Collaboration and Creativity: The Small World Problem[1]

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Small world networks have received disproportionate notice in diverse fields because of their suspected effect on system dynamics. The authors analyzed the small world network of the creative artists who made Broadway musicals from 1945 to 1989. Using original arguments, new statistical methods, and tests of construct validity, they found that the varying "small world" properties of the systemic-level network of these artists affected their creativity in terms of the financial and artistic performance of the musicals they produced. The small world network effect was parabolic; performance increased up to a threshold, after which point the positive effects reversed.

Creativity aids problem solving, innovation, and aesthetics, yet our understanding of it is still forming. We know that creativity is spurred when diverse ideas are united or when creative material in one domain inspires or forces fresh thinking in another. These structural preconditions suggest

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that creativity is not only, as myth tells, the brash work of loners, but also the consequence of a social system of actors that amplify or stifle one another's creativity. For example, tracing the history of key innovations in art, science, and politics in the ancient Western and Eastern worlds, Collins (1998) showed that only first-century Confucian metaphysicist Wang Ch'ung, 14th-century Zen spiritualist Bassui Tokusho, and 14th-century Arabic philosopher Ibn Khaldun fit the loner model, a finding supported by historians and cultural sociologists who have shown in great detail that the creativity of many key figures, including Beethoven, Thomas Hutchinson, David Hume, Adam Smith, Cosimo de'Medici, Erasmus Darwin (inventor and naturalist grandfather of Charles Darwin) and famed bassist Jamie Jamison—who, as a permanent member of the Funk Brothers, cowrote more number-one hit songs than the Beatles, the Rolling Stones, the Beach Boys, and Elvis combined—all abided by the same pattern of being embedded in a network of artists or scientists who shared ideas and acted as both critics and fans for each other (Merton 1973; DeNora 1991; Padgett and Ansell 1993; Slutsky 1989).

One form of social organization that has received a great deal of attention for its possible ability to influence creativity and performance is the small world network. Since Stanley Milgram's landmark 1967 study, researchers have plumbed the physical, social, and literary realms in search of small world networks. Although not universal (Moody 2004), small worlds have been found to organize a remarkable diversity of systems including friendships, scientific collaborations, corporate alliances, interlocks, the Web, power grids, a worm's brain, the Hollywood actor labor market, commercial airline hubs, and production teams in business firms (Watts 1999; Amaral et al. 2000; Kogut and Walker 2001; Newman 2000, 2001; Davis, Yoo, and Baker 2003; Baum, Shipilov, and Rowley 2003; Burt 2004).

In contrast to most other types of systemic-level network structures, a small world is a network structure that is both highly locally clustered *and* has a short path length, two network characteristics that are normally divergent (Watts 1999). The special facility of a small world to join two network characteristics that are typically opposing has prompted researchers to speculate that a small world may be a potent organizer of behavior (Feld 1981; Newman 2000). But do small worlds make the big differences implied by their high rates of incidence? Surprisingly, research on this question is just beginning to form. Instead, most work has only hinted at this proposition by using the small world concept to classify types of systems rather than quantify differences in the performance of systems. Newman (2001) examined scientific coauthoring in seven diverse science fields and found that each had a small world structure, leading to the conclusion that small worlds might account for how quickly ideas flow through disciplines—a conclusion echoing Fleming, King, and Juba's (2004) study of the small world of scientific patents and Davis et al.'s (2003) study of the small world of corporate directors. Using simulations to study diffusion, Watts and Strogatz (1998) showed that in a small world, actors in the same cluster were at high risk of contracting an infectious disease, but so were actors distant from an infected actor if separate clusters had even a few links between them, an outcome that is also consistent with the microlevel diffusion function of weak ties (Granovetter 1973) and structural holes (Burt 2004). A pioneering study by Kogut and Walker (2001) examined the small world of ownership ties among the 550 largest German firms and financials from 1993 to 1997. They determined that the central firms were more likely to acquire other firms and that the virtual deletion of many interfirm links would not splinter the small world—suggesting that small worlds can forcefully affect behavior and that their effects are robust over a range of values.

We attempt to extend this line of research by developing and testing arguments on how a small world affects actors' success in collaborating on new products. If a small world is more than a novelty or collection of "spandrels"—inconsequential side effects of micronetwork variables—then it should independently impact the performance of actors in the system.

We argue that a small world network governs behavior by shaping the level of connectivity and cohesion among actors embedded in the system (Granovetter 1973; Markovsky and Lawler 1994; Frank and Yasumoto 1998; Friedkin 1984; Newman 2001; Moody and White 2003; Watts 1999). The more a network exhibits characteristics of a small world, the more connected actors are to each other and connected by persons who know each other well through past collaborations or through having had past collaborations with common third parties. These conditions enable the creative material in separate clusters to circulate to other clusters as well as to gain the kind of credibility that unfamiliar material needs to be regarded as valuable in new contexts, thereby increasing the prospect that the novel material from one cluster can be productively used by other members of other clusters. However, these benefits may rise only up to a threshold after which point they turn negative. Intense connectivity can homogenize the pool of material available to different groups, while at the same time, high cohesiveness can lead to the sharing of common rather than novel information, suggesting the hypothesis that the relationship between a small world and performance follows an inverted U-shaped function.

Our context is the Broadway musical industry, a leading U.S. commercial and cultural export and, like jazz, an original and legendary American artistic creation (White 1970; DiMaggio 1991). Examining the population of shows from 1945 to 1989, we examine how variation in the small world network of the artists who create musicals affects their success in inventing winning shows. As an industry in which both commercial and artistic recognition matters, our measures of creative success quantify a show's success in turning a profit and receiving favorable notices by the Broadway critics. In our design, we control for alternative factors that affect a show's success, including talent, economic conditions, and the local network structure of production teams, which helps us to isolate small world effects relative to other conditions known to favor creativity (Becker 1982; Uzzi 1997; Collins 1998; Ruef 2002; Burt 2004). Our data also contain rare failure data on musicals that died in preproduction—a condition similar to knowing about coauthors' papers that never made publication but that produced the same tie-building (or tie-breaking) consequences as published papers—which enables us to avoid underestimating key relations in the network (Wasserman and Faust 1994).

To bolster the strength of our inferences, we use a new statistical model for examining bipartite-affiliation networks. Occurring often in social life, bipartite-affiliation networks occur when actors collaborate within project groups—for example, directors on the same board within the wider network of interlocks or authors on the same paper within the wider citation network. Bipartite-affiliation networks are distinctive in that all actors in the network are part of at least one fully linked cluster (e.g., all directors on the same board are linked directly to each other), which affects critical social dynamics as well as artificially inflates key small world network statistics. We use the Newman, Strogatz, and Watts (2001) method to adjust properly for these unique network dynamics.

We begin by describing the original Milgram thesis and finding, which illustrates the basis of the small world concept, and then develop our conceptual model with a focus on the mechanisms by which variation in a small world affects behavior. We then turn to applying the abstract small world model to the case of the Broadway musical industry with an eye to developing testable conjectures about performance and to testing the construct validity of our small world mechanisms.

MILGRAM'S SMALL WORLD THEORY

Although the general notion of a small world had been in circulation in various disciplines, the powerful idea has been best illustrated by the famous work of Stanley Milgram. Milgram was interested in understanding how communication worked in social systems in which each member of the social system had far fewer ties than there were members of the total social system. To explain this process, Milgram hit on the idea of a small world and described its remarkable nature with the story of a chance encounter between two strangers who meet far from home and discover they have a close friend in common:

> Fred Jones of Peoria, sitting in a sidewalk cafe in Tunis, and needing a light for his cigarette, asks the man at the next table for a match. They fall into conversation; the stranger is an Englishman who, it turns out, spent several months in Detroit studying the operation of an interchangeable-bottle cap-factory. "I know it's a foolish question," says Jones, "but did you ever by any chance run into a fellow named Ben Arkadian? He's an old friend of mine, manages a chain of supermarkets in Detroit . . ." "Arkadian, Arkadian," the Englishman mutters. "Why, upon my soul, I believe I do! Small chap, very energetic, raised merry hell with the factory over a shipment of defective bottle caps." "No kidding!" Jones exclaims in amazement. "Good lord, it's a small world, isn't it?" (Milgram 1967, p. 61)

In large networks, Milgram surmised that connections influence behavior because most people's friendship circles are highly clustered; that is, most people's friends are friends with each other ("I know a guy who knows a guy who knows me"). And in a small world network, the clusters can be linked by persons who are members of multiple clusters, making it possible for even large communities that are made up of many separate clusters to be connected and cohesive. To test this idea, he concocted an ingenious experiment to see just how small the world actually was. In one experiment, Milgram randomly chose a stockbroker in Boston and 160 residents of a small town near Omaha, Nebraska. He sent each person in the small town a letter with the stockbroker's name and asked them to send the letter to the stockbroker if they knew him personally, or to send it to someone they knew personally who could deliver it to the stockbroker or deliver it to him through a personal contact of their own. Counting the number of intermediaries from the senders in Nebraska to the target in Boston, Milgram found that it took "six degrees of separation" or just six intermediaries on average to link the two strangers, a finding that prompted intense inquiry in science and pop culture (Watts and Strogatz 1998; Watts 1999; Amaral et al. 2000; Gladwell 2000; Moody 2004).[2]

[2] Another way to look at these ideas is through the parlor game Six Degrees of Kevin Bacon, which does a better job of capturing a key feature of bipartite networks by examining the connections among actors who appear in the same movie. The game works as follows: Name an actor or actress. If the person acted in a film with Kevin Bacon, then they have a "Bacon number" of "1." If they have not acted in a film with Kevin Bacon but have acted in a film with someone who has, they have a Bacon number of "2," and so on. Using the Internet Movie Database (www.imdb.com), University of Virginia computer scientist Brett Tjaden, the inventor of the game, determined that the highest Bacon number is "8," but that Bacon himself is connected to

Milgram's conjecture on why small world networks could connect strangers rested not only on the surprising finding of few degrees of separation but on the supposition that people interact in dense clusters; friends of friends tend to be friends. Friends are close to one another—they have just one degree of separation. But if at least one person in a cluster also is in another cluster, that person could create shortcuts between many people. This means that people and their ideas no longer have to travel along long paths to reach distant others because they can *hop* from cluster to cluster. Linked clusters enable degrees of separation to be much shorter across the global network than is anticipated; the average person can theoretically link to anyone else by using shortcuts, enabling resources to flow from different ends of the network. Milgram illustrated this idea with a folder that made it from Kansas to Cambridge in just two steps:

> Four days after the folders were sent [from Cambridge] to a group of starting persons in Kansas, an instructor at the Episcopal Theological Seminary approached our target person on the street. "Alice," he said, thrusting a brown folder toward her, "this is for you." At first she thought he was simply returning a folder that had gone astray and had never gotten out of Cambridge, but when we looked at the roster, we found to our pleased surprise that the document had started with a wheat farmer in Kansas. He had passed it on to an Episcopalian minister in his home town, who sent it to the minister who taught in Cambridge, who gave it to the target person. Altogether, the number of intermediate links between starting person and target amounted to two! (Milgram 1967, pp. 64–65)

The powerful idea that even distant individuals who are cloistered in densely connected local clusters could be linked through a few intermediaries drew attention by highlighting how resources, ideas, or infection can rapidly spread or dissipate in social systems. Clusters hold a pool of specialized but cosseted knowledge or resources, but when clusters are connected they can enable the specialized resources within them to mingle, inspiring innovation.

Small World Theory for Bipartite (Affiliation) Networks

Watts (1999) built on prior work (Feld 1981) and provided a sophisticated theoretical advance in small world analysis. Focusing on important social and structural aspects of large, sparely linked networks, Watts (1999)

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less than 1% of the actors. Similarly, if one looks for the most connected actor or actress in Hollywood, it turns out to be Rod Steiger. Why are Bacon and Steiger well-connected actors? Steiger is even more connected than Bacon because he has worked in more diverse film genres than most actors, making him a node who links diverse movie-cast clusters.

showed that two theoretical concepts define a small world network: short global separation and high local clustering. Short global separation could be quantified by the average path length (*PL*), which measures the average number of intermediaries between all pairs of actors in the network, while the cluster coefficient (*CC*) measures the average fraction of an actor's collaborators who are also collaborators with one another (Holland and Leinhardt 1971; Feld 1981).[3] To determine whether a network is a small world, Watts's model compares the actual network's path length and clustering coefficient to a *random graph* of the same size, where random graphs have both very low path lengths and low clustering. Specifically, the closer the *PL* ratio (*PL* of the actual network/*PL* of a random graph comparison) is to 1.0 and the more the *CC* ratio exceeds 1.0 (*CC* of the actual network/*CC* of the random graph comparison), or simply the larger the small world quotient (*Q*), which is *CC* ratio/*PL* ratio, the greater the network's small world nature.[4]

Newman et al. (2001) added a significant theoretical innovation to Watts's integrative work by reformulating the general small world model for bipartite networks. As noted above, bipartite networks are widespread and occur whenever actors associate in teams: directors on the same board, collaborators on the same project or paper, banks in a syndicate, actors in a movie, or, in our case, the creative artists who make a musical. Bipartite networks have a special structure: all members on the same team form a *fully linked clique*. When these teams are combined into a systemic-level network, the global network is made up of fully linked cliques that are connected to each other by actors who have had multiple team memberships. Figure 1 illustrates a theoretical bipartite network and its unipartite projection.

A key structural implication of the unipartite projection of the bipartite network is that it significantly overstates the network's true level of clustering and understates the true path length when compared to the relevant random network because of the pervasiveness of fully linked cliques. Newman et al. (2001) showed that once the small world statistics of the

[3] A note on terminology to avoid confusion: the term *cluster coefficient* has been used to refer to two different quantities. The *local CC* is an egocentric network property of a single actor and indicates how many of an actor's ties are tied to each other, an index often called *density*. The *global CC* is a property of the macronetwork and can be computed as (1) the weighted average of each actor's local density, or (2) the global network's ratio of open to closed triads, i.e., the fraction of transitive triplets (Feld 1981). In this analysis we use operationalization (2) because it is properly distinguished from local density and is consistent with recent small world analysis (Newman 2001; Newman et al. 2001). For more details, see the *PL* and *CC* equations in the methods section.

[4] Davis et al. (2003), Kogut and Walker (2001), and Amaral et al. (2000) present values across a range of networks.

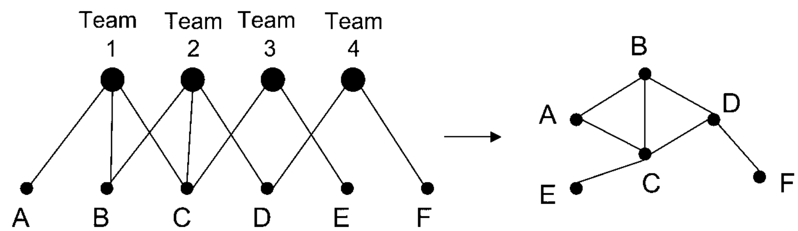

FIG. 1.—Bipartite-affiliation network and its unipartite projection. Top row represents four teams, and the bottom row represents the teams' members (e.g., coauthors on a paper or artists who make a show). Teammates are members of a fully linked clique (e.g., ABC, BCD, CE, and DF). Connections form between agents on separate teams when links like BC connect the ABC, BCD, and CE teams.

network of the boards of directors of major U.S. companies were corrected for their bipartite structure, the level of clustering in the network was not appreciably greater than would be expected in a random bipartite network of the same size—suggesting that the *CC* of the one-mode projection from a bipartite network could be a misleading indicator of a small world if it is not correctly adjusted.

Following this line of reasoning, Newman et al. (2001) developed a model for correcting the estimates of the *CC* and *PL* in random bipartite networks. They reasoned that the "true" clustering in a bipartite network is the clustering over and above the "artifactual" within-team clustering, which is the *between-team clustering* or how clustered actors are *across* teams, a view that draws on the theory of cross-cutting social ties and community embeddedness (Frank and Yasumoto 1998; Moody and White 2003). A way to visualize the logic of between-team clustering is to imagine a bipartite network where all actors are part of only one team—no actors are members of multiple teams. In the unipartite projection of this bipartite network there will be many small but disconnected fully linked clusters. Consequently, if one created a bipartite random network of the same size, then the level of clustering in the random and actual network would be the same because any random *re*assignment of links among the actors on the teams reproduces the structural topology of fully linked cliques of the actual network.

Returning to the original theoretical concepts that define a small world, the *PL* ratio and *CC* ratio, Newman et al. (2001) showed that the bipartite *PL* ratio has the same interpretation as in a unipartite network—the greater the *PL* ratio, the greater the mean number of links between actors. In contrast, the bipartite *CC* ratio has a related but *different* interpretation than the unipartite *CC* ratio. They showed that when the bipartite *CC* ratio is approximately 1.0, the clustering in the actual network is a result mostly of *within-team clustering*, and there is *little between-team clustering*. As the *CC* ratio exceeds 1.0, there are increasing amounts of between-team clustering that connect the network's separate teams and personnel. Moreover, as the *CC* ratio rises, the cross-team links are increasingly made up of actors who have previously collaborated (i.e., repeated ties) or who have third-party ties in common. This occurs because actors who work on multiple project teams are inclined to prefer teammates with whom they have worked in the past or who have worked with others with whom they have worked in the past, a process that is a result of reciprocity and reputation principles (Granovetter 1985). For example, Newman et al. (2001) showed that the *CC* ratio is positively correlated with between-cluster ties that are made up of repeated ties similar to the BC link shown above in figure 1.

These structural changes suggest that a small world influences behavior through two mechanisms in bipartite networks: (1) *Structurally*, the more a network becomes "small worldly" (formally, the more the small world quotient exceeds 1.0), the more links between clusters increase in frequency, which potentially enables the creative material within teams to be distributed throughout the global network. (2) *Relationally*, the more a network becomes small worldly, the more links between clusters are made up of repeated ties and third-party ties, which potentially increases the level of cohesion in the global network. Thus, as the small world quotient increases, the clusters within the network become more connected and connected by persons who know each other well. It is the small world consequences on the level of connectivity and cohesion among actors in the global network that we expect to affect their ability to collaborate successfully and create winning productions.

COLLABORATION AND CREATIVITY: THE BROADWAY MUSICAL

While associated with Broadway in Midtown Manhattan, the neighborhood from which it takes its name, the eldest ancestor of the modern Broadway musical debuted in Philadelphia, the original capital of the United States, 11 years before the Revolutionary War. An American company tried to produce the musical *The Disappointment* but was prevented from doing so by the town elders, because the portrayals of racy social values, though dressed up in song and witty innuendos, were considered unfit for the stage (Bordman 1986). This combination of entertaining yet critical viewpoints on American values, though the source of the first production's censorship, eventually became the industry's professional aspiration and moniker of fame in such classics as *Gay Divorce*, *Cabaret*, *Hair*, *Evita*, *Rent*, and *On the Town* (which was nicknamed "On the

Make"). By cleverly embedding rebellious or taboo ideas in irresistible comic songs and dance, creative giants like Noël Coward, Anne Caldwell, Irving Berlin, Richard Rodgers and Oscar Hammerstein, Agnes de Mille, Harold Prince, and Stephen Sondheim could artistically treat and make approachable to the general public issues of oppression, civil rights, alienation, bigotry, or homosexuality.

During the 1945–89 historical period that we study, the industry supported many of its most renowned talents even as greats from previous eras such as Cole Porter, Rodgers, Berlin, and Oscar Hammerstein II extended their pre–World War II success. New talent with innovations in directing and producing, composing, writing, choreography, and marketing also entered the network. Prince, Sondheim, Leonard Bernstein, David Merrick, Cameron Macintosh, Andrew Lloyd Webber, Tim Rice, and Bob Fosse—the first man to win the Triple Crown, an Oscar for *Cabaret*, a Tony for *Pippin*, and an Emmy for *Liza with a Z*, all in the same year—produced unmatched hits (and flops) with shows like *Cats*, *Les Misérables*, *Sweeney Todd*, *Hair*, *Evita*, *The Pajama Game*, *A Chorus Line* (the longest-running show in Broadway's history), and *West Side Story* (whose soundtrack remained the number-one album in the country longer than any other album in U.S. history). While great talent continued to flourish, a mix of coinciding phenomena battled for Broadway's talent and consumer dollars. Hollywood and television thrived, creating appealing options for Broadway's creative talent, while the drug and protest culture, the alienated and crime-stricken New York City, the Civil Rights movement, new family values, and the internationalization of the musical, while lowering the curtain on earlier subject matter and artistic conventions, raised it on new ones.

Dynamic Structure of the Creative Artist Network

Though it has varied throughout the history of Broadway, the core team that makes a musical is made up of six freelance artists: a composer, a lyricist, a librettist who writes the story's plot and dialogue (a.k.a. the "book"), a choreographer, a director who facilitates the team's collaboration, and a producer who manages financial backing. In most cases, there is one specialist per role, although a single artist can play two roles (e.g., composer and lyricist), or two artists might partner on a single role.

Figure 2 illustrates the bipartite structure of the Broadway musical network of artists. The top row of the model represents musicals, and the middle row represents the fully linked cliques of artists formed by musicals. The bottom row of the figure represents how the global network emerges from the separate creative artist teams that enter the industry each year with new productions. Consistent with figure 1, which illustrates

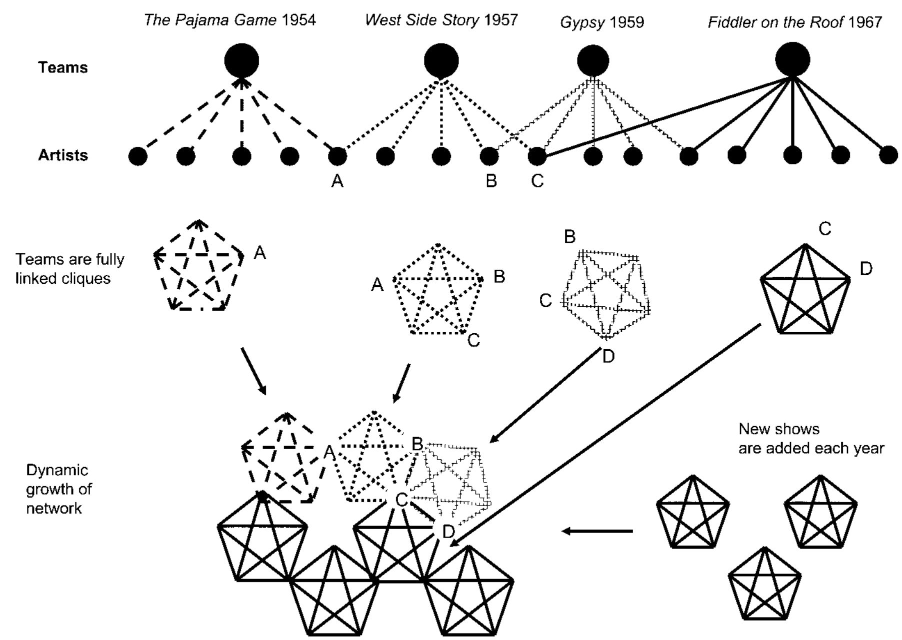

FIG. 2.—Broadway creative artist network. Figure is illustrative but based on actual data; A = Harold Prince (producer), B = Stephen Sondheim (composer/lyricist in *Gypsy* and lyricist in *West Side Story*), C = Arthur Laurents (librettist), and D = Jerome Robbins (director). As the fully linked cliques are connected to each other through artists who are part of multiple teams, the frequency of between-clique connections is disproportionately made up of repeated ties and third-party ties. This pattern is illustrated by the high connectivity among the artists who separately worked on *West Side Story*, *Gypsy*, and *Fiddler*, and the frequency of the repeated and third-party ties among B and C, and C and D, Sondheim and Laurents, and Laurents and Robbins.

the generic bipartite structure, the Broadway musical network shows that between-team links arise when artists work in more than one musical and create dense overlapping clusters of the type that are prototypical of a small world network. (Note: the resemblance between our fully linked cliques and satanic pentangles in this figure is coincidental.) Using an illustrative example based on the actual data (Uzzi and Spiro, in press; Guimera et al. 2005), figure 3 shows the internal typology of the small world with different levels of Q. When there is a low level of Q, there are few links between clusters, and these links have low cohesion in the sense that they are not disproportionately formed through third-party or repeat ties among the actors in the network. As the level of Q increases, the network becomes more interconnected and connected by persons who know each other well because there are more between-team links, and these links are disproportionately made up of repeat collaborators and collaborators who share third parties in common. At high levels of Q, the small world becomes a very densely woven network of overlapping clusters. Many teams are linked by more than one actor, and the relationships that make up the between-team ties are highly cohesive.

The production routine of a musical is varied yet follows a basic pattern. A show originates when at least one artist develops material for a show and then recruits other artists to develop their specialized parts. For example, *A Chorus Line* began as a medley of dance numbers by choreographer Michael Bennett before the music (Marvin Hamlisch) and other elements were added by other artists; a new musical could also begin around a librettist's (Mel Brooks) book as in the case of *The Producers* (Kantor and Maslon 2004). Once the artists have their material in prototype form, they work together in an intensive, team-based collaboration in which they simultaneously incorporate their separate material into a single, seamless production. It involves full days of collaborative brainstorming, the sharing of ideas, joint problem solving, and difficult editing, as well as flash points of celebration and commiseration that promote strong social bonds among the teammates. After this "preproduction stage" has finished, the musical is evaluated in previews. If a show is deemed worthy for Broadway during previews it is released as a Broadway musical; otherwise, it is considered a failure and never released in its current form. Shows that make it to Broadway go on to be hits or flops.

Creative Material and Creativity

Because a musical is a serious art form as well as a business venture (as the song says, "There's no business like show business"), shows are created with an eye to both artistic and commercial value. Although successful shows can emphasize one aspect of success over the other, paying audi-

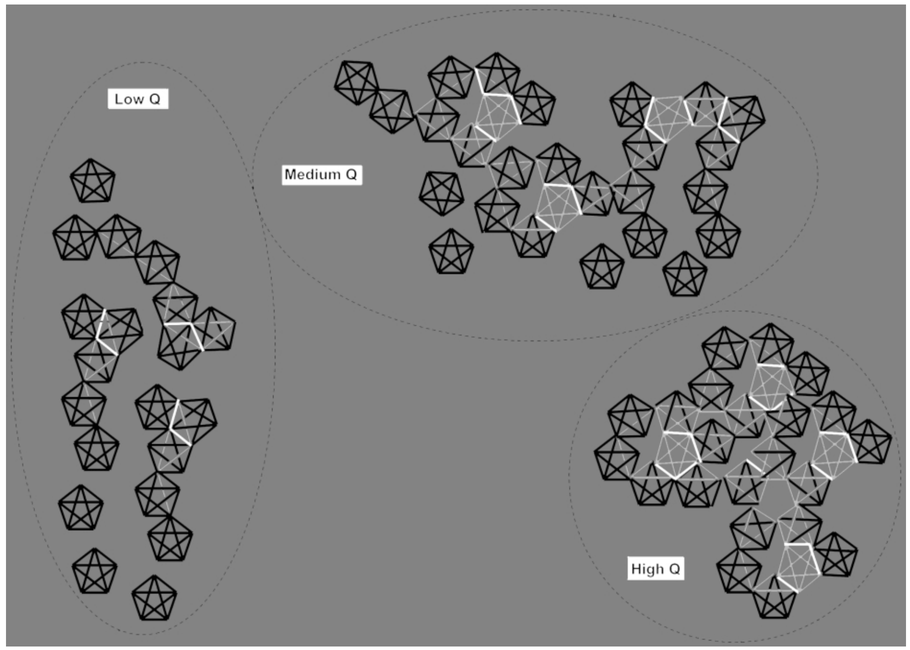

FIG. 3.—Variation in small world network structure. Figure is illustrative but based on the actual structure of our network data for various years. Each inset reflects the structure that is multiplied many times to create a large global network for three levels of Q. When Q is low there are few links between teams (cliques), and the ties that make up these links are not disprotionately made up of repeated and third-party ties as represented by the white (repeated tie) and gray (third-party tie) links. This topology has low connectivity and cohesion. As Q tends toward a high level, there are many between-team links, and these links are disproportionately made up of repeated and third-party ties—there is high connectivity and cohesion in the network's topology. At medium levels of Q the small world network has an intermediate amount of connectivity and cohesion.

ences demand entertainment, and critics (while understanding the requisite need to please audiences) demand that serious subject matter be treated beneath the surface of hit tunes and infectious dance, characters, and story lines (Rosenberg and Harburg 1992). Nevertheless, while there is no certain formula for a hit, and the inner workings of the synaptic lighting behind creativity remain illusive (Flaherty 2004), it is hypothesized that the more accessible and diverse the creative material available to artists and the more artists can lower the risks of experimentation, the more likely it is that artists can see opportunities for creativity or be forced to assimilate material from earlier periods into something fresh and new that succeeds with audiences, critics, or both (Becker 1982; Lawrence 1990; Garebian 1995). For example, in his classic study of art and the marketplace, Becker concluded that the distribution of available material shapes the ambitions and capabilities behind the creativity of artists:

> Artists use material resources and personnel. They choose these out of the pool of what is available to them in the art world they work in. Worlds differ in what they make available and in the form in which they make it available. . . . What is available and the ease with which it is available enter into the thinking of artists as they plan their work and into their actions as they carry out those plans in the real world. Available resources make some things possible, some easy, and others harder; every pattern of ability reflects the workings of some kind of social organization and becomes part of the pattern of constraints and possibilities that shapes the art produced. (Becker 1982, p. 92)

What constitutes creative material in the art world of the musical? Becker (1982) showed that creative material is embedded in conventions—accepted standards of construction of basic components of music, dance, lyrics, and more (see chap. 2 for examples). These conventions provide standards around which artists can easily collaborate. They tend to produce predictable reactions from mass audiences as well as potentially gain the critics' praise when innovatively embedded in productions that only the trained ears of a professional can appreciate. In music, categories such as jazz, rock, hip-hop, and so forth all have their separate conventions. The genre of the "musical" organizes the separate artistic parts into a whole that is distinguished from related arts such as burlesque, opera, operetta, and vaudeville, which use elements of music, dance, plot, and so on. Original artists, as opposed to cover artists, create styles that personalize conventions by adding novelties, twists, and fresh ideas. As styles become popularized and imitated they become conventional material. In the early 1970s, choreographer Bob Fosse worked within the historic dance conventions of old vaudeville and burlesque. He added the distinctive novelties of dancing with down-rounded shoulders, small, rapid, twinkle-toe steps, straight arms, and the wearing of hats to the basic conventions. After winning the first Triple Crown his style became conventional material for other artists to mimic and creatively extend.

Artists learn material through personal collaborations, wherein they can observe firsthand the production process and not just the final product (Becker 1982). Other artists can observe performances of material. Although they do not observe firsthand how the material is created, they can at least extract elements of the material for their routines. The distribution of conventions and styles practiced by related artists for the music, dance, lyrics, and song that combine into a Broadway musical provide the extensive "pool of variation" (Becker 1982, p. 92) from which artists create original work.

Any successful production is likely to be a combination of convention and innovative material—material that extends conventions by showing them in a new form or mode of presentation. "Without the first it becomes unintelligible; without the second, it becomes boring and featureless" (Becker 1982, p. 63). An example of innovation and convention is provided by *Carousel* (1945), a Rodgers (music) and Hammerstein (book and lyrics) show that creatively extended the convention of the big love song. Because the conventional use of the big love song required it to come in at roughly the middle of the program after the leads meet, audiences had to wait to hear the show's favorite number. Rodgers and Hammerstein reasoned that they could enhance the appeal of their shows by adding more big love songs. But how could they have a love song before the leads had a chance to know each other? The extension they hit upon was to take the convention of the love song being sung in the present time and extend it to "dream" time and future time (Kantor and Maslon 2004). In the former case, they created a love song about an imaginary lover, and in the latter case, a love song about falling in love with a future lover.

Just as conventions are learned and gather strength within networks of personal contact and repeated public performance, innovative extensions often emerge when artists are exposed to other conventions besides the ones they have been gifted in applying, inspiring or forcing creativity (Becker 1982). To continue with the example of *Carousel*, it has been estimated that the cynicism about love that had been Rodgers's forte in writing love songs before collaborating with Hammerstein came into contact with Hammerstein's command of the conventions for writing about wide-eyed, optimistic love to create the right balance between fantasy love, future love, and dream love. Together they creatively combined the musical and lyrical conventions of the whimsical lovers with those of the doomed lovers (in collaboration with de Mille's innovative choreography), keeping the fantasy behind the songs and plot real enough for audiences to believe in (Kantor and Maslon 2004). This risky creative gamble was supported by their close personal relationship, which had formed two years earlier during *Oklahoma* (1943), their first musical together. In this way, the distribution of different conventions and personal relations around an art can inspire creativity either by revealing previously unseen connections in material or by necessitating that an innovative solution be found that enables a synthesis of different material.

SMALL WORLDS AND EXPECTATIONS FOR PERFORMANCE

While the above cases recount the dynamics of creativity at the level of specific team interactions, we are interested in how the *distribution* of talent around the small world of artists affects the creativity of individual teams and the creativity of the industry as a whole. The concept of the small world suggests that it can productively organize the distribution of creative material in an art world as well as promote the ability and desire of artists to take risks collaboratively on creating something new. Clusters of interacting artists help incubate conventions. As the same time, between-cluster connections increase the likelihood that different conventions will come into contact, while the between-cluster connections, which are disproportionately made up of people who know each other well, further encourage risk taking on new material. In this way a small world works not just by bridges that bring together different ideas (Burt 2004) but also by creating the cohesion needed for innovators to take risks on unfamiliar material.

We argue that as the distribution of connections and cohesion across the small world changes, the likelihood of creative discoveries should also go up and down. This is because artists' creativity will be partly governed by the increase or decrease in contact among collaborators embedded in separate clusters, and because successful new material innovations, once publicly shown, also stimulate creativity among artists in other parts of the network that attempt to incorporate successful fresh ideas into their material. In this way, the distributed nature of creativity and creative material cannot be fully captured by ego- or team-level network effects because they do not account for how the joint distribution of links among individuals and teams are embedded in the larger, bipartite global network of relations.

The structural and relational mechanisms by which a small world affects behavior suggest that when the small world Q of the network is low, the ability of creative artists to develop successful shows is also low. Because there are few between-team links to promote the transfer of creative material between teams in the global network, the creative material that is generated within a production team is unlikely to circulate to other teams. At the same time, because the between-team links are made up of few repeated or third-party-in-common ties, the creative material passed between teams in the global network may be perceived as having indefinite value. This is because it has not been spread by known and trusted sources who can effectively communicate to new teammates the value of unfamiliar yet novel ideas imported from other teams they have worked on, making promising material costly to obtain or risky to employ. This remains true even if creative material can be observed after the musical is staged because the finished product only partly reveals the full effort needed to adapt the material for new purposes (see Menon and Pfeffer [2003] on the reverse engineering of innovations).

For the same reasons, as Q begins to increase, the network's more connected and cohesive nature should facilitate the flow of creative material and promising collaborations across clusters. This argument is consistent with Merton's studies of the "invisible college" (1973), which showed that connectivity between coauthors and labs nurtured research through the sharing of ideas, soft information, and resources—a finding reproduced in contemporary studies of science and the arts (Etzkowitz, Kemelgor, and Uzzi 2000). Granovetter's (1985) arguments about relational embeddedness also suggest that the greater the level of repeated and third-party links, the greater the risk sharing and trust in a community. Repeated ties can lower innovation costs by spreading the risk of experimentation over the long term. In a similar view, repeated interactions tend to create expectations of trust and reciprocity that "roll over" to common third-party ties, increasing the likelihood that risks of collaboration or creativity are spread among friends of friends (Uzzi 1997). These findings suggest that increases in a network's small world character can boost the performance of the global network by making the exchange of conventions as well as risk taking more likely.

While theory implies a positive relationship between small worldliness and success, research also suggests that connectivity and cohesion can be a liability for creativity. A robust social psychological finding is that cohesive cliques tend to overlook important information that is discrepant with their current thinking because members tend to exchange common rather than unique perspectives. Kuhn's (1970) study of creative change in science showed that the inability of cohesive teams of scientists to react to inconsistencies in their thinking can hold true despite empirical data that clearly refutes the current paradigm, especially if cluster members have had "hits" with the old research tradition or style. Moody and White's (2003) analysis of political behavior showed that as a cluster's connectivity intensifies, actors behave more similarly despite freedom to be different, while Becker (1982, p. 57) found that when groups with tastes and skills in the same convention or style work predominantly with each other, the convention "becomes the automatic basis on which the production of art works can proceed, even among people deeply devoted to not doing things in the conventional way."

In exclusive ongoing relationships where friends are friends of friends, feelings of obligation and camaraderie may be so great between past collaborators that they risk becoming an "assistance club" for ineffectual members of their network (Uzzi 1997). Preserving a space for "friends" can further hamper the recruitment of outsiders that possess fresh talent into a cluster (Portes and Sensenbrenner 1993) or promote recruitment by homophily, minimizing diversity and reproducing rather than advancing existing ways of thinking (McPherson, Smith-Lovin, and Cook 2001). Expectations of reciprocity intensify an actor's exclusive involvement with certain others at the cost of forming new ties with persons who have a fresh artistic view or who are "with-it." These findings suggest that the high levels of connectivity and cohesion associated with a high Q can potentially undermine a productive distribution of the kinds of conventions and extensions that are critical for creativity in an art world.

How can these opposing arguments about a small world's effect on performance be reconciled? We suggest that the effect may be parabolic. When there is a low level of Q, there are few links between clusters, and the links are more hit-and-miss, on average, in the sense that they are not disproportionately formed through credible third-party or repeat ties, isolating creative material in separate clusters. As the level of Q increases, separate clusters become more interlinked and linked by persons who know each other. These processes distribute creative material among teams and help to build a cohesive social organization within teams that support risky collaboration around good ideas. However, past a certain threshold, these same processes can create liabilities for collaboration. Increased structural connectivity reduces some of the creative distinctiveness of clusters, which can homogenize the pool of creative material. At the same time, problems of excessive cohesion can creep in. The ideas most likely to flow can be conventional rather than fresh ideas because of the common information effect and because newcomers find it harder to land "slots" on productions.

These arguments suggest that a small world network affects the performance of the actors within it by shaping the distribution of creative material and talent available to them—specifically, the joint distribution of actors and teams. The small world quotient tells how connected and cohesive the relations in the global network are, indicating how productive or unproductive the distribution of creative material and relationships are across the global network. Are creative ties and materials poorly distributed among strangers in disconnected cliques or tightly woven into a single, undifferentiated mass of close relations? Or are they richly distributed in a structure that is between these extremes? In this sense, the small world simultaneously governs the distribution of material for all the actors in the network. Thus, while collaboration happens between direct relations, the small world influences lower-level mechanisms such as actors' egocentric webs (Burt 2004) that generate their returns contingent on the distribution of resources of the small world network in which they are embedded. In this sense, the small world network influences to different degrees, but by the same mechanisms, the performance of individual actors as well as the performance of the aggregate system.

HYPOTHESIS.—*The relationship between a network's small world typology and performance is* U-*shaped. Specifically, the financial and artistic success of a production increases at medium levels of Q and decreases at either low or high levels of Q. The financial and artistic success of a season of productions increases at medium levels of Q and decreases at either low or high levels of Q.*

DATA AND METHODS

Our data include the population of all 2,092 people who worked on 474 musicals of new material produced for Broadway from 1945 to 1989. For each musical, we know the opening and closing date, artists on the creative team, theater of showing, and measures of commercial and artistic success. In addition to the shows that were released on Broadway, our sample also includes data on 49 shows that died in preproduction. The artists on these shows experienced the same intense collaborative interactions as the artists who worked on shows that did get released on Broadway. Consequently, they provide rare "failure" data that is often inaccessible for the purposes of studying networks and that can cause statistical biases when excluded from the analysis. The sources of the above data are Bloom (1996), Green (1996), and Simas (1987), which are directories that record the above data for each musical from the musical's original Playbill. Following the industry convention of dating events in the industry by the calendar year, we measure time in years. Revivals and revues of non-original shows were excluded.

The nodes in our network are all the creative artists who have worked on Broadway musicals during this time period. Actors who perform the shows are excluded. In the global network, artists are directly linked to each other when they collaborate on the same show and indirectly to each other through third parties when their separate shows share at least one common artist (see figs. 2 and 3).

In defining a tie, the issue arises as to how long it should persist. In the extreme case of no relationship decay, all artists from 1945 and 1989 would be linked in the global network. However, this is unrealistic and skews many network statistics because it maintains false links to inactive artists (i.e., Andrew Lloyd Webber ca. 1970–2001 would be linked to Cole Porter ca. 1920–50 [Porter died in 1964]). Our review of the literature and interviews with industry experts suggested that if an artist was inactive for seven years (did not collaborate on a musical during that time), that artist and all of his or her links should be removed from the network in year seven. If an inactive artist reactivates in a new show after being removed, the artist and his or her recent ties are added to the network—ties that were deleted are not reconstituted on the basis that experts described this pattern of reentry as "breaking back into the business."[5] We also used decay functions of five and 10 years, and the results were very similar.

Using the above definitions for nodes, links, and decay, we constructed the global network. We began with the creative artists who worked on the shows that opened in 1945 and then added to that network all the active artists who had worked on shows prior to 1945 to make the information on the 1945 network match all subsequent years. After that step, we worked forward in time, adding new artists to the network each calendar year in accordance with the release of new shows.

The so-called giant component of a network measures the collection of actors that are linked to each other by at least one path of intermediaries (Moody 2004). Despite the conservative decay function, the giant component in this network averages over 94% from 1945 to 1989. In the average year, the average number of active artists is about 500, and the average number of links per artist is 29. Consistent with other work on small worlds, our network is both very large and sparse and made up of essentially one large interconnected network (Watts 1999).

Dependent Variables

To operationalize financial success, we used the industry standard measure, a three-category index devised by *Variety* (1945–89). A "hit" is a production that makes enough money to recoup its costs before ending its run, a "flop" makes money but fails to recoup its costs before ending its run, and a "failure" is a musical that closes in preproduction before it makes any money at all. Data on how much money a hit makes or a flop loses is not publicly available for our shows. Of the 474 musicals, we have complete data for 442. The distribution for hit or flop or fail is what is

[5] We interviewed Stuart Okun, former vice president of Disney Stage Productions International, and Frank Galati, actor, writer, and Tony Award winner.

expected in show business. Of a total of 442 shows, 23.68% are hits, 65.06% are flops, and 11.26% are failures. In constructing this variable we defined failures equal to zero, flops equal to one, and hits equal to two. In order to be most conservative in our coding we also coded financial success as a two-category variable with a hit equal to one and a flop equal to zero by recoding failures to flops (collapsing the two financial dud categories into one category) and by excluding flops from our analysis. These changes did not affect the reported results (see app. table A1).

To measure artistic success, we used another industry gold standard, the average of the critics' reviews of the musical (Suskin 1990; Rosenberg and Harburg 1992). Broadway critics' reviews partly define shows as being "art," "not art," "good or bad," "beautiful," "imaginative," "derivative," and so on (Becker 1982). Our data on reviews come from Suskin (1990, 1997), who coded and recorded all critics' reviews from 1945 to 1981 from the following publications: the *Daily News*, the *Herald Tribune*, the *Journal-American*, the *Mirror*, *PM*, the *Post*, the *Star*, the *Sun*, the *New York Times*, and the *World-Telegram and Sun*. Critics' reviews exist on a five-point critics' scale: pan (−2), unfavorable (−1), mixed (0), favorable (+1), and rave (+2). For each musical, we averaged the reviews, which resulted in score ranges from −2 (all pan reviews) to +2 (all rave reviews). These data are not available for 1982 to 1989, dropping our N for artistic success from 435 to 315.

The virtue of the average is that it measures the overall critical artistic impression of a show (Baumann 2001). On Broadway this scoring takes place on opening night, making the review process fairly independent of the exchange of opinions among critics.[6] We confirmed the validity of this measure in several ways. First, we checked to see if the number of critics varied across review categories. The average number of reviews across our five categories was nearly identical. Second, we examined whether the scores of shows receiving mixed reviews might be confounded with the variance of agreement among critics. That is, do the middle three categories indicate the mean strength of the valance of the reviews or

[6] The sociology of culture literature suggests that other measures of artistic success exist and that the appropriateness of a measure is partly contingent on the historic and cultural conditions of the time (White 1993). For example, another measure of critical success is the variance of reviews rather than the average, which operationalizes critics' agreement about, rather than keenness for, a production. The Tony Award is a broad measure of artistic success because it is influenced by end-of-the-season economic information and the career-long celebrity of the artist (Faulkner and Anderson 1987). Others cite the production of a legitimate product of high culture (Bourdieu 1996), genius and patronage (DeNora 1991), or reputation (Becker 1982). Our measure of artistic success reflects a standard used by artists to evaluate their own work in a field where critics can define what has artistic merit (as well as entertainment value) in the world of the professional performing arts (Verdaasdonk 1983; Baumann 2001).

simply shows that had more variable reviews? The data showed that the variance around the mean for mixed notices was lower than around hits or flops, suggesting that a musical receiving a mixed review is picking up valance rather than level of agreement among critics.

In this industry, financial and artistic success are correlated 0.56, a situation that is expected given the aims of creative artists. However, the measures are not substitutes for one another either substantively or empirically. Table 1 shows that the better the review, the better the show tends to do financially. This is because (*a*) artists *actively* strive for success in both arenas, and (*b*) consumers shy away from pricey shows that critics pan. Nevertheless, it is clear that a nontrivial number of shows overcome poor notices, and critics do frequently praise what the public ignores; 23% of the shows with rave reviews were financial flops, and 13% of the shows with pan reviews were hits. This disparity creates a need for both dependent variables.

Finally, we constructed three system-level variables: (1) the annual percentage of hits, (2) the annual percentage of rave reviews, and (3) the annual average of reviews. We modeled both percentage of rave reviews and the average of all reviews because both measures of artistic success are used to describe the performance of the industry. These variables were operationalized as the yearly number of hits divided by the yearly number of new shows, the yearly number of shows with rave reviews (values between one and two on our critics' scale) divided by the yearly number of new shows reviewed, and the average of each individual show's critic score divided by the total reviews made that year. This yielded an N of 45 for the percentage-of-hits model and an N of 37 for the percentage-of-rave models, two small samples that test the power of the model.

Independent Variables

To generate our *CC* ratio, a *CC* for our actual network and a random network of the same size must be computed. To compute the *actual CC*, we determined how many pairs of artists have a shared acquaintance, or how many triads are "closed" (Feld 1981; Newman et al. 2001). Three different configurations can yield a triad: person A is linked to person B who is linked to person C, both persons A and B are linked to person C, or both persons B and C are linked to person A. Three links among persons A, B, and C comprise a closed triad (i.e., a triangle). Thus, the percentage of closed triads in the network is three times the total number of closed triads (to account for the three possible configurations of triads) divided by the total number of triads (eq. [1]). The actual *CC* is on a scale from zero to one. Zero represents no clustering, and one represents full

TABLE 1
Distribution of Financial Hits and Artistic Success, 1945–1989

Range of Artistic Score	No. of Observations	Hit Percentage
Favorable to rave (1 to 2)	71	.77
Mixed to favorable (0 to .99)	79	.29
Unfavorable to mixed (−.99 to −.01) ...	91	.15
Pan to unfavorable (−2 to −1)	80	.13
Total	321	28.97

Note.—Only 321 cases have artistic review data while 442 cases have hit, flop, failure data.

clustering. An actual *CC* value of .65 means that 65% of the triads are closed:[7]

$$CC = \frac{3 \times \text{no. of triangles on the graph}}{\text{no. of connected triplets of vertices}}. \tag{1}$$

To calculate the *random CC*, we use Newman et al.'s (2001) solution for a bipartite graph. The logic that created a random bipartite graph counterpart to our actual network followed these steps. First, we calculated the tie distributions (i.e., k) for teams as well as artists from the actual network for each year. Second, for each show and artist in the random graph, we created as many links as its degree distribution dictates by linking team and teammate nodes randomly.

Specifically, the bipartite random *CC* computes two different degree distributions in the network: the number of individuals per team and the number of teams per individual. The probability that an individual is in j groups is p_j. The probability that a group has k individuals is q_k. These probabilities are used to construct the functions in equation (2):

$$f_0(x) = \sum_j p_j x^j, \quad g_0(x) = \sum_k q_k x^k. \tag{2}$$

[7] To make our link to past work clear, it is worth noting the relation between the *CC* and the concept of transitivity (Holland and Leinhardt 1971; Feld 1981; Wasserman and Faust 1994). Eq. (1), the equation for the actual *CC*, is identical to the equation for "transitivity." Because of this history, it might be apt to refer to the actual *CC* as transitivity. However, two factors appear to make the term *CC* more apt in our study. First, prior work treats transitivity and clustering as almost empirically interchangeable because they operationalize the same concept of clustering. For example, Feld (1981, p. 1022) observes, "The extent of clustering is equivalent to the extent of 'transitivity' among mutual relationships." Second, because we use the Newman et al. (2001) model, we follow their nomenclature, for consistency, while recognizing its debt to the concept of transitivity.

The above functions are then used to calculate the number of neighbors that an individual has in a unipartite projection of the network, a network represented by actors only (teams are not shown):

$$G_0(x) = f_0(g_0'[x])/g_0'[1]). \tag{3}$$

Equations (2) and (3) are used to calculate a bipartite random cluster coefficient (eq. [4]). In equation (4), M is the total number of groups in the network, and N is the total number of individuals in the network:

$$bCC_r = \frac{M}{N}\frac{g_0'''(1)}{G_0''(1)}. \tag{4}$$

The random CC lies on a scale that varies from zero to one and has the same interpretation as the actual CC except for the random graph. The CC ratio is CC actual/CC random. As noted above in the theory section, as this ratio exceeds 1.0, the amount of true clustering, or between-team clustering, increases, and the types of ties that account for the clustering are disproportionately repeated ties and ties with third parties in common.

The actual PL is calculated by taking the weighted average of the PL of each actor in the network. The average path length for a random bipartite graph is computed by using the same degree distribution as the bipartite random cluster coefficient. In a unipartite random graph, the PL is estimated as $\log(n)/\log(k)$, where k is the number of links, and n is the number of actors in the network for large networks. In the bipartite network, paths are traced from both the perspective of the actor and the team of which the actor is a member. This is done by using the first derivative of the functions defined in equation (2), evaluated as one. This is used to construct equation (2), which is the random bipartite path length (Newman et al. 2001). The PL ratio is equal to PL actual/PL random. Formally, the random PL is

$$bPL_r = \ln(n)/\ln[f_0'(1) \cdot g_0'(1)]. \tag{5}$$

To test our hypothesis inclusively, we use two specifications of the small world model. First, we separately include the CC ratio and PL ratio as linear and squared terms in our equations. Second, we enter the small world quotient (hereafter, small world Q), calculated as CC ratio/PL ratio as a linear and squared term.[8]

[8] Because in a mature small world like ours, the PL ratio behaves like a fixed effect with a constant value near one, many researchers have used the small world quotient to incorporate the effects of the CC ratio and PL ratio in one variable (Kogut and Walker 2001; Davis et al. 2003). This measure's drawback, however, is that the separate effects of each ratio are hard to discern. Consequently, we apply an inclusive treatment of the theory and model the small world quotient, as well as the CC ratio and PL ratio, as separate variables.

Construct Validity

As one of the first empirical tests of the effects of a small world on performance, we conducted tests of construct validity to bolster our inferences about how changes in the small world Q affect changes in the network's level of connectivity and cohesion. We use the widely accepted multimethod-multitrait matrix (MMTM) approach. In the MMTM approach, the theoretical construct under scrutiny is valid if it positively correlates with related constructs (convergent validity) and is unrelated to different constructs (discriminant validity).

Structurally, we argued that increases in the small world quotient positively correlate with more between-team ties. This happens when more people work on multiple productions. If every artist made just one show or made multiple shows but always with the same teammates, the network would be made up of isolated clusters. This suggests that a network is more connected if 20% of the artists have worked on 10 shows versus 5% on 10 shows. This distributional relationship is conveyed in a power-law graph, which graphs on the y-axis the probability of an actor having worked on a certain number of shows against the number of shows on the x-axis; formally prob(no. of shows) versus number of shows. When the regression line coefficient fit to the above quantities is *nearer zero*, the odds of working on one show are closer to the odds of working on many shows and vice versa. If the odds of working on one show are close to the odds of working on many shows, it indicates that there are many between-team ties connecting the global network. Thus, if we are correct in arguing that the structure of the network becomes more connected as Q increases, the coefficient of the line fit to prob(no. of shows) versus number of shows should move closer to zero as the small world Q increases.

To test this relationship, we constructed power-law graphs by calculating how many links each artist has per year in the global network (Moody 2004). To account for the bipartite structure, we used number of shows as a proxy for number of ties. From these numbers, we calculated the probability of having a given number of links as well as the probability of having more than a given number of links. These probabilities were then graphed as the prob(no. of shows) versus number of shows for each year, and a regression coefficient was calculated to estimate the power-law exponent for each year. Thus, if we are right that global connectivity increases with the small world, then there should be a positive and significant correlation between the regression coefficients from the power-law graphs and Q. Consistent with this test, we found that the correlation was $\rho = .81$ ($P < .000$).

Similarly, if changes in the small world nature of the network signify changes in the type of connectivity of the network, then Q should be positively correlated with the number of ties per artist per year, or k, because global connectivity increases with k (Moody and White 2003). Consistent with this expectation, table 2 shows that for a given k equal to at least 10, 20, 30, 40, or 50 ties, the probability of any artist having k or more ties is positively and significantly related to the small world Q. After about 50 ties the correlations remain positive but drop off in magnitude because the number of artists with more than 50 ties is small. Consequently, the correlation between the small world Q and the cumulative probability of prob(k) has fewer observations and many zeros. The statistical insignificance of 10 ties or more also makes sense because nearly all actors have about 10 ties, since the average team size is about seven.

Relationally, we argued that as a small world network becomes more connected, repeated and third-party-in-common ties disproportionately make up the connecting links. To test these relationships, we constructed a variable that is the percentage of teams each year with at least one repeated tie, where a repeated tie indicates that those individuals worked on at least two shows and with one another. This variable provides the most conservative test of our claim because we underestimate the number of repeat ties to the degree that teams have more than one repeated tie at a time. Consistent with our arguments the small world Q and repeated ties are highly positively correlated ($\rho = .47$, $P < .001$), which indicates that as Q increases, connectivity is increasingly a result of repeated ties.

To test the relationship between the small world Q and third-party ties, we constructed a variable with the percentage of teams with at least three, five, seven, and 10 third-party ties in common. A third-party tie occurs when two collaborators work with each other for the first time on a show and have previously worked with the same person or persons on a prior show. If there are five third-party ties on a team, it means that two collaborators can have five prior third-party collaborators in common, or that two teammates have two third-party collaborators, and two other teammates have three prior third-party collaborators. Thus, the more third-party ties in common, the more the global network is linked via cohesive ties. Consistent with our expectations, Q is positively correlated with the number of third-party ties per team: three third-party ties per team ($\rho = .61$), five third-party ties per team ($\rho = .63$), seven third-party ties per team ($\rho = .65$), and 10 third-party ties per team ($\rho = .60$), where $P < .000$ for all tests.

Finally, when all the comparisons between Q and the above variables are tested for the CC ratio, the same patterns emerge as expected given the relative constancy of the PL ratio in this mature network. Thus, the

TABLE 2
RELATIONSHIP BETWEEN NUMBER OF TIES PER ARTIST, k, AND SMALL WORLD Q

Power-Law Estimate of the Probability of an Artist with This Many Ties or More	ρ with Q	P-Value
10 ties or more	.2154	.1554
20 ties or more	.4349	.0028
30 ties or more	.6650	.0000
40 ties or more	.4962	.0005
50 ties or more	.3021	.0437

above evidence corroborates our arguments that our small world measures operationalize what they purport to measure.

Control Variables

To account for other factors that can affect the success of a musical production, we control for production-team-level network structures, the human capital of creative artists on each team, and economic variables at the level of the production and the economy. Production-team-level network variables capture the degree to which the network arrangements of the team shape success (Faulkner and Anderson 1987; Lazer 2001), human capital variables capture the degree to which talent rather than the organization of talent affects success (Faulkner 1983; Baker and Faulkner 1991), and market controls capture the degree to which economic and period conditions independently affect success. Although we do not make hypotheses about these effects, we control for them empirically in our models.

Team Network

To control for the production team's ability to reach talent in the global network of artists, we computed the *closeness centrality* of the production team by calculating the closeness centrality for each team member (i.e., librettist, composer, etc.), summing the centrality scores, and then dividing that sum by the number of teammates. Teams with a high centrality score are at the center of the network and can reach the greatest number of other artists through the fewest intermediaries (Borgatti and Everett 1999).

Weak tie bridges and structural holes also govern a team's ability to reach easily the talents of diverse artists (Granovetter 1973; Burt 2004).

To account for these relationships, we computed Burt's (2004) *structural hole* measure for each person on the team, summed these quantities, and divided the sum by the number of teammates. To be conservative, we also adjusted this measure for the number of "redundant" holes there are among teammates for cases where two or more teammates were the only third persons to connect two otherwise disconnected artists. Each nonredundant hole got a score of one; if there were two teammates who acted as structural holes between the same two people, each hole got a score of 1/4 (one divided by the number of people squared, 1/4 for two, 1/9 for three, etc.) so that the value of the structural hole was shared among teammates. The adjusted measure was highly correlated ($P < .000$) with the unadjusted measure and produced similar results.

We controlled for a production team's local cohesion with several measures. First, we used the standard measure of *local density*, which looks at the fraction of each teammate's ties that are tied to each other. We constructed this measure by calculating the density of each artist on the team (number of each artist's ties that are tied to each other divided by the total possible number of ties among the focal artist and all his or her ties), summing that ratio for each artist on the team, and then dividing that sum by the number of team members. Second, to gauge the importance of the connections between individuals, it is important to differentiate between single- and multiple-time encounters. In the Broadway musical industry, artists have significant control over whom they work with and probably prefer to repeat collaborations with others whom they believe will enhance their chances of future success. To construct a measure of this construct, we created *percentage of repeat ties*, which is a count of the number of repeat ties on each production team divided by the number possible. We also tried the count of repeated ties per team, which did not alter the results. Third, to measure the degree of similarity among the members of the production team, we calculated a *structural equivalence* score for each team. A high structural equivalence score indicates that the production team is made up of artists who have worked with many of the same past collaborators even if they have not worked with each other before, a condition that increases cohesiveness and familiarity with similar creative material. If the structural equivalence score is low, then the artists have had few collaborators in common, and it is plausible to assume that the creative team's makeup has varied artistic styles. We calculated structural equivalence two ways. First, we used the straightforward Euclidian distance measure. Second, we used Jaccard matching, which is specifically designed for binary data like ours. It is computed by taking a, the number of links that both artists share, and dividing by the sum of a, b—the number of links artist 1 has but artist 2 does not have—and c—the number of links artist 2 has but artist 1 does not have, or $a/(a + b + c)$. Both measures produced similar results. Consequently, we presented the more familiar Euclidian distance measure.

Individual Talent

To gauge the past talent of the production team, we calculated the *success in prior shows* by summing across teammates the number of unique past hits that they had achieved. A high number indicates that the production team members on average have been hit makers and have established reputations that can influence the success of the current show (Baker and Faulkner 1991). However, the binary nature of hits excludes shows that were good but not quite great. Consequently, we also calculated success in prior shows by taking the average of the count of the number of performances of each teammate's prior shows. Empirically, number of prior hits and length of prior runs were indistinguishable in the analyses, and so we present only the number of hits. To measure the accumulated past experience, know-how, and developed skill of the production team, we computed the *number of past collaborators* for the production team by counting the number of past collaborators of each teammate and then dividing by the number of teammates.

Market Characteristics

We constructed an extensive range of market variables to account for differences in the cost of a show, competition among shows, location, economic conditions, period effects, and year. The production costs of a show are typically associated with a large cast that drives up recruitment, directing, and salary costs; set and costume design costs; and other administrative costs. Because this effect is likely to diminish as the production grows, we took the log of the size of the cast to operationalize *production size*.

Independent of a new musical's quality, the competition among shows for the consumer's dollar can also affect success. New shows benefit from competition when the market has a small fraction as opposed to a large fraction of new releases (Faulkner 1983). To control for competition, we created a variable called *percentage of new show openings that year*, which is the number of new shows opening that year divided by the number of shows playing. Another possible specification of this variable is to split it into two separate variables where one variable is the numerator and the other is the denominator of the percentage of new shows variable. The drawback of this measure is that the number of new releases and number of shows playing is highly correlated ($\rho = .84$), creating multicollinearity problems. Nevertheless, to be conservative we tried both specifications, and the results were similar.

Another measure of competition among shows is the theater in which the show plays. It is well known that the Broadway region between 42d Street, 49th Street, 8th Avenue, and Broadway is the "core district." The playhouses in the core district are tightly packed and located next to bistros, pubs, and convenience stores. Thus, independent of the show's quality, the bustling, well-lit, and public environment makes shows in this district "crime safest" as well as best situated for a night out on the town, especially for the out-of-town theater goer who will likely gravitate toward the center of the action. To measure this effect, we categorized each theater's physical location as being in the center or periphery of the district with the variable *core theater* (1 = yes). It is notable that the placement of a show in a core playhouse is driven by numerous factors—competition (i.e., the other shows already playing in the core theaters), size of musicals, and perhaps the anticipated hit potential of the show. In our model, we control for competition and production size. We cannot control for the anticipated hit quality of the show. However, this factor is unlikely to create a systematic bias because of the difficulty of predicting a hit show (Rosenberg and Harburg 1992). Thus, this variable may correlate with factors other than theater goers' convenience, but probably in unsystematic ways.

We included the standard economic control variables for this industry (Vogel 2001). To control for changes in sources of revenue, we included the variable *inflation-adjusted ticket price*, where tickets are the main source of revenue. This variable was measured as the average yearly ticket prices for a Broadway show (*Variety* 1945–89) adjusted for inflation relative to other goods and services that compete for the consumer's leisure dollar. Because the price of a Broadway show is relatively similar across all shows within seating categories (e.g., house seats vs. mezzanine), one average price controls for how differences in yearly ticket prices might affect a show's success over time (Vogel 2001). We used the following formula to compute the inflation-adjusted ticket price per year: adjusted price per year = 1989 price × (year's CPI/1989 CPI). For example, the inflation-adjusted price for 1945 is \$5.09 = \$35.07 (18/124).

The cost of capital can affect the scale of a production, the hiring of top talent, or the length of time investors permit a weak show to stay open in the hope of rebounding from a poor start. To control for the cost of capital, we included the *prime rate*.

General economic conditions also affect the level of disposable income consumers have for entertainment, the amount of investment capital in the hands of financiers, and inflation. To control for this bundle of economic conditions, we included *change in the GDP*.

Finally, to control for key changes in the marketing- and performance-related technology of the industry between 1945 and 1989, we included a period effect called *post-1975* (1 = yes). After 1975, "twofers" were introduced—discount two-for-one tickets that made the high price of a Broadway show more affordable to the masses. At nearly the same time, inconspicuous microphones for vocalists were introduced. This allowed a "new breed" of voices to appear in musicals. Before that time, Broadway favored vocalists like Ethel Merman who could "sing to the back row." After 1975, critics' notices also grew longer in allied arts like film, which enabled reviews to contain more commentary than before (Baumann 2001). Table 3 presents descriptive statistics on our variables.

Statistical Model

Our design uses an ordered probit to model for the three-category hit-flop-failure financial success variable and uses ordinary least squares (OLS) regression to model critics' reviews as well as system-level outcomes, which are measured on a continuous scale. To capture the effect of a small world on the performance of a musical, we follow the multilevel modeling practice of regressing the lower-level variable (i.e., the probability of a musical's success) on the higher-level variable (i.e., the small world *Q*).

Although the multilevel modeling technique is common practice in many scholarly domains (Maas and Hox 2004) the method can suffer from three methodological threats to validity. These threats are reverse causality, omitted variables, and clustering (Duncan and Raudenbush 2001). We handle these issues as follows. Reverse causality concerns whether individual-level action causes the macrolevel outcome, rather than the reverse. In our case, this problem is negligible because our small world constructs are measured prior to the musical's opening, while the musical's performance is measured after the musical's opening. The omitted variable issue reflects the concern that some third, unmeasured variable accounts for the macrovariable's effect. While it is impossible to control for all imaginable variables, there is a relatively finite set of critical variables for which to control. We control for change in the GDP, prime rate, ticket prices, and intershow competition. In particular, GDP is important because it correlates at about .90 with many other macroeconomic variables that affect the industry such as the unemployment rate, DOW, and disposable income (Vogel 2001). Moreover, we control for most individual-level and production-team-level variables, further minimizing the chance that we have omitted a crucial variable at higher or lower levels of analysis. Clustering is appropriately handled by adding Huber-White corrections to control for the nonindependence of observations across rows (i.e.,

TABLE 3
Descriptive Statistics

Variable	Mean	SD	Min	Max
Hit, flop, or fail	1.127	.577	.000	2.000
Artistic score	−.142	1.164	−2.000	2.000
% hits per season	.226	.130	.000	.600
% raves per season	.154	.132	.000	.444
Average artistic score per season	−.14	.53	−1.2	.75
Small world Q	1.853	.447	1.331	3.019
Small world Q squared	3.635	1.952	1.771	9.117
Cluster coefficient ratio	1.971	.500	1.437	3.313
Cluster coefficient ratio squared	4.136	2.358	2.065	10.977
Path length ratio	1.348	.058	1.258	1.471
Closeness centrality	2.952	.431	1.000	5.185
Structural holes	.273	.160	.000	.679
Local density	.354	.220	.101	1.000
% repeated ties	.096	.157	.000	1.000
Structural equivalence	5.221	2.066	.000	10.899
No. of past hits	3.311	5.854	.000	43.000
No. of ties	28.571	25.568	2.000	396.000
Production size	1.694	.604	.000	2.639
% of new musicals released	.482	.102	.238	.667
Core theater (1 = yes)	.315	.465	.000	1.000
Adjusted ticket prices	10.595	8.012	4.800	35.070
Prime rate	6.528	3.996	1.500	21.500
% change in GDP	.006	.023	−.007	.154
1975 year indicator	.284	.451	.000	1.000

shows) opening the same year (Duncan and Raudenbush 2001). We also ran the reported models with a year trend. Because year trend did not affect the reported results, was not of theoretical significance, and had to be omitted to include the Huber-White correction, we did not include it in the analysis. Along with the sandwich estimator approach, the hierarchical linear model (HLM) can be used to model multilevel analyses. HLM confirmed the sandwich estimator's results.[9]

SMALL WORLDS AND PERFORMANCE

Table 4 displays the number of new musicals, average team size, Q, actual CC, random CC, and CC ratio, and the same quantities for PL for each

[9] The sandwich estimator in OLS is considered statistically preferable to HLM because it produces more reliable estimates of the SEs despite the fact that the coefficient estimates might be more reliable in HLM (Maas and Hox 2004). However, precise estimates of the coefficients are important only if one is interested in computing the variance of the group-level variable across groups, which we are not. Consequently, we present the more familiar and straightforward OLS sandwich model.

year in our data. Consistent with small world theory, the table shows that the CC ratio varies considerably, that the actual CC is always significantly greater than the random CC, and that the PL ratio is consistently near 1.0.

Our main independent variable, Q, peaks in the 1940s and then declines at an uneven rate from the 1950s through the early 1970s. From the early 1970s through the early 1980s it significantly rises and then levels off before dropping again through the mid-1980s, after which it rebounds to its mid-1960s level. This drop and rise in Q signifies that the small world nature of our network decreased and increased over the time frame of this analysis. How does this pattern agree with the historical narrative of the period?

As mentioned above, while the hit machine of Broadway slowed and quickened from 1945 to 1989 it was not because Broadway suffered from a lack of outstanding creative talent, nor did it fail to produce some of its biggest hits of all time. Nevertheless, it faced an accumulation of overlapping conditions that dislocated and relocated the industry's creative talent and traditional audience, reducing and increasing the degree to which the network was strongly or weakly organized as a small world. For creative artists, the historic impact of Hollywood and television (and, to some extent, rock and roll) furnished new prospects for lucrative forms of their artistry. For audiences, Hollywood and television meant that the same entertainment dollars could be split among three rather than just one medium. Both effects created the kind of career uncertainty that would make it less likely for the same creative artists to work on multiple shows and for artists to coordinate their repeat collaborations predictably. Although there are no systematic data on how many Broadway artists split their time between artistic media, Bob Fosse's winning of the Triple Crown indicates that the elites of the network received high praise for working in multiple artistic domains, while the co-location of the television industry and Broadway in New York City meant that television probably recruited local Broadway talent. At the same time, the post–World War II peep shows of 42d Street and the high crime and offensive decay of the 1960s and 1970s Midtown Manhattan area made planning and bankrolling a show a bigger gamble, which further lowered the ability of creative artists to coordinate their collaborations.

While the historical record has provided an indeterminate answer as to whether the "moonlighting" of Broadway's talent on television and in Hollywood brought more back to Broadway than Broadway gave to television and Hollywood, our results suggest that it was disruptive to the small world order of the network. Q's decline reflects the drop in connectivity and cohesion across the global network as it became harder

TABLE 4
SMALL WORLD STATISTICS WITH NEWMAN ET AL. (2001) CORRECTION FOR BIPARTITE NETWORKS

Year	New Musicals	Average Team Size	Cluster Coefficient			Path Length			Q
			Actual	Random	Ratio	Actual	Random	Ratio	CCr/ PLr
1945 ...	14	7.1	.287	.077	3.7	3.13	2.23	1.40	2.63
1946 ...	19	6.8	.295	.073	4.02	3.11	2.24	1.38	2.90
1947 ...	12	6.7	.311	.074	4.15	3.12	2.27	1.37	3.01
1948 ...	16	6.6	.315	.078	4.04	3.14	2.34	1.34	3.01
1949 ...	9	5.8	.319	.089	3.55	3.04	2.36	1.29	2.75
1950 ...	16	8.4	.325	.097	3.34	3.09	2.40	1.28	2.59
1951 ...	11	6.4	.33	.109	3.02	3.06	2.41	1.26	2.38
1952 ...	8	7.0	.328	.109	3.01	3.03	2.36	1.28	2.35
1953 ...	8	8.0	.338	.116	2.9	2.98	2.28	1.30	2.22
1954 ...	11	7.9	.328	.115	2.85	2.98	2.24	1.32	2.15
1955 ...	12	7.8	.33	.133	2.47	2.93	2.22	1.31	1.88
1956 ...	10	7.8	.345	.135	2.55	2.93	2.24	1.31	1.94
1957 ...	11	7.2	.355	.14	2.53	2.97	2.25	1.31	1.92
1958 ...	11	7.0	.353	.136	2.58	3.06	2.25	1.36	1.89
1959 ...	16	7.4	.342	.139	2.45	3.03	2.27	1.33	1.84
1960 ...	13	6.8	.343	.144	2.38	3.06	2.34	1.31	1.81
1961 ...	17	6.1	.338	.146	2.31	3.09	2.38	1.29	1.78
1962 ...	13	6.0	.344	.16	2.13	3.14	2.39	1.31	1.63
1963 ...	13	6.9	.324	.154	2.09	3.21	2.38	1.34	1.55
1964 ...	17	6.9	.314	.147	2.12	3.17	2.38	1.33	1.59
1965 ...	18	7.2	.304	.141	2.15	3.12	2.40	1.29	1.65
1966 ...	13	7.5	.301	.146	2.05	3.04	2.37	1.28	1.59
1967 ...	7	8.3	.302	.148	2.04	2.98	2.33	1.27	1.59
1968 ...	16	7.9	.329	.165	1.98	2.96	2.32	1.27	1.55
1969 ...	13	7.3	.33	.166	1.97	2.97	2.36	1.25	1.57
1970 ...	14	7.0	.331	.167	1.98	2.97	2.36	1.25	1.57
1971 ...	17	6.0	.354	.18	1.96	3.2	2.46	1.30	1.51
1972 ...	16	6.7	.381	.188	2.02	3.53	2.51	1.40	1.43
1973 ...	12	7.4	.389	.193	2.01	3.48	2.56	1.36	1.47
1974 ...	9	6.4	.391	.189	2.06	3.54	2.57	1.37	1.49
1975 ...	17	7.3	.371	.146	2.54	3.74	2.58	1.44	1.75
1976 ...	14	7.7	.376	.146	2.57	3.75	2.58	1.45	1.77
1977 ...	7	7.0	.375	.139	2.69	3.72	2.53	1.47	1.82
1978 ...	19	6.6	.364	.141	2.57	3.61	2.49	1.44	1.78
1979 ...	16	8.6	.358	.148	2.41	3.42	2.45	1.39	1.72
1980 ...	14	7.9	.365	.149	2.43	3.54	2.49	1.42	1.71
1981 ...	17	7.8	.355	.153	2.31	3.48	2.53	1.37	1.68
1982 ...	15	7.1	.355	.169	2.09	3.57	2.53	1.41	1.48
1983 ...	10	8.6	.361	.178	2.02	3.61	2.59	1.39	1.45
1984 ...	4	7.0	.358	.178	2	3.59	2.58	1.39	1.44
1985 ...	9	7.9	.366	.183	2	3.58	2.61	1.37	1.46
1986 ...	8	7.5	.369	.173	2.12	3.69	2.61	1.41	1.50
1987 ...	8	6.3	.383	.207	1.85	3.71	2.67	1.39	1.33
1988 ...	8	6.9	.409	.2	2.04	3.87	2.69	1.43	1.42
1989 ...	10	6.9	.406	.182	2.23	3.6	2.62	1.37	1.62

NOTE.—All figures use the Newman et al. (2001) correction for the estimation of the *CC* and *PL* of a bipartite random graph and include a decay function of seven years (see methods section for details).

for creative artists to coordinate their collaborations predictably than it had been in the past.

Also, consistent with these observations is the recovery of *Q* in the 1980s with the renaissance of Times Square and the influx of international tourists to New York City. (Remember the I Love NY marketing campaign?) The reelevated artistic and commercial options of Broadway enticed creative artists to return to Broadway and to coordinate their collaborations better, prompting a rise in *Q*. Thus, *Q* agrees with the historical narrative while quantifying how exogenous shocks decreased and increased the small world's potential ability to shape the collaboration and creativity of the artists embedded within it, a conclusion examined in more detail below in our statistical tests.

Table 5 and table 6 present our multilevel analysis of the success of a musical. Models 1 and 2 look at the control variables, and models 3 and 4 present our two operationalizations of a small world as linear and as quadratic terms. Appendix table A1 shows the full model with three separate specification tests: (1) outliers removed from the data, (2) a probit specification instead of an ordered probit specification that collapses failure and flops into one category, and (3) standardized coefficients.

Financial Success of a Musical

Table 5 presents the results of the financial success analysis. Together, the control variables for economic and team-level network variables explain about 27% of the variation in hit, flop, and failure according to our pseudo-R^2—a high value given the common belief that the success of artistic productions is essentially unpredictable (Bielby and Bielby 1994). Of the economic variables, size of production and playing in a core theater have two of largest and most stable effects across the models. This suggests that a larger budget and cast widen the appeal of the show, presumably through investments in more extravagant visuals and performing talent, while a show in the core of the district is attractive to theater goers. Our measure of competition failed to reach a level of significance. One explanation for this is that while competition among shows may influence which shows theatergoers will pay for, the amount of money theatergoers are willing to spend increases with the number of quality shows available. Our year dummy for 1975 does not reach significance, indicating that its effect on financial performance is netted out by other variables. This may be a result of the fact that the financial effects of television, Hollywood blockbusters, and cable television could only be partially offset by new technology and "two-for-one" marketing strategies.

The team-level network variables have important effects, increasing R^2 by about 12%, but the effects are unevenly distributed across our mea-

TABLE 5
ORDERED PROBIT ESTIMATES OF THE EFFECTS OF SMALL WORLDS ON THE FINANCIAL SUCCESS OF A MUSICAL, 1945–1989

Variable	Model 1	Model 2	Model 3	Model 4
Small world Q				4.045**
				(1.680)
Small world Q squared				−.836**
				(.359)
CC ratio			3.181***	
			(1.001)	
CC ratio squared			−.490***	
			(.157)	
PL ratio			.766	
			(1.895)	
Closeness centrality		.421**	.485***	.452**
		(.180)	(.187)	(.186)
Structural holes		.846	1.215**	1.220**
		(.530)	(.552)	(.557)
Local density		.875	1.222*	1.214*
		(.571)	(.651)	(.646)
% repeated ties		.294	.276	.328
		(.571)	(.605)	(.587)
Structural equivalence		.028	.039	.035
		(.043)	(.042)	(.042)
No. of past hits		.032***	.030***	.030***
		(.011)	(.011)	(.011)
No. of ties		.001	.001	.001
		(.002)	(.002)	(.002)
Production size	1.284***	1.285***	1.324***	1.315***
	(.164)	(.189)	(.196)	(.195)
% of new musicals	−1.164*	−1.480**	−.594	−.797
	(.698)	(.708)	(.801)	(.786)
Core theater (1 = yes)	.565***	.480***	.476***	.483***
	(.115)	(.118)	(.118)	(.120)
Adjusted ticket prices	−.002	.003	.031	.026
	(.016)	(.016)	(.019)	(.020)
Prime rate	−.038	−.031	.005	−.002
	(.027)	(.026)	(.028)	(.028)
% change in GDP	−3.439*	−3.328	−3.053	−3.121
	(2.018)	(2.154)	(2.183)	(2.194)
1975 year indicator	−.182	−.112	−.730	−.428
	(.419)	(.457)	(.529)	(.473)
Observations	462	442	442	442
χ^2	130.76	157.1	169.2	172.0

NOTE.—Robust SEs in parentheses. See methods section and app. table A1 for additional specification tests.
* $P < .10$; two-tailed tests.
** $P < .05$.
*** $P < .01$.

TABLE 6

OLS Estimates of the Effects of Small Worlds on the Artistic Success of a Musical, 1945–1989

Variable	Model 1	Model 2	Model 3	Model 4
Small world Q				4.311**
				(1.794)
Small world Q squared				−.942**
				(.379)
CC ratio			3.584***	
			(1.253)	
CC ratio squared			−.580***	
			(.198)	
PL ratio			.344	
			(1.904)	
Closeness centrality		.591**	.558**	.527*
		(.265)	(.258)	(.261)
Structural holes		−.105	.117	.147
		(.517)	(.491)	(.471)
Local density		−.464	−.286	−.264
		(.570)	(.597)	(.564)
% repeated ties		.556	.636	.629
		(.382)	(.392)	(.386)
Structural equivalence		.067	.070*	.071*
		(.040)	(.039)	(.039)
No. of past hits		.031***	.028***	.028***
		(.009)	(.009)	(.009)
No. of ties		−.015***	−.015***	−.014***
		(.003)	(.004)	(.004)
Production size	.341	.282	.365	.350
	(.225)	(.230)	(.227)	(.227)
% of new musicals	−.171	−.437	.277	−.048
	(.724)	(.690)	(.837)	(.845)
Core theater (1 = yes)	.333***	.149	.130	.139
	(.118)	(.119)	(.111)	(.115)
Adjusted ticket prices	.003	.015	.004	.006
	(.048)	(.055)	(.043)	(.045)
Prime rate	−.063	−.063	−.021	−.033
	(.038)	(.042)	(.048)	(.051)
% change in GDP	−2.166	−1.389	−1.505	−1.387
	(2.414)	(2.565)	(2.643)	(2.578)
1975 year indicator	−.164	−.062	−.498	−.266
	(.515)	(.609)	(.654)	(.617)
Constant	−.442	1.526	−4.906	−3.833
	(.645)	(1.179)	(3.437)	(2.707)
Observations	321	315	315	315
R^2	.09	.20	.22	.21

Note.—See methods section and app. table A1 for additional specification tests. Robust SEs in parentheses.

* $P < .10$; two-tailed tests.

** $P < .05$.

*** $P < .01$.

sures. While the more central teams and teams with past hits are more likely to launch a hit, as expected, the number of past collaborators has a null effect, suggesting that for success, quality of experience is more important than quantity. Teams with more structural holes also affect success in the full model, consistent with recent findings by Burt (2004) on the network sources of good ideas. Local density, repeated ties, and structural equivalence have null effects. Thus, a team that is locally densely connected, made up of many repeated ties, or made up of members who have had similar experiences with the same third parties is not a reliable indicator of financial success or failure once we control for other factors.

Our hypothesis predicted an inverted U-shaped relationship between our network's level of small worldliness and the probability of financial success. We argued that an intermediate level of small worldliness would increase the probability of success, while low and high levels of small worldliness would dampen prospects of success. To test this hypothesis we used two specifications of small worldliness. First, we introduced into our control variable models the small world Q as a linear and as a quadratic term. Consistent with our prediction, the linear small world Q was positive and significant, and the squared small world Q was negative and significant. Second, we introduced into control variable models the CC ratio and CC ratio squared along with the PL ratio as a control. Again, consistent with our prediction, the linear term was positive and significant, and the quadratic term was negative and significant. These findings suggest that as the level of connectivity and cohesion increase at the global level of analysis, the probability of success increases up to a certain threshold, after which point increases in the amount of order harm financial success.

Artistic Success of a Musical

Artistic success is affected by economic and team-level network variables in ways that are similar to financial success but with notable exceptions. As with financial success, a team with central artists and a track record of past hits gets high artistic marks from the critics. The number of previous collaborators had no effect on the financial success model but had a negative effect on artistic success. This negative effect seems somewhat counterintuitive given that conventional wisdom holds that experience breeds success. One reason for this discrepancy may be that artists who develop expansive contact networks do so at the expense of depth (Faulkner and Anderson 1987).

Two other notable differences exist between the artistic and financial success models. Whereas in the financial success models size of production and core theater had large effects, in the artistic success model these variables have null effects. This suggests that whereas the public gravitates to large, extravagant, and centrally located shows, critics' notices are not swayed by these factors—a finding that is consistent with the belief that a critic's impression of a musical's artistic merits should be independent of factors that are weakly related to content.

As predicted by our hypothesis, both our operationalizations of small worldliness are in the expected directions. The linear term was positively related, while the squared term was negatively related for both the small world *Q* model as well as the *CC* ratio model, holding the *PL* ratio constant. Thus, consistent with our theory and prediction, we found that the small worldliness had a robust effect on two separate but related performance behaviors of the system, reinforcing the generality and originality of our results.

Financial and Artistic Success of a Season

It follows logically from our multilevel arguments that if a small world affects the behavior of actors within the system, it should also affect cognate behavior at the system level. If we are correct that the small world structure influences the creativity of production teams through variations in the level of connectivity and cohesion in the global network, then during periods of optimal connectivity and cohesion the *collective* success of teams in that year should also be superior to the collective success of teams in years of suboptimal connectivity and cohesion. By looking at the effect of a small world at multiple levels, we submit our arguments to tests that are both conservative and multifaceted.

To test the effects of small worlds at the system level, we regressed our three system-level variables: (1) the annual percentage of hits; (2) the annual percentage of rave reviews; and (3) the annual average of reviews on the other relevant system-level control variables: number of teams with a past history of producing hits, number of shows opening in core theaters, percentage of shows that were new musicals that year, ticket price, prime rate, and GDP.

Table 7 presents the results of our three system-level dependent variables. The models show good fit to the data, with an R^2 of .37, .40, and .48, respectively. Consistent with our predictions, all three measures of systemic-level performance have an inverted U-shaped relationship with our two operationalizations of a small world. These results provide another array of confirmatory evidence in support of our small world theory.

TABLE 7

OLS Estimates of the Effects of a Small World on the Percentage of Hit Shows, Percentage of Rave Shows, and Average Critics' Reviews per Season, 1945–1989

	% Hit Shows			% Rave Shows			Average Critics' Score across All Shows	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Small world Q			1.436***			1.636***		5.553***
			(.505)			(.493)		(1.865)
Small world Q squared			−.311***			−.357***		−1.212***
			(.114)			(.111)		(.419)
CC ratio		1.117***			1.162***		3.953***	
		(.354)			(.350)		(1.314)	
CC ratio squared		−.181***			−.188***		−.639***	
		(.059)			(.058)		(.219)	
PL ratio		.262			−.090		−.913	
		(.588)			(.560)		(2.10)	
No. of teams with hits	−.001	.001	−.001	.002	.002	−.000	−.016	−.021

	(.012)	(.011)	(.011)	(.012)	(.011)	(.010)	(.039)	(.039)
No. of shows in core theaters	.004	−.000	.005	.013	.009	.016	−.006	.017
	(.018)	(.017)	(.017)	(.020)	(.018)	(.017)	(.067)	(.066)
% of new musicals	−.311	−.065	−.148	−.203	.151	.024	.827	.351
	(.294)	(.285)	(.279)	(.295)	(.284)	(.273)	(1.06)	(1.032)
% change in GDP	1.184	1.461*	1.309	.129	.458	.333	5.75*	5.400*
	(.907)	(.835)	(.836)	(.877)	(.780)	(.766)	(2.93)	(2.899)
Adjusted ticket prices	−.003	.007	.005	−.009	.002	.001	−.032	−.033
	(.005)	(.006)	(.005)	(.012)	(.012)	(.011)	(.044)	(.042)
1975 year indicator	−.060	−.202	−.114	−.037	−.156	−.120	−.312	−.284
	(.090)	(.125)	(.085)	(.110)	(.138)	(.099)	(.517)	(.375)
Constant	.415***	−1.717*	−1.266**	.310*	−1.478	−1.623***	−4.630	−5.929
	(.131)	(1.010)	(.582)	(.161)	(1.005)	(.585)	(3.770)	(2.215)
Observations	45	45	45	37	37	37	37	37
R^2	.18	.37	.34	.13	.40	.39	.48	.46

NOTE.—OLS results are shown; Tobit models of the percentage dependent variables produced nearly identical estimates. See methods section and app. table A1 for additional specification tests.

* $P < .10$; two-tailed tests.

** $P < .05$.

*** $P < .01$.

Effect Sizes

Figures 4, 5, 6, and 7 visually present the bivariate relationships for our small world Q and the probability of a hit versus a flop, an artistic success, percentage of hits, and percentage of raves, respectively. All four graphs support one inference: an intermediate level of small worldliness produces the most beneficial small world effect on *both* financial and artistic success. Either too little order or too much order in the level of small worldliness dampens the likelihood that a musical succeeds.

Figure 4 shows the magnitude of the effect of Q on financial performance. The results indicate that at the predicted bliss point of Q (about 2.6), a musical's probability of being a hit is about 2.5 times greater than the lowest value of Q (about 1.4), while the probability of a flop drops by 20%. Figure 6 shows that the chance of the percentage of hits in a season is over three times greater at the bliss point (about 2.37) than when small worldliness is low (about 1.4). Figures 5 and 7 display the relationship between the small world Q and artistic success. The graphs show that the chances of a show's being an artistic success are about three times greater at the bliss point (about 2.3) than at the lowest level of Q, while in figure 7, the chances of the percentage of raves per year goes up about four times at the bliss point in figure 7.

Several noteworthy patterns are prompted by a comparison of the effects of small worlds on commercial and artistic success. First, the patterns suggest that both fiscal and artistic success is hurt more by too little connectivity and cohesion than by too much connectivity and cohesion, at least within the range of Q in our data. Too little order is worse than too much. Second, while artistic and commercial success are affected differently by different variables (e.g., being in a core theater had no effect on critics' appraisals), the effects of the small world structure on our dependent variables are similar across different specifications and levels of analysis. The consistency of effects of the small world suggest that they are structurally robust in their effect on behavior, perhaps governing a fundamental aspect of creativity in teams such that whether the objective is commercial success, artistic success, or both, an optimal balance of order in the network generates a regular pattern of effects, an effect that could partly account for the high incidence of small world networks in diverse systems of exchange as well as their robustness.

Post Hoc and Out-of-Sample Confirmatory Tests

Despite the consistent confirmation of the U-shaped effects for multiple estimators and model specifications, the removal of outliers, and compound levels of analysis, it is worth noting the uneven dispersion of data

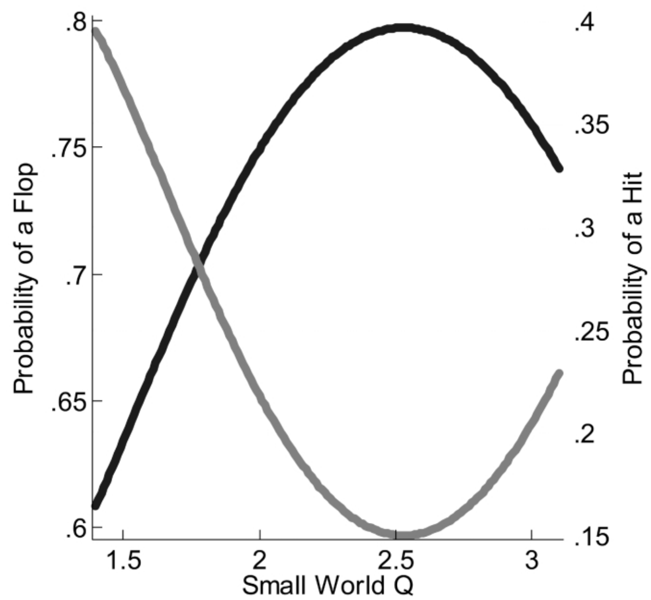

FIG. 4.—Financial success of a show

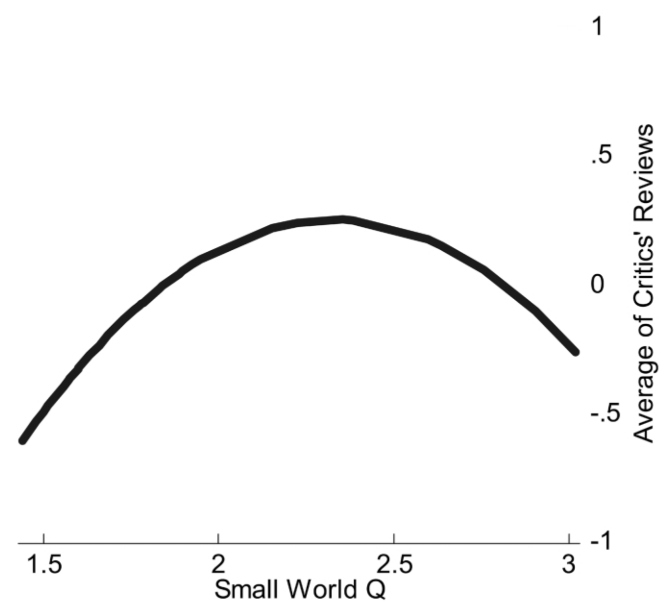

FIG. 5.—Artistic success of a show

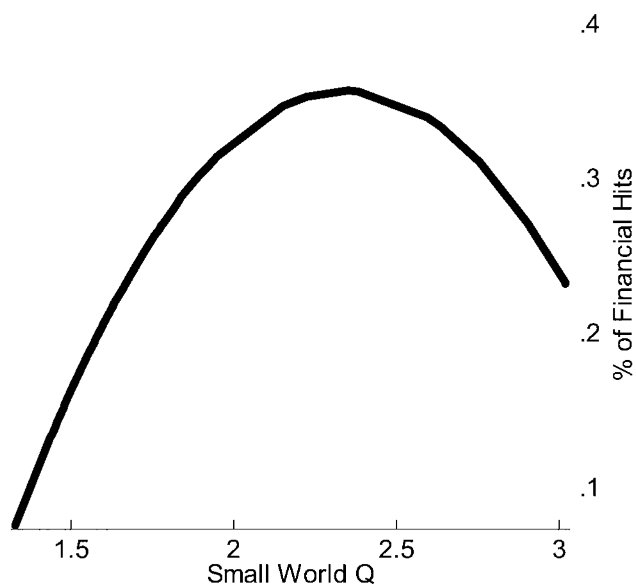

FIG. 6.—Financial success of a season

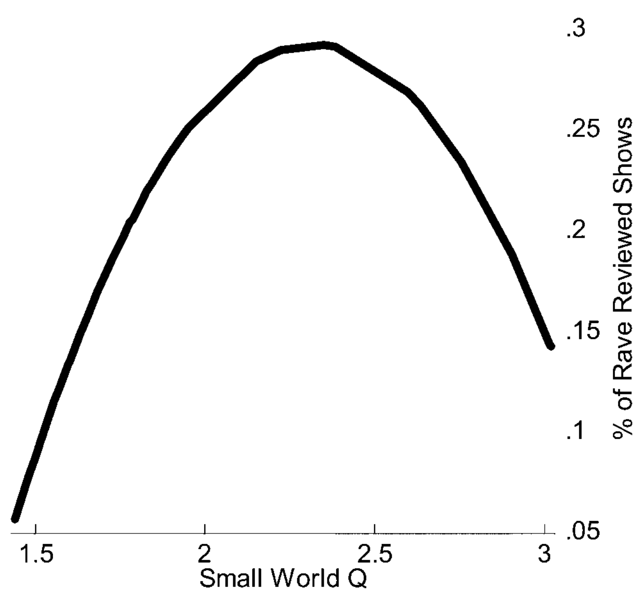

FIG. 7.—Artistic success of a season

across the curves. About 80% and 85% of the data lie to the left of the crest for the artistic and financial success models, respectively. These figures might suggest that the data to the right of the bliss point are rare, and if so, the analysis can simplify to a positive and linear relationship.

While a positive and linear relationship would still be an important finding for a truncated sample of data, we believe this conclusion is premature and may be misleading. First, under most circumstances, a result that involves 15%–20% of the population is nontrivial. Second, the inclusion of these cases is vital for theory building because they show how performance changes over the range of our small world's variation rather than a truncated sample. Third, a straightforward regression of the dependent variables on Q as a linear term does not reach significance (available from authors). Thus, if these data were disqualified they could produce misleading conclusions. One could falsely infer that increasing small worldliness is uniformly beneficial, leading to suboptimal decisions.

Another way to view this problem is to extend our analysis backward in time to the years prior to 1945, namely, 1900–1945, where Q is often above our bliss point value of 2.5. This suggests that Q-values to the right of our bliss point are not rare, but normative, when considered over a fuller time frame. Unfortunately, we could not include the Q-values from before 1945 in our statistical analysis because the detailed multilevel, multivariate data that we have for the 1945–89 period does not exist for the earlier period. The only data that were available for the earlier period were the names of the creative artists who worked on each musical, which we used to compute Q, and a list of hits for 1919–30 that was compiled by Bordman (1986) and corroborated by Jones (2003, p. 360–61). These hit data offer two experts' opinions of the successful shows for the 1919–30 period using criteria that are comparable to the hit criteria we used in the above statistical analysis. Another advantage of this period for comparison purposes is that it can be ruled out that either a poor economy or a lack of talent affected the rate of flops during the 1919–30 seasons, because the economy was strong, and Broadway was flush with talent (Porter had 2 shows; Rodgers and Lorenz Hart, 12 shows; Hammerstein, 13 shows; Berlin, 1 show; Eubie Blake, 3 shows; Anne Caldwell and Jerome Kern, 15 shows; Coward, 1 show; and Gershwin, 12 shows). Thus, while these data cannot definitively test our model outside the range of data we examined in this article, they do furnish data that can broadly refute or support the representativeness of our findings.

When we examined the relationship between Q and the percentage of hits 1919–30, the analysis substantiated our findings. From 1919 to 1930, Q attained an average value of 4.8, which is among the highest in the history of Broadway. According to our theory, this would suggest a low hit rate. Consistent with this prediction, about 90% of the new shows were flops from 1919 to 1930. By comparison, in the 1945–89 period, when Q was around the bliss point, about 75% of the shows were flops. Thus, these data and tests, while only circumstantial, corroborated the U-shaped relationship for periods beyond the one studied.

DISCUSSION

Small world networks have been shown to arise in a surprisingly wide variety of organized systems, from power grids to brain cells to scientific collaborations. The high incidence with which they occur has led to the speculation that there is something fundamental and generalizable about how they organize and govern success in biological, physical, and social systems alike. The objective of this research was to test that speculation directly with regard to human creativity and to specify theoretical mechanisms that can explain it. We had hoped to create an understanding of the key performance properties and conditions that lead to beneficial, disadvantageous, or benign small world network effects.

Our context for study was the network of creative artists who create original Broadway musicals. We reconstructed the network from archival data that included every artist who worked on every original Broadway musical released from 1945 to 1989. These data also included vital time-varying statistics on the economic characteristics of the market, the productions, the relative talent of artists, the local network characteristics of the creative teams, and two measures of creativity on the musical—financial success and artistic merit. We found that small world networks have a robust and novel impact on performance. Small world networks do benefit performance but only up to a threshold, after which the positive effects of small worlds reverse.

To explain this behavior we focused on the two properties that define a small world—the CC ratio and the PL ratio, or simply the small world Q (formally, CC ratio/PL ratio). We reasoned, following various branches of network theory, that as the small world Q increases, the separate clusters that make up a small world become more connected and connected by persons who know each other well through past collaborations or through having had past collaborations with common third parties. This suggested that if the small world Q is low, creative material remains cloistered in the separate teams that make up the small world. This isolating process is aggravated by the fact that the few links that do exist between teams and that can transfer novel but unfamiliar material are also more likely to be hit and miss in the sense that they are not disproportionately made up of firsthand third-party ties in common or repeat ties. As the level of the small world Q increases to a medium level, the level of connectivity and cohesion in the network also rises. There is an increase in the level of connections among teams in the network, and these connections are increasingly made up of cohesive ties—repeated and third-party-in-common relationships—that add the necessary level of credibility needed to facilitate the spread of potentially fresh but unfamiliar creative material by artists in the network. We also reasoned that too much small worldliness can undermine the very benefits it creates at more moderate levels. If the small world Q rises beyond a threshold, the network increases in connectivity and cohesion to a point at which the positive effects of connectivity turn negative. High levels of connectivity homogenize the pool of creative material, while repeated ties and third-party-in-common ties promote common information exchanges, decreasing artists' ability to break out of conventional ideas or styles that worked in the past but that have since lost their market appeal.

Consistent with our hypotheses, we found that the level of small worldliness has a curvilinear effect on performance. Adding to the confidence of our inference is that these effects hold independent of levels of analysis, multiple operationalizations of our small world concepts, several model specification tests, and two different dependent variables.

Bipartite (Affiliation) and Unipartite Small World Networks

An important part of our framework rests on the distinctiveness of unipartite projections of bipartite graphs or what are also called affiliation networks. These types of networks are common in many types of social systems. For example, bipartite-affiliation networks characterize board of directors networks, scientific collaboration networks, movie actor networks, and project teams of all kinds (see figs. 1 and 2). In general, they occur whenever invention is based on teamwork such that the end product is collaborative handiwork. What is unique about these networks is that at the team level, they constitute fully connected cliques, and at the global level, they create a network of dense overlapping clusters joined together by actors who have multiple team memberships—or classic small world networks. Our conceptualization of how a small world affects behavior was specific to bipartite-affiliation networks. We did not speculate on how our theory would change for unipartite theories, a natural direction for future research.

Nevertheless, by addressing the key role and special features of bipartite-affiliation networks for social behavior, as well as their relative lack of attention in past network research, we hope to have enhanced the potential impact of this work. In that regard, the generality of our model seems most apropos for the many kinds of networks where production is team based and roles are specialized, decentralized, and interdependent.

For example, one could imagine extensions of our model for project teams, boards of directors, voluntary and community service teams, small-size military units and other security teams, or government cabinets. With regard to project teams based in commercial business firms or labs in research and development organizations, it follows logically that a testable hypothesis would be that the optimal level of product success increases with a medium level of small world connectedness and cohesion. In commercial firms, this level could even be targeted by design with purposeful levels of task rotation, job reassignment, or cross-training across practice areas. In more market-governed project teams such as coauthor or copatenting networks in science, the model might be developed to compare the relative creative potential of different fields (see Guimera et al. 2005). For example, do fields that come to rest too far to the left of the bliss point indicate a lack of ability to assimilate the diverse talent in their fields successfully? Will the science produced from fields far and close to the bliss point vary in their impact factors?

From another direction, a question could be asked as to whether our results hold for the creative enterprises not at the center of a field but at its edge. Would we find the same patterns for off-Broadway and experimental theater, where there is less of a focus on creativity through convention plus extension than there is for Broadway? While more research is obviously needed before extensions of this research can be made to other contexts and to target levels of Q, it does provide a new avenue of research that follows in the tradition of research on the strength of weak ties and embeddedness, which have been extended from their original sites of job search and organizational behavior to social movements, gender and race studies, mergers and acquisitions, norm formation, price formation, international trade, and other socioeconomic phenomena (Montgomery 1998; Rao et al. 2001; Lincoln, Gerlach, and Takahashi 1992; Sacks, Ventresca, and Uzzi 2001; Ingram and Roberts 2000; Uzzi and Lancaster 2004).

Egocentric and Global Networks

The small world problem also relates to the interplay between egocentric and global network structures. While it seems true that most network research has focused on local network effects that are attached to specific individuals, or what is called egocentric network phenomena, it is also true that there exists a powerful literature on community structures (Feld 1981; Baker and Faulkner 1991; Padgett and Ansell 1993; Markovsky and Lawler 1994; Frank and Yasumoto 1998; Friedkin 1984; Stark and Vedres 2005; Kogut and Walker 2001; Moody and White 2003; Moody 2004; Bearman, Moody, and Stovel 2004). Our work follows other community-level analysis in looking at how the global structure affects performance. In this work, we have shown how one of possibly several conceptualizations of the global network can influence a system's performance, while treating the interplay of global and local network effects as net of one another.

Our main concept in discussing this aspect of the relationship between local and global properties is that the global network affects the *distribution* of creative materials, that is, the joint distribution of actors and teams, available to all actors in the network, and therefore the effects of their egocentric characteristics are contingent on the small world network within which they are embedded. This suggests that egocentric properties such as structural holes, weak ties, or embedded ties (Granovetter 1973; Uzzi 1997, 1999; Burt 2004) are likely to have consistent but conditional effects that depend on the small worldliness of the network they are embedded in. Thus, one path for new research could concentrate on the statistical interactions between global and local network mechanisms.

Another important distinction between egocentric and global network conceptualizations is that the behavior of the global network may be only partly a consequence of egocentric behavior, and its strategic design is therefore partly beyond the control of individual actors. This important concept of *randomness* is rarely addressed in the empirical modeling of egocentric networks but is actively conceptualized and estimated when computing the global structure as a way of separating systematic global network effects from a simple model of random consequences that can arise in a global network, like Broadway's, where actors act separately from each other and without knowledge of, or perhaps intention to shape the global network. Nonetheless, they affect each other's behavior through their collective simultaneous actions in the global network. This view implies an invisible-hand-like phenomenon for global social network structures. While this view may be in contradiction to the historic dichotomy of markets and networks as well as the emphasis of egocentric network analysis on strategic design and nonmarket behavior, it has a basis in other scientific disciplines where the robustness of the global network to breakdown, the emergence of networks, global welfare benefits, and other systemic network behaviors have been examined relatively more than egocentric behavior. Thus, one possible way to begin looking at the relations between egocentric and global network phenomena is to bring these two research traditions together, a process that is already showing fruitfulness (Frank and Yasumoto 1998; White 2003; Burt 2004; Bearman, Moody, and Stovel 2004; Moody 2004; Guimera et al. 2005; Powell et al. 2005; Stark and Vedres 2005).

Another path is to link the small world conception of global networks with other global conceptions such as cohesive subgroupings, community partitions, or the core/periphery hierarchy. In particular, an important problem to analyze is how these other approaches to global network structure treat bipartite networks. We spot two issues. First, because of the dense overlapping nature of fully linked cliques in a bipartite network, it is not clear where the partitions of communities might begin and end (Abbott 1996). This is because the criteria used to define a community's boundary is that set of agents with more in-group than out-group ties, which in a bipartite-affiliation network is the team itself, because each team is a fully linked clique. Obviously, to make community partitions viable scientifically, there would need to be a logic for aggregating communities from teams, which brings up the second issue worth pursuing. As noted above, in bipartite-affiliation graphs, there is an inflated level of clustering because of the fully linked cliques. This means that before progress can be made toward analyzing the community structure of bipartite-affiliation graphs, there needs to be a null model of what constitutes the correct ratio of in-group and out-group ties as well as the correct number of partitions. We estimate that an answer to this issue might lie in a solution similar to that of the bipartite small world model. The key measures of connectivity and cohesion are not the within-team ties that have been typical of community network analysis, but the between-team ties. An examination of these methodological issues is beyond the scope of this article, yet provides one possible route for future research that can begin to show the points of commonality and complementarity between different approaches to the global structure of networks.

Small Worlds, Culture, and History

To better relate how our specific quantitative measures of the network coevolved with the culture and history of this creative industry, we showed how the behavior of Q varied with exogenous conditions, dropping and rising as other artistic domains struck at the foundations of artists' intentions and ability to plan their Broadway collaborations reliably. For Broadway, the emerging artistic media of television, post–World War II Hollywood, and rock and roll raised the uncertainty associated with building network ties with other artists. Artistic collaborations became more competitive to create and harder to schedule as artists split their time between domains, experimented in other domains, or permanently lost collaborators to non-Broadway undertakings, particularly television, which stole market share and tempted Broadway stars with a chance for overnight national stardom (e.g., Rodgers and Hammerstein agreed to be the first guests to appear on the *Ed Sullivan Show*).

It is worth mentioning here in more detail how our mathematical model registers these historic cultural changes in this creative industry. As we noted above, the drop in Q represents a decrease in the number of between-team ties and the number of cohesive ties in the creative artist network. But Q is the *CC* ratio/*PL* ratio, and so the exact source of the change may be a result of the numerator, denominator, or both. Our above results indicated that the *PL* ratio was relatively constant from 1945 to 1989. This means that the change in Q resulted from the *CC* ratio. When we examined the *CC* actual and *CC* random separately, we found that both quantities increased over the time period, but that the *CC* random increased faster than the *CC* actual (hence, the net drop in Q, holding *PL* ratio constant).

But what does it mean for the *CC* random to increase faster than the *CC* actual in terms of actual human behavior? The increase in the *CC* actual means that more artists were working on only one production. (Remember, in the extreme case where all artists work on one production only, the network is made up of many isolated, fully linked cliques, and therefore would have a *CC* actual of 1.0, where 0.0 is no clustering and 1.0 is complete clustering.) By the same logic, the estimate of the *CC* random for a network of isolated, fully linked teams would also have to be 1.0. Thus, the faster rise in the *CC* random relative to the *CC* actual means that our model (Newman et al. 2001) estimated that the percentage of between-team ties that were attributable to *random connections among artists* rose more quickly than did the actual percentage of between-team ties calculated with the *CC* formula.

This reasoning produces the interesting conclusion that the rising uncertainty in partnering and network building experienced by creative artists instigated a rise in the propensity of artists to form random links. This is not to say that artists randomly formed teams, but that the ability to forecast and design collaborations regularly was curtailed, infusing happenstance into the process by which collaborators were chosen. If an artist's first choice for a collaborator was unavailable for a production (perhaps the artist's first choice was waiting on a television or film production), the artist would be more inclined to experiment with partners with whom they had not worked in the past or with whom they did not have third-party ties in common. This is what is meant by more randomness in the network—the choices of our collaborators are less dependent on the persons with whom we have worked in the past or the affiliations of our third-party ties, and more on who is the best available of those beyond our circle of cohesive relations. In essence, as the intensity of the small world properties of our network decreased, the network acted more like a public market for talent.

Although these connections between history and our quantitative model are somewhat speculative, they raise interesting questions regarding the response of the network to uncertainty. One might argue that increased uncertainty would have motivated actors to go with well-known associates rather than with strangers (Granovetter 1985), yet our findings suggest that the opposite occurred. What we cannot unequivocally determine at this point is whether the observed result was a second-best solution to being able to work with known associates who were simply unavailable, or whether the experimentation with new ties was a desirable strategy for coming up with fresh artistic material in an industry that was trying to adapt to the social milieu of the times.

Dynamics

These observations suggest that a next step is the study of network dynamics. If small world networks can have positive and negative impacts, how do they arise and evolve? What factors lead to the formation of a small world as opposed to another type of network? What factors lead to small worlds that have optimal Q's? What is the role of the intentionality of individuals beyond the compositions of their local network ties? And conversely, what factors lead to stasis, the lock-in of a high- or low-performing network, or a network's transformation from one type of network into another? While work in this area is nascent, the findings that a small world affects performance can be enriched by understanding how they come to pass and change—an important goal in an epoch of connectedness.

APPENDIX A

TABLE A1
Sensitivity Specification Tests of Small World Effects

Variable	Outlier Sensitivity Financial Success		Outlier Sensitivity Artistic Success		Probit of Hit versus Flop		Standardized Coefficients for Financial Success		Standardized Coefficients for Artistic Success	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Small world Q		5.930***		7.483***		5.795**		1.8117		1.9338
		(2.048)		(2.699)		(2.403)				
Small world Q squared		−1.312***		−1.729**		−1.369**		−1.6337		−1.8735
		(.468)		(.654)		(.543)				
CC ratio	4.431***		6.305***		4.730***		1.9855		2.1872	
	(1.199)		(1.412)		(1.385)					
CC ratio squared	−.727***		−1.092***		−.835***		−1.82312		−2.1291	
	(.206)		(.240)		(.231)					
PL ratio	.904		.513		1.808		.1177		.0775	
	(1.828)		(1.690)		(1.786)					
Closeness centrality	.497***	.449**	.522*	.467	.275	.227	.2074	.1945	.1892	.1803
	(.178)	(.177)	(.270)	(.279)	(.243)	(.241)				
Structural holes	1.304**	1.335**	.212	.324	.652	.675	.1958	.1949	.0243	.0215
	(.584)	(.588)	(.557)	(.509)	(.728)	(.729)				
Local density	1.289*	1.306*	−.112	−.042	1.129	1.111	.2718	.2671	−.0445	−.0502
	(.695)	(.686)	(.659)	(.605)	(.833)	(.816)				
% repeated ies	.446	.519	.666	.664	.742	.829*	.0427	.0515	.0993	.1001
	(.668)	(.651)	(.462)	(.453)	(.516)	(.482)				
Structural equivalence	.044	.038	.074*	.077*	.099	.088	.0806	.0733	.1379	.1370

	(.047)	(.046)	(.040)	(.042)	(.061)	(.058)				
No. of past hits	.030***	.030***	.026**	.026***	.026**	.026**	.1728	.1743	.1797	.1803
	(.011)	(.011)	(.010)	(.010)	(.012)	(.012)				
No. of ties	−.001	−.000	−.013***	−.012**	−.001	−.000	.0211	.0279	−.2827	−.2769
	(.006)	(.006)	(.004)	(.005)	(.008)	(.007)				
Production size	1.245***	1.234***	.309	.297	.447**	.428**	.7993	.7943	.1448	.1382
	(.190)	(.189)	(.238)	(.238)	(.208)	(.207)				
% of new musicals	−.323	−.631	.660	.228	−.706	−1.027	−.0852	−.0814	.0013	−.0049
	(.869)	(.855)	(.900)	(.936)	(.933)	(.929)				
Core theater (1 = yes)	.497***	.510***	.131	.143	.458***	.473***	.2251	.2250	.0665	.0669
	(.120)	(.121)	(.110)	(.117)	(.141)	(.143)				
Adjusted ticket prices	.037**	.033*	.000	.006	.021	.016	.2448	.2102	.0260	.0204
	(.019)	(.019)	(.043)	(.043)	(.026)	(.028)				
Prime rate	.005	−.003	−.011	−.027	−.003	−.012	.0328	−.0066	−.0824	−.1295
	(.028)	(.028)	(.046)	(.049)	(.033)	(.033)				
% change in GDP	−3.335	−3.322	−1.543	−1.330	−4.512	−4.628	−.0679	−.0709	−.0282	−.0274
	(2.188)	(2.178)	(2.626)	(2.527)	(3.401)	(3.424)				
1975 year indicator	−.794	−.473	−.638	−.350	−.615	−.211	−.3460	−.1926	−.1947	−.0982
	(.507)	(.449)	(.627)	(.602)	(.603)	(.563)				
Constant			−8.987**	−7.373**	−10.622***	−7.569**				
			(3.409)	(3.434)	(3.464)	(3.120)				
Observations	408	408	288	288	401	401				
R^2	.27	.27	.23	.21	.14	.14				

* $P < .10$; two-tailed tests.
** $P < .05$.
*** $P < .01$.

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