MASTER'S THESIS

THE RESILIENCE OF DYNAMIC HUB STRUCTURE AND DECAY IN HUBS' CREATIVE CAPABILITY IN THE KOREAN POP MUSIC INDUSTRY, 1929-2012.

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ABSTRACT

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This study examines how decay in hubs' creative capability and their inter-temporal changes influence performance in a creative field. Drawing on the literature on complex networks and the concept of knowledge recombination, I find that the proportion of hubs with decay in creative capability has curvilinear (i.e., inverted U-shaped) effect on creative performance in a network with static hubs – that is, a social system can reach the highest level of performance when few static hubs refrain from adopting new knowledge. This study also finds that a network with inter-temporal changes in hubs is resilient to such decay and consistently result in higher performance than a network with static hubs, since such changes serve as crucial access to knowledge diversity within the whole system.

Keywords: Network; Hub; Knowledge Recombination; Innovation; Music Industry.

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INTRODUCTION

Recent years have seen a surge of interest in the effects of network structure on creative performance (e.g., Uzzi & Spiro, 2005; Guimera, Uzzi, Spiro, & Amaral, 2005; Singh, 2005; Newman, Barabasi, & Watts, 2006; Fleming & Marx, 2006; Fleming, King III, & Juda, 2007a; Fang, Lee, & Schilling, 2010; Mason & Watts, 2012; Chang, Lee, & Song, 2013). A stream of research has identified that hubs play an important role in many creative fields – from technological innovation and academic research to Hollywood movies and Broadway musicals (e.g., Newman, 2000, 2004; Albert & Barabasi, 2000, 2002; Barabasi, Jeong, Neda, Ravasz, Schubert, & Vicsek, 2002; Girvan & Newman, 2002; Moody, 2004; Uzzi & Spiro, 2005; Guimera et al., 2005; Goyal, van der Leij, & Moraga-González, 2006; Clauset, Shalizi, & Newman, 2009; Azoulay, Zivin, & Wang, 2010). A hub refers to an individual with extremely large number of social ties, far more than most, which tends to have disproportionate influence over the social system (Barabasi & Albert, 1999). By interconnecting many different small groups, such individuals act as essential ingredients to the cohesiveness of the whole system (Albert, Jeong, & Barabasi, 2000; Cohen, Erez, Ben-Avraham, & Havlin, 2000, 2001). Yet, to date, the role of these hubs and their benefits remain inconclusive (Guimera et al., 2005; Barabasi, 2005).

The objective of this paper, therefore, is to take a step forward to shed light on the role of hubs on creative performance of a social system. As an exploratory analysis, this paper first examines the large-scale dataset of 277,086 collaborations among 24,986 songwriters (i.e., composers and lyrists) in the Korean pop music industry over the period from 1929 to 2012. Consistent with prior work, the results shows that the collaborative network in the Korean pop music industry has been largely shaped by a few individuals who have produced approximately 5,000 songs by collaborating with more than 700 other songwriters – more than two orders of magnitude larger than the industry average of 6.8 collaborations.

What is interesting in my result is that hubs are not static over time, unlike the results of much of prior research. The hubs have changed over time, as established hubs stumble and lose their connectivity and new hubs suddenly emerge gaining vast connectivity with other individuals. However, most prior studies assume static structure – i.e., hubs do not change over time (Bianconi & Barabasi, 2001; Barabasi, 2005; Braha & Bar-Yam, 2006; Hill & Braha, 2010). Furthermore, much of existing literature tacitly presumes that individuals within a social system constantly possess creative capability to recombine and diffuse new information and ideas. Yet, contrary to the prevalent assumption, anecdotes and remarks of prominent creatives suggest that such established individuals as hubs may lose their creative capability and disengage themselves from acquiring new knowledge.

How does decay in hubs' creative capability affect performance in a creative field? Are inter-temporal changes in hubs conducive to creative performance? If so, what are the underlying mechanisms that allow the whole system to become innovative? In order to address these questions, this study draws on long line of the literature on innovation. This stream of research suggests that the essence of creative performance lies in the dynamics of knowledge recombination (Schumpeter, 1939; Nelson & Winter, 1982; Kogut & Zander, 1992; Hargadon & Sutton, 1997; Fleming, 2001, 2002). Furthermore, it highlights that the efficacy of knowledge recombination depends on the existence of knowledge diversity (Campbell, 1965; Cohen & Levinthal, 1990; March, 1991; Kauffman, 1993; Fang et al., 2010; Posen, Lee, & Yi, 2012; Chang et al., 2013).

Integrating this line of reasoning with the recent advances in complex network theory, I predict that the proportion of hubs with decay in creative capability has curvilinear (i.e., inverted U-shaped) effect on creative performance in a network with static hubs (i.e., static hub structure). That is, a social system of static structure may reach the highest level of performance when a small proportion of static hubs crease to learn new knowledge. Furthermore, this study argues that network with inter-temporal changes in hubs (i.e., dynamic hub structure) will be resilient to the adverse consequence of decay in hubs' creative capability and consistently outperform network with static hubs, since such changes serve as a vital source of knowledge diversity within the whole system. In line with the theoretical discussions, I implement a computational model that runs the dynamics of knowledge recombination (Holland, 1992) on theoretical model of network evolution (Bianconi & Barabasi, 2001) to distinguish and examine the effects of both decay in hubs' creative capability and their inter-temporal changes on creative performance.

The remainder of the paper is structured as follows. First, in order to get a clear picture of inter-temporal changes in hubs, this study explores the evolution and the topological properties of collaborative network in the Korean pop music industry. Second, I articulate the theoretical reasoning behind the linkage between such dynamics and creative performance. Building on the theoretical foundation, I then outline an argument on how decay in hubs' creative capability and their inter-temporal changes influence creative performance. Third, the computational models and the results of the simulation are presented in the following sections. Finally, I conclude by discussing the contributions of this paper and their implications for future research.

INTER-TEMPORAL CHANGES IN HUBS

This paper begins by examining how the formation, dissolution, and rewiring of collaboration ties have shaped the social network in the Korean pop music industry, the world's 10th largest and the world's fastest growing music industry (IFPI, 2013), during the period from 1929 to 2012. This study constructs explicit network of such connections using data drawn from the Korea Music Copyright Association (KOMCA). The dataset consists of the entire population of 303,461 copyrighted songs in the Korean pop music industry over the 84-year period. Each copyright lists (1) the song title, (2) the album, (3) the music artists (i.e., singers who perform the music on stage), (4) the songwriters (i.e., composers and lyrists), (5) the music publishing firm, and (6) the filed date of the copyright.[1]

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[1] Constructing such network of distinct individuals using empirical data is complicated by two problems (Newman, 2000, 2001; Fleming et al., 2007). First, two individuals may have the same name. Second, an individual may identify herself in different ways – for instance, using initials or stage names. These issues may cause misidentification of individuals, thereby over- or underestimating the number of collaborative ties. However, this study avoids this problem as the Korea Music Copyright Association (KOMCA) labelled each individual with a 'Trustor code,' a unique identifier that reliably distinguishes distinct artists, composers, and lyrists from one another.

Songwriting in the Pop Music Industry

Here I focus on the collaborations among songwriters, because they comprise the creative individuals responsible for the artistic creation of music (Berkenstadt & Cross, 1998; Shuker, 2007). Preliminary interviews with key informants [2], observation (see Figure 1), and existing documentation on the music industry (e.g., Slutsky, 1989; Gillet, 1983; Miller, 1999; Negus, 1993; Shuker, 2007; Bennett, 2010, 2012; Pettijohn II & Ahmed, 2010) confirmed that work in each setting is highly participatory and knowledge intensive. That is, new idea and knowledge are central to songwriting, in that each song is a unique creative product and requires creative collaboration among songwriters in order to be completed.

Insert Figure 1 about here

During the process of collaboration, individuals interact, observe, and learn firsthand the production process of recombining a vast spectrum of musical skills and knowledge. In an interview, Gun-hyung Yoo, the co-writer and co-producer of PSY's 'Gangnam Style,' highlighted this collaborative process in songwriting:

> PSY and I usually come up with an idea during a casual conversation. "How about this?" I ask, and instantly play a rhythm. He then adds some lyrics to my melody. We would go on and on – improvising and replacing fragments of usable melody and lyrics. For weeks, we would work on the song day and

[2] The informants include composers and lyrists in the four largest Korean music publishing companies – SM Entertainment, JYP Entertainment, YG Entertainment, and CJ E&M.

> night, sometimes separately but mostly together. 'Gangnam Style' was just the same. The released version of the song is very different from the initial one. The song got simpler and trendier. … After that, we spent many nights with the choreographer, testing various animal-inspired dance moves. Not just horse, but panda and bear – literally, everything. And, we finally got something. … It was the horse-riding dance and the music video, along with the effort to combine recent trends and music elements, that led to this sensation.[3]

By doing so, Gun-hyung Yoo and PSY created what London's Mayor Boris Johnson considers "the greatest cultural masterpiece of 2012" (Johnson, 2012).

Paul McCartney provides a more detailed account of such process in recollections of his collaboration with John Lennon (Miles, 1997):

> I wrote it as a more up-tempo thing, country and western. I had the idea, the title, had a couple of verses and the basic idea for it, then I took it to John to finish it off and we wrote the middle together. … Then it was George Harrison's idea to put the middle into waltz time, like a German waltz. That came on the session, it was one of the cases of the arrangement being done on the session. The other thing that arrived on the session was we found an

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[3] The music video of 'Gangnam Style' became the first Youtube video to reach a billion views and, as of May 31, 2014, has been viewed over two billion times. In September 2012, it was recognized by Guinness World Records as the most "liked" video on Youtube, and subsequently won Best Video at the MTV Europe Music Awards. The song topped the music charts of more than 30 countries, including China, United Kingdom, France, Germany, Spain, Australia, and Canada.

> old harmonium hidden away in the studio, and said, “oh, this’d be a nice color on it.” We put the chords on with the harmonium as a wash, just a basic held chord.

By conflating each other’s distinct ideas and musical skills, the Beatles wrote “We can work it out,” the fastest-selling single since “Can’t buy me love” (MacDonald, 2007).

During such collaborative events, songwriters actively engage in the process of continuous improvement by recombining multiple components of prior knowledge. For instance, Bob Dylan, one of the most prolific and arguably the greatest American songwriter of all time (Greene, 2011), initially modeled his performance style on that of Little Richard and his writing style on the songs of Woody Guthrie, the blues of Robert Johnson, and what he considered the “architectural forms” of Hank Williams songs (Dylan, 2004). Yet, he added more sophisticated lyrical compositions and techniques to folk music of the early 1960s and to rock ‘n’ roll of mid-1960s. In Mike Marqusee's (2005) words: “Drawing on folk, blues, country, R&B, rock ‘n’ roll, gospel, British beat, symbolist, modernist and Beat poetry, surrealism and Dada, advertising jargon and social commentary, Fellini and Mad magazine, he forged a coherent and original artistic voice and vision. The beauty of these albums retains the power to shock and console.” In 2008, the Pulitzer Prize awarded him a special citation for “his profound impact on popular music and American culture, marked by lyrical compositions of extraordinary poetic power.”

PSY, in an interview with the New York Times on ‘Gangnam Style,’ further elaborated such recombinatory nature (Ryzik, 2012):

> Every musician in Korea … learns from your (i.e., American) pop – we get inspired. … My lifetime role model and hero is Freddie Mercury of Queen. His songwriting skills, I cannot even approach, but his showmanship, I learned it from videos. … Queen and Bon Jovi, Aerosmith and Guns N’ Roses – I had a huge rock-band mania. … I tried to compose a song – I was in the United States and it was all about hip-hop at the time, 1999-2000. I got inspiration from that kind of music: Tupac, Notorious B.I.G., Dr. Dre, Eminem, and Snoop Dogg. But my spirit and my agenda is play – it’s a mixture right now, I’m doing rockable dance, or danceable rock.

PSY’s exploratory approach was recognized in About.com’s rave review on ‘Gangnam Style’: “Take one part LMFAO's synth-based party music, another part Ricky Martin's Latin dance party and the rest a powerfully charismatic South Korean showman, and you have the first worldwide K-Pop smash hit.”

Combinatory play of musical elements and ideas as such may, in turn, foster innovation in the field of music – generally signaled by the wide use of a new name for a style of music (Peterson & Berger, 1996). Rock ‘n’ roll, one of the non-trivial innovations in popular music, is widely regarded as a blend of rhythm and blues (R&B), folk, country, and gospel music (Gillet, 1983; Miller, 1999; Shuker, 2007; Fleming, Mingo, & Chen, 2007b). On the other hand, K-Pop (i.e., Korean pop music) can be described as a recombination of Western music (e.g., pop, rock, hip-hop, R&B, and electro) and Japanese flavor (e.g., strong visuals) (Benjamin, 2012).

In sum, collaboration among songwriters, as those in scientific research (Newman, 2000, 2004; Barabasi et al., 2002; Girvan & Newman, 2002; Fleming et al., 2007a), document the presence of social interaction (i.e., knowledge recombination) between the involved individuals (i.e., nodes), and can be represented as time-dependent social ties (i.e., edges).

Analysis on the Korean Pop Music Industry

Using records of the filed date of each copyright, I track the time evolution in population growth and connectivity for moving five-year windows (e.g., Newman, 2000; Fleming et al., 2007a).[4] For simplicity, the network considered here is represented as connected graphs, consisting solely of undifferentiated nodes and unweighted, undirected edges (e.g., Newman, 2000, 2004; Albert & Barabasi, 2000, 2002; Barabasi et al., 2002; Girvan & Newman, 2002; Moody, 2004; Uzzi & Spiro, 2005; Guimera et al., 2005; Clauset et al., 2009; Azoulay et al., 2010). As a result, I identified 277,086 collaborations among 24,986 songwriters in the Korean pop music industry during the period from 1929 to 2012.

[4] This study, thus, assumes that an individual enters the industry when she files her first copyright and exits five years after the last enlisted copyright. In addition, I consider two songwriters to be connected if they have produced a music together for moving five-year windows. All the results in this section are fairly consistent regardless of the time horizon of the moving window.

Insert Figure 2 about here

In line with prior research on creative fields (e.g., Newman, 2000, 2004; Albert & Barabasi, 2000, 2002; Barabasi et al., 2002; Girvan & Newman, 2002; Moody, 2004; Uzzi & Spiro, 2005; Guimera et al., 2005; Clauset et al., 2009; Azoulay et al., 2010), the result clearly indicates the presence of dominant hubs in the industry. These prolific individuals have produced approximately 5,000 songs by collaborating with more than 700 other songwriters – exceeding two orders of magnitude larger than the industry average of 6.8 collaborators. One can, thus, see that the tail of cumulative degree distribution with logarithmic binning follows a power-law, $P_{Cum}(k) \sim k^{-\gamma}$, with the degree exponent $\gamma = 1.88$ (see Figure 2).[5] The estimate of the degree exponent is consistent with the scale-free nature of the connectivity in complex network (Barabasi & Albert, 1999), a form commonly seen in physical systems yet hardly observed in social networks (Newman, 2000; Guimera et al., 2005).[6] This contrasts with the Gaussian distribution, for which there is a well-defined scale, in Watts & Strogatz's (1998) small world architecture. Simply put, Watts & Strogatz's (1998) formalization, upon which majority of studies have drawn

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[5] $P(k)$ is the probability that a node in the network is connected to k other nodes, and γ is a positive real number determined by the given network. The term "cumulative" indicates that the data was accumulated over the entire time of observation without taking the moving five-year window into account.

[6] One of the key challenges in assessing social network lies in the fact that the objects of analysis, such as friendship ties, are hard to observe, especially for large numbers of people over extended period of time (Newman, 2001; Watts, 2007). As a result, network data have historically comprised one-time snapshots, often for quite small groups of less than 1,000 agents. Most studies, moreover, have relied on self-reports from participants, which suffer from cognitive biases, errors of perception, and framing ambiguities.

their findings (e.g., Uzzi & Spiro, 2005; Fleming et al., 2007a; Fang et al., 2010; Mason & Watts, 2012; Chang et al., 2013), lacks the prominent role of hubs (Barabasi & Albert, 1999; Watts, 1999). Hence, although prior studies have produced a plethora of findings on social bridges, they have been much less successful in addressing the role of hubs.

Insert Figure 3 & 4 about here

Figure 3, on the other hand, illustrates the degree distribution of snapshots at different times using the moving five-year window. Although the size of the hubs varies in each period, the degree exponent, γ, seems to be independent of time since 1975 (i.e., $\gamma = 2.1 \pm 0.1$). This indicates that, regardless of the time period, topological properties have been rather consistent. However, unlike results of much of prior research, the collaborative network in Korean pop music industry shows inter-temporal changes in hubs (see Figure 4). That is, while a prior hub loses its preeminent ties, a formerly marginal individual gains vast connectivity to become the new nucleus of the system. Accordingly, these individuals have not only redefined the structure of the system over the time period, but also played different roles in the social interaction at different point of time, depending on their position in the social structure (Kossinets & Watts, 2006; Braha & Bar-Yam, 2006; Watts, 2007). This finding demonstrates that the static structure, which is widely assumed in prior literature (Barabasi, 2005), may not properly capture the social dynamics (Feld, 1981; McPherson, Smith-Lovin, & Cook, 2001; Eckmann, Moses, & Sergi, 2004; Kossinets & Watts, 2006; Braha & Bar-Yam, 2006; Hill & Braha, 2010).

THEORY

The Macro Perspective on Networks and the Role of the Hub

The macro-architecture of interpersonal network in a social system provides powerful insights to social dynamics (Granovetter, 1973, 1983, 2005; Blau, 1977; Watts, 1999; Barabasi, 2005; Uzzi & Spiro, 2005). Researchers have suggested that if the system is fragmented into small heterogeneous subgroups, the social dynamics may be maladaptive (Simon, 1962; Granovetter, 1973; Blau, 1977; Barabasi, 2009). This is because the isolated clusters will be deprived of non-redundant knowledge from distant parts of the system and be confined to the provincial, specialized ideas within the intimate clique (Granovetter, 1983; Burt, 2004). But, when the disparate clusters are interconnected, they can exchange and mingle their heterogeneous set of knowledge to inspire innovation (Granovetter, 1973, 1983, 2005; Merton, 1973; Fleming, 2002; Uzzi & Spiro, 2005; Fang et al., 2010; Chang et al., 2013). Therein lies the importance of the interconnecting mechanisms that integrate the decoupled clusters in a social system and serve as an important channel of knowledge flow and recombination.

In this regard, pioneering studies have identified two key interconnecting mechanisms: (1) social bridges (Erdős & Rényi, 1959; Granovetter, 1973; Watts & Strogatz, 1998) and (2) hubs (Barabasi & Albert, 1999). A social bridge refers to a tie between two individuals which is the shortest path by means of which the two and their direct contacts are joined in a system (Granovetter, 1973; Watts & Strogatz, 1998). A hub, on the other hand, refers to an individual with exceptionally large number of ties (Barabasi & Albert, 1999; Albert et al., 2000). Along these lines, a large number of recent studies have confirmed that such hubs play an important role in many creative fields – from technological innovation and academic research to Hollywood movies and Broadway musicals (e.g., Newman, 2000, 2004; Albert & Barabasi, 2000, 2002; Barabasi et al., 2002; Girvan & Newman, 2002; Moody, 2004; Uzzi & Spiro, 2005; Guimera et al., 2005; Goyal et al., 2006; Clauset et al., 2009; Azoulay et al., 2010).

The most well-known example of a hub in a creative field would arguably be Paul Erdős – one of the most prolific mathematician of all time who wrote more than 1,400 papers with over 500 co-authors (Hoffman, 1998; Barabasi, 2005). The concept of the Erdős number, which describes the social distance between an individual and Paul Erdős as measured by co-authorship of academic papers, illustrates how hubs integrate isolated substrates into a cohesive social system (Barabasi et al., 2002). Recent studies have found that the average Erdős number is approximately 4.7 and the maximum known finite Erdős number is 15 (Grossman & Ion, 1995; De Castro & Grossman, 1999; Batagelj & Mrvar, 2000). These individuals with a finite Erdős number have academic disciplines as diverse as mathematics, physics, biology, chemistry, geology, engineering, genetics, medicine, meteorology, astronomy, crystallography, linguistics, economics, finance, psychology, and philosophy (De Castro & Grossman, 1999). By interconnecting these disparate "communities, or networks, of practice (Wenger, 1998; Brown & Duguid, 2001)," Erdős has facilitated access to new knowledge (e.g., mathematical models and tools, especially in graph theory) and greatly increased the rate at which such knowledge propagates throughout the whole system (Hoffman, 1998; De Castro & Grossman, 1999; Newman, 2001).

Decay in Creative Capability

However, an individual's creative capability tends to gradually decline with timespan in the industry; beyond certain point of time, it becomes completely lost (Lehman, 1953; Cole, 1979; Simonton, 1984; Levin & Stephan, 1991; Galenson & Weinberg, 2001; Jones & Weinberg, 2011).[7] This phenomenon is bluntly phrased in G.H. Hardy's essay *A Mathematician's Apology*, the most famous literary work in mathematics (Hoffman, 1998): "I do not know an instance of a majority mathematical advance initiated by a man past fifty. … A mathematician may still be competent enough at sixty, but it is useless to expect him to have original ideas" (Hardy, 1940). C.P. Snow, in his foreword of the 1967 edition of this book, describes such remark as "a passionate lament for creative powers that used to be and that will never come again."

In a similar vein, Billy Joel, a six-time Grammy Award-winning singer-songwriter, revealed such difficulty in songwriting in a recent interview (quoted from Howard Stern's Town Hall on April 28, 2014): "I just don't want to [write new songs]. You have to want to write new songs. Elton John asked me 'when are you going to make another album?' And I said to him, 'Why don't you make less albums?'" He explained, in an earlier interview with the New York Times (Goldman, 2013), that: "I

[7] Here the term "creative capability," for simplicity, is used to account for both physical (e.g., health) and mental (e.g., motivation, cognition) attributes that generate an individual's creative performance.

got tired of it. I got bored with it. I wanted something more abstract, I wanted to write something other than the three-minute pop tune even though that's an art form unto itself. … For me, it was a box. I want to get out of the box. I never liked being put in a box. … I haven't put out an album in 20 years. Let's face it. I am an oldies act."

As a result of such decay in creative capability, individuals tend to stop acquiring new knowledge and exploit their existing set of knowledge. Anecdotal evidence is well illustrated by Cornelius Lanczos' reminiscence about Einstein (quoted in Chandrasekhar, 1975):

> From 1925 on his interest in the current affairs of physics begins to slacken. He voluntarily abdicated his leadership as the foremost physicist of his time, and receded more and more into voluntary exile from his laboratory, a state into which only a few of his colleagues were willing to follow. During the last thirty years of his life he became more and more a recluse who lost touch with the contemporary developments of physics.

Einstein's example points toward an important feature that has been largely neglected in a bulk of prior literature. The decay in individuals' creative capability and their cease of learning causes change in the processes of knowledge accumulation and diffusion within the system. Especially, considering that hubs participate in a very large number of collaborative activities and dictate the communication channel of knowledge flow, decay in hubs' creative capability may have significant consequence on creative performance of the whole system.

Knowledge Recombination and Creative Performance

Hence, a question with theoretical and empirical implication arises: how do decay in hubs' creative capability and their inter-temporal changes influence creative performance of a social system? To draw a more systematic answer this question, I build up on the significant body of research on innovation.

This stream of thinking characterizes creative performance as the systemic consequences of knowledge recombination (Schumpeter, 1939; Nelson & Winter, 1982; Kogut & Zander, 1992; Fleming, 2001). When individuals interact, they pool and refine the set of knowledge possessed by each individual (Holland, 1975, 1992; March, 1991; Argote, 1999; Guimera et al., 2005). They continuously search for successful combinations by varying the composition of knowledge elements (Fleming, 2001, 2002). In doing so, synthesis of existing but previously uncombined knowledge encourages success in generating creative ideas that are both novel and useful (Hargadon & Sutton, 1997; Fleming, 2002; Uzzi & Spiro, 2005).

The mathematician Poincaré (1921) offered this account: "Ideas rose in crowds; I felt them collide until pairs interlocked, so to speak, making a stable combination." Einstein also wrote that "combinatory play seems to be the essential feature in productive thought" (quoted in Simonton, 1999: 29). In their in-depth field studies of IDEO and Hewlett-Packard, Hargadon & Sutton (1997) and Fleming (2002) describe how creative performance can be spurred when knowledge in one domain is introduced into a new domain. Chang et al. (2013) further exemplify this essential feature: Young-Woo Park, an inventor of Samsung Electronics newly assigned to the NAND division from the DRAM subunit, and his new colleagues combined proven knowledge from DRAM with NAND technology to solve various problems in semiconductor device. By building from existing but previously unconnected ideas as such, Samsung Electronics acquired numerous patents on semiconductors (e.g., Park, Choi, & Sim, 2007).

Existing literature in this stream also asserts that knowledge diversity is indispensable for innovation (Campbell, 1965; Cohen & Levinthal, 1990; March, 1991; Kauffman, 1993; Fang et al., 2010; Posen et al., 2012; Chang et al., 2013). The process of knowledge recombination simultaneously eliminates differences in the set of knowledge that each individual possesses. That is, as an individual refines her knowledge set, she engages in competing process of adopting a certain element in her set at the expense of discarding another (Holland, 1975, 1992; March, 1991; Chang et al., 2013). If knowledge diversity is completely lost within the population as a consequence, knowledge recombination can no longer improve the creative performance (Posen et al., 2012). In this context, recent empirical studies (e.g., Rodan & Galunic, 2004; Guimera et al., 2005; Wuchty, Jones, & Uzzi, 2007; Jones, Wuchty, & Uzzi, 2008; Singh & Fleming, 2010) and in-depth case analysis (e.g., Hargadon & Sutton, 1997; Shane, 2000; Fleming, 2002) have demonstrated the importance of exploiting, preserving, and revitalizing knowledge diversity and avoiding "combinatoric exhaustion (Fleming, 2002)" – i.e., complete loss of knowledge diversity.

PROPOSITION

Combining the dynamics of knowledge recombination with the recent advances in complex network theory, I propose that dynamic hub structure (i.e., a network with inter-temporal changes in hubs) will be resilient to decay in hubs' creative performance, and will constantly outperform static hub structure (i.e., a network with static hubs). This is because inter-temporal changes in hubs serve as a vital source of knowledge diversity within the whole system.

If hubs do not change over time (i.e., static hub structure), these individuals will continuously have inordinate influence over the process of knowledge recombination within the population. They will quickly aggregate ideas through their exceptional connectivity with other individuals, and recombine their set of knowledge. At the same time, these hubs will accelerate the speed of knowledge diffusion by dramatically shortening the social distance in the whole system. When a system is characterized by short average distance, some lower-performing individuals may discard rare, useful knowledge components in the process of assimilating higher performer's knowledge set (Posen et al., 2012; Chang et al., 2013). This happens because the rapid diffusion of some knowledge set drives out other knowledge components. I expect that this tendency will be more pronounced in static hub structure than dynamic hub structure. This precipitated loss of knowledge diversity, in turn, may result in premature convergence around a suboptimal set of knowledge, and thus thwart creative performance in the long run.

In such static structure, decay in hubs' creative capability will have curvilinear (i.e., inverted U-shaped) effect on the creative performance of a social system. That is, the system may reach the highest level of performance when a small proportion of hubs crease to learn new knowledge. If hubs lose their creative capability and refrain from assimilating heterogeneous ideas, their performance will stagnate to a suboptimal level. Individuals within immediate proximity to those hubs will stop learning from those hubs as they outperform those hubs. This may lessen precipitated convergence around a set of knowledge disseminated by those hubs, and allow the population to preserve knowledge diversity for a longer period of time. If only a small proportion of hubs lose their creative capability, the system will diffuse and recombine superior knowledge components overlooked by those hubs. Thus, the system will surpass the suboptimal performance of a static hub structure without decay in hubs' creative capability. When the proportion increases beyond a certain point, however, it will have significant adverse consequence on creative performance. As a large number of hubs fail to accumulate and propagate non-redundant knowledge across the system, disparate clusters of individuals will be deprived of such knowledge. In turn, although knowledge diversity is well preserved within the population, decay in creative capability of a large proportion of hubs will substantially deter knowledge diffusion and result in significantly lower performance.

On the other hand, in a dynamic hub structure, inter-temporal changes in hubs may encourage creative performance by providing access to knowledge diversity within the population. As established hubs lose their connectivity, the population is less exposed to the knowledge disseminated by these hubs. This may, in turn, attenuate convergence around a certain set of knowledge. Meanwhile, as new hubs suddenly arise gaining exceptional connectivity within the network, these individuals may mix and widely diffuse formerly neglected, superior elements in the lower performer's knowledge set. As these hubs obtain connectivity, these previously overlooked attributes are more likely to be vastly propagated and recombined within the population. This will, in turn, revitalize knowledge diversity and increase the number of recombinatorial possibilities available within the population. Consequently, inter-temporal changes in hubs permit the system to be resilient to the adverse consequence of decay in hubs' creative capability, and allow it to escape from and even surpass the suboptimal performance of static hub structure.

COMPUTATIONAL ANALYSIS

Dynamics of Knowledge Recombination

To systematically explore the effect of decay in hubs' creative capability and their inter-temporal changes on creative performance, I construct a computational model which incorporates the dynamics of knowledge recombination in Holland's (1975, 1992) model of genetic algorithms.

1. **Entities**: This model has two main entities – *the external reality* and *the population of individuals.*
   (1) **Reality (R)** – The concept of reality allows us to highlight the consequences of knowledge recombination (Holland, 1975, 1992; March, 1991). In this study, I assume that reality consists of m dimensions – i.e., $R =$

$\{r_1, r_2, \cdots, r_m\}$. Each element in reality, r_k, is assumed to have only two discrete states which take on a randomly assigned value of either 0 or 1 (e.g., Holland, 1975, 1992; Rivkin, 2000; Ethiraj & Levinthal, 2004; Chang et al., 2013).[8] The binary representation of reality may correspond to non-numerical attributes of the fitness landscape - for instance, genre or lyrics in the pop music industry.

(2) **Individuals (X_i)** – In this model, individuals are considered reservoirs of ideas and knowledge (Argote, 1999). There are n individuals, each initially endowed with idiosyncratic set of knowledge – i.e., $X_i = \{x_{i1}, x_{i2}, \cdots, x_{im}\}$. In accordance with reality, each element in an individual's set of knowledge, x_{ij}, has a randomly assigned value of either 0 or 1 (e.g., Holland, 1975, 1992; Rivkin, 2000; Ethiraj & Levinthal, 2004). Thus, each individual has m elements in her set of knowledge that correspond to the elements of reality.

2. **Payoff function** ($\Pi(i)$) – The performance of an individual is evaluated at each time step by a given payoff function – i.e., the number of matches between her set of knowledge, $X_i = \{x_{i1}, x_{i2}, \cdots, x_{im}\}$, and the reality, $R = \{x_{i1}, x_{i2}, \cdots, x_{im}\}$ (March, 1991; Fang et al., 2010; Posen et al., 2012). To take into account the notion of "knowledge indivisibility (Arrow, 1962)," I

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[8] The independent probability that any one element will have the value of 1 is 0.5 (i.e., $r_k \sim Bernoulli(0.5)$ ($\forall k = 1,2,\cdots,m$)).

parameterize the interdependence, φ, across knowledge components (e.g., Kauffman, 1993; Rivkin, 2000; Fang et al., 2010; Posen et al., 2012; Chang et al., 2013). By increasing the value of $\varphi \in [0, m]$, the search problem becomes more interdependent – i.e., the performance will not improve unless all the elements in a certain subset jointly match corresponding elements of reality. Thus, the generalized payoff function is

$$\Pi(i) = \frac{1}{m}\sum_{j=1}^{m}\left(\delta_j \cdot \prod_{k=1}^{\varphi}\phi_k^j\right)$$

where $\delta_j = 1$ if the jth element in individual i's set of knowledge matches that in reality (i.e., $x_{ij} = r_j$); $\delta_j = 0$ otherwise (i.e., $x_{ij} \neq r_j$). On the other hand, $\phi_k^j = 1$ if the kth element of the subset with φ elements matches the corresponding element of reality; otherwise $\phi_k^j = 0$. For instance, consider a case in which there is maximum interdependence across knowledge components (i.e., $\varphi = 4$) in four dimensions in reality (i.e., $m = 4$). The individuals have to correctly identify all four knowledge components to reach the performance of 4. If any component is incorrect, the performance is 0. On the other hand, if there is no interdependence across knowledge components (i.e., $\varphi = 0$), an individual's performance would simply be the number of matches between her set of knowledge and the reality.

3. **Procedure**: At each time step, I implement the process of knowledge recombination according to the collaborative network (e.g., Fang et al., 2010;

Chang et al., 2013). That is, a collaborative tie between two individuals indicates that each acts as sources of knowledge recombination for the other.[9] The collaborators first look at each other's performance and identify individuals with the higher performance. Yet, they cannot directly observe how each element of the set of knowledge contributes to their performance. Thus, the lower performer identifies the majority belief of each m elements from the higher performers' knowledge sets, and then refine her set of knowledge by imitating a subset of knowledge with some probability – i.e., the rate of learning, θ. Consequently, the process of knowledge recombination eliminates differences between the individuals, and individuals become more homogeneous in terms of knowledge. In the end, a stable equilibrium is reached at which all individuals have the same set of knowledge.

4. **Decay in Creative Capability**: In order to take into account decay in hubs' creative capability, I incorporate a time-scale parameter, τ, after which a proportion hubs do not conduct the process of knowledge recombination illustrated above. For example, $\tau = 0$ indicates that, immediately after the initial construction of or after an inter-temporal change in network structure, individuals who occupy the structural position of hubs will refrain from learning new knowledge through their social ties. On the other hand, if $\tau = 50$, these individuals will engage in the process of knowledge recombination for 50 time

[9] Networks do not act; they are a context for action (Burt, 2004).

steps and then stop such procedure from then onwards. By doing so, this model distinguishes the net effect of decay in creative capability on creative performance, without changing topological properties of the collaborative network.

Dynamics of Network Evolution

To examine such dynamics while controlling other factors, this study builds on Bianconi & Barabasi's (2001) fitness model, in which the probability that a preexisting node will gain a new connectivity depends on its fitness parameter and current degree jointly.[10] This allows a node with a higher fitness to enter the network late in the evolution process, but still become more connected than nodes that have stayed in the system for a much longer period. By implementing this theoretical model of network evolution and changing the network structure in every period of T in the dynamics of knowledge recombination, I generate inter-temporal changes in hubs and distinguish their effect on knowledge recombination, while controlling the effect of network evolution and its topological change – e.g., changes in network size, characteristic path length, and clustering.

[10] Fitness parameter accounts for the difference in the node's ability to compete for connectivity. Hence, starting with a small number of nodes, at each time step a new node j with fitness parameter of η_j is added. An incumbent node's probability of gaining connectivity is proportional to $\eta_i \cdot k_i$:

$$\Pi_i = \frac{\eta_i \cdot k_i}{\sum_m \eta_m \cdot k_m}$$

RESULTS

Using the model described above, I run a series of simulations to investigate the effect of decay in hubs' creative capability and their inter-temporal changes on creative performance. Since realization of the process is subject to stochastic variability, I repeat the simulation 300 times using the same initial conditions and parameters to estimate the distribution of outcomes. All parameters used in the simulations are specified in Appendix A.

Result 1: Decay in Hub's Creative Capability in Static Hub Structure

To examine the effect of decay in hubs' creative capability on creative performance, I first consider a static structure in which hubs play an important role in social cohesiveness – i.e., Bianconi & Barabasi's (2001) fitness model of scale-free network. I then implement decay in hubs' creative capability by limiting process of knowledge recombination to a proportion of hubs after a certain period of time τ. The numerical results are illustrated in Figure 5, which shows variation in the level of creative performance by the proportion of hubs with decay in creative capability.

Insert Figure 5 about here

Intuitively, it may seem that larger proportion of hubs with loss of creative capability should linearly result in lower creative performance of the whole system. However, the analysis confirms that such proportion has curvilinear (i.e., inverted U-shaped) effect on creative performance – that is, the system reaches the highest level of creative performance when few hubs lose their creative capability. This curvilinear relationship is consistent regardless of how quickly the hubs lose their creative capability. Why do we observe such results?

To better understand the equilibrium performance results presented above, it is useful to observe the micro-dynamics of knowledge recombination process as it unfolds. I conjecture that this curvilinear relationship is driven by knowledge diversity within the whole system (Campbell, 1965; Cohen & Levinthal, 1990; March, 1991; Kauffman, 1993; Fang et al., 2010; Posen et al., 2012; Chang et al., 2013). Hence, I measure knowledge diversity, ξ, using a pair-wise comparison of all the individuals in the system (e.g., Fang et al., 2010; Posen et al., 2012; Chang et al., 2013). For each pair of individuals (i.e., total $\frac{n\cdot(n-1)}{2}$ number of pairs), m elements in the knowledge sets are compared. Then, I calculate knowledge diversity according to the following equation:

$$\xi = \frac{2}{m \cdot n \cdot (n-1)} \sum_{i=1}^{\frac{n\cdot(n-1)}{2}} \sum_{j=1}^{m} \varepsilon_{ij}$$

where $\varepsilon_{ij} = 1$ if the jth element have different beliefs in the ith pair of individuals; otherwise $\varepsilon_{ij} = 0$. Figure 6 exhibits the degree of knowledge diversity within the population over time for different proportion of hubs with decay in creative capability.

Insert Figure 6 about here

As shown in Figure 6, the population tends to lose knowledge diversity most rapidly when hubs sustain, or do not lose, their creative capability. Hubs, through their exceptional connectivity, disseminate their set of knowledge quickly throughout the whole system. This prematurely eliminates superior ideas overlooked by those hubs, and thus reduces the number of recombinatorial possibilities available within the population. Such precipitated combinatoric exhaustion lowers the likelihood of achieving its best possible performance and result in suboptimal level of creative performance.

On the other hand, if a small proportion of hubs lose their creative capability, knowledge diversity within the population decays slowly – i.e., diverse ideas and knowledge among individuals are well maintained for a longer period. As few hubs lose their creative capability and cease exploring new knowledge, their performances do not increase beyond a certain level. In turn, when individuals with close proximity to those hubs achieve a level of performance higher than that of hubs, those individuals stop learning from those hubs. This limits the premature convergence around a certain set of knowledge diffused by those hubs, and allows the population to assimilate heterogeneous knowledge components neglected by those hubs. By maintaining knowledge diversity longer, the system achieves higher creative performance when a small proportion of hubs lose their creative capability.

However, if such proportion increase beyond a certain level, the creative performance of the population tends to drop substantially. Why do we systematically observe lower performance although the population consistently sustain knowledge diversity? The underlying problem is that heterogeneous ideas do not easily spread within the population. As elaborated in the previous sections, hubs play an important role in both social cohesiveness and knowledge diffusion within a social system. If a large proportion of hubs neglect to adopt new knowledge, they simultaneously block the flow of heterogeneous knowledge among disparate clusters. Since there are very limited channels for previously neglected, superior knowledge components to be exchanged, those ideas cannot be effectively shared and recombined within the population. Consequently, although knowledge diversity is well preserved, the population cannot benefit from this diversity if a larger proportion of hubs lose their creative capability.

Result 2: Resilience of Dynamic Hub Structure

Next, I investigate the question of how inter-temporal changes in hubs influence creative performance when a proportion of hubs lose their creative capability. In order to do so, I first implement Bianconi & Barabasi's (2001) fitness model of scale-free network, and then change the network structure in every period of $T = 50$ in the dynamics of knowledge recombination. The simulation results are numerically illustrated in Figure 7.

Insert Figure 7 about here

This study finds that dynamic hub structure consistently outperforms static hub structure, regardless of the proportion of hubs with loss of creative capability. That is, the system constantly achieves a higher level of creative performance in dynamic hub structure than in static hub structure. What is more, dynamic hub structure maintains a persistent level of creative performance although the proportion of hubs who lose their creative capability increases. Why do we observe in a dynamic hub structure such resilience to decay in hubs' creative capability?

As already noted, the difference in performance between static and dynamic hub structures may stem from knowledge diversity within the population (Campbell, 1965; Cohen & Levinthal, 1990; March, 1991; Kauffman, 1993; Fang et al., 2010; Posen et al., 2012; Chang et al., 2013). In this regard, Figure 8 helps us understand how inter-temporal changes in hubs influence creative performance and knowledge diversity. In the light of these events (i.e., when $T = 50$), creative performance noticeably escalates while knowledge diversity suddenly drops. This happens because inter-temporal changes in hubs provide access to superior knowledge components formerly neglected by the established hubs. Thus, although the established hubs lose their creative capability and fail to accomplish their role of interconnecting mechanism, the system can exchange and mix new ideas through inter-temporal changes in hubs. Thus, such changes serve as a vital source of knowledge diversity within the whole system.

Insert Figure 8 about here

Sensitivity Analysis

This study conducts sensitivity analysis on four parameters: (1) the size of the population, n, (2) the level of interdependence among knowledge elements, φ, (3) the rate of learning, θ, and (4) the frequency of inter-temporal changes in hubs, T. First, I vary the size of the population at $n = 300$ and 1000. Second, this study incorporates an additional set of simulations to examine sensitivity to the level of interdependence among knowledge elements, φ. In these robustness tests, I modify the value of the parameter at levels ranging from $\varphi = 1$ to 10.[11] Third, I test whether the results are sensitive to the rate of learning by altering the value of θ from 0.1 to 0.7. Lastly, I alter the value of parameter, $T = 0,\ 10,\ 50$ and 80, that corresponds to the time period in which change in hub structure occurs. The results not reported here are remarkably consistent to variations in the four parameters.

DISCUSSION

In this study, I sought to understand how decay in hubs' creative capability and their inter-temporal changes affects performance in a creative field. Drawing on the existing literature on complex networks and the concepts of knowledge recombination, I argued that the disruptive consequence of combinatoric exhaustion is particularly severe when static hubs sustain their creative capability. I proposed that a social system of static hub structure can reach the highest level of performance when a small proportion of hubs lose their creative capability. I further hypothesized that dynamic hub structure is resilient to decay in hubs' creative capability and consistently outperforms static hub structure because inter-temporal changes in hubs revitalize knowledge diversity within the population. My results, from computational analysis of knowledge recombination on collaborative network, confirm that such

[11] As the interdependence among knowledge elements increases, the search process becomes more complex (Kauffman, 1993; Levinthal, 1997; Rivkin, 2000). Yet, prior literature argues that many real-world problems are moderately complex (Kauffman, 1993; Rivkin, 2001).

changes have conducive effect on creative performance. These results are robust to a number of different simulations and controls for alternative explanations. I discuss below the contribution and implication.

The main contribution of this paper is to present comprehensive understanding of the role of hubs and its underlying dynamics in creative performance of a social system. Majority of prior studies (e.g., Uzzi & Spiro, 2005; Fleming et al., 2007a; Fang et al., 2010; Mason & Watts, 2012; Chang et al., 2013) have developed their arguments upon Watts & Strogatz's (1998) formalization of small world network, which lacks the prominent role of hubs (Barabasi & Albert, 1999; Watts, 1999). Although considerable attention has been directed at understanding social bridges, prior studies have been much less successful in addressing the role of hubs. In this regard, this study takes a step forward to unveil the role of hubs as an interconnecting mechanism that both integrates disparate clusters in the social system and serves as an important channel of knowledge flow and recombination. This paper provides insights into their role by assessing the process of how hubs influence process of knowledge recombination. This study finds that hubs substantially increase the speed of knowledge diffusion within the population, simultaneously aggregating and spreading knowledge rapidly through their vast connectivity. This may result in precipitated depletion of knowledge diversity and thus suboptimal performance of the whole system.

Another implication is that it is important to take into account the dynamic changes in the network structure in studying its effect. As already noted, most previous studies have analyzed snapshots of social network, assuming static structure in which all individuals sustain their creative capability. On the other hand, based on preliminary analysis on the Korean pop music industry, anecdotes of prominent creatives, and interviews with practitioners, this study highlights two social dynamics that cast a different light on some of the arguments in prior literature – i.e., decay in hubs' creative capability and their inter-temporal changes. First, contrary to intuitive thinking, computational analysis suggests that decay in creative capability of a small proportion of hubs can actually be conducive to creative performance of the whole system. This is because such decay diminishes the speed of knowledge diffusion and thus enables the population to preserve knowledge diversity for longer period of time. Yet, if a large proportion of hubs lose their creative capability, the system reaches substantially lower level of performance as such loss significantly deters knowledge diffusion. This study also identifies the effect of inter-temporal changes in hubs: they serve as a vital source of knowledge diversity. In the light of these events, knowledge diversity within the population is revitalized to escape from and even surpass the suboptimal performance of static hub structure. Such revitalization allows dynamic hub structure to be resilient to decay in hubs' creative capability. Hence, in line with theoretical discussion in a few previous studies (e.g., Feld, 1981; McPherson, Smith-Lovin, & Cook, 2001; Eckmann, Moses, & Sergi, 2004; Kossinets & Watts, 2006; Braha & Bar-Yam, 2006; Hill & Braha, 2010), my results confirm that such static structure provides an incomplete picture of social dynamics.

Last but not least, this study contributes and speaks to the broader literature on social network. The preliminary analysis on the collaborative network in the Korean pop music industry unveils on some important deviations from the prior literature on social network and the contemporary graph theory and its models. I find that real world social networks have properties that cannot be fully accounted for by either Watts & Strogatz's (1998) small world formalization or Barabasi & Albert's (1999) scale-free architecture. The collaborative network forms a small-world in which randomly chosen pairs of songwriters are typically separated by only a short path of intermediate acquaintances, while demonstrating the presence of dominant hubs and significant clustering – key features that contemporary graph theory and its models fail to incorporate simultaneously (Newman, 2000). Furthermore, unlike the results of much prior research and Barabasi & Albert's (1999) original scale-free model, the collaborative network in Korean pop music industry shows inter-temporal changes in hubs.

Before concluding, we would like to draw attention to some features of this paper that have so far remained only implicit, as well as to highlight some directions for future research. The computational model in this study assumes the simplest possible setting for individuals (i.e., undifferentiated nodes) – e.g., homogeneous rate of learning, no individual innovation, and no entry or exit. Furthermore, this study considers collaborative network as fully connected graph with unweighted, undirected edges. Lastly, I treat the environment as exogenously given and stable. These assumptions may be relaxed in future work.

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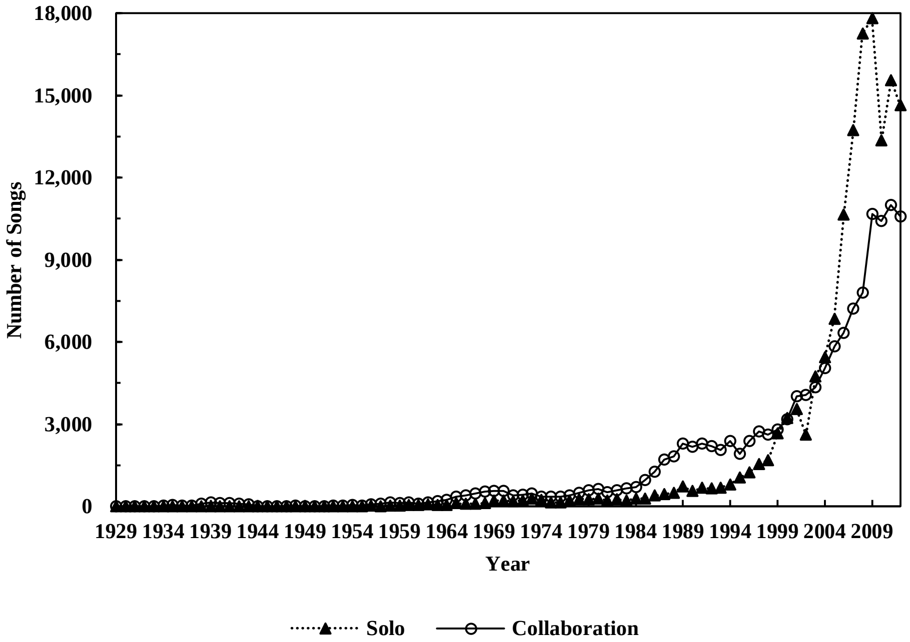
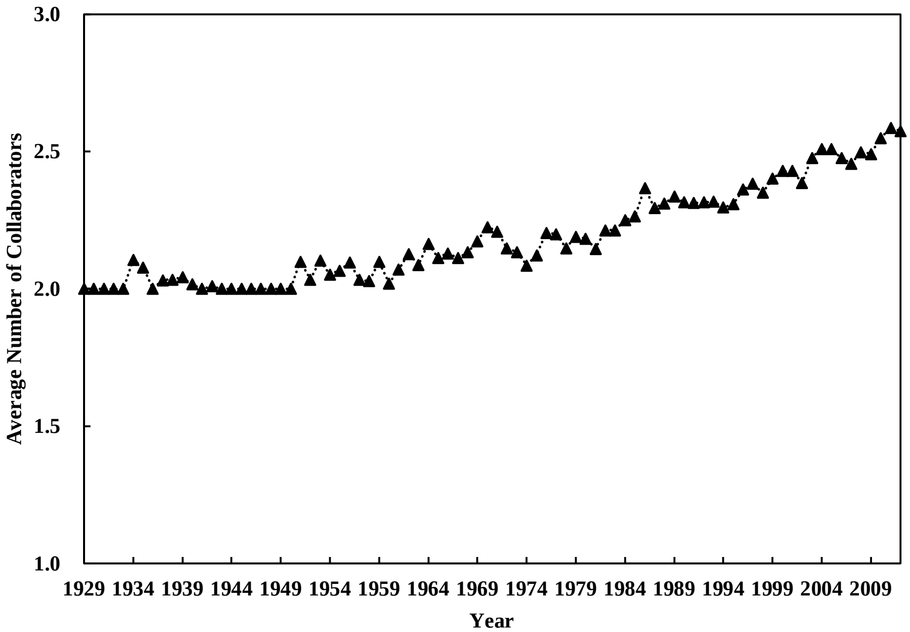
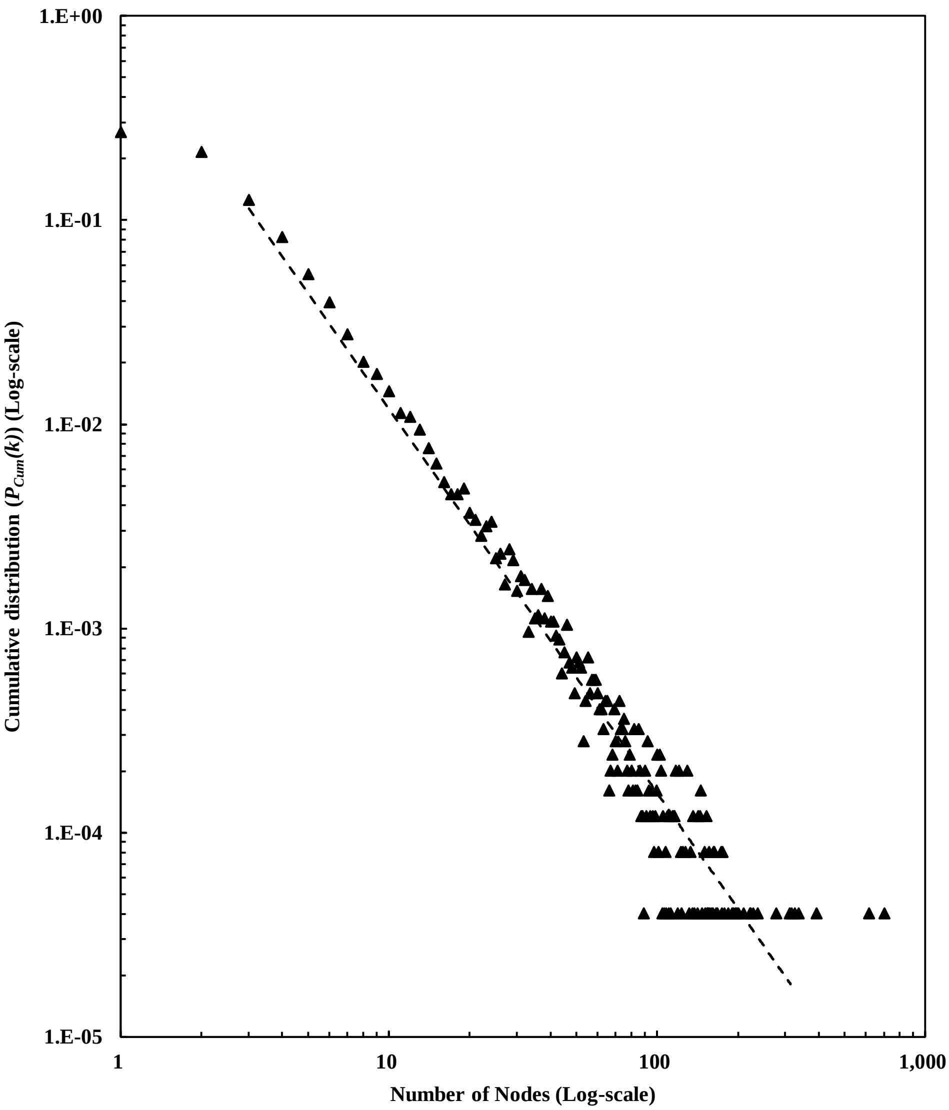
Figure 1. Solo vs. Collaborative Works





Note. The number of creative works has increased during the time of observation. The size of collaboration has steadily increased, as is in the case of Broadway musical industry, academic research, and technological innovation (Guimera et al., 2005; Wuchty et al., 2007).

Figure 2. Cumulative Degree Distribution



Note. The dashed line has slope of $\gamma = 1.88$.

Figure 3. Evolution of Degree Distribution

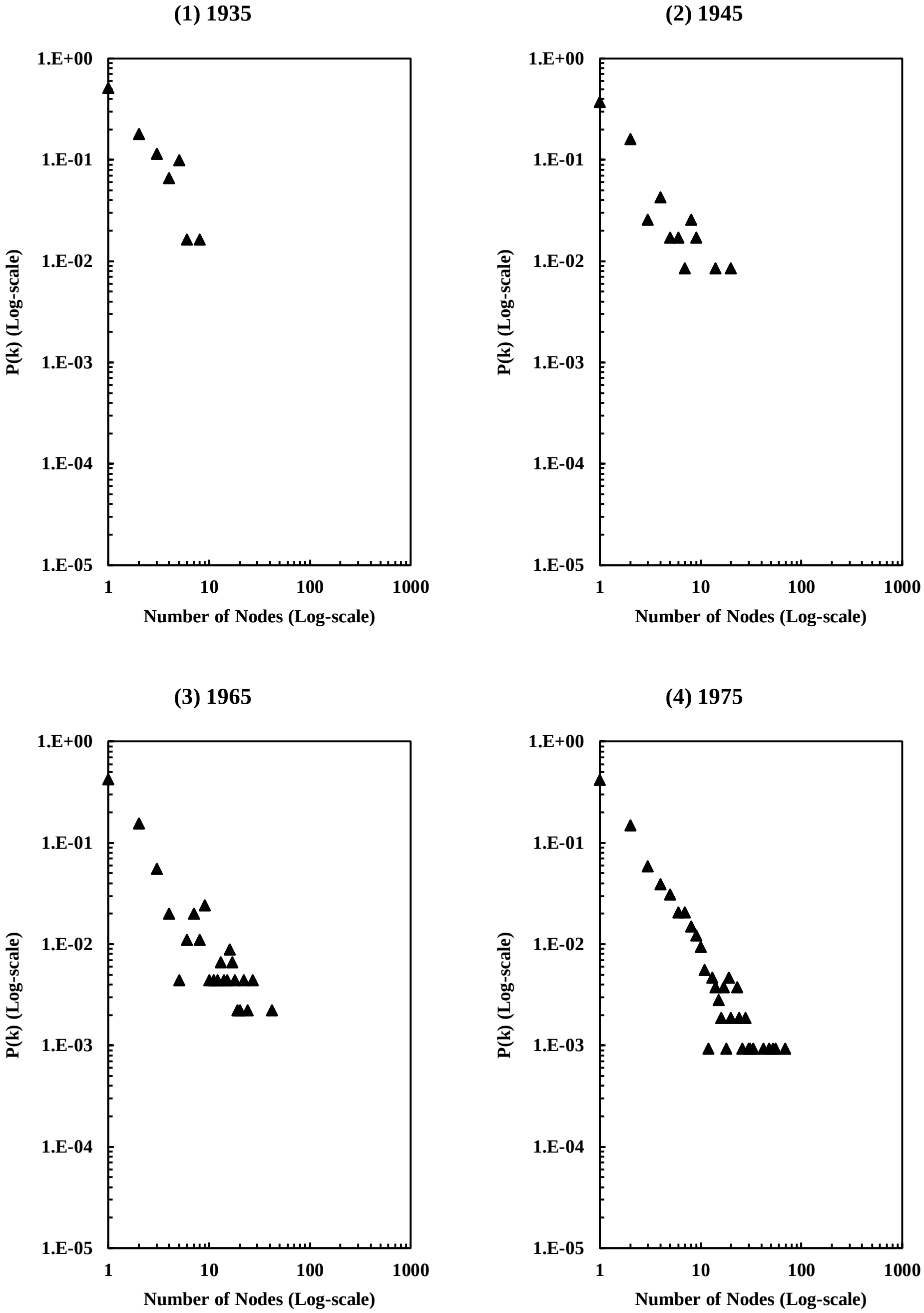
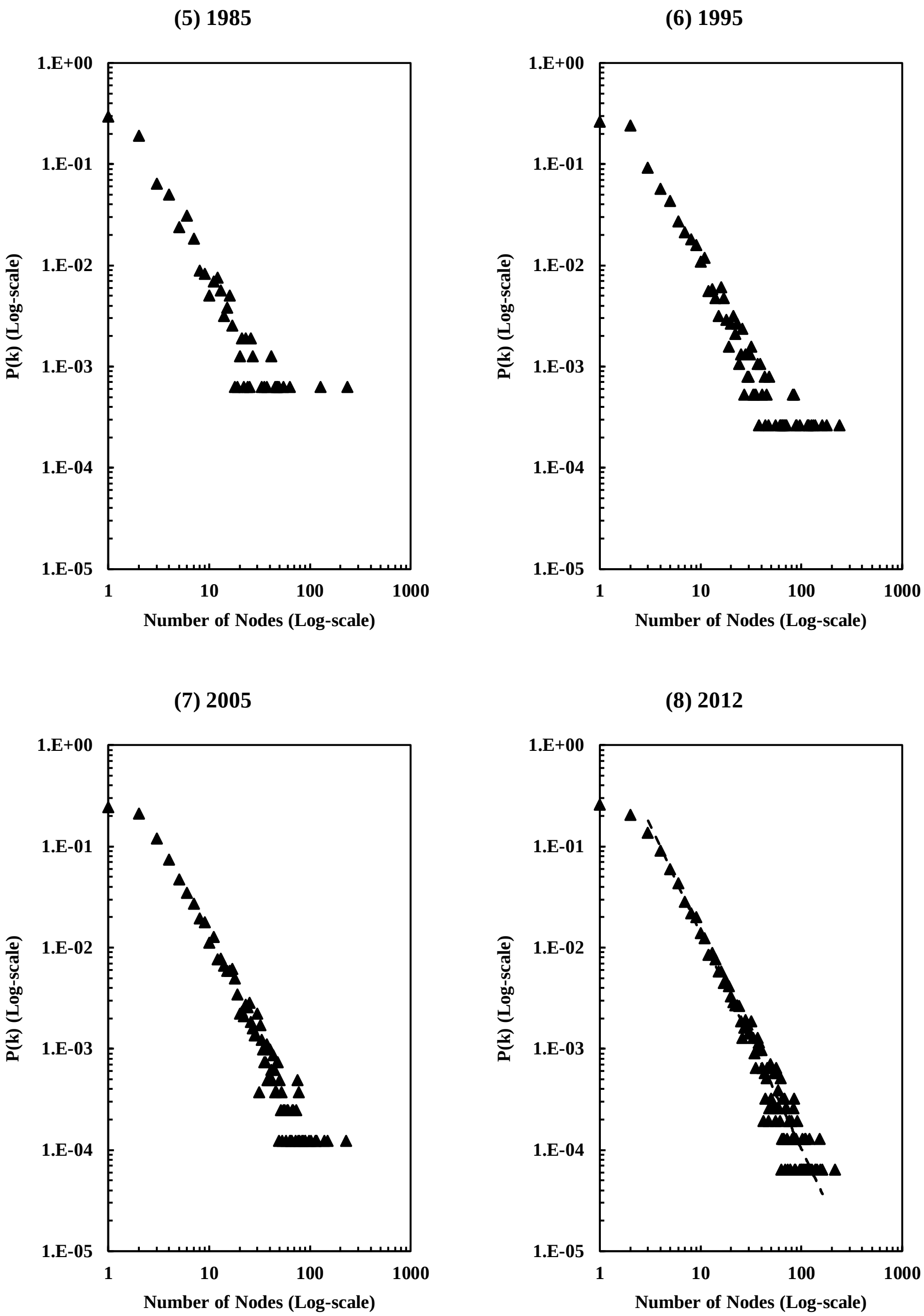
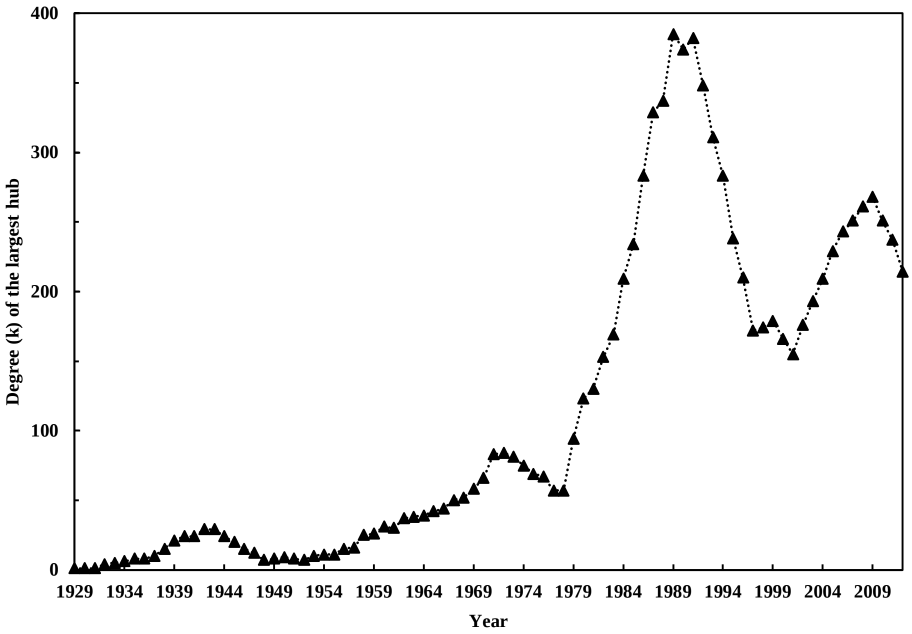


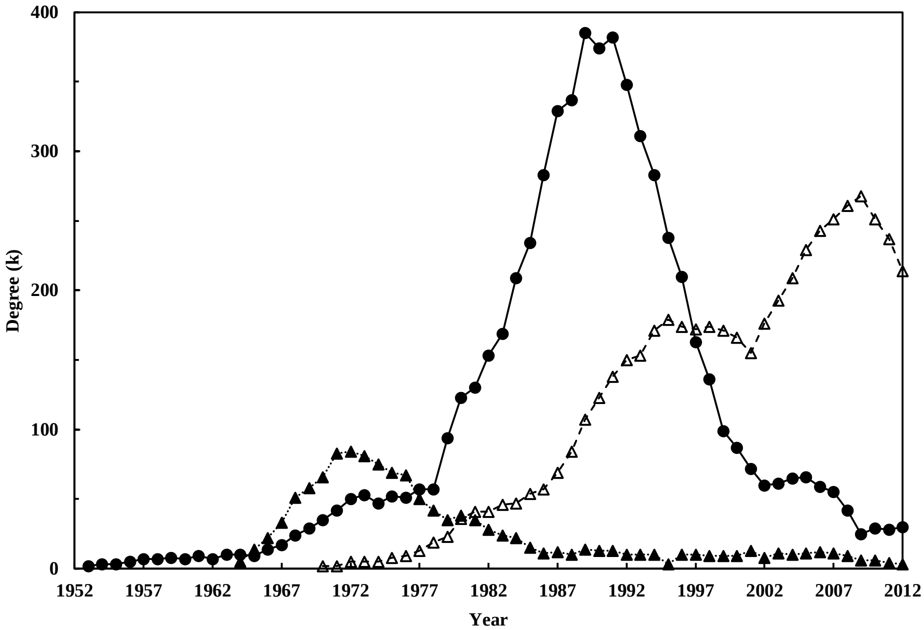
Figure 3. Evolution of Degree Distribution (Continued)



Note. The dashed line in '(8) 2012' has slope of $\gamma = 2.13$. Since 1975, we can observe a power-law behavior, $P(k) \sim k^{-\gamma}$, with $\gamma = 2.1 \pm 0.1$. Although the size of the hub changes over time, the power-law exponent, γ, seems to be independent of time.

Figure 4. Inter-temporal Changes in Hubs





Note. The collaborative network in Korean pop music industry shows inter-temporal changes in hubs. The second graph illustrates the key changes in the hubs during the period from 1952 to 2012.

Figure 5. Decay in Hubs' Creative Capability in Static Hub Structure

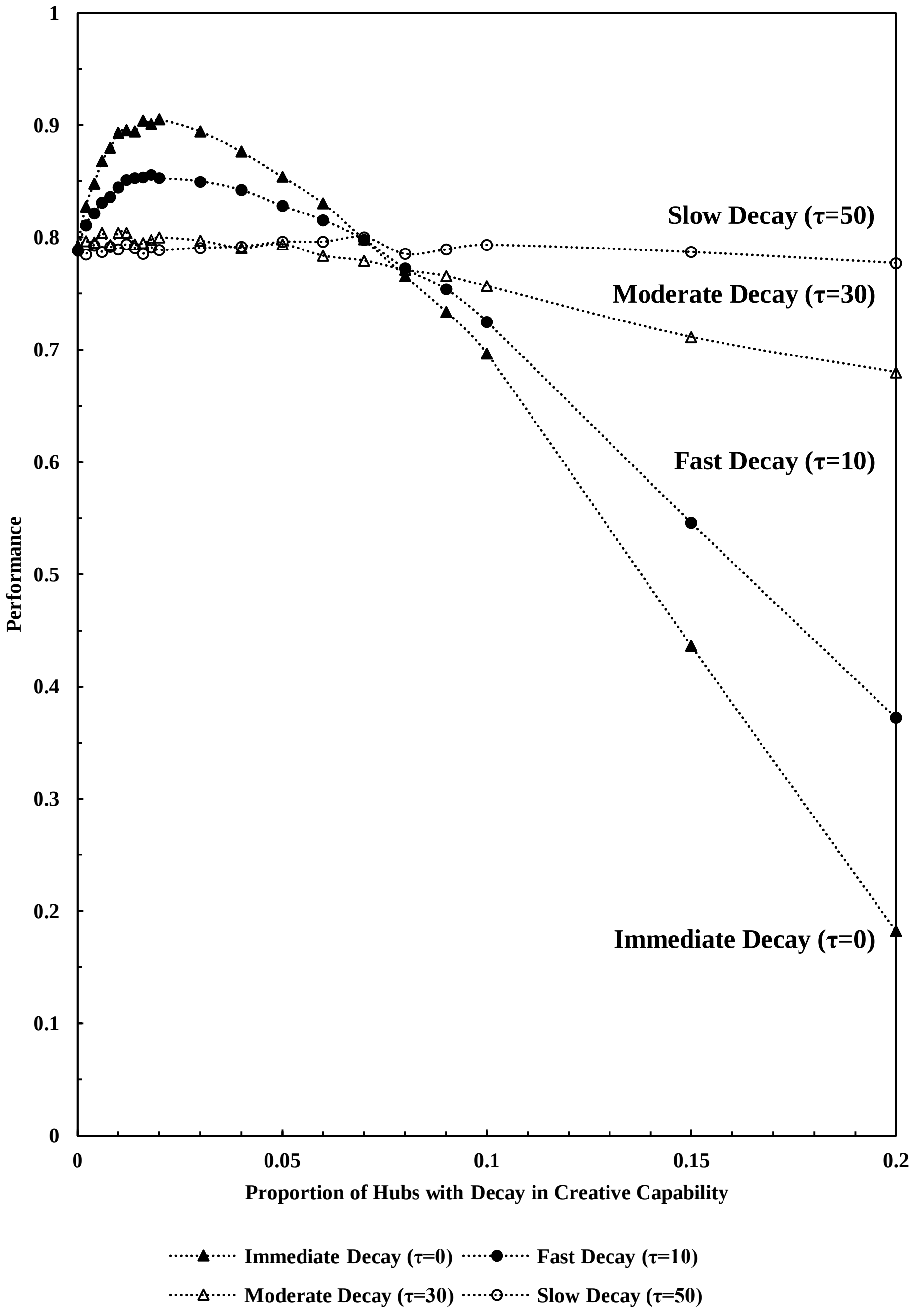


Figure 6. Knowledge Diversity in Static Hub Structure

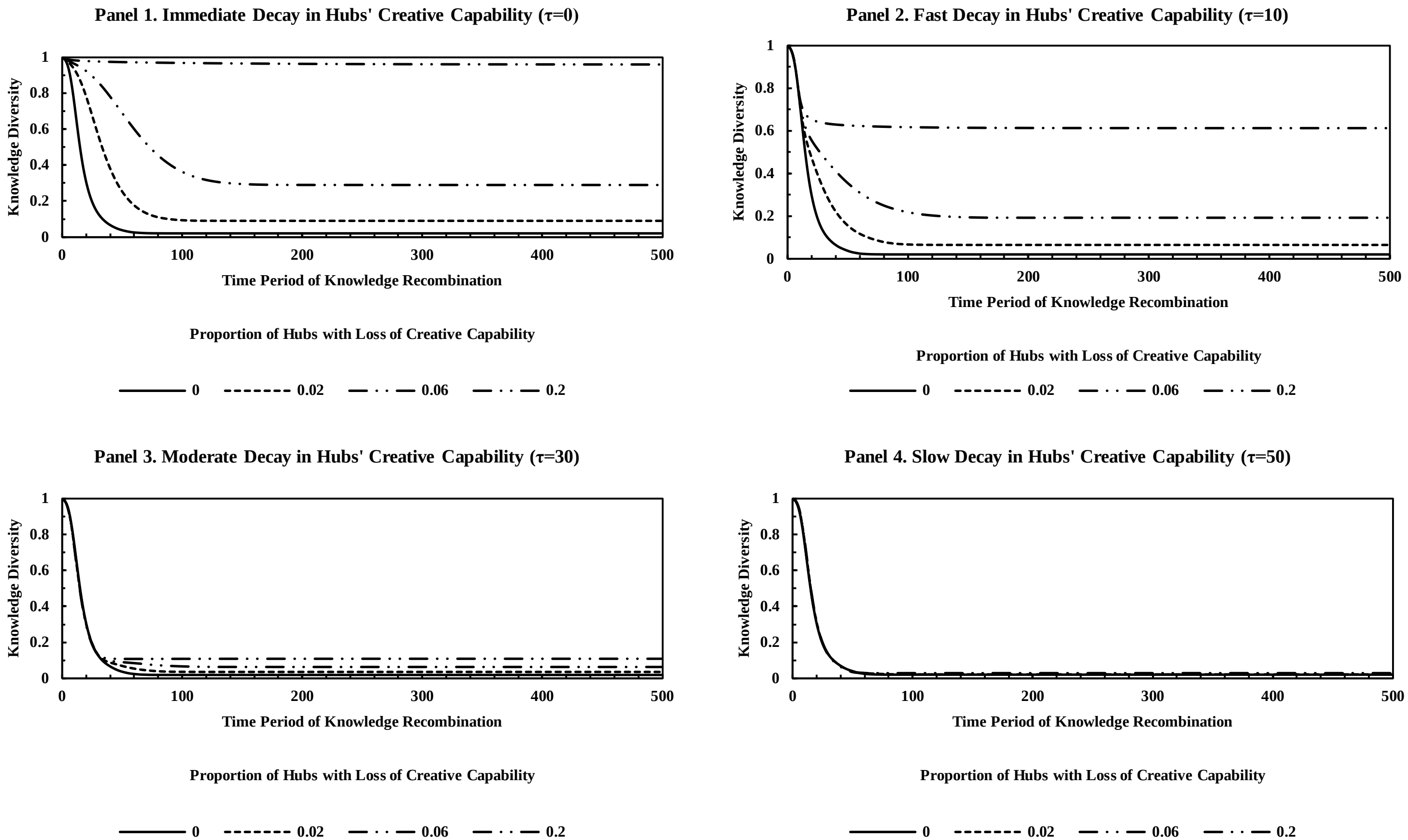


Figure 7. Resilience of Dynamic Hub Structure

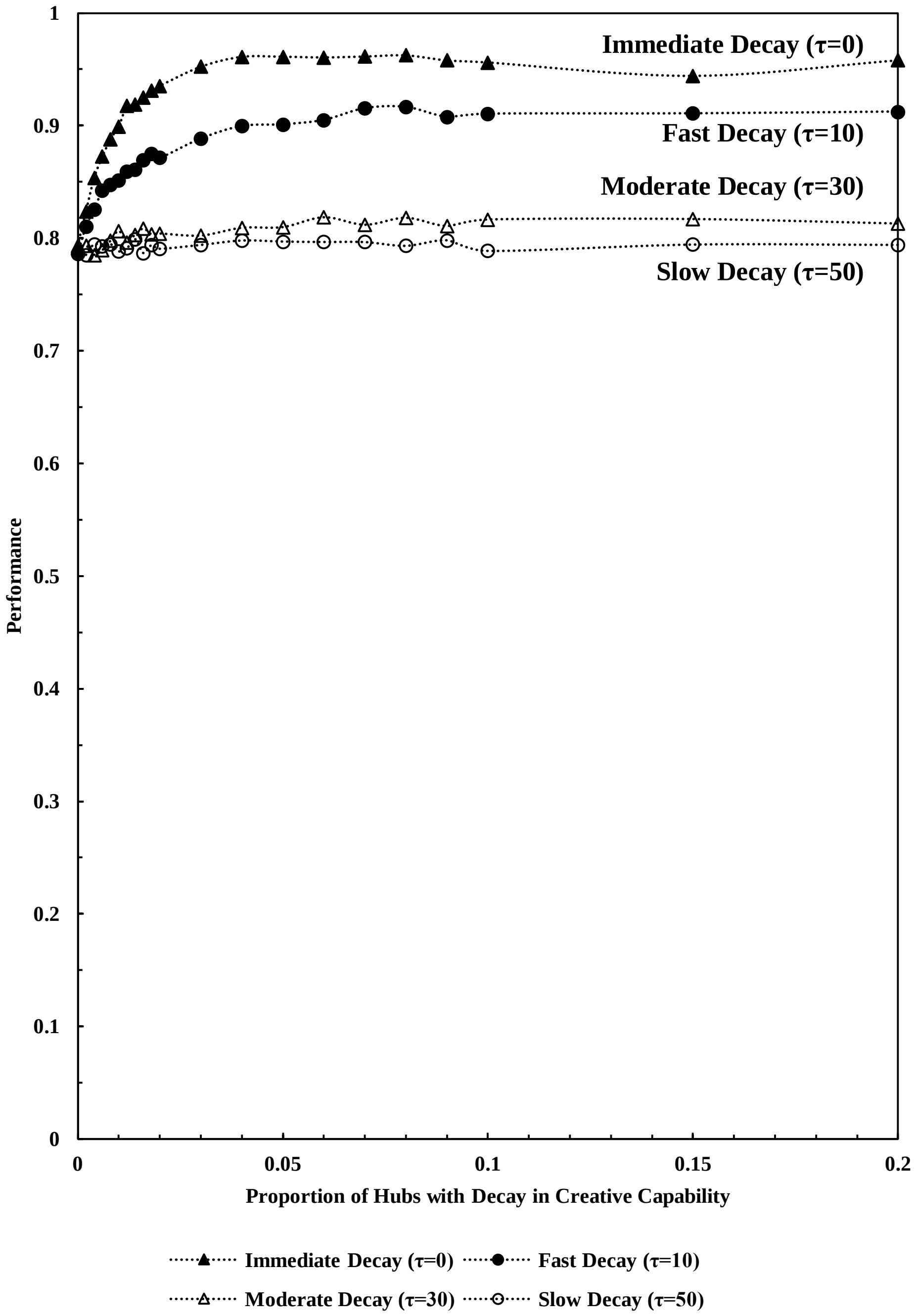


Figure 8. Creative Performance and Knowledge Diversity in Dynamic Hub Structure

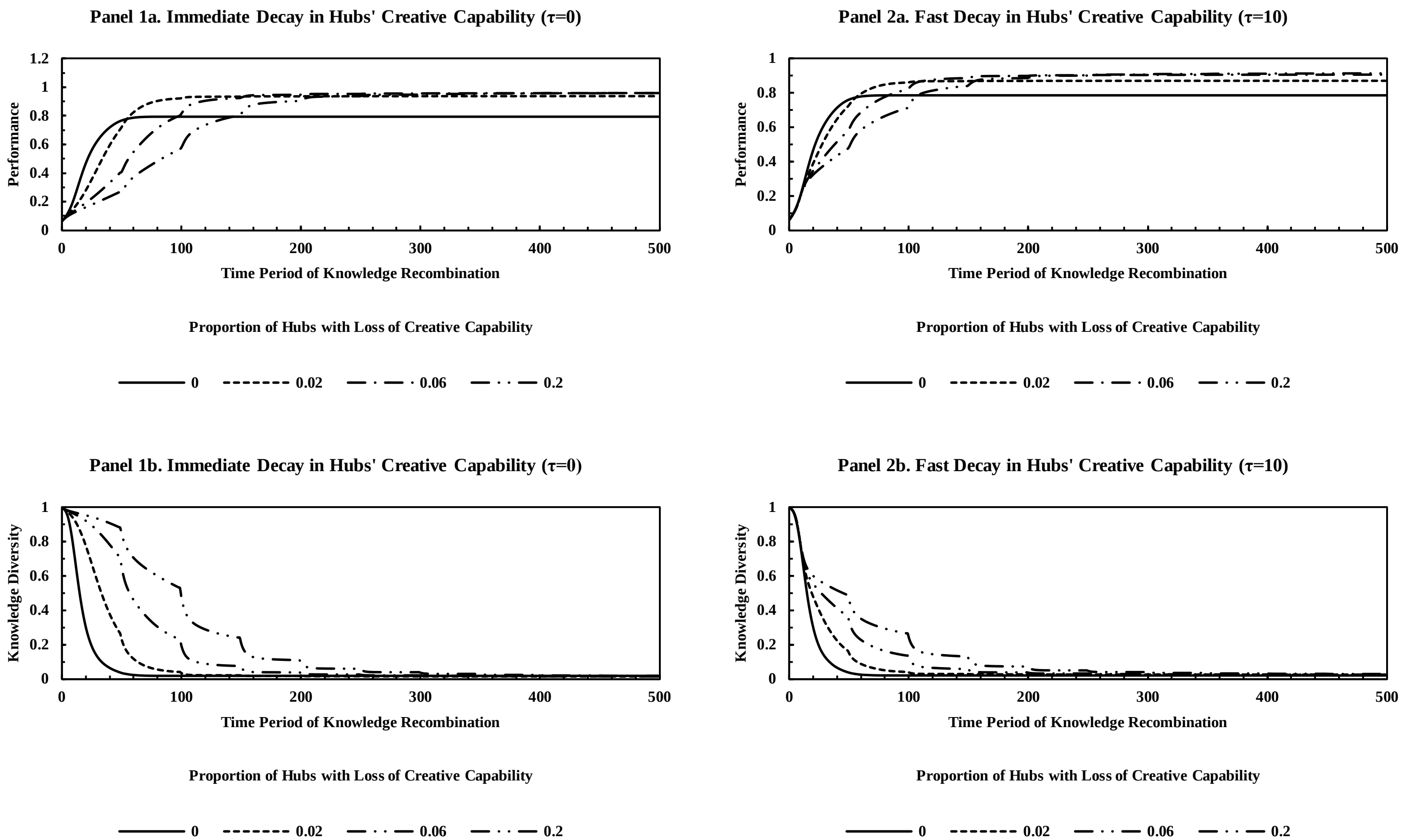
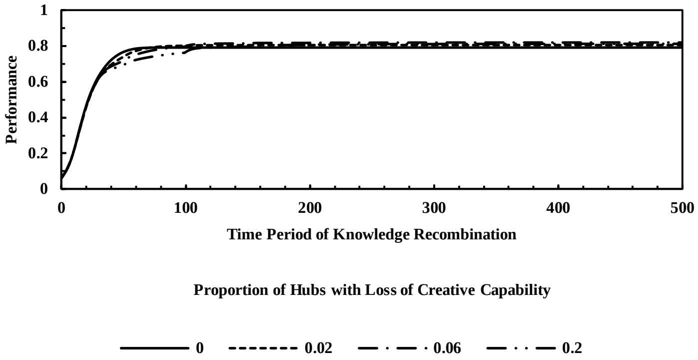
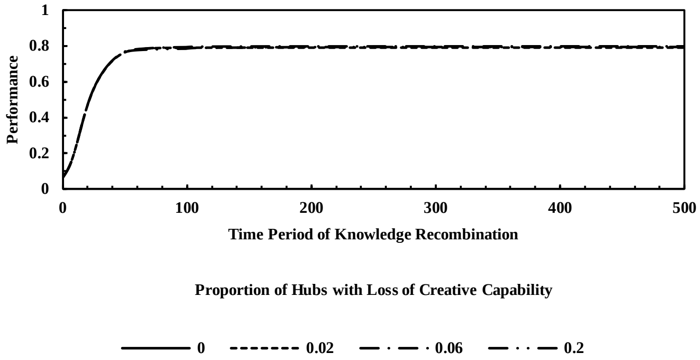


Figure 8. Creative Performance and Knowledge Diversity in Dynamic Hub Structure (Continued)

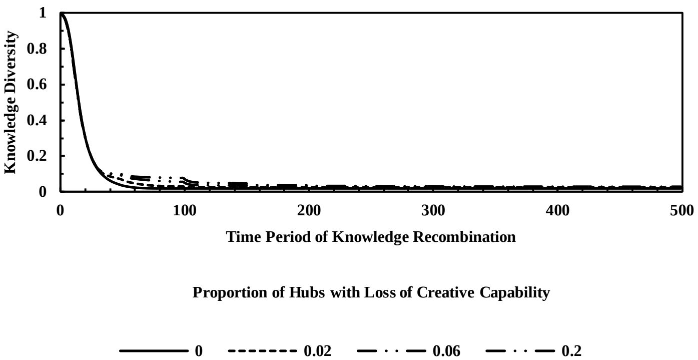
Panel 3a. Moderate Decay in Hubs' Creative Capability (τ=30)



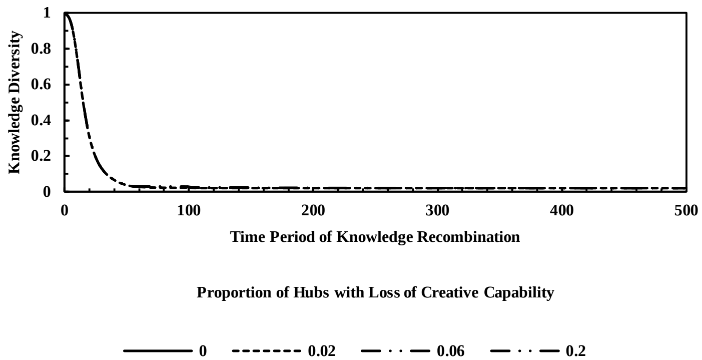
Panel 4a. Slow Decay in Hubs' Creative Capability (τ=50)



Panel 3b. Moderate Decay in Hubs' Creative Capability (τ=30)



Panel 4b. Slow Decay in Hubs' Creative Capability (τ=50)



Appendix A. Parameters for Simulation

Dynamics	Parameters	Remarks	Null Model	Sensitivity Analysis
Knowledge Recombination	t	Time period of knowledge recombination	500	
	m	Number of dimensions in reality and number of elements in an individual's knowledge set	120	
	φ	Degree of interdependence among knowledge elements	4	0, 2, 6, 10
	θ	Rate of learning	0.3	0.1, 0.5, 0.7
	τ	Time period of decay in hubs' creative capability	0, 10, 30, 50	
	T	Time period of inter-temporal changes in hubs	50	0, 10, 80
Network Evolution	n	Number of individuals within the population	500	300, 1000

국 문 초 록

허브의 창의력 상실과 동태적 허브 구조가 전체 시스템의 창의적 성과에 미치는 영향에 관한 연구

서울대학교 경영대학원

국제경영 전공

이 새 롬

본 연구는 허브들의 창의력 상실(Decay in hubs' creative capability)과 그들의 동태적 변화(Inter-temporal changes)가 창의적 분야의 성과(Creative performance)에 미치는 영향에 대하여 살펴보았다. 이 연구는 시스템 내 창의력을 상실한 허브들의 비중과 정적 네트워크 구조(Static structure)의 창의적 성과 간에 역 U-자형 관계를 가진다는 것을 검증하였다. 즉, 창의력을 상실하여 새로운 지식을 습득하는 것을 멈춘 허브들이 시스템 내에 소수가 존재할 때, 시스템 내에 지식 다양성(Knowledge diversity)이 보존되어 오히려 전체 시스템의 성과가 극대화된다는 것을 밝혔다. 더 나아가, 이 연구는 허브들의 동태적 변화가 시스템 내 지식 다양성을 확산시키는 메커니즘으로 작용하여, 허브들이 동태적으로 바뀌는 시스템(Dynamic hub structure)이 허브가 정태적인 시스템(Static hub structure)보다 항상 좋은 창의적 성과를 창출할 수 있다는 것을 검증하였다.

주 요 어: 네트워크(Network); 허브(Hub); 지식 재조합(Knowledge Recombination); 혁신(Innovation); 음악산업(Music Industry)

학 번: 2012-20506