Game Changer: The Topology of Creativity[1]

Mathijs de Vaan
Columbia University

David Stark
Columbia University

Balazs Vedres
Central European University

This article examines the sociological factors that explain why some creative teams are able to produce game changers—cultural products that stand out as distinctive while also being critically recognized as outstanding. The authors build on work pointing to structural folding—the network property of a cohesive group whose membership overlaps with that of another cohesive group. They hypothesize that the effects of structural folding on game changing success are especially strong when overlapping groups are cognitively distant. Measuring social distance separately from cognitive distance and distinctiveness independently from critical acclaim, the authors test their hypothesis about structural folding and cognitive diversity by analyzing team reassembly for 12,422 video games and the career histories of 139,727 video game developers. When combined with cognitive distance, structural folding channels and mobilizes a productive tension of rules, roles, and codes that promotes successful innovation. In addition to serving as pipes and prisms, network ties are also the source of tools and tensions.

INTRODUCTION

What accounts for creative success when the unit of innovation is a team? In particular, what are the sociological factors that explain why some ensembles are able to meet the challenge of creating a cultural product that

[1] Research for this paper was supported by a grant from the National Science Foundation (SES-1123807). This is a fully coauthored paper. We are rotating the order of authors' names across a set of publications from our network analytic project. For their comments, criticisms, and suggestions, we are grateful to Shamus Khan, Gianluca Carnabuci, Matteo Prato, Elena Esposito, Koen Frenken, Monique Girard, Gernot

0002-9602/2015/12004-00XX$10.00

is not only inventive but also critically acclaimed? In striving for novelty, a creative team risks producing a product that cannot be assimilated to the tastes of critics and consumers. Whether wide or razor thin, the difference between "exciting" and "weird" can be the difference between a hit and a flop (DiMaggio 1997; Lampel, Lant, and Shamsie 2000; Hutter 2011). Novelty is neither sufficient nor necessary for success—for sometimes consumers and critics reward conformity. To be a game changer in a creative field the team must make a product that is not only distinctive but also highly regarded. It must stand out and be deemed outstanding.

Network analytic research suggests that social structural factors are important for team success. Some point to levels of cohesion, arguing that redundant ties promote trust and improve communication for better implementation (Reagans and McEvily 2003; Obstfeld 2005). Others argue that cohesion can be excessive, pointing to findings of a curvilinear relationship between cohesion and performance (Berman, Down, and Hill 2002; Uzzi and Spiro 2005). Still others argue for the importance of brokerage, sometimes in opposition to cohesion (Burt 1995), sometimes in conjunction with it (Obstfeld 2005; Burt 2005). Some researchers argue that brokers transfer ideas across structural holes (Burt 1995) or themselves come up with good ideas (Burt 2004). Others argue for a different conception of brokerage, as integrative work generating new ideas by bringing together team members that were previously disconnected (Lingo and O'Mahony 2010).

We draw on these works and our earlier work (Vedres and Stark 2010), which shows that brokerage and cohesion do not exhaust the network properties of team production. We return here to *structural folding*—the network property of a cohesive group whose membership overlaps with that of another cohesive group. This line of thinking reaches back to the Simmelian idea that individuality itself might be a product of the unique intersection of network circles (Simmel [1922] 1955). Such overlapping structures are also potential sources of transformative agency (Sewell 1992). We found that structural folding significantly contributed to higher performance of business groups in Hungary and argued that success is a product of familiarity and diversity, occurring when diverse elements can be brought together in an uneasy fit that is generative precisely because it is in tension (Vedres and Stark 2010). Our data, however, did not allow us to test the explanatory mechanism at play. We do so here.

Grabher, Michael Hutter, Francesco Mazzucchelli, Damon J. Phillips, and the participants of the CODES seminar at Columbia's Center on Organizational Innovation. Thanks to the European University Institute in Florence and to the Netherlands Institute for Advanced Study for supporting Stark during his leave year while this manuscript was in preparation. Direct correspondence to David Stark, Department of Sociology, Columbia University, 606 West 122d Street, New York, New York 10027. dcs36@columbia.edu

We begin by considering new work in cultural sociology. The critical juncture in that field is Swidler's (1986) reconceptualization of culture not as internalized beliefs, norms, and shared values but as "resources that can be put to strategic use" (DiMaggio 1997, p. 265). Swidler's statement generated new research (Lamont 1992; Zerubavel 1997; Ganz 2000; Alexander 2004) that viewed culture less as a set of rules and more as a set of skills. But as Swidler herself later lamented, much of this work looked, mistakenly, to the level of the individual as the actor deploying the skills from the cultural tool kit (Swidler 2008; see Jerolmack and Khan [2014], for discussion). An exception was the study by Eliasoph and Lichterman (2003), who eschewed this individualism in favor of "group styles." Their concept of "culture in interaction" was based on observations of how *groups* coordinate themselves (Eliasoph and Lichterman 2003, p. 740).

We build on this conception of culture, shifting attention from individual deployment to skills that develop in an ongoing dynamic of relations between people. To this now thoroughly relational view of culture, we address several questions that have not been previously posed. First, recognizing with Eliasoph and Lichterman that cultural styles are properties of groups, we ask: Where do group styles come from? Second, recognizing culture in interaction, we go on to ask: What happens when groups with different cultural styles interact? That is, we adopt a realist perspective acknowledging that many, if not most, settings of sociological interest are likely to involve more than one group style. Our study involves cases of stylistic diversity, and we are particularly interested in the consequences for creative success when groups with very different (cognitive/cultural) styles interact.

Our study is, thus, part of a new effort in sociology (Pachucki and Breiger 2010; DiMaggio 2011) that can be equally well described either as bringing the analytic tools of network modelling onto the terrain of cultural sociology or as bringing the analytic tools of cultural sociology onto the terrain of network analysis. We seek to develop a *cultural network analysis* equally attentive to cultural-cognitive structures as to group structures.

We identify group structures and cognitive structures by tracing back the careers of the individuals who comprise a team. Throughout their careers, individuals working in project-based industries (Peterson and Berger 1971; Caves 2002; Grabher 2002, 2004) move from one project to another. What they know and who they know is, in large part, a function of the patterns of their movement through this project space. Viewed through the lens of a given project, these affiliations in different teams and their reassembly in that distinct project result in exposure to particular methods of production as well as accumulation of social relations. That is, the cultural-cognitive structure of a given team (i.e., the relative homogeneity or diversity of cognitive styles) is shaped by its members' histories of prior exposure in previous teams. Similarly, its social structure (the relationship among its constituent communities) is shaped by its members' histories of prior collaboration in previous teams.

Thus, prior participation shapes cognition (what you know) and groups (who you know). A given team can have multiple groups based on the patterns of who worked with whom in the past. These might be separated or overlapping. And a given team can have members who are cognitively close or distant, similar or diverse, based on the stylistic elements that they worked with in the past. We trace these stylistic and social exposures in order to demonstrate how they result in sociocognitive topologies that explain culturally innovative success.

Our core hypothesis is that the effects of structural folding on inventiveness and game changing creative success are especially strong when overlapping groups are cognitively distant. Restated, teams are most likely to be creatively successful when their cognitively heterogeneous groups have points of intersection. In developing the argument that leads to this hypothesis we draw on work on topologies of knowledge in the field of semiotics (Lotman 1990, 2009; Eco 1990). Folding does not eliminate or conquer distance. It does not harmonize. Instead, it channels and mobilizes a productive tension of rules, roles, and codes that promotes successful innovation.

In the first section of the article, we elaborate our argument about the network structure of innovation in settings where teams are the unit of creativity. First, we argue that teams are comprised of cohesive groups based on patterns of prior coparticipation. Second, we make the case that network analysis should include not only social structures but also cognitive structures based on patterns of prior exposure to stylistic codes. Third, prompted by work in semiotics on topologies of knowledge, we bring together the constructs of structural folding and cognitive diversity, arguing that network structures of overlapping cohesive groups contribute to creative success when they involve higher levels of cognitive diversity. That is, structural folding contributes to creative success when it encompasses more diverse cultural elements.

To test our hypotheses, we study video game development. In the article's second section, we elaborate our analytic strategy, starting with a description of data collected on 12,422 video games that were produced from the inception of the industry in 1979 to 2009. In addition to recording the stylistic elements present in each game, we also compiled a complete list of all team members. Assigning unique IDs to each of the resulting 139,727 individuals allows us to reconstruct, for each team, the complete careers of all of its team members in the video game industry.

We construct our independent and dependent variables specifically with an eye to address questions at the intersection of network analysis and cultural sociology. Testing propositions about the relationship between structural folding and cognitive diversity requires that we have concepts and methods for understanding and measuring cognitive distance independently from social structural features. Cognitive distance and social distance need not coincide. For example, we should not assume that long-distance social ties are a proxy for cognitive distance. By constructing analytic tools to measure cognitive distance explicitly, we can observe that two structures that span the same social distance (as measured by levels of cohesion or by longer distance bridging ties) can be at differing levels of cognitive distance. These measures then allow us to test the independent and combined effects of cognitive diversity and social structure in predicting successful innovation.

Testing propositions about the factors that explain game changing creative success requires, also, that we explicitly address the problem that novelty and critical acclaim need not coincide. Often research assumes that a successful product must have been innovative (see Vedres and Stark 2010) as an example of such a flawed assumption), or it assumes conversely that if it was inventive, it must have been a success. Thus, just as we develop methods for distinguishing social and cognitive distance, in this article we also develop analytic tools for conceptualizing and measuring *inventiveness* independently from *critical acclaim*—in order to be able to construct a third dependent variable that captures the *game changing* outcome as the combination of both.

We present our findings in the final section. Employing novel simulation techniques, the results show that groups formed through prior coparticipation in teams are indeed salient social structures. These groups have not only had the opportunity to build social ties; its members have also been exposed to similar cultural and stylistic elements allowing the group to maintain a "group style." When groups move on to other projects, their contribution to the innovative performance of the team is highest when they are structurally folded and their styles are cognitively distant. That is, distinctive and critically acclaimed products are created when heterogeneous group styles are socially intersected.

THE SOCIOCOGNITIVE TOPOLOGY OF CREATIVITY

A Team Made of Groups

Whether in sports, business, science, or the arts, teamwork is a skilled performance, requiring players with deep knowledge of the field and acute skills in execution. But in such creative endeavors it takes more than assembling a cast of brilliant performers (Becker 1974). To be successful, they must play together *as a team*. And to play together well it matters whether you have played together in the past.

A prior history of working together contributes to higher performance by increasing noncodified knowledge—a metaknowledge that researchers refer to as "transactive memory" (Wegner 1995; Carley 2001). Rather than technical or artistic, this metaknowledge includes, for example, knowledge of the nuances and subtleties of *how one's fellows* interpret a script, play the sport, or write software code for a video game (De Nooy 2003). To achieve an unconscious synchronicity of action, a successful team requires a group-level pattern-recognition capability. It is only through the experience of working with each other that players can construct the interpretive schemata required for split-second, on-the-spot, mutual adjustment (Berman et al. 2002, p. 16).

Working together in the past further facilitates coordination by producing shared notions of the informal rules and implicit protocols for how to get things done. Such informal protocols are especially important in project work where tight deadlines mean that there is no time to wait for formal organizational routines to be developed or disseminated (Grabher 2002, 2004). In addition to being able to anticipate how a teammate will act, these norms produce a sense of "This is how we do things." The felt presence of such a "we" need not be explicitly voiced in order to be shared. Project work—with its tight deadlines, intense work rhythms, and frequent collaboration across disciplines—creates particularly strong bonds of affiliation and attachment (Ibert and Schmidt 2012). Working together produces a community. This is how *we* do things.

In sum, to work with others is to learn how they work; to work together is also to develop unstated norms and informal rules about how to work; and sharing such tacit knowledge of roles and codes with two or more others is to have a sense of community. Teams then are composed not simply of *individuals*, or simple pairs of individuals, but also of *groups* based on the shared experiences of working together.

Day 1 of a new project thus assembles people; but it also assembles groups. If you have participated in a large research project, served on a task force at your place of work, or attended a workshop, you are familiar with the experience of walking into the first meeting of a new group and the looks of recognition exchanged between members who have worked together before. Since it is not likely that everyone will have worked together with everyone else, some members will be more familiar with the work habits of particular others, making them more likely to call on each other in a pinch, whether that be early in the project or, later, in the most nerve-wracking periods of deadlines. That is, patterns of interaction based on prior coparticipation can endure well into the life of a new project (Stark 2009, chap. 3).

We argue that team composition in creative fields is increasingly a task of composing modules—groups of experts with a proven added value of

403133.proof.3d 6 Achorn International 03/05/2015 10:58AM

synergy—together into a larger collective that will be the new team. The building blocks of teams (especially teams relying on the creative collaboration of complex skills) might not be individuals, but groups. An HR specialist, or a project director might greatly reduce the complexity of making a large number of individuals with diverse sets of expertise "click"—work together effectively—in a large team by hiring groups.

Cognitive Diversity

Whether one relies on biologists,[2] mathematicians,[3] musicians (Gould 1994), or economists (Schumpeter [1942] 2012; Weitzman 1998), there is strong support for the notion that a novel, innovative idea is the result of recombination (Lopes 1992; Hargadon and Bechky 2006; Stark 2009; Carnabuci and Bruggeman 2009). In order to be creative, the team needs the requisite diversity of stylistic elements available for reworking. In cultural fields, where teams assemble, dissolve, and reassemble in the episodic project form, the knowledge base of the team does not reside in an organizational repository (Bird 1994; Rowlinson et al. 2010). Instead, it is a function of its members' experience with various styles during prior episodes of production. A team will be more diverse to the extent that its players have more varied exposure to stylistic practices in the field. We refer to this as *cognitive diversity*.

Where cognitive distance is low across the groups that comprise a team, the members of the team share a common language. Because nearly all the members have more or less the same prior exposure to stylistic features, they are familiar with the terms that their fellow team members are using. But low cognitive distance can mean that the team confronts an impoverished repertoire of cultural elements. The very ease of communication across the already familiar means that a team with stylistically homogenous groups will be likely to take the path to conformity.

By contrast, where the groups comprising a team are cognitively (stylistically) distant, members might confront a babel of dissonant languages, where even the same term might not have the same meaning. Cognitive diversity has potential to shake up existing codes and categories, leading to the development of innovative products (Brown and Duguid 1991; Stark

[2] "Novelties come from previously unseen association of old material. To create is to recombine" wrote the great French biologist François Jacob (1977, p. 1163). Or, in the words of Santa Fe Institute researcher John Holland (1992, p. 20), "Recombination plays a key role in the discovery process, generating plausible new rules from parts of tested rules."

[3] Henri Poincaré: "To create consists precisely in not making useless combinations and in making those which are useful and which are only a small minority. Invention is discernment, choice. Among chosen combinations the most fertile will often be those formed of elements drawn from domains which are far apart" (Poincaré [1908] 1985).

2009). But it is not enough for codes and categories to collide. The team requires structures that make it possible for these to be expressed anew in a lexicon formed out of but not reducible to the simple sum of the multiple untranslatable languages. Teams that have this ability will be more likely to fully exploit the benefits of this tension. How then can cognitive diversity be organized and mobilized for productive ends?

For a Topology of Sociocognitive Space

We seek answers to this question by combining attention to social and cognitive structures. In so doing, our solutions draw on and depart from recent work in cultural sociology and in network analysis. Like Eliasoph and Lichterman (2003), we are interested in culture as styles. Like them (and others; see, e.g., Becker 1974), we see groups rather than individuals as the relevant units in which culture is relationally performed. And similarly, as well, we conceive of culture in interaction. The differences are that (1) we adopt a more dynamic view by reconstructing where stylistic features come from; (2) we recognize that some settings (perhaps many if not most) are likely to involve a plurality of groups; and (3) we are attentive to these settings as sites where interaction is occurring across groups.

Like other network analysts (Ruef, Aldrich, and Carter 2003; Uzzi and Spiro 2005; Bellotti 2012; Grund 2012), we see network topology and the forms of connections across cohesive group structures as important for explaining performance. But, first, unlike much of that research, we do not regard the concepts of brokerage and closure, whether separately or in "small world" combinations of long-distance and cohesive ties, as sufficient for representing network properties. With the concept of structural folding we point to a distinctive position in network topology at the intersection of cohesive communities. As noted elsewhere (Vedres and Stark 2010, p. 1156), since the time of Simmel network theory has been cognizant of the fact that someone could simultaneously be a member of more than one cohesive community. But despite the theoretical insight, methodological limitations forced researchers to parse members into mutually exclusive cohesive structures. The concept of structural fold dispenses with that constraint and opens up new ways of thinking about network structures and attendant processes.

Our second departure is to question the transmission model of networks (Podolny 2001; Owen-Smith and Powell 2004). That is, we challenge the deeply taken-for-granted notion that network analysis should model flows of information. Whereas the transmission model of networks refers to how ideas flow (Coleman 1988; Borgatti and Cross 2003), structural folding refers to how ideas are generated. In the former view, networks function as a kind of transportation system, moving information from one social location to another, transplanting the kernel of an idea to organizationally more nourishing conditions. Structural folding, by contrast, is more of a production process where new problems are conceptualized as new resources are identified.

Thus, the network analytic question we pose for cultural sociology concerns the relationship *among groups* within a team—in particular, whether groups are isolated or folded. The cultural sociology question we pose to network analysis concerns whether the groups are cognitively (culturally, stylistically) proximate or distant.

To elaborate this latter problem, we draw on work in semiotics, in particular on that of Yuri Lotman, a Russian semiotician who argued that the representation of semiotic space as composed of a single language was an "erroneous abstraction" (Lotman 2009, p. 24). A given cultural sphere, Lotman maintained, was composed of a multiplicity of codes. Lotman begins with a thought experiment in which we "assume an addresser and an addressee possessing identical codes and fully devoid of memory" (Lotman 2009, p. 4). In these ideal circumstances of perfect communication, an identical addresser and addressee would understand each other very well . . . but they would have nothing to talk about.

Lotman then presents a figure of two circles A and B (see fig. 1) showing "an area of intersection in the lingual space" (Lotman 2009, p. 5). This space of intersection appears as the natural basis of communication in which the nonintersecting parts are excluded from the dialogue. But, on further thought, we can question such an idea since the intersection suffers from the selfsame flaw of triviality. The real value of the dialogue is in the relationship between the nonintersecting parts: "The more difficult and inadequate the translation of one nonintersecting part of the space into the

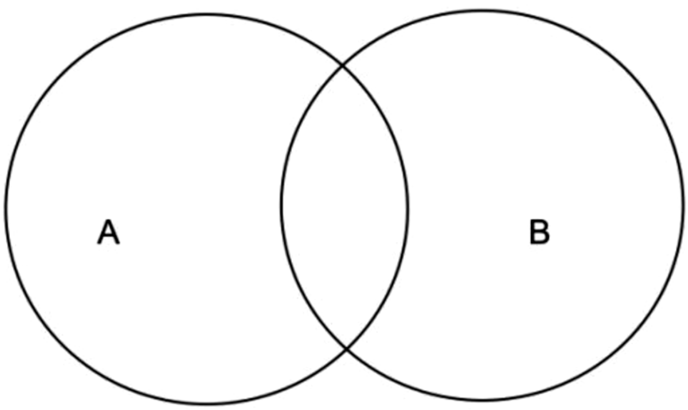


Fig. 1.—Intersection in lingual space (Lotman 2009, p. 5)

language of the other, the more valuable, in informative and social terms, the fact of this paradoxical communication becomes" (Lotman 2009, p. 5). This structure gives rise to a contradictory tension: (1) on the one hand, the struggle to facilitate understanding by expanding the area of the intersection, and (2) on the other, the struggle to increase the value of the communication by maximally amplifying the nonintersecting spaces (Lotman 2009, p. 5).

Lotman's analysis of cultural "explosions" as the result of tensions between "untranslatable" codes (Lotman 2009, p. 5; Eco 1990, p. ix) suggests a way to combine the structural thinking of network analysis with the attention to cognition and styles characteristic of new work in cultural sociology (DiMaggio 1997, 2011). For us, the value of the intersection (the structural fold) is proportional to the difficulty (the distance) of translating the cognitively diverse material of the nonintersecting parts of the folded groups. Similarly, the vital action is not all at the intersection but in the kind of interaction between intersecting and nonintersecting parts that is not captured with the notion, much emphasized in the conventional network literature, of the smooth flow of information.

Actors at the structural fold are insiders—insiders to more than one community. As insiders, they are trusted. What's more important, as the trusted insiders of multiple groups, they can vouch within one group for the members of another. This is an asset for a creative team, especially in times when things get difficult. "Trust me. You can count on her." Trust is not characteristic of brokerage across the structural hole. In fact, the opportunism of the less constrained broker was seen as one of its key features (Burt 1995). But trust is a resource, doubled, to groups that have a structural fold. And the more distant the groups within the team, the more trust matters in regards to the tension—*not for eliminating it but for holding it in place* until new kinds of creatively stylistic combinations can emerge.

Moreover, actors at the structural fold are insiders to the tacit knowledge and informal codes of more than one community. Structural folding matters because it does not simply facilitate a translation from one code to another but fosters the emergence of the primitive lexicon for new languages. That is, structural folding is the agent space for developing *creole*. Working within communities and sometimes acting in concert with others who are with them at the overlap, the structural fold makes it possible to develop a rudimentary language. Where cognitive distance is great, even a primitive lexicon can be an opportune starting point for a truly creative innovation. Together with trust, it can create a setting in which actors can cope with ambiguity and the tensions of nontranslatability.

Actors at the structural fold have access to more solutions. They are like the leaders of the United Farm Workers (UFW) studied by Ganz (2000), a "leadership team of 'insiders' and 'outsiders'" (p. 1015) whose diverse ties

403133.proof.3d 10 Achorn International 03/05/2015 10:58AM

from diverse life experiences gave them a diversity of salient collective action repertoires (p. 1016). Because its leaders had "'borderland' experience straddling cultural and institutional worlds" (p. 1015), the UFW was able to prevail against a traditional union with vastly superior resources.

Teams with highly cognitively diverse groups held in tension by structural folds not only have a greater repertoire of action; they also have the ability to recontextualize knowledge, recognizing that the given array of known solutions does not exhaust the possibilities for new solutions (Ganz 2000, p. 1012) and, in fact, for new problems (Lester and Piore 2004). Structural folding improves the likelihood of innovation by enhancing the possibility to override the taken-for-granted and to think deliberately (DiMaggio 1997) and reflexively (Stark 2009). By one way of thinking, the mixing of cognitive styles and lexicons, the ambiguous semantics of multiple identities, and the tensions about overlapping pragmatics should be a recipe for disaster (Zuckerman 1999). But we argue that cognitively distant but overlapping cohesive group structures can be productive not despite such mixing, ambiguities, and tensions but because of them (Giuffre 2001).

Structural folding, especially when the former occurs among cognitively distant groups, is different from brokerage.[4] In brokerage, to Burt (2005) for example, "the certain path to feeling creative is to find a constituency more ignorant than you and poised to benefit from your idea" (Burt 2005, p. 389). Our view is different: the path to promoting creativity is to belong to two constituencies as knowledgeable as you and to ignite the value of their misunderstood differences.

Folded diversity, our concept of structurally folded but cognitively distant sociolinguistic communities, therefore, differs from the notion of "long-distance ties" that one typically encounters in social network analysis, where distance is social distance. For us, structural folding is about the closeness of the multiple insiders. And, for us, distance refers to cognitive distance. Thus, our concept of folded diversity points to a contradictory and creative tension. The image we wish to convey is of a topology in which structural folding is pulling the groups closer while cognitive dissimilarity is pulling

[4] In a very recent paper, Ronald Burt (Burt 2014) proposes the notion of "reinforced structural hole" as a way of conceptualizing a network feature similar to our concept of structural fold. We do not agree with Burt's characterization of a structural fold as a reinforced structural hole. Whereas Burt's focus is on the difficulties of individual brokerage across reinforced holes, ours is on the generative tension that fuels creativity in the dense clusters. Moreover, the term reinforced structural hole implies that the bridge comes first and then gets reinforced. But it could just as well be the case that the fold comes first and, with the breaking of some ties, becomes a bridge across a hole. There are interesting theoretical issues here about network properties and their contribution to innovation as well as questions about network dynamics that are open to debate and testing. Our earlier work (Vedres and Stark 2010) suggests that the presence of brokers and bridging ties between groups do not contribute to performance, while structural folding is a predictor of performance.

them apart. The greater the stylistic distance, the higher the value of the communication, provided that folding offers structural organization for creolizations.

DATA

The Setting: Video Game Development

To test our hypotheses about structural folding and cognitive diversity, we study video game development. Video games, like art, film, and dance are expressions of culture. Not only do video games contain already existing expressions of culture, they also redefine and recreate them. In recent years, the importance of culture in video games has been recognized by many. Examples of this recognition include a recent exhibition in the Smithsonian American Art Museum called The Art of Video Games, which celebrated the successful assimilation of video games into the mainstream of American life,[5] and the launch of the academic journal *Games and Culture* in 2006 that aims to promote "innovative theoretical and empirical research about games and culture within interactive media."[6]

Few if any cultural forms have been marked by such explosive growth as that of video gaming. Nonexistent 40 years ago, by 2007 global spending on video games surpassed that of the film industry. In 2011 it eclipsed that of music as consumers around the world were estimated to spend nearly \$18 billion on hardware and \$44.7 billion on software for these games (Gartner 2011).

During the three decades of our study, the gaming industry evolved from simple two-dimensional table tennis games, to side-scrolling games, to fully equipped three-dimensional virtual worlds. Its unprecedented growth has been sparked by nearly relentless innovation across several cycles of successive generations of gaming consoles driving changes in "game mechanics" and game design rules (Aoyama and Izushi 2003; Bissell 2011; Tschang 2007).

Like many other cultural fields, the video game industry is one that rewards novelty, especially when it is packaged in terms that are recognizable to consumers and critics (Lampel et al. 2000; Hutter 2011). Doubtless, some video games are little more than simple imitations of already existing games. But the forefront of the industry finds continuous experimentation with the singular challenge of video gaming: how to create a convincing form of narrative storytelling that is nonetheless animated, perhaps uniquely so, by the actions of the users (Bissell 2011).

[5] http://www.nytimes.com/2012/03/16/arts/video-games/an-exhibition-in-easy-mode.html
[6] http://gac.sagepub.com/

In this perpetual search for an ever more creative (yet always unresolved) tension between the framed (fixed) narrative and the fluid "ludonarrative," a new video game project seeks to differentiate itself from others by introducing radically new game mechanics, new perspectives, and enhanced graphics as well as by crafting new genre combinations and new narrative strategies of character development made possible by (and, in turn, further stimulating) new technological capabilities (Delmestri, Montanari, and Usai 2005; Tschang 2007; Bissell 2011; De Vaan 2014). Video game production is thus a setting of continuous innovation motivated by the need to cope with episodic technological disruptions amidst incessant demand by consumers and critics for fresh ideas.

Data Collection

Our goal was to collect comprehensive data on every commercially-released video game in this global industry. To do so, we have drawn data from various sources. The main source was the Game Documentation and Review Project MobyGames.[7] MobyGames is an exhaustive repository of software titles, covering the individuals involved in the development process, the release date of each title, the platform(s) on which the game can be played, and game specific characteristics such as genre and perspective, as well as critics' reviews. The database covers this data from the inception of the industry in the 1970s to the present. The second step involved matching MobyGames to the German Online Games Datenbank (OGDB).[8] This database complements MobyGames by providing more detailed information on the release dates of video games. Both MobyGames and OGDB are crowd sourced and all entries into these databases are checked for accuracy by moderators and the users of the websites. In the rare case that neither of the two resources provided reliable quality information on a video game, or in the rare case that the information in the two databases was contradicting, we consulted other online or hardcopy resources, such as gamasutra.com, ign.com, *Crash*, *PC Gamer*, *GameInformer* and *GamePro*.

[7] The Game Documentation and Review Project MobyGames can freely be consulted at http://www.MobyGames.com. The MobyGames database is a catalog of "all relevant information about electronic games (computer, console, and arcade) on a game-by-game basis" (http://www.MobyGames.com/info/faq1#a). The information contained in MobyGames database is the result of contribution by the website's creators as well as voluntarily contribution by MobyGames community members. All information submitted to MobyGames is checked by the website's creators and errors can be corrected by visitors of the website.

[8] The Online Games Datenbank can freely be consulted at http://www.ogdb.de.

The resulting data set includes information on 12,422 production teams and the video games that they published between 1979 and 2009. For each of these video games we also compiled a complete list of all team members (as in film credits, according to their specialized tasks such as programming, imaging, scripting, design, music, etc.). Assigning unique IDs to each of the resulting 139,727 individuals allows us to reconstruct, for each team, the complete careers of all of its members in the video game industry.[9]

In addition to the data on the team members of a video game, for each video game in our population we record all game-specific stylistic elements (including eight genres, e.g., action, role-playing, simulation, etc., with distinctive subcategories within each) as well as six perspectives (e.g., first person, third person, topdown, sidescroll, etc.). These and other features result in the 105 stylistic elements that form the basis for our measures of inventiveness and of cognitive distance.[10] We also record, for each game, the release date, the computer platform for which the game is released, its developer studio and publishing house, and its level of critical acclaim. From this working database we excluded games that were released as compilation disks, "shovelware" (large compilations that aim to impress the consumer by the quantity, rather than the quality, of games), or rereleases. We also excluded games that were produced for mobile phones.[11] The final database includes 8,987 video games produced for 81 unique computer platforms involving PCs, game consoles, and handhelds. Despite the exclusion of 3,435 cases (12,422–8,987), we did use the information about membership of these teams to construct our historical network variables. The following section further explains how we did this.

[9] Note that our theoretical and empirical definition of the history of teams is specific to teams that are fabricated for one-off projects. Thus, we are not interested in a team's history, as, e.g., in the total win-loss record of the New York Yankees, the profitability of IBM under its management team during the past five years, or the continued prominence of the Department of Sociology at the University of Chicago during the past century (Abbott 1999). Unlike these institutionalized structures in which the identity of the team persists even as its members are replaced, the problem of a "team history" is more challenging for teams that assemble members for a particular project and disperse them upon project completion (think, e.g., of film production).

[10] List is available from authors upon request.

[11] Since mobile phones as gaming devices are a fairly recent phenomenon and because mobile phones opened up a new consumer market—i.e., mobile phone gamers are underrepresented in the group of contributors (mostly avid gamers) to crowd-sourced video game databases—the data on video games produced for mobile phones are incomplete. In addition to this shortcoming, video games produced for mobile phones are so different from console, PC and handheld games that they are difficult to classify within the structures upon which the crowd-sources databases used by us are build.

ANALYTIC STRATEGY

Dependent Variables

In order to define innovation in the context of video game development we gather data about characteristics of the product—a video game in this case—and data about how experts evaluate the product. First, while video games are built up from code written in languages unknown and invisible to most video game consumers, pieces of the code compose signs and expressions that can be interpreted and classified by virtually anyone (Bowker and Star 2000). We use the classification of signs and expressions—stylistic elements in the case of video games—to determine the distance of a video game relative to other video games. More precisely, we locate video games in a style space where being in the center refers to conventionality, while the periphery is associated with distinctiveness.[12]

Second, we capture critical acclaim (noting that this is not yet game changing creative success) through the evaluation of video games by experts. In our data, video game critics are the experts, and their opinion is expressed through a textual elaboration *and* a numerical grading. Moreover, changes in the numerical grading are strongly and positively correlated with the expert's evaluation of the level of innovation in a video game.[13] However, we do acknowledge that the field of video game reviewing is governed by rules and norms that guide the evaluation strategies used by reviewers. Such institutional forces could potentially inhibit reviewers from recognizing novelty in video games that separates a good video game from a "game changer." In a similar fashion, rules and norms can also urge reviewers to celebrate incremental refinement, a change that can definitely boost sales but is unlikely to change the cognitive boundaries within which video game developers produce games and video game consumers consume games.

Finally, it is only when the unconventional is successfully recognized and embraced that we can speak of a game changer. We therefore construct three dependent variables through which we can evaluate the innovative character of video games.

Distinctiveness measures the extent to which a game stands out in terms of the stylistic elements present in the game relative to all games produced in the preceding five years (if t was the year of publication of the given

[12] Prior work has argued that the meaning of a cultural symbol is not so much a function of the characteristics of that symbol, but rather of the relationships with other cultural symbols (Mohr 1994; Wuthnow 1987). We build on this work and use the cultural network that represents these relationships to capture the distinctiveness versus conventionality of cultural products.

[13] A thorough reading of a large volume of reviews revealed that critics reward innovative elements upon which video games are built.

game, we compared it to all games published from t-5 to t-1). We use the preceding five years as the window of comparison.[14] We did not include games in the year of publication to avoid reverse temporal ordering (as data about the day of release is not available for all games in our sample). To construct the variable, we code the presence of stylistic elements covered in a video game as a binary vector of 105 elements.[15] We then compare the vector of our focal game to the vectors of all games produced in the preceding five years, and we compute the distance between the focal game i and each other game j as follows:

$$d_{ij} = 1 - \left[\sum_{k=1}^{K} f_{ik} f_{jk} \Big/ \left(\sum_{k=1}^{K} {f_{ik}}^{2} \right)^{1/2} \left(\sum_{k=1}^{K} {f_{jk}}^{2} \right)^{1/2} \right], \tag{1}$$

where f_{ik} equals $1/K$ if stylistic element k is covered in game i (and K equals the total number of elements covered in a game) and 0 otherwise. This index is known as the cosine index and is a robust and widely used measure in a variety of disciplines (Jaffe 1986; Sohn 2001; Evans 2010) to capture the similarity between vectors. By normalizing the number of stylistic elements in game i and j, the cosine index captures similarity without overly penalizing differences in the number of stylistic elements used in a game (Evans 2010).

For each video game we get a vector of distances between focal game i and all other games $\{1, 2, \ldots, j\}$ that were developed in the preceding five years. To construct the variable of distinctiveness of this vector, we average the distances:

$$distinctiveness_i = \sum_{j=1, j \neq i}^{N} d_{ij} / N. \tag{2}$$

Critical acclaim captures the average score awarded to a video game by professional industry critics. We used an indicator from the MobyGames database that is a weighted average of normalized ratings and reviews by professional critics in prominent online, television, and print media outlets

[14] We have experimented with moving windows of seven, five, and three years, and 1 year. Although the precise estimates of the coefficients and SEs differ between models based different windows, the direction and significance levels of the variables are stable across these different specifications.

[15] Some of the stylistic elements are lower-level elements of higher-level elements. For example, "basketball" is a lower level element of "sport." To account for this hierarchy in the data, we experimented with a method of adjusting the set of stylistic elements associated with a video game. This method involved removing the higher-level stylistic element if lower-level stylistic elements related to this higher level were present. We replicated all analyses in this article based on these adjusted sets of stylistic elements associated with video games. The results from these replications show similar signs and significance levels as the results presented here (which are based on the unadjusted sets of stylistic elements).

(the normalization is needed, as rating systems vary—some range from one star to five, others from 1 point to 10 points, etc.). The score ranges between 0 and 100. The higher the score, the higher the collective critical opinion of the game.[16] The typical review source is a magazine or a gaming website. Examples of such sources include *Game Informer* (in the United States), *PC PowerPlay* (Australia), *Jeuxvideo.com* (France) as well as the German website eurogamer.de. MobyGames adamantly maintains quality standards for the review sources indexed in the score.[17] To be included, a review source must, for example, have published a minimum of 100 reviews, meet professional writing standards, and be published within a month of the game's release date. Scores represent contemporaneous judgment of quality, rather than an ex-post reflection with nostalgic tint. Blogs are excluded, as are media outlets that aggregate scores of individual users or critics.[18]

We define a game to be a *game changer* if it is stylistically distinctive *and* highly regarded by critics. To identify such games we partition the data set into two mutually exclusive subsets (i.e., game changers vs. non–game changers) based on thresholds imposed on the distributions for *distinctiveness* and *critical acclaim*. These partitions form the basis of a dummy variable that equals 1 for all game changers and 0 for all non-game changers. We start by coding games as game changers if their values for *distinctiveness* and *critical acclaim* exceed the value of the 60th percentile for both variables. Games that have lower values on one or both dimensions are coded to be non–game changers. This method results in 929 game changer games and 4,579 non–game changer games. The next step is to narrow down the set of games that are classified as game changers. We therefore raise the threshold to the 70th and the 80th percentile. Using the 70th percentile as the minimum threshold results in a set of 502 games representing 10% of all games in the sample. The 80th percentile of the distributions results in 212 game changers, which equals 4% of the sample. Since these thresholds are somewhat arbitrary, we test the robustness of our findings by varying the threshold. The tables in this article present the coefficient estimates for the 60th percentile threshold, but in the presentation of the results we also provide the coefficient estimates for the models based on the 70th and 80th percentile.

In figure 2, we present graphically the process of the method used to partition the dataset into game changers and non–game changers. The left panel shows a scatterplot of all observations, while the right panel only shows those observations coded as game changers.

[16] MobyGames Website (accessed on 10–22–2013).

[17] See http://www.mobygames.com/info/mobyrank for more information (accessed on 10-22-2013).

[18] Websites such as MetaCritic, GameRankings, Rotten Tomatos, and GameStats are considered aggregate sources and are thus not included in the score.

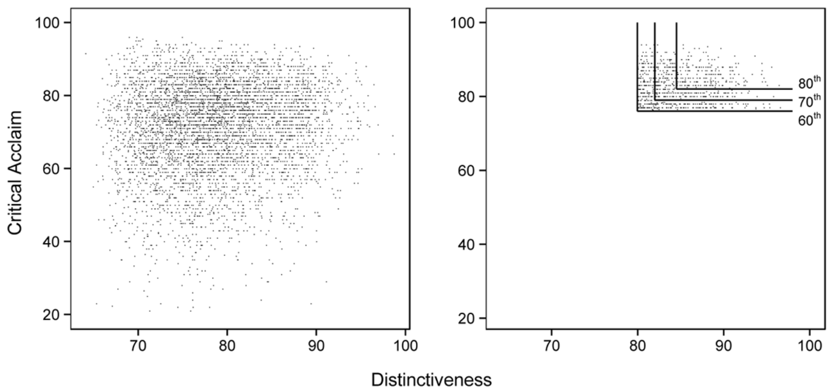


FIG. 2.—Visualization of the definition of *game changer*

Independent Variables

We first define two operational concepts that form the bases for the measurements of multiple independent variables: (1) groups and (2) cognitive distance. First, we identify *groups* by recording all instances in which *at least three* members of the focal team have coparticipated in a prior game project. Naturally, in some of these instances fully similar groups (in terms of its member composition) or partly similar groups will be identified. If for example, individuals A, B, and C have coparticipated in production projects in 1999, 2001, and again in 2003, then for the 2003 team this social structure of three individuals is recorded as one group. Similarly, if individuals A, B, and C have coparticipated in a production project in 1999 and individuals A, B, C, and D in 2001 and again in 2003, then for the 2003 video game, these sets of three individuals and four individuals are merged and will be recorded as one group because the first group is *a proper subset* of the second and third, $\{A, B, C\} \subseteq \{A, B, C, D\}$.[19] Thus, a given group accommodates a subset of all team members who have collaborated on one or more projects at least once.[20]

[19] We have experimented with several alternative definitions of groups. First, we redefined groups as social structures that had collaborated prior to the focal game in *at least two* instances. This threshold produced results similar to the ones presented here. Using higher thresholds (more than two) however, reduced the number of teams that had multiple groups in them to less than 5% of the sample making the estimation of precise coefficients unfeasible.

[20] An example of a context in which individuals are organized in a similar fashion are boards of directors (Mizruchi 1996). Much of the director interlock literature collapses the two-mode network into a one-mode network to study how firms are connected through directors. But, in an interesting sense, the counterparts of our *teams* are the

Second, we define *cognitive distance* between two individuals or groups as the dissimilarity of the vectors that comprise counts of the stylistic elements to which these individuals or groups have been exposed. Rather than recording the exposure in binary terms, we use frequencies. The stylistic portfolio of a team member or group describes the distribution of the level of exposure to the possible set of 105 unique elements described above in the data section. We then calculate the distance between team member pairs or group pairs by calculating the cosine index—shown in equation (1)—based on their stylistic portfolios.

We examine how groups are connected and, in particular, whether they exhibit structural folding where cohesive groups overlap. Because we have distinctive measures for cognitive structures and social structures, we can test whether the variance in our dependent variables is accounted for by structurally folded groups that encompass larger cognitive distances.

Structural folding measures the extent to which groups are structurally folded into one another. Different groups may have one or more members in common. We record for each pair of groups the proportion of group members shared. Then we sum these proportions and divide this number by the maximum possible number of folds given by $[N^*(N\text{-}1)]/2$ for the set of N groups. In other words, this variable captures the average overlap between groups in a team.

Folded diversity is our main variable of interest, as it captures the extent to which cognitively distant groups are folded—by individuals who are present in both groups. First, we construct a matrix that describes the cognitive distance between each pair of groups in a video game production team. The distance is based on the exposure of the group members to different stylistic elements and follows the specification introduced in equation (1). Then, we multiply the elements of this distance matrix and the elements of the structural folding matrix. Finally, we divide the sum of these element-wise multiplications by the $[N^*(N\text{-}1)]/2$ possible edges between groups. In other words, each pair of folded groups is weighted by the cognitive distance between each of them.

Cognitive diversity captures the level of dissimilarity between the stylistic portfolios of team members. We calculate the distance between each team member's stylistic portfolio and the portfolios of all other team members using the cosine index where f_{ik} is the fraction of stylistic element k in all stylistic elements K covered by team member i. We then used every value of d_{ij} to construct a matrix D_g for every game g which allows us to calculate the *cognitive diversity* variable for game g as follows:

actual *boards*—where directors sit together. These directors often have (had) multiple appointments and if multiple directors of a focal board have also jointly been on the board of another company they may act as a group and develop a group style.

$$cognitive\ diversity_g = \sum_{i=1}^{N} d_{ij*} \frac{1}{N}, \tag{3}$$

where d_{ij} is the dissimilarity (1 – fully different, 0 – identical) between team member i and team member j, and the $1/N$ term simply transforms the sum of all pairs into an average.

To illustrate the calculation of this variable, think of two teams of three team members. In the first, the prior stylistic exposure of the members is represented as ABC, ABC, ABC. In the second, members' prior exposure was AAA, BBB, and CCC. Each has the same range of elements. The first team, however, has lower cognitive distance. All its members share the same repertoire and each can communicate with each of the others just as easily about any of the stylistic elements. Cognitive distance is higher for the second team.

Control Variables

We include Burt's measure of *constraint* (Burt 2005) to account for brokerage opportunities present in a team. Constraint may affect both the dependent variables and *folded diversity*, thereby acting as a confounder.[21]

Mean group size is operationalized by counting the mean number of individuals in the groups observed within a team. We also include a squared term for this variable in the model to assess whether the effect of *mean group size* on our dependent variables changes as groups grow. *Number of groups* captures the number of groups present in a team.

Number of team members is a count of the number of individuals involved in the production of the video game. We include this variable in the regression model to control for variation in the dependent variable that is related to a simple increase the number of human resources. One may argue, for example, that more members result in higher quality games regardless of the fact that they are more diverse or more cohesive. The variable *newbies* counts the number of team members that have no prior experience in the production of video games. In contrast to their experienced counterparts who have well established track records, and identifiable talents, these newcomers are expected to have little experience and unseasoned skills (Guimera et al. 2005). *Games tenure* measures the average number of games that the team members of the focal game have produced prior to the year of production of the focal game. In particular, this variable measures the

[21] Brokerage opportunities (low levels of constraint) may represent an alternative causal mechanism through which articulated group structures can affect team performance. What we might interpret as the recombinatory work happening across overlapping groups could be stemming from an increase of performance that developers at group overlaps experience, because they can take advantage of brokerage opportunities.

403133.proof.3d 20 Achorn International 03/05/2015 10:58AM

effect of the influence of experienced video game professionals. This variable is likely to proxy the average amount of experiences and skills held by team members.

Past review score measures—for each team—the average review score of the games that the members of the focal game had participated in during the previous five years. The variable accounts for the average quality of the team members active in the production of the focal game. Although we do not directly measure the quality of each individual team member—but rather the critical success of the games they have coproduced—we argue that the variable is a good indicator of the quality of an individual. We include this variable to account for the possibility that the quality of team members affects the team formation process.

High performers captures exceptional performance of team members rather than the average performance. In particular, we count the number of team members who in the past five years have been involved in the production of a game that was rated in the 95th percentile of all games produced in a given year. Being involved in the production of such a high scoring game is as much an indication of one's individual capabilities as it is a factor that contributes toward an individual's status within the industry.

Awarded member is a dummy variable indicating whether one or multiple team members have been awarded a Game Developers Choice Award.[22] This variable controls the variation in team selection processes that can be caused by changes in status and resource allocation.

Single-firm production is a dummy variable equal to 1 if the publisher and the developer of the video game are different legal entities and equal to 0 if both the publishing activities and the development activities are in the hands of one firm or different divisions of the same legal entity.[23]

Firm age captures the average number of years that the publisher and developer firm have been active in the video game industry. The variable is included to account for the routines and levels of experience that were built up within a firm and are available as a resource for the team. In case that a video game is produced by a single firm, the value equals the number of years that this firm has been active in the industry.

[22] The Game Developers Choice Awards are awarded annually by the Game Developers Conference to the most innovative and creative game designers. The awards were introduced in 2001 and were preceded by the Spotlight Awards, which were presented from 1997 to 1999. We used information from both award shows.

[23] To construct this variable we traced the founding and merger and acquisition histories of all firms in the data set. Firms that were set up as divisions, subsidiaries or labels of other firms were coded as being dependent on a parent firm. In the case that a firm was acquired by another firm we also coded the firm as being dependent on a parent firm from the acquisition data onwards.

Number of elements is a count variable that equals the number of elements covered in a video game. We include this variable to account for the complexity of a game.

We include *genre dummies* in our models to account for variation in the dependent variable that is associated with the average popularity of specific genres. Video games in highly competitive genres are benchmarked against much more and possibly higher-quality games that are expected to influence the score that a reviewer would award a game. The genre dummies are not mutually exclusive. Games can have elements of multiple genres in the gameplay and therefore all eight genres are included as dummy variables in the analyses.

Year dummies account for temporal trends in how games are reviewed by critics. Throughout the course of the video game industry, critics' standards evolve, and critics become socialized with one another. Another time-related issue picked up by the year dummies is the fact that throughout the course of the industry teams inherently become more diverse. *Country dummies* account for the fact that games that are released in multiple countries will likely be reviewed by a larger number of critics with different cultural backgrounds. Last, we include *platform dummies* in our models to account for variation in the dependent variable that can be attributed to characteristics of the platform a video game is produced for. Platforms have their own ecologies and these demarcate the boundaries within which video game producers can position their product. Moreover, video game reviewers may use structurally different criteria to evaluate video games produced for different platforms.

Methods

To test our hypotheses about the role of groups within teams and their relation to innovative performance we conduct simulation and regression analyses. First, in order to show that teams are built from groups, rather than by adding individuals, we develop a simulation framework that compares network density within observed teams with the network density within teams that were generated through a series of alternative processes of team assembly. Second, to show that folded diversity contributes to innovative performance of teams we use multiple regression methods. We further describe these methods below.

Simulations.—We simulate the processes through which teams *could* have been assembled. The gist of these simulation models is that if groups are indeed recognizable and identifiable, and individuals are selected into a team *as members of groups*, the network density of the team will be high relative to the network density of teams formed through a selection process that ignores group structures.

We draw from Ruef et al. (2003) and identify three basic alternative principles that can guide the formation of professional teams: (1) selection based on social networks, (2) selection based on skill similarity, and (3) selection based on organizational boundaries. We employ these three selection principles and operationalize them by simulating team formation based on each of them. For each simulation we take the developers in the observed team as the starting point. We identify their characteristics (social network, skills, firm affiliations) and we ask the question: What would the network density have been if the recruitment process were guided by these principles without paying attention to group structure? The strategies that we adopt to operationalize these processes are the following.

As a baseline model, we simulate a naïvely constructed team by sampling potential team members from all available individuals in the industry in a given year. Clearly this model is unlikely to guide the formation of video game production teams but observing its outcome and comparing it to the other simulation strategies may provide an important benchmark.

For the skill similarity scenario, each member of the original team is matched with a sample of its N nearest neighbors. Nearest neighbors are defined as the individuals that have the most similar skill portfolio to the focal team member in the year prior to the production of the focal game. The N varies from year to year and is defined as the number of developers in the first percentile of the distance distribution of a video game developer.[24] That is, after calculating the skill similarity between developer i and all other developers $1, \ldots, j$, the 1% most similar developers are selected into the sample. Then, for each team member we randomly select one individual from the union of focal team member i and its sample of N nearest neighbors. We do this for every team member and we repeat the process 100 times.

We also use organizational structures in the data to simulate teams. We sample not only from employees that had been employed by the firms that produced the observed game; doing so would lead us to eliminate all cases that involve a new firm (i.e., no prior history in the industry). Moreover, even for firms that had already produced a game prior to the focal game, but had done so with fewer team members than the ones in the focal team, no simulated teams could be constructed—simply because the ecology from which we can draw is too small. We therefore sample from the individuals who had been employed by the firms that the members of the observed team had worked for in the past five years.[25] That is, selection

[24] The 1% is the fraction for which the number of alternative developers for developer i is at least one in any of the years.

[25] We also experimented with other thresholds and the outcomes were qualitatively similar. Moreover, we account for the overrepresentation of people employed by the organizing firm in the observed team by introducing weights when selecting from the

into the team is bounded by a focus on a limited number of firms with which the actual team members have had a recent affiliation. From the individuals in the resulting pool of individuals (which again includes the observed team members), we select *N* individuals where *N* equals the number of team members of the observed team. We repeat this process 100 times and calculate the average network density across the 100 simulation runs.

Finally, for selection through social ties, we identify all alters in the ego networks of the members of a focal team. These ego networks are the relations formed through coparticipation in projects in the five years prior to the focal project. The union of the set of alters and the set of egos is the pool that represents all potential members of the simulated team. Essentially, this team assembly method selects members from the local social networks in which the members of the actual team are embedded. We then randomly select *N* individuals from this pool where *N* equals the number of members in the originally observed team. We repeat this process 100 times for each observed team and calculate the average density in these simulated teams.

Regressions.—A second strategy through which we investigate our hypotheses involves running multiple sets of regression analyses. The first set of models aims to show how the social and cognitive composition of production teams in the video game industry relates to the level of *distinctiveness* of a video game. This dependent variable is available for all 8,987 video games in our dataset and since it is a normally distributed continuous variable we test our hypotheses through the estimation of a pooled ordinary least squares (OLS) regression.

In the second set of regression models we estimate the coefficients for the independent variables with *critical acclaim* as the dependent variable. Similar to the *distinctiveness* variable, *critical acclaim* is a continuous normally distributed variable. We therefore estimate the coefficients for the independent variables using OLS regressions. The *critical acclaim* variable is only observed for a subset (5,508) of all video games in the sample meaning that 61% of the games is reviewed in the selected review outlets. As a result, sample selection bias may plague our primary findings. A commonly used approach to address such selection issues is by estimating a two-stage Heckman selection model (Heckman 1979). In appendix A we have included a discussion of this modeling technique, and we have estimated our regression models with *critical acclaim* as the dependent variable by employing a two–stage Heckman model to provide robustness checks for the models used in this article.

pool of potential members. In other words, if there are two firms that have employed members of the focal team and one of those firms accounts for the majority of the employment, we account for this overrepresentation by adopting a stratified random sampling approach, given the pool of potential members.

Game changer is a binary variable and is therefore estimated using logistic regression. *Game changer* equals 1 if a game's *distinctiveness* variable exceeds its 60th percentile and if that game's *critical acclaim* variable also exceeds the 60th percentile. Since *game changer* is constructed on the basis of *critical acclaim* its value also remains unobserved for 39% of the sample. In order to verify that the estimates presented in this paper do not suffer from selection bias we present in appendix A the results of a bivariate probit regression model that corrects for selection bias.

Finally, we address the potential issues arising from any unobserved factors that are stable at the organizational level but vary *between* organizations and are correlated both with our dependent variables and our independent variables. One may argue that many teams are nested within a firm and that these firms may hold unobserved competencies that can cause us to spuriously identify relationships between independent and dependent variables in our models. We therefore rerun the models using a firm fixed effects specification. The results and a discussion of the results can be found in appendix B.

In table 1 we report the descriptive statistics and in table 2 and table 3 we report the correlation matrices for the full sample and the truncated sample respectively. These tables show that the correlation for some variable pairs exceed 0.70. These pairs include but are not limited to *folded diversity* and *structural folding*, *number of team members* and *number of groups*, and *newbies* and *number of team members*. To assess whether the

TABLE 1
Descriptive Statistics

	No. Obs.	Min	Max	Mean	SD
Distinctiveness	8,987	60.88	98.94	79.33	6.78
Critical acclaim	5,508	21.00	96.00	71.44	12.33
Game changer	5,508	.00	1.00	.17	.37
Folded diversity	8,987	.00	1.00	.30	.27
Cognitive diversity	8,987	.00	1.00	.42	.16
Structural folding	8,987	.00	.94	.24	.22
Constraint	8,987	.00	77.48	7.22	5.67
Mean group size	8,987	.00	211.00	6.66	5.76
No. of groups	8,987	.00	186.00	7.85	12.34
No. of members	8,987	6.00	459.00	40.55	46.63
No. of newbies	8,987	.00	247.00	10.34	12.95
Games tenure	8,987	.00	9.17	2.07	1.08
Past review score	8,987	.00	95.00	69.03	17.49
High performers	8,987	.00	355.00	14.49	26.60
Star developer	8,987	.00	1.00	.01	.09
Single firm	8,987	.00	1.00	.32	.47
Mean firm age	8,987	1.00	31.00	13.72	6.75
No. of elements	8,987	1.00	21.00	4.66	1.60

403133.proof.3d 25 Achorn International 03/05/2015 10:58AM

TABLE 2
CORRELATION MATRIX FULL SAMPLE

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. *Distinctiveness*															
2. *Folded diversity*	0.01														
3. *Cognitive diversity*	.02	−.01													
4. *Structural folding*	.02	.78	−.16												
5. *Constraint*	−.24	.18	.07	.07											
6. *Mean group size*	−.07	.19	−.31	.25	.26										
7. *No. of groups*	−.22	.20	−.03	.06	.75	.29									
8. *No. of members*	−.23	.13	.02	.01	.74	.45	.85								
9. *No. of newbies*	−.13	.02	.14	−.07	.45	.15	.44	.71							
10. *Games tenure*	−.11	.30	−.13	.30	.34	.29	.36	.19	−.21						
11. *Past review score*	−.09	.19	.22	.16	.20	.19	.14	.18	.12	.26					
12. *High performers*	−.19	.12	−.06	.03	.59	.48	.79	.89	.48	.28	.21				
13. *Star developer*	−.02	.02	.01	.00	.12	.07	.18	.17	.06	.09	.03	.19			
14. *Single firm*	.04	.09	−.06	.07	−.04	.05	.05	.05	.05	−.02	.06	.08	.03		
15. *Mean firm age*	−.18	.19	.03	.12	.48	.26	.48	.47	.24	.36	.24	.45	.12	−.06	
16. *No. of elements*	−.29	.00	−.01	−.01	.06	.06	.06	.08	.06	.01	.04	.07	.01	−.01	0.07

TABLE 3
Correlation Matrix Truncated Sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. *Distinctiveness*																	
2. *Critical acclaim*	0.09																
3. *Game changer*	.44	.41															
4. *Folded diversity*	.01	.08	.07														
5. *Cognitive diversity*	.04	−.05	−.01	−.06													
6. *Structural folding*	005	.06	.07	.76	−.22												
7. *Constraint*	−.26	.06	−.06	.06	.08	−.07											
8. *Mean group size*	−.08	.16	.06	.17	−.41	.25	.19										
9. *No. of groups*	−.24	.09	−.06	.14	−.07	−.01	.73	.29									
10. *No. of members*	−.24	.16	−.02	.06	−.02	−.07	.72	.45	.84								
11. *No. of newbies*	−.11	16	.05	−.02	.14	−.11	.43	.15	.42	.70							
12. *Games tenure*	−.14	.02	−.03	.27	−.23	.27	.32	.30	.38	.19	−.24						
13. *Past review score*	−.01	.30	.13	.13	.12	.11	.12	.19	.10	.15	.10	.16					
14. *High performers*	−.18	.23	.03	.08	−.12	−.02	.57	.51	.78	.89	.45	.30	.22				
15. *Star developer*	−.01	.05	.01	.02	.00	−.01	.12	.08	.17	.16	.05	.11	.04	.19			
16. *Single firm*	.01	.16	.09	.10	−.07	.05	−.01	.06	.08	.09	.08	.00	.13	.12	.04		
17. *Mean firm age*	−.19	.13	.01	.15	−.04	.06	.44	.23	.46	.44	.20	.39	.20	.44	.13	.04	
18. *No. of elements*	−.26	.03	−.11	−.01	−.02	−.02	.05	.05	.05	.06	.05	.01	.03	.05	.01	.00	0.04

high correlation coefficients inflated the variances of these variables we calculated the variation inflation factor (VIFs) and concluded that we can safely interpret the estimates in our models (the VIF did not exceed three for any of the variables).

FINDINGS

Simulations

In figure 2 we have plotted the distributions of the *differences* between the observed network density and simulated network densities for the four scenarios of team assembly. All four graphs clearly show that the density of the observed team is higher than the density of the simulated teams. In the scenarios where teams are simulated from industry peers, none of the

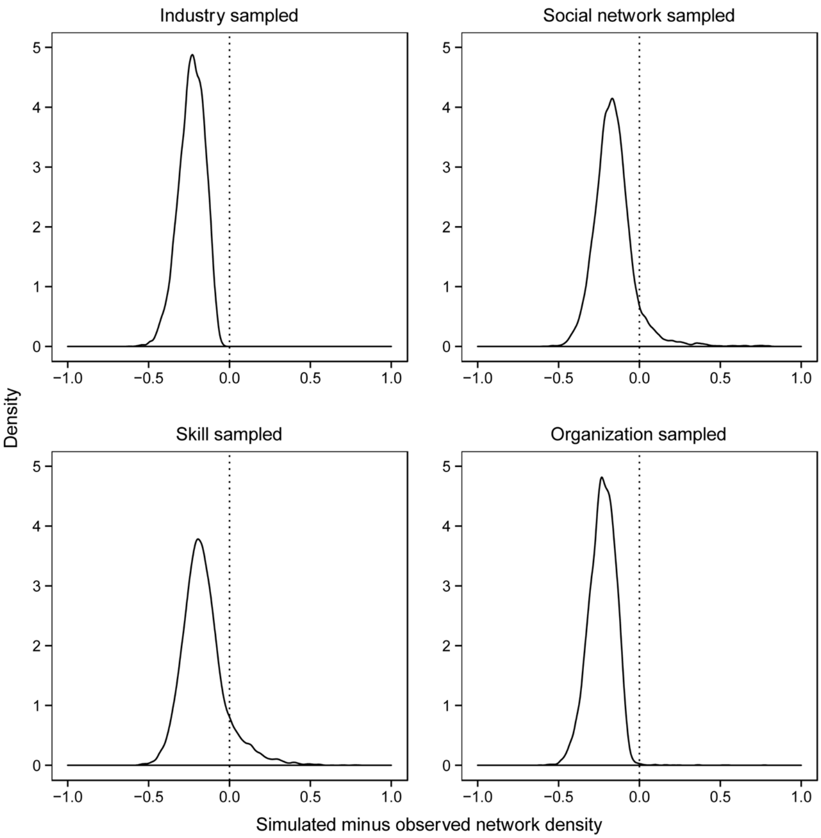


FIG. 3.—Difference between simulated and observed network density

simulated teams have a higher network density than the network density of the observed team. In the simulations that build on the social networks of the members of the observed team 7% of the simulated teams has a network density that is higher than the network density of the observed team. For the simulations that draw from skill peers and organizational peers that number is equal to 10% and 6% respectively.

We also performed two formal tests based on these comparisons. The first test, the Kolmogorov-Smirnov (K-S) test, evaluates the hypothesis that the two distributions of network density—observed and simulated—are sampled from different continuous distributions. The null hypothesis is that the two distributions are drawn from the same population. The test statistic and the P-value ($P < .0001$ for all four benchmarks) indicate that we can reject the null hypothesis, making it likely that the two distributions come from different populations. This finding holds across the four simulation strategies. A second test, the Wilcoxon signed rank test (Bauer 1972; Agresti and Finley 2009), evaluates whether the rank of the means differs between the two variables. Similar to the K-S test, the Wilcoxon signed rank test indicates that the means rank differently for the data generated from the simulated teams versus the observed teams ($P < 0.0001$ for all four benchmarks).

We interpret these findings as evidence that groups formed through prior coparticipation and collaboration affect the process through which teams are selected. Rather than selecting team members exclusively based on individual qualities, teams are assembled by taking earlier group structures into account. That is, teams in the video games industry are composed of groups, rather than just individuals. This finding indicates that groups within teams are recognizable and identifiable and that the processes upon which we focus our hypotheses are likely not to have occurred merely through data artefacts or through spurious associations caused by the omission of variables.

The history of video games is a large team mixing machine, where the grains are subgroups, small communities that carry their history of trust and shared understandings. These communities are plunged into the uncomfortable zoo of day 1 of a game project, with many unfamiliar faces and a few at the folds that can help knit the small groups into an experimenting ensemble—a proposition we test with regression analyses.

Regression Analyses

Table 4 displays the coefficient estimates for the regression models. The dependent variable in models 1, 2, and 3 is *distinctiveness*, the dependent variable in models 4, 5, and 6 is *critical acclaim*, while the dependent variable in models 7, 8, and 9 is *game changer*. The first models for each dependent

TABLE 4
COEFFICIENT ESTIMATES OF THE PREDICTORS OF *DISTINCTIVENESS*, *CRITICAL ACCLAIM*, AND *GAME CHANGER*

	Distinctiveness			*Critical Acclaim*			*Game Changer*		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Folded diversity			1.198**			2.422*			.614**
			(.413)			(.981)			(.227)
Cognitive diversity			2.887***			−5.875***			.235
			(.505)			(1.382)			(.356)
Structural folding		.998**	−.074		.904	−1.577		.515**	−.057
		(.338)	(.523)		(.854)	(1.276)		(.199)	(.298)
Constraint		−.057**	−.065**		.113**	.131**		.019	.018
		(.021)	(.021)		(.042)	(.042)		(.012)	(.013)
Mean group size^2		.000**	−.001***		−.004***	−.003*		−.001*	−.001*
		(.000)	(.000)		(.001)	(.001)		(.000)	(.000)
Mean group size		.093***	.146***		.302***	.193**		.051***	.058***
		(.020)	(.022)		(.061)	(.066)		(.014)	(.016)
No. of groups		.015	.023		−.023	−.047		−.011	−.012
		(.013)	(.013)		(.025)	(.025)		(.007)	(.007)
No. of members	−.064***	−.064***	−.071***	−.102***	−.124***	−.113***	−.035***	−.037***	−.038***
	(.005)	(.007)	(.007)	(.010)	(.014)	(.015)	(.004)	(.005)	(.005)
No. of newbies	.058***	.063***	.067***	.181***	.197***	.190***	.054***	.055***	.056***
	(.010)	(.011)	(.011)	(.019)	(.021)	(.021)	(.006)	(.006)	(.007)
Games tenure	−.157*	−.249**	−.234**	−.156	−.496*	−.568**	.029	−.038	−.037
	(.079)	(.085)	(.085)	(.190)	(.208)	(.208)	(.046)	(.052)	(.052)

Past review score	−.015***	−.017***	−.026***	.240***	.225***	.240***	.030***	.025***	.025***
	(.004)	(.004)	(.004)	(.014)	(.015)	(.015)	(.006)	(.006)	(.006)
High performers	.049***	.041***	.046***	.186***	.198***	.192***	.038***	.038***	.039***
	(.007)	(.007)	(.007)	(.013)	(.014)	(.014)	(.004)	(.005)	(.005)
Star developer	1.680*	1.828*	1.722*	.109	.325	.577	.358	.452	.458
	(.781)	(.779)	(.777)	(1.420)	(1.417)	(1.416)	(.328)	(.333)	(.334)
Single firm	.534***	.437**	.455**	2.459***	2.493***	2.340***	.311***	.310***	.297***
	(.145)	(.146)	(.146)	(.336)	(.337)	(.338)	(.079)	(.080)	(.080)
Mean firm age	−.047***	−.044***	−.049***	.127***	.126***	.125***	.012	.013	.012
	(.012)	(.012)	(.012)	(.028)	(.028)	(.028)	(.007)	(.007)	(.007)
No. of elements				.214***	.206***	.211***			
				(.026)	(.026)	(.026)			
Distinctiveness				.386***	.368***	.364***			
				(.103)	(.102)	(.102)			
Intercept	82.401***	82.259***	81.413***	31.522***	31.860***	33.391***	−4.112***	−4.107***	−4.208***
	(.318)	(.320)	(.354)	(2.558)	(2.552)	(2.570)	(.420)	(.414)	(.446)
R^2	.086	.092	.096	.177	.183	.186			
Adjusted R^2	.084	.089	.094	.174	.179	.182			
No. observations	8,987	8,987	8,987	5,508	5,508	5,508	5,508	5,508	5,508
AIC							4,685.736	4,659.079	4,654.237
BIC							4,811.401	4,817.814	4,826.200
Log likelihood							−2,323.868	−2,305.539	−2,301.118

NOTE.—All calculations include year dummies and platform dummies.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

variable include the control variables that describe the size of the team, the past performance of its members, and the two firm characteristics. In the second set of models (model 2, model 5, and model 8) we include some of the variables that characterize the groups in a team and the social networks within a team. Finally, in models 3, 6, and 9 we show the estimates for the full models that include our variable of interest: *folded diversity*. We first discuss the findings for *folded diversity*, and then we describe our models in full, step by step, by interpreting the coefficients and by highlighting salient alternative explanations.

Cognitive folding is a predictor of *distinctiveness*, and its effect is significantly different from zero. Distinctive games are borne out of generative tensions across cognitively distant but socially intersecting groups. The same holds for the model that assesses *critical acclaim* as a function of *folded diversity*. *Folded diversity* is a predictor of critical success, which implies that teams characterized by cognitive friction across folded groups are likely to produce games that are highly regarded among critics. When we examine *critical acclaim* that is innovative (standing out and being outstanding), that is, when we consider true game changers as opposed to success borne out of incremental change, we see that *folded diversity* is a positive and statistically significant predictor. *Game changers* are likely to be developed by teams that comprise cognitively different groups (subgroups with varying cognitive sets) that tolerate and exploit overlapping membership across such groups.

Distinctiveness is the dependent variable in models 1, 2, and 3. It captures the extent to which a game is distinctive in its feature combination compared to all other video games in the preceding five years. Model 1 shows the baseline model, and model 2 enters variables of network structure: *structural folding, constraint, group size*, and *number of groups*. Model 2 shows that an increase of *structural folding* of different groups is a positive and significant predictor of the *distinctiveness* of the game developed.

In model 3 we enter variables describing the cognitive composition of the team: *folded diversity* and *cognitive diversity*. This model shows that if one accounts for the cognitive distance that is socially folded by groups in a team, the main effect of *structural folding* is no longer significant. However, the coefficient estimate of *folded diversity* is positive and significant. Moreover, an F-test of the joint significance of *structural folding* and *folded diversity* ($P < 0.01$) indicates that the variables are jointly significant. These results imply that teams with overlapping groups that are cognitively distant tend to develop more distinctive video games. As hypothesized, generative tensions within teams allow for the development of products that stand out. It is neither the overlapping social structure in itself, nor the cognitive distance that fosters the creation of a distinctive video game, but rather an overlapping structure of groups at larger cognitive distances.

We now consider the other variables included in this model and discuss how these variables shed additional light on how distinctive video games are produced. These control variables are included in the models to minimize the risk of falsely rejecting the null hypothesis that *folded diversity* has no effect on *distinctiveness*.

The inclusion of *cognitive diversity* tests for the alternative explanation for our main finding that *folded diversity* captures the cognitive dissimilarities between team members regardless of social structures. Model 3 shows that although *cognitive diversity* is positively and significantly related to the distinctiveness of the video game, the coefficient of *folded diversity* is positive and significant. This implies that the two variables capture different characteristics of video game development teams and that *folded diversity*—the overlapping of cognitively distant groups—cannot be reduced to just *cognitive diversity* in the team.

A second alternative explanation for the positive and significant effect of *folded diversity* on *distinctiveness* is that *folded diversity* captures team cohesion and that such cohesion allows for the production of more or less distinctive video games. *Folded diversity* might just represent the benefits of having larger cohesive groups, more groups, and increased density as a result of large overlaps among these groups. Constraint could potentially add another alternative explanation: variance in *folded diversity* might be related to the beneficial work of individual brokers, affiliated with multiple groups. Such brokers have a unique vantage point, and can take advantage of this, claiming credit for new ideas. The coefficient of the *constraint* variable indicates that an increase in *constraint* (less opportunities to broker) results in a decrease of the *distinctiveness* of the game. This finding is in line with Burt's (2005) argument that fewer brokerage opportunities are likely to result in lower levels of novelty. Model 3 also indicates that a game is more distinctive if the developer team accommodates larger cohesive groups (*mean group size*) but that this effect declines as the mean size of groups grows further. We interpret this finding as follows: as groups in teams grow sufficiently large they may be large enough to sustain internal work ecologies without allowing for creolization.

A set of additional factors that relate both to our dependent variable and *folded diversity* include *number of groups* and *number of team members*. These variables are controlled for because larger teams can accommodate more variety in expertise and experience. At the same time, a larger team can contain more overlapping groups. Models 1–3 indicate that teams with a lower number of developers produce more distinctive video games. Our interpretation of this result is that smaller projects with lower budgets are less constrained by financial pressures and are more likely to experiment, while larger teams with larger budgets adopt safer strategies by staying closer to the average set of features.

We include a variable that counts the number of newbies, as these new developers are isolates in the network by definition. The variable controls the fact that an increase in the number of newcomers (given X number of team members) is associated with a decrease in the number of groups within a team. Models 1–3 show that *newbies* is a significant positive predictor of *distinctiveness*. This finding may indicate that although we do not observe the cognitive profiles of *newbies* (since they don't have a history in game development yet), their actual profiles are cognitively distant and valuable allowing these newcomers to transform their ideas into distinctive product features.[26] One may use a similar line of reasoning to explain the negative and significant coefficient for *game tenure*. Teams comprising industry veterans are less likely to produce games that deviate from the norm.

Past success is a potential confounder for structurally folded cognitive distance. Developers with success in the past are likely to be employed again, and it is likely that successful collectives stick together. They are also more likely to create distinctive video games, for example, by relying on the legitimacy acquired through past success that allows them to engage in more explorative projects. Similarly, the presence of star developers and high performers might explain both a distinctive product and cohesive group structures. We see that past average success results in less distinctive games, but that teams that accommodate exceptional developers (as measured both by *high performers* and by *star developer*) are more likely to produce games that stand out. This finding indicates that the legitimacy argument might hold but only once it passes a certain threshold: teams with many above-average developers are unlikely to develop distinctive games, while teams with a few absolute standouts (and some that performed poorly in the past) are more likely to produce creative outliers.

The final two variables in models 1–3 are *single firm* and *mean firm age*. These variables describe the organizational structure in which teams are embedded. The coefficient on *single firm* shows that games developed and published by one firm are more likely to be distinctive than games produced by multiple firms. An interpretation of this finding could be that in negotiating the characteristics and dimensions of a game, two firms need to reach consensus, whereas a single firm is unconstrained by demands from another organization. The coefficient for *mean firm age* shows that as teams are embedded within older firms, the games that they produce are less likely to stand out. We interpret this result as evidence that older firms, that have

[26] Perhaps industry newcomers within a team form (a) clique(s) (precisely because they have no social or cognitive history), and their status as *newbies* allows them to pitch their ideas into yet existing groups.

established their position within the industry, are less likely to provide the context in which distinctive games can be developed.

Critical Acclaim

In this section we describe the predictors of *critical acclaim* for those games that were reviewed. Although receiving critical acclaim for a game is an important dimension of success it does not imply that those games are the games that stand out and potentially change the game of the industry. We therefore compare models 4–6 with the models predicting *distinctiveness*.

Model 5 is the baseline, model 6 enters network structure variables, and model 7 enters variables that capture the cognitive dimensions of the video game. Similar to its coefficient estimates in the *distinctiveness* models, the *folded diversity* coefficient is positively and significantly associated with *critical acclaim,* which implies that teams characterized by socially connected groups with different cognitive profiles are able, on average, to develop video games that are appreciated by experts. In contrast, teams with a cognitively diverse range of developers (but lack social cohesion) produce video games that score poorly with the video game critics. Moreover, model 5 and model 6 show that higher levels of *constraint* (cohesive teams with few opportunities for brokerage) in teams allow these teams to develop games that please that taste of the critics. As we have seen in model 2 and model 3, teams with higher levels of *constraint* are less likely to produce distinctive games. If reviewers value coherence over *distinctiveness*, then one may argue that teams with few brokerage opportunities are better able to develop games that are coherent. From the coefficients for *distinctiveness* and *number of elements* in table 4, models 4, 5, and 6, one can conclude that reviewers indeed value games that are coherent but combine many typically combined stylistic elements.

Similar to the findings from model 3 *mean group size* and its squared term indicate that teams that accommodate larger groups produce critically acclaimed games but that the effect of group size levels off. Critically acclaimed teams also tend to accommodate more seasoned team members: the higher the average number of games that developers worked on in the past, the higher the *critical acclaim* for their current game. A higher *past review score* and a higher number of *high performers* also contributes to the likelihood of receiving beneficial reviews, while the presence of a star developer per se does not increase the review score of the game. A larger number of newbies is beneficial. If a game is developed and published by the same firm review scores are higher. The same holds for older firms: firms that managed to survive for several years are more likely than new entrants to accommodate teams that develop games assimilated to the tastes of game critics.

Game Changers.—Thus far we analyzed *distinctiveness* and *critical acclaim* as a function of a set of predictors describing the cognitive structure, the network structure, and performance history of a team. In this section we turn to game changers: predicting the extent to which a game is both *distinctive* and has *critical acclaim.* These games introduce a distinctive combination of features with considerable critical acclaim.

As in our previous models, we start with a baseline (model 7), then we enter variables of network structure (model 8) and cognitive distance (model 9). As we add network structure variables in model 9, we see that *structural folding* is a significant and positive predictor of innovative success. This is in line with prior findings (Vedres and Stark 2010) about the innovative potential of *structural folding*. *Mean group size* is also a positive predictor and again we find that the relation between the dependent variable and *mean group size* assumes an inverted U-shape.

As we enter the cognitive distance variables in model 10, we see that *folded diversity* is a significant and positive predictor of *game changer* while the coefficient on *cognitive diversity* is positive but not significantly different from zero. *Structural folding* itself is no longer significant after we enter the two additional variables describing the cognitive profile of the team. This suggests that the mechanism through which *structural folding* contributes to innovative success of teams in the video game industry is by bringing cognitively distant groups into contact. It is not the overlapping structure of the network itself, but the generative tension that overlapping groups experience when their cognitive makeup is different.

Models 7– 9 also indicate that smaller teams are more likely to produce a video game that is game changing. The result finds resonance in a recent article on destructiod.com with the title “More People, More Problems,” which discusses how large video game development teams are characterized by “lack of cohesion” and “jack-of-all-trades approaches” and how large teams may develop games that “reach for the stars but barely lift off the ground.”[27]

Similar to the findings for the first six models, game changers are more likely to be produced by teams that comprise a fair share of *newbies*. We also find that innovative games that are critically acclaimed are likely to be produced by teams that accommodate individuals with prior success. However, although the coefficient of *star developer* is positive it is not significantly different from zero.

Finally, we find that games produced by teams from a single firm are more likely to be game changing. We already argued that the involvement of multiple firms may flatten ideas because a consensus needs to be reached.

[27] http://www.destructoid.com/aaa-game-development-teams-are-too-damn-big-247366.phtml (accessed on October 10, 2013)

Moreover, games produced under the auspices of a single firm may form a larger liability for the firm and therefore warrant additional funding and access to the best resources.

Please note that the results presented in models 7–9 are based on the 60th percentile cutoff used to construct the dependent variable *game changer*. In figure 4 we have plotted the point estimates and the confidence intervals for the *folded diversity* variable when more narrow cutoffs are used. The graph shows that although the precise estimates change slightly, the direction and the significance level are stable.

Sociocognitive Maps of Developer Teams

To illustrate the findings presented in the previous section, we develop a method for visualizing both cognitive distance and group structures to show how cognitive dissimilarity can be spanned by structural folds. We draw two-mode graphs of groups (dark nodes) and their members (white nodes) by superimposing two visualization techniques. First, we use the distance matrix of the group profiles of cognitive elements, and employ non-metric multidimensional scaling to derive the locations of groups in a two dimensional cognitive space. The second step is to include the members of these groups

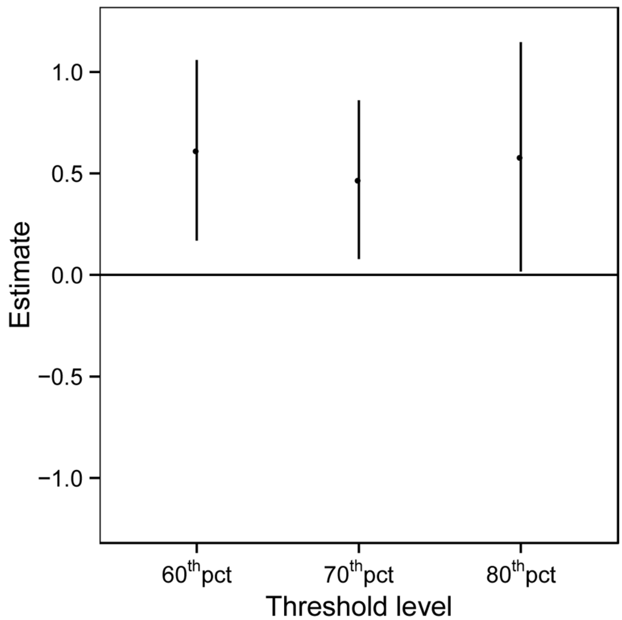


FIG. 4.—Coefficient estimates and confidence intervals for *cognitive folding*

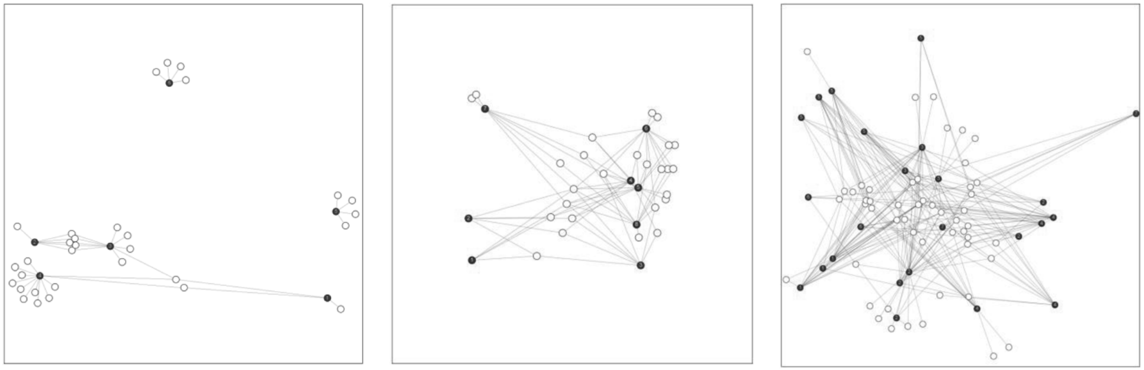
and their membership ties to groups. We position the developers using a spring-embedding algorithm that finds the optimal location of developers vis-à-vis the communities, which stay fixed according to their coordinates in the cognitive space. The resulting diagrams show the spread of groups (whether they were near or far to one another in terms of cognitive profiles) and the mesh of social ties (whether they connect groups, and the cognitive distance that membership ties might span). Figure 5 shows the results of this dual visualization technique for three games. The cognitive distances among groups use the same scale for comparability across graph panels.

High cognitive distance can be risky without the connecting mesh of group overlaps. The team in figure 5, panel 1, developed a game, *Riven*, published in 1997. This game was distinctive almost to the point of incoherence: a puzzle-solving game that was set in the future on an island where secret technologies are being developed. The player needs to gather subtly placed clues and manipulate complex mechanical devices in order to advance in the game. The truly distinctive aspect was that the game was not only 2D, but it was built of still images. While the game attracted a small and committed fan base, many players and critics alike were appalled by the slideshow-like gameplay and by the difficulty of the puzzles. In other words, this was a game that required intense immersion and concentration, but nevertheless offered little of the graphical tools that the audience had become used to by the end of the nineties: "If you don't like the idea of having to learn a new number system, copying down symbols for later reference, and solving abstract puzzles, you're not going to like *Riven*."[28]

Groups came from cognitively distant prior projects and were hardly connected to one another. The longest cognitive distance that is folded by group overlap is between developers of a submarine game (*WolfPack*) and an adventure game set in a courtroom (*In the 1st Degree*). Otherwise the team includes groups from car racing, puzzle solving games, and 2D role playing games.

While too much cognitive distance without social cohesion may jeopardize the success of a game project, the opposite sociocognitive structure can also be risky. Figure 5, panel 2 shows a team with high cohesion, but with cognitively close developers. This cohesion without much cognitive distance leads to a narrow focus. This is an example of a team that developed a true flop: a role playing game that most reviewers found boring, with repetitive dialogues and tired humor. A role playing game set in the adult film industry might have seemed to be a good idea for a developer team too narrowly focused on one kind of humor (that of the *Worms*

[28] Just Games Retro, http://justgamesretro.com/win/riven-the-sequel-to-myst (accessed on October 22, 2013).



1. *Riven*: Sequel to *Myst*   2. *Leisure Suit Larry*: Box Office Bust   3. *Fallout*

FIG. 5.—Cognitive group graphs of three production teams

series of games, where invertebrates set on a side-viewed 2D terrain try to blow each other up). While the developers collaborated on various games together—there were several communities, and they were overlapping—the lack of the generative tension created by cognitive distance is likely to have prevented success. "*Leisure Suit Larry: Box Office Bust* is a cesspool of foul language and ugly personalities. The terrible gameplay is stretched thin over hours and hours of redundant, repetitive quests, and it's a bad purchase even at its discount price."[29]

Figure 5, panel 3, shows a true game changer, a game that created its own category: *Fallout*, published in 1997. Set in a postapocalyptic world devastated by a nuclear war, the game was the first to set a role-playing and puzzle-solving game in an open environment. Prior role-playing games were practically all set in a medieval fantasy environment (a dungeon), leading the player along on a set path. In *Fallout* the player was set free to roam the landscape and accomplish parts of the mission in a unique order, or to go after achievements that were not even necessary for the mission. The developer team was organized into many groups each with very unique prior experiences. The high cognitive distance among these groups was spanned by many folds. Developers were able to collaborate across skills and traditions of shooter games, role playing games, puzzle solving games, real time strategy games. Groups with experience in 2D, 3D, first-person or third-person perspectives were brought into contact by overlapping members. The group structure, we argue, is likely to have turned a possible cacophony into generative tension. "*Fallout* truly is the 'War and Peace' of the gaming world: a masterwork of brilliance, an undying statement of fiction, and a cast of characters you need a database to keep track of."[30]

CONCLUSION

From Pipes and Prisms to Tools and Tensions

In his overview statement of how social networks operate, Joel Podolny (2001) proposes that ties between social actors serve both as the *pipes* through which information flows and as the *prisms* that allow ego to evaluate and make inferences about the quality and trustworthiness of alter. Although the identification of these mechanisms (that make relations between social actors such a salient unit of analysis) has advanced the discipline of sociology by providing a basic understanding of how social structure guides

[29] GameSpot, http://www.gamespot.com/leisure-suit-larry-box-office-bust/reviews/leisure-suit-larry-box-office-bust-review-6207462/ (accessed on October 22, 2013).

[30] Inside Mac Games, http://www.insidemacgames.com/reviews/view.php?ID=299&Page=4 (accessed on October 22, 2013).

action, our findings suggest that these are not the only mechanisms through which social networks are made productive. In addition to serving as pipes and prisms, network ties are also the source of *tools* and *tensions*.

Tools.—The findings presented here suggest that the repertoire (or portfolio) of styles and skills, acquired throughout the careers of members of video game production teams allows these members to carve out the contours and set the boundaries of the product during the production process. For example, our analyses indicate that teams composed of stylistically different individuals (i.e., the overall measure of cognitive diversity at the team level) are more likely to produce video games that are distinctive but are unlikely to produce games that are appreciated by critics. This idea that the repertoire of styles guides action resonates with Swidler's (1986) understanding of culture.

More recent work on the sociology of culture has extended Swidler's (1986) understanding of culture by explicitly stressing the relational basis of cultural tool kits. Eliasoph and Lichterman (2003), for example, rephrased culture in action as *culture in interaction*. Rather than describing the tool kits of skills and habits as pertaining to the individual, they maintain that the relevant location of tool kits is the group. Interaction and communication within groups are shaped by the "shared assumptions about what constitutes good or adequate participation in the group setting." (Eliasoph and Lichterman 2003, p. 737). These shared assumptions are the outcomes of a series of interactions over time in which meaning is negotiated (sometimes explicitly, sometimes implicitly) and a group style emerges. In more recent work, Swidler (2008, p. 617) shares this definition: "Cultural meanings are organized and brought to bear at the collective and social, not the individual, level."

Both the theory and the empirical strategy developed in this article start from the proposition that styles and skills become meaningful elements in the production of creativity when they are built, held, and adjusted by groups rather than by individuals. In adhering to this definition of culture as a constructed repertoire of skills and styles, we ask: How do groups of video game developers put culture to use in their everyday work life?

While the new research influenced by Swidler has shaped the debate on the definition of culture and the role of culture in everyday life, this literature has remained silent about how culture evolves. For example, while the claim that "tools give people . . . the shared language for thinking and talking" (Eliasoph and Lichterman 2003, p. 743) informs us about how culture is put to use *within* groups, we know very little about what happens when groups characterized by *different* tool kits are required to interact. Our findings suggest that the starting point for answering questions about how culture evolves is to be attentive to the symbols and styles that define the boundaries of groups. This then forms the basis for the analysis

403133.proof.3d 41 Achorn International 03/05/2015 10:58AM

of different groups that intersect socially. That is, *in understanding networks as sources of tools*, our findings indicate that network ties formed across careers gives groups access to tools and that the patterns of interaction across group within a team shape the ways in which tools evolve.

Tensions.—Instances in which different groups meet, in which they intersect socially, and in which each of these groups is characterized by their own group style, can lead to awkward and unproductive situations. Most people can recall that birthday or wedding where multiple groups of friends or family are invited. Tensions caused by the differences in group styles—some of which are rigid and stable—may spoil an otherwise fun party and may further accentuate the differences between groups. Such situations occur in various contexts including academic conferences, large corporate departments, sports teams, and even within community events organized in the neighborhood. Often these tensions are associated with negative outcomes and they are avoided, rather than welcomed. In contrast to this intuitive understanding of tensions, this article shows how tensions are made productive.

"The smooth flow of information" is surely among the leading candidates for the most ubiquitous phrase in accounts of success of groups. The phrase is so familiar that we can scarcely imagine replacing the adjective "smooth" if to indicate the contrary: the turbulent flow of information, the rough flow, or the eddied flow, for example, all sound foreign. When it is not smooth (or at least steady), it is because the flow of information has been interrupted or disrupted. Just as "friction" was the problem to be overcome by "lowered transaction costs" in economics (Williamson 1981), so the goal of much of the network analytic literature has been to identify those structures that facilitate the transmission of information in a smooth flow (Borgatti and Cross 2003; Coleman 1988).

In that effort, network analysis shares much with the perennial preoccupations of the broader discipline of sociology in studying the basis for societal order, social harmony, and coordinated action. The standard sociological recipe for such has long been something like *mutual understanding* or *shared understanding,* and the basic ingredients have been the norms, styles, and habits that were *shared*. Information flows. Values are shared. Sometimes values are shared because of the network lines of communication; at other times information flows along the course of the shared values. For some, smooth transactions are embedded in social ties (Borgatti and Cross 2003); for others, they are embedded in shared cultural elements (Portes and Sensenbrenner 1993; Eliasoph and Lichterman 2003). But it seems there is little question that things go better when they run smoothly. Dissonance, like conflict, might rear its disruptive head, but these are impediments to coordination and can be resolved, in the pop sociology vernacular "if we could all just get together and iron out our differences."

While accounts of the negative effects of insurmountable differences are plentiful, yet another literature stresses the importance of benefits of differences. The claim is that differences packaged as diversity are something else again, for diversity is a positive value and organizations can handle a lot of it—provided there are underlying shared values, including a commitment to the value of diversity. Missing from these accounts however is an appreciation of the group. If group styles are homogenous within, but heterogeneous across groups, then how do these groups jointly draw from the elements of culture at their disposal? This article suggests that cultural elements held by the members of a team are most productive when the groups that accommodate these styles and skills intersect socially. The position of the structural fold at the intersections of multiple groups allows these actors to make tensions generative rather than destructive.

In this study we have found that teams in the video game industry are built from groups. Moreover, the analyses indicate that creative success was facilitated when cognitively distant groups were socially folded. Yes, something must be shared. But it is not necessarily mutual understanding. In the dynamics that we suggest are at play, social intersections between groups do not immediately resolve a tension or create an instant comprehension. It creates a workable space where some misunderstanding is tolerated in the interest of creating a new creole that can escape the limitations of the mutually untranslatable. Along with the Russian semiotician Yuri Lotman and the American pragmatist philosopher Charles Sanders Peirce (and see Stark 2009, pp. 190–95), our findings suggest that misunderstanding in communication can be as important as successful transmission. As Lotman (2009, p. xxiii) writes: “Non-comprehension (conversation in languages which are not fully identical) reveals itself to be just as valuable a meaning–making mechanism as comprehension.” By contrast to the imagery of smoothly flowing information, characteristic of the transmission model, the process of folding diversity is a messy process. Although these styles may seem incommensurable at times, structural folding allows the differences to be made productive rather than destructive.

APPENDIX A

Regression Models with Publisher Fixed Effects

Teams that produce video games can be organized as temporal organizations that break up once the project has come to an end. However, teams may also be organized within the boundaries of one or multiple firms. In some of those cases, a video game production project only involves one formal organization that is responsible both for the development of a game and its publishing stage, in other cases the project involves a publisher and a developer. Since the mid-1980s, about 50% of the games have been produced by one firm while the other 50% of the games have been produced by multiple firms. Our database comprises 1,575 unique firms—1,385 developers and 190 publishers—that developed or published a video game.

In order to account for this organizational characteristic of the industry and to eliminate the possibility that our findings are the result of one or more confounding factors that are stable at the firm level, we estimate model 3, model 6, and model 9 using a firm fixed effects specification. In table A1 we present the publisher fixed effects models. We also experimented with developer fixed effects, but although the results remain stable many observations are dropped from the analysis because there is no within firm variation.

The dependent variable in model 10 is *distinctiveness*, and it replicates model 3 and adds the publisher fixed effects. Model 11 replicates model 6 (*critical acclaim*) and model 12 (*game changer*) replicates model 9, and in both instances the publisher fixed effects are added to the model. The findings for our main independent variables remain stable. Similar to the models presented in table 2, models 10, 11, and 12 indicate that *folded diversity* is positively related to *distinctiveness*, *critical acclaim*, and game changer. The direction and significance of the coefficients for *cognitive diversity* also remain stable. Similar to the original models presented in table 2, *structural folding* is negatively related to our three dependent variables but none of the coefficients differs significantly from zero.

In sum, the findings presented in the article are not altered by switching the specification of our models from pooled to fixed effects. This indicates that it is unlikely that there is variation in the dependent variables that can be accounted for by omitted variables that are stable at the firm level and correlated with our main explanatory variables.

APPENDIX B

Regression Models with Selection Correction

Two of our three dependent variables, *critical acclaim* and *game changer*, are observed only for a subset of all video games in the sample. A total of 5,508 of all 8,987 video games are covered in reviews that were published in the selected review outlets, while 3,479 games are not. The implications of this discrepancy can be severe, both substantively and methodologically.

First, developing a game with novel features is just one phase in the process toward creative success. To be included in the competition for critical approval a video game must first be recognized by the professional field of games journalism as something worthy of attention. In the simplest terms, will the new video game be reviewed at all? There is something

TABLE A1
Coefficient Estimates Based on Publisher Fixed Effects Models

	Distinctiveness	*Critical Acclaim*	*Game Changer*
	Model 10	Model 11	Model 12
Folded diversity	1.266**	2.732**	.783**
	(.423)	(1.022)	(.258)
Cognitive diversity	1.908***	−5.975***	.078
	(.549)	(1.485)	(.406)
Structural folding	−.362	−2.238	−.348
	(.531)	(1.322)	(.336)
Constraint	−.080***	.099*	.004
	(.021)	(.042)	(.014)
Mean group size^2	.000**	−.004**	.000
	(.000)	(.001)	(.000)
Mean group size	.100***	.243***	.052**
	(.023)	(.069)	(.018)
No. of groups	.012	−.034	−.009
	(.013)	(.026)	(.008)
No. of members	−.060***	−.084***	−.035***
	(.007)	(.014)	(.005)
No. of newbies	.053***	.152***	.052***
	(.011)	(.021)	(.007)
Games tenure	−.214*	−.824***	−.073
	(.091)	(.220)	(.060)
Past review score	−.013**	.194***	.011*
	(.005)	(.017)	(.005)
High performers	.040***	.157***	.036***
	(.007)	(.014)	(.005)
Star developer	.916	−.476	.182
	(.750)	(1.376)	(.341)
Distinctiveness		.192***	
		(.027)	
No. of eements		.429***	
		(.103)	
Intercept	87.017***	45.577***	−2.314
	(1.633)	(5.980)	(1.237)
R^2	.243	.295	
Adjusted R^2	.200	.258	
No. observations	8,652	5,318	5,318
AIC			4,568.947
BIC			6,292.606
Log likelihood			−2,022.473

Note.—All three models include dummies for year, platform, and firm.
* $P < .05$.
** $P < .01$.
*** $P < .001$.

worse than failing to meet expectations and that is being ignored by the evaluation process entirely.

A second result (and the focus of this appendix) of the discrepancy between the number of games and the number of reviewed games is that sample selection bias may plague our primary findings. This bias may arise if video games that are reviewed are not representative of all video games in the sample. For example, video games developed by low quality teams are unlikely to end up in the pool of reviewed video games. However, some of these games developed by low quality teams *are* reviewed. Such exceptions owe perhaps to one or multiple unmeasured characteristics, such as the presence of a high quality marketing specialist in the team. As a result, the presence of such video games (games made by low quality teams that make into the sample of reviewed video games) in the sample yields observations with large error terms. The problem is that whether or not the quality of a team is correlated with the unmeasured presence of a high quality marketing specialist, the two variables will by definition be correlated in the selected sample. If high quality marketing managers know how to communicate the quality of a game rather than its lack thereof (and thereby providing grounds for video game critics to review the game) *and* if high quality marketing managers have a positive effect on the review score that a game receives, our estimations of the effect of team quality on *critical acclaim* will be negatively biased because in the selected sample low quality teams have unusually good marketing managers (Sartori 2003).[31]

Selection bias can be addressed by specifying a Heckman selection model (1979). The Heckman selection model consists of two equations. The first equation—the selection equation—includes all games in the sample since it is designed to model the decision taken by reviewers to review a game or not. Here, we employ a binary dependent variable, Getting Reviewed, that describes whether a game is reviewed or not. The sample in the second equation is restricted to include only games that receive reviews. The coefficients in the Heckman model can be estimated consistently using a two-step procedure. The first step is to estimate the selection equation, using probit; the estimates are then used to calculate an inverse Mills ratio. The second step is to estimate an OLS regression that specifies the dependent variable as a function of independent variable and the calculated Mills ratio. Obviously, our model in which the *game changer* variable functions as the dependent variable can be estimated through a linear probability model using OLS. However, limited dependent variable models are more efficiently estimated using maximum likelihood (ML) techniques. We therefore use an adaptation of the original Heckman selection model that allows for the estimation of the outcome variable using a probit model (Sartori 2003).

The sets of Heckman selection models for both of our truncated variables—*critical acclaim* and *game changer*—follow the same steps as the models we estimate for *distinctiveness*. The findings presented in table B1

[31] If the error terms in the two equations are correlated, the error term in the outcome equation is not of mean zero and it is correlated with the explanatory variable. This violates the exogeneity assumption (Sartori 2003).

TABLE B1

Coefficient Estimates Based on Selection Correction Models

	Selection	*Critical Acclaim*	*Game Changer*
	Model 13	Model 14	Model 15
Folded diversity		2.496*	.340**
		(.981)	(.112)
Cognitive diversity		−5.805***	.013***
		(1.383)	(.167)
Structural folding		−1.599	−.051
		(1.276)	(.147)
Constraint		.137**	.014*
		(.042)	(.006)
Mean group size^2		−.003*	−.000*
		(.001)	(.000)
Mean groupsize		.205**	.032***
		(.067)	(.008)
No. of groups		−.048	−.008
		(.025)	(.004)
No. of members		−.115***	−.019***
		(.015)	(.002)
No. of newbies		.194***	.029***
		(.022)	(.003)
Games tenure		−.588**	−.032
		(.209)	(.025)
Past review score		.241***	.009***
		(.015)	(.002)
High performers		.192***	.020***
		(.014)	(.002)
Star developer	1.138***	.939	.397*
	(.311)	(1.427)	(.181)
Single firm	−.044	2.280***	.128***
	(.032)	(.339)	(.041)
Mean firm age	.054***	.167***	.028***
	(.002)	(.036)	(.004)
Distinctiveness	−.027***	.197***	.148***
	(.004)	(.027)	(.005)
No. of elements	.037**	.379***	.042*
	(.011)	(.103)	(.018)
Intercept	.504	32.791***	−2.660***
	(.318)	(2.588)	(.160)
R^2		.186	
Adjusted R^2		.182	
No. observations	8,987	5,508	5,508
AIC	9,759.753		13,219.65
BIC	10,107.827		13,766.62
Log likelihood	−4830.877		−6,532.824

Note.—Model 13 includes dummies for year, platform, genre, and country. Models 14 and 15 include dummies for year and platform only.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

show that accounting for selection bias does not alter the main findings presented earlier in the paper. However, since we estimated the coefficients in a new equation, we briefly discuss these results.

The results from the estimation are listed in model 13. We find that both firm age and having a star developer are significant predictors. Teams with a star and working for an older firm are more likely to produce a game that gets reviewed, suggesting that reputation buys entry into the evaluative arena. The results also show that the more complex, feature rich the game—as measured by the number of elements—the more likely it will get reviewed. The distinctiveness of a game, however, is negatively related to review chances. The more a game deviates from the norm (possibly to the extent that it is hardly recognizable along received categories), the less likely it will enter the evaluative arena of reviews. This highlights the risk of standing out—standing far apart from games that are the norm can make a product less recognizable and thus excluded from even being evaluated.

REFERENCES

Abbott, Andrew. 1999. *Department and Discipline: Chicago Sociology at One Hundred*. Chicago: University of Chicago Press.

Agresti, Alan, and Barbara Finlay. 2009. *Statistical Methods for the Social Sciences*: Upper Saddle River, N.J.: Pearson Prentice Hall.

Alexander, Jeffrey C. 2004. "Cultural Pragmatics: Social Performance between Ritual and Strategy." *Sociological Theory* 22 (4): 527–73.

Aoyama, Yuko, and Hiro Izushi. 2003. "Hardware Gimmick or Cultural Innovation? Technological, Cultural, and Social Foundations of the Japanese Video Game Industry." *Research Policy* 32 (3): 423–44.

Bauer, David F. 1972. "Constructing Confidence Sets Using Rank Statistics." *Journal of the American Statistical Association* 67:687–690.

Becker, Howard S. 1974. "Art as Collective Action." *American Sociological Review* 39 (6): 767–76.

Bellotti, Elisa. 2012. "Getting Funded. Multi-Level Network of Physicists in Italy." *Social Networks* 34 (2): 215–29.

Berman, Shawn, Jonathan Downs, and Charles Hill 2002. "Tacit Knowledge as a Source of Competitive Advantage in the National Basketball Association." *Academy of Management Journal* 45 (1): 13–31.

Bird, Allan. 1994. "Careers as Repositories of Knowledge: A New Perspective on Boundaryless Careers." *Journal of Organizational Behavior* 15 (4): 325–44.

Bissell, Tom. 2011. *Extra Lives: Why Video Games Matter*. New York: Vintage Books.

Borgatti, Stephen, and Rob Cross. 2003. "A Relational View of Information Seeking and Learning in Social Networks." *Management Science* 49 (4): 432–45.

Bowker, Geoffrey C., and Susan Leigh Star. 2000. *Sorting Things Out: Classification and Its Consequences*. MIT Press: Cambridge, Mass.

Brown, John S., and Paul Duguid. 1991. "Organizational Learning and Communities-of-Practice: Toward a Unified View of Working, Learning, and Innovation." *Organization Science* 2 (1): 40–57.

Burt, Ronald. 1995. *Structural Holes: The Social Structure of Competition*. Cambridge, Mass.: Harvard University Press.

———. 2004. “Structural Holes and Good Ideas.” *American Journal of Sociology* 110 (2): 349–99.
———. 2005. *Brokerage and Closure: An Introduction to Social Capital*. New York: Oxford University Press.
———. 2014. “Reinforced Structural Holes.” Working paper. Booth School of Business, University of Chicago. August.
Carley, Kathleen M. 2001. “Computational Approaches to Sociological Theorizing.” Pp. 69–83 in *Handbook of Sociological Theory*, edited by Jonathan H. Turner. New York: Kluwer Academic/Plenum Publishers.
Carnabuci, Gianluca, and Jeroen Bruggeman. 2009. “Knowledge Specialization, Knowledge Brokerage and the Uneven Growth of Technology Domains.” *Social Forces* 88 (2): 607–41.
Caves, Richard. 2002. *Creative Industries: Contracts between Art and Commerce*. Cambridge, Mass.: Harvard University Press.
Coleman, James. 1988. “Social Capital in the Creation of Human Capital.” *American Journal of Sociology* 94:S95–S120.
De Nooy, Wouter. 2003. “Artistic Classifications as Collective Representations.” Paper presented at the sixth conference of the European Sociological Association. http://www.uva.nl/binaries/content/documents/personalpages/n/o/w.denooy/en/tab-one/tab-one/cpitem%5B98%5D/asset. Accessed October 22, 2013.
De Vaan, Mathijs. 2014. “Interfirm Networks in Periods of Technological Turbulence and Stability.” *Research Policy* 43 (10): 1666–80.
Delmestri, Guiseppe, Fabrizio Montanari, and Alessandro Usai. 2005. “Reputation and Strength of Ties in Predicting Commercial Success and Artistic Merit of Independents in the Italian Feature Film Industry.” *Journal of Management Studies* 42 (5): 975–1002.
DiMaggio, Paul. 1997. “Culture and Cognition.” *Annual Review of Sociology* 23: 263–87.
———. 2011. “Cultural Networks.” Pp. 286–300 in *The SAGE Handbook of Social Network Analysis*, edited by John Scott and Peter J. Carrington. Three Oaks, Calif.: SAGE Publications.
Eco, Umberto. 1990. I limiti del interpretazione. (The Limits of Interpretation). Milan: Bompiani.
Eco, Umberto. 2001. “Introduction to Yuri Lotman.” Pp. vii–xiii in *Universe of the Mind: A Semiotic Theory of Culture* by Yuri Lotman. Bloomington: Indiana University Press.
Eliasoph, Nina, and Paul Lichterman. 2003. “Culture in Interaction.” *American Journal of Sociology* 108 (4): 735–94.
Evans, James. 2010. “Industry Induces Academic Science to Know Less about More.” *American Journal of Sociology* 116 (2): 389–452.
Ganz, Marshall. 2000. “Resources and Resourcefulness: Strategic Capacity in the Unionization of California Agriculture, 1959–1966.” *American Journal of Sociology* 105 (4): 1003–62.
Gartner. 2011. *Market Trends: Gaming Ecosystem*. June 10. Gartner, Inc. https://www.gartner.com/doc/1724014/market-trends-gaming-ecosystem-
Giuffre, Katherine. 2001. “Mental Maps; Social Networks and the Language of Critical Reviews.” *Sociological Inquiry* 71 (3): 381–93.
Gould, Glenn. 1994. “Forgery and Imitation in the Creative Process.” *Grand Street* (50): 53–62.
Grabher, Gernot. 2002. “Cool Projects, Boring Institutions: Temporary Collaboration in Social Context.” *Regional Studies* 36 (3): 205–14.
Grabher, Gernot. 2004. “Learning in Projects, Remembering in Networks? Communality, Sociality, and Connectivity in Project Ecologies.” *European Urban and Regional Studies* 11 (2): 103–23.

Grund, Thomas U. 2012. “Network Structure and Team Performance: The Case of English Premier League Soccer Teams.” *Social Networks* 34 (4): 682–90.
Guimera, Roger, Brian Uzzi, Jarrett Spiro, and Luis Amaral. 2005. “Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance.” *Science* 308 (5722): 697– 702.
Hargadon, Andrew, and Beth Bechky. 2006. “When Collections of Creatives Become Creative Collectives: A Field Study of Problem Solving at Work.” *Organization Science* 17 (4): 484–500.
Heckman, James J. 1979. “Sample Selection Bias as a Specification Error.” *Econometrica* 47 (1): 153–61.
Holland, John. 1992. “Complex Adaptive Systems.” *Daedalus* 121 (1): 17–30.
Hutter, Michael. 2011. “Infinite Surprises: Value in the Creative Industries.” Pp. 201–20 in *The Worth of Goods: Valuation and Pricing in the Economy*, edited by Jens Beckert and Patrick Aspers. New York: Oxford University Press.
Ibert, Oliver, and Suntje Schmidt. 2012. “Acting on Multiple Stages.” *Raumforschung und Raumordnung* 70 (4): 349–61.
Jacob, François. 1977. “Evolution and Tinkering.” *Science* 196 (4295): 1161–66.
Jaffe, Adam. 1986. “Technological Opportunity and Spillovers of R&D: Evidence from Firms’ Patents, Profits, and Market Value.” *American Economic Review* 76 (5): 984–1001.
Jerolmack, Colin, and Shamus Khan. 2014. “Talk Is Cheap: Ethnography and the Attitudinal Fallacy.” *Sociological Methods and Research* 43 (2): 178–209.
Lamont, Michèle. 1992. *The Dignity of Working Men*. Harvard University Press: Cambridge, Mass.
Lampel, Joseph, Theresa Lant, and Jamal Shamsie. 2000. “Balancing Act: Learning from Organizing Practices in Cultural Industries.” *Organization Science* 11 (3): 263–69.
Lester, Richard, and Michael Piore. 2004. *Innovation–the Missing Dimension*. Harvard University Press: Cambridge, Mass.
Lingo, Elizabeth, and Siobhán O’Mahony. 2010. “Nexus Work: Brokerage on Creative Projects.” *Administrative Science Quarterly* 55 (1): 47–81.
Lopes, Paul D. 1992. “Innovation and Diversity in the Popular Music Industry, 1969 to 1990.” *American Sociological Review* 57:56–71.
Lotman, Yuri. 1990. *Universe of the Mind: A Semiotic Theory of Culture*. Bloomington: Indiana University Press.
———. 2009. *Culture and Explosion*. Berlin: De Gruyter Mouton.
Mizruchi, Mark. 1996. “What Do Interlocks Do? An Analysis, Critique, and Assessment of Research on Interlocking Directorates.” *Annual Review of Sociology* 22: 271–98.
Mohr, John W. 1994. “Soldiers, Mothers, Tramps, and Others: Discourse Roles in the 1907 New York City Charity Directory.” *Poetics* 22: 327–57.
Obstfeld, David. 2005. “Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation.” *Administrative Science Quarterly* 50 (1): 100–130.
Owen-Smith, Jason, and Walter W. Powell. 2004. “Knowledge Networks as Channels and Conduits: The Effects of Formal Structure in the Boston Biotechnology Community.” *Organization Science* 15 (1): 5–21.
Pachucki, Mark A., and Ronald L. Breiger. 2010. “Cultural Holes: Beyond Relationality in Social Networks and Culture.” *Annual Review of Sociology* 36:205–24.
Peterson, Richard A., and David G. Berger. 1971. “Entrepreneurship in Organizations: Evidence from the Popular Music Industry.” *Administrative Science Quarterly* 16 (1): 97–106.
Podolny, Joel M. 2001. “Networks as the Pipes and Prisms of the Market.” *American Journal of Sociology* 107:33–60.
Poincaré, Henri. (1908) 1985. *Papers on Fuchsian Functions*. Springer-Verlag: Berlin.

403133.proof.3d 50 Achorn International 03/05/2015 10:58AM

Portes, Alejandro, and Julia Sensenbrenner. 1993. "Embeddedness and Immigration: Notes on the Social Determinants of Economic Action." *American Journal of Sociology* 98 (6): 1320–50.

Reagans, Ray, and Bill McEvily. 2003. "Network Structure and Knowledge Transfer: The Effects of Cohesion and Range." *Administrative Science Quarterly* 48 (2): 240–67.

Rowlinson, Michael, Charles Booth, Peter Clark, Agnes Delahaye, and Stephen Procter. 2010. "Social Remembering and Organizational Memory." *Organization Studies* 31 (1): 69–87.

Ruef, Martin, Howard Aldrich, and Nancy Carter. 2003. "The Structure of Founding Teams: Homophily, Strong Ties, and Isolation among U.S. Entrepreneurs." *American Sociological Review* 68 (2): 195–222.

Sartori, Anna. 2003. "An Estimator for Some Binary-Outcome Selection Models Without Exclusion Restrictions." *Political Analysis* 11: 111–38.

Schumpeter, Joseph. 2012. *Capitalism, Socialism and Democracy*. London: Routledge.

Sewell, William F. 1992. "A Theory of Structure: Duality, Agency, and Transformation." *American Journal of Sociology* 98 (1): 1–29.

Simmel, Georg. (1922) 1955. *Conflict and the Web of Group Affiliations*, translated and edited by Kurt Wolff. Glencoe, Ill.: Free Press.

Sohn Min-Woong. 2001. "Distance and Cosine Measures of Niche Overlap." *Social Networks* 23 (2): 141–65.

Stark, David. 2009. *The Sense of Dissonance: Accounts of Worth in Economic Life*. Princeton, N.J.: Princeton University Press.

Swidler, Ann. 1986. "Culture in Action: Symbols and Strategies." *American Sociological Review* 51 (2): 273–86.

———. 2008. "Comment on 'Socrates, Skinner, and Aristotle: Three Ways of Thinking About Culture in Action' by Stephen Vaisey." *Sociological Forum* 23 (3): 614–18.

Tschang, Ted. 2007. "Balancing the Tensions between Rationalization and Creativity in the Video Games Industry." *Organization Science* 18 (6): 989–1005.

Uzzi, Brian, and Jarrett Spiro. 2005. "Collaboration and Creativity: The Small World Problem." *American Journal of Sociology* 111 (2): 447–504.

Vedres, Balazs, and David Stark. 2010. "Structural Folds: Generative Disruption in Overlapping Groups." *American Journal of Sociology* 115 (4): 1150–90.

Wegner, Daniel M. 1995. "A Computer Network Model of Human Transactive Memory." *Social Cognition* 13:1–21.

Weitzman, Martin. 1998. "Recombinant Growth." *Quarterly Journal of Economics* 113 (2): 331–60.

Williamson, Oliver E. 1981. "The Economics of Organization: The Transaction Cost Approach." *American Journal of Sociology* 87 (3): 548–77.

Wuthnow, Robert. 1987. *Meaning and Moral Order: Explorations in Cultural Analysis*. Berkeley and Los Angeles: University of California Press.

Zerubavel, Eviatar. 1997. *Social Mindscapes: An Invitation to Cognitive Sociology*. Cambridge, Mass.: Harvard University Press.

Zuckerman, Ezra. 1999. "The Categorical Imperative: Securities Analysts and the Illegitimacy Discount." *American Journal of Sociology* 104 (5): 1398–1438.

QUERY TO THE AUTHOR

No Query.