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# The Nested Structure of Emergent Supply Networks

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***Abstract*—Inspired by studies in ecological networks, we look for a nested pattern in a large-scale data set describing the global automotive industry, including more than 18 000 firms, their clients, and products. Two bipartite networks are formed, namely, supplier–product distribution and supplier–manufacturer relations. Both networks are found to be significantly nested. The pattern means that suppliers produce proper subsets of what other suppliers produce and rare products are produced only by those suppliers that already produce high numbers of product types. In addition, the manufacturers that procure from few suppliers procure from those that supply to most other manufacturers in the network. Similarly, suppliers that supply to few supply to those manufacturers that procure from most others. A nested structure is more robust than a nonnested structure as disrupted suppliers can be substituted, but nestedness also means that small suppliers face more competition as their production can be redundant. Our finding is contrary to conventional wisdom that associates large diversified firms with efficiency and small specialist firms with rare products, showing that large-scale complex system analysis can lead to the discovery of important systemic characteristics, which are obscured when viewed from local points of view. We then propose a multiagent model that creates more realistic nested structures to study systemic outcomes influenced by topology.**

***Index Terms*—Automobile manufacture, complex supply network, ecology, multiagent system, nestedness.**

## I. Introduction

A supply network is composed of many companies that make products necessary for the delivery of the final goods to the end customers. Suppliers are responsible for producing products, assembling subsystems from other suppliers, and selling to a manufacturer, which assembles final goods. Typically, the system is neither designed nor controlled but emerges as a complex adaptive system (CAS) over time as companies decide what to produce and with whom to link [10], [29], [31].

A CAS is a system where local interactions of individuals result in self-organizing systemic behavior that cannot be predicted by observing individuals using a reductionist approach. Thus, studying the system at both individual and collective levels is important to gain an understanding of its behavior. A well-known example is the flocking of birds, which is not a centrally controlled phenomenon, resulting from individual birds that mimic the speed of neighboring birds and keep a set distance from them. Similarly, supply networks are formed by individual companies attempting to maximize their gains through decision variables such as cost, quality, and flexibility. They link with other companies to produce and deliver a product and may be cooperating or competing for common resources. The environment is dynamic as links in the system are constantly reviewed and rewired by individual firms.

Several tools for the study of CAS are available, such as statistical mechanics, data analysis, network science, and agent-based modeling and simulation.

The first line of attack for studying supply networks as CAS has been agent-based modeling, where researchers modeled system characteristics such as decentralized data, asynchronous decisions, and impartial knowledge to devise better planning and coordination policies (e.g., [16], [25], [35]). Due to a chronic lack of empirical studies on emergent supply networks, such models were typically small scale and carry simplistic assumptions on emergent system structure.

Lack of data has become a bigger issue as manufacturers realized their vulnerability to risks cascading from suppliers to whom they were indirectly connected. The Japanese earthquake in 2011 and Thailand floods in 2013 halted production lines of major original equipment manufacturers (OEMs) and highlighted the importance of system structure. Following the headlines, several OEMs, including Toyota, Jaguar Land Rover, and Boeing, joined forces to map their networks with the help of third-party supplier base management companies such as Achilles and supply chain data providers such as Bloomberg.

New found data made the use of network science, another CAS tool, applicable for the study of supply networks. Systemic data have shown what researchers have been suspecting all along: Supply networks are a type of CAS. Some of the first large-scale studies identified typical complex network characteristics such as community structures, exponential and power law degree distributions, and assortative mixing [8], [17] and assessed how these properties relate to system robustness [31].

These initial studies have paved the way for better understanding of systemic properties; however, research of supply networks as CAS is in its infancy. Extracting universal properties of these systems can be informative to companies embedded within and helps engineers that study their performance by replacing structural assumptions with more accurate frameworks.

In this paper, we contribute to extant literature in two respects. First, we discover an important systemic property called *Nestedness* in supply networks.

A nested network in ecology refers to the universal self-organized structure of bipartite networks. These could include, for example, mutualist interactions between species such as insects that feed from and also pollinate plants. In these networks, “generalist” species (those with a high number of connections)

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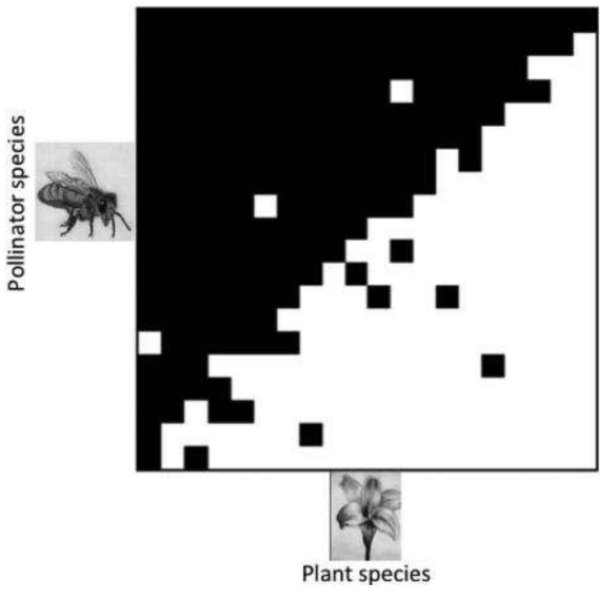


Fig. 1. Illustration of a nested plant–pollinator interaction pattern through a binary matrix depicting the (black) presence and (white) absence of interactions.

interact with their generalist counterparts constituting a highly connected "core" (see Fig. 1). In addition, "specialists" (species with low number of connections) also tend to interact with generalists, rather than among themselves. Ecologists argue that the pattern is ideal for conserving biodiversity as rare species are conserved within the highly connected core of the network. The disappearance of a random plant means that most insects still survive by feeding from other plants, and the disappearance of a random insect means that most plants can be still pollinated and reproduce.

We investigate nestedness in supply networks by collecting large-scale data from the automotive industry. We found two types of unambiguously nested bipartite networks coexisting in supply networks, namely, a supplier–product network and a supplier–manufacturer interaction network. Generalist suppliers produce both ubiquitous and rare products, and specialist suppliers produce products that most other suppliers produce, including those that are produced by generalists. Generalist suppliers are also those that connect with most manufacturers, including those manufacturers that procure from only a few suppliers. This highly connected core means that the system is robust to the disappearance of product demand or failures in suppliers. However, it also means that specialist suppliers and manufacturers are competing with generalists and other specialists.

Our second contribution is the construction of a multiagent model that creates nested topologies. The model takes inspiration from pollinator–plant network dynamics and can be calibrated to experiment with different levels of nestedness. The model is aimed at aiding researchers that would like to work with more realistic supply network structures when investigating systemic outcomes.

In what follows, first, a literature review is presented, followed by a description of data collection and methodology. Then, the results of the nestedness analysis are given, followed by the development of our model.

## II. Literature Review

The study of nestedness is grounded in two types of networks in ecology. First of these is the analysis of mutualistic networks, which are formed when interactions between two species are mutually beneficial. Examples include pollinator–plant species, where insect species feed from plants while pollinating them [5]. It was long believed that mutualistic interactions between species were highly specialized, where two species would maximize their gains from the interaction through coevolution, with the most famous example being Darwin's Malagasy Orchid and the long-tongued Spinghid Moth. However, most observations of such mutualism have been rather small scale, which obscured statistical features only observable at large scales. When large-scale systemic properties were considered, "nested" patterns were found to be prevalent [3].

A nested pattern is analyzed by creating an adjacency matrix that records species interactions, the rows and columns of which are ordered in decreasing degree. For example, in a plant–pollinator network, the rows of the matrix are ordered from the most generalist pollinator species (insects feeding from many plants) to the most specialist (insects feeding from few plants), and then the columns of the matrix are ordered from the most generalist plant species (plants that have many species feeding from it) to the most specialist (plants that have few species feeding from it). A nested pattern results in most of the interaction presences lying above a curve and interaction absences underneath it (see Fig. 1).

The pattern points to the fact that specialist species tend to interact with proper subsets of mutualistic partners of more generalist species. That is, the set of interactions recorded for any species is likely to be nested within the more generalist species interactions. From another perspective, generalist animal species interact mostly with generalist plants, and specialists also interact with generalists but not with other specialists.

In addition to mutualistic interaction networks, the pattern has been observed in the distribution of species over island habitats. Here, the pattern refers to the fact that generalist islands host a larger number of species and specialist islands host a smaller number of species, which constitute proper subsets of species residing in generalist islands. It is only the generalist islands that host rarely found species. Islands that host only a few species are most likely to host species that already exist in the generalist islands. In other words, it is diversity that generates diversity.

After the discovery of this universal pattern, ecologists debated how the pattern affects stability and persistence of species [6], [14], [24] and how suitable tools could be constructed to quantify the degree of nestedness accurately [2], [22], [27], [28], [32]. Some recent studies investigate the reasons of nested pattern emergence, correlating it with species abundance [1], and large-scale network connectance, debating whether nestedness may be a reason or a consequence of a truncated power law degree distribution and a modular structure [30].

One of the major reasons of the interest in nestedness is ecological robustness and stability. In a nested network, most

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plants would continue reproducing after random perturbations to insect species because most insects can still continue to pollinate most other plants [15]. Similarly, most insects would continue surviving if random plant species disappear because they can feed from other plants. Researchers have modeled how nested structures allow the addition and deletion of species with minimal disturbance to the rest of the network [6], whereas others argued this finding could be also dependent on the frequency of interactions and sensitivity to external changes in the environment [1].

Although a vastly different type of complex system, there are several reasons why investigating nestedness in supply chain networks makes sense. Recent studies have found supply networks to exhibit complex network patterns such as truncated power laws and modularity [8], [13]. These patterns shape systemic robustness, which is a significant concern with far-reaching consequences ranging from financial stability of nations to socioeconomic performance in today's globalized industries [34]. Given recent studies on the correlation between these patterns and the presence of nestedness in ecological networks (e.g., [30]), it is plausible that a nested pattern can emerge in supply networks. Its analysis therefore could generate additional insight into the emergent structure with which supply networks are structured and how the pattern or lack of it impacts the robustness of the overall system. Furthermore, two previous works investigated ecological patterns in specific supply networks. Saavedra *et al.* [23] looked at interactions between producers and suppliers in the New York Garment Industry, whereas Brintrup *et al.* [7] looked at the distribution of production over the supplier network of Toyota. Although nested patterns were hinted, neither of these studies investigated the coupling of both supplier–product network (hereafter SPN) and supplier–manufacturer network (hereafter SMN) interaction in these networks. For robustness in a supply network, the two aspects cannot be separated because each node produces one or more types of products and supplies them to other firms, eventually ending with the manufacturer, which assembles the products. For a supply network to be functional, both SPN and SMN should be robust and contain redundancies at system level. Thus, we extend previous work on complexity in supply networks by: 1) searching for a nested pattern, which has robustness implications at the systemic level; 2) coupling the SPN and SMN to provide a complete picture of the system; and 3) creating a multiagent model that generates nested topologies.

Consider the manufacturing of an automobile dashboard. The final assembly would contain several parts, including wipers, headlight switches, and entertainment systems such as a radio. Each of the parts may entail complex subassemblies and software. All of these would be made from a variety of parts and raw materials, including plastic, metals, and ceramics. The assembler would decide on which parts to outsource and which to produce in-house. A "generalist" strategy can be adopted, wherein the firm would maintain an extensive product portfolio and produce most of the dashboard itself, or follow a "specialist" strategy by outsourcing the dashboard and focusing on some other types of work. The supplier entrusted with producing the dashboard could source the entertainment system. That subsystem supplier could adopt a specialist strategy or become a generic entertainment system manufacturer with an automotive division. These local decisions would create an emergent distribution of production over a chain of firms dependent on each other to produce the automobile.

The resulting distribution would be important because redundancies in the SPN can create buffers against disruptions. For the SPN to remain operational, production must continue even when some of the firms that contribute to production do not. This requires that firms have at least partially overlapping product portfolios so that firms can replace each other when disruptions occur. A nested pattern could help understand where and how these buffers are distributed. In addition, the pattern can reveal the level of competition between producers. For example, distributions with an oversupply of products would also affect the level of competition in the network, i.e., the more firms overlap in their portfolios, the more competition they would face. At the abstract system level, animals competing to feed from same resources and thus creating redundancies for plant reproduction are analogical to suppliers competing for market share of products and also creating redundancies for the final assembly of goods.

A similar reasoning could be drawn for suppliers' interactions with manufacturers. Manufacturers and suppliers form mutually beneficial relationships where manufacturers rely on suppliers to produce products necessary for assembling the final product. In SMN, if suppliers fail to deliver, manufacturers must continue producing by sourcing from alternative suppliers, and if manufacturers do not produce demand, suppliers must find alternative buyers.

Nestedness in both the SPN and SMN would create redundancies against disruptions. In SPN, generalist suppliers would create most product types, including rare products, and specialist suppliers would produce ubiquitously produced products. This would mean that, for the system to fail in delivering assemblies, only production of a rare product from the generalist supplier must halt, as most other suppliers could be replaced. In SMN, generalist suppliers would interact with most manufacturers, including manufacturers that buy from few suppliers, and specialist suppliers would interact with manufacturers that buy from many other suppliers. This would mean that, for the system to disconnect, either a generalist supplier or a generalist manufacturer must become disrupted.

To analyze nestedness, we first collect data on a particular supply network, i.e., that of the global automotive industry. Data from the automotive industry are sufficiently large and comprehensive enough to derive meaningful statistical analysis regarding both SPN and SMN. The industry has been a pioneer of supply chain engineering, providing us with mature network structures. The automotive industry is also one of the first industries in which a network view has been adopted with commercial supply chain solutions for design and optimization (e.g., [20]). However, to date, very little has been reported about emergent patterns in the industry and how emergence affects systemic outcomes (few works on general network structure include [7] and [18]. Next, we describe data collection and analysis followed by the development of a multiagent-based model for nested topology generation.

## III. Data and Methods

### A. Data Collection

To maximize our chances of identifying clear patterns, we collected supply network data from the automotive industry for which a large sample size is available. This industry choice allows us to use network data from a single database managed by an independent agency.[1] This database is comprehensive and offers consistency when compiling data.

Data were downloaded from the database during October 2013–January 2014 and included firm identity, clients, suppliers, and products offered. Three independent researchers have cross-validated data. After data codification, firms that do not have outgoing links have been captured as manufacturers, whereas all other downstream firms have been captured as suppliers. As every supplier is coded with a unique identification, intertier linkages and supplier links to multiple clients could be also identified.

Our construction of the SMN includes 18 942 firms, of which 16 468 are supplier firms and 2474 are manufacturers, with 103 602 relationships among them. There are a total of 934 product types in the network, produced by 16 468 supplier firms, creating the SPN.

Please note that the term products, product categories, and product types are used interchangeably throughout the manuscript. A product refers to one of the product categories in the network, which are generic automobile components and subsystems, rather than model specific. These could include categories such as gearbox, air conditioner, and wiper switch. Product categories are thus viewed as substitutable. Generic processing capabilities such as forging and plastic molding were ignored. Our view is that suppliers that create these generic product categories could be substitutable as they have the general capability and tools to produce a given product.

Furthermore, supply networks are dynamic constructs, changing frequently; thus, efforts to map them, such as the study we currently undertake, would only represent a cross-sectional reality in time. Conclusion should therefore be taken as suggestive rather than definitive given the lack of nonautomotive firms in the data and knowledge on what proportion of the network is composed of them.

Despite these shortcomings, the data set is the most comprehensive data set reported to date on automotive supply networks, and analysis shows that statistically significant patterns can be identified.

Following data collection and validation, data analysis took place. Analysis is divided into two main parts.

1) Standard metrics have been used to analyze the degree of nestedness in the sample. Both the SMN and the SPN have been found to be significantly nested.
2) A multiagent model has been created for supply network researchers to create benchmark nested topologies with a minimal set of parameters for hypothesis testing. The model was then calibrated using the original sample.

Next, we describe the metrics used to identify nested patterns in the sample.

[1] www.marklines.com

### B. Analysis of Nestedness

Several metrics have been proposed to compute nestedness of bipartite networks (please see [33] for an excellent review). Although accuracy of each metric is debated [27], [33], the most commonly accepted and used metrics include matrix temperature (MT) by Atmar and Patterson [3] and nested overlap and decreasing fill (NODF) by Almeida-Neto *et al.* [2]. These have been used to calculate the nestedness of empirical sample and the multiagent model proposed in Section V. In addition, we report on the more recent spectral radius metric proposed by Staniczenko *et al.* [27] as we feel that this metric will become another standard. The main reasons for the selection of these metrics are their availability in standard calculator packages and their popularity, which allows for comparison to other nested complex networks reported in literature. In all metrics, first, a packing procedure is applied, which reorders the binary matrix according to row and column totals. Afterward, the metrics are calculated using the Nestedness for Dummies (NeD) package [28] .

The large sizes of the SMN and SPN meant that standard nestedness calculators could not be used to analyze the whole network. Furthermore, a smaller network size would make comparison with ecological reports of nestedness possible. We therefore opted for a sampling approach, where we composed adjacency matrices by sampling 50 suppliers and listed their products in SPN and the manufacturers they interact with in SMN. In addition, 1000 samples have been drawn for each of SPN and SMN. The approach resulted in slightly different numbers of product types and manufacturers at each sampling, descriptive statistics of which are given in Table I.

A brief overview of nestedness metrics is given as follows.

*MT:* As the earliest metric to calculate nestedness, MT first calculates an "*isocline of perfect nestedness (IPN)*" of a matrix of the same size. The algorithm then notes all expected observations and unexpected absences before and after the isocline. The average residual from the isocline gives a nestedness temperature $T$, between 0 and 100, with 0 being a perfectly nested matrix.

*NODF:* The temperature metric might overestimate the degree of nestedness observed in real networks, giving rise to type-I statistical error [33]. The alternative measure of NODF checks for two properties that a nested matrix should have, i.e., "decreasing fill" and "paired overlap." Decreasing fill is the gradual reduction of the number of interactions from the most generalist to the most specialist firms in the matrix, whereas paired overlap determines whether the number of interactions of a given species overlaps with those of the subsequent most generalist species.

*SR:* SR is a recently proposed metric, which computes nestedness as the maximum eigenvalue of the adjacency matrix.

The significance of a nested pattern is examined by comparison to randomized null models. Two null models described below are used to assess significance. For a detailed review of appropriate null models for testing nested patterns, please see [33].

*EE (Equiprobable Row and Column Totals):* This model maintains the total number of species occurrences in the matrix but allows both row and column totals to vary freely. In the

TABLE I
NESTEDNESS METRICS OF EMPIRICAL SPN AND SMN SAMPLES COMPARED WITH ECOLOGICAL SAMPLES OF SIMILAR FILL RATE

| | $N_{row}$ | $N_{col}$ | $N_{links}$ | Fill rate | NODF | T | SR |
|---|---|---|---|---|---|---|---|
| *Supplier-Product Network* | 50 | 260 ±3.08 | 978.80 ± 37.88 | 0.08 ± 0.002 | 17.88 ± 0.9 | 9.28 ± 0.51 | 17.23 ± 0.42 |
| *Supplier-Manufacturer Network* | 50 | 58.03 ± 2.61 | 264.38 ± 13.47 | 0.09 ± 0.004 | 19.70 ± 0.86 | 11.27 ± 0.58 | 8.89 ± 0.46 |
| *Great Basin fish (Smith, 1978)* | 48 | 78 | 237 | 0.06 | 23.16 | 5.70 | 9.22 |
| *South Africa Sciobius weevil (Morrone 1994)* | 21 | 47 | 124 | 0.13 | 22.90 | 22.60 | 7.18 |
| *Desert scrub mice (Brown and Kurzius 1987)* | 140 | 27 | 460 | 0.12 | 29.132 | 18.32 | 12.77 |

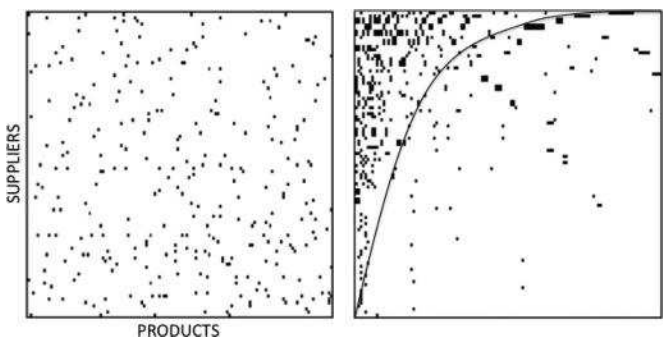


Fig. 2. Typical nested ordering of suppliers and their products. (a) Randomly organized matrix. (b) Packed matrix.

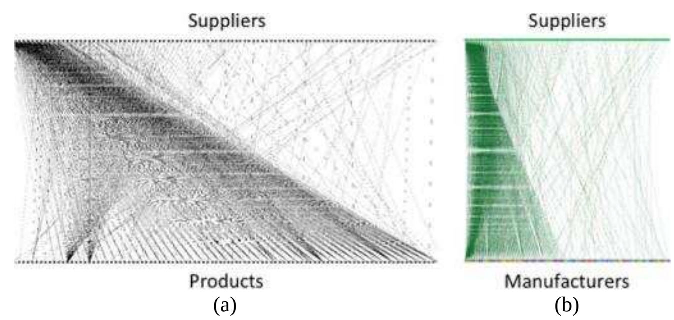


Fig. 3. Bipartite (a) SPN visualization. Suppliers are at the top, and products are at the bottom. Most suppliers produce subsets of each other's products, making most products ubiquitously produced. A few rare products are produced by those suppliers that produce most other products. The left-hand side of the network has high density of connections, showing the generalist suppliers connecting to ubiquitously produced products. A similar pattern is observed in the SMN: (b) SMN visualization with suppliers on top and manufacturers on the bottom. Suppliers supply to subsets of each other's buyers. The manufacturers that connect to few suppliers connect to those that supply to many others. The suppliers that supply to a few manufacturers supply to those that buy from many others. The generalists also connect to specialist products. Specialist-to-specialist connection space on the right-hand side is sparser in both SPN and SMN.

case of SMN, this null model varies the number of interactions between suppliers and manufacturers while keeping their total number fixed. In the case of SPN, this null model varies the number of products offered by suppliers while keeping the total number of suppliers and products fixed.

*CE (Proportional Row and Column Totals):* This model assigns a probability of occupation proportional to the corresponding row and column totals of each cell. The probability of a presence in cell $x_{ij}$'s occupation is given as

$$\frac{\frac{R_i}{C}}{\frac{C_j}{R}}$$

where $R_i$ is the number of presences in row $i$, $C_j$ is the number of presences in column $j$, $C$ is the number of matrix columns, and $R$ is the number of matrix rows. Hence, the mean row (suppliers) and column (number of manufacturers in SMN or products in SPN) totals are not biased and match to that of the original matrix. This null model is considered the most realistic because it is restrictive and can identify differences between segregated and nested patterns [33].

## IV. NESTEDNESS ANALYSIS

Fig. 2 shows a typical sample and how a nested pattern is revealed after reordering. The figure depicts the IPN and how sample data show clustering of presences above the IPN and absences below. Another visualization can be observed in Fig. 3, which illustrates the bipartite graphs associated with SMN and SPN. It appears that most suppliers produce subsets of each other's products, whereas few specialized products are produced by those suppliers that produce most other products. The same pattern is observed in the SMN. Most suppliers supply to subsets of each other's buyers (i.e., manufacturers). Manufacturers that procure from a few suppliers procure from those that supply to many others. Similarly, suppliers that sell to a few manufacturers sell to those that buy from everyone else. Table I reveals the formal results on the empirical samples. Both SPN and SMN are significantly nested in all three metrics studied (all $p < 0.001$, except one SMN case where $p < 0.05$). For comparison, we included nestedness metrics from ecological samples reported in literature: These samples have been selected because of the similar fill rate and scale of their adjacency matrices.

This result is intriguing in terms of both cause and implication. We discuss these next.

The emergence of a nested pattern in SPN contradicts classical management thinking that predicts either niche or generalist production in cooperative organizational ecosystems (e.g., [11]). On the other hand, conventional supply chain management thinking would suggest that an idealized cooperative supply network matrix would have a block-diagonal structure, with all suppliers producing specialized products and each sharing responsibility in the final assembly. A purely competitive market, on the other hand, could aggregate in communities producing similar goods (e.g., [12]). In the samples studied, "specialists" are not specialists in the conventional sense at all, in that

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TABLE II
EXTREME GENERALISTS AND SPECIALISTS

| **Most generalist products (products supplied by highest number of suppliers)** | **Most specialist products (random selection of products supplied by least number of suppliers)** |
|---|---|
| Elemental components: bush / seal, pipes, spring, bearing, gear, shaft, pin, valve, etc.<br><br>Engine main structural part: crank shaft, piston, drive plate, con rod<br><br>Brake parts<br><br>Interior trims :door trim, roof trim, carpet | Drive train: Multiple Disc and Viscous LSD<br>Drive train: Power take off<br>Alternate fuel system: LPG and CNG<br>Current collector for nickel metal hybrid battery<br>Anode current collector for lithium ion battery<br>Heater solenoid valve |
| **Most generalist suppliers in SPN (suppliers offering highest number of products)** | **Most specialist suppliers in SPN (random selection of suppliers producing least number of product types)** |
| Magna International<br>Denso Corporation<br>Robert Bosch LLC<br>TRW Automotive Holdings Corporation<br>Delphi Automotive PLC<br>Aisin Seiki<br>Hitachi Automotive Systems<br>Dongfeng motor parts<br>Valeo S.A.<br>Continental AG | Huari Paint<br>Shenyang Tim-High Material Development Co., Ltd.<br>Rayconnect Inc.<br>Beijing National Battery Technology Co. Ltd.<br>Shin Etsu Magnetics Inc.<br>Malaysian Sheet Glass Bhd |
| **Most generalist suppliers in SMN (suppliers linking to highest number of manufacturers)** | **Most specialist suppliers in SMN (random selection of suppliers linked to least number of manufacturers)** |
| Magna International<br>Denso Corporation<br>Robert Bosch LLC<br>TRW Automotive Holdings Corporation<br>Delphi Automotive PLC<br>Aisin Seiki<br>BorgWarner BERU Systems Inc.<br>Johnson Controls<br>ZF Friedrichshafen AG | LEONI Automotive<br>Tianjin Toyotsu Otsuka Textile Co. Ltd<br>Eikoh Plating Co. |
| **Most generalist manufacturers (manufacturers linking to highest number of suppliers)** | **Most specialist manufacturers (random selection of manufacturers linked to least number of suppliers)** |
| Ford<br>Toyota<br>Honda<br>General Motors<br>Nissan<br>Volkswagen | Dorsey Trailers<br>Norinco<br>Yunding FAW<br>Sumimoto Construction Machinery<br>Guilin Daewoo<br>The London Taxi Company |

they produce redundant products and serve companies that are served by others. It is the "generalists" that are at the same time specialists, in that they produce rare products and serve to manufacturers that buy from only a few.

Several alternative hypotheses might support the formation of a nested pattern in SPN. Looking at the suppliers and products at the extreme ends of the matrix reveals some hints (see Table II). The most generalized suppliers have an average of 126 666 employees, with an annual revenue of \$2.7 billion in 2014. They are bigger firms compared with specialized suppliers. It is also apparent that the least ubiquitous products are, in general, more complex and higher value than most ubiquitously produced product types. An explanation as to why only large suppliers produce these product types could be that they require higher investments in production, which only these companies can afford. Another non-mutually exclusive reason could be that these companies acquire newer more complex technology as they have had more mergers and acquisitions in the past ten years (average of 4.7). However, while this reasoning explains why complex products are produced by generalist suppliers, it does not explain why these firms do not let go of the production of simpler product types. It could be that these products still offer value to the supplier through the efficiency with which they are produced or the volume with which they are demanded in the market. Further longitudinal analysis would be necessary to understand the extent to which these two dynamics affect the evolution of the product portfolio.

The pattern has two implications in terms of robustness of the SPN system. First, if suppliers fail to deliver their products, then there is sufficient redundancy in the network to procure from other suppliers. Second is that rare, complex, and high-value products are produced by large suppliers who might be more stable. Hence, rare products being produced by generalists could make the system more stable. On the other hand, small suppliers seem to produce products that can be procured from elsewhere, making them compete with both small and large suppliers, possibly making them more vulnerable to changes in demand and other market conditions. Turning our attention to SMN, we notice another side of the story embedded in the structure. In SMN, both generalist suppliers and generalist manufacturers are on average, bigger, and have higher revenues compared with specialist suppliers and manufacturers (see Table II). Generalist manufacturers that depend on a few suppliers depend on those generalist suppliers that sell to many other manufacturers. Suppliers that sell to a few manufacturers sell to those that buy from many. Most generalist

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manufacturers buying from many suppliers include well-known automotive producers, whereas specialist manufacturers occupy niche positions. For example, Dorsey Trailers is a USA-based trailer manufacturer, Norinco produces defense vehicles for China, Sumitomo Construction is specialized in construction vehicles, London Taxi Company manufactures black cabs for London, and Guilin Daewoo is a bus and coach producer in China. Similar to generalist manufacturers, these manufacturers also tend to buy from the most generalist automotive suppliers in the network. As such, specialist manufacturers are competing over the same resources with generalist manufacturers, which could include products, production capabilities, or administrative teams that handle procurement.

In network terms, both in SPN and SMN, high degree nodes of one type connect to high degree nodes of another, and low degree nodes connect to high degree nodes of either type. The pattern would suggest a connected core, where only the failure of large degree nodes would fail the system. A simple preferential attachment dynamics applied to bipartite convention could explain this formation [30]. Ecological studies of nested networks prove that these networks are robust as a whole [6], [14], [24] yet also caution that they are so, at the expense of vulnerability of species that contribute most to the nested architecture as they face more competition over resources [24].

Nestedness in both types of networks occurring in supply networks necessitates us to revisit our assumptions on topology. Manufacturing engineering has long modeled supply networks as simple chain-like local structures, to which the reality does not match. These models have been used to optimize operational performance and robustness to uncertainties. The reason for this has been the lack of data and understanding of emergence at systemic levels, resulting in an assumption that supply networks are designed at the local level and do not have predictable CAS patterns. Using topologies based on real life would help inform existing models and create more accurate assessments of system performance.

## V. Multiagent-Based Model for Supply Network Formation

Our analysis showed that both SMN interactions and the distribution of production among supplier firms show nested patterns. With this motivation, we create and test a model for researchers to create benchmark topologies with a minimal set of parameters for hypothesis testing.

The model is inspired by the feeding behavior of insects. A number of insects are created at the same position in a habitat, which contains a number of plants. The plants are randomly distributed over the habitat. The insects drink nectar from plants, which gives them energy to move around the habitat. The nectar of plants decreases as insects forage; however, the nectar regenerates after a set amount of time. The more energy insects have, the more they can travel to discover plants that have nectar. The diversity of feeding resources gives insects a slightly higher efficiency in the amount of energy they can harvest per time period. All insects and plants start off with the same levels of energy and nectar. The simulation continues until the amount of nectar stabilizes. The main steps of the model are presented in Fig. 4, and a visualization of the habitat is presented in Fig. 5.

(1) Initialise plant habitats with $P$ number of plants in randomly distributed positions.
(2) Assign same nectar level $N_p$ to each plant
(3) Initialise $B$ number of insects at the centre of the habitat with energy $E_b$ drawn from a uniform distribution. Each insect needs to drink $\acute{N}$ nectar level when it visits a plant
(4) For each bee:
    If : $E_b > \mathit{Energy\ threshold}$, find plant P with $\max(N_p)$ within radius R
    Else: move to nearest plant with highest nectar
    Lose a unit of energy at each move
    When on plant $p$, add $p$ to set of plants $P_b$: {} visited by b
    Drink nectar from $p$
    $E_b = E_b + E_b * F_b$, where $F_b$ is efficiency of insect
    $F_b = \frac{|P_b|}{P}$
(5) For each plant:
    If: $N_p > \acute{N}$, give nectar to the next insect that visits. $N_p = N_p - \acute{N}$
    Else: Wait $I$ iterations for nectar replenishment

Fig. 4. Algorithm for the multiagent model.

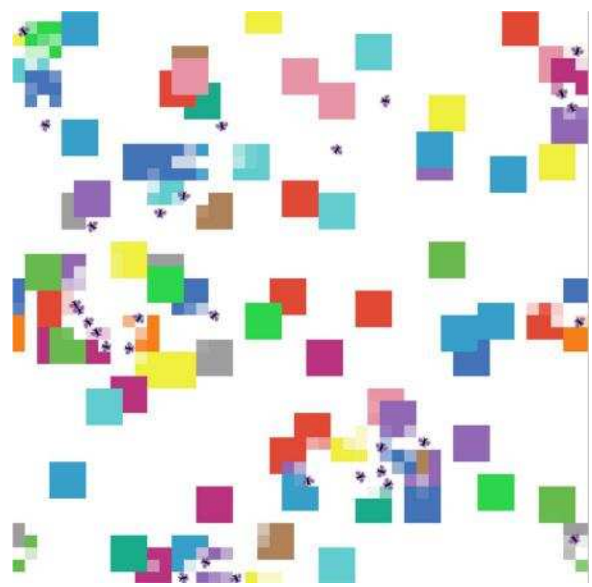
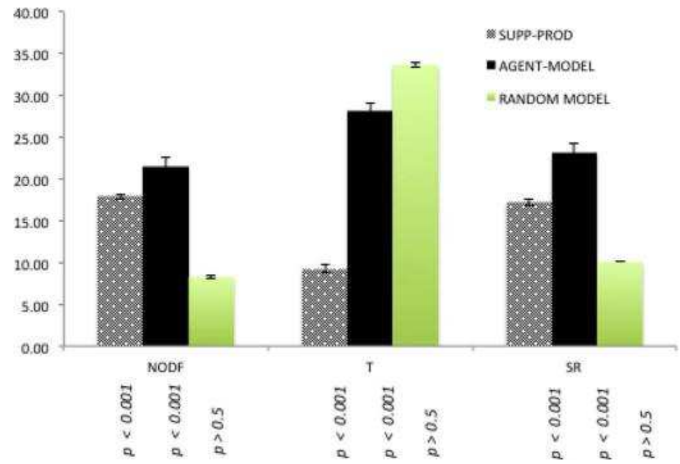


Fig. 5. Multiagent model simulating insect nectar-harvesting behavior. Colored patches are plants that provide nectar harvested by insects. Insects start from the same position and travel through patches as they extract more energy.

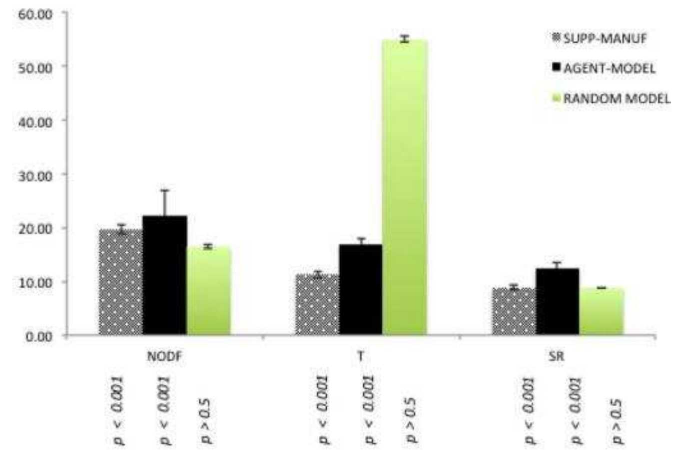
Although inspired by insect behavior, the model itself is generic, in that it can be calibrated to create nested topologies for any kind of network, be it plant–pollinator networks or supply networks. The model is then calibrated to represent the SPNs and SMNs and validated by comparing to nestedness values in the automotive network samples reported in Section IV. Our model success criterion is thus a close match in nestedness to values obtained from the real-life supply network system studied in this paper.

In order to facilitate comparison with empirical data, insects (e.g., suppliers) are not allowed to go extinct even if their energy level becomes zero. This means that existing species are preserved and members of neither species can be deleted.

The model is coded using the multiagent simulation package NetLogo (see Fig. 5). Model calibration is then carried out to include same levels of insects (e.g., suppliers) and plants (e.g., products or manufacturers) and links between them.



(a)



(b)

Fig. 6. Comparison of nestedness of the agent-based model with empirical (a) SPN sample and (b) SMN sample.

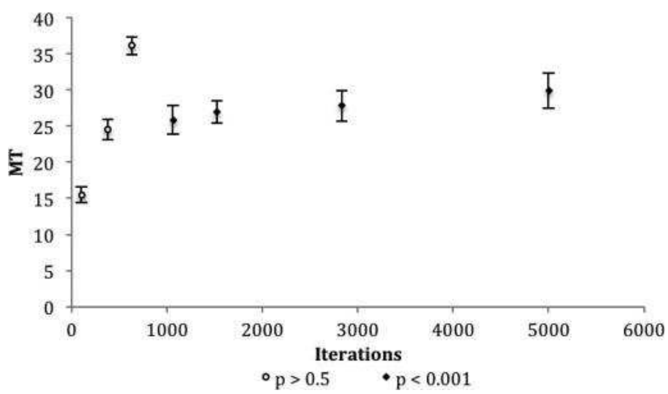



Fig. 7. MT value becomes significant as insects discover their habitat.

Fig. 6(a) and (b) shows that results obtained from the model closely match results from the empirical data on all nestedness metrics used in the empirical sample. A comparison between the level of nestedness obtained from the empirical samples, the multiagent model, and a randomized network based on the CE (proportional row and column totals) null model is also illustrated. The $p$ values for all runs for the random model have been $p > 0.5$, whereas for the multiagent model, the values have been $p < 0.001$. Fig. 7 shows the change in MT as insects move around the habitat. In addition, 100 runs were repeated. After initial random distribution, the MT value gradually stabilizes and becomes more significant $(p < 0.001)$.

The simple set of rules given above creates a "rich-get-richer" phenomenon. Over time, some insects get better at harvesting nectar and feed from a more diverse set of plants. Other insects never have the chance to travel as they need to wait at the same location for nectar replenishment due to their lack of energy. Most insects fall somewhere in between in their energy and feeding diversity levels. While most insects ubiquitously feed on the nectar of central plants, insects that manage to outcompete other insects and feed more from ubiquitously harvested plants can go on to discover new plants with more nectar. This dynamic is analogous to suppliers adding new products and clients to their portfolio as their production and investment capabilities grow if they succeed in competition.

## VI. Concluding Remarks

Inspired by studies on ecological networks, we looked for a nested pattern in two types of coexisting bipartite supply networks, namely, the SPNs and the SMNs. Our analysis on the automotive industry highlighted a systematic relationship between firm-level procurement decisions and the resultant system structure. Using three metrics and large-scale data from the automotive industry, it was shown that both networks are nested. Firms that produce rare products are those that are highly diversified (generalist firms), and firms with small portfolios produce products that are common in the market. This finding is in contrast to the conventional wisdom, which prescribes market segmentation with specialized firms producing a small number of rare products and generalist firms producing large portfolios with standard products. The most ubiquitous products are standardized lower value goods, whereas the rare products are those that are more complex to produce and are of higher value. Generalist suppliers tend to supply products that are supplied by other generalist firms; nondiversified firms tend to supply what all other firms supply. This means diversified firms have more rare products in their portfolios, in addition to ubiquitous products. An evolutionary stance could suggest that, as suppliers grow, they become more diversified and add more niche products to their portfolio while keeping to their old products; however, we would need longitudinal studies to confirm this hypothesis. In the automotive industry sampled, large firms such as Bosch or Denso produce innovative products, whereas small supplier firms produce standard parts such as fasteners and plastic molding parts. Thus, the pattern forces us to redefine generalist and specialist firms in supply networks because "generalist" firms are the companies that tend to produce niche products in the network, and "specialist" firms tend not to produce them.

Most generalist suppliers are involved in a higher number of mergers and acquisitions, which makes vertical integration one possible explanation. This, in turn, might mean that companies that only produce rare products are more likely to be integrated with other companies, creating larger suppliers with diverse product portfolios. In addition, we observe that generalist suppliers have higher revenues and therefore higher capabilities for larger investments in production. Since it appears that the rare products tend to be more complex and are of higher value, they may require higher investments in production, which only generalist suppliers can afford.

The question remains as to why generalist suppliers hold on to the ubiquitously produced products. One explanation could be that there is more demand for these products and producing them is still profitable. Another explanation could be capacity constraints on ubiquitous products, which increases demand for them.

Specialist suppliers compete within the ubiquitous product space, which means that they face more competitors in the market, including large diversified suppliers. Of course, they might be able to handle the competition because of logistical advantages or because there is enough demand in the market for ubiquitous products. One could also imagine that their product offering might include other characteristics such as more labor-intensive work content.

Nested arrangement in the SMN offers a similar insight. Generalist suppliers supply to both specialist and generalist manufacturers. Specialist suppliers supply to manufacturers that buy from many others. Specialist manufacturers of vehicles such as construction machinery, trailers, or buses mostly buy from generalist suppliers. The most generalist suppliers in both SMN and SPN form the core of the network. Specialist suppliers compete over same manufacturers as generalists, and specialist manufacturers compete over same suppliers as generalists. One could imagine specialist and generalist manufacturers to have different volume requirements, and specialists possibly have less bargaining power over generalist suppliers.

Nestedness gives rise to important systemic properties. Nested networks are robust to disruptions such as the loss of certain products or disruptions at suppliers or manufacturers. As such, losses are more likely to impact products that can be replaced in the network. Since generalist firms tend to be large multinationals, we might also reflect that they would be more likely to have resources to dedicate to recovery from disruptions, making unique complex products safely cocooned within the network. Of course, here, we are bound by the assumption that firms can readjust their links and replace lost production by buying from alternative suppliers while such decisions would inevitably be constrained by cost, risk, capacity, and capability constraints.

After detection of nested patterns, we proceeded to create a multiagent-based model that results in nested patterns, which could be used by supply network analysts to work with more realistic topologies in the absence of empirical data. For example, the structure with which production responsibility of an assembly is shared among suppliers is often assumed when modeling dynamics of a network to estimate lead times and inventory. Such assumptions would impact the flow of materials and, thus, conclusions drawn from the model. If most likely structures are known in advance, more realistic systemic outcomes can be drawn.

The analysis has a number of limitations providing future opportunities for research. First of these is a lack of quantitative detail on the interaction matrices. While the presence of an interaction is known, its extent is not. Studying the amount of trade between suppliers and manufacturers and the volume of products produced by suppliers would make the analysis more informative and help overcome any erroneous interpretation. A recent metric proposed by Staniczenko [27] enables the detection of nestedness on quantitative matrices and highlights the need for further study. Second, we have used standard null models from the field of ecology. The creation of specific null models for supply networks could help compare results to more realistic structures. This inevitably depends on the gathering of more empirical data on large-scale supply networks from different industries. Recent advances in traceability technology offer promise in this respect. Furthermore, longitudinal data would help detect the extent to which nested patterns result from evolutionary processes.

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