceability	0-1	Describes how suitable a track is for dancing. This measure includes tempo, regularity of beat, and beat strength.
Energy	0-1	A perceptual measure of intensity throughout the track. Think fast, loud, and noisy (i.e., hard rock) more than dance tracks.
Key	0-11 (integers only)	The estimated, overall key of the track, from C through B. We enter key as a series of dummy variables
Liveness	0-1	Detects the presence of the live audience during the recording. Heavily studio-produced tracks score low on this measure.
Mode	0 or 1	Whether the song is in a minor (0) or major (1) key
Speechiness	0-1	Detects the presence of spoken word throughout the track. Sung vocals are not considered spoken word.
Tempo	Beats per minute	The overall average tempo of a track.
Time Signature	Beats per bar / measure	Estimated, overall time signature of the track. 4/4 is the most common time signature by far, and is entered as a dummy variable in our analyses.
Valence	0-1	The musical positiveness of the track

TABLE 3

Descriptive Statistics and Pearson Correlations for Independent and Control Variables

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1 Duration	237.84	113.34	1																									
2 Key	0.3765	0.289	-0.018	1																								
3 Energy	0.574	0.263	0.032	0.014	1																							
4 Liveness	0.234	0.215	0.037	-0.001	0.17	1																						
5 Tempo	0.462	0.113	0.007	-0.002	0.226	0.009	1																					
6 Speechiness	0.074	0.102	-0.057	-0.02	0.046	0.175	-0.017	1																				
7 Acousticness	0.347	0.344	-0.122	-0.005	-0.694	-0.029	-0.178	0.031	1																			
8 Mode	0.711	0.453	-0.076	.001	-0.032	0.005	0.014	-0.044	0.051	1																		
9 Time Signature	0.554	0.07	0.047	-0.002	0.163	-0.005	0.028	-0.029	-0.163	-0.011	1																	
10 Valence	0.531	0.263	-0.185	0.017	0.288	-0.047	0.125	0.012	-0.162	0.03	0.116	1																
11 Danceability	0.521	0.175	-0.036	-0.015	0.04	-0.156	-0.08	0.113	-0.091	-0.03	0.139	0.554	1															
12 Female	0.104	0.305	0.017	-0.016	-0.333	-0.031	-0.109	0.013	0.356	0.025	-0.05	0.002	0.079	1														
13 Decade	2.47	0.863	0.122	-0.059	0.037	-0.037	0.053	0.067	-0.093	-0.039	0.023	-0.142	-0.014	-0.015	1													
14 Group	0.49	0.554	0.019	0.002	0.338	0.057	0.116	0.003	-0.365	-0.024	0.056	-0.018	-0.102	-0.729	0.08	1												
15 Popular	0.446	0.497	-0.059	0.038	-0.004	0.022	-0.063	-0.059	-0.007	0.029	0.024	0.176	0.185	0.073	-0.342	-0.097	1											
16 US-based	0.412	0.486	-0.068	0.016	-0.089	-0.002	-0.048	0.008	0.114	0.032	-0.012	0.043	0.013	0.164	-0.037	-0.044	0.239	1										
17 # of Genres	4.82	3.7	0.026	.001	0.017	0.046	.001	-0.036	-0.001	0.021	0.002	0.034	0.011	0.1	-0.071	0.066	0.273	0.265	1									
18 Tenure	2076.05	3099.76	-0.013	-0.012	-0.111	0.022	-0.023	-0.072	0.15	0.031	-0.014	0.047	0.018	0.179	0.137	-0.101	0.404	0.17	0.282	1								
19 Cumulative Production	0.0004	0.0016	-0.026	0.002	-0.013	0.016	.001	-0.023	0.027	0.016	-0.004	0.026	-0.003	0.013	-0.178	0.016	0.141	0.014	0.09	0.134	1							
20 Cumulative Production (novel)	0.011	0.0385	-0.005	0.004	-.001	0.007	-0.003	-0.005	0.003	-.001	0.003	0.021	0.008	0.021	-0.062	-0.001	0.058	0.007	0.035	0.048	0.039	1						
21 Recent Production	0.0004	0.0016	-0.017	.000	-0.012	0.013	0.002	-0.012	0.019	0.009	-0.003	0.006	-0.011	0.016	-0.096	0.013	0.079	0.007	0.072	0.088	0.771	0.04	1					
22 Recent Production (novel)	0.0066	0.0479	0.01	-0.008	-0.137	-0.018	-0.047	-0.001	0.127	-0.021	-0.037	-0.108	-0.095	0.087	0.015	-0.074	-0.042	0.028	-0.038	0.018	0.068	0.02	0.08	1				
23 Social Embeddedness	0.0204	0.1994	-0.003	.001	0.004	0.003	.000	-0.008	-0.008	.000	0.001	0.005	0.006	-0.013	0.009	0.008	-0.004	-0.026	-0.034	-0.003	-0.008	.000	-0.004	-0.003	1			
24 Cultural Embeddedness	10.2008	15.6324	-0.029	.001	-0.09	0.005	-0.029	-0.019	0.096	0.016	-0.013	-.001	.000	0.134	-0.054	-0.04	0.134	0.084	0.11	0.235	0.112	0.076	0.143	0.132	-0.002	1		
25 Organizational Embeddedness	4.5981	21.5429	-0.006	.001	-0.021	0.009	-0.01	0.002	0.018	0.009	-0.003	0.018	0.025	0.018	-0.054	0.002	0.142	0.041	0.073	0.091	0.034	0.023	0.005	.000	-0.012	0.079	1	
26 Geographic Embeddedness	105.524	228.442	0.003	.000	-0.023	-0.005	-0.013	-0.004	0.002	0.003	0.005	-0.007	0.015	0.051	0.052	.000	0.117	0.355	0.149	0.048	0.024	0.065	0.069	0.066	-0.034	0.366	0.119	1

Note: mean and standard deviation reflect normalized measures for variables 2–11.

TABLE 4

Parameter Estimates for REM's Predicting the Production of a Novel Song

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Song-level controls						
Duration	-0.35* (0.015)	-0.035* (0.015)	-0.017 (0.016)	-0.017 (0.016)	0.024 (0.017)	-0.002 (0.018)
Key	-1.096*** (0.086)	-1.078*** (0.089)	-1.086 (0.092)	-1.084 (0.092)	-1.130 (0.098)	-1.122 (0.102)
Energy	-2.230*** (0.137)	-2.410*** (0.144)	-2.328*** (0.149)	-2.331*** (0.149)	-2.197*** (0.160)	-2.343*** (0.167)
Liveness	1.083*** (0.105)	1.250*** (0.110)	1.338*** (0.113)	1.342*** (0.113)	1.395*** (0.119)	1.391*** (0.124)
Tempo	-1.675*** (0.187)	-1.871*** (0.193)	-1.729*** (0.199)	-1.732*** (0.199)	-1.651*** (0.211)	-1.713*** (0.217)
Speechiness	3.261*** (0.154)	3.057*** (0.158)	2.947*** (0.164)	2.949*** (0.164)	2.946*** (0.178)	2.802*** (0.185)
Acousticness	0.961*** (0.102)	0.923*** (0.108)	0.865*** (0.114)	0.864*** (0.114)	1.016*** (0.123)	0.889*** (0.128)
Mode	-3.016*** (0.062)	-3.072*** (0.065)	-3.116*** (0.068)	-3.118*** (0.068)	-3.190*** (0.073)	-3.170*** (0.075)
Time signature	-2.941*** (0.189)	-3.023*** (0.194)	-3.125*** (0.200)	-3.132*** (0.200)	-3.154*** (0.214)	-3.090*** (0.220)
Valence	-4.805*** (0.172)	-4.534*** (0.176)	-4.502*** (0.183)	-4.508*** (0.183)	-4.574*** (0.194)	-4.580*** (0.202)
Danceability	-4.473*** (0.187)	-4.565*** (0.192)	-4.160*** (0.200)	-4.161*** (0.200)	-4.000*** (0.212)	-4.388*** (0.222)
1960s		-1.099*** (0.168)	-0.890*** (0.193)	-0.898*** (0.194)	-0.446* (0.204)	-0.819*** (0.214)
1970s		-2.123*** (0.236)	-2.114*** (0.277)	-2.112*** (0.277)	-1.930*** (0.291)	-1.999*** (0.304)
1980s		-1.430*** (0.086)	-1.403*** (0.094)	-1.403*** (0.094)	-1.425*** (0.101)	-1.501*** (0.105)
Artist-level controls						
Individual		-0.241 (0.130)	-0.302* (0.136)	-0.307* (0.136)	-0.342* (0.151)	-0.156 (0.156)
Female		0.133 (0.077)	0.170* (0.081)	0.170* (0.081)	0.414*** (0.086)	0.237** (0.090)
Popular		-0.185** (0.060)	-0.174* (0.075)	-0.171* (0.075)	-0.239** (0.080)	-0.265*** (0.082)
# of Genres					0.207*** (0.033)	0.022 (0.037)
US-based					-0.757*** (0.071)	-0.554*** (0.075)
Artist history measures						
Tenure			0.019 (0.091)	0.012 (0.091)	-0.389*** (0.098)	-0.558*** (0.102)
Tenure (squared)					0.556*** (0.088)	0.604*** (0.090)
Cumulative production			-0.973*** (0.114)	-0.973*** (0.114)	-0.857*** (0.115)	-0.877*** (0.116)
Recent production			0.946*** (0.061)	0.947*** (0.061)	0.752*** (0.065)	0.755*** (0.067)
Cumulative production (novel)			0.046* (0.021)	0.046* (0.021)	-0.012 (0.023)	0.002 (0.024)
Recent production (novel)			0.135*** (0.011)	0.136*** (0.011)	0.093*** (0.012)	0.109*** (0.013)
Embeddedness measures						
Social				-0.052 (0.033)	-0.052 (0.033)	-0.007 (0.033)
Cultural					0.319*** (0.020)	1.422*** (0.060)
Cultural (squared)						-0.874*** (0.044)
Organizational					0.017 (0.027)	0.003 (0.029)
Geographic					0.461*** (0.025)	0.354*** (0.026)
Goodness of Fit						
-2 Log Likelihood	7,829.054	7,306.796	6,806.067	6,803.465	5,950.125	5,524.358
Observed (potential) events			2,500	(77,760)		

Standard errors in parentheses; * p < .05, ** p < .01, *** p <.001

Note: the number of observed events represents the number of novel songs predicted across the dataset, while the number of potential events includes a risk set constructed by selecting random combinations of artists and songs over time that are then used to test the robustness of our effects. The total number of observed events (novel and not-novel) in our dataset is 114,386.

TABLE 5

Estimates for Significant Interactions with Cultural Embeddedness

	Model 7	Model 8	Model 9
Artist-level controls			
Female	0.456*** (0.087)	-0.276* (0.128)	0.411*** (0.086)
# of Genres	-0.156*** (0.047)	0.189*** (0.034)	0.205*** (0.033)
Artist history measures			
Tenure	-0.419*** (0.099)	-0.416*** (0.099)	-0.319*** (0.102)
Tenure (squared)	0.536*** (0.088)	0.556*** (0.088)	0.562*** (0.087)
Embeddedness measure			
Cultural	0.135*** (0.025)	0.546*** (0.039)	0.353*** (0.024)
Interaction terms			
Cultural embeddedness x # of genres	0.524*** (0.043)		
Cultural embeddedness x Female		0.266** (0.034)	
Cultural embeddedness x Tenure			-0.102* (0.041)
Goodness of Fit			
-2 Log Likelihood	5,799.112	5,850.518	5,943. 579
Observed (potential) events		2,500 (77,760)	

Standard errors in parentheses; * p < .05, ** p < .01, *** p <.001

Note: Models include all other control variables from Model 5 (Table 4), but they are not listed here for clarity's sake. The number of observed events represents the number of novel songs predicted across the dataset, while the number of potential events includes a risk set constructed by selecting random combinations of artists and songs over time that are then used to test the robustness of our effects. The total number of observed events (novel and not-novel) in our dataset is 114,386.