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Network Structure and Evolvability of Innovation Ecosystems

Jianxi Luo
Singapore University of Technology and Design
Engineering Product Development
luo@sutd.edu.sg

Abstract

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Keywords: innovation ecosystem, networks, hierarchy, evovleability, NK model.

1. Introduction

The design and integration of contemporary products and technologies are increasingly carried out by complementary firms participating in an innovation ecosystem (Rosenberg 1982; Moore 1996; Iansiti and Levien 2004; Adner 2006; Baldwin 2012), instead of vertically-integrated corporations (Chandler 1962; Williamson 1985). While the accurate meaning of innovation ecosystem may vary across contexts, here we view and investigate innovation ecosystem as the network of co-specialized and technologically-interdependent firms linked by formal transactional relationships that together collectively design a coherent set of complex system products and services (Langlois and Robertson 1992; Sturgeon 2002; Prencipe et al 2005; Adner and Kapoor, 2010).[1] For example, the smart phone ecosystem includes firms specialized in system design, central processors, telecommunication chipsets, LED displays, GPS, camera, audio, etc., plus developers of operating systems and application software, as well as material suppliers, etc.

Participating firms of an ecosystem are co-specialized but also interdepend on each other, so as to inter-influence the strategies, behaviors and performances of each other. As a result, they co-create value and co-evolve, as Nelson (1994) put it. Recently, increasing attention is paid to the architecture and evolutionary dynamics of such ecosystems for electronics, automobiles, financial products, etc (Fine 1998; Baldwin and Clark 2000; Takeishi and Fujimoto 2001; Paprzycki 2005; Jacobides 2005; Adner 2006; Adner and Kapoor, 2010; Luo et al 2012). However, there is a lack of understanding of specific correlations between the architecture of interdependences among the co-specialized firms and their eco-evolution prospects. This study addresses this gap.

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[1] While government agencies, pure research institutions, and intermediary organizations are often also considered part of a national innovation system (Lundvall 1992; Nelson 1993; Freeman 1995), we do not include them here because we focus on interdependences among technologically-complementary firms. In addition, our definition of innovation ecosystems overlaps much with the more general concepts of “business ecosystems” (Baldwin, 2012) and/or “sectors” (Malerba, 2000) in the literature.

The evolution of an ecosystem can be ignited by the innovation introduced by a single firm or relevant innovations introduced by a subset of accompanying firms within the ecosystem. Inter-firm independences may also end up hindering the diffusion of innovation and the evolution of the ecosystem. The driving and/or hindering effects of inter-firm technological interdependences to technology-ecosystem co-evolution have been documented in previous studies on steel, airplane, and other industries (Rosenberg 1963; Constant 1980; Hughes 1983). Different ecosystems may exhibit varied innovation dynamism and evolutionary prospects (Fine 1998). The capacity of an ecosystem, at a given point of time, to evolve beyond its status quo implies the "evolvability" of that ecosystem at that time.

In fact, "evolvability" has not been formally defined in the strategy literature, despite that the word has been spontaneously used. For instance, Ethiraj and Levinthal (2004) implicitly considered evolvability as the efficiency of search for optimal organizational architectures, and Frenken and Mendritzki (2012) analyzed it as the speed to find the global optimum in the search. The term "evolvability" was originally from biology, where it is more formally defined, as "an organism's capacity to generate heritable phenotypic variation" (Kirschner and Gerhart, 1998). Following the biological definition of evolvability, in this paper, we define the evolvability of an innovation ecosystem as its capacity to change its technology configuration, i.e. the combination of interdependent technologies designed by different firms, and evolve beyond its current status.

Evolvability may vary across different ecosystems that have different evolutionary trajectories and/or "technology regimes" (Dosi 1982; Winter 1984; Malerba and Orsenigo 1997; Malerba 2002). Also, the systemic effects of innovations from one firm or a set of firms propagate throughout the entire ecosystem (Anderson and Joglekar 2012) in particular ways defined by the stable but evolving patterns of interdependences among firms (Jacobides et al 2006). We call such patterns “ecosystem architecture”. In the meantime, the studies of complex systems have taught us that the architecture of a complex adaptive system is a key determinant of the behaviors of individual elements, and thus conditions the subsequent evolution of the whole system (Alexander 1964; Anderson 1972; Strogatz 2001; Whitney et al 2004; Arthur 2007). Innovation ecosystem is a typical complex adaptive system. Therefore, it is reasonable to hypothesize that, the innovation ecosystem’s architecture, i.e. the structure of interdependences among firms, may condition the choices and overall ease or difficulty for firms to co-evolve, i.e. evolvability of the ecosystem.

The present paper aims to specify how the architecture of an innovation ecosystem may condition its evolvability. Our main methodology is network modeling and simulation. Innovation ecosystem is modeled as a directed network of firms connected by technological interdependences through transactions. In characterizing ecosystem network architectures, our primary lens is “hierarchy”, defined as the degree to which transactions flow in one direction, from “upstream” to “downstream” (Luo et al 2012). Concerning ecosystem evolvability, we focus on the “ruggedness” of performance landscapes generated by the NK model, measured as the number of local peaks of a performance landscape (Kauffman 1993; Levinthal 1997). By examining a wide spectrum of ecosystem-like networks with varied degrees of hierarchy, generated by our adaptive niche model (introduced in section 4), we show that increasing degree of hierarchy in networks generally gives rise to performance landscape ruggedness, indicating a higher likelihood for the ecosystem to be locked at local optima, and the difficulty to evolve further. In brief, high degree of hierarchy in an innovation ecosystem limits its evolvability. We also applied these results to link and interpret the differences in inter-firm network structures and evolvability of the automotive and electronics ecosystems.

Our study contributes to the growing literature on innovation ecosystem (Adner, 2006; Adner and Kapoor, 2010) in several aspects. First, our network model makes possible the investigation of ecosystems with a wide variety of network structures, for which empirical studies have been constrained by the scarcity of ecosystem level network data. Also, the adoption of NK model from the studies of organization to analyzing inter-firm technological interdependences opens a new path to understanding the emergent properties and evolution of ecosystems, and also new areas to apply NK model analysis. Second, to our best knowledge, we are the first to specify the impact of the architecture of an ecosystem to its evolutionary prospect, adding new understanding to the ecosystem literature. The new understanding also allows practitioners and firms to better understand the environmental forces as well as systemic constraints and opportunities to their own operations and performances, induced by the architecture of the ecosystem where it is embedded. Making use of this understanding and their knowledge of the architecture of their respective ecosystems, firms may formulate novel strategies to design and manage their architecture of participation in the larger ecosystem for their own strategic interests.

The remainder of the paper is organized as follows. In Section 2, we review the relevant literature and introduce the main hypothesis. Section 3 lays out our methodology and research design. Section 4 introduces our network model to generate ecosystem-like networks, and section 5 reviews the NK model in the ecosystem context and presents simulation exercises and results. Section 6 discusses the implications of our findings to firm strategies. Section 7 concludes.

2. The Architecture and Evolution of Innovation Ecosystems

This study is mainly related to the literature on the evolution and architecture of innovation ecosystems as well as business/industrial ecosystems. We also review the organizational search literature which inspired our use of the NK model to analyze ecosystem evolvability. The literature related to our network generation model will be reviewed in section 4.

2.1 Ecosystem Evolution

The mainstream innovation literature has focused on how a single technology changes over time and how a new technology substitutes an established one (Utterback 1994; Christensen 1997). Such studies treat technologies as black boxes and stand-alone units in their evolution (Rosenberg 1982). In fact, the advances of a technology are influenced by the changes of accompanying technologies and the interdependent efforts of the co-specialized component, complement and customer firms within the same ecosystem (Rosenberg 1972; Iansiti 1998; Brusoni et al 2001; Teece 1996). Therefore, it is important to analyze how interdependent technologies and firms co-evolve together.

Empirical studies on a variety of ecosystems (Rosenberg 1963; Constant 1980; Hughes 1983) have shown that inter-firm technological independences may end up either driving or hindering ecosystem evolution when a single technology innovation emerged somewhere in the ecosystem.[2] For a recent example, Ander and Kapoor (2010) empirically showed that greater upstream innovation challenges in components increase the benefits to technology leaders in the focal segment of semiconductor lithography equipment, while greater downstream challenges in complements may erode such benefits. Jacobides and Billinger (2006) documented how a vertically-integrated European clothing manufacturer proactively engaged itself, through transactional relationships, with other both downstream and upstream complementary firms in

[2] Within an ecosystem, firms may achieve their own innovations by making use of supplier, customer, and complement innovations (Adner and Kapoor, 2010). If these interdependent firms achieve better performances from their interlinked innovations, it is very likely they will collectively adopt the new set of accompanying technologies, thus co-evolving beyond status quo. However, certain firms may fail to either technically or economically take advantage of innovations introduced by other firms. Such a firm may become a bottleneck for co-evolution as it hinders the diffusion of new technologies from other firms. If its competitor succeeds in making use of the new complementary technologies so as to benefit other species and itself, the ecosystem will evolve further with leaving that stagnant firm behind.

the ecosystem, and in so doing, successfully improved its innovative capacity, production efficiency, and overall performance. However, most of these studies have not analyzed the indirect influences from more distant firms, e.g. suppliers of the suppliers or suppliers of complements, to the innovation and performance of the focal firm.

The co-evolving firms in an ecosystem should share a coherent set of goals and problems, and a specific technological knowledge base for the solutions to shared problems, that is, "technology paradigm" (Dosi 1982) and/or "technology regime" (Winter 1984; Malerba and Orsenigo 1997). In turn, the "technology regime" of an innovation ecosystem is expected to condition firms' collective learning, behaviors and organization of innovative and production activities specific for the ecosystem (Malerba 2002). As a result, different innovation ecosystems may exhibit different evolutionary patterns and trajectories. However, our knowledge of the effects of inter-firm technological interdependences on their co-evolution is still fuzzy and limited.

It might be illuminative to consider ecosystem evolution as the collective search of interdependent firms as they explore and exploit different combinations of accompanying technologies (Nelson and Winter 1982; Nelson 1994; Jacobides and Winter 2005; Arthur 2007). Search has been a key topic in management and strategy literatures since the seminal work of March and Simon (Simon 1955; March and Simon 1958). Innovation and new product development have also been studied as a search problem (Stuart and Polodny 1996; Martin and Mitchell 1998; Katila and Ahuja 2002; Knudsen and Levinthal 2007; Terwiesch 2008; Fleming and Sorenson, 2001; 2004; Mihm et al 2003; Yassine et al 2003; Mihm et al 2010; Kornish and Ulrich 2011).

In particular, the introduction of formal models (March 1991), especially, the NK model adapted by Levinthal (1997) from evolutionary biology (Kauffman 1993), surged a fruitful stream of studies of organizational search (just to name a few, Levinthal and Warglien 1999; Rivikin 2000; Rivkin and Siggelkow 2003; Siggelkow and Rivkin 2005; Ethiraj and Levinthal 2004a; 2004b; Sommer and Loch 2004; Lenox et al 2006; Knudsen and Levinthal 2007; Fang and Levinthal 2009). The NK framework mathematically models an organization of N elements (e.g. decisions, choices, activities) each of which has a few choices and an average of K interactions with others, and simulates the landscape of payoffs corresponding to the full space of choice combinations. Because the payoff of one decision is dependent on other decisions in a way defined by the structure of their interdependences, NK simulation creates a mapping from an organizational structure to a performance landscape.

The performance landscape of a given organizational structure can be used as the search space of the organization to study the outcome of various strategies or modes of exploration versus exploitation, and the evolutionary prospects of the organization (Ethiraj and Levinthal 2004a; 2004b; Ghemawat and Levinthal 2008; Fang et al, 2010; Mihm et al 2010). Especially, the landscape's ruggedness, measured by the number of local peaks, has been a key characteristic of NK landscapes, as it increases the chance for a low-exploratory firm to quickly reach a local optimal (and then stay there), and thus increases the value of broader exploration (Levinthal 1997; Rivkin 2000; Rivkin and Siggelkow 2003). A local optimal or peak is a combination of decision choices which has a higher performance level than their immediate neighboring combinations which are different from the peak in only one choice.

There have been NK model applications to the studies of multi-organization co-adaptation. Levinthal and Warglien (1999) first suggested coupling the landscapes of self-interested interacting organizations. The NK(C) model from Kauffman (1993) captures the idea of coupled landscapes, where the parameter C refers to the number of the elements linked across autonomous systems. Such models of coupled landscapes may result in intractable dynamics due to the challenges in modeling cooperation and games. Instead of coupling landscapes, Almirall and Casadesus-Masanell (2010) examined a single landscape for a product, whose complementary subsets of features are separately determined by two groups of firms. Frenken (2000) applied NK model to analyzing the innovation network of three self-organizing but complementary actors, including producer, user and government, each of which has a number of interacting choices regarding new technologies. The level of our innovation ecosystem concerning inter-firm interactions is in the middle ground of the levels of these studies, and appears to be suitable for NK analyses.

In brief, despite the clear effects of inter-firm interdependences on the co-evolution of interdependent firms, we still know very little how specifically inter-firm interdependences may influence the ecosystem's evolvability. But the NK model, which has supported the studies of organizational search, poses a potential for similar analysis at the ecosystem level to develop new understanding of the evolutionary prospects of an innovation ecosystem.

2.2 Ecosystem Architecture

The growing studies of large ecosystems for automobiles, airplanes, telecommunication equipment, consumer electronics and even financial products (Langlois and Robertson, 1992; Baldwin and Clark, 2000; Sturgeon, 2002; Jacobides, 2005; Dalziel, 2007) have exhibited somewhat stable but also evolving patterns through which innovation activities are organized throughout the ecosystem. We call such a pattern "ecosystem architecture" in this paper, whereas the similar concept "industry architecture" from Jacobides et al (2006) considered the division of labor and activities broadly for not only innovation but production.

Prior studies have investigated certain ecosystem architectures that emerge and stabilize as a result of co-specialized firms' strategic choices and interactions (Jacobides 2005; Luo et al 2012). In particular, "hierarchy" rises to be a prime architectural lens of the analyses and observations of general industrial ecosystems (Dalziel 2007; Nakano and White 2007; Luo et al 2012), as design and production processes are organized into sequential stages. "Hierarchy" is the "persistent directionality in continuing flows of intermediate goods" from "upstream" to "downstream" in transaction networks (White, 2002a; 2002b), or a form of continual sequential interdependences throughout the network (Thompson, 1967).

Whereas a pure hierarchy means that the firms that perform higher-level tasks depend upon firms that perform lower-level tasks (Jacobides, 2005; Dalziel, 2007), often hierarchy does not exist in a pure form in real world ecosystems as demonstrated by the examples in Figure 1. Especially, the firms in Figure 1C display some degree of "reciprocal interdependence" (Thompson, 1967). Luo et al (2012) empirically showed that the electronics ecosystem in Japan was only partially hierarchical, whereas the automotive ecosystem exhibited an extremely high degree of hierarchy in early 1990s, using a measure of the degree to which a transaction network embeds sequential, rather than reciprocal, interdependences (Thompson, 1967).

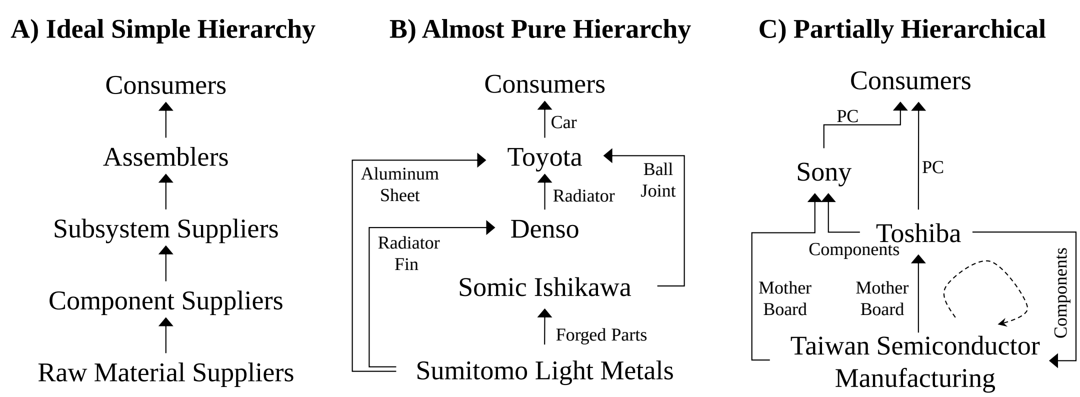

Figure 1. Examples of purely and partially hierarchical ecosystems (by courtesy of Daniel Whitney)

In turn, the overall ecosystem architecture, especially hierarchy, may introduce constraints and opportunities to the strategies and behaviors of firms in the ecosystem, thus influencing their performances and further shaping the evolution of the ecosystem (Casadesus-Masanell and Yoffie 2007; Adner and Kapoor 2010). The field of complex systems has long accepted system architecture as a key determinant of the system's emergent behaviors and performances (Alexander 1964; Anderson 1972; Strogatz 2001; Whitney et al 2004). In evolutionary systems, the interacting elements adapt and react to the aggregate pattern that they co-create. In turn, such aggregate patterns will condition behaviors of individual agents and subsequent changes of the system (Arthur 1999). Since the innovation ecosystem of our interest is a typical complex evolutionary system, its architecture at a point of time should condition its subsequent evolution.

Rivkin and Siggelkow (2007), using NK model-based simulation, showed that a shift in a few commonly-observed interdependence patterns (e.g. centralization, small-world, scale-free, hierarchy) in organizational, social, technological and other general systems can significantly alter the ruggedness of NK landscapes, and long-run performances from varied ranges of exploration. Putting their finding in the innovation ecosystem context makes one think that the architecture of an ecosystem should also influence the characteristics of its search space, and condition its evolutionary prospect. The Rivkin and Siggelkow (2007) study also illuminates the potential of using NK model-based analysis to study ecosystem architectures and evolution.

Recently, a rich stream of NK-based simulation studies of organization search have explored various impacts of modular vs. coupled (Ethiraj and Levinthal 2004a; Fang et al 2010; Frenken and Mendritzki 2012) and the hierarchical vs. reciprocal architectures of decision interactions within an organization to its search space characteristics and search dynamics (Rivkin and Siggelkow 2003; Ethiraj and Levinthal 2004b; Siggelkow and Rivkin 2005; Ghemawat and

Levinthal 2008; Mihm et al 2010). Such NK model analyses of organization hierarchy and search dynamics imply the possibility to apply it to analyzing the impact of ecosystem hierarchy to ecosystem evolvability.

In brief, the literature has illuminated that innovation ecosystems may embed certain regular architectural patterns, primarily hierarchy, but varied degrees. In turn, such hierarchical architecture of an ecosystem may influence the behaviors and performances of firms, and thus condition the evolutionary prospect of the whole ecosystem. However, we still know little about the impact of the aggregate hierarchical architecture of an innovation ecosystem on its evolvability.

2.3 Hierarchy and Evolvability

Simon (1962) argued that hierarchy facilitates complex problem solving and thus emerges in organizations and other general systems as they evolve. Ethiraj and Levinthal (2004b) used NK model to analyze the varied degrees of coupling and hierarchy of interactions between subgroups/departments in an organization. They found that hierarchical interdependences between departments facilitate boundedly-rational search to quickly stabilize. In contrast, when inter-departmental interactions are more reciprocal (i.e. non-hierarchical), it takes a longer time for the search process to reach a local optimal. Their results seem to tell that hierarchy is favorable for organizational exploitation and quick stabilization, versus sustaining exploration. Does this insight about organizational hierarchy and search also apply to the hierarchy and evolution of an ecosystem? One caution to make such an analogy is that an ecosystem is not composed of departments of a firm, but firms. Also, the analysis of hierarchy in an ecosystem concerns more straightforwardly about the sequence of interdependences between individual firms than the grouping of individuals and interactions in departmental boundaries. In addition, the present study is more interested in the kind of "evolvability" that allows a given ecosystem to change its technological configuration and depart from its status quo, rather than to stabilize into certain state.

So, what does the hierarchy of an innovation ecosystem imply about its evolvability, i.e. the capacity to change from its status quo? Prior studies that have argued for the existence of pure hierarchical ecosystem architecture were mostly based on empirical observations of production-oriented ecosystems, where firms tend to take rather fixed positions and roles (White 2002a; 2002b; Nakano and White 2007). Such ecosystems are characterized by low innovation dynamism, and value creation is mainly driven by efficiency improvement, cost reduction, and other exploitation-oriented activities. These may drive one to speculate if ecosystems with lower innovation dynamism and limited exploratory activities tend to be more hierarchical.

In more dynamic and innovation-driven ecosystems, firms may tend to take multiple value-chain roles, and meanwhile simultaneously buy intermediate inputs from and sell intermediate outputs to other ecosystem participants, that is, "vertically permeable boundary (VPB)" (Jacobides and Billinger 2006).[3] Firms adopt VPB for integrative capabilities that will give them the potential of systemic innovations (Teece 1996; Jacobides and Winter 2005) via easy access to and mix-and-match of component level technologies, while keeping internal upstream units competitive by allowing them to directly compete and benchmark with the best ecosystem peers (Jacobides and Billinger 2006; Kapoor 2012). Luo et al (2012) further showed that, firms' adoption of VPB creates the condition for inter-firm transaction cycles to emerge, reducing the degree of sequence or directionality in transaction flows. They also found the Japanese

[3] For example, Apple Inc. designs system products (e.g. iPhone, iPad, etc) and also components (e.g. A6 chipsets and iOS) of such systems. Apple simultaneously sells A6 chipsets to other firms (e.g. Sony) and buys chipsets from outside firms (e.g. Qualcomm and also Sony). Sony also had vertically permeable boundaries at certain point of time in history, as it sold camera chipsets to Apple when it simultaneous procured A6 chipsets from Apple.

automotive transaction network is almost purely hierarchical, whereas the electronics transaction network has many transaction cycles, in the early 1990s.

The understanding of the variation of hierarchy across automotive and electronics ecosystems is echoed by enormous qualitative sector-level and firm-level studies contrasting the innovation and evolution dynamisms of these two ecosystems (Womack et al 1990; Langlois and Robertson 1992; Fine 1998; Baldwin and Clark 2010; Paprzycki 2005; Takeishi and Fujimoto 2001; MacDuffie 2010; Luo 2010; Jacobides et al 2012). These studies have consistently characterized the automotive ecosystem as a stagnant and slow-paced one, where innovation is limited and difficult, firm strategies for performance elevation are mostly oriented for exploitation rather than exploration, centered on quality improvement and cost reduction. In contrast, the electronics ecosystem is commonly characterized as a highly dynamic and evolvable one, where technologies change rapidly and firm strategies are mostly exploration-oriented.

Such insights were also confirmed by the company interviews conducted by the author of the present paper with senior company executives from automotive and electronics companies.[4] In particular, one interviewee from Panasonic Automotive System which develops electronics components and modules for use in automobiles commented that innovation in automotive electronics is much more difficult than innovation in consumer electronics products of other subsidiaries of the Panasonic Corporation. She specifically attributed the relatively stronger

[4] In 2009 and 2010, the first author conducted interviews at the following companies in Japan: Toyota, Nissan, Denso, Sumitomo Light Metal, Kanto Auto Works, Panasonic Automotive Systems, in the automotive sector; Panasonic, Fujitsu, Casio-Hitachi, Seiko Epson, Sony, Takashima, in the electronics sector. This diverse set of firms is representative to some breath of the value chains in both sectors. At each firm, 1 to 3 executives were interviewed for 2-5 hours. The interviewees normally held high-level positions, such as president, board member, director for procurement, and manager for corporate strategy, which allowed discussions on not only day-to-day operations, but also corporate strategies, industry trends, and business environment. The interview questions were semi-structured around the following main aspects: 1) the managers' perception on the economic and technological characteristics of their ecosystems; 2) firms' strategic responses to ecosystem environment conditions; and 3) speculations on the future evolution of their respective ecosystems. The interviews were transcribed. The results are rather consistent within one ecosystem but differ between ecosystems.

innovation challenge to their dependence on the specific needs of the automotive assemblers, high degree of compatibility and customization required for quality integration with other parts of the automotive system. Their story implies that the same firm can face vastly different innovation challenges when it participates, or is embedded, in different ecosystems architectures, which lead to different innovation and evolution prospects.

Taken together, using the lens of ecosystem architecture and evolvability, one may argue that the automotive ecosystem is relatively more hierarchical but less evolvable than the electronics ecosystem. If such limited observations of two contrasting ecosystems happen to be generalizable, they may suggest that an increase in the degree of hierarchy of an ecosystem limits its evolvability. In the present paper, we aim to test this hypothesis by using a network analysis and NK model to investigate various ecosystems with a wide spectrum of hierarchy degrees.

3. Research Design and Methodology

As firms technologically interdepend on each other for complementarities, they form transaction networks.[5] Industrial ecosystems for automobiles and consumer electronics have been interpreted, represented, modeled and analyzed as networks of firms, which design and produce various components, parts, subsystems of end-user products, and integrate them through supplier-customer relationships (Langlois and Robertson 1992; Sturgeon 2002). While inter-firm collaboration or stake-holding relationships may also create value for innovation, transactions appear to be the most formal and relevant interactions that result from technological interdependences between firms (Jacobides and Winter 2005; Jacobides et al 2006; Baldwin 2008; Luo et al 2012). Therefore, the analysis of inter-firm transaction networks induced by

[5] In the literature, such networks are variously called "value networks" (Christensen and Rosenbloom, 1995), "modular production networks" (Sturgeon 2002), among others.

technological interdependences offers opportunities to study the architecture of interdependences of the participants of an innovation ecosystem, and their co-evolution.

However, quantitative and longitudinal analysis that correlates the architecture, performance and evolution of innovation ecosystems is still lacking, primarily due to the difficulty to collect ecosystem-level and longitudinal data. Empirical data on transaction networks have been scarce and limited in terms of industrial diversity and time period covered, primarily because records on inter-firm transactions are usually undisclosed by firms. Thus, the present study uses modeling and simulation methodology to overcome the data challenge. Simulations can generate a large amount of data for statistical analyses of many scenarios and situations, to explore regularities and test hypotheses.

An innovation ecosystem is first conceptualized and modeled as a directed network of firms connected by transactional relationships induced by technological interdependences. Then, the simulation-based network analysis follows three major steps.

1) First, we create a new random network model to generate various samples of ecosystem-like networks with parametric controls, and calculate the average hierarchy degree of each sample.
2) Second, we use the NK model to generate "performance landscapes" of the networks, and then evaluate the ruggedness (number of local peaks) of the performance landscapes for implications to ecosystem evolvability.
3) Finally, we correlate the average degrees of hierarchy of the full spectrum of network samples with the average numbers of peaks of their performance landscapes.

Our research design is also inspired by Rivkin and Siggelkow (2007) who used NK-based simulations to examine a few network structures, including centralization, small-world connections, power-law distributions, hierarchy, and preferential attachment. While they analyzed a specific network with a fixed structure in each pattern category, we focus on the hierarchy pattern but make it variable, and generate and evaluate networks with gradually-changed degrees of hierarchy.

Figure 2 summarizes the design of this research. In next two sections, we will introduce our network generation model and the NK model in the context of innovation ecosystem.

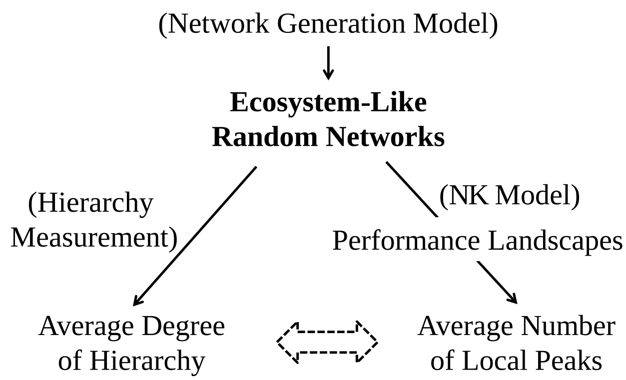

Figure 2. Research design

4. Generation of Ecosystem-like Networks

4.1 The Mechanisms

To simulate networks that can represent innovation ecosystems, we draw on three well-accepted economic-sociology rules on market structures and inter-firm networks:

1) The mapping relationship between "roles" and "positions" of networked firms (White et al, 1976; Wasserman and Faust, 1994). A firm is situated in its position within the network according to its role. Its role determines its position, and in turn, its position institutionalizes its role. For example, in the network, the supplier of a component is positioned upstream to the customer firm that integrates the component into its system product, based on their respective roles as suppliers and customers.

2) Market niche (White 2002b; Burt and Talmud 1993; Podolny et al 1996): a subset of firms which play similar roles in the ecosystem and are similar in terms of what they buy and what they sell. Firms taking the same role in an innovation process tend to be situated proximately in a niche within the network. For example, the firms that focus on semiconductors belong to the same niche, thus their transaction network positions in the electronics ecosystem are proximate.

3) Hierarchy (Coase 1937; White 2002a; 2002b; Dalziel 2007; Luo et al 2012): for efficiency and learning, firms take technologically-specialized roles corresponding to the parts of the technical hierarchy of the system to be designed (Christensen and Rosenbloom 1995; Murmann and Frenken 2006), or the sequential and interdependent stages in the innovation process (Ulrich and Eppinger 2001; Jacobides 2005; Dalziel 2007). For example, in the automotive ecosystem, firms are hierarchically organized by their transactional relationships into tier 1 (the automakers), tier 2 (system suppliers), tier 3 (component and part suppliers), and tier 4 (raw material suppliers). If such a hierarchy is true, the niches in a transaction network will be organized hierarchically.

4.2 Model Description

In our mathematical model, three control parameters are designed to implement the aforementioned rules in generating ecosystem-like networks:

1) Network Size (N): the total number of interdependent firms in the network, i.e., the population of the ecosystem.

2) Transaction Breadth (K): the average number of unique customer firms that each firm has. In a directed network with N firms and M links, K=M/N. It equals the average nodal degree

in network sciences (Newman 2003) and the interaction density, denoted as K in the NK model (Kauffman 1993; Levinthal 1997).

3) Transaction Specificity (S): the degree to which a firm is captive to a specific niche of customers positioned closely in the transaction network. It is quantified as the percentage of a firm's outgoing transactional relationships that fall within a specific niche range downstream to it in a predefined ecosystem hierarchy. It can also be interpreted as the degree to which a particular firm fulfills a specific niche role in the ecosystem, indicated by the proximity of network positions of its customers.

Our model to construct networks of innovation ecosystems was also mathematically inspired by a number of ecological network models which were developed to model the hierarchy and niches within food webs in ecological studies (Williams and Martinez 2000; Stouffer 2006; Allesina 2008). A good analogy exists between an innovation ecosystem and a food web (i.e. ecological ecosystem) in that, both are evolutionary systems and embed hierarchies and niches to varied degrees. Next, we describe the procedure to generate an ecosystem-like network, given N, K and S.

A) Baseline scenarior (S=1): Hierarchical niches

We begin by creating an upstream—downstream relationship between firms in the transaction network. To do this, each of the N firms is assigned to a uniformly-distributed random position λ_i, along an axis ranging from 0 to 1. 0 is the farthest upstream that a firm can be; 1 is the farthest downstream. Consider a focal firm i with position value λ_i, the entire downstream interval for firm i has a length $(1-\lambda_i)$. Next, we define the firm's niche range r_i as the interval containing the firm's customers:

$$r_i = X(1-\lambda_i) \tag{1}$$

where X is a random variable between 0 and 1, and the probability distribution of X is firm-independent. The focal firm's customer niche range can be located anywhere downstream. The position parameter b_i fixes the location of firm i's niche range by defining its left most point. b_i is assumed to be uniformly distributed between λ_i and $(1-r_i)$.

These assumptions jointly ensure that, each firm sells products only to the firms strictly downstream from it, and the niche range is smaller than (or equal to) the entire downstream interval (see Figure 3). Although randomly generated, the network displays strict hierarchy. There is no cycle.

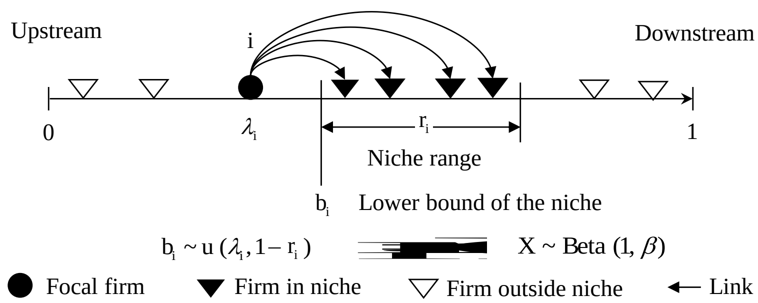

Figure 3. The hierarchical random network configuration.

The niche range of a particular firm r_i is a random variable whose statistical properties are affected by the number of firms, N, and transaction breadth, K. First, the density of firms on the entire segment is N. Because the distribution of these firms is uniform, the expected number of firms in the niche for firm i is:

$$E(K_i) = N \cdot E(r_i) \tag{2}$$

For the entire system excluding the rightmost firm, the sum of the expected number of customers for each firm is:

$$E(M) = \sum_{i=1}^{N-1} E(K_i) = N \sum_{i=1}^{N-1} E(r_i) \tag{3}$$

And, the expected average number of customers per firm is simply:

$$E(K) = \frac{E(M)}{N} = \sum_{i=1}^{N-1} E(r_i) = \sum_{i=1}^{N-1} E(1-\lambda_i)E(X) = \frac{(N-1)}{2} E(X) \tag{4}$$

Thus, the random variable X is not only constrained to be between 0 and 1, but its expected value is

$$E(X) = \frac{2E(K)}{N-1} \tag{5}$$

E(K) is given as the input variable K, i.e. transaction breadth. Note that, although K_i is firm-specific and randomly distributed in our model, K, as the average across all firms, is an empirically measurable property of a given network.

To generate an instance of a hierarchical random network, we need to choose an appropriate functional form for the distribution of X, and then impose the constraint of (5). For computational ease, we use a beta-distribution with parameters (1, β) for the random variable X. This allows E(X) to be in a computationally convenient form $1/(1+\beta)$. Given K and N as inputs, β will be determined by

$$\beta = \frac{N-1}{2K} - 1 \tag{6}$$

Then a random niche range constrained by (6) can be given to each of the aforementioned array of firms randomly located between 0 and 1 on the axis. The focal firm is then linked to each firm in its niche range.[6]

[6] The random hierarchical networks generated using this model have several non-trivial statistical properties:

1) k of the model-generated random directed networks might not be equal but close to the input value.
2) Firms close to, but to the left (upstream) of the rightmost (downstream) firm, may have an empty niche range. This network in effect will have multiple sinks (final integrators), something that commonly occurs in real-world innovation ecosystems.
3) If a firm has an empty niche, and is not included in any other firm's niche, it becomes an isolate.
4) Equation (1) indicates that, a firm's expected niche range is a decreasing function of the firm's position. In effect, downstream firms have fewer potential customers, hence average lower transaction breadth than upstream firms. Symmetrically, the upstream firms have fewer potential suppliers. This property makes our model different from other network generation models using constant K for each node (Kauffman 1993; Watts

B) Hybrid (0<S<1): Random Rewiring

Now we generate a network that lies between the extreme types of fully-hierarchical and fully-random by "rewiring" some of the links in a hierarchical network. The extent of rewiring is determined by the tuning parameter "transaction specificity (S)". In the model, S is operationalized as the percentage of a firm's transactional relationships (i.e. customers) that fall within its pre-defined niche range as given in the baseline model above.

When S is 1, all firms fulfill defined roles and the result is a hierarchical random network (Figure 4). At another extreme, when S is zero, all firms fulfill fully variable roles, their respective transactional linkages are free to go anywhere. This means any firm may transact with any other firms, neither niche rule nor hierarchy rule applies. K_i of each firm is still preserved, while the firm's transaction links are now totally non-specific to any predefined niche.[7]

Between these two extremes, for the focal firm i, $S \cdot N \cdot r_i$ transaction links will be targeted at a specific niche of firms and $(1-S) \cdot N \cdot r_i$ links become nonspecific and may go anywhere (including the pre-assigned niche). Figure 4 demonstrates a hybrid configuration after rewiring. Cycles and backward links can emerge in such a hybrid network.

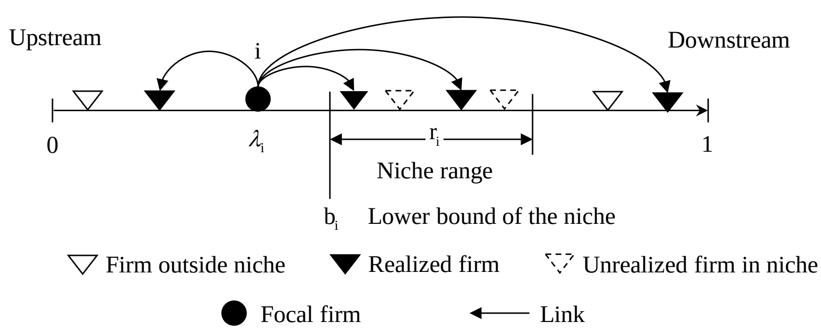

Figure 4. The mixture configuration after rewiring.

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and Strogatz 1998).

[7] The resulted networks with S=0 are not pure random, but reserve a property of real-world ecosystems, i.e. the firms that are primarily in more upstream of a value chain have a broader scope of potential industrial customers than firms that are in more downstream. That is, property 4) in footnote 5 still holds. In our later simulation exercises reported in section 5.3, we also relaxed K_i of firm I and checked the differences in results.

The model allows the approximation for two realistic properties of a niche in the networks. First, it generates intervals inside a niche when S < 1, i.e., the discontinuity of a niche. More simply, a firm may not sell to all occupants of its downstream niche. Second, by random rewiring, it creates random linkages that reflect the firm's adaptive and exploratory behaviors, i.e., possible multiple niches, or a major niche plus several minor trials.

Therefore, the model can simulate firms' variable mix of transaction relationships resulted from variable degrees of balance between exploration and exploration behaviors (March 1991), by creating regular niches in the baseline but allowing transactions going out of niches. Therefore, we name it "Adaptive Niche Model" as it allows freedom for adaptive transactional relationships that deviate from pure hierarchy and niche rules.

This model appears to be the first in the strategy literature that generates random tunable networks to represent industrial ecosystems. Specifically, by tuning the transaction specificity parameter, we are able to generate a wide spectrum of ecosystem-like networks with gradually-varied degrees of hierarchy and niche embeddedness. See Appendix A for a series of model-generated networks with gradually-varied degrees of hierarchy. Next, we evaluate such networks in terms of their degrees of hierarchy.

4.3 Calcuation of the Hierearhcy Degree of a Network

Following the prior work on the quantification of hierarchy in general directed networks (Luo and Magee 2011) and transaction networks (Luo et al 2012), we calculate the degree of hierarchy (H) of a given network as the percentage of links that are not included in any cycle:

$$H = \frac{\sum_{i=1}^{M} e_i}{M} \qquad (7)$$

where M is the number of links in the network and e_i=0 if link i is in a cycle and 1 otherwise. A pure flow hierarchy generalizes Thompson's notion of "sequential interdependence" (Thompson, 1967). Cycles or reciprocal interdependence (Thomson 1967) violate the principle of asymmetry of hierarchy in that flows can come back to their origin. This metric captures the extent to which a network embeds cycles. When H=1, the network is purely hierarchical (see example A in Figure 5); when 0<H<1, the network is partially hierarchical (see example B in Figure 5); and when H=0, any link is on a cycle with some others so the network is purely cyclic or non-hierarchical (see example C in Figure 5).

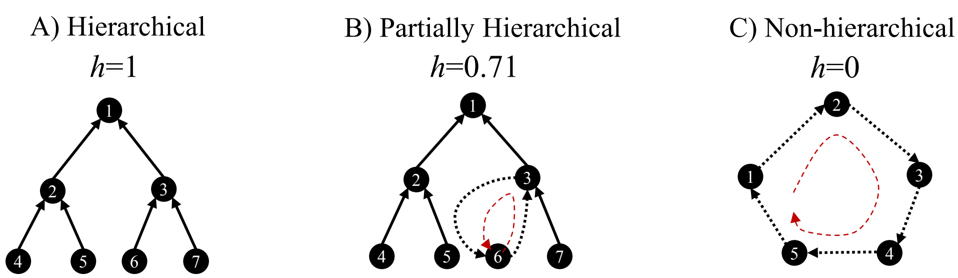


Figure 5. Example Networks and their Hierarchy Degrees

4.4 Propoerties and Validation of the Simulated Networks

Adaptive Niche Model is repeatedly run to simulate many network samples. For each given combination of inputs (N, K, S), we simulate 2,000 networks and calculate the average hierarchy degree of each sample of 2,000 networks. In order to improve the fitness of the randomly-generated networks, only the ones with the given N firms fully connected and K within 3% of the target value were accepted as valid trials. These simulated network samples are first assessed in terms of the relationships between H and the input parameters N, K and S.

First, hierarchy degree appears almost unaffected by changes in network size (N) when it is sufficiently large, primarily because hierarchy is an architectural property and independent of network scale. Second, hierarchy degree (H) increases with transaction specificity (S) at different levels of K. When S=1, H equals 1 for all values of K. When S=0, hierarchy degree varies with K. The lower K is, the higher H is. When K is lower, H decreases more slowly with the decrease of S. Third, hierarchy degree (H) decreases with transaction breadth (K), except for S=1. When S is lower, H decreases more rapidly with the increase of K.

Average hierarchy degree as a function of K and S (when N=100) is plotted in Figure 6. In brief, transaction breadth (K) tends to pose a cap on the increase of hierarchy degree (H) driven by any potential increase in transaction specificity (S). In particular, the relationship between K, S and H is monotonic, so that one can invert the relationship to infer S from the empirically-measurable K and S of a given real-world network.

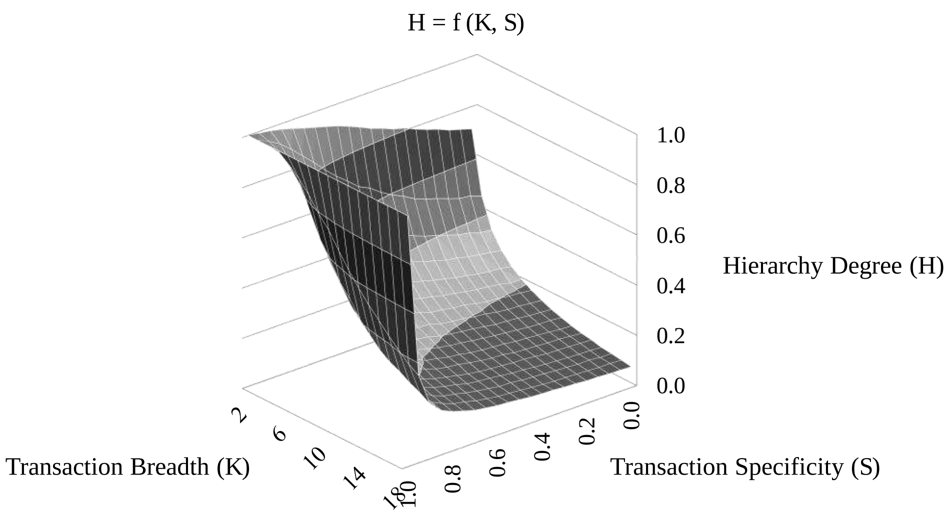
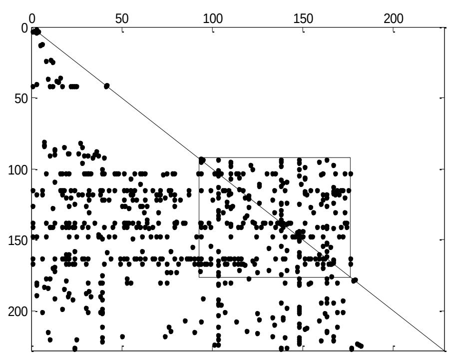


Figure 6. Impact of transaction specific (S) and breadth (K) on hierarchy degree (H)

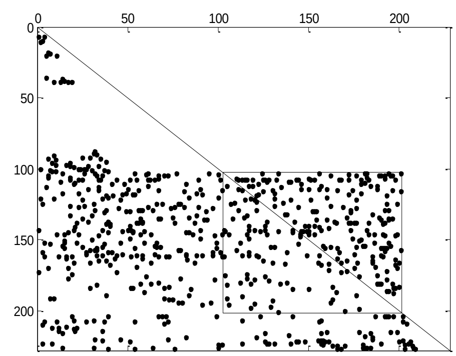
We also use Dependency Structure Matrix (DSM) to visualize and compare the structures of simulated and empirical networks for validating the simulated networks as viable representations of real-world ecosystems (see Figure 7). In a DSM, firms are listed on the horizontal and vertical axes in the same order according to their visibilities, i.e. the count of all the direct and indirect dependencies that a firm possesses with other firms. The dots represent dependencies among them. Firms on connected cycles are structurally symmetrical and must have the same count of visibility, so they must be located together connectively on the axes.

From the literature, we found only one empirical ecosystem network which might be suitable for the validation purpose, the Japanese electronics transaction network in 1993 from Luo et al (2012), because it is sufficiently large and has a rather sophisticated and partially hierarchical architecture. That empirical network is also not a pure representation of the innovation ecosystem for electronics products, but the industrial ecosystem, because inter-firm transaction relationships included in that network might result from other social-economic factors than technological interdependences. Figure 7 shows the DSMs for both the empirical network and a network generated by Adaptive Niche Model.



A) Japanese electronics transaction network, 1993 (Luo et al 2012)

N=227, K=0.2855, S=0.3218, H=0.5957



B) Simulated network

N=227, K=0.2855, S=0.3218, H=0.6905

Figure 7. DSMs of a simulated network and an empirical network

We actually simulated many networks controlled to have the same size, density and hierarchy degree as the empirical electronics transaction network, and found their structures are quite similar to that of the empirical one. In particular, all simulated networks capture the empirical architecture that has a single strongly-connected large component in which inter-firm cycles are intertwined together. The specific network shown in Figure 7B is just a typical one. Clearly a single case is not sufficient for validation, and more cases of testing are needed to increase our confidence level of the model. The challenge for validation lies in the limited empirical ecosystem network data.

Next, we introduce the NK model to generate performance landscapes of the networks generated by the adaptive niche model, and evaluate such landscapes to for indications on ecosystem evolvability.

5. NK Model and Simulations

5.1 NK Landscape for Innovation Ecosystem

Following the general NK model, we conceptualize an innovation ecosystem as a network of N firms with a number of alternative "states" representing their alternative technologies. Each firm has on average K transactional relationships induced from technological interdependences with other firms. This formulation is similar to Frenken (2000)'s NK model for a national innovation network, which determines the "states" of three actors: "producer" by its "technology", user by its "market segment", and government by its "country". Our NK model is simpler in that the actors are uniformly firms whose "states" are technologies. Our analysis also specifically focuses on the degree of hierarchy in the inter-firm networks as independent variable. Each configuration of an ecosystem represents a combination of interdependent technologies of all the firms.

We consider the simplest case that each firm has two states, i.e. two major technology alternatives. The state of a firm is mutated between 0 and 1 whenever the firm's technology is changed due to innovation. Thus, we can configure an ecosystem of N firms by an N-digit string of 1s or 0s, denoted as $s_i = d_1 d_2 \cdots d_N$, with $d_j = 0$ or 1, for $i=1,2,3 \cdots 2^N$. The combinatory space of N firms has total 2^N such configurations. The performance of a firm is randomly drawn from uniform distribution [0,1], each time the firm's technology is changed, or the technology it depends on from any other firm is changed. For each configuration of an ecosystem, its overall performance is evaluated as the average value of the performances of all firms. The performance levels of all ecosystem configurations (i.e. the combinations of interdependent firm technologies) together form the "performance landscape" for a network give its structure.

On an NK landscape, if a configuration's performance is better than that of any of its immediate neighbor (which has only one element different the focal combination), this configuration is a local peak. If the performance level of a local peak is the highest among all 2^N configurations, it is a global peak. In the NK-based studies in management sciences, the number of local peaks has been a key metric to depict the ruggedness of an NK landscape. The proliferation of local peaks makes it difficult for a firm to continue its local search for a better performance as it will quickly climb up to the closest local peak and stay there as it cannot find any higher immediate neighbor (Levinthal 1997; Rivkin and Siggelkow 2007).

5.2 The Meanings of Landscape Ruggedness to Innovation Ecosystem

Extending an analogy from firm search to ecosystem evolution, the ruggedness of the NK fitness landscapes for an ecosystem with a given network structure may condition the subsequent changes of the entire innovation ecosystem and thus its evolvability. For instance, on a not-so-rugged or single-peak landscape, an ecosystem's exploitation through one innovation of one firm at a time might be sufficient to drive the ecosystem to sprawl a wide portion of the landscape, evolve for a long while, and reach a sufficiently high performance point on the landscape.

However, in a highly rugged landscape with many local peaks, such exploitation will lead the ecosystem quickly to stabilize at the local peak closest to the starting point of the evolution (as there are many peaks on it) and get stuck there. As a result of quick hill-climbing and locking-in to the first local optima, a strong form of path dependence and modest ecosystem performance is expected. A good example of such lock-in is the automotive innovation ecosystem that has been locked at a local optimum characterized by a dominant design of internal combustion engine-powered automobiles, for about a century.

Besides the ruggedness of the landscapes, the scope of simultaneous innovations in the ecosystem, implying the extent of exploitation vs. exploration of the ecosystem in a given landscape, may also affect ecosystem evolvability. If only one firm or a very small number of firms change technologies or innovate at the same time, the ecosystem is primarily in a mode of exploitation. In contrast, in an exploring ecosystem, a large number of firms change their technologies at the same time, in either a coordinated or autonomous manner.

Intuitively, a wider scope of simultaneous innovations by many firms creates a greater chance of encountering a dramatic ecosystem-wide improvement, than one trial by a single firm at a time. A higher variance also allows the exploring ecosystem to continually discover better configurations of technological choices and thus sustaining its evolution for a longer time, whereas an exploiting ecosystem quickly exhausts its improvement opportunities and gets stuck at a local peak close to its starting point, and thus stop evolving. Eventually, exploratory ecosystems may evolve for a longer time and reach relatively higher performances, than exploiting ecosystems, given the same landscape ruggedness.

Taken together, the ruggedness of the landscape and co-searching scope of firms both influence the evolution of the ecosystem. In particular, considering that the landscape is where exploration versus exploitation happens, one can say that the shape of the landscape actually conditions the exploration versus exploitation of the ecosystem as a whole. When the scope of exploration (and other conditions) is fixed, an increase in landscape ruggedness increases the chance for an ecosystem to be stuck at local optima and cease evolving. Therefore, our analysis will use the average number of local peaks on the simulated performance landscapes of an ecosystem network as the key reverse indicator of the ecosystem's evolvability, when holding the firm co-searching mode fixed.

5.3 Generation and Analysis of Landscapes

In principle, over a directed "supplier->customer" relationship, the directions of dependence (or influence) might be unidirectional or mutual, implying three possible scenarios.

1) First, the customer firm highly depends on the technology of the supplier, which, however, is not specific to the system of the customer firm. That is, possible influence on performance is unidirectional from the supplier to the customer. Only the supplier affects the customer. Such relationships may widely exist between the personal computer manufacturers and suppliers. Suppliers like Intel and Microsoft are dominant and can influence the behaviors and performances of downstream computer manufacturers, whereas the reverse influence is almost non-existent. The driving forces of co-evolution are mostly from bottom up, i.e. from upstream to downstream.
2) Second, the technology of the supplier is specifically designed to the system of the customer, which is not specific for the use of the supplier's technology. Thus, the change made at the supplier is not influential to the customer but just to itself. Possible influence is unidirectional, only from the customer to the supplier. Only the customer affects the

supplier. Possible examples might be found in the smart phone industry, where the technology and strategy changes of a powerful downstream integrator like Apple can drive its component suppliers, such as Cornings, Qualcomm and Foxconn, to change their technologies, operations strategies, resulting performance changes. In contrast, reverse influence is limited. Currently the driving forces for the evolution of the smart phone ecosystem are mostly from top down, i.e. from downstream to upstream.

3) Third, the technologies of the supplier and customer are highly coupled, and changes in one will influence the other's performance. Suppliers and customers mutually affect each other's performance, i.e. mutual technological dependences. For example, the automotive OEMs and their suppliers may be connected by such relationships, where the competition requires tight integration of systems and specific customization of components, giving rise to co-specialization, hand-in-glove relationship, and mutual dependences.

A real world ecosystem is most likely to have a mix of varied supplier-customer relationships falling into any of the three extreme scenarios. Thus, we simulate all three extreme scenarios, in each of which the directions of influence over all transaction relationships homogenously follow just one of three possible directions of influence between supplier and customer, and take the results from all the extreme scenarios as the bound for possible real-world situations.

For our simulation exercises, we fix N=12, tune K from 2 to 5 by step of 1, and S from 0 to 1 by step of 0.05. For each given combination of inputs (K, S), we simulate a sample of 2,000 networks, calculate their average hierarchy degree. For each network in the sample, we generate 200 performance landscapes using the NK model.

The correlation between the average hierarchy degree (H) and average number of local peaks (P) of the performance landscapes of a series of controlled network samples is reported in Figures 8, 9 and 10 for three scenarios of influence direction. Standard deviations are included in the form of error bars to add more accurate statistical interpretation of the results.

A) Influence Direction and Ecosystem Evolvability

First, we found clear patterns and distinctions among the three influence direction scenarios in terms of the effect of hierarchy degree on average peak number, and the magnitudes of average peak numbers, consistently across various levels of K.

When only the customer can affect the performance of the supplier over any transaction relationship across a network (Figure 8), hierarchy degree is hardly correlated with the number of local peaks, implying that the hierarchy in ecosystem architecture does not affect ecosystem evolvability. The innovation ecosystem around Apple Inc might be such a case, where the “powerful” system integrator maintains strong architecture controls.

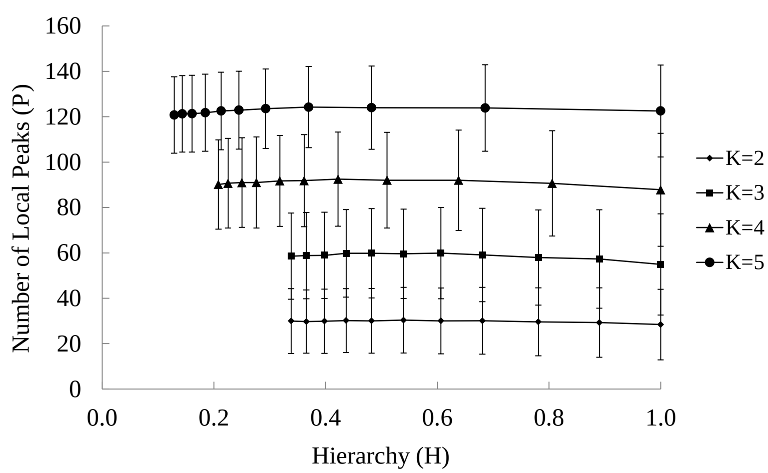


Figure 8. Hierarchy and NK Landsacpe Peaks (Customer Influence Only)

When only suppliers can have an influence to their customers (Figure 9), the magnitude of average peak numbers is clearly the lowest, that is, ecosystem evolvability is the highest, among all three scenarios, for any level of K and H. In such cases, the innovation of suppliers that improve performances of systems and system integrators will be highly effective to drive ecosystem evolution.

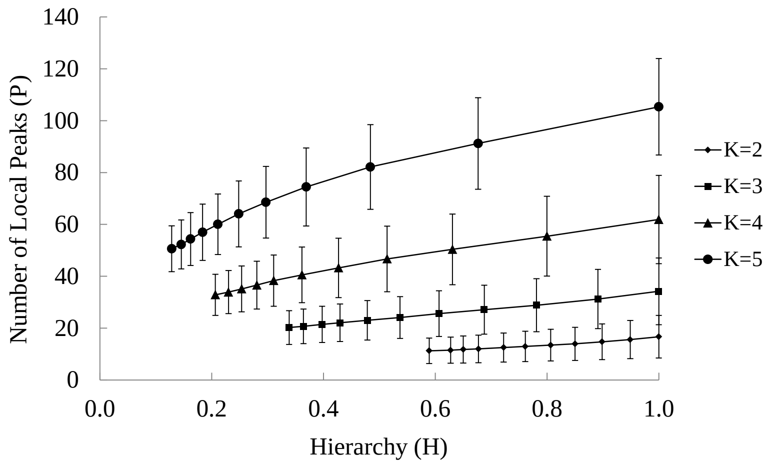


Figure 9. Hierarchy and NK Landsacpe Peaks (Supplier Influence Only)

On K=5 landscapes, for instance, the range of the average number of local peaks is from 51 to 105 when only supplier has an influence, from 121 to 123 when only customer has an influence, and from 169 to 260 in the scenario of mutual influence. Similarly, for K=2 landscapes, the range of the number of local peaks is from 11 to 17 when only supplier influence is in place, from 28 to 30 when only customer has an influence, and from 44 to 49 in the scenario of mutual influence.

When any pair of supplier and customer can influence each other, ecosystem appears to be the least evolvable as indicated by the highest number of peaks (Figure 10). This might represent the sitautions where mutually-locking or doubled density of conflicting constraints due to mutual interdependences increases the difficulty for innovations to diffuse across firms in the ecosystem and drive its overall evolution. This result may explain why innovation and evolutin is difficult in the autmotive ecosystem where customers and suppliers relationships are largely hand-in-glove and mutually-specific.

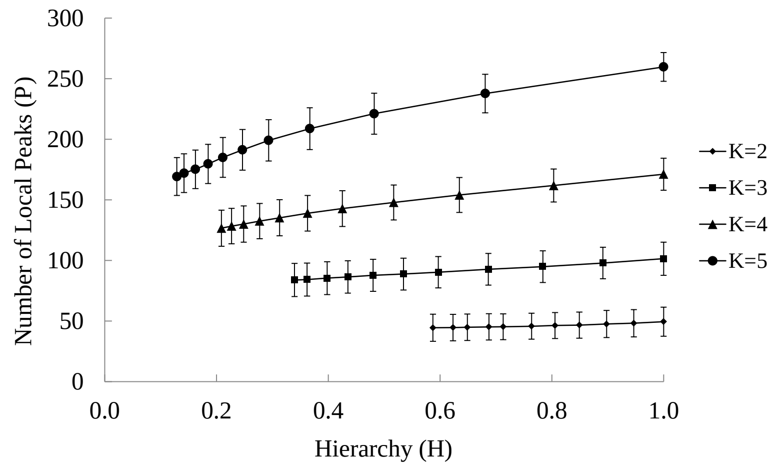


Figure 10. Hierarchy and NK Landsacpe Peaks (Mutual Influences)

B) Hierarchy and Ecosystem Evolvability

In the two influence-direction scenarios where a supplier innovation can influence customer performance (both Figures 9 and 10), consistantly hierarchy gives rise to the average number of local peaks, when holding fixed the transaction breadth (K). Even in the third scenario (Figure 8), hierarchy does not reduce the average number of peaks. Furthermore, through a simple checking of simulation exercises, we found that if the variable ecosystem-like networks are generated without perseving each firm's preassigned number of customers (K_i) when rewiring (Figure 4),[8] the postive influence of hierarchy to the avarage number of locak peaks is also observed in the scenario when only customer can influence supplier, whereas their relative differences in magnitude remain.

Therefore, considering that a real-world ecosystem is most likely to have transactional relationships with a mix of inter-firm influence direction scenarios, the hierarchy in ecosystem

[8] That means both the start (supplier) and end (customer) of a transactional relationship are changed, when a link is chosen to be rewired. The resulted networks with S=0 are pure random network and the property 4) in footnote 5 no longer holds.

networks in general will give rise to landscape ruggedness. In turn, the landscape ruggedness implies a high chance for the ecosystem to be locked at local optima, difficulty to make changes, and thus lower evolvability. Vice versa, less hierarchical ecosystems will have less rugged NK landscapes and be more evolvable.

Furthermore, three detailed patterns are noteworthy. First, the increase in the number of local peaks (P) is fairly linear with respect to average hierarchy degree (H). The Pearson correlation coefficients for P and H range from 0.9807 for K=5 to 0.9904 for K=2 in the scenario where only supplier has an influence, and from 0.9800 for K=5 to 0.9828 for K=2 in the scenario where both supplier and customer can influence each other. Second, when tranasction breadth (K) is higher, P increases faster with the increase in H. For instance, in the scenario of only supplier influence, the slope of P-H linear regression curve is 63.7 for K=5 and is much higher than the slope of 12.8 for K=2. In the scenario of mutual influences, the slope of the P-H linear regression curve is 105.7 for K=5 and much higher than the slope of 11.6 for K=2. This difference in slopes across the values of K indicates a reinforcing effect of transaction breath on the limiting effect of hierarchy on ecosystem evovability.

C) Transaction Breadth and Ecosystem Evolvability

Transaction breadth (K) here is mathematically equivalent to the interaction density variable in the standard NK model. Prior NK model analyses have found local peaks (P) proliferate when interaction density increases (Kauffman 1993; Levinthal 1997; Rivkin 2000; Rivkin and Siggelkow 2007). Our result is also consistent with them. As Figures 8, 9 and 10 show, the number of local peaks (P) increases as transaction breadth (K) increases, when the influence scenario and hierarchy degree (H) are fixed. A possible interpretation might be that, if the performance of a particular firm depends on the technological choices of many other firms, the performance landscape will be rather rugged, increasing the chance of lock-in at local peaks and the difficulty to evolve to a spot with a better performance. In brief, the density of inter-firm technological interdependences limits ecosystem evolvability.

C) Other Results

Furthermore, we also tracked 1) the degree of clustering of local peaks as the fraction of all local peaks within Hamming distance of 4 of the global peak, 2) the average local-peak performance (measured as a portion of the maximum attainable performance), 3) the average performance of the highest peaks, and 4) the average performance of the lowest peaks, in response to the changes in hierarchy degrees in the simulations. The results show these parameters are remarkably insensitive to hierarchy degree (H), and thus imply hierarchy degree does not influence other aspects of characteristics of the performance landscapes, but only the ruggedness of the landscapes.

5.4 Discussions: Hierarchy and Evolution

A) Coherence with prior understandings of hierarchy and evolvability

On the first glance, our main finding, i.e. hierarchy of an ecosystem imposes a limiting effect on its evolvability, contradicts with the arguments of Simon (1962), Ethiraj and Levinthal (2004b) and Frenken and Mendritzki (2012) that hierarchy in an organization facilitates its evolution because hierarchy promotes stability. First of all, their concepts of hierarchy mainly considered "nested hierarchy" between levels of organizational decomposition,[9] while our hierarchy focuses on the directionality of the relationships among the generic-level elements of the system. Second, their context is organization search, whereas ours is ecosystem evolution (see more discussion

[9] Ethiraj and Levinthal (2004b)'s concept of hierarchy considers both the nested units in an organization and the directional interactions among them.

regarding this difference in part B of this section later). Third, our concept of evolvability emphasizing the capacity to make changes and variations is different from theirs which focuses on the efficiency and speed to stabilize.

In the meantime, interesting complementarities exist between the findings from the simulation analysis in the present paper and the earlier understandings developed by other scholars. For instance, our finding that hierarchy degree is negatively related to the system's capability to generate variation (that is our definition of "evolvability") is in fact coherent with Ethiraj and Levinthal (2004b)'s finding that hierarchy facilitates speedy stabilization, rather than variation or deviation. It is also coherent with Simon (1962)'s view that hierarchy emerges in evolutionary process as it stabilizes, because when a system stabilizes its capacity to change and evolve further should decline. A system oriented toward stabilization may tend to select a more hierarchical system architecture which limits further variation and thus facilitates stabilization (we will discuss this view in detail in the context of automotive versus electronics ecosystem in section 6.1).

B) Hierarchy and Long-run Performance over the Evolutionary Process

Our results inform the capacity of an innovation ecosystem to evolve beyond its current technological configuration (i.e. the location on the landscape), given the degree of hierarchy embedded in the architecture of interdependences between firms, at a given point of time, when other conditions including the co-searching strategies of individual firms are fixed. While the results can imply how evolvability may change when an ecosystem's architecture (in terms of hierarchy) changes over time, our analysis is static by nature.

We were in fact also curious about the long-run performance prospects of ecosystems with different degrees of hierarchy over time. Earlier studies have shown that the proliferation of local peaks limits long-run performances, no matter if the proliferation originates from an increase in K (Kauffman 1993; Rivkin and Siggelkow 2003) or a shift in network interaction patterns (Rivkin and Siggelkow 2007). With that knowledge, one can possibly infer that, an increase in hierarchy degree of an innovation ecosystem, which leads local peaks to proliferate (we just learned in section 5.3), will impose limits to the long-run performances of ecosystems. We also followed the simulation exercise of Rivkin and Siggelkow (2007) to compare long-run performances of ecosystems of different degrees of hierarchy, and obtained consistent results.

However, such analysis, while being worth running for inspiration, is dubious because the models from prior studies (Rivkin and Siggelkow 2003; 2007) were for adaptive search process of a firm, which are fundamentally different from the co-evolution process of self-interested firms. In an ecosytem, individual firms may have varied perceptions and inaccurate information of the performance of their ecosystem, varied capabilities to capture the co-created overall value, varied rationales and thus varied responses to the same ecosystem performance. There is neither perfect feedback nor perfect adaptation in the ecosystem evolution process. Also, there is no central control over autonomous firms which normally do not make strategic moves to improve the performances of the ecosystem but their own payoffs. Thus, "optimization" also cannot describe to the nature of ecosystem evolution.

For these reasons, the models built on the rationales for the adaptive search process of a firm, i.e. an alternative configuration will be bounded-rationally adopted if it is better than the previous one, are inaccurate to describe the co-evolution of interdependent firms in an ecosystem. For modeling co-evolution or co-adaptation, Kauffman (1993) and Levinthal and Warglien (1999) suggested the "NK(C)"-type of model to couple the landscapes of self-interested firms by linking some of the decision elements of respective firms, and also by incorporating the mechanisms of cooperation and games in the model. Clearly, such models are highly complex and may introduce intractable dynamics.

As a result, it is still challenging to model the perceptions on, and rationales and decisions related to the reactions of individual firms to the performances of the whole ecosystem, and the resulted changes in inter-firm relationships and network structures. In the following section (6.1), we will continue to discuss and speculate how firms might react to the evolvability resulted from different network architectures, and how such reactions in turn may influence the ecosystem's network architecture. In general, we still do not have a good mathematical model for the actual process of the co-evolution of firms, technologies, and ecosystem architectures.

6. Implications

Our main finding, i.e. hierarchy of an ecosystem has a limiting effect on its evolvability, offers fresh theoretical as well as managerial implications.

6.1 Theoretical Implications

The specified understanding of the impact of hierarchy on the evolvability of an innovation ecosystem may allow one to infer and predict the evolvability of a real world ecosystem, once its degree of hierarchy is empirically known. For instance, Luo et al (2012) empirically showed the electronics transaction network in Japan, with H=0.59, was much less hierarchical than the Japanese automotive transaction network, H=0.99, in the same year 1993. Based on that, one can infer the electronic ecosystem at the time might be more evolvable than the automotive ecosystem,[10] following on our finding from the simulation analysis. This inferred difference of

[10] Also considering that, the electronics ecosystem saw a wider range of firms introducing modular and autonomous innovation at the same time, than the automotive ecosystem, in the 1990s. As discussed earlier in section 5.2, wider scope of autonomous innovation also favors evolvability.

evolvability between these two real ecosystems is in line with insights (see section 2.3) from the enormous, but mostly qualitative, studies on the differences of these two sectors (Womack et al 1990; Fine 1998; Baldwin and Clark 2000; Papzycki 2005; MacDuffie 2010; Jacobides et al 2012).

Therefore, the difference in the architecture of interdependences between firms might provide a partial explanation to the limited evolvability of the automotive ecosystem and the high evolution dynamism of the electronics ecosystem observed in past two decades. In contrast, the prior ecosystem-level studies have only conceptually and blurrily related sectorial difference in innovation patterns and evolutionary dynamics to the "technology trajectories" (Dosi, 1982) or "technology regimes" (Nelson and Winter 1982; Malerba and Orsenigo 1997; Malerba 2002). While the "technology regime" framework remains useful at a fundamental level to explain industry-technology co-evolution, the present study adds that ecosystem architecture also matters to condition ecosystem evolvability, at a different level of analysis and from a different angle.

Furthermore, if the hierarchical architecture of inter-firm interdependences has an constraining effect on the overall ecosystem's performance elevation and evolution, firms that perceive such limits are likely to adapt and react with exploiting (rather than exploratory) strategies and behaviors, which further institutionalize the firms' specialized roles, positions, and interdependences, thus reinforcing the hierarchy in the ecosystem architecture.

For instance, during the first author's fieldwork and interviews in the automotive and electronics sectors, senior managers from the electronics firms shared the same perception and belief on the high dynamism and evolvability of their business ecosystem. In turn, such perceptions have driven them to embrace strategies and operations similarly for innovation and exploration. In contrast, senior managers from automotive suppliers and manufacturers perceived that innovation is difficult in their ecosystem which appears to be stagnant. Strategies for performance elevation are mostly exploitation-oriented, and centered on quality improvement and cost reduction. As a result, fewer firms introduce innovation simultaneously in the automotive ecosystem than in the electronics ecosystem. The automobiles have had a dominant design for a century and the architecture of the ecosystem is also stable, despite the enormous efforts to improve automobile technologies in terms of energy efficiency, emission, safety, etc. Automotive firms are highly co-specialized and comply with a rigid industrial hierarchy.

That is, the relationship between hierarchy and evolvability of an ecosystem is not one-directional, but mutual: 1) hierarchy limits the evolvability of the ecosystem, and 2) ecosystem hierarchy might be reinforced when firms react to limited ecosystem evolvability with exploitation-oriented strategies and operations for incremental improvement on an existing trajectory. The first assertion has been supported by our simulations. The latter is more of an argument, based on qualitative evidence and reasoning from the literature and fieldwork.

6.2. Strategic Implications

What can firms do strategically to lift an ecosystem with high degree of hierarchy and low evolvability out of the mutually self-reinforcing loop, if evolvability is desirable?[11] The new understanding of the impact of hierarchy on the evolvability of ecosystems offers a new guidance. That is to reduce landscape ruggedness, by reducing the degree of hierarchy in ecosystem architecture via fostering inter-firm transaction cycles (Luo et al, 2012).

[11] However, it is also important to understand that evolvability is not always desirable. In ecosystems such as aerospace, where safety and reliability are of paramount importance but the complexity of such technical systems makes high quality integration extremely difficult, a high level of evolvability might be undesirable. Such ecosystems for aerospace etc. may remain highly hierarchical (pending empirical tests).

To pursue this direction, previously vertically-integrated firms may intentionally adopt vertically permeable boundaries (Jacobides and Billinger 2006; Luo 2012; Kapoor 2012), which create the condition to allow transaction cycles to emerge so as to reduce the ecosystem's hierarchy degree that limits its evolvability. Vertically permeable boundary of a firm means it (1) participates in multiple stages of the value chain, hence is vertically integrated, but also (2) allows both downstream units to purchase intermediate inputs from and upstream units to sell intermediate goods to other firms (Jacobides and Billinger 2006; Luo et al 2012). In the meantime, vertically-specialized firms may intentionally choose to transact with vertically-integrated firms to form transaction cycles. Therefore, vertically permeable boundary, which arguably provides dynamic capabilities to firms according to prior studies, may also contribute to the evolvability of the ecosystems where these firms are embedded.

If the architecture of interdependences of participating firms in an ecosystem is not to be changed, the interest to elevate its evolvability may call for a broader scope of firms to introduce innovations at the same time, i.e. simultaneous innovations (as explained in section 5.2). Simultaneous innovations may be possibly promoted via the adoption of technology standards, or via the coordination of innovation efforts of multiple firms whose technologies interdepend on each other to introduce accompanying new technologies simultaneously.

7. Conclusions

This study makes both theoretical and methodological contributions to the studies of innovation ecosystems. First, our investigation of a wide spectrum of ecosystem-like networks with variable hierarchy shows the limiting effect of hierarchy on the evolvability of innovation ecosystems. Such new understanding allows firms to infer the evolution potential of their respective business ecosystem environment with the knowledge of the structure of inter-firm networks at a given point of time. The new understanding also provides guidance for firms to formulate high-level strategies, regarding the design and management of the architecture of their participation in the ecosystem, in order to possibly influence landscape ruggedness for desirable ecosystem evolvability.

Second, methodologically, our simulation model makes it possible to systematically explore and test possible correlations between network structures and evolutionary prospects of ecosystems. In contrast, prior studies on the architectures of innovation ecosystems or sectors were mostly conceptual or cover only one or two ecosystems, and prior NK model-based analyses were mostly applied to fixed network structures. In particular, to our best knowledge, the Adaptive Niche Model introduced in this paper is the first of its kind to generate random tunable networks that can potentially represent innovation ecosystem networks. The use of this model in the present study has advanced the NK model-based simulations as previously static structures of the networks are made variable. Generally, with the model and the tuning parameter "Transaction Specificity", we are now able to generate a wide spectrum of ecosystem-like networks with varied degrees of hierarchy, which are further useful for the studies of a wide range of topics related to innovation ecosystems, organizations, and general systems.

The present study has a several limitations. First of all, the basic NK model only considers the landscape of the overall value contributed by all individual firms, but does not model how value may be captured unevenly across firms (Jacobides et al, 2012). For instance, the strategic options, opportunities and constraints to the value capture of different firms at different network positions might be worth further consideration. This is a venue to improve the NK model for ecosystems. Also, our analysis only sheds light on a static property of an ecosystem given a specific network structure. The actual process of the co-evolution of technologies, firms, and their interdependence structures, is only speculatively discussed in section 6.1, but not scientifically modeled. Some of the challenges to modeling ecosystem evolutionary processes are discussed in section 5.4. An expected model should take into account the change of network structures as the result of firms' varied value captures of the ecosystem's overall payoff, and varied reactions (as well the rationales behind) to the ecosystem evolvability that they asymmetrically perceive. Modeling so many factors may introduce high computational complexities and challenges, but appears to be an important venue for future research.

Despite these limitations, we hope our study is sufficiently inspirational, and invite broader research using modeling and simulation methodology to explore the architecture and evolution of innovation ecosystems.

REFERENCES

Adner, R. 2006. Match your innovation strategy to your innovation ecosystem. *Harvard Business Review*, 84(4), 98-107.

Adner, R., Kapoor, R. 2010. Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal*, 31, 306-333.

Alexander, C. 1964. *Notes on the Synthesis of Form*. Harvard University Press, Cambridge, MA.

Allesina, S., Alonso, D., Pascual, M. 2008. A general model for food web structure. *Science*, 320, 658-661.

Almirall, E., Casadesus-Masanell, R. 2010. Open versus closed innovation: A model of discovery and divergence. *Academy of Management Review*, 35(1), 27-4.

Anderson, E. G., Joglekar, N. R. 2012. The innovation butterfly: Managing emergent opportunities and risks during distributed innovation. Springer.

Anderson, P. W. 1972. More is different. *Science*, 177, 393-196.

Arthur, W. B. 1999. Complexity and the Economy, *Science*, 284, 107-109.

Arthur, W. B. 2007. The structure of invention. *Research Policy*, 36, 274-287.

Baldwin, C. Y. 2008. Where do transactions come from? Modularity, transactions, and the boundaries of firms. *Industrial and Corporate Change*, 17(1), 155-195.

Baldwin, C. Y. 2012. Organization design for business ecosystems. *Journal of Organization Design*, 1(1), 20-23.

Baldwin, C. Y., Clark, K. B. 2000. *Design Rules, Volume 1: The Power of Modularity.* Cambridge, MA: MIT Press.

Brusoni, S., Prencipe, A., Pavitt K. 2001. Knowledge specialization, organizational coupling, and the boundaries of the firm: why do firms know more than they make? *Administrative Science Quarterly*, 46, 597–621.

Burt, R., Talmud, I. 1993. Market niche. *Social Networks*, 15, 133-149.

Casadesus-Masanell, R., David B. Y. 2007. Wintel: Cooperation and Conflict. *Management Science*, 53(4), 584–598.

Chandler Jr, A. D. 1962. *Strategy and Structure*. Cambridge, MA: MIT Press.

Christensen, C. M. 1997. The innovator's dilemma: When new technologies cause great firms to fail. Boston, Massachusetts, USA: Harvard Business School Press.

Christensen, C. M., Rosenbloom, R. S. 1995. Explaining the attacker's advantage: Technological paradigms, organizational dynamics, and the value network. *Research Policy*, 24, 233-257.

Coase, R. H. 1937. The nature of the firm. *Economica*, 4(4), 386-405.

Constant, E. W. 1980. The Origins of the Turbojet Revolution. Baltimore: Johns Hopkins University Press.

Dalziel, M. 2007. A systems-based approach to industry classification. *Research Policy*, 36, 1559-1574.

Dosi, G. 1982. Technological paradigms and technological trajactoreis: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11, 147-162.

Ethiraj, S. K., Levinthal, D. A. 2004a. Modularity and innovation in complex systems. *Management Science*, 50(2), 159-173.

Ethiraj, S. K., Levinthal, D. A. 2004b. Bounded rationality and the search for organizational architecture: An evolutionary perspective on the design of organizations and their evolvability. *Administrative Science Quarterly*, 49, 404-437.

Fang, C., Levinthal, D. 2009. The near term liability of exploitation: Exploration and exploitation in multi-stage problems. *Organization Science*, 20(3), 538-551.

Fang, C., Lee, J., Schilling, M. 2010. Balancing exploration and exploitation through structural design: The isolation of subgroups and organization learning. *Org. Science*, 21(3), 625-642.

Fine, C. H. 1998. *Clockspeed: Winning Industry Control in the Age of Temporary Advantage*. Reading, MA: Perseus Press.

Fleming, L., O. Sorenson. 2001. Technology as a complex adaptive system: Evidence from patent data. Res. Policy, 30(7), 1019-1039.

Fleming, L., O. Sorenson, 2004. Science as a Map in Technological Search. *Strategic Management Journal*, 25, 909-928.

Freeman,C. 1995. The national system of innovation in historical perspective. Cambridge Journal of Economics, 19, 5–24.

Frenken, K. 2000. A complexity approach to innovation networks: The case of the aircraft industry 1909–1997. Research Policy, 29, 257–272.

Frenken, K., Mendritzki, S. 2012. Optimal modularity: A demonstration of the evolutionary advantage of modular architectures. *Journal of Evolutionary Economics*, 22, 935–956.

Ghemawat, P., and Levinthal, D. A. 2008. Choice Structures and Business Strategy, *Management Science*, 54: 1638-1651.

Hughes T. P. 1983. *Networks of Power: Electrification in Western Society 1880–1930*. Johns Hopkins University Press: Baltimore, MD.

Iansiti, M. 1998. *Technology Integration: Making Critical Choices in a Dynamic World*. Harvard Business School Press: Boston, MA.

Iansiti, M., Levien, R. 2004. *The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability*. Boston, MA: Harvard Business School Press.

Jacobides, M. G., S. Billinger. 2006. Designing the boundaries of the firm: From "make, buy, or ally" to the dynamic benefits of vertical architecture. *Organization Science*, 17(2), 249–261.

Jacobides, M. G., Winter, S. G. 2005. The co-evolution of capability and transaction costs:

Explaining the institutional structure of production. *Strategic Management Journal*, 26(5), 395-413.

Jacobides, M. G., Knudsen, T., Augier, M. 2006. Benefiting from innovation: value creation, value appropriation and the role of industry architectures. *Research Policy*, 35, 1200-1221.

Jacobides, M. G., MacDuffie, J. P., Tae, C. J. 2012. When value sticks around: Why automobile OEMs still rule their sector. Industry Studies Association Conference, Pittsburgh, PA, May 29-31, 2012.

Jacobides, M. G. 2005. Industry change through vertical disintegration: How and why markets emerged in mortgage banking. *Academy of Management Journal*, 48(3), 465-498.

Kapoor, R., 2012. Persistence of integration in the face of specialization: How firms navigated the winds of disintegration and shaped the architecture of the semiconductor industry. *Organization Science* (Forthcoming).

Katila, R., G. Ahuja. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Acad. Management J.*, 45(6), 1183–1194.

Kauffman, S. A. 1993. *The Origins of Order: Self-Organization and Selection in Evolution.* Oxford University Press, New York.

Knudsen, T., D. A. Levinthal. 2007. Two faces of search: Alternative generation and alternative evaluation. *Management Sci.*, 18(1) 39–54.

Kornish, L. J., Ulrich, K. T. 2011. Spaces in innovation: Empirical analysis of large samples of ideas. *Management Science*, 57(1), 107-128.

Langlois, R. N., Robertson, P. L. 1992. Networks and innovation in a modular system: lessons from the microcomputer and stereo component industries. *Research Policy*, 21, 297-313.

Lenox, M., Rockart, S., Lewin, A. 2006. Interdependency, competition and the distribution of firm and industry profits. *Management Science*, 52, 757–772.

Levinthal, D, M. Warglien. 1999. Landscape design: Designing for local action in complex worlds. *Organizational Science*, 10, 342-357

Levinthal, D. A. 1997. Adaptation on rugged landscapes. *Management Sci.*, 43(7), 934–950.

Lundvall, B.-A.(Ed.),1992.N*ational Innovation Systems: Towards a Theory of Innovation and Interactive Learning*. Pinter, London.

Luo, J, Baldwin, C. Y., Whitney, D. E., Magee, C. L. 2012. The architecture of transaction networks: A comparative analysis of hierarchy in two sectors. Industrial and Corporate

Change, 21(6), 1307-1335.

Luo, J. 2010. Hierarchy in industry architecture: Transaction strategy under technological constraints. Doctoral Dissertation, Massachusetts Institute of Technology.

Luo, J., Magee, C. L. 2011. Detecting evolving patterns of self-organizing networks by flow hierarchy measurement. *Complexity*, 16(6), 53-61.

MacDuffie, J. P. 2010. Modularity-as-property, modularization-as-process, and 'modularity'-as-frame: lessons from product architecture initiatives in the global automotive industry," Wharton School of University of Pennsylvania Working Paper.

Malerba, F. 2002. Sectoral systems of innovation and production. *Research Policy*, 31, 247-264.

Malerba, F., Orsenigo, L. 1997. Technological regimes and sectoral patterns of innovative activities. *Industrial and Corporate Change*, 6(1), 83-118.

March, J. 1991. Exploration and Exploitation in Organizational Learning. *Organization Science*, 2, 71-87.

March, J., Simon, H. 1958. Organizations. Blackwell, Cambridge, MA.

Martin, X., Mitchell, W. 1998. The influence of local search and performance heuristics on new design introduction in a new product market. Research Policy, 26(7–8), 753–771.

Mihm, J., C. H. Loch, A. Huchzermeier. 2003. Problem-solving oscillations in complex engineering projects. *Management Science*, 49(6), 733-750.

Mihm, J., Loch, C. H., Wilkinson, D., Huberman, B. A. 2010. Hierarchical structure and search in complex organizations. *Management Science*, 56(5), 831–848.

Moore J. F. 1996. The death of competition: Leadership and strategy in the age of business ecosystems. Harper Business: New York.

Murmann, J. P., K. Frenken. 2006. Toward a systematic framework for research on dominant designs, technological innovations, and industrial change. *Research Policy*, 35, 925-952.

Nakano, T., White, D. R. 2007. Network structures in industrial pricing: the effect of emergent roles in Tokyo supplier-chain hierarchies. *Structure and Dynamics*, 2(3), 1-23.

Nelson, R. 1993. *National Innovation Systems: A Comparative Analysis (Ed.)*. Oxford University Press, NewYork/Oxford.

Nelson, R., Winter, S. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, MA: Harvard University Press.

Nelson, R., 1994. Economic growth via the co-evolution of technology and institutions. In:

Leydesdorff, L., Van den Besselaar, P. Eds., *Evolutionary Economics and Chaos Theory: New Directions in Technology Studies*. Pinter, London, pp. 21-32.

Paprzycki, R. 2005. *Interfirm networks in the Japanese electronics industry*. RoutledgeCurzon: London and New York.

Podolny, J., Stuart, T. E., Hannan, M. 1996. Networks, knowledge, and niches: competition in the worldwide semiconductor industry, 1984-1991. *American Journal of Sociology*, 102(3), 659-689.

Prencipe, A., Davies, A., Hobday, M. 2005. *The Business of Systems Integration*. Oxford University Press, USA.

Rivkin, J. W. 2000. Imitation of complex strategies. *Management Science*, 46, 824–844.

Rivkin, J. W., Siggelkow, N. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Science*, 49, 290-311.

Rivkin, J. W., Siggelkow, N. 2007. Patterned interactions in complex systems: Implications for exploration. *Management Science*, 53(7), 1068–1085.

Rosenberg, N. 1963. Technological change in the machine tool industry, 1840-1910. *Journal of Economic History*, 23(4), 414-443.

Rosenberg, N. 1972. Factors affecting the diffusion of technology. *Explorations in Economic History*, 10(1), 3–33.

Rosenberg, N. 1982. *Inside the Black Box: Technology and Economics*. Cambridge University Press: Cambridge, U.K.

Siggelkow, N., Rivkin J. W. 2005. Speed and search: Designing organizations for turbulence and complexity. *Organization Science*, 16, 101-122.

Simon, H. A. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*, 69(1), 99-118.

Simon, H. A. 1962. The architecture of complexity, *Proceedings of the American Philosophical Society*, 106, 467-82.

Sommer, S. C., Loch, C. H. 2004. Selectionism and learning in projects with complexity and unforseeable uncertainty. *Management Science*, 50(10), 1334–1347.

Stouffer, D. B., Camacho, J., L. A. N. Amaral. 2006. A robust measure of food web intervality. *Proc. Natl. Acad. Sci. U.S.A.*, 103(50), 19015–19020.

Strogatz, S. H. 2001. Exploring complex networks. *Nature*, 410, 268-276.

Stuart, T. E., Podolny, J. M. 1996. Local search and the evolution of technological capabilities. *Strategic Management J.* 17(1) 21–38.

Sturgeon, T. J. 2002. Modular production networks: a new American model of industrial organization. *Industrial and Corporate Change*, 11(3), 451-496.

Takeishi, A., Fujimoto, T. 2001. Modularisation in the auto industry: Interlinked multiple hierarchies of product, production and supplier systems, *International Journal of Automotive Technology and Management*, 1(4), 379-396.

Teece, D. J. 1996. Firm organization, industrial structure, and technological innovation. *Journal of Economic Behavior and Organization*, 31, 1993-224.

Terwiesch, C. 2008. Product development as a problem solving process. S. Shane, Eds. *Handbook of Technology and Innovation Management*. John Wiley & Sons, UK, 143–172.

Thompson, J. D. (1967), *Organization in Action*. Chicago: McGraw-Hill.

Ulrich, K. T., Eppinger, S. D. 2001. Product design and development. New York: Irwin/McGraw-Hill.

Utterback, J. M. 1994. *Mastering the Dynamics of Innovation.* Harvard Business School Press.

Wasserman, S., Faust, K. 1994. *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press.

Watts, D. J., Strogatz, S. H. 1998. Collective dynamics of 'small-world' networks. *Nature*, 393, 440-442.

White, H. C. 2002a, *Markets from Networks: Socioeconomic Models of Production*. Princeton, NJ: Princeton University Press.

White, H. C. 2002b, Businesses mobilize production through markets: parametric modeling of path-dependent outcomes in oriented network flows. *Complexity*, 8(1), 87-95.

White, H., Boorman, S. A., Breiger, R. L. 1976. Social structure from multiple networks: Part I. block models of roles and positions. *American Journal of Sociology*, 81, 730-780.

Whitney, D., Crawley, E., de Weck, O., Eppinger, S., Magee, C.L., Moses, J., Seering, W., Schindall, J., Wallace, D. 2004 The Influence of Architecture in Engineering Systems. Engineering Systems Monograph, MIT Engineering Systems Division.

Williams, R. J., N. D. Martinez. 2000. Simile rules yield complex food webs. *Nature*, 404, 180-183.

Williamson, O. E. 1985. *The Economic Institutions of Capitalism*. New York: Free Press.

Winter, S. 1984. Schumpeterian competition in alternative technological regimes. *Journal of Economic Behaviour and Organization*, 5, 287–320.

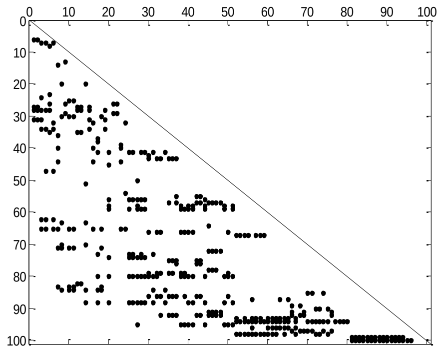
Womack, J. P., Jones, D. T., Roos, D. 1990. *The machine that changed the world: the story of lean production*. New York, NY: Rawson Associates.

Yassine, A., N. Joglekar, D. Braha, S. Eppinger, D. Whitney. 2003. Information hiding in product development: The design churn effect. Research in Engineering Design, 14(3), 145-161.

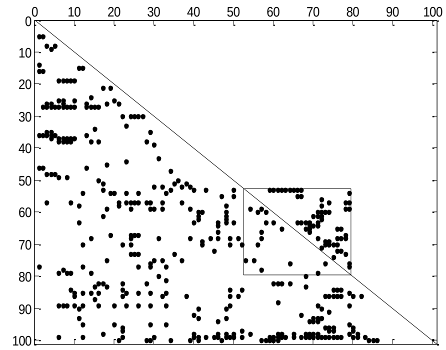
APPENDIX A

Dependency Structure Matrix Visualization of Simulated Networks with Fixed *N*=100 and *K*=4.

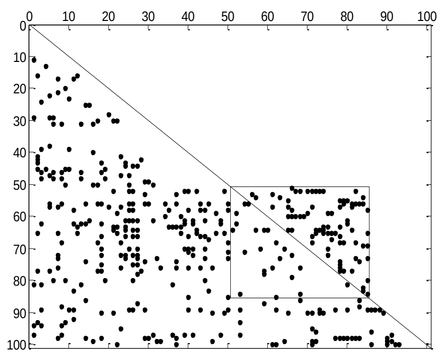
S=1.0 *H*=1.00



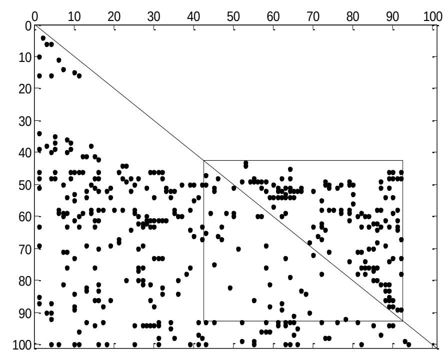
S=0.8 *H*=0.82



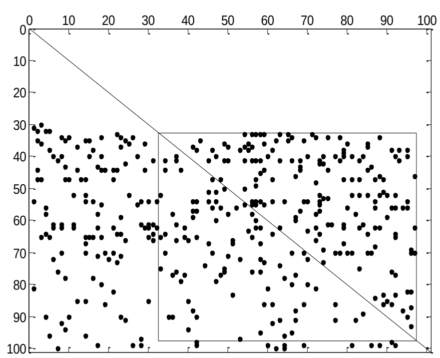
S=0.6 *H*=0.74



S=0.4 *H*=0.59



S=0.2 *H*=0.34



S=1.0 *H*=0.22