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Measuring and Understanding Hierarchy as an Architectural Element in Industry Sectors

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Working Paper

09-144

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Working Paper
May, 2009

Abstract

Hierarchy is a generic structure in which levels are asymmetrically ordered. In an industry setting, classic supply chains display strict hierarchy, whereas clusters of firms have linkages going in many different directions. Previous theory has often assumed the existence of the hierarchical relationships among firms and empirical work has focused on a single level of an industry or bilateral relationships. However, quantitative evidence on the deep hierarchy in large industrial sectors is lacking. In this paper, we develop metrics and methods to define and measure the degree of hierarchy in transactional relationships among firms, and apply the methods to two large industrial sectors in Japan: automotive and electronics. We compiled the networks of firms connected by transactional relationships. Our empirical analysis shows that the automotive sector exhibits a higher degree of hierarchy than the electronics sector. We further analyze the differences in hierarchy using a simulation model based on transaction breadth and transaction specificity. The empirical measurement and model analysis together indicate that it is the low transaction specificity that drives down the degree of hierarchy in the electronics sector. Differences in transaction patterns in turn may result from the differences in the power level of underlying technologies, which affect product specificity and asset specificity. Thus, the degree of hierarchy in an industry sector may be traced back to fundamental properties of the underlying technologies.

1 Introduction

Hierarchy is a generic structure in which levels are asymmetrically ordered. In an industry setting, classic supply chains display strict hierarchy, whereas clusters of firms have linkages going in many different directions. Previous theory has often assumed the existence of the hierarchical relationships among firms and empirical industry studies tend to focus on a single-layer industry, or a two-layer structure comprising buyers and suppliers. And yet, some industries have a multi-layer structure with a multi-step supply chain. Others comprise a cluster of complementary firms producing different parts of a large system. In this paper, we use network analysis to study multi-layer industries both empirically and theoretically. For an overview of recent work in network analysis methods, see (Newman, 2003). In our research, the prior work in social network analysis (Wasserman and Faust, 2004) is most relevant and particularly related the work on roles and positions started by White et al (1976).

Previous studies in the industrial economics tradition have investigated industry structures in terms of vertical integration versus outsourcing (Nishiguchi, 1994; Nagaokaa, Takeishi and Norob, 2008; Dyer, 2000), diversification versus concentration within a single layer (Davis and Duhaime, 1992; Nobeoka, 1996), and changes within such conceptual frameworks. These studies focus on the division of labor between two groups, customer and supplier, but do not address multiple supplier/customer layers, nor the possibility that numerous complementary goods will be combined into large systems.

This paper takes an industry sector, i.e., a group of industry layers, as the unit of analysis.

Following Malerba (2002) we use the term "sector" to mean a network of firms in different sub-industries, which supply complementary goods for making a set of system products. For example, an automobile sector includes system integrators, sub-system integrators, component suppliers and materials suppliers that are involved in the making of automobiles. To avoid confusion, we consider <u>firms</u> in a particular role (such as sub-system integrators) to form an "industry", and the collection of these industries to be the "sector". Various relationships may connect the firms in a sector, such as alliances, joint ventures, competition. In this paper, we investigate transactional relationships, i.e., the transactional exchanges of components and parts for making the final system product.

This research follows the definition of "industry architecture" from Jacobides et al (2006) as the stable but evolving relationships along the value chain, i.e. the patterns in which labor is divided in a sector between different types of industry participants, and the associated set of "rules and roles" that emerge (Jacobides, Knudsen, and Augier, 2006). The notion of industry architecture considers the overall template that describes the distribution of labor among a set of co-specialized firms across a set of industries. The necessary level of analysis is the network of firms across the complementary industries in a sector.

Studies of industrial sectors often observe or suggest a hierarchical architecture (Coase, 1937; Malerba, 2002; Dalziel, 2007), in which production processes are organized into sequential stages (Coase, 1937; Abernathy, Clark and Kantrow, 1983). Firms that perform higher level tasks depend upon firms that perform lower level tasks (Dalziel, 2007). Such hierarchy does not exist in a pure market such as a stock market, where traders can buy from and sell to any other trader. In an industrial sector, a firm may also perform multiple industry roles in different production stages. This makes the hierarchy of industry architecture potentially ambiguous (Jacobides, 2005; Jacobides, Knudsen, and Augier, 2006; Dalziel, 2007), and difficult to determine objectively. Robust methods to measure the patterns of industry architectures, in particular how hierarchical an industrial sector is, need to be developed.

This research addresses these challenges. We aim to conduct a macro-level analysis of the overall industry architecture, as well as build a micro-level theory on the mechanisms by which individual firms collectively influence and are influenced by industry architectures.

Our methods and analysis differ from traditional institutional economics in four fundamental ways. First, the unit of analysis is a sector, instead of a narrower industry. Second, we examine macro industry architectures rather than the relationship between two industry layers. Third, we view and model an industry sector as a network of manufacturers and suppliers, and conduct network analysis. Four, we define the *degree of hierarchy* of a sector, but allow for non-hierarchical industry architectures.

Below, we will introduce an algorithm that quantitatively measures and compares the degree of hierarchy in different industry sectors. We apply these measures to two comparative cases: the Japanese automotive and electronics sectors in the early 1990s. In order to explore the mechanisms underlying the empirical observations, we use an analytical network model to generate a wide spectrum of sector-like random networks lying between two extreme scenarios: a pure random network and a hierarchical random network. The model incorporates two causal factors, transaction breadth and transaction specificity, which interact to influence the degree of hierarchy in the directed network. Transaction breadth is the number of transactional relationships that a firm enters into. Transaction specificity represents how specific a firm's transaction relationships are with respect to potential market niches (Burt and Talmud, 1993). With the results from the measurement and the model, we then conduct a micro-level causal analysis with the comparison of the two empirical industrial sectors, in order to explain how hierarchy in industrial sectors may be collectively determined by technological and economic forces.

This research integrates concepts and methods from institutional economics, industrial economics, economic sociology, network sciences and systems engineering. For academics, it aims to provide a quantitative methodology for analyzing hierarchy as an architectural element in industry sectors. This methodology will allow more exploratory work to be done in comparing the architectures of different industrial systems, observing the architectural evolution of a single industry sector, and comparing the evolving patterns of different sectors in terms of industry architecture. The application of network analysis permits institutional economics to be extended from the structure of an industry to the architecture of a sector comprising several industries.

For industry practitioners, this research suggests that industry architectures may follow partially predictable patterns which are largely determined by the nature of the underlying fundamental technologies and the architectures of products produced in the sector. A better understanding of industry architectures in turn can guide companies in identifying opportunities and adopting strategies that are appropriate for the architecture and evolutionary status of the sector.

The remainder of the article is organized as follows. Section 2 below introduces the hierarchy typology, defines the type of hierarchy crucial for industry architectures, and summarizes the metric and algorithm used to quantify and measure hierarchies. Section 3 introduces transaction breadth as one factor that influences the degree of hierarchy of an industrial sector. Section 4 introduces data and the empirically measured hierarchy degree and transaction breadth. Section 5 introduces the analytical model that generates stochastic sector-like networks, and analyzes the results of a simulation experiment. Section 6 speculates about the technological mechanisms that might explain the empirical and analytical results. Section 7 concludes.

2 Hierarchy in Industry Architecture

In practice, analyzing hierarchy by objective measurements is difficult for two reasons. First, hierarchy appears in various forms, hence the term has different meanings in different contexts. Second, real systems may not be "pure" hierarchies in a theoretical sense, and thus it is necessary to develop measures of the deviation between an actual system and some theoretical ideal hierarchy.

In this section, we first introduce a generalized definition of hierarchy and identify different types. We then focus on a particular type - a "flow hierarchy", which characterizes transactional relationships between industrial firms. Finally we develop a metric that measures how much a given industrial sector deviates from the standard of a pure flow hierarchy.

2.1 Typology of Hierarchy

A hierarchy is a generic structure, in which levels are asymmetrically ranked according to a specific type of relation. Two types of hierarchies are useful for understanding network architectures: **containment hierarchy** and **flow hierarchy**.

A containment hierarchy is similar to the concepts of "nested hierarchy" from Ahl and Allen (1996) and "hierarchy of inclusion" from Wilson (1969) (Murmann and Frenken, 2006). In a containment hierarchy, lower levels lie within or are aggregated into upper levels, and upper levels contain lower levels. The classic Russian dolls make up a containment hierarchy. Complex products like airplanes are often viewed as containment hierarchies, because they are made up of subsystems, which contain smaller components and parts (Tushman and Murmann, 1998). All containment hierarchies can be represented in terms of a pure tree or dendrogram (Wasserman and Faust, 1994; Clauset, Moore and Newman, 2008).

A flow hierarchy arises when there is directional movement of transactions through a series of stages. For example, if B purchases a good from A, the good flows from A to B. The order of stages is essentially determined by the direction of the flows of goods, energy, materials, payments, or information. Other clear examples of a flow hierarchy include food webs and software routine networks. In a food web, energy flows. In a software routine network, it is information that flows as subroutines feed parent routines. A flow hierarchy can be described in terms of a network of nodes and directed links. A classic supply chain is a flow hierarchy in which components and parts flow from upstream suppliers to downstream manufacturers, and ultimately to users.

However, the transactions or supply flows between firms in an industry sector do not necessarily obey a strict asymmetric ordering. Hence industry architectures are not necessarily hierarchical. For example, FoxConn, the largest Taiwanese original design manufacturers (ODM) of personal computers, supplies finished computers directly to the personal computer makers, such as Dell and Apple, but it also produces and sells many connecters, cables, PCB, etc to other suppliers in the personal computer manufacturing sector. Thus, Foxconn's transactional relationships are directed both upstream and downstream. As a result, Foxconn's position in the sector hierarchy is ambiguous. And if most firms in the sector are like Foxconn, it is difficult for the sector to keep itself hierarchically organized. It is this aspect of industry architecture that we are seeking to investigate both empirically and theoretically.

2.2 Representing Flow Hierarchies as Networks

Many flow hierarchies can be graphed as "tree networks", such as a military chain of command, where each node is assigned not only a rank, but also a single link to a higher up node. A tree is the generic hierarchical structure for a flow network. A classic tree hierarchy is shown in Figure 1A.

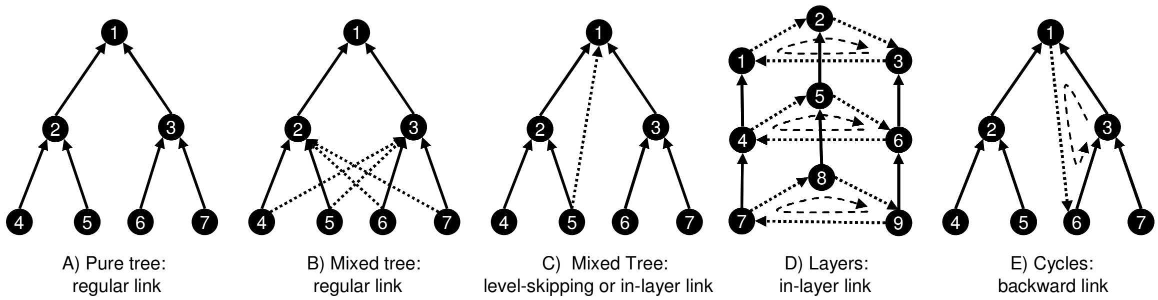


Figure 1 Generic Structure and Generic Links in Example Networks

The first variant from the pure tree hierarchy arises when a node has multiple inbound and outbound links, as demonstrated by Figure 1B. We call this a "mixed tree hierarchy". Both the pure tree and the mixed tree are strictly hierarchical because all the links connect from a lower level to an adjacent higher level. Hence there is strict asymmetric ordering of relationships. The links in Figure 1A and 1B are all "regular links".

In the third case shown in Figure 1C, a link may skip its adjacent pre-indentified level. We call this a "level-skipping" link. The network in Figure 1C can be viewed as a mixed tree, with level skipping. Level-skipping links make it difficult to assign an unambiguous level rank to a node. This in turn makes it difficult to organize a given flow hierarchy into layers or stages. Indeed, this is one of the key challenges in designing a hierarchy metric. Identification of level-skipping links and in-layer links relies on the pre-identification of layers. For example, in Figure 1C, if node 2 and 5 are defined to be in the same layer, the link from node 5 to 2 can be viewed as an "in-layer link", while the link from node 5 to 1 no longer skips a level and becomes a regular link.

Networks often exhibit layered structures as shown in Figure 1D. In this example, if the nodes in the same directed cycle are presumed to be in a layer, there are “in-layer links” between firms, but flows proceed in one direction from layer to layer. A layered hierarchy emerges only if the links between layers are hierarchical.

Both level-skipping and in-layer links are still hierarchical (Moses, 2002; 2004). However, in the example in Figure 1E, a link connects from a pre-identified higher level backward a lower one, i.e., a cycle emerges in a network. This violates the fundamental principle that, in a flow hierarchy things move in one general direction.

In the examples in Figure 1, we observe regular links, in-layer links, level-skipping links and backward links. Among them, the first three types are hierarchical because the links connect from a lower layer to a higher or same layer, while a backward link is not. However, the identification of these link types is arbitrary and depends on pre-assigned level ranking. A more consistent way to identify the network’s hierarchical degree is to decompose the network into such structures as tree and cycle, which are fundamental generic structures and can be identified without arbitrary level ranking. In particular, tree and layer are regarded as hierarchical structures, while a cycle is not (Moses, 2004) because it violates our hierarchy definition.

Real world systems are often a mixture of various generic structures, including tree, layer, cycle, in particular. The co-existence of generic structures within the same network makes it difficult to detect hierarchy architecture. On this basis, previous ways of defining hierarchy are of limited value. In the next section we define the degree of hierarchy and present a new way to detect and measure it so as to avoid most of these difficulties.

2.3 Metric for Flow Hierarchy

In this section, we introduce a metric to detect and measure the degree of hierarchy in industrial networks. A qualified hierarchy metric must be unambiguous in differentiating the hierarchical components and non-hierarchical components in order to measure how hierarchical an industrial network system is. If we choose to measure hierarchy by identifying hierarchical and non-hierarchical links, a predefined ordering of levels is required. However, in many cases, level order is ambiguous and must be decided through subjectively chosen rules. In comparison, if we focus on identifying hierarchical and non-hierarchical generic structures, the metric can be unambiguous and deterministic.

Accordingly, we propose a hierarchy metric (h) that measures the extent to which all the local flows follow a consistent "underlying direction". *The hierarchy metric is calculated as the percentage of links that are* ***not*** *included in any cycle.* (In weighted networks, the metric can be calculated as the ratio of the weights of the links which are not included in any cycles over the total weight of all links. In the present paper, we will focus on unweighted networks.)

Hierarchy degrees for several typical example networks are calculated and shown in Figure 2. The dashed lines indicate cycles.

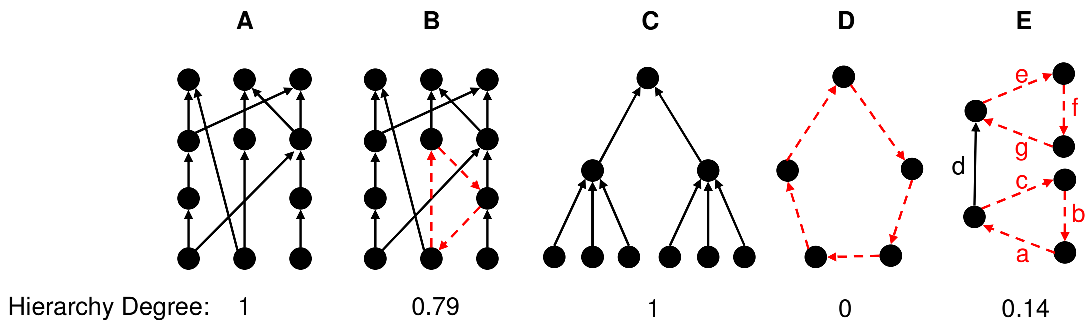


Figure 2 Example Networks and Corresponding Hierarchy Degrees

Networks A and B in Figure 2 are used to demonstrate the correlation between the overall system direction and local cycles in a directed network. In network A, all flows proceed in one general direction, no cycle exists, and *h*=1. Network B is almost the same as A, but has two extra links, which cause a cycle. The network is no longer purely hierarchical, and *h*=0.79. Network C is a directed tree, which is a pure hierarchical structure, so its hierarchy degree is 1. Network D is a pure cycle thus *h*=0. Network E presents a layered hierarchy, in which all the nodes are involved in cycles, but there are 2 clean layers connected by a hierarchical link in between. Its hierarchy degree is 1/7.

The algorithm we use to calculate the hierarchy metric is as follows: First, we construct the link adjacency (LA) matrix of the original network. We name the cell (i,j) in the LA matrix x_{ij}. $x_{ij} = 1$ if and only if the end of link i is directly connected to the start of link j by a node. Otherwise, $x_{ij} = 0$. Second, we raise LA matrix's power p to find the link distance matrix M_d. We name the cell (i,j) in the link distance matrix d_{ij}. d_{ij} is the distance from link i to j, defined as the minimum number of unique nodes which a uni-directed flow has to travel through from the end of link i to the start of link j. d_{ij} is found as the value of the power, at which cell (i,j) of the power matrix M^p has a non-zero value for the first time.

When p=1, the power matrix M^1 is the same as the LA, so that if x_{ij}=1, the distance from i to j is 1. If x_{ij} =0, and $x^{[2]}_{ij}$>0, then the distance is found as 2. And so forth. Consequently, the first power p for which the $x^{[p]}_{ij}$ element is non-zero gives the distance from i to j, i.e. the value of d_{ij} in the link distance matrix M_d. Mathematically, $d_{ij} = \min_p x^{[p]}_{ij} > 0$, for p from 1 to *n*, the total number of nodes (equal to the length of the longest possible cycle of links). We leave d_{ij} empty if link i does not participate in a cycle.

Fig. 3 below illustrates the process to derive the link distance matrix for the layered network in Fig. 2E. We pair M^p and the M_d with the state of knowledge after p steps. M^1 is the LA matrix for the network in Fig. 2E. The distance identified at each intermediate step is bold and its cell is shadowed. The M_d paired with M^6 is the final link distance matrix.

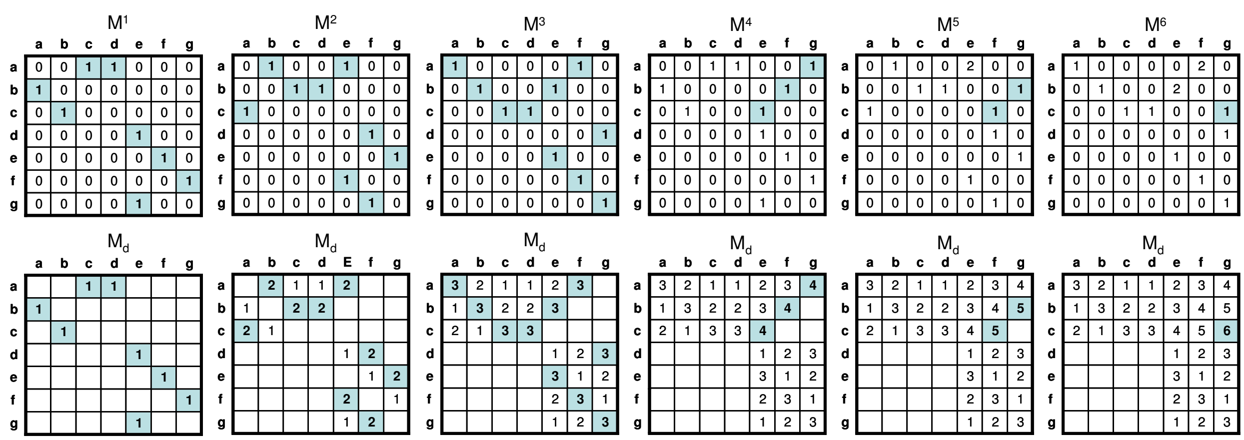


Figure 3 Derivation of Link Distance Matrix by Raising Power of Link Adjacency Matrix

Given the link distance matrix, we are able to judge if a link is on any directed cycle by looking at values on the main diagonal. If d_{ii} =0, then link i is not involved in any cycle. In the layered network in Fig. 2E, only link d is not involved in any cycle, and this agrees with our direct observation. Thus this network's flow hierarchy degree is 1/7. For more details on this metric of flow hierarchy and an assessment of alternative metrics, see Luo and Magee (2009).

3 Transaction Breadth

Another aspect of network structure that has an impact on the flow hierarchy in industry architecture is how densely the firms are connected to each other. To quantify this factor, we define the average number of transactional relationships per firm in a sector as "transaction breadth", and denote it as "k". It is the same as average nodal degree in the network analysis field. In a network with n firms and m transactional relationships, $k=m/n$. In this section, we will explain what the transaction breadth parameter economically represents.

In a fully connected industrial network of n firms, the lowest possible k arises when the "in-degree" or "out-degree" of each firm equals one. In this case, $k= (n-1)/n$. For example, suppose each supplier can only supply one customer, the transaction network is a top-down tree (example shown in Figure 4A). There are n-1 links and n firms, thus $k= (n-1)/n$. If any link is broken, the network will no longer be fully connected. Similarly, if each customer firm can only purchase from one supplier, the network will be a bottom-up tree (example shown in Figure 4B), and k must also equal $(n-1)/n$. In the extreme where each supplier has only one customer and each customer has only one supplier, the network will be a pure line (example shown in Figure 4C), and k is still equal to $(n-1)/n$.

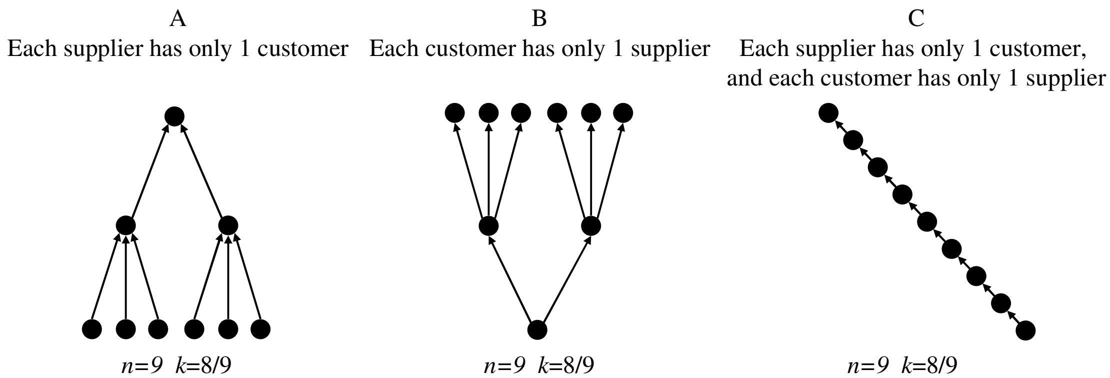


Figure 4 Non-market scenarios

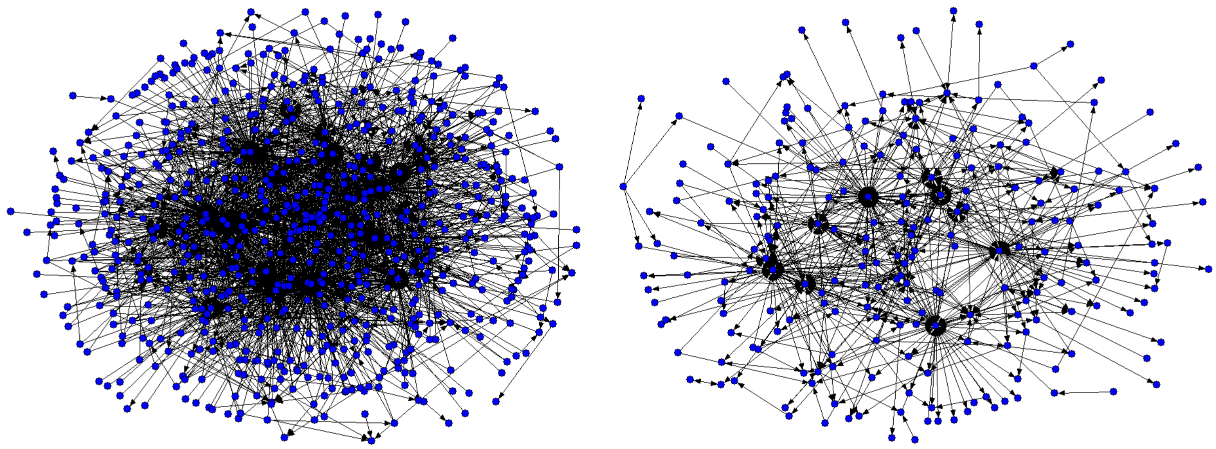
In these three scenarios, the potential freedom of market transactions is not fully utilized by firms: either the suppliers or the customers, or both, are "captive" of the firms to which they sell or from which they buy. Extra linkages cause the network to deviate from the pure "tree" structures in Figure 4, and will at the same time cause k to be larger than $(n-1)/n$. Hence, the transaction breadth metric ($k=m/n$) captures the extent to which an industrial sector contains "true" markets, with firms buying from and selling to several others as opposed to captive supplier or customer arrangements.

4 Data and Empirical Measurements

In our exploratory study, we measured hierarchy (h) and transaction breadth (k) for two industrial sectors: the Japanese automotive production sector and electronics production sector in the early 1990s.

We extracted the supplier-customer relationship data from the data books "*The Structure of Japanese Auto Part Industry*" and "*The Structure of Japanese Electronics Industry*" based on regular surveys by Dodwell Marketing Consultants. The company directories in these two data books provide the information on the major customers and suppliers for each firm. Such information makes it possible to extract "who-supplies-whom" type of connections, and to build multi-tier sectoral supply networks. The data books are only available in hard copy form, and had to be manually entered into an electronic database. We used the data books published in 1993, but believe the data represents actually the scenario in years between 1990 and 1992 because the publication is refreshed every 2~3 years.

The automotive directory lists 679 firms connected by 2,437 supplier-customer relationships. The electronics directory lists 256 firms, but 29 of them are not connected to any other firm in the directory. Thus we studied the 227 electronic firms connected by 648 directed supplier-customer relationships. For each sector, we constructed a directed network, in which nodes are manufacturing firms and links are supplier-customer transactional relationships. For instance, if company A sells a product to company B, there is an arrow from A to B in the network. The transactions indicated are compensated transactions of physical products, excluding services and intellectual property. Figure 5 shows the supplier-customer supply relationship networks of the two industry sectors, based upon our data and visualized using the software NetDraw. It is not surprising but important that such visualization tools while useful do not allow one to see very significant differences in hierarchy. For that, the metric developed in section 2 must be applied to these networks.



A) Automotive Sector B) Electronics Sector

Figure 5 Sectoral supply networks in Japan in the early 1990s

The hierarchy degree (*h*) and transaction breadth (*k*) for the two industrial sectors are calculated and shown in Table 1. The comparison shows that, despite its higher transaction breadth, the automotive production sector is quantitatively much more hierarchical (0.9988) than the electronics production sector (0.5957).

Table 1 Empirical Measurement Results

Network Attributes	Japanese Automotive Production Sector	Japanese Electronics Production Sector
Time	Early 1990s	Early 1990s
Number of Firms (*n*)	679	227
Number of Transactional Relationships (*m*)	2437	648
Transaction Breadth (*k*)	3.589	2.855
Hierarchy Degree (*h*)	0.9988	0.5957

5 Industrial Network Model

Industry architecture is essentially the collective result of the local decisions and behaviors of individual firms on their transactional links with other firms. In the previous sections, we have empirically calculated the hierarchy degree and transaction breadth of two different industrial networks, and observed their differences. In this section, we will introduce a random network model to relate the macro pattern, e.g. hierarchy, to local or micro patterns of connection at the level of individual firms, and analyze how the micro factors may interact and lead to different degrees of hierarchy in an industrial sector.

5.1 Model Description

In this section, we develop a model that builds on two idealized rules of market structures: hierarchy (Coase, 1937; Simon, 1962) and niche (Burt and Talmud, 1993; Podolny at al, 1996). The niche models in turn depend upon social network models of roles (Wasserman and Faust, 1994; White et al., 1976). We build our model in such a way to describe how the hierarchy (h) of an industrial network may be collectively determined by three causal variables:

1) n (Network Size, i.e. Market Size): the total number of firms connected in the network.
2) k (Transaction Breadth): the average number of unique customers each firm has. It equals the average number of unique suppliers each firm has in a given network. It is measurable, and is the same as k in the NK framework (Kauffman, 1993; Rivkin and Siggelkow, 2002) and is the average nodal degree in network analysis (Newman, 2003).
3) s (Transaction Specificity): The degree to which a firm's transactional links are constrained

to a specific set of similar firms (discussed below).

Our network model is built on two extremes according to connection pattern: a pure random network and a hierarchical random network. For networks of a given size, *n*, and transaction breadth, *k*, by varying a key parameter, *s*, we can systematically create mixtures of these two polar extremes, weighted to one extreme or the other, by controlling the parameter *s*. This in turn will allow us to discover the mathematical relationship between the degree of hierarchy, *h*, and the causal parameters, *n*, *k*, *s* in the generated random networks. By inverting this relationship, we can then infer the unobservable variable *s*, i.e., transaction specificity, from the empirically observable variables, *n*, *k* and *h*.

Hierarchical Random Network with Niche

At one extreme, we build a purely hierarchical network that connects the randomly-arranged *n* firms. The network is constrained to have the same *k* as a random non-hierarchical network, or a given empirical network. Particularly, our hierarchical random network combines a market niche mechanism with a hierarchy mechanism.

We begin by creating an upstream/downstream relationship between firms in the network. To do this, we assign each of the *n* firms to a uniformly distributed random position (λ_i), along an axis ranging from zero to one. Zero is the farthest up stream that a firm can be; one 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 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 $(1-r_i)$.

All these assumptions jointly ensure that, in our hierarchical random network each firm sells products only to the firms strictly downstream from it, and the niche range is smaller than (or equal to) the downstream interval (See Figure 6). Although randomly generated, the network displays strict hierarchy. There are no cycles.

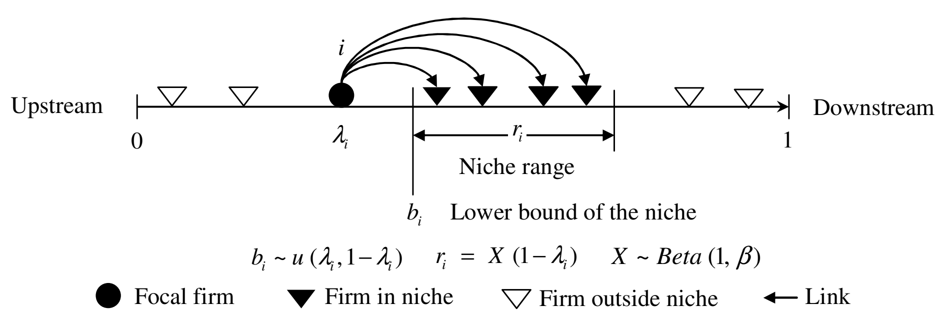


Figure 6 The hierarchical random network configuration

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 of firm i is:

$$E(k_i) = nE(r_i) \tag{2}$$

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

$$E(m) = \sum_{i=1}^{n-1} E\,(k_i) = (n-1)nE\,(r_i) \tag{3}$$

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

$$\begin{aligned} E(k) = \frac{E(m)}{n} = (n-1)E\,(r_i) &= (n-1)E\,(X\,(1-\lambda_i)) \\ &= (n-1)E\,(X)E(1-\lambda_i) \\ &= \frac{(n-1)}{2}E(X) \end{aligned} \tag{4}$$

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

$$E(X) = \frac{2E(k)}{n-1} \tag{5}$$

$E(k)$ is given as an input k, the transaction breadth (average number of customers per firm, equal to average number of suppliers per firm). Note that, although k_i is firm-specific and randomly distributed in our model, k is an empirically measurable macro property of the 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 Equation (5). For computational ease, we use a beta-distribution with parameters $(1, \beta)$ 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

$$\beta = \frac{n-1}{2k} - 1 \tag{6}$$

Given the aforementioned array of firms randomly located between zero and one, the simulation generates for each firm a random niche range constrained by Equation (6). The focal firm is then linked to each firm in its niche range.

Properties of the Hierarchical Random Network

The hierarchical random network model suggests several non-trivial statistical properties:

(1) The model will create random directed networks with k that might not be equal but close to the input value.

(2) Firms close to, but to the left of the rightmost firm may have an empty niche range. This network in effect will have multiple top-tier assemblers, something that commonly occurs in practice.

(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 models using constant k for each node (Watts and Strogatz, 1998; Woodard, 2006).

Hybrid Networks as Mixtures of Hierarchical Random and Pure Random Networks

We can generate a network that lies between the ideal types of random but fully hierarchical and fully random by "rewiring" some of the links in a hierarchical network. The extent of rewiring is determined by a parameter *s,* which we call "transaction specificity" and can be "tuned" between 0 and 1. Mathematically, *s* is the percentage of a firm's transactional relationships that fall within its (pre-defined) niche range. Intuitively, *s* represents the degree to which a firm's sales are targeted to a specific group of customers or the degree to which a particular firm fulfills a specific role in the network (sector) (Wasserman and Faust, 1994; White et al, 1976)

When *s* is 1, all firms fulfill defined roles and the result is a hierarchical random network. At another extreme, when *s* is zero, all firms fulfill fully variable roles, transactions are free to go anywhere, and the result is isomorphic to a pure random network. This means any firm may transact with any other firms, neither niche rule nor hierarchy rule applies, and k_i is no longer constrained by firm *i*'s position. (Properties of such pure random networks are shown in the simulation section later)

Between the two extremes, for the focal firm *i*, $s \cdot n \cdot r_i$ transaction links will be targeted at a specific group of firms and $(1-s) \cdot n \cdot r_i$ may go anywhere. Figure 7 demonstrates a hybrid configuration after rewiring. Cycles and backward links can emerge in the hybrid network.

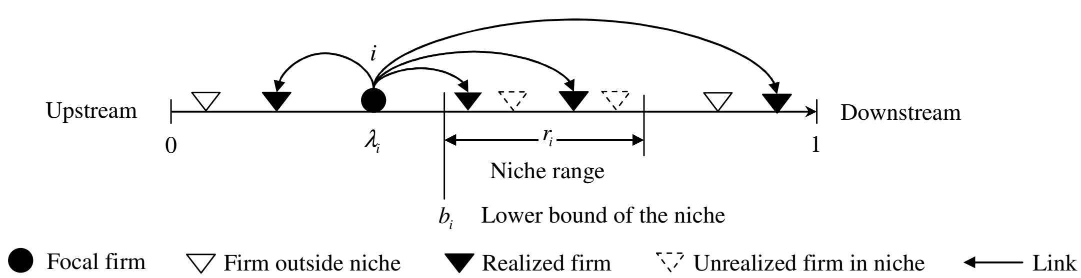


Figure 7. The mixture configuration after rewiring

The model allows the approximation for two realistic properties of a niche in 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 or adaptation effects, i.e., possible multiple niches, or a major niche plus several minor trials. Therefore, we name it "*Adaptive Niche Model*" as it allows freedom for adaptive transactional relationships deviating from the pure hierarchy and niche rules.

Using randomly-generated network models with tunable parameters, we can look at the properties not of a single industrial sector network, but of a whole class of networks, each of which differ in detail from all the others but nonetheless obey certain structural rules established by n, k, and s and their relationships. And, by tuning the transaction specificity parameter s, we will be able to explore a wide spectrum of industrial systems and their architectures, in order to understand how market size, transaction breadth, and transaction specificity may give rise to different hierarchical architectures.

5.2 Simulation Results

Because the *Adaptive Niche Model* is analytically intractable, we choose to analyze the model by simulations. For each given combination of inputs (n, k and s), we simulate 2,000 networks, calculate the hierarchy degree for each and take the average. In order to improve the fitness of the generated hierarchical random networks, only the simulated networks with the given n firms fully connected and k within 3% of the target value were accepted as valid trials.

Impact of Network Size (n)

Figure 8 tracks the influence of network size (n) on average hierarchy degree (h) at various combinations of k and s. As introduced in section 2.3, h is calculated as the percentage of links that are not included in any cycle in a simulated network. The results show that hierarchy degree is essentially unaffected by changes in network size (n), when $n > 80$, regardless of s and k. This means that we can use networks with a relatively small number of nodes (e.g. 100) to investigate the hierarchies of networks with a much larger number of nodes. Therefore, our later simulations use n=100.

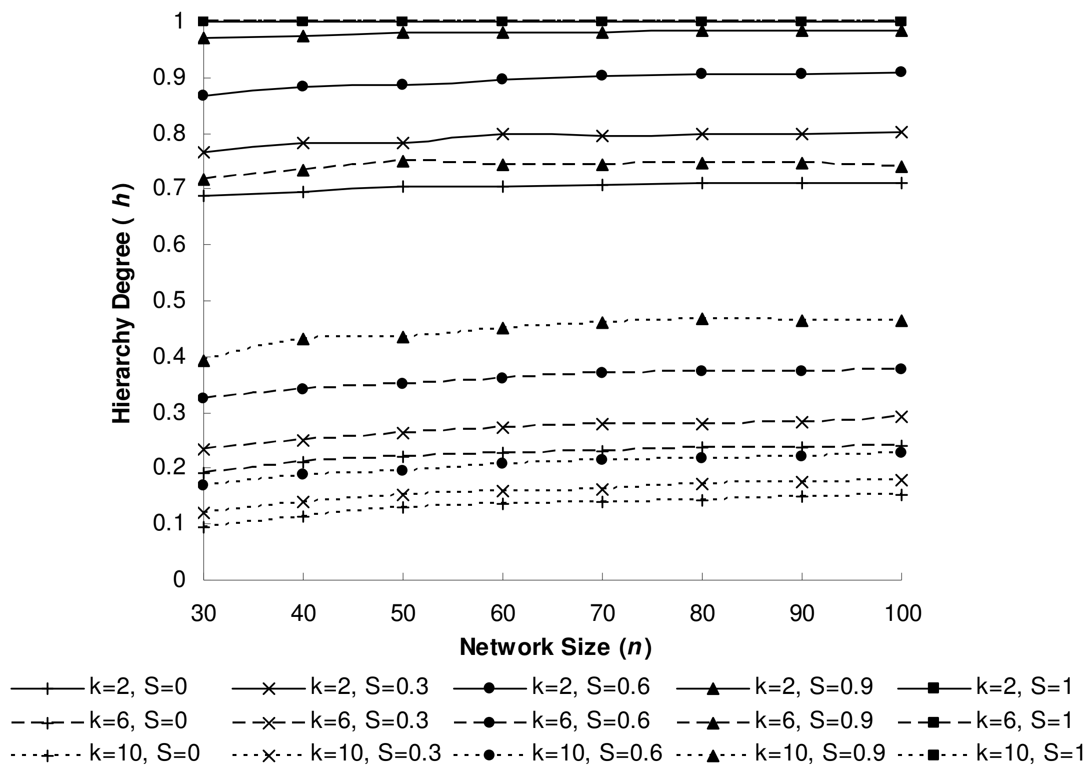


Figure 8 Impact of network size on hierarchy degree

Impact of Transaction Breadth (k)

Figure 9 shows that hierarchy degree (h) decreases with transaction breadth (k) at various levels of transaction specificity, except s=1. When s is lower, h decreases more rapidly with the increase of k. When s=1, constantly h=1 regardless of k, by definition. When s=0, then the networks generated are pure random networks, essentially determined by given n and k. In particular, the result shows that hierarchy degree (h) for a purely randomly-wired network is not necessarily zero, depending only on k, when network size (n) is sufficiently large.

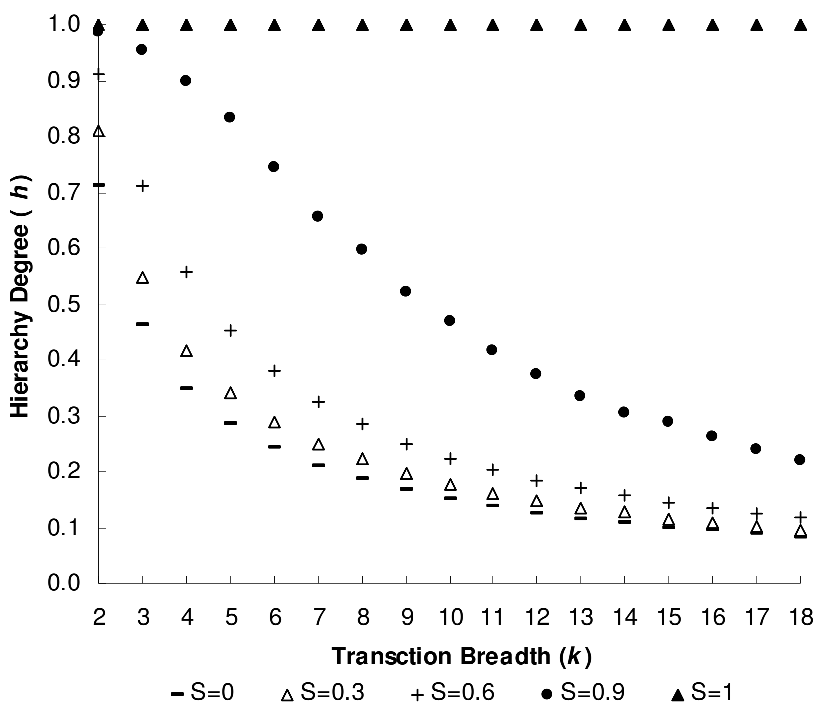


Figure 9 Impact of transaction breadth on hierarchy degree

Impact of Transaction Specificity (s)

Figure 10 shows 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*.

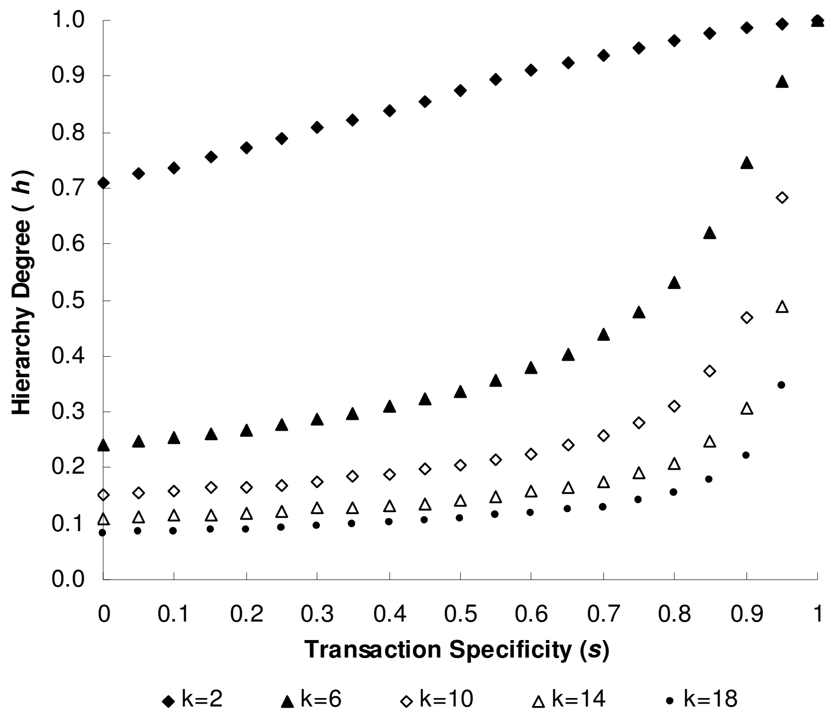


Figure 10 Influence of transaction specificity on hierarchy degree

Generally, 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, because *h* is monotonic with the changes in *s* and *k*, as shown in the results, the implicit function theorem ensures *s* can be associated with *h* and *k* by a single function, inverted from the results above. It follows that, in the context of this model of three micro-causal determinants of hierarchy, the automotive sector has a higher *s* than the electronics sector, because it has been empirically observed that the automotive sector has a higher *h* and a higher *k* than the electronics sector. By interpolating the empirically measured transaction breadth and hierarchy degree in table 1 within the simulation results in Figures 9 and 10, we infer transaction specificity of the automotive sector is *0.9982*, much higher than the transaction specificity of the electronics sector *0.3219*.

Therefore, with the hierarchy metric and the *Adaptive Niche Model* including the design of the tuning parameter -- transaction specificity, we have advanced our probing tool for understanding industry architectures, and gained new insights from the comparative empirical cases. In the next section, we will discuss and explore the technological and microeconomic mechanisms that may underlie the observable in the hierarchical architectures of these two sectors.

6 Technological Influences on Transaction Specificity

In the previous sections, we observed higher hierarchy degree, predicting higher transaction specificity, in the automotive sector than in the electronics sector. Such differences in industry architecture and inter-firm transaction pattern may result from differences in the fundamental technological bases of the industrial sectors. In this section, we present a conjecture on how technologies may affect industry architectures.

The influence of product architecture on industry architecture has been studied in terms of the abstractions of modularity and integrality (Langlois and Robertson, 1992; Sanchez and Mahoney, 1996; Baldwin and Clark, 2000; Schilling, 2000; Sturgeon, 2002; Langlois, 2002; MacDuffie, 2006; Fixon and Park, 2008). Automobiles are often accepted as an integral system product, while electronics are regarded as modular. However, we also observe modular components and parts in automobiles, as well as many integral electronics and electrical products (Fujimoto, 2002). Thus it is difficult to say unambiguously that one sector is more modular or integral than the other.

However, based on our hierarchy metric we *can* say that the automotive sector is more hierarchical than the electronics sector. Specifically, the direction of “upstream” and “downstream” is very clear in the automotive sector, and there are almost no “backward-flowing” transactions. In contrast, 40% of the transactions in the electronics sector are part of a cycle. Therefore, it is not clear which firms are “upstream” and which are “downstream”. The sector is closer to a bazaar or pure market in which any firm may buy from any other firm.

Sectors differ greatly in terms of their technological regimes (Malerba, 2002). Such regimes define the nature of the problems that a population of firms has to solve in their learning, innovation and production activities. The technological regime also shapes the incentives and constraints of organizations, and affects the basic processes of generation, selection and retention (Nelson and Winter, 1982; Malerba and Orsenigo, 1996). In principle, different technological regimes may lead to different sector architectures.

Technologies that underlie the designs of specific products in production sectors can be classified by their basic functions (Hubka and Eder, 1988; vanWyk, 1988; Magee and de Weck, 2004), in terms of operands (matter, energy, and information) being changed by operations (storage, transformation, and transport) (Koh and Magee, 2007). For instance, in the two sectors we are studying, the electronics products mainly store, transform, and transport information, while automobiles mainly store fuel (matter), transform energy (from physical-chemical energy to kinetic energy), transport energy (from engine to wheels), in order to transport human and goods (matter).

While our two subject sectors are similar in many business and economic ways, they differ substantially in the constraints imposed on them by the basic ways their products deliver their respective functions. In the following we explore the influence that these fundamental differences in technologies may exert in order as a possible, partial explanation of the differences in industry architecture we observed and modeled above.

Automotive Sector

In an automobile, significant energy is processed, and significant power is involved in the functioning and interactions of its components and parts. Although there is a trend to replace mechanical signal processors in automobiles with analog or digital electronics (Whitney, 1996), such substitution has physical limits because an automobile is basically demanded by customers for motion. High power is thus the basis for automobile’s behavior and the main expression of its basic functions.

The high power energy-processing technologies in automobiles are naturally constrained by the fact that high power components exchange power with each other. High power also creates some difficult-to-anticipate side effects, such as heat and vibration (Whitney, 1996). As a result, there is a high level of interdependency in the design and use of the components. These interdependencies manifest themselves as carefully specified performance requirements that require a tailored response by a supplier who designs the item and its interfaces to other items in order to satisfy those requirements. Components cannot be designed independently of, or without detailed knowledge of, the products in which they will be used. Significant investments of time and effort are required to guarantee the quality of component matching, coupling and integration. Therefore, automotive components and their mutual interfaces are basically product-specific (MacDuffie, 2006). Piston rings, seats, and mufflers, while obeying well-known physical laws and performing well-understood functions, nevertheless are designed again each time a new vehicle is designed, and the specific designs are used in only that vehicle and are made and shipped only as ongoing orders are received. Even in cases of some re-use items (e.g. door handles sometimes) that are standardized for multiple vehicle models, the transacted products still move from upstream to downstream because they are still specific for being used in automobiles, obeying the hierarchical rule.

This component specificity, which Schilling (2000) called “synergistic specificity”, may give rise to asset specificity (Williamson, 1981) between buyers and suppliers. Both sides must invest in assets (including knowledge) that are valuable only in the context of their specific relationship (Baker, Gibbons and Murphy, 2002; Baldwin, 2008). Such asset specificity in turn gives rise to what we are calling “transaction specificity”. Product designs must be specifically tailored and contracts between firms are “hand-in-glove”. In the language of our model, each upstream firm has a well-defined “niche range” of customers that are “close” to each other in terms of what they make and what they need to know in order to deal with each other efficiently and effectively.

The pattern of a well-defined set of similar customers was in fact confirmed in our interviews in Japan in March, 2009, with three major automotive suppliers, including one material supplier and two component suppliers (Luo and Kim, 2009).

In general, Japanese automotive suppliers described how they tailored their product designs and production processes to their customers specific needs in order to achieve acceptable levels of quality and cost. At the same time, they invested in deep, ongoing relationships with a stable group of customers. Such relationships generally take a long time to build and may give rise to organizational rigidities (Kaplan and Henderson, 2005).

The Japanese automotive suppliers we interviewed claimed that their product designs, production processes and transactional relationships had to be tailored to their specific customers' requirements. The requirement to provide customized products not only reduced the firms' incentives to diversify their product portfolios but also limited their capabilities to create new products for customers in markets outside their main niches. As our model shows, when the pattern of high transaction specificity is aggregated to the sector as a whole, it gives rise to hierarchy – that is, a one directional flow of goods in the sector as a whole.

<u>Electronics Sector</u>

In electronics products, information or signals are processed and transferred in binary logic. Such processes are relatively economical, accurate and reliable, and can be accomplished at very low power levels. The components in electronics do not draw or transfer significant power between each other but instead pass logical information for signal or control. In one sense, these items do not "know" that they are hooked to anything else, and their behavior does not change when they are hooked together as long as some design rules are obeyed. This fact makes it possible for electronic components to have standardized interfaces and codified behaviors. In contrast to automobiles, the design and production of electronic components can be conducted without detailed knowledge of the products in which they are used (Whitney, 1996).

Standardization has several further implications for transaction patterns. First, the thin crossing points at the standardized boundaries of electronics components result in low asset specificity between suppliers and customers (Williamson, 1981; Baldwin, 2008). This in turn makes arm-length contracts and/or spot-market transactions economical: there is no need for the specific hand-in-glove relationships that are common in the automotive sector. Second, with standardized interfaces, many electronics components can be easily mixed and matched with each other to generate a variety of distinct electronics products at the system level (Whitney, 1996). This means that a firm making particular components can have a wide range of customers making very different products. For example, a flash memory chip supplier may have customers that produce cell phones, cameras, or the components of larger system products. As a result, the customers of an electronics supplier are not constrained to a well-defined niche, but may be located "anywhere" in the industry. Our simulation models show that, when aggregated, this low level of transaction specificity gives rise to a correspondingly low degree of hierarchy in the overall sector.

Standardization also facilitates independent, unsynchronized (vs. interdependent and simultaneous) development activities, which in turn leads to high rates of product innovation (Baldwin and Clark, 2000). Koh and Magee (2008) showed that information technologies achieved much higher progress rates than energy technologies in the past 100 years. A high rate of product innovation in turn creates volatile demand—what customers want this year is not the same as last year— and thus increases firms' need to develop and maintain customers in more than one well-defined market niche.

Furthermore, the standardization and lack of asset specificity has allowed, and the innovation dynamics, has driven some electronic firms (e.g. FoxConn, the major Japanese electronics conglomerate firms) to gain access to complementary assets and capabilities, and produce diverse lines of products for distinct customer firms in its both upstream and downstream market niches, i.e. fulfill multiple roles, reducing transaction specificity and hierarchy. Paprzycki (2005) observed in several case studies that, the increasing sourcing of standardized electronic and optical parts and components from the subsidiaries of electronics giants or independent common suppliers has driven hierarchical inter-firm relationships to crumble to some degree, while the customer-specific suppliers are still preferred for structural and mechanical components, since the 1990s in the Japanese electronics industrial networks.

In summary, we have argued that industry architectures are in part influenced by the physical nature of products manufactured and exchanged in the production network of a sector. On the one hand, the high power nature of an automobile promotes mutual specificity in automotive components, production assets, and transactional relationships, and hand-in-glove contracts. Interdependency between customers and suppliers is needed to guarantee the quality of system integration and to deal with difficult-to-anticipate side effects. And high levels of transaction specificity across a sector give rise to a hierarchical industry architecture. On the other hand, the low power of electronic components enables standardization of interfaces, low asset specificity between supplier and customer, leading to low transaction costs, spot-market transactions and high rates of innovation. Low levels of transaction specificity across a sector give rise to a non-hierarchical, and multidirectional industry architecture.

In the two sectors we have studied, high and low levels of transaction specificity can be logically traced back to differences in the power level of underlying product technologies. In our causal model, high and low levels of transaction specificity lead to high and low levels of hierarchy in the resulting network of transaction flows. Thus the concept of transaction specificity serves as a bridge between an observable macro property of the sector's architecture—hierarchy— and its technological regime—the requirements that technology places on individual transactions between firms.

In a nutshell, we have argued that the higher the power level of a sector's technologies, the higher the degree of transaction specificity, and the more hierarchical the sector's transaction flows. This hypothesis, which was based on our exploratory analysis of two sectors, can be taken to other technologies and sectors to see if it holds up to further empirical tests.

7 Conclusions

This paper has explored how industries are organized at the sector level in an attempt to reveal the underlying rules that determine how industry architectures form and change. Though historical studies and theories have suggested that hierarchy is a key feature of industry architectures, empirical research has been largely descriptive because of difficulties in defining and measuring hierarchy in different industry settings as well as difficulty obtaining data.

We have combined several research traditions in order to shed light on this complex topic. These include institutional economics, industrial economics, economic sociology, network theory and graphical representations, and the constraints imposed by the laws of physics. Among these, only the laws of physics seem to differentiate the industrial sectors we looked at here, while the other considerations tend to have similar effects (both sectors must make profits, establish relationships with other firms, develop the necessary knowledge to compete, etc.)

The networks obtained from available data are quite complex and do not by themselves reveal much architecture. We therefore sought to establish a few defining characteristics that could help reveal the kind of architecture we need to understand: directed supplier-customer relationships at multiple levels; the fact that complex products are made of nested sets of subsidiary subsystems and components that are themselves products of other firms; the fact that firms have different degrees of choice about whom they buy from or sell to; and the possibility that the overall industry architecture in a sector and detailed firm-to-firm choices are influenced by the technologies embedded in the products themselves. These characteristics are captured in our model by transaction breadth and transaction specificity while the industry architecture is captured by its degree of hierarchy.

We first developed network-based metrics and methods to measure the degree of hierarchy of an industry sector, and then applied the methods to compare two large industrial sectors in Japan: automotive and electronics. Our empirical analysis shows that the automotive sector exhibits a significantly higher degree of hierarchy and higher transaction breadth (average number of customers per firm) than the electronics sector.

We then made a simple network-construction model grounded on two idealized rules of market structure, hierarchy and niche, called the "*Adaptive Niche Model.*" This model captures the variables of interest: the size of the sector, the number of customers each firm has on average, and the range of choice of customers or suppliers. We used this model with different amounts of transaction specificity as a tuning parameter to generate intuitively appealing simulated supply networks with corresponding amounts of hierarchy that are consistent with the data.

In essence, the *Adaptive Niche Model* connects the macro pattern, i.e., hierarchy, to local or micro patterns of connection at the level of individual firms, e.g. transaction breadth or how many connections are executed, and transaction specificity or where the connections are oriented. Our simulations establish the relationship between hierarchy and transaction breadth and transaction specificity in sector-like networks. Then, by interpolating the empirical measurement results within the simulation results, we further infer transaction specificity, which is significantly higher in the automotive sector than in the electronics sector.

Furthermore, based on a micro analysis on the technological bases of industrial sectors, we propose that the higher hierarchy degree and transaction specificity in the automotive sector compared to the electronics sector may result from the high-power nature of energy and matter processing of the components and parts in an automobile, and the low-power nature of information processing of the electronic components and parts in electronics products.

This research hopefully points the way to new approaches for understanding industry architectures and the factors that influence the architecture of industry sectors. To advance further, a number of hurdles must be overcome. Data are difficult to obtain, and the data available contain some confounding factors. Primary among these is the diversity of the firms themselves, especially in the electronics industry. Large firms may have many product lines representing different levels of component, subsystem, or final consumer product. Data will then show that they sell both "up" and "down" the supply chain, reducing its hierarchy. These are facts, not contradictions to the theory presented here, and more refined theory should take these facts into account, perhaps by representing the different business lines of large firms as separate elements in the network.

Second, we lack sufficient means for visually representing these large and complex networks. This is a known problem in network theory, and we have followed the traditional method of dealing with it, namely to seek statistical metrics that are easy to calculate and have some explanatory power (Newman, 2003). The risk is that they summarize too much. There is great value in being able to "see" the network in order to tease out important architectural patterns that correlate with the quantitative aggregate metrics.

Third, while automobiles and electronics operate under different technological constraints, these constraints are summarized here in terms of the amount of power involved in their functions. This is also an aggregate characterization which overlooks important facts. For example, some electronic products, such as laptop computers, use large amounts of power, a fact that constrains their performance in many noticeable ways. In addition, automobiles contain significant information processing capability and thus contain substantial amounts of electronics, a fact that joins the two industries in ways not represented here. It goes without saying that there may be additional mechanisms that lead to asset and transaction specificity beyond the high power and low power technologies considered here.

At a more detailed level, the simulation model treats many variables, such as transaction specificity, as uniform within each firm and as the same for all firms in a given network. Numerous ways to relieve this simplification are available, and using them will add nuance to the model, probably by differentiating suppliers that play different roles at the system, subsystem, or discrete component levels of the network.

In addition, the empirical measurement bears the risk of the deficits in the data. It is usually difficult to collect and compile industry-wide data not only because of the unclear industry boundaries but also the hesitance of some of the firms to share complete information on their transaction connections. This may lead to certain hidden sampling bias.

These limitations may be looked at as an invitation to explore these connections further in order to gain more understanding into both the common and different forces that act to create the architecture of industry sectors.

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