Abstract

How does culture change? We unify disconnected explanations of change that focus either on individuals or on public culture under a theory of cultural evolution. By shifting our analytical lens from actors to public cultural ideas and object, our theory can explain change in cultural forms over large and long frames of analysis using formal evolutionary mechanisms. Complementing this theory, the paper introduces a suite of novel methods to explain change in the historical trajectories of populations of cultural ideas/objects (e.g., music groups, hashtags, laws, technologies, and organizations) through diversification rates. We deploy our theory and methods to study the history of Metal Music over more than three decades, using a complete dataset of all bands active between 1968 and 2000. Over the course of its history, we find strong evidence that the genre has been fundamentally shaped by competition between ideas for the cognitive resources actors can invest in learning about and reproducing this cultural form over time.

1 Introduction

How does culture change? From fads and fashions to the emergence of new cultural forms, cultural change is undeniable. Culture is found both in the brains and bodies of individual actors (i.e. personal culture) as well as in the products of social action (i.e. public culture) (Lizardo, 2017). Contemporary sociological explanations of macro-cultural change typically proceed from one of these two perspectives. Most "actor-centric" accounts of cultural change (e.g., practice theories, network theories) view culture from the eyes of the individual to explain the learning, transmission, and production of personal cultural ideas (i.e. belief, values, skills, or practices) (Swidler, 2001; DiMaggio, 1997; Fuhse, 2009; Centola, 2020; Bourdieu, 1996; Fligstein and McAdam, 2015). In contrast, a smaller "culture-centric" literature (e.g., systems theories, some evolutionary theories) focuses on change in the heterogeneous ideas, material objects, institutions, and relational structures that make up public culture over larger and longer frames of analysis (Lieberson, 2000; Hannan, 2005; Luhmann, 1995).

Even together, these approaches provide an unsatisfying account of cultural change because few adequately bridge the gap between personal and public culture. Many actor-centric and culture-centric theories elide this challenge by decontextualizing personal cultural change from public cultural change. Actor-centric perspectives have articulated cognitive explanations for the individual acquisition of culture and its transmission across groups, but they do so by homogenizing and stabilizing public culture as an individual idea, institution, category, or Bourdieusian habitus. But if public culture is monolithic and homogenous, it is difficult to explain change without deferring to *deus ex machina* like stochastic events, exogenous shocks, or potent social actions that are not explicitly connected to individual cognition or transmission (Swidler, 1986; Knorr-Cetina, 1988; Collins, 1981; Fligstein and McAdam, 2015). In contrast, several culture-centric theories have articulated clear, endogenous mechanisms for change in heterogeneous ideas and public cultural objects distributed across groups of actors. However these theories tend to portray actors as non-dynamic, passive, or even non-existent (Lieberson, 2000; Hannan, Pólos, and Carroll, 2012; Luhmann, 1995).

In this paper, we propose an evolutionary theory of cultural change that unites actor-centric and culture-centric perspectives under a burgeoning cultural evolution literature emerging across other social sciences (Mesoudi, Whiten, and Laland, 2006; Acerbi and Mesoudi, 2015). Briefly, we see culture as a heterogeneous population of "ideas" and material objects that circulate amongst a group of actors (Sperber, 1996; Richerson and Boyd, 2008). Cultural ideas are those that carry shared meaning among a group of actors and are common due to social interaction (Foster, 2018). Because these ideas are often unobservable empirically, they are publicly represented by material cultural objects: archival materials, survey responses, digital trace data, texts, speech, consumer goods, or other physical materials that are produced, recognized, referred to, or otherwise in relation to these cultural ideas (Griswold, 2008; Foster, 2018; Taylor, Stoltz, and McDonnell, 2019). Individuals learn new personal cultural ideas through interaction with public cultural objects, and reproduce public culture through the creation and usage of cultural objects that circulate related ideas. The cycle of cultural learning and public cultural reproduction not only transmits ideas between individuals, but also creates cultural change: Public cultural ideas are filtered through and scaffolded upon individuals' existing personal cultural schemata of the world, and ideas are only learned and retained in memory when salient (DiMaggio, 1997). Individuals reproduce these ideas publicly as objects with reduction, imperfection and contextual creativity. This creates a constellation of more or less similar ideas circulating amongst actors. Some of these variants will propagate to create long chains of learning and reproduction, while others will languish and be forgotten (Sperber, 1996; Scott-Phillips, Blancke, and Heintz, 2018).

As these moments of transmission, variation, and differential survival are extrapolated across the population of actors, we gain a new perspective on culture as an evolving population of associated ideas and objects which we call a "cultural form." By tying personal cultural ideas within minds directly to their public cultural counterparts, our theory is intelligible both from the actor-centric perspective of the individual, and when applied to actual public cultural data. Compared to other theories of cultural change, evolutionary dynamics allow for change and stability in personal and public culture as *equally* plausible options. Most importantly, the evolutionary perspective allows for a universal and concise definition of cultural change as shifts in the amount, diversity, and quality of cultural ideas over time.

The analytical value of our theory of cultural change is that it allows us to link a mature, cognitive, actor-centric understanding of culture in sociology to culture-centric evolutionary mechanisms that explain how, when, and why public cultural change is occurring in context (DiMaggio, 1997; Lizardo, 2017). Evolutionary mechanisms such as changes in cultural carrying capacity, the birth and death of lineages of ideas, key innovations, mass extinctions, and competition for actor resources provide a framework to assess how and to what extent endogenous evolutionary dynamics, historic events, or influential actions have effected shifts over time in the stock of ideas and objects that make up a cultural form. Because these evolutionary mechanisms provide a compact, realist account of certain regularities in cultural change, they allow analysts to test concrete hypotheses about the causes of cultural change in a wide variety of contexts (Watts, 2014).

We link our theory to new methods, introduced here, for studying change in material public culture. Specifically, we identify and analyze evolutionary mechanisms through changes in the diversity of public cultural objects over time. We study cultural objects because the personal culture inside people's brains varies widely and is opaque to outside analysis. Diversification (i.e., birth and death) rates of cultural objects capture how public cultural objects and ideas "beget" other objects and ideas, without strong assumptions on the specific actor-level transmission patterns driving the process of innovation. Advanced theory in both biological macroevolution[1] and social science has articulated how evolutionary mechanisms like competition and mass extinction can be seen in diversification rates (Stadler, 2013; Morlon, 2014; Carroll and Hannan, 2004; Ruef, 2000).

While specialized, diversification rate analysis complements popular actor-centric methods for studying cultural change like social network analysis by shifting focus from actors to objects. Because it is a culture-centric approach, it does not require complete knowledge of social actors, their configuration in a social structure, or the exact particularities of how personal culture is transmitted between them. Because online and social media data on cultural objects is often more plentiful, more accessible, and of more even quality than data on individuals, we see this as a key strength of the framework for computational social scientists.

In the second half of this paper, we introduce a statistical framework that allows analysts to test hypotheses about the role of evolutionary mechanisms in cultural change using diversification rates. Here we present a novel unsupervised machine-learning/non-parametric approach that cuts through stochastic noise in historical data to identify major shifts in the diversification rates of cultural populations over time (Gjesfjeld et al., Feb. 2020). We then propose more mechanistic models specific to certain evolutionary mechanisms (e.g.,

[1]Biological macroevolution is the subfield of evolutionary biology that seeks to "[explain] the origin, development, and extinction of major taxonomic groupings: species, genus, family" (Sepkoski, 2008).

competition for cultural/cognitive resources, growth of cultural carrying capacity due to key innovation, and exogenous environmental effects), and compare their ability to explain these significant shifts.

As an empirical case we apply our theory and methods to explore how Metal music has changed over time. Metal has several attractive properties as an illustrative example. First, art genres are textbook cultural forms where evolution is obvious; musicians draw inspiration from previous musical ideas, and dueling pressures to both affiliate with an existing tradition and innovate drive high-fidelity transmission and variation, respectively (Kahn-Harris, 2006; Prior, 2008). Second, alongside a rich history punctuated by commercial dominance and moral panics, Metal has spawned a variety of subgenre "scenes" (e.g. Black, Death, Thrash) that represent cultural forms in their own right (Lena, 2012). Third, because phyletic (i.e., familial) classification of these subgenres is a large part of Metal culture, these populations are clearly delineated through language used and generated by the actors themselves. Especially since Metal's stylistic diversification in the 1980s, fans have relished debates about whether bands belong to a certain style/subgenre of Metal or not. These highly-technical genre labels allow us to closely track cultural diversity over time without constructing features as analysts. Fourth, a remarkable commitment to archival work emerges from Metal fans' focus on classification. This led to the creation of the manually-curated, population-size dataset we use in this study to follow 30,217 bands active from 1968 to 2000. Using this data, we model the evolution of Metal through both the birth and death of subgenres and the birth and death of unique musical lineages represented by bands. Our analyses highlight the importance of competition between ideas for the resources actors can dedicate to the learning and reproduction of Metal on the cultural form's trajectory.

The paper is organized as follows. First we review existing actor-centric and culture-centric explanations of cultural change in Sociology. We then synthesize these ideas with two contemporary cultural evolution programs, Dual Inheritance Theory and the Epidemiology of Representations (also called Cultural Attraction Theory) (Richerson and Boyd, 2008; Sperber, 1996; Scott-Phillips et al., 2018) for a uniquely sociological cultural evolution narrative that stresses the importance of cultural objects and culture-centric evolutionary mechanisms. The second half of the paper is dedicated to the identification of evolutionary mechanisms in diversification rates, the introduction of our diversification rate models, and our case study of Metal music from 1968 to 2000.

2 Review of Sociological Literature on Cultural Change

We now review sociological treatments of public cultural change from both actor-centric and culture-centric perspectives. First, we highlight a micro-/macro- duality that is specific to cultural change: in order to explain how individuals learn, transmit, and use personal culture, actor-centric perspectives must present public culture as homogeneous and static (i.e., a single idea, institution, category, or habitus), making it hard to articulate public cultural change. In contrast, presenting public culture as heterogeneous (i.e., sets or combinations of ideas and material objects) makes it easy for culture-centric approaches to explain dynamics within public culture endogenously, but makes it challenging to connect these endogenous mechanisms to individual-level processes. Second, on a finer level, we break down each theory's ability to address public cultural change by noting how it treats the birth, death, and variation of ideas. Third, we note how our methodological contributions augment or complement these literatures.

2.1 Primarily Actor-centric Theories

In the late 20th century, **practice theories** used the learning and performance of practices to explain personal cultural change, but rarely public cultural change (Swidler, 1986; Collins, 1981; Knorr-Cetina, 1988). This position was perhaps militated by the crucial role of practice as the foundation of static public cultures for theories of this style (Swidler, 2001). For example, the tight coupling between individual practice and a homogeneous, stable public culture in Giddens' structuration theory and neo-institutionalist theory leaves little room for the endogenous birth or death of new practices at scale (DiMaggio and Powell, 1991; Giddens, 1984). Thus even in populational settings, practice theorists gravitated towards heteronomic shocks like historic events or transformative action by powerful actors, not the birth, death, or spread of practices, to explain public cultural change (Swidler, 1986; Collins, 1981; Knorr-Cetina, 1988). Our methodological framework explicitly captures the endogenous transmission of ideas (through practice) as the primary vehicle of change, while also allowing analysts to formulate testable hypotheses about how heteronomic shocks and evolutionary mechanisms modulate this endogenous change.

Theorists have connected **social network analysis** to cultural change in three ways, but none allow the methodology to understand personal and public cultural change simultaneously (Emirbayer and Goodwin, 1994; Fuhse, 2009). The first actor-centric perspective views relations between actors and the social opportunities emergent from those relations as determined by static, homogeneous public cultural categories (e.g. gender, class, party affiliation) (Fuhse, 2009).[2] This perspective is generally not conducive to understanding public cultural change (beyond the network's genesis) because change would mean breaking the stable ties that give the theory its analytical power. In contrast, the second culture-centric approach models public culture as networks of heterogeneous ideas, and analyzes how these networks change topologically over time (Foster, Rzhetsky, and Evans, 2015; Rule, Cointet, and Bearman, 2015). However, this approach is completely divorced from the behaviors and beliefs of individual actors. The final actor-centric approach views cultural ideas as transmitted across networks, and elucidates the mechanisms and network topologies that modulate patterns of cultural diffusion (Rossman, 2014; DellaPosta, Shi, and Macy, 2015; Goldberg and Stein, 2018; Centola, 2020). While this approach can explain the distribution/variation of ideas across actors, the literature again often portrays public culture as a single, homogeneous, static idea for simplicity. Moreover, the diffusion literature rarely treats the birth or death

[2]Methodologically, this perspective is linked to centrality scores, block models, and exponential random graph models.

of ideas, and thus yields no insight into how heterogeneous public cultural forms emerge from transmission processes (Fuhse, 2009). Our theory connects the actor-centric network diffusion perspective to public cultural change using cultural evolution. Our methodological framework complements network methods by giving analysts a "top-down" perspective on the birth, death, and variation of ideas without relying on actor-level data.

Field theories are actor-centric practice theories that situate actors within a structure (the field) where they compete for cultural capital. Bourdieu himself generally avoided discussion of public cultural change, instead elaborating on how a "habitus" (his static, homogeneous vision of public culture) is acquired, reproduced, and transmitted by actors within stable fields (Bourdieu, 1996; Sewell Jr, 1992).[3] However, further work on fields has bridged the actor-centric culture-centric gap by articulating how ideas within fields are born and die through actor turnover and heteronomic shocks (e.g., the unseating of powerful incumbents, historic events) (Fligstein and McAdam, 2015). Unfortunately, field theory is still limited to contexts where actors are unified by common cultural goals (e.g. professions, social movements) and the field-like social structure that follows from this common purpose. Cultural evolution makes no such constraints on personal or public culture. Methodologically, a lack of formalization in the fields literature has also made it difficult to hypothesize how, when, and why change should occur in populations of actors (i.e., fields) empirically.[4] In addition to explaining change in populations of ideas, our statistical framework can be applied to fields of actors to address this gap.

2.2 Primarily Culture-Centric Theories

Lieberson's evolutionary theory of fashions drew on biological metaphors to explain public cultural change, but he largely ignored personal cultural change (Lieberson, 2000). Our view on public cultural change is consistent with Lieberson's: fashions in baby names, clothing, and music (i.e., public cultural forms) change endogenously through the birth,

[3]For an exception see some of his later work on science (Bourdieu, 2004).
[4]F&M are agnostic on this point (Fligstein and McAdam, 2015, 185-186).

death, and distributional variation of ideas. Like us, he also articulates several culture-centric evolutionary mechanisms (e.g. the "ratchet effect" or "symbolic contagion") to explain observed dynamics. However actor-centric explanations of change were not necessary for his narrative, and his book tacitly assumes culture flows unilaterally from the public to the personal through imitation. Our theoretical contribution connects Lieberson's culture-centric perspective to actor-centric perspectives on culture (e.g. practices, networks, fields), and our statistical framework allows analysts to formalize Lieberson's ideas as testable hypotheses.

Our approach also takes inspiration from **Organizational Ecology**'s portrayal of public cultural change, but makes explicit the connection between these ideas and personal cultural change (Hannan and Freeman, 1977; Ruef, 2000; Carroll and Hannan, 2004). Organizational Ecology seeks to explain the variation within organizational fields and the birth, death, and longevity of individual organizations using many of the same culture-centric evolutionary mechanisms argued for here (e.g., competition within niches). A key insight from Organizational Ecology was that the diversity of types of organizations could be understood as populations of "organizational forms" (Hsu and Hannan, 2005; Hannan, 2005) or market **"categories."** But rather than leverage this idea to describe populational change in other types of "cultural forms," the community pivoted to studying how organizations and cultural products should optimally position themselves in market categories (Hannan et al., 2012) with respect to the tastes and cognitive abilities of their audiences (Hsu, 2006; Hannan et al., 2012; Askin and Mauskapf, 2017). Although category theory has recently been situated more fully within cognitive sociology to explain the representation of categories in the minds of individuals, actor-centric explanations of change in these representations are still under-theorized (Hannan et al., 2019). Our work fills gaps in this literature's treatment of personal cultural change, the generalization of evolutionary mechanisms beyond market contexts, and the connection between the actor-centric change in understanding categories and culture-centric change in forms. Methodologically, we provide organizational ecologists with novel, contemporary Bayesian tools from biology.

3 A Sociological Theory of Cultural Evolution

To explain public cultural change, we now synthesize a broad theory of cultural evolution that stitches together an actor-centric, sociological perspective on culture and cognition with two leading contemporary cultural evolution programs: "Dual Inheritance Theory" (DIT) and the "Epidemiology Of Representations" (EOR) (Richerson and Boyd, 2008; Sperber, 1996; Scott-Phillips et al., 2018). Built in the 1980s on the idea that cultural dynamics mirror and modulate population genetics, DIT's influence has broadly permeated social science in recent decades (Cavalli-Sforza and Feldman, 1981; Boyd and Richerson, 1985; Mesoudi et al., 2006). In the 1990s, EOR emerged as a counterpoint to DIT that was rooted in cognitive science (Sperber, 1996; Claidiere, Scott-Phillips, and Sperber, 2014; Scott-Phillips et al., 2018). The two programs differ in that one views cultural learning as primarily imitative (DIT) while the other views learning as essentially transformative (EOR), but they have increasingly converged on a shared vision of cultural evolution in recent years (Acerbi and Mesoudi, 2015). For cultural evolution, ours is among the first major works to theoretically generalize these approaches beyond adaptive behaviors (Foster, 2018).

We borrow from both sociology and cultural evolution to develop the concept of dynamic, public "cultural forms" grounded in personal cultural learning and production. From cognitive sociology, we take the distinction between personal and public culture, an increasingly rich understanding of how ideas are learned and scaffolded in the brain as schemata, and how actors relate to cultural objects (DiMaggio, 1997; Lizardo, 2017; Foster, 2018; Taylor et al., 2019). The key insight from cultural evolution is that actor-centric and culture-centric perspectives on cultural change are linked through transformative learning. From DIT and EOR, we also take a rich explanation of how transformative learning and reproduction create cultural variation, and how behavioral biases shape the transmission of culture between actors.

Finally, we further extend all of these literatures by showing how culture-centric evolutionary mechanisms can be used to explain change and stability in public cultural forms. Because it connects personal cultural change to public cultural change, our theory is broadly consistent with most of the theories outlined in Section 2. Foreshadowing our case study, we use the Metal music genre to illustrate our points throughout.

3.1 Cultural Forms as Evolving Populations of Lineages

Following EOR, we view culture as sets of ideas[5] stored in the brains of actors, where it is structured heterogeneously in complex schematic associations unique to each individual (Sperber, 1996; DiMaggio, 1997). Sets of ideas are "cultural" when they are common due to social interaction and sufficiently similar that they are recognized by participants and analysts alike as tokens of the same type (Foster, 2018). In music genres, cultural ideas include the stylistic parameters of the music, as well as non-musical aesthetics, practices, and beliefs (Lena, 2012).

When individuals externalize ideas for whatever reason, we call the physical results (sets of) material objects.[6] Cultural objects are objects produced, recognized, referred to, or otherwise in relation with cultural ideas. Cultural objects include textual, visual, and aural media that we use to learn ideas from others (Taylor et al., 2019). They include the material affordances which enable and shape cultural practice or reify our institutions. The linguistic label "Metal" is just one of many cultural objects (e.g., recordings, written and spoken media) that circulate amongst actors. Beyond persistent materials, cultural objects also include ephemeral materials like speech, gesture, or more general practiced behaviors. This is how sound becomes "music" and technical guitar work becomes "Metal shredding." For Latour, cultural objects come together in space and time to construct culture (Latour, 2005). This perspective underscores that the repeated creation, usage, and consumption of cultural objects is necessary to stabilize and reproduce cultural ideas within a supporting population

[5]We replace EOR's term "representation" with "idea" for broader legibilty.

[6]Again EOR uses the the term "public representations," but the term object is familiar to culture and cognition scholars.

of actors over time.

Both personal and public cultural change are a byproduct of the cycle of personal cultural learning and public cultural re-production. Cultural ideas are not copied from one mind to another (Wrong, 1961). Instead, they are transmitted between actors along complex chains of learning from and re-production of cultural objects (Sperber, 1996; Foster, 2018). When there is high-fidelity, mutually intelligible reproduction of relevant cultural objects by actors across space and time, core sets of ideas and supporting objects will circulate and persist amongst an appreciable portion of the population. We call each idea, along with its representative objects, that endures across actors a **"cultural lineage"** (Gjesfjeld et al., Feb. 2020). In our empirical study, we consider each Metal band and subgenre to be a unique lineage represented publicly by recordings, musician-actors, and linguistic labels. Other example lineages in Metal include record labels (an institution), blast beat drumming, and the tradition of wearing black t-shirts to concerts (both practices).

We recognize populations of related cultural lineages that circulate amongst the same supporting actors as "**cultural forms**."[7] When cultural forms circulate for long and wide enough, they are canonized by linguistic labels (cultural objects) that stabilize their meaning over time and space. Music genres are textbook cultural forms constituted by a heterogeneous mix of musical, cultural, and social lineages. Forms may also be supported by other subforms. For example, the Black, Death, and Post-metal subgenres are all associated with our broader understanding of Metal. Furthermore, lineages may belong to multiple different cultural forms simultaneously (e.g., a band being identified as a "Blackened" Death Metal band).

Structurally, the population of actors that supports a cultural form may be as formal as a field or as flexible as a social network. This population includes anyone who holds relevant

[7] Our cultural forms are theoretically consistent with both "organizational forms" in the organizational ecology literature (Hannan, 2005; Hsu and Hannan, 2005), categories in the later categories literature (Hannan et al., 2019), as well as Fuhse's and Mark's uses of the term (Fuhse, 2009; Mark, 2003). Cultural forms are called "cultural cognitive causal chains" and later realized "attractors" in EOR (Scott-Phillips et al., 2018).

cultural ideas: explicit creators of cultural objects (artists, label managers, media), intentional consumers of these objects (fans), as well as those actors who absorb them passively and subconsciously (casual radio listeners).

The fulcrum that links actor-centric and culture-centric explanations of cultural variation is EOR's transformative learning (similar to "guided variation" in DIT) (Sperber, 1996; Richerson and Boyd, 2008). Cognitively, EOR and DIT agree that learning is critically shaped by the limited time, attention, motivation, and memory actors dedicate to learning and producing cultural lineages. These limited resources are both restrictive and generative. From an actor-centric perspective, individuals are unlikely to acquire, remember, or accurately reproduce lineages that are complex, not useful, or not relevant to them. As memories fail, objects fall into disuse, and transmission slows, some lineages in the cultural form will eventually "die" from lack of circulation (culture-centric perspective).[8] For example, consider a drummer that blends Samba rhythms with Metal elements in their band. By identifying their band as a Metal band, they have introduced Samba ideas into the population of Metal lineages. But depending on the circulation and acceptance of their music and surrounding media, these lineages can either be incorporated into conceptions of Metal by actors, or be forgotten and die within the form.

On the other hand, the fact that individuals learn and reproduce cultural lineages with imperfection and ingenuity (actor-centric perspective) "births" new variation within forms (culture-centric perspective). Each time a song is performed, a new lineage within the form is created due to changes or differences in the skills, experiences, and cognitive/material resources of the performers. Birth also comes from the fact that lineages are not learned or reproduced in isolation: (sets of) lineages are filtered through and incorporated into existing schemata, and subsequently reproduced with entirely different bundles of lineages (Goldberg and Stein, 2018). Fans and media can thus shape the meaning of the Metal form, creating novel associations between ideas through conversation, zines, labels, and online forums.

[8] If enough of the lineages that make up a cultural form fail to circulate, the meaning attributed to the form's linguistic label will deteriorate, become fuzzy, and the form itself may die.

Lastly, the birth of cultural lineages can result from intentional creativity when actors reconfigure, tinker, and augment existing lineages to produce novel ones. Professional musicians innovate explicitly, both for gratification and social capital within their field (Kahn-Harris, 2006; Lena and Pachucki, 2013; Prior, 2008).

From an actor-centric perspective, the distribution of lineages within a cultural form like Metal is also shaped by behavioral and cognitive factors that modulate which ideas an actors learns and reproduces. Many of these factors are legible both as network diffusion mechanisms and what are called "transmission biases" in DIT (Richerson and Boyd, 2008). Transmission biases include "model-based biases", where actors acquire an idea based on their similarity to the teacher (i.e., homophily) or the prestige of the teacher (i.e., status); "frequency-based" biases where actors prefer either rare or common variants of ideas (e.g., complex contagion); and "content-based" biases where actors adopt ideas based on the perceived functionality, usefulness, or social success of the idea.

3.2 Evolutionary Mechanisms

We originally defined cultural change as shifts in the amount, diversity, and quality of cultural ideas over time. With the birth and death of lineages, we now have theoretical tools to explain public cultural change that are grounded in a sociological, actor-centric understanding of cultural learning and reproduction. Stability and change in cultural forms can now be articulated simply through the turnover of lineages: when older lineages endure, the form is stable. Conversely, when older lineages are more often replaced by younger ones, culture changes. We leverage evolutionary mechanisms from biology (e.g., competition, key innovation, mass extinction) to make sense of actual, observed dynamics of change and stability in public culture from a culture-centric perspective.[9]

One idea we find useful is the extrapolation of actor-level constraints on time, attention, motivation, and memory to theorize a public **"cultural carrying capacity"** for a cultural

[9]For brevity, we note that many other evolutionary mechanisms can be imported and formalized within this theoretical and statistical framework (Lieberson, 2000; Hannan et al., 2012).[10]

form that spans the population of actors.[11] Through intentional creativity and transformative learning, actors are constantly proposing novel ideas and objects in association with cultural forms to their peers. Because individuals lack the bandwidth to process all of the lineages they are exposed to, some must inevitably fall by the wayside if the form is to maintain some coherent cultural meaning across actors (Martin, 2010). We therefore define the carrying capacity as a theoretical limit on the maximum number of distinct, circulating lineages within a cultural form at a given time.

Lineages that push up against this theoretical limit can be understood as **"competing"** for the limited resources of individual actors (actor-centric perspective) or "space" within the collective cultural carrying capacity (culture-centric perspective). Once the cultural carrying capacity of a form has been reached, lineages can either die completely through forgetting and lack of reproduction, or they may be interpreted as constitutive of adjacent cultural forms instead. For example, sonic lineages introduced by the Metal-Samba band might be recognizable by actors as affiliated with either genre-form, both, or neither. Biogeographers and organizational ecologists have used the topological metaphor of an "ecological niche" to describe carrying capacities for individuals, species, and organizations (Holt, 2009; McPherson, 1983). In this paper, we model the cultural carrying capacity uni-dimensionally as the absolute number of lineages (bands or subgenres) that actors can sustain, but we might imagine a coordinate system where each dimension corresponds to different types of actor resources and environmental factors (Mark, 2003). This multi-dimensional metaphor can be used to give greater insight into why cultural change is fast or slow, in what contexts, and for what kinds of actors.

[11] The production and learning from cultural objects encourages the alignment of actors' schemata, but each has varying resources (i.e. time, attention, motivation, memory) to apply to learning and production. Musicians who derive social and professional benefits from participating in Metal "scenes" may dedicate extensive resources to creating music, sharing media, and sustaining institutions like venues; while those who hear Metal on the radio may not (Lena and Pachucki, 2013; Kahn-Harris, 2006). Due to the piecemeal nature of cultural learning, these differences (e.g. time dedicated to listening to music) may lead musicians, fans, and casual listeners to have widely different schemata for the form. For example, some listeners may be able to identify subtle non-declarative sonic attributes that distinguish "Post-Metal" and "Brutal Death Metal," while others may only identify Metal as being "loud" or having distorted guitars. Nonetheless, we can view the collective potential resources of actors as the carrying capacity for the genre.

Other population-level mechanisms include **"key innovation"** and **"mass extinction."** In a biological context, key innovations are traits that allow for the rapid expansion of a taxonomic clade (e.g. the emergence of multi-cellularity) (Hunter, 1998). We conceptualize key innovations as influential lineages that open space for new ideas in the minds of individuals, greatly expanding the amount or diversity of viable ideas within the carrying capacity. Empirically, ideas core to Metal music (e.g. distorted guitars, technical musicianship, ultra-masculine aesthetics) that emerged in the late 1960s and early 1970s can be seen as key innovations that allowed a large population of actors to converge on a coherent, mutually intelligible understanding of Metal by the late 1970s. Conversely, mass extinctions are significant events that kill off a large number of ideas, creating space for new ones in the carrying capacity. Empirically, we later consider the explosive growth of Grunge Music in the early 1990s as an event that may have caused a mass extinction of Metal lineages. Practice theories have identified transformative social action and exogenous shocks from both within or outside the actor population as powerful vehicles of key innovation and mass extinction.[12]

The second half of this paper introduces a statistical framework that allows analysts to identify the influence of evolutionary mechanisms on the history of cultural forms. Empirically, we apply this framework to understand public cultural change in Metal music between 1968 to 2000.

[12]For example, Knorr-Cetina's micro-interactionalist theory focuses on choices by organizational and influential actors, who are likened to individuals with more power (Knorr-Cetina, 1988). Collins and Swidler argue that historical contingency creates space for transformative action. Collins points to "the introduction of new technologies of communication" or "emotional technologies" (i.e. key innovations) that realign the distribution of sociocultural resources to make some actors more powerful than others (Collins, 1981). Swidler contrasts "settled times," where habitual practice reign supreme, to "unsettled times" where social turbulence leads to collective action around strong semiotic symbols (Swidler, 1986) Note that the "settled/unsettled times" dichotomy is used to explain changes in behavior both over the individual lifecourse and in collective populations. In a field context, collective action can set the stage for mass extinctions or key innovations by rapidly changing the composition of the actor-population supporting the form (Fligstein and McAdam, 2015).

4 Metal as an Empirical Case

4.1 Background

Metal's roots can be traced to the late 1960s and early 1970s as British rock bands like Black Sabbath, Deep Purple, and Led Zeppelin began incorporating blues and psychedelic influences into increasingly hard rock sounds (Christe, 2010). Throughout the 1970s, an underground UK Metal scene fermented these sounds with elements of Punk to converge on a core set of ideas: sonically, "Metalheads" sought to coax churning distorted guitar patterns called "riffs," energetic tempos, and virtuosic musicianship from a traditional rock band ensemble. Aesthetically and socially, they cultivated an irreverent, ultra-masculine aesthetic that was free from the political messaging that had charged popular music of the past two decades. Spearheaded by bands like Iron Maiden and Def Leppard, these key innovations rocketed a new cultural form known as the New Wave of Britsh Heavy Metal (NWOBHM) into the 1980s mainstream. Despite being (or perhaps because it was) apolitical, Metal's transgressive aesthetic resonated with youth in the 1980s and achieved broad popularity and commercial success.

From NWOBHM, three independent sub-cultural forms emerged (Weinstein, 2000). One form was the industry-supported glam or hair Metal bands like Cinderella, Motley Crue, and Europe. Characterized by their flamboyant costumes, hair, and makeup, glam bands controlled a major slice of popular music radio-time in the second half of the 1980s. This lineage of pop Metal bands is often derided by Metal purists as "not truly Metal," and is conspicuously absent from our dataset, the Encyclopedia Metallum (EM). A second form was mid-1980's Power Metal. Pioneered by American bands like Manowar in the US and Helloween in Europe, power Metal curated symphonic elements, virtuosic guitar solos, clean vocals, and fantasy themes to create an epic sound. These bands enjoyed moderate commercial success in the U.S. in the second half of the 1980s, but were also successful in Europe through the mid 1990s.

Lastly, a parallel underground movement called Thrash emerged in the early 1980s as a reaction to the decadence and technical flashiness of pop Metal. With foundations laid by bands like Motorhead, Venom, and Void, Thrash Metal emphasized a raw Punk-like sound with fast simple riffs, gruff vocals, and "extreme occult imagery" (Kahn-Harris, 2006). This harsher, more masculine aesthetic also gained commercial success, peaking in the late 1980s and early 1990s through bands like Metallica, Megadeth, Slayer, and Anthrax. In the last three years of the 1980s, bands from these three forms consistently occupied the top 20 albums on the Billboard 200 (Klypchak, 2007). The mid to late 1980s on also saw a proliferation of Extreme Metal subgenres speciating from Thrash that dominate Metal today (e.g., Black, Death, Doom, Metalcore).[13] In general these subgenres took the aggressive, masculine, and macabre themes of heavy music and intensified them with even more abrasive distortion, guttural melody-less vocals, minor/dissonant harmonies, and vivid imagery.

Metal has a rich culture and history punctuated by popular peaks, moral panics,[14] and even sensational acts of terrorism[15] (Christe, 2010; Kahn-Harris, 2006; Klypchak, 2007; Walser, 1993; Weinstein, 2000). However, one event we are particularly interested in is Metal's decline from popularity in the late 1980s and early 1990s as a possible mass extinction. The commercial Metal landscape at this time was profoundly reshaped after the release of Grunge band Nirvana's *Nevermind* in 1991 (Kahn-Harris, 2006; Klypchak, 2007).

[13] A reticular cross-pollination with Hardcore Punk spawned Metalcore (e.g., Converge), and the even farther afield Grindcore (e.g., Napalm Death, Pig Destroyer), a subgenre famous for chaotic "microsongs" lasting just a few seconds. The most prolific, and perhaps most "scenic" Metal subgenre, Black Metal, took its name from a Venom album and embraced minor modes and dark, satanic imagery (Christe, 2010). Death Metal took Black aesthetics and re-infused the technical virtuosity that had been de-emphasized by the Thrash movement, along with growled vocals and ultra-violent, gory lyrics. Doom Metal and its popular subgenre Funeral Doom took the opposite approach, slowing down tempos to create bleak, suffocating soundscapes.

[14] In the 1980s, Metal was at the epicenter of a "Satanic Panic" that the subgenre was eroding the Christian values of the United States. The panic apexed with senate hearings of Metal musicians, a controversial parenting book by Tipper Gore, and the introduction of parental advisory labels for recordings. For the interested reader, Dee Snider of Twisted Sister's testimony before congress is a highlight.

[15] The history of the early Norwegian Black Metal scene active from 1993-1995 is a saga of suicide, church burnings, and murder. Perhaps because of its notoriety, it was formative in shaping Black Metal's musical and cultural aesthetics (Christe, 2010).

As Kahn-Harris puts it, “It is no hyperbole to state that an entire generation of bands had their careers ended overnight [by Grunge rock]” (Kahn-Harris, 2006, 1). The implications of the Grunge Rock takeover were long-lasting, effectively removing Metal as a cultural tradition from popular music, particularly in the United States. Popular hard rock forms like Alternative and Nu-metal drew heavily on Grunge and Punk, and any relationship with Metal of the 1980s was mutually disavowed. However, the effect of Grunge on the broader diversity of Metal ideas has not been studied.

4.2 Research Questions

We now apply our theory of evolutionary mechanisms to explore public cultural change in our case study, Metal music. Because our historical analyses evolved abductively (Lieberson and Lynn, 2002), we present the following research questions instead of hypotheses. Each of the first three research questions addresses the impact of a specific evolutionary mechanism (i.e., mass extinction, competition, and key innovation), while the fourth allows for alternative explanations:

RQ1: *Did the rise of Grunge music cause a mass extinction of ideas within Metal writ large?* (Analysis 1)

We might expect the replacement of commercial Metal with Grunge to depress the diversity of Metal ideas more generally (Kahn-Harris, 2006). However, given that Metal was a truly international (albeit Western) music form in the 1990s, it is hard to know how impactful this event was on the genre’s global trajectory.

RQ2: *How significantly did competition for cultural carrying capacity shape the diversity of ideas within Metal between 1968 and 2000?* (Analysis 2)

Competition is endogenous to cultural forms, but it may be especially intense in art genres where many of the supporting actors are also arrayed in a social field (Bourdieu, 1996; Kahn-Harris, 2006). In this context, there is constant pressure among artists to innovate new ideas to acquire social capital, even as the persistence of cultural objects like albums across space and time allows existing ideas to occupy "sonic niches" within the carrying capacity over long periods of time.

RQ3: *Is there evidence of key innovations in the history of Metal music?* (Analysis 3)

We might expect key innovations to emerge early in the trajectories of cultural forms. In inchoate music genres, we imagine a slow churn of ideas being and born and dying until early leaders define the sonic, aesthetic, and social parameters of the new genre (Lena, Peterson, and Peterson, 2011). Once these key innovations materialize, the form is named, the population of supporting actors grows, and new artists will enter the genre.

RQ4: *As a non-evolutionary alternative explanation, has the diversity of ideas within Metal simply tracked the form's visibility within popular culture?* (Analysis 4)

Under this alternative explanation, we might expect diversity in Metal to grow through the 1980s as the genre's popularity increases, and then decline as Metal enters its "Dark Ages" in the 1990s (Kahn-Harris, 2006).

4.3 Data

The dataset we use in this study, the Encyclopedia Metallum (www.metal-archives.com), was founded in 2002, just one year after Wikipedia. As of August 2017, the EM contained over 117,000 Metal bands, with exhaustive data on their dates and places of formation, discography, personnel, and record labels (Fig. D1). The most unique characteristic of the dataset is the manual curation of genre information. Bands may not be included in the encyclopedia without a recording sample and review by the moderation staff to determine that the music they play is indeed "Metal." Bands that are deemed to fundamentally be rooted in another music genre, for example Glam Metal bands in Pop, or Metalcore bands in Hardcore Punk, are excluded. Once a page is active, only experienced community members may edit a band's genre information. Changes by novice members must be approved by a moderator. Although subjective, we find that the subgenre labels in the EM are remarkably consistent with the actual co-listening/co-labeling of bands in another online music community, Last.FM (B.2). We thus view the EM as a manually curated approximation of the complete population of Metal bands from 1968 through today, with subgenre labels generated by and for the community itself.

Although the database is currently active, we limit our primary analyses to the 30,217 bands that released an album before the year 2000 for a number of reasons. First, by focusing on bands active before the database was created, we minimize the effects of both curatorial lag and any possible curatorial bias that might occur due to fluctuations in website usage over time. Second, we study this period because there is strong qualitative scholarship covering this era (Klypchak, 2007; Kahn-Harris, 2006; Walser, 1993), but less comprehensive literature written about Metal in the past two decades. Third, this cutoff occurs before the widespread adoption of the internet, which significantly altered how Metal culture was shared and reproduced globally (Mayer and Timberlake, 2014). To calculate diversification rates of bands and their affiliated subgenres, we use the formation and dissolution years of these bands. For the 15.6% of bands where it was unclear whether the band was extant or broken-up, we imputed their dissolution time stochastically and show this procedure does not affect our main findings (A.2; Fig. D2). For subgenre analyses, we inferred subgenre affiliations from the open field used to describe each band's musical style (A.1).

5 Methodology: Diversification Rates

Following our definition of cultural change, we study public cultural change empirically through shifts in the diversification (i.e., birth and death) rates of cultural lineages. Consistent with our theory, diversification rates capture how lineages "birth" other lineages through transformative learning, as well as how lineages "die" from disuse and forgetting. Advanced theory in biological macroevolution and organizational ecology has already articulated how evolutionary mechanisms like competition and mass extinctions can be seen in diversification rates (see 5.2 below) (Carroll and Hannan, 2004; Etienne et al., 2012; Silvestro et al., 2015; Rabosky, 2009; Ruef, 2000).

Practically, we focus on the diversification rates of cultural objects as proxies for lineages because we cannot peer into the minds of actors to measure ideas. Because culture can only be studied through cultural objects, it is also extremely difficult to provide a fully mechanistic account of the actor-level conditions that led to historical change in cultural forms. Empirical work in the networks, fields, and cultural evolution literatures has therefore often focused on elucidating actor-level processes using simulations, small field/case-studies, and experiments, rather than applying the theory to population-scale historical data.

Unlike these approaches, a key strength of diversification rate analysis is that it provides a culture-centric, rather than actor-centric, perspective on cultural change. This means we can identify the action of evolutionary mechanisms empirically, without fully elucidating the actor-level dynamics that gave rise to them. We need not make strong assumptions on actor-level circumstances (as in agent-based simulations), or the exact sequence of transmission and variation events (as in networks and phylogenies).[16] It follows that we do not necessarily need high-resolution actor-level data to justify these assumptions, just the birth and death times of objects. In an era where online data about cultural objects (e.g. social media data) is likely to be more plentiful, accessible, and often higher quality than data on actors, we see this as a big advantage for computational social scientists.

5.1 Birth-Death Process Models

Once popular in the Organizational Ecology literature (Ruef, 2000), we hope to revitalize diversification rate analysis with a modern statistical framework: birth-death processes. In general, we can calculate the birth rate λ and death rate μ of a population of objects

[16] This has been a point of criticism for phylogenetic analyses of macro-culture (Gould, 2010; Foster and Evans, 2019).

empirically as the number of objects born/dying within a time window, divided by the total time lived by objects during that time window. If the window is a single unit of time (e.g., year), the denominator reduces to the number of objects alive in a single unit.

$$\lambda_{MLE} = \frac{number\ of\ lineage\ births}{total\ time\ lived} \quad \mu_{MLE} = \frac{number\ of\ lineage\ deaths}{total\ time\ lived}$$

However, the empirical rates are noisy, randomly fluctuating, and approximately measured representations of the "true" underlying birth and death rates. In the following analyses, we therefore fit data to models based on the stochastic linear birth-death process, a popular model of evolutionary change across biology (Crawford, Ho, and Suchard, 2018). The likelihood of the linear birth-death process (Kendall, 1948) is:

$$P(\mathbf{s}, \mathbf{e} | \lambda, \mu) \propto \lambda^B \mu^D e^{-(\lambda+\mu)S} \tag{1}$$

Consider birth and death rates within the population of Metal bands. Here the likelihood of vectors $\mathbf{s}$ and $\mathbf{e}$, where $\mathbf{s}$ and $\mathbf{e}$ would respectively be the birth ("formation") and death ("break-up") years of bands, is a function of the unknown rates of birth (λ) and death (μ), the number of birth (B) and death events (D) within the time frame, and the cumulative time lived by the population within this time frame (S). As a generalized Poisson process, this likelihood can be understood as consisting of two event components (λ^B, μ^D), and two waiting time components ($e^{-\lambda S}, e^{-\mu S}$) between events. For a fuller exposition of birth-death processes, see (Crawford et al., 2018).

All of the models used in the main analyses are built on the linear birth-death process in Equation 1. First, we introduce here a new unsupervised machine-learning algorithm called *LiteRate*, adapted from current methods in macroevolutionary biology (Gjesfjeld et al., Feb. 2020; Silvestro et al., 2014b; Silvestro, Salamin, and Schnitzler, 2014a). LiteRate cuts through stochastic noise in empirical rates by concatenating an *a priori* unknown number of birth-death processes together to estimate diversification rates in a population of cultural objects. At the joints of these birth-death processes are statistically-significant shifts in the diversification rates that theoretically correspond with major historical events and/or the action of evolutionary mechanisms. LiteRate is described in greater detail in A.3.

After using LiteRate to generate hypotheses and identify potential key innovations or mass extinctions, we apply more mechanistic Bayesian models to explore the extent that competition, carrying capacity expansion due to key innovation, or popular music trends shaped the history of the bands and subgenre forms that constitute Metal music. In each of these models we reformulate the constant birth-death process in equation 1 so that it is calculated for each individual in each year:

$$P(\mathbf{s},\mathbf{e}|\lambda,\mu) = \prod_{i=1}^{N} \lambda(s_i)\mu(e_i) \times \exp\left(-\int_{s_i}^{e_i} \lambda(t) + \mu(t)\mathrm{d}t\right) \tag{2}$$

where the notation $\lambda(s_i)$ and $\mu(e_i)$ indicates the birth and death rates at the time of lineage i's birth and death, respectively. Rather than making $\lambda(t)$ and $\mu(t)$ constant across time, in Analyses 2-5 we make them parametric functions to test our hypotheses. These models are described in more detail in the Analyses section.

5.2 Evolutionary Mechanisms as Diversification Rate Patterns

In this section we introduce theoretical diversification rate patterns for three evolutionary mechanisms: mass extinction, competition for a fixed carrying capacity, and competition for a carrying capacity that grows due to key innovation. We also consider how exogenous trends might shape diversification rates as an alternative to these evolutionary explanations. We created birth-death process simulations to demonstrate these patterns in Fig. 1.[17] These rate signatures will allow us to explore the general research questions in 4.2 quantitatively.

Mass extinctions (RQ1) occur when transformative action or exogenous shocks disrupt the existing dynamics of the cultural form, causing the death of some lineages and creating space for new ones in the cultural carrying capacity. We would expect mass ex-

[17] The simulator can be found in the tutorials (AVAILABLEUPONREQUEST).

tinctions to manifest as a spike in extinction rates followed by a rise in birth rates after the event occurs (Fig. 1A). The LiteRate model (described in Analysis 1) finds statistically-significant shifts in birth and death rates over time, and can be used to identify this signature.

[FIGURE 1 ABOUT HERE]

Competition (RQ2) for cultural carrying capacity manifests as a population-level rate signature called diversity-dependent diversification (Etienne et al., 2012). In diversity dependence, birth rates slow and death rates accelerate as a function of the number of extant lineages. The idea is that lineages are forced to compete for the increasingly limited capacity of actors to learn, circulate, and reproduce new lineages. Eventually the carrying capacity will saturate and birth and death rates should converge, indicating a constant churn of lineages that leaves some forgotten or associated with proximal cultural forms (Fig. 1B). The competition model used in Analysis 2 enforces these constraints to estimate birth and death rates.

Key innovations (RQ3) are novel ideas that (re)define the parameters of a cultural form, expanding the breadth of viable ideas within a form and potentially opening it to new audiences. In other words, key innovations expand the cultural carrying capacity. Key innovations manifest as sudden, enduring increases in the birth rates. In this paper, we explicitly model the growth in carrying capacity that follows key innovations using a logistic growth curve (Analysis 3). Fig. 1C shows how this growth in carrying capacity modulates competition.

Lastly, to allow for **alternative explanations** outside of normal evolutionary dynamics **(RQ4)**, we can also model diversification rates as complicated nonlinear functions of some exogenous trend (Fig. 1D; Analysis 4).

6 Analyses: Cultural Change in Metal Music

We now apply our birth-death process models to abductively characterize cultural change in Metal Music between 1968-2000. Our core analyses (Analyses 1-4) focus on diversification rates within the population of bands, unique cultural lineages that are core to the Metal cultural form. However we also corroborate our findings through analyses on the populations of subgenre and sub-subgenre labels that are used to described bands by the actors themselves (Analysis 5). Models are elaborated in more detail when used. We outline the analyses below:

Analysis 1 uses the unsupervised LiteRate to identify shifts in the diversification rates of bands between 1968-2000 that theoretically correspond with historical events and/or evolutionary mechanisms. We use these shifts to partition the history of Metal into five phases. The LiteRate-estimated rates also allow us to assess evidence for a Grunge-driven mass extinction of Metal bands in the 1990s (RQ1).

Analysis 2 tests the hypothesis that the diversification rates of Metals bands from 1981-2000 are primarily driven by competition for a fixed cultural carrying capacity (RQ2).

Analysis 3 considers a model where competition is modulated by key innovation because competition alone does not capture the observed empirical birth rates in the formative years of the genre from 1968 to 1986 (RQ3).

Analysis 4 proposes an alternative hypothesis to the key innovation + competition model by considering whether the diversification rates of bands simply track popular music trends (RQ4).

Analysis 5 explores corroborative support that there is competition for cultural carrying capacity. Here we conduct LiteRate analyses on Metal subgenres, sub-subgenres within the seven largest subgenres, and bands within the seven largest subgenres.

6.1 Analysis 1: Generating Hypotheses with LiteRate

Motivation: To identify major shifts in noisy empirical rates, we introduce the unsupervised LiteRate model. The statistically-significant rate shifts identified by LiteRate correspond with major events in the history of Metal, and can help develop hypotheses about change due to evolutionary mechanisms or exogeneities.

Methods: LiteRate estimates a piecewise-constant birth-death process in which birth and death rates change at times of shifts, using Reversible Jump Markov chain Monte Carlo (RJMCMC) (Green, 1995) to discover the number, timing, and magnitude of these shifts. Statistically-significant shifts theoretically correspond with major events and/or evolutionary mechanisms. See A.3 for details.

We ran LiteRate for 10,000,000 generations (20% burn-in) for each of the 100 imputed datasets described in A.2, and then averaged parameter estimates across chains. Beyond giving us confidence in our imputations, this procedure also gives us confidence that our MCMCs are converging consistently on the same optimum. We repeat this procedure identically for all subsequent analyses.

Results: The rates estimated by LiteRate largely support the multi-stage diversification rate trajectory observed in the empirical rates (Fig. 2 dashed lines). For clarity, we partition this trajectory into five stages that have both largely monotonic slopes and are separated by statistically-significant ($2 * \log(Bayes\ Factor) > 2$) rate shifts.

[FIGURE 2 ABOUT HERE]

In Phase 1, early Metal experimentation begins from 1968-1978 with a U- or V-shape in which birth rates start out high, decline, and begin to rise again. The extent of this phenomenon is hard to gauge given that there are so few bands (large 95% credible interval [CI]). By 1978, the genre form appears to solidify around a few key innovations (i.e. bands and associated musical, aesthetic, and social ideas) and there is sharp growth through 1981, coupled with increased turnover as bands rapidly explore the genre space (Phase 2).

We identify Phase 3 as 1981-1988. From 1981-1984, birth rates are stable and high, while death rates rise. In Biology, the rapid churn of species early in a clade's history has been interpreted as necessary for clades to build a population of fit species that stabilize the clade's existence (Budd and Mann, 2018). From 1984-1988, birth rates fall while death rates stabilize. The overall signature of converging birth and death rates in Phase 3, called diversity-dependent diversification, is interpreted in biology as consistent with competition (Fig. 1B). In Phase 4 (1988-1993), birth and death rates are stable. Finally, Phase 5 (1994-2000) begins with another diversity dependence-like signature, before both birth and death rates slow, ossifying the stable of bands that make up Metal.

It is striking that not only are birth rates greater than death rates *on average*, they are *always* greater than death rates. If there is competition in Phases 3-5 while diversity is increasing, this suggests that the entire population does not actually reach a cultural carrying capacity by 2000. Moreover, while there is some range in death rates, they are not nearly as dynamic, suggesting that this is a birth-driven process. This is evident in the net diversification rates (birth minus death rate), which bear similar contours to the birth rates (Fig. D3).

It is also striking that two periods of apparent competition (Phases 3,5) are separated by a shelf with stable rates (Phase 4). The first possible interpretation of Phases 3-5 is that there is global competition operating from the genre's solidification in the early 1980s through 2000, and that Phase 4 is a momentary contextual deviation from this process. The second possible interpretation is that Phase 4 separates two independent periods of competition, potentially by two different groups of bands.

The fact that the shelf in Phase 4 also corresponds with Metal's peak in commercial appeal suggests that, at least for the majority of bands, the rise of Grunge music did not cause a significant extinction (RQ1). However, the contraction in rates in Phase 5 suggests the what scholars call the Metal "Dark Ages" in the second half of the 1990s does correspond with a chilling of growth after the fall from pop music (Kahn-Harris, 2006; Christe, 2010).

6.2 Analysis 2: Diversity-Dependent Competition Between Bands

Motivation: We interpret the competition signature across Phases 3-5 as evidence for a carrying capacity on the limited resources of actors. Once the sonic, aesthetic, and social parameters of the genre have become clear in the early 1980s, there is only so much cultural space for new bands to occupy while still being understood as Metal by actors. We now explore this formally using a mechanistic competition model.

Methods: Under diversity-dependent competition, we would expect birth rates to decrease over time and death rates to increase over time as the carrying capacity becomes filled (Figure 1B). Within the expanded birth-death likelihood specified in Equation 2, we can deploy this theory by parameterizing $\lambda(t)$ and $\mu(t)$ so that they are functions of the fraction of the carrying capacity filled at time t:

$$\lambda(t) = \lambda_{\max} - (\lambda_{\max} - \kappa)\left(\frac{D(t)}{K}\right)^{\delta} \qquad \mu(t) = \mu_{\min} + (\kappa - \mu_{\min})\left(\frac{D(t)}{K}\right)^{\gamma} \tag{3}$$

where,

$$\lambda_{max} = \kappa + \lambda_{mul} * \kappa \qquad \mu_{min} = \kappa - \mu_{mul} * \kappa \tag{4}$$

Our model has four main parameters: the value at which birth rates and death rates will converge κ, the size of the carrying capacity K filled when the rates arrive at κ, a convenience multiplier λ_{mul} for parameterizing the maximum birth rate λ_{max}, and a convenience multiplier μ_{mul} for parameterizing the minimum death rate μ_{min}. We calculate the fraction of the carrying capacity filled as the size of the current population at time t, $D(t)$, divided by K. Additional parameters δ and γ allow the rates to vary non-linearly with the proportion of the carrying capacity filled. In other words, these parameters modulate whether earlier bands or later bands are more important drivers of competition (e.g., with $\delta < 1$ and $\delta > 1$, respectively).

For the exponential parameters we place gamma priors concentrated around 1: $\delta_{prior} \sim Gamma(\alpha = 2, \beta = 2)$ and $\gamma_{prior} \sim Gamma(\alpha = 3, \beta = 2)$. From a frequentist perspective, these priors are regularizers that will shrink to a linear diversity dependence relationship. For the linear parameters, we use regularizing priors concentrated around 0: $\lambda_{mul} \sim Gamma(\alpha = 1, \beta = 1)$ and $\mu_{mul} \sim Beta(\alpha = 1, \beta = 1.2)$ that shrink the model to the null hypothesis of no competition, leaving us with constant rates. Full details of the implementation can be found in A.4.

Results: Descriptively, this model seems to closely match both the empirical and LiteRate birth rates from 1986 onwards (second half of Phase 3). However, it misses the initial growth phases of the genre from 1968-1982, averaging over the experimentation in Phase 1 and explosive growth in Phase 2, as well as the shelf in Phase 4.

The model is a significantly poorer fit for death rates, and the γ parameter effectively shrinks the model to a constant death rate over time. Although this result is not consistent with the LiteRate model, it suggests that competition (at least over a constant carrying capacity) is not a driving force behind the death rates we observe.

One of the most appealing features of this model is that we are able to estimate the theoretical maximum carrying capacity (Fig. 3C). We estimate a mean overall carrying capacity of 15,400 (95% CI 14544,16296), suggesting that this is the maximum number of bands the form could have supported over our analysis period while maintaining coherence.

[FIGURE 3 ABOUT HERE]

6.3 Analysis 3: Competition + Key Innovation

Motivation: In cultural history, we can very clearly observe the coalescence of new cultural forms and supporting actor populations (Phase 2). In Metal for example, the capacity for new bands and other lineages is a direct function of key innovations by early trendsetters who defined the parameters of the genre (Phase 1). After this early groundwork, we might expect the space for new ideas to grow in Phase 2 as the actor population expands, people gain and broaden the understanding of what the form means, and there is more overall actor resources dedicated to consuming and producing cultural objects. Nevertheless, we still expect competition to set in after the form solidifies as the diversity of ideas approaches an expanded cultural carrying capacity.

We explore this hypothesis because the competition model in Analysis 2 does not adequately capture the birth dynamics in Phases 1-2. During this period, empirical birthrates start high, then decline until 1973, and finally start to rise again until 1981. While the extent of these fluctuations is largely moderated in the LiteRate-inferred rates (which we speculate is a result of limited data), they are weakly evident there as well.

Methods: To model carrying capacity expansion due to key innovation, we add another layer to equation 5 by allowing the carrying capacity K to grow over time,

$$\lambda(t) = \lambda_{\max} - (\lambda_{\max} - \kappa)\left(\frac{D(t)}{K(t)}\right)^{\delta} \qquad \mu(t) = \mu_{\min} + (\kappa - \mu_{\min})\left(\frac{D(t)}{K(t)}\right)^{\gamma} \tag{5}$$

where $K(t)$ changes according to the parameters of a logistic function (Fig. 1C),

$$K(t) = d + \frac{L}{1 - \exp(-k * (t - x_0))} \tag{6}$$

and d specifies the minimum carrying capacity, L is the maximum of the logistic function ($L+d$ is the maximum carrying capacity), $k \in \mathcal{R}^+$ determines the speed at which the carrying capacity grows, t is time, and x_0 is the year at which the carrying capacity is growing the fastest due to key innovation. The entire hierarchical model has 9 parameters. See A.4 for details.

Results: Broadly speaking, this model reproduces the trends observed in the empirical and LiteRate rates: the birth rate starts high, declines, and then re-emerges to enter a characteristic diversity dependence signature (1981-2000). The mean midpoint of logistic growth is 1979.89 (95% CI 1977.96, 1981.59), which corresponds closely with the spike in LiteRate-estimated birth rates attributed to key innovations in Phase 2 (Fig. 3C). We can again estimate a maximum carrying capacity: 16,172 (95% CI 15003,17437) bands across chains (Table 1).

6.4 Analysis 4: Rates Follow Popular Trends

Motivation: The evolutionary narrative of early carrying capacity expansion and subsequent competition is a compelling explanation of Metal's broad historical trajectory from 1968-2000 (Phases 1-3,5) (Fig. 3B). However, the model from Analysis 3 averages over the large shelf in rates in Phase 4 (1988-1994). This period corresponds with Metal's surge in popularity in the second half of the 1980s and the emergence of Grunge music in the early 1990s. Both of these phenomena are evident in the number of songs charting on the Billboard 100 music chart (Fig. 4A). We therefore consider a model where rates are a flexible non-linear function of Metal songs on the BillBoard 100 US pop music charts.

Methods: In this model, rather than make $\lambda(t)$ and $\mu(t)$ functions of diversity and/or a logistic curve, we vary them as a function of the proportion of songs C by broadly-labeled Metal bands charting on the Billboard 100 from 1968-2000. The equation below is still nested inside equation 2. We again place regularizing parameters on the priors as described in Analysis 2 (A.4).

$$\lambda(t) = \lambda_{const} + \alpha * C^{\delta} \qquad \mu(t) = \mu_{const} + \beta * C^{\gamma} \tag{7}$$

We measure Metal's popular success using any song that is labeled as some subgenre of Metal on Discogs (*Discogs API*, 2019) or is released by an artist who is listed as Metal (including Glam Metal) in their Wikipedia sidebar (using the DBPedia API) (Auer et al., 2007). We also manually checked the Wikipedia abstracts for descriptions as "Metal" for boundary cases that were not genre-labeled in either dataset or are labeled as "Hard Rock" in Discogs. Overall we found 560 broadly understood Metal singles out of the 14,608 unique songs on the Hot100 chart between 1968 and 2000.

Results: Even with extremely flexible models, these data do not seem to model the empirical or LiteRate estimated rates in Phase 4 or the rest of Metal's history. We thus reject the hypothesis that the diversification rates of Metal bands broadly follows the genre's success in popular music.

However, the fact that Metal does not broadly follow popular trends from 1968-2000 does not mean that the rise of Metal and fall to Grunge are not reflected in the Phase 4 rate plateau. We explore Phase 4 in more detail in Analysis 5.

[FIGURE 4 ABOUT HERE]

6.5 Analysis 5: Corroboration of Cultural Competition

Motivation: While we find evidence for competition between bands compelling, this could be primarily competition between bands as actors in a social field (Fligstein and McAdam, 2015), rather than competition between the musical, aesthetic, and social ideas that these bands represent. We therefore analyze diversification rates between purely cultural objects: new subgenre labels within Metal and new sub-subgenres labels within the seven largest subgenres: Death, Thrash, Heavy, Black, Power, Doom, and Progressive. These seven subgenres collectively label 94.9% of bands in the dataset. To better understand Phase 4, we also analyze diversification rates of bands within these seven subgenres.

Methods: To look for evidence of competition between subgenres and sub-subgenres for the limited resources of actors, we use LiteRate to estimate diversification rates of subgenre labels in all of Metal (e.g. Death, Black, Post-, etc...) and sub-subgenre labels within the seven largest genres (e.g. Technical Death, Brutal Death, Blackened Death within Death). In parallel, we perform LiteRate analyses on bands within these seven subgenres.

Results: Lending further support for cultural competition, we observe a decline in the LiteRate-estimated birthrate for subgenres until it is effectively zero by 1997 (Phase 5), suggesting that Metal cannot accommodate any more subgenres. 95% CIs are much broader for sub-subgenres because of sparse data, but similar patterns are observed. We focus on birth rates here because subgenres rarely if ever "die," but this pattern still shows the full diversity dependence signature of rates converging at maximum carrying capacity.[18]

We also observe diversity-dependent competition signatures in the rates of bands in the seven largest subgenres. Interestingly, it is the commercially viable genres (Thrash, Heavy) that seem to hit carrying capacity in the early 1990s (Phase 4), while Extreme Metal genres (Death, Black, Doom) and Progressive Metal continue to grow throughout Phase 4 and begin to compete in Phase 5. This phenomenon can also be clearly seen in plots of the number of bands within these subgenres over time (Fig. D4).[19]

[FIGURE 5 ABOUT HERE]

7 Discussion of Metal Analyses

How have evolutionary processes shaped the history of Metal Music? We began by using the unsupervised LiteRate model to identify statistically significant shifts in the birth and death rates of all Metal bands active between 1968-2000 (Analysis 1). We then partitioned this diversification rate trajectory into five phases separated by significant shifts and changes in slope (Fig. 2). Next, we checked whether the rate patterns in any of these phases were consistent with research questions about the evolutionary mechanisms described in Section 5.2: mass extinction (RQ1), competition for cultural carrying capacity (RQ2; Analysis 2), or key innovation (RQ3; Analysis 3). Finally we considered the alternative explanation

[18] Genres rarely die because at least one band is often active at all times. In genres/subgenres that experience mainstream commercial success, bands may remain active for decades (e.g., Metallica).

[19] Note that there is a smaller shelf which we do not discuss between 1986-1988 to avoid over-complicating the narrative. Fig, D4 suggests that this shelf reflects staggered competition setting in at different times in the U.S. and the rest of the world.

that band diversification rates simply follow popular music trends (RQ4; Analysis 4). We find a combination of key innovation and competition between cultural lineages the most compelling overall explanation of public cultural change in Metal between 1968 and 2000, both qualitatively and statistically (Analysis 3). We support this conclusion with further evidence of cultural competition between subgenres and sub-subgenres (Analysis 5).

A theoretical interpretation of our results contextualizes these models within the five historical phases delineated by the LiteRate analysis (Fig. 2). These phases are interpretable within both our own theory of culture, as well as Lena and Peterson's four-stage lifecourse for music genres (i.e. an experimental phase, a scene-based phase, a popular phase, and a traditionalist phase) (Lena and Peterson, 2008; Lena, 2012).

In Phase 1 (1968-1978), a few trendsetting bands are experimenting with new sounds and trying on different ideas for the form. Because the circulation of these ideas is so limited, the effective capacity of listeners to collectively recognize these different sounds, aesthetics, and practices as Metal music is also limited. Bands that are creating music adjacent to early Metal bands like Black Sabbath may thus be interpreted as "not Metal" because the parameters of the genre are small/narrow. The only model to adequately capture the U- or V- shaped birth dynamics during this period models competition between bands for an extremely limited carrying capacity (approximately 50 bands) (Analysis 3; Fig. 3B,C).

From 1978 to 1981 (Phase 2), a critical number of actors (e.g. bands, fans, passive listeners) coalesce around a shared set of ideas to create a coherent, mutually intelligible conception of the Metal genre form. The key innovation of these ideas allows the birth rate of bands to explode by establishing a bounded space of sonic, aesthetic, and social parameters which new artists can explore (RQ3). Again, the only model that can explain observed dynamics here is one in which the carrying capacity expands rapidly due to key innovation (Analysis 3; Fig. 3B).

In the beginning of Phase 3 (1981-1988), bands rapidly fill up available "sonic niches" within the form. But by 1984, competition sets in for the time, attention, memory, and motivation (i.e., cultural carrying capacity) that the actor population can devote to Metal (RQ2). Even though the number of listeners is growing, a coherent understanding of the genre (i.e. a core set of circulating ideas) can only expand so much. This competition does not prevent new Metal-influenced bands from being formed on the frontiers of the genre, it simply prevents them from being recognized as Metal bands. By 1984 our modeled carrying capacity is fixed, and the competition (Analysis 2), and competition + niche expansion (Analysis 3) models are functionally equivalent (Fig. 3).

Phase 4 (1989-1994) corresponds with the climax of Metal as a popular form and its dethronement by Grunge rock, but neither LiteRate (Analysis 1) or a model that tracks Metal's pop chart marketshare (Analysis 4) show that the mass extinction observed in commercial Metal bands (Klypchak, 2007; Christe, 2010; Kahn-Harris, 2006) generalized to Metal bands writ large (RQ1). Instead, both birth and death rates are curiously stable over this period. In Analysis 5, we show that the deviation from global competition in Phase 4 likely represents two staggered processes of competition by two different groups: commercially-viable (e.g. Heavy, Thrash) bands and Extreme (e.g. Doom, Black, Death) bands. Having saturated their carrying capacities, rates in commercially-viable genres plateau because they are no longer capable of growth (Fig. 5 top and middle rows). In contrast, Extreme Metal genres plateau during this period because they are building a "fit" population of bands at the peak of innovation before competition begins in Phase 5. During Phase 5, Metal's "Dark Ages," birth rates resume declining, and death rates begin to decline as well (1994-2000). We speculate that the contraction in death rates in Phase 5 reflects relaxing competition as the genre transitions from a popular form into a combination of traditionalist commercial and scene-based Extreme forms (Lena, 2012).

Overall, the competition + key innovation model provides a more compelling explanation of the dynamics of Metal bands between 1968-2000 than either competition alone or the hypothesis that band dynamics track the genre's commercial success. Statistical comparison corroborates this visual assessment. To compare the models in Analyses 2-4, we concatenated birth and death rates and OLS regressed them on both the mean empirical rates and the mean LiteRate rates. The coefficient of determination (R^2) of these regressions is a measure of the models' *adequacy* in capturing the linear variation in both the stochastic empirical and estimated rates.[20] Table 1 illustrates not only that the competition + key innovation model has the highest adequacy among mechanistic models to the LiteRate rates, but that it is relatively parsimonious with only 9 parameters. It also provides estimates for two interesting quantities: the year when key innovation had the greatest impact on carrying capacity and the maximum carrying capacity that the cultural form can theoretically sustain.

[TABLE 1 ABOUT HERE]

If bands truly represent cultural lineages and not only social actors competing for cultural capital, we would expect to see evidence of competition between other lineages within the Metal form (Bourdieu, 1996; Kahn-Harris, 2006). Indeed, the competition between Metal genres evident in Analysis 5 is purely cultural. By 1997 no new Metal genres are being born, and we see similar slowdowns in the birth rates of subgenre labels within Metal's seven largest genres over time. These findings demonstrate that even in a community that relishes technical language, there are real cognitive limits on the diversity of ideas the form can sustain while maintaining coherence. This conclusion is reinforced by a supplementary Shannon entropy analysis that shows that actors labeling bands in the EM only ever exploit a constant proportion of the previously introduced genre possibilities available to them (B.3). Corroborating this narrative, the same phenomenon is reproduced amongst available subgenres of Metal (Fig. D5D) and amongst the 2,033 combinations of unique genre descriptors used in the EM (Fig. D6B).

Our broad conclusion that Metal music has been fundamentally shaped by competition

[20] We also calculated the harmonic mean of the likelihood (Raftery et al., 2007). For bands, the ordinal rank of this statistic corresponds with R^2_{emp} except that the LiteRate model has the highest harmonic mean and competition + key innovation has the second highest. However, we do not include this statistic in Table 1 because it is not a reliable estimate of the marginal likelihood due to its infinite variance.

between cultural lineages is based primarily on evidence from birth rates, not death rates. While we initially thought that rising LiteRate-estimated band death rates (Analysis 1) suggested competition, this hypothesis was not born out by our models. Both the competition and competition + key innovation models estimated essentially flat death rates from 1968-2000, and these flat rates do not converge with birth rates by the year 2000.[21] However, we do observe the full diversity-dependent competition signature where birth and death rates converge in our analyses of Thrash bands, Heavy bands, subgenre labels, and sub-subgenre labels with multiple subgenres (Fig. 5). Furthermore, net diversification (birth minus death) rates of all bands and genres show that death rates contribute little to the overall dynamics of Metal between 1968 and 2000 compared to birth rates (Fig. D3).

7.1 Future Directions and Limitations

One direction for future work could explore how the saliency of lineages within a form varies across individuals and over time. In this paper we made the simplifying assumptions that all lineages are equally important to the dynamics of a form, and that this importance does not vary over the lineage's lifecourse. The first assumption is reasonable because schemata are heterogeneous across individuals, and ideas that are crucial to one actor's conceptions of the form might be absent from another's. For the garage and touring bands that comprise the majority of our dataset, we also think it reasonable to assume a band's ideas are "dead" when the band dissolves and stops actively circulating them. The advantage of these simplifying assumptions is that they allowed us to analyze tens of thousands of bands not found in commercial datasets like Spotify or iTunes for which saliency data (e.g., album sales) are not available. Focusing on heterogeneous cultural saliency would have resulted in a bias towards commercially successful and recent bands. Nevertheless, we consider modeling cultural saliency an important direction for future work (Candia and Uzzi, 2020).

[21] A preliminary analysis of diversification rates through 2016 suggests that rates eventually *do* converge as predicted by competition. Howevever, we conservatively stop our analysis at 2000 for reasons described in the data section (Section 4.3).

Although there is strong evidence for competition in birth rates, future work might also explore why we observe flat death rates within the population of bands. One possibility is that competitive effects on extinction only become visible when the carrying capacity has been reached after our window of analysis. An alternative explanation is that band break-ups are not driven by competition, but moreso by changing life circumstances for actors that are exogenous to the form. A third possibility is that competition affects the death rates of younger, less-established bands disproportionately, as observed in several biological systems (Hagen et al., 2018). Richer actor-level data and age-dependent extinction models could tease these hypotheses apart.

Are there other interpretations of sustained, slowing birth rates over two decades beyond cultural competition? Other than the declining pop music relevance ruled out in Analysis 4, we could not think of any. We stress here that the culture-centric mechanism of competition between ideas is consistent with a number of actor-centric mechanisms that can explain slowing cultural transmission over time (Rossman, 2014; Centola, 2020). These explanations could be formulated in the language of cultural evolution (e.g., frequency or content biases) or in the language of network science (e.g., preferential attachment, information cascades, or complex contagion). All are at least in part dependent on the limited time, attention, motivation, and memory actors can dedicate to learning ideas and reproducing cultural objects (i.e., cultural carrying capacity). With richer data on individuals, our understanding of the diversication process could certainly be strengthened by demonstrating how a cultural carrying capacity emerges from an actor-centric perspective.

8 Sociological Contributions and Conclusions

How do public cultures change? We propose an evolutionary perspective on culture that unifies actor-centric and culture-centric explanations of change by linking personal cultural learning of ideas to the production of public cultural objects. Variation between lineages of objects and ideas is "birthed" through transformative learning and creativity, and cultural "death" results from forgetting and disuse. These processes create cultural forms: populations of associated cultural lineages circulating amongst actors. Our theory allows for an explicit definition of cultural change as shifts in the amount, diversity, and quality of cultural ideas over time. Lastly, it allows us to leverage culture-centric evolutionary mechanisms like competition, key innovation, and mass extinction to explain historical change in public cultural forms like Metal music. These mechanisms are quite general and can be used to understand dynamics within any cultural form. We introduce a suite of novel diversification rate models: an unsupervised model to generate hypotheses about the role of evolutionary mechanisms in historical cultural dynamics (Analysis 1), and restricted models to explicitly test these hypotheses (Analyses 2-4). Applying these models to a population-scale dataset of Metal bands, we find evidence that enduring competition between ideas for the time, attention, motivation, and memory of actors (i.e., cultural carrying capacity) has fundamentally shaped the trajectory of the genre from 1968-2000. In the rest of this section, we expand on how our approach can generalize to other contexts, and how it makes distinct contributions to sociological methodology, the sociology of culture, and cultural sociology.

Our case study focuses on a classic cultural form, the art genre, but the theoretical constructs and models proposed here can help understand change in forms as varied as news cycles, scientific fields, organizational forms, conspiracy theories, and attitudes towards historical taboos like face tattoos or homosexuality. For example, the population of ideas about homosexuality consists of distinct lineages that view homosexuality as identity, homosexuality as behavior, and homosexuality as sin, as well as lineages of positions on public displays of affection, marriage, and HIV that result from these views (Hart-Brinson, 2016). Attitudes towards homosexuality buck an emerging consensus that many personal cultural beliefs are firmly held over an individual's lifetime (Kiley and Vaisey, 2020). In this case, cultural evolution might be illuminating because it underscores that *ideas must circulate* for cultural change to occur. To explain the modal shift in attitudes towards homosexuality in less than a generation, scholars have pointed to mechanisms such as increased dialogue with contacts who started coming out as gay (Rosenfeld, 2017; DellaPosta, 2018). From an evolutionary perspective, the "contact hypothesis" suggests that the bundling of taboo ideas (key innovations) with more socially acceptable ones broadened conceptions of what homosexuality could look like and expanded the carrying capacity of the form. Although we do not want to leave the reader with the impression that carrying capacity dynamics are the only evolutionary mechanisms of interest, we leave a fuller analysis of attitudes towards homosexuality to future work.

For sociological methodology, we provide a complete suite of cutting-edge, Bayesian birth-death process models for the analysis of diversification rates in demography, social fields, organizational ecology, and the computational analysis of culture. The unsupervised LiteRate can discover significant shifts in rates and help generate hypotheses, while our more mechanistic models can be used to test hypotheses about key innovation, competition, and the influence of exogenous trends on rates. Our models are easy to apply and we have created extensive tutorials for their usage at `AVAILABLEUPONREQUEST`. Diversification rates are powerful because they allow analysts to abductively compare hypotheses explaining cultural change using only minimal data on the presence/absence of cultural objects. These methods do not require assumptions or data on actors, their behaviors, or their structural configuration. We see this culture-centric approach as complementary to actor-centric methods like social network analysis that can provide a fine-grained explanation on how change occurs when high-resolution actor-level data *is* available.

For the sociology of culture, our work makes inter-related contributions to the sociology of music genres, Metal Studies, and the theory of creative fields. Our population-scale analysis of Metal music largely squares with (Lena and Peterson, 2008; Lena, 2012) four-part trajectory for individual music genres, and nuances histories of Metal Music that focus on events in popular music (Christe, 2010; Weinstein, 2000; Klypchak, 2007). By looking at tens of thousands of bands with limited economic motivation, our analysis suggests that changes in Metal in the late 1980s and early 1990s represent more of a phase transition between senescing popular forms and emerging Extreme forms, rather than a generalization of the sudden Grunge-driven mass extinction observed within popular music. Our approach also challenges analysts of creative fields like science and art to broaden their focus beyond competition between actors for social and cultural capital, and consider how cultural ideas compete for the resources of actors. For example, a populational reimagining of Bourdieu's habitus might yield insight into how habitus evolves over time and shapes the decisions of actors within a field (Bourdieu, 1996).

For cultural sociology, we link contemporary cognitive perspectives with cultural evolution to explain public cultural change. Our approach exposes an underappreciated micro-/macro- duality first suggested in Elias' comparison of psychogenesis and sociogenesis: explaining cultural change requires the analyst to choose between a focus on the agentive *individual actor* who learns, embodies, and interfaces with some homogeneous, non-dynamic public culture, or a focus on dynamic, heterogeneous *public culture* that changes across groups of passive individuals (Elias, 1994). Like Breiger's duality between people and groups, both perspectives are valid, but it is impossible to hold them simultaneously (Breiger, 1974). By placing the central drama on the individual actor, leveraging cognitive science to explain learning and practice, and elaborating on stable institutions/structures, cultural sociology has decidedly coalesced around the former perspective (Swidler, 1986; DiMaggio, 1997; DellaPosta et al., 2015; Hannan et al., 2019; Lizardo, 2017; Kiley and Vaisey, 2020). By presenting culture as a heterogeneous population of ideas and leveraging insights from cultural evolution, our hope is that this paper will revitalize interest in public, culture-focused approaches to cultural change going forward.

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9 Figures

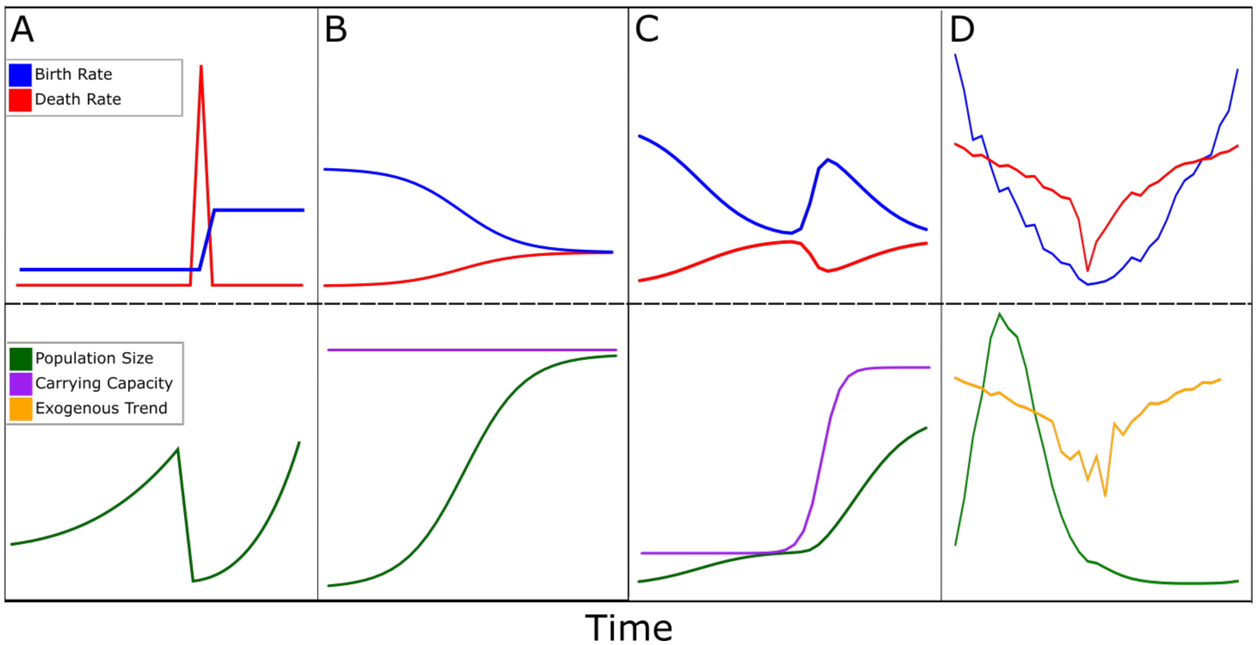

Figure 1: **Theoretical Rate Signatures.** Top row shows theoretical rates corresponding with evolutionary mechanisms, bottom row shows population size and, when appropriate, carrying capacity or exogenous trends. Theory and rate signatures proposed in 5.2. **Column A: Significant extinctions.** Death rates spike, creating space for new lineages in carrying capacity (rising birth rates). Statistical model to identify significant extinctions and study of Metal bands in Anal. 1. **Column B: Competition.** Rates converge and population size plateaus as population approaches cultural carrying capacity (Anal. 2). **Column C: Competition + Key innovation.** Key innovations permanently expand the carrying capacity creating space for new lineages. As in B, but carrying capacity grows according to a logistic growth curve (Anal. 3). **Column D: Exogenous Trend.** Rates are a function of some exogenous influence (orange line) outside normal evolutionary dynamics (Anal. 4).

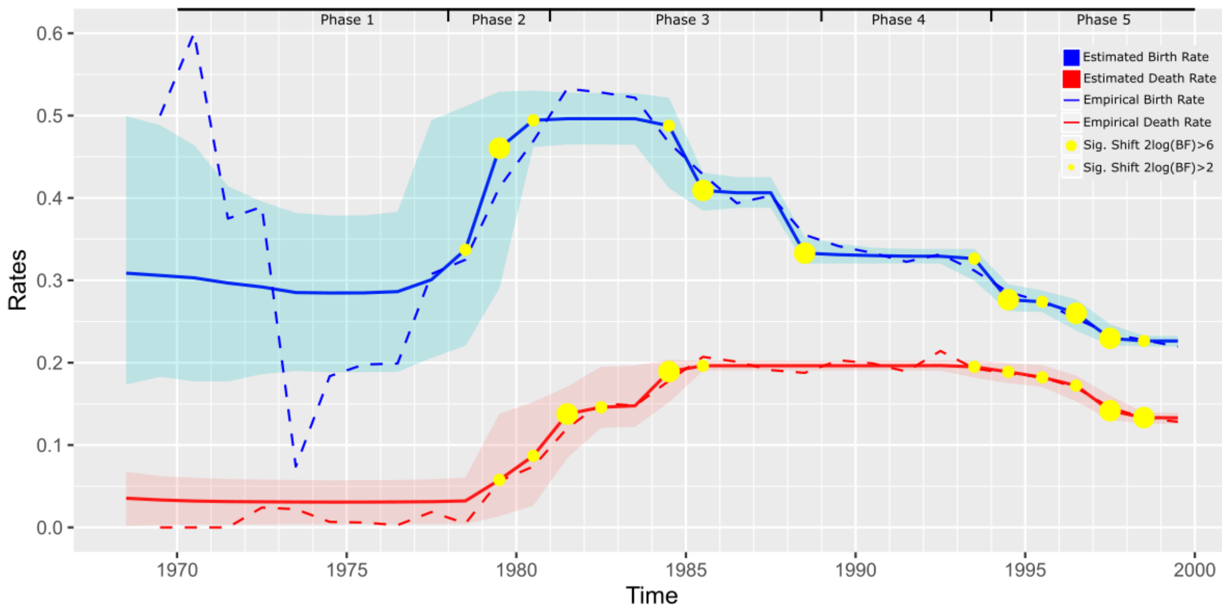

Figure 2: **Estimated Diversification Rates from Analysis 1.** Dashed lines indicate empirical birth (red) and death (blue) of EM metal bands (first year dropped for clarity). Estimated rates and their 95% highest posterior density intervals shown in solid colors. Significant rate shifts shown as yellow circles. Five historical phases visible in estimated rates (partitioned by significant rate shifts) denoted at top of plot.

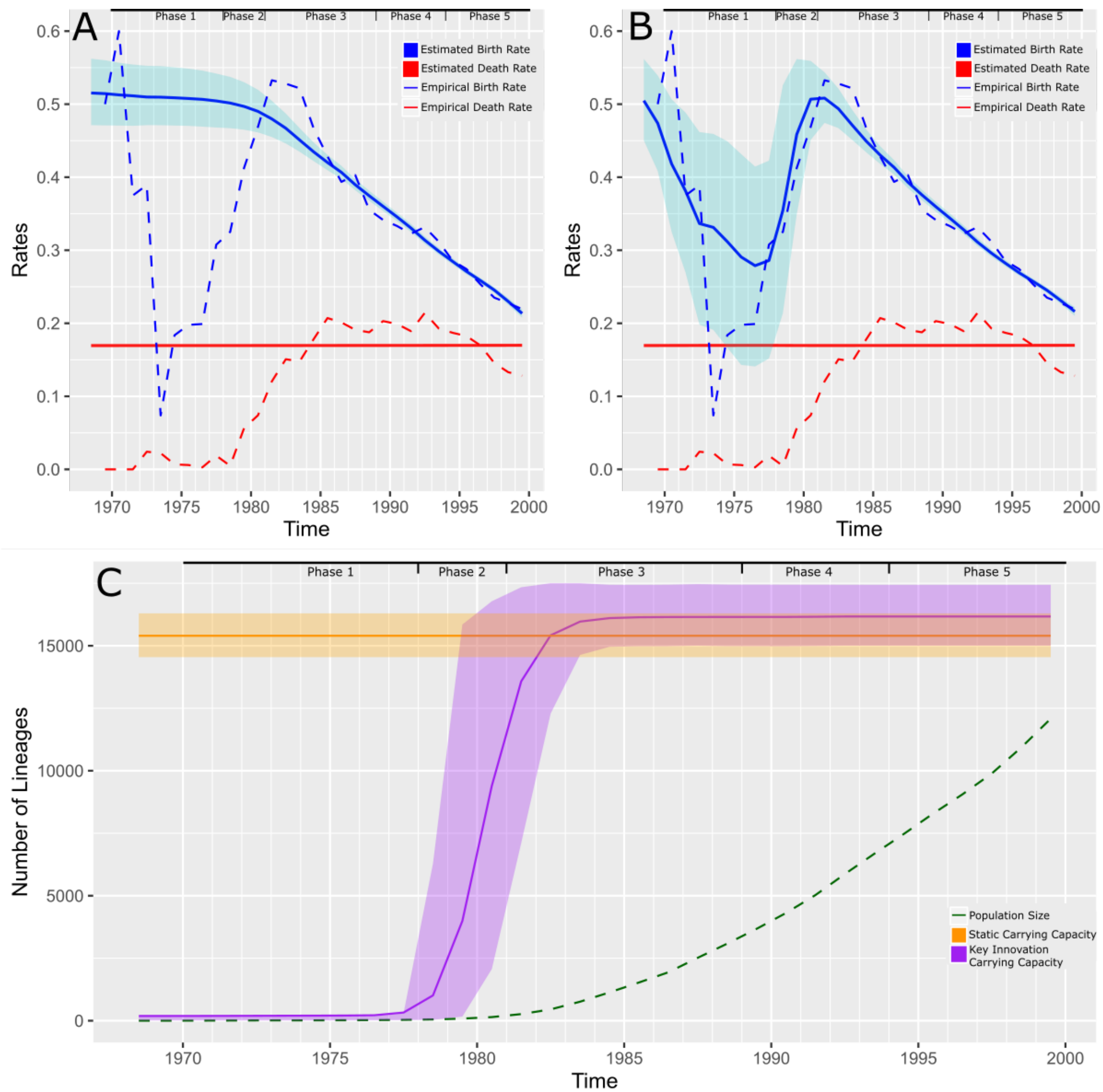

Figure 3: **Estimated Diversification Rates and Carrying Capacities from Analyses 2 and 3.** Dashed lines indicate empirical birth (red) and death (blue) of EM metal bands (first bin dropped for clarity). Estimated rates and their 95% highest posterior density intervals shown in solid colors. **A**: Estimated birth and death rates over time for diversity-dependent competition model in Analysis 2. **B**: Estimated birth and death rates for diversity-dependent competition with carrying capacity expansion due to key innovation in Analysis 3. **C**: Estimated carrying capacities over time in Analyses 2 (orange) and 3 (purple) with 95% highest posterior density intervals. Empirical population size shown in green.

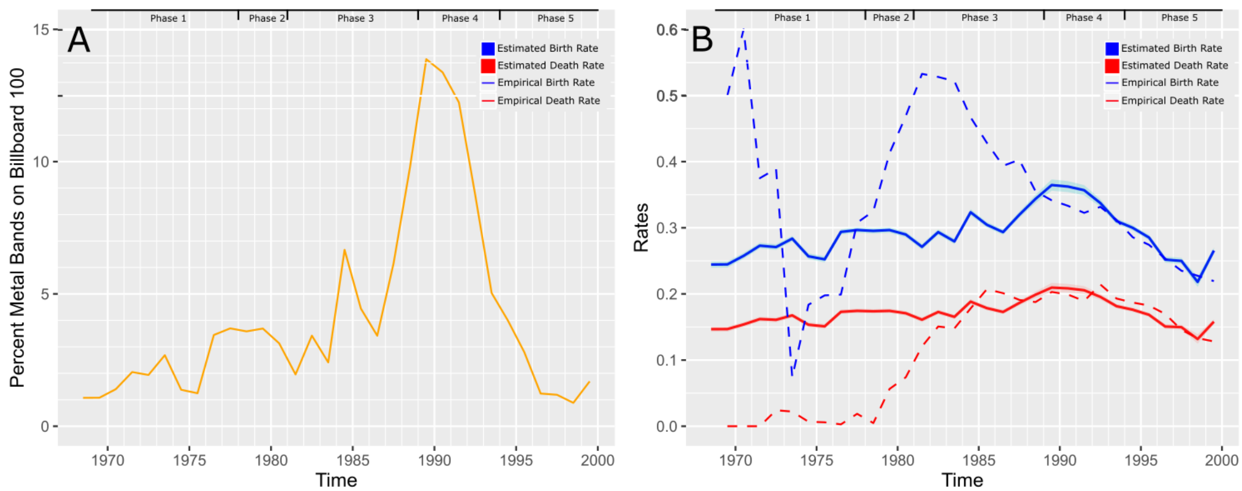

Figure 4: **Estimated Diversification Rates from Analysis 4.** Estimated diversification rates (**B**) when rates are a function of the proportion of broadly-understood "Metal" bands (i.e., labeled as Metal in Wikipedia or Discogs) on the Hot 100 chart 1968-2000 (**A**). Dashed lines indicate empirical birth (red) and death (blue) of EM metal bands (first bin dropped for clarity). Estimated rates and their 95% highest posterior density intervals shown in solid colors.

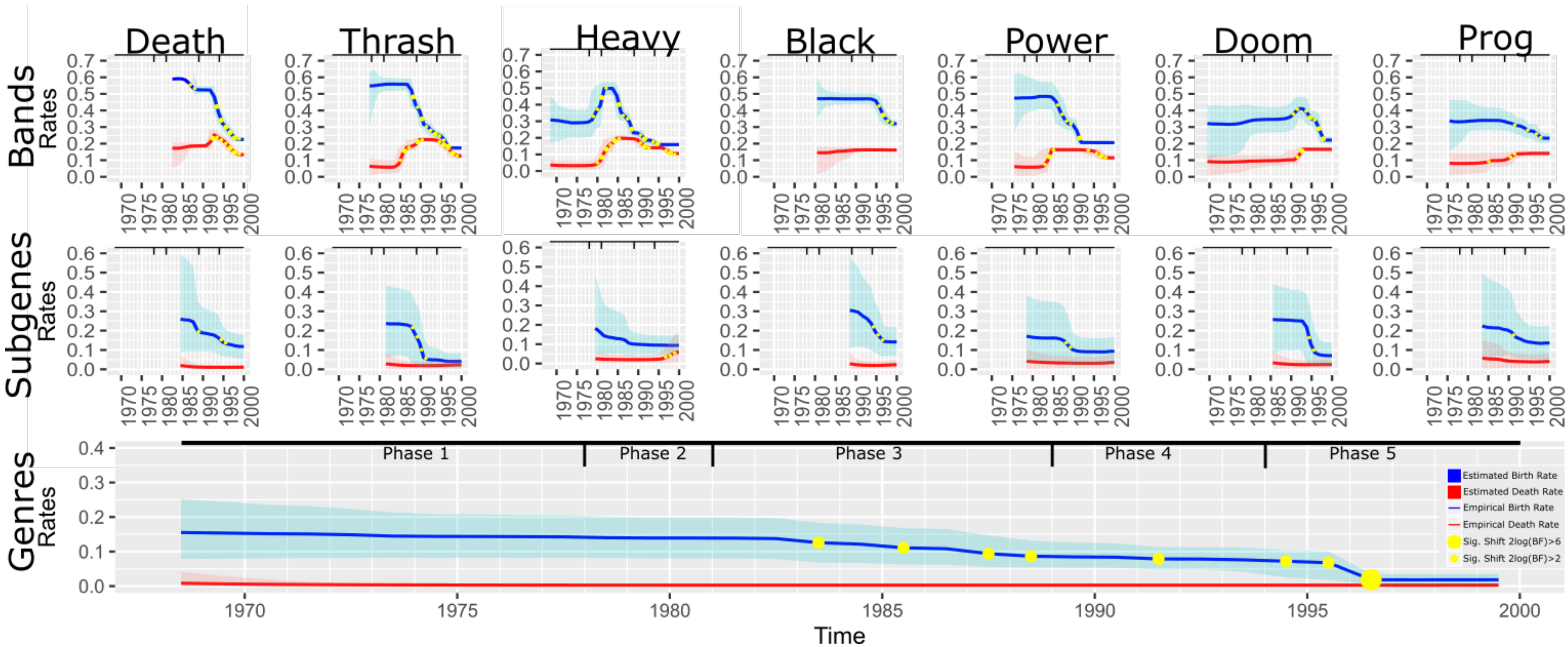

Figure 5: **Estimated Diversification Rates from Analysis 5.** Estimated diversification rates for new genres (bottom row), subgenres in the seven largest genres (middle row), and bands within these genres (top row) using LiteRate. The inset genres, presented from left to right in order of size, collectively label 94.9% of all bands. Estimated rates and their 95% highest posterior density intervals shown in solid colors. Statistically significant rate shifts marked in yellow.

10 Tables

Table 1: **Comparison between diversification rate models for band analyses.** Each row corresponds to a model: LiteRate (Analysis 1), diversity-dependent competition (Analysis 2), competition and key innovation (Analysis 3), and popular music trends (Analysis 4). "Parameters" are the number of parameters in the model (or average number of parameters across chains in the LiteRate model), R^2_{emp}, a measure of model adequacy, is the coefficient of determination of this model to the empirical rates, $R^2_{LiteRate}$ is the coefficient of determination to the LiteRate rates, "Max Carrying Capacity" is the maximum of parameter K in Analysis 2 & $d+L$ in Analysis 3. "Max Growth Date" is the midpoint of the logistic curve (parameter x_0) in Analysis 3. 95% highest posterior density intervals shown in parentheses where appropriate.

Analysis	Parameters	R^2_{emp}	$R^2_{LiteRate}$	Max C.C.	Max Growth Date
LiteRate (1)	25.68 (23,31)	0.85	N/A	N/A	N/A
Competition (2)	6	0.55	0.62	15400 (14544, 16296)	N/A
Comp. + Key Innov. (3)	9	0.77	0.78	16172 (15003, 17437)	1979.89 (1977.96,1981.59)
Popular Music Trend (4)	6	0.55	0.69	N/A	N/A

11 Appendix

A Methods

A.1 Lexical Parsing of EM Subgenres

In the EM, users describe the subgenre of an artist using an open text field. These descriptions can be extremely sophisticated.To parse these descriptions into meaningful subgenres we:

- Cleaned data for words like "(early)" or "(later)", removed any appended "with X influences" tags.
- Split subgenres on commas, semicolons, and slashes.
- Labeled the first word before a punctuation mark (as above) or the word "Metal" as a subgenre. If the word, "rock" appeared it was also labeled as a subgenre. In the Amorphis example the genres are: "Progressive," "Death," "Doom," "Heavy," and "Rock."

- Any words that appeared before a subgenre, but after a punctuation mark or the word “Metal” were preprended to create a sub-subgenre. In instances where the term “Metal/Rock” appeared, secondary terms were also prepended to the subgenre “Rock.” In the Amorphis example, the sub-subgenres are “Melodic Heavy,” and “Melodic Heavy Rock”

- We assume that later sub-subgenre terms are more meaningful. We therefore add all possible secondary tags that can be created by removing the first sub-subgenre term in a subgenre description to create additional sub-subgenres. For example a description of “Brutal Technical Death Metal” would yield the subgenre “Death,” and the sub-subgenres “Brutal Technical” and “Technical.”

A.2 Imputation of Band Death Times

For the 15.6% of bands that were not listed as “Split-up” (i.e., either “On-hold” or page not recently updated) but also had not released an album since 2000, we imputed death times $\mathbf{e}$ stochastically. We assumed that a band’s lifespan since its last release is exponentially distributed, where the rate parameter is the band’s average inter-album time. If a band had released only one recording, we used the population’s average inter-album time. Sensitivity analyses assuming that all of these bands were either dead at 2000 or alive at 2000 conducted with the LiteRate model, suggest that these imputations do not bias our results (see Fig. D2). We also conducted a sensitivity analysis to make sure that bands that went on extended hiatuses were not biasing our results (not shown). We created 100 stochastic imputations of the data in this manner.

A.3 LiteRate Reversible Jump MCMC Algorithm

A.3.1 LiteRate Likelihood

In the LiteRate likelihood (equation 8), Λ and M are now vectors of rates with length J and K corresponding to the number of time frames with different birth rates $\Lambda = \{\lambda_1, \lambda_2, \ldots \lambda_J\}$, and death rates $M = \{\mu_1, \mu_2, \ldots, \mu_K\}$, respectively. Similarly, B and D are now each vectors $B = \{B_1, B_2, \ldots, B_J\}$ and $D = \{D_1, D_2, \ldots, D_K\}$, each counting the number of birth or death events within that time frame. We also now need two new parameter vectors, $\tau^\Lambda = \{\tau_0^\Lambda, \tau_1^\Lambda, \ldots, \tau_{J-1}^\Lambda\}$,and $\tau^M = \{\tau_0^M, \tau_1^M, \ldots, \tau_{K-1}^M\}$ corresponding to the timings of the birth and death rate shifts, respectively. Lastly, the cumulative time lived by bands in time frame j is denoted $S_{[}\tau_{j-1}^\Lambda, \tau_j^\Lambda]$, and the cumulative time lived by bands in time frame k is denoted $S_{[}\tau_{k-1}^M, \tau_k^M]$:

$$P(\mathbf{s}, \mathbf{e}|\Lambda, M, \tau_\Lambda, \tau_M) \propto \prod_{j=1}^{J} [\lambda_j^{B_j} \times \exp(-\lambda_j S_{[\tau_{j-1}^\Lambda, \tau_j^\Lambda]})] \times \prod_{k=1}^{K} [\mu_j^{D_k} \times \exp(-\lambda_k S_{[\tau_{k-1}^M, \tau_K^M]})] \tag{8}$$

As an example, suppose that between 1968 and 2000 Metal had a single shift in birth rates in the year 1990 and no death shifts. $J = 2$, $\Lambda = \{\lambda_1, \lambda_2\}$, where λ_1 is the rate from 1968-1990, $\tau^\Lambda = \{1990\}$, and $B_{j=1}$ is the total number of bands founded from 1968-1990. $S_{[\tau_0^\lambda, \tau_1^\lambda]}$ would be the total time lived by bands from 1968-1990. $K = 1$, $M = \{\mu_1\}$, where μ_1 is the rate from 1968-2000, and $S_{\tau_0^\mu}$ would be the total time lived by bands from 1968-2000. In LiteRate, the addition or removal of a rate shift from τ^Λ or τ^M is periodically proposed (with equal probability) throughout the chain using RJMCMC (Green, 1995). Details of the algorithm can be found in A.3 and in (Silvestro et al., 2019).

A.3.2 Statistical Significance of Rate Shifts

As a means to consider whether the posterior rate shifts estimated by the LiteRate Model are significant, we compute the sampling frequency of each rate shift and compare it to the results of an MCMC simulation where rate shifts are purely sampled from their priors (no data). The significance of a shift can then be computed as a Bayes factor of the posterior odds ($P(s|D)$) over the simulated prior odds ($P(s)$) as in equation 9. We consider significant rate shifts to be those supported by $2 \log BF > 2$ as "Positive" and $2 \log BF > 6$ as "Strong", following (Kass and Raftery, 1995).

$$BF = \frac{P(s|D)}{1 - P(s|D)} / \frac{P(s)}{1 - P(s)} \tag{9}$$

A.3.3 Reversible Jump Markov Chain Monte Carlo

Algorithmically, the addition or removal of a rate shift from τ^{Λ} or τ^{M} is periodically proposed (with equal probability) throughout the chain using RJMCMC (Green, 1995). When a new rate shift is added, a time window within J or K is randomly selected, and split into two. The timing of the rate shift within the chosen window is drawn from a uniform distribution, and a draw from a beta distribution is used to determine new rates that geometrically average (weighted by the length of their windows) to the old rate. Because the number of rate shifts in the model is considered unknown, we assign a Poisson distribution as a prior on J and K. The rate parameter of the Poisson prior is itself considered as unknown and assigned a Gamma hyper-prior. Lastly, the priors for the rates in Λ and M are again gamma distributions, but this time we place gamma hyperpriors on the gamma distributions' rate parameters. The use of hyper-priors makes the selection of these prior distributions less arbitrary as their shape is driven by the data (Gelman et al., 2006).

Compared to a simple MCMC, the acceptance probability in RJMCMC is complicated by the change in dimensionality of the parameter space. Let the acceptance probability be defined as $A(\theta, \theta')$ where θ is the current set of parameters of model W, and θ' is the proposed set of parameters for model W' with an additional rate shift. In RJMCMC, the acceptance probability is thus the product of three terms: the standard *posterior ratio* and *Hastings Ratio*, but also the *Jacobian* of the parameter changes, separated in equation 10 with square brackets.

$$A(\theta, \theta') = \min \left(1, \quad \underbrace{\frac{\pi(\theta')}{\pi(\theta)}}_{\text{Posterior Ratio}} \times \underbrace{\frac{P(W'|W)}{P(W|W')} \times \frac{P(\theta'|\theta)}{P(\theta|\theta')}}_{\text{Hastings Ratio}} \times \underbrace{\left| \frac{\partial(\theta')}{\partial(\theta, \mu)} \right|}_{\text{Jacobian}} \right) \tag{10}$$

The first term in the acceptance probability, the *posterior ratio*, is the ratio of the unnormalized posterior probabilities of the new state over the current state. The *Hastings ratio* consists of two terms. The first term of the Hastings ratio includes the probability of proposing a new model W' conditional on the current model W, where a model $W = \{J, K\}$ is defined by the number of birth and death rates. In our implementation we set equal probabilities to adding or removing a rate shift so that $P(W'|W) = P(W|W') = 0.5$, thus making this term equal to 1. The second term in the *Hastings ratio* is the probability of proposing a new parameter state given the current one over the opposite scenario. The final term in the acceptance probability is the Jacobian of the mapping function that transforms the parameters of the current state to the proposed state. This term accounts for the change in dimensionality of the parameter space. The acceptance probability of removing a rate shift is simply the inverse of the addition: $A(\theta', \theta) = A(\theta, \theta')^{-1}$.

A.4 Further Details on Implementations of Restricted Models

All models are sampled with a simple MCMC sampled as described in Analysis 1.

A.4.1 Competition Models

The full competition and competition + key innovation models are specified as follows:

$$\begin{gathered} \lambda_{max} = \kappa + \lambda_{mul} * \kappa \qquad \mu_{min} = \kappa - \mu_{mul} * \kappa \\ \lambda(t) = \lambda_{\max} - (\lambda_{\max} - \kappa) \left(\frac{D(t)}{K(t)} \right)^{\delta} \qquad \mu(t) = \mu_{\min} + (\kappa - \mu_{\min}) \left(\frac{D(t)}{K(t)} \right)^{\gamma} \\ K(t) = K \; \forall \; t \qquad \mathit{or} \qquad K(t) = d + \frac{L}{1 - \exp(-k * (t - x_0))} \end{gathered} \tag{11}$$

Priors:

$\kappa \sim \Gamma(\alpha = 1, \theta = 10)$ support: $\in \mathcal{R}^+$

$\lambda_m \sim \Gamma(\alpha = 1, \theta = 1)$ support: $\in \mathcal{R}^+$, null: 0

$\mu_m \sim \beta(\alpha = 1, \theta = 1.2)$ support: $\in [0, 1]$, null: 0

$\gamma \sim \Gamma(\alpha = 3, \beta = 2)$ support: $\in \mathcal{R}^+$, null: 1

$\delta \sim \Gamma(\alpha = 3, \beta = 2)$ support: $\in \mathcal{R}^+$, null: 1

For the competition model (static K) in Analysis 2:

$K \sim \Gamma(\alpha = 1, \theta = max(D_t))$ support: $\in \mathcal{R}^+$

For the competition + key innovation in Analysis 3:

$k \sim \mathcal{N}(\mu = 0, \sigma = 1)$ support: $\in \mathcal{R}$, null: 0

$d \sim \Gamma(\alpha = 1, \theta = max(D_t))$ support: $\in \mathcal{R}^+$

$L \sim \Gamma(\alpha = 1, \theta = max(D_t))$ support: $\in \mathcal{R}^+$

$x_0 \sim \mathcal{U}(a = min(t), b = max(t))$ support: $\in [min(t), max(t)]$

Proposals: All parameters have multiplier proposals except x_0 and μ_{mul}, which use sliding window proposals.

A.4.2 Trend Model

$$\lambda(t) = \lambda_{const} + \alpha * C^{\delta} \qquad \mu(t) = \mu_{const} + \beta * C^{\gamma} \tag{12}$$

All trends C are first normalized between 0 and 1 to improve convergence.

Priors for model in Analysis 4:

$\lambda_{const} \sim \Gamma(\alpha = 1, \theta = 10)$ support: $\in \mathcal{R}^+$

$\mu_{const} \sim \Gamma(\alpha = 1, \theta = 10)$ support: $\in \mathcal{R}^+$

$\alpha \sim \mathcal{N}(\mu = 0, \sigma = 5)$ support: $\in \mathcal{R}$, null: 0

$\beta \sim \mathcal{N}(\mu = 0, \sigma = 5)$ support: $\in \mathcal{R}$, null: 0

$\gamma \sim \Gamma(\alpha = 3, \beta = 2)$ support: $\in \mathcal{R}^+$, null: 1

$\delta \sim \Gamma(\alpha = 3, \beta = 2)$ support: $\in \mathcal{R}^+$, null: 1

B Supplemental Analyses

B.1 Transmission/Reproduction of Subgenres

Motivation: We wish to demonstrate that the movement of musicians between bands of the same subgenre is a plausible mechanism for cultural transmission, reproduction, and creation within Metal subgenre forms.

Methods: We performed a simple bivariate logistic regression analysis of the subgenre and sub-subgenre choices of musicians in the EM who have participated in two or more bands. For each band, we curated the identities of all members who played on a founding album, and then tabulated the subgenres of previous bands these founders played in. Limiting our data to bands with musicians with prior experiences in the EM reduced us to 12,155 bands.

Reducing our sample further to subgenres/sub-subgenres where we have at least 10 bands with data on band members' past band experiences, we have 19 subgenres and 26 sub-subgenres. For each of these subgenres and sub-subgenres, we then logistically regressed the subgenre (1 for in subgenre, 0 for not in subgenre) on the proportion of founding members who had previously played in a band of that subgenre. We used Firth's penalized likelihood model for highly imbalanced classes in the R "logistf" package (Heinze and Puhr, 2010). Exponentiated odds ratios with 95% confidence intervals and penalized likelihood ratio test shown in the second column block of Table C1.

Results: We find evidence that founders' past band experiences are significantly predictive of the current band's subgenre for 16 of 19 subgenres at a p-value threshold of .05. We similarly find significant evidence for 17 of the 26 sub-subgenres.

B.2 Stability and Validation of Cultural Forms

Motivation: We now wish to demonstrate that Metal music, its subgenres, and its sub-subgenres are stable, coherent cultural forms mutually understood and supported by a broad population of fan-actors.

Methods: We cross-tabulated EM subgenre affiliations of bands with another online music community, Last.FM (www.last.fm). Last.FM is a music radio and community website founded in 2002 with over 40 million lifetime users (Gallagher, 2012). The site allows users to journal artists, albums, and tracks they are listening to, tag these entities with descriptors, and annotate open-source abstract pages for both entities and tags. We collected tag information for 107,666 EM bands cross-listed in Last.FM, as well as up to 20 "similar artists" for each band that were co-listened or similarly tagged by Last.FM listeners (which we call "sonic neighbors").[22] Of our 30,217 bands of interest, there are 17,087 uniquely named EM bands with an artist entry page in Last.FM.

If cultural forms are coherent, actor-listeners should preferentially co-label and co-listen to bands in the same EM subgenre, and use the same subgenre labels for bands across both datasets. For Metal overall and each EM genre/subgenre, we therefore computed two statistics: the percentage of bands that share the genre label across both datasets (Table C1 column block 3), and the average percentage of sonic neighbors that are also in the same subgenre (in network terms, the proportion of edges pointing into the community) (Table C1 column block 4).

Results: For 24 of the 46 EM subgenres, a majority of bands are cross-labeled as within the same subgenre in Last.FM as well (Table C1 column block 3). This also holds for 9 of the 50 sub-subgenres. For Metal bands overall, we find that on average 52% of an EM band's sonic neighbors are also Metal bands. Furthermore, the majority of sonic neighbors are within the same subgenre for 12 of the 46 subgenres and 2 of the 50 sub-subgenres (Table C1 column block 4). We note that these estimates are likely biased downwards since a single Last.FM page does not disambiguate between similarly-named artists of different music genres (i.e., non-Metal artists).

[22] We collect 100,000+ Last.FM bands because sonic neighbors for our 30,217 bands of interest may have been born after 2000.

Table C1: **Results from Analyses C.1 and C.2**. Rows sorted by size of genre (column 2) in full dataset, divided by subgenres and sub-subgenres. Column block 2 shows the number of bands with members in previous bands in the data, the exponentiated odds ratio, and 95% confidence interval for the Firth regression in Analysis C.1. * indicates p-value < .05 on a likelihood ratio test. Column block 3 shows the uniquely labeled bands in Last.FM and the % of bands in which the genre label is used in both EM and Last.FM (Analysis C.2). Column block 4 shows the number of bands with sonic neighbors, the mean and standard deviation of the percentage of sonic neighbors also in that subgenre, and the mean and standard deviation of the age of sonic neighbors. "-" indicates insufficient data (fewer than 10 bands). Subgenres with percentage > 50 or p-value < .05 are bolded.

		Analysis C1			Analysis C2		Analysis C2		
	# Bands	# Previous	OR	95% CI	# in LFM	% Label	# w/ SN	% SN	% SN Age
Whole Dataset	30217	NA	NA	NA	17087	NA	13207	**52**+/-33	1997.29+/-7.06
Death	9907	477	**5.7***	(4.58,7.14)	5097	**68**	3856	**73**+/-35	1998.45+/-5.58
Thrash	7868	127	**3.73***	(2.57,5.44)	4051	**51**	2925	**60**+/-40	1994.53+/-7.36
Heavy	6345	231	**12.08***	(8.97,16.45)	3796	50	2894	**62**+/-37	1990.98+/-8.05
Black	5333	284	**6.16***	(4.79,7.96)	3201	**87**	2586	**84**+/-28	2000.42+/-4.2
Power	2679	83	**5.89***	(3.63,9.4)	1529	49	1231	**52**+/-36	1995.04+/-7.46
Doom	1962	106	**8.23***	(5.37,12.46)	1191	**64**	968	**63**+/-39	1999.03+/-5.07
Progressive	1360	37	**8.0***	(3.33,17.22)	895	**52**	699	**51**+/-39	1998.78+/-5.74
Rock	1345	200	**10.71***	(7.39,15.35)	974	**54**	807	27+/-31	1992.46+/-9.64
Grindcore	1149	41	**6.14***	(2.72,12.6)	707	**60**	579	**51**+/-36	1998.25+/-4.87
Speed	1038	21	**10.41***	(4.05,25.18)	527	45	436	30+/-28	1988.98+/-6.39
Gothic	903	54	**7.03***	(2.59,15.95)	600	**52**	493	49+/-36	1999.79+/-3.74
Groove	726	19	7.24	(0.86,29.18)	482	17	344	22+/-31	1999.3+/-7.03
Crossover	612	13	**17.13***	(4.11,55.33)	414	28	303	37+/-37	1991.15+/-6.31
Punk	426	52	**21.65***	(9.64,44.63)	302	**60**	251	25+/-33	1993.92+/-7.5
NWOBHM	263	-	-	-	138	**81**	132	**77**+/-33	1981.87+/-2.31
Metalcore	223	-	-	-	173	**57**	148	42+/-36	2002.04+/-3.33
Industrial	211	17	**27.58***	(5.08,97.45)	151	**53**	127	25+/-31	1994.31+/-5.95
Folk	207	16	8.4	(0.43,43.94)	157	**61**	135	39+/-33	2000.72+/-3.8
Stoner	193	-	-	-	146	**54**	134	**63**+/-36	2000.87+/-3.73
Ambient	189	41	**23.21***	(10.18,48.58)	136	**66**	120	33+/-28	1999.83+/-5.04
Sludge	171	10	**128.11***	(32.78,455.46)	126	**84**	119	**66**+/-35	2001.24+/-3.5
Shred	97	-	-	-	86	31	71	47+/-40	1995.33+/-5.43
Dark	85	-	-	-	41	22	24	0	-
Pagan	73	-	-	-	58	**64**	50	17+/-18	2003.05+/-3.19
Viking	65	-	-	-	48	**77**	45	34+/-24	2000.12+/-3.61
Neoclassical	64	-	-	-	54	26	50	21+/-26	1996.77+/-5.04
Symphonic	57	-	-	-	38	47	31	13+/-16	2001.42+/-3.15
Goregrind	54	-	-	-	41	**80**	38	45+/-22	2000.25+/-4.19
Avant-Garde	50	-	-	-	40	**62**	33	28+/-25	1996.85+/-4.2
Experimental	42	-	-	-	31	23	24	1+/-4	2013.0+/-0.0
'N'Roll	40	14	13.04	(0.05,116.24)	29	21	27	17+/-28	1997.27+/-5.05
Alternative	39	-	-	-	32	16	26	0+/-2	1983.0+/-0.0
Noise	38	-	-	-	26	31	25	7+/-15	2005.34+/-5.55
Nu-Metal	37	-	-	-	23	4	19	3+/-6	1997.5+/-2.68
Melodic	32	-	-	-	18	22	16	0	-
RAC	32	-	-	-	23	**100**	21	48+/-44	1996.23+/-7.42
Deathcore	29	-	-	-	19	26	15	2+/-5	2005.0+/-0.0
Darkwave	27	-	-	-	23	43	21	25+/-32	1995.44+/-1.33
Glam	27	-	-	-	19	37	18	5+/-14	1984.25+/-1.75
Electronic	26	-	-	-	18	11	18	10+/-24	1991.97+/-5.12
Fusion	25	-	-	-	16	44	14	8+/-8	1995.88+/-5.37
Pop	21	-	-	-	18	6	18	0	-

Continued on next page

		Analysis C1			Analysis C2		Analysis C2		
	# Bands	Previous	OR	95% CI	# in LFM	% Label	# w/ SN	% SN	% SN Age
Southern	20	-	-	-	18	39	14	18+/-24	1995.42+/-6.65
Drone	17	-	-	-	13	**69**	13	33+/-28	2003.09+/-1.64
Grunge	16	-	-	-	14	**56**	13	26+/-38	1990.33+/-2.72
Hard Rock	874	144	**18.08***	(11.58,27.82)	610	45	488	25+/-30	1988.62+/-9.0
Melodic Death	779	142	**16.99***	(10.43,27.1)	466	**55**	386	**50**+/-39	2000.4+/-3.98
Brutal Death	683	136	**29.2***	(16.79,50.0)	411	**59**	321	**54**+/-35	2000.87+/-3.16
Melodic Heavy	428	66	**22.02***	(8.88,48.82)	259	7	210	10+/-20	1995.35+/-8.32
Melodic Black	323	62	**9.88***	(3.73,22.18)	195	44	162	18+/-19	1997.92+/-3.89
Hardcore Punk	301	38	**29.21***	(10.63,69.93)	213	**56**	169	15+/-25	1991.18+/-7.07
Technical Death	203	44	6.46	(0.86,23.96)	117	**74**	100	41+/-30	1999.64+/-5.32
Symphonic Black	199	43	**10.57***	(2.72,29.62)	142	**56**	125	26+/-27	1999.89+/-3.73
Progressive Death	160	28	**24.2***	(7.25,64.91)	107	**53**	95	22+/-22	2000.07+/-6.09
Melodic Power	129	22	**41.85***	(7.77,150.17)	85	6	70	8+/-10	2002.02+/-4.16
Pagan Black	108	26	**56.5***	(18.75,148.45)	73	40	65	16+/-21	2000.8+/-3.79
Progressive Power	105	25	4.18	(0.01,34.24)	72	7	59	4+/-6	1996.52+/-6.73
Technical Thrash	105	19	14.53	(0.66,81.17)	49	49	40	11+/-19	1988.04+/-2.16
Raw Black	103	31	**93.71***	(36.47,226.81)	71	32	58	5+/-8	2003.23+/-4.59
Progressive Thrash	96	15	9.6	(0.02,89.89)	58	33	49	8+/-12	1991.64+/-3.74
Atmospheric Black	84	17	6.46	(0.03,52.08)	60	30	47	9+/-13	2002.22+/-4.62
Progressive Heavy	78	17	**95.55***	(8.77,555.96)	47	0	36	1+/-3	1998.5+/-9.76
Crust Punk	69	13	**183.55***	(44.77,654.08)	50	50	49	36+/-35	1996.18+/-6.91
Atmospheric Death	64	12	15.6	(0.09,134.58)	40	22	27	6+/-17	2002.64+/-3.43
Dark Ambient	64	29	**65.29***	(22.15,170.63)	46	**59**	40	15+/-16	1998.28+/-4.38
Industrial Death	60	16	30.82	(0.09,322.6)	42	26	28	9+/-12	1997.77+/-5.15
Atmospheric Doom	54	16	**46.61***	(4.74,220.41)	34	26	31	10+/-14	1999.33+/-4.9
Melodic Doom	51	13	**61.56***	(6.07,304.56)	36	8	28	10+/-11	1998.98+/-5.27
Melodic Thrash	50	-	-	-	27	11	19	1+/-4	2003.5+/-0.0
Melodic Progressive	47	-	-	-	30	0	24	1+/-2	2006.0+/-0.0
Epic Heavy	45	11	**83.26***	(3.76,583.7)	29	21	26	28+/-23	1996.58+/-5.3
Progressive Rock	41	-	-	-	28	**54**	25	6+/-13	1984.0+/-16.01
Alternative Rock	39	-	-	-	30	7	26	1+/-2	1999.67+/-3.86
Funeral Doom	33	-	-	-	21	**95**	21	**73**+/-28	2003.02+/-2.99
Death 'N'Roll	32	12	34.41	(0.1,373.66)	22	27	21	15+/-25	1996.71+/-5.45
Industrial Black	32	-	-	-	27	48	23	20+/-17	2000.63+/-3.66
Avant-Garde Black	29	15	20.11	(0.1,184.98)	21	43	20	15+/-27	2004.1+/-3.31
Brutal Technical Death	28	-	-	-	20	5	18	15+/-16	2000.43+/-2.35
Epic Black	27	-	-	-	22	32	18	8+/-10	2003.97+/-6.1
Melodic Speed	27	-	-	-	17	12	13	0	-
Gothic Doom	26	-	-	-	19	26	14	2+/-6	2002.33+/-0.0
Experimental Death	26	-	-	-	16	12	15	1+/-3	1998.0+/-3.0
Symphonic Power	25	-	-	-	17	28	17	19+/-14	2002.46+/-3.04
Symphonic Death	25	-	-	-	17	28	14	4+/-7	2007.92+/-3.67
Gothic Rock	21	-	-	-	17	28	16	1+/-2	2004.0+/-0.0
Punk Rock	21	-	-	-	15	20	11	0	-
Epic Power	20	-	-	-	13	15	11	0	-
Progressive Black	18	-	-	-	15	33	14	4+/-9	2001.28+/-3.91
Industrial Thrash	18	-	-	-	15	0	10	2+/-4	2006.0+/-0.0
Experimental Black	16	-	-	-	13	23	13	9+/-27	2001.67+/-2.05
Melodic Rock	16	-	-	-	14	0	12	0	-
Neoclassical Power	15	-	-	-	12	0	10	6+/-8	2000.5+/-5.67
Symphonic Gothic	15	-	-	-	12	0	12	10+/-11	2000.75+/-2.17
Hard Melodic Rock	15	-	-	-	12	0	10	0	-
Atmospheric Gothic	14	-	-	-	12	0	10	0	-

B.3 Entropy of Bands Across Subgenres

Motivation: To better understand the mechanisms of competition and causes of the Phase 4 rate shelf, we analyze the Shannon entropy of bands across subgenres and sub-subgenres. One interpretation of the Shannon entropy is as a measure of the evenness of the distribution of quantities across categories. Pielou evenness is a derivative metric from Ecology that normalizes the observed entropy over the maximum possible entropy (e.g., the scenario where there are an equal number of bands in each subgenre) (Pielou, 1966). Entropy dynamics can give insight into how bands explore the cultural carrying capacity over time. For example, a decrease in entropy over time would suggest that bands preferentially attach to larger genres, or that not all genre niches are equally accessible/exploitable. Pielou evenness dynamics contextualize observed exploration against the backdrop scenario where all genres are equally easy to exploit and bands do so equitably. A Pielou evenness close to zero indicates that bands are concentrated in a few genres, while an evenness of one suggests that bands are evenly distributed across all available subgenres.

Methods: In each year y from 1968 to 2000, we compute the entropy $H(y)$ for the standing diversity of bands alive in that year D_y across all subgenres that have been previously introduced to Metal G_y before year y (up to 110 by 2000). Formally the entropy is computed as:

$$H(y) = -\sum_{g=1}^{G_y} \frac{D_{yg}}{D_y} \cdot \ln(\frac{D_{yg}}{D_y}) \tag{13}$$

We also compute the Pielou evenness (Pielou, 1966) $J(y)$ in each year by normalizing the observed entropy by the maximum possible entropy in each year:

$$J(y) = \frac{H(y)}{-\sum_{g=1}^{G_y} \frac{1}{D_y} \cdot \ln(\frac{1}{D_y})} \tag{14}$$

We further compute these metrics for bands across the sub-subgenres of the seven largest genres.

Results: Within both Metal overall (Fig. D5C) and the seven largest genres (Fig. D5D), we find that the evenness of bands across categories initially sharply decreases over time. This behavior is to be expected when the number of subgenres is small: bands concentrated in one of one subgenres are evenly distributed, while bands concentrated in one of seven subgenres are not. However, the evenness eventually levels off for Metal and six of the subgenres (not Death) suggesting that Metal overall and each of the seven largest subgenres settles into a stable arrangement of small genres and large genres that persists over time.

This surprisingly constant evenness must be interpreted against the backdrop of increasing numbers of actors and shifting popularity of subgenres over time. Given that the actor population is growing, we might expect the evenness of bands to increase across categories as additional actors can accommodate more categories. The fact that the evenness does *not* increase over time is evidence of a top-down cultural carrying capacity. The fact that the evenness does not drop below .3 is consistent with the shifting popularity of genres (Fig. D4), suggesting that a stable cultural dynamics might correlate with having a mixture of broadly-circulated and specialized lineages. Furthermore, the trend observed in subgenres for Pielou evenness is similarly reproduced at the sub-subgenre level and across all 2,033 possible descriptions for a band that have ever been used, we see the same trend (Fig. D6B).

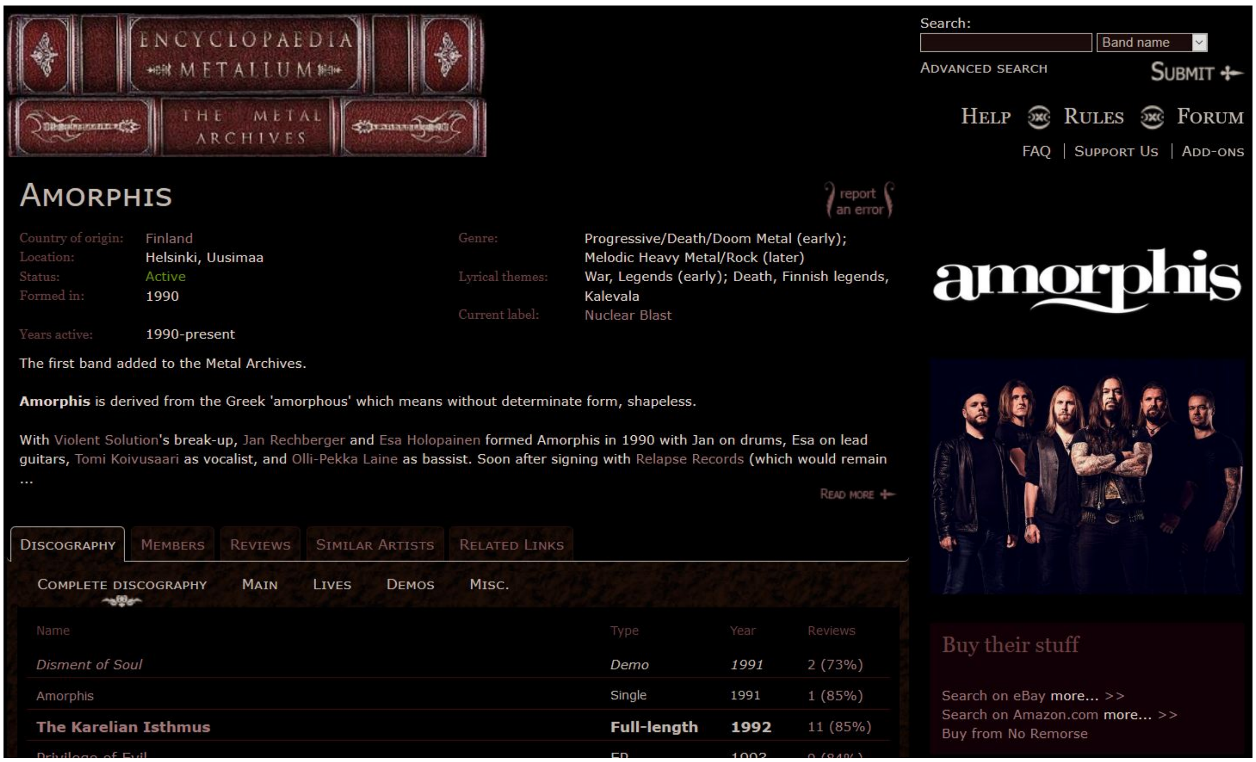

Figure D1: Example Encyclopedia Metallum (EM) Band page. The EM contains information about the formation date, discography, status, personnel and subgenres of $\tilde{1}$41,000 Metal bands as of 2020. Open subgenre classification field in top right.

C Supplemental Figures

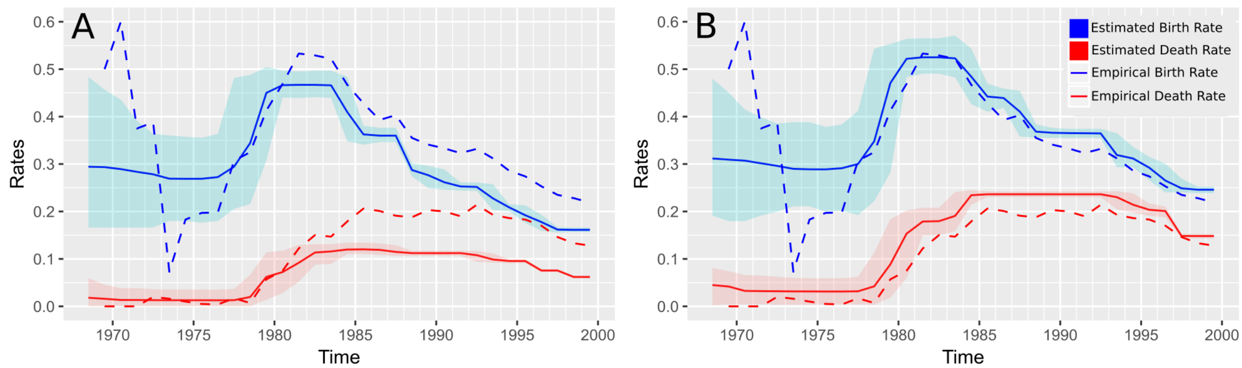

Figure D2: **Estimated Diversification Rates from Analyses 2B Without Imputation.** Dashed lines indicate empirical birth (red) and death (blue) of EM metal bands. The first bin of empirical rates is dropped for clarity. Estimated rates and their 95% highest posterior density intervals shown in solid colors. **A**: Estimated birth and death rates over time when the imputed 15% of band's death times are set to their last recording. **B**: Estimated birth and death rates over time when the imputed 15% of band's death times are set to 2000.

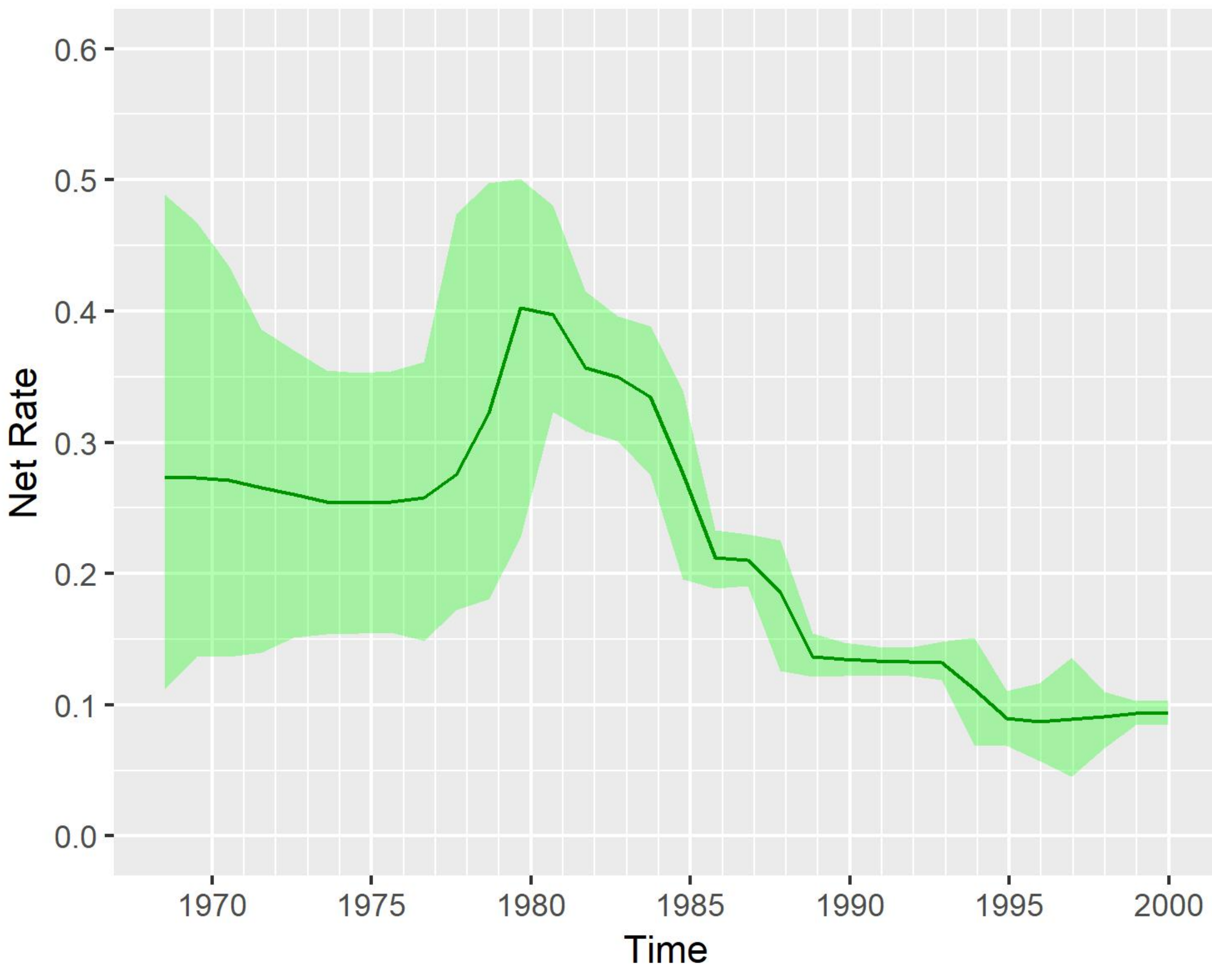

Figure D3: **Estimated Net Diversification Rates from Analysis 2B.** LiteRate-estimated net diversification rates (birth minus death) and their 95% highest posterior density intervals shown in green.

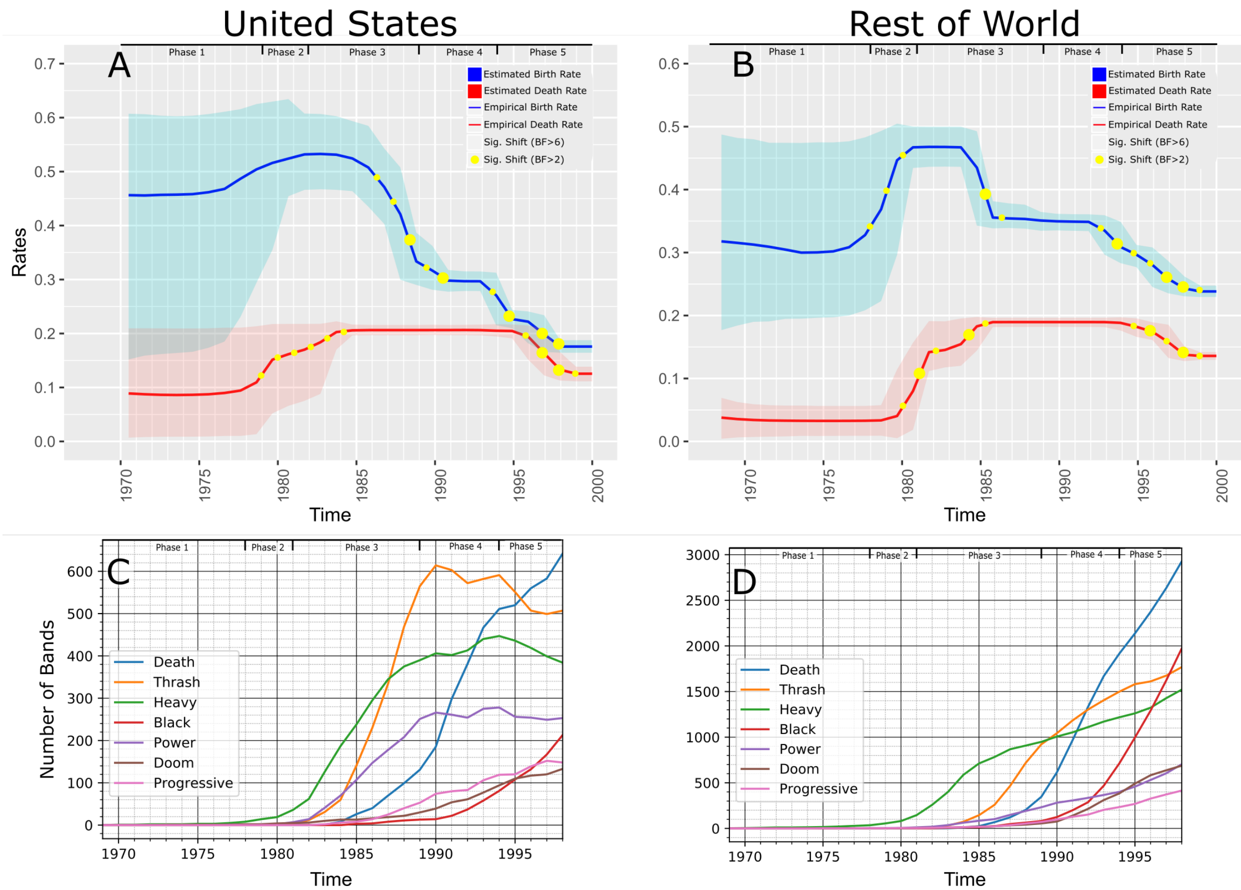

Figure D4: **Estimated Diversification Rates for US and non-US bands.** **A**: LiteRate-estimated diversification rates for bands born in the United States. **B**: LitRate-estimated diversification rates for bands born outside the United States. **C**: Standing diversity of US-bands for seven largest subgenres. **D**: Standing diversity plots for non-US bands in seven largest subgenres. Estimated diversification rates and their 95% highest posterior density intervals shown in solid colors. Yellow dots indicate statistically-significant rate shifts.

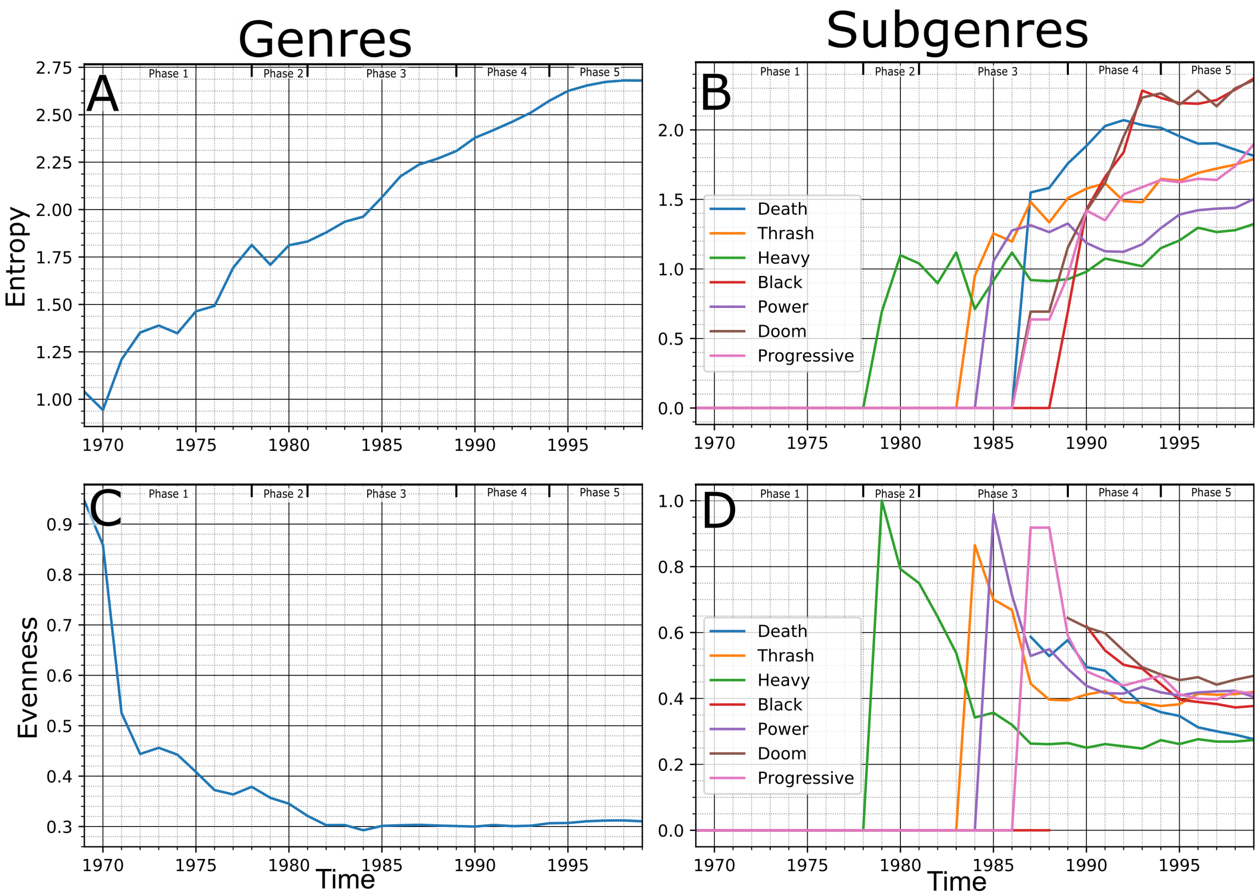

Figure D5: **Shannon Entropy and Evenness Plots from Analysis 3C. A:** Shannon entropy of all bands across all subgenres. **B:** Shannon entropy of all bands across all subgenres, normalized by possible entropy (Pielou evenness). **C:** Shannon entropy of bands in top seven subgenres across sub-subgenres. **D:** Shannon entropy of bands in top seven subgenres across sub-subgenres, normalized by maximum possible entropy (Peilou evenness).

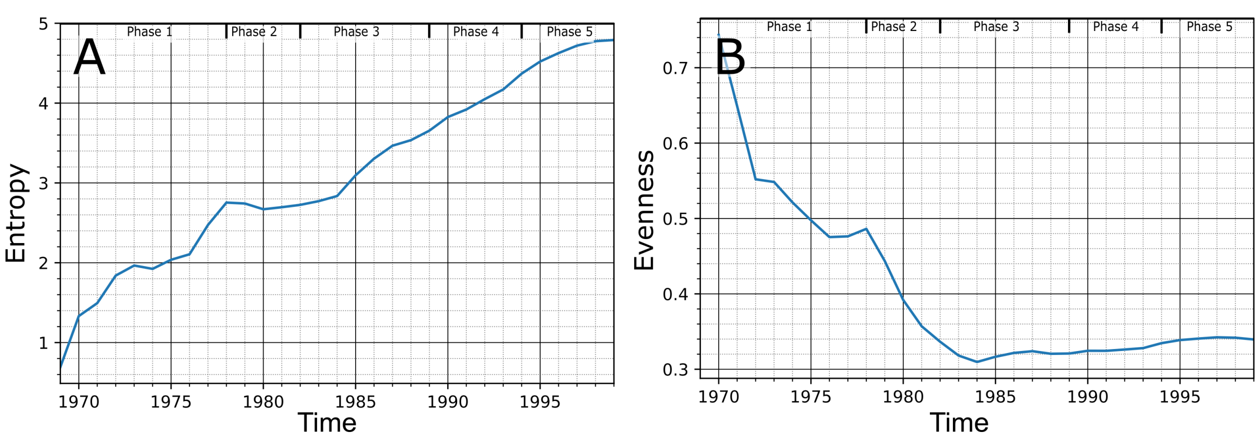

Figure D6: **Shannon Entropy and Evenness Plots for all possible genre descriptors in EM A:** Shannon entropy of all bands across all 2,033 possible combinations of genre and subgenre descriptions used in the EM. **B:** Pielou Index of all bands across all genres (Shannon Entropy normalized by maximum possible entropy).

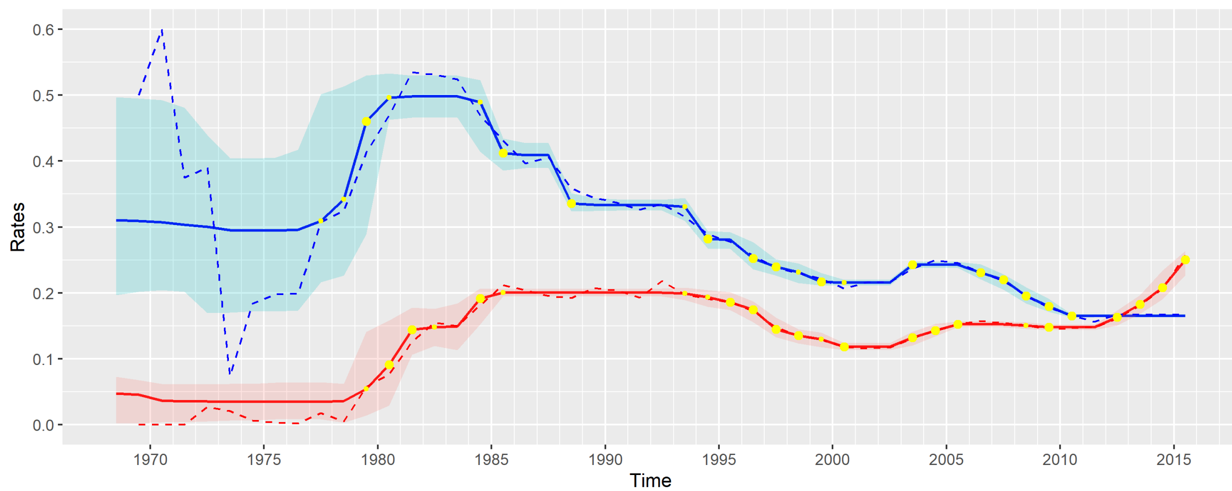

Figure D7: **LiteRate-estimated rates of all bands through 2016.** Death times were imputed using the procedure described in A.2.