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The Effects of Endogenous Interdependencies on Trade Network Formation across Space among Major Japanese Firms

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Abstract

The network structures of interfirm interactions have been linked previously to disaster resilience. However, the dynamic drivers of interfirm network structures rarely have been explored in the literature. This paper uses stochastic actor-oriented modeling to examine how networks of economic interactions among the 500 largest Japanese companies were created and maintained between 2010 and 2011, i.e., before and after the Great East Japan Earthquake. Controlling for geographical distance between firms' headquarters and for firm size, we find that firms preferred trading partners that generally were popular among other firms, had clients in common with them, and also had bought some products or services from them, and that firms avoided firms with connections to independent suppliers in other cliques. These tendencies have potential implications for disaster resilience and the revival of the Japanese economy.

Keywords: Economic networks, Network evolution, Stochastic actor-oriented models, Geography
JEL classifications: O14, O33, R12

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1. Introduction

In March 2011, Japan was struck by an earthquake that has come to be known as the Great East Japan Earthquake. In the days following the disaster, electricity and supply shortages—even in regions that were distant from physically damaged areas of the country—highlighted the interconnectedness and vulnerability of the Japanese economy. The aftermath of the disaster demonstrated the importance of interfirm networks for disaster resilience and recovery when disruptions spread and support is exchanged among business partners across a disaster-stricken country (Tokui et al. 2012, Todo et al. 2014, Sato 2012).

Understanding the mechanism of interfirm network formation is crucial to identifying potential sources of vulnerability to disasters and pathways for national economic revival. New modeling methods have made it possible both to uncover previously neglected endogenous network mechanisms through which economic structures emerge and to test various firm management strategies across industries regarding their tendencies to concentrate or diversify economic interactions across groups of firms or space.

It is most important to elucidate these tendencies for the main actors in an economy because a small number of companies may have a disproportionately large influence over the economy of an entire nation (Aoyama et al. 2010, Gabaix 2011). For example, the top five Japanese firms account for one fifth of Japanese exports (Canals et al. 2007). Thus, the failure of such prominent nodes critically impairs the connectivity of the entire network (Albert et al. 2000), and their successes can positively affect the entire country (Canals et al. 2007, Gabaix 2011).

Considering the role of geography and differences among industrial sectors, this paper examines which endogenous network interdependencies played important roles in forming trade structures among major Japanese firms during the one-year period around the Great East Japan Earthquake.

2. Theoretical framework

2.1 Industrial agglomeration and economic interactions across space

As a result of the rapid development of communication technologies and the accompanying changes in how companies manage their operations, bestselling authors predicted the "the death of distance" and suggested that the world would become "flat". (Cairncross 2001, Friedman 2005). In this new world, firms were expected to interact regardless of their location. However, numerous studies conducted globally have repeatedly reaffirmed that geography is still important to many types of social and economic interactions (Carrasco et al. 2008a, Carrasco and Miller 2006, Carrasco et al. 2008b, Carrasco and Miller 2008, Greenbaum and Greenbaum 1985, Hipp and Perrin 2009, Van Der Berg et al. 2010, Wellman and Tindall 1992, Schaefer 2012, Preciado et al., Gonzalez et al. 2008, Song et al. 2010, Onnela et al. 2011, Caplow and Forman 1950, Duranton and Overman 2005, Nakajima et al. 2012, Daraganova et al. 2012, Koskinen and Lomi 2013, Matous et al. 2013). The world has not become flat, and the tendency of economic actors to agglomerate in space have not diminished (Fujita and Thisse 2013).

The major benefits of the spatial agglomeration of firms may be threefold (Marshall 1890): (1) availability of specialized intermediate goods, (2) pooling of specialized labor, and (3) information spillovers. The second and third factors are not directly related to supply networks. Thus, if major Japanese firms agglomerate mainly for better access to specialized labor and information, the number of partners located at short distances may not be particularly high compared with the number of large firm headquarters concentrated in urban centers. In such a case, geographical distance may not be a significant predictor of the creation or dissolution of network ties after accounting for the highly concentrated spatial distribution of major firms in Japan.

However, the first potential reason for agglomeration, i.e., proximity to suppliers, is directly related to the formation of trading networks and may confound endogenous dynamic network mechanisms. Therefore, in the present study, we control for the possible effects of physical distance to examine network interdependencies among the trading links described below.

2.2 Endogenous network formation

The assumption in this study (in contrast to the typically implicit assumptions found in traditional econometric studies) is that economic links do not exist in isolation. It is highly plausible that firms take existing alliances and associations among other firms into account when they choose their business partners. This paper tests the following hypotheses regarding network interdependencies among supply-purchase trading relationships.

Hypothesis 1: Supply chains are hierarchical.

During the data-gathering process, the informants were asked to identify interactions in which they purchase goods or services from suppliers and interactions in which they sell goods or services to clients. Hypothesis 1 tests whether supply chains are hierarchical entities in which materials, goods, and services move unidirectionally from primary producers through intermediaries to users (Mentzer et al. 2001) or whether bidirectional flows of goods and services are more common than would be expected by chance. The rejection of this hypothesis would imply that there is no strict hierarchy in dyadic economic interactions (i.e., trading partners can be both a supplier and a client of the same firm) and that firms prefer to obtain supplies from firms that have purchased goods or services from them, possibly as a result of social obligations (Lincoln and Gerlach 2004).

The next set of hypotheses extends beyond the dyadic interdependencies between pairs of companies to test how external actors affect trade among pairs of firms. The following two hypotheses are related to the access to and sharing of suppliers, which has been considered one of the main advantages of industrial agglomerations (Rosenthal and Strange 2001, Amiti and Cameron 2007, Puga 2010).

Hypothesis 2: Firms tend to choose suppliers that also supply their trading partners.

Hypothesis 2 predicts that economic interactions are more likely among firms that have trading partners in common. Such interactions may occur for several reasons. Firms might be introduced to new potential partners through their existing partners, or firms with mutual partners may be interested in the same markets or work on compatible products. Moreover, firms embedded in a dense network of relationships with mutual partners are less likely to defect (Granovetter 1985, Coleman 1988). The formation of trading groups seems to be an important driver of economic exchange, particularly in Japan (Granovetter 2005). It has been suggested that the tendency to turn to these groups is highest during difficult economic periods (Lincoln and Gerlach 2004), which Japan has been experiencing for the last two “lost decades”.

Hypothesis 3: Firms prefer suppliers that are generally popular with other firms.

This hypothesis predicts that firms prefer to obtain supplies from firms that supply to many other firms. It may be more economical to share a supplier with a large number of other firms; suppliers that serve a wider clientele may be able to provide better services; they may also be more credible and relatively easier to notice. Popular suppliers may be considered more desirable and dependable or may be preferred because of economies of scale or because they can provide services on popular platforms that are used by other clients or customers. Such tendencies would lead naturally to network centralization, particularly if it is possible to create and maintain links over long distances (Barthélemy 2011). Increased tendencies toward both network centralization and embeddedness among organizations have also been reported during times of crisis (Robins 2013).

Hypothesis 4: Firms avoid suppliers that depend on many other suppliers.

This hypothesis predicts that firms avoid (not necessarily consciously) suppliers that rely on many different sources for the products or services that they require. The evidence suggests that such suppliers may fail if any of their sources fail. Firms that were connected to many firms through large supply chains were more likely to experience supply shortages and consequently operational interruptions after the Great East Japan Earthquake (Todo et al. 2014). Thus, firms might have been particularly likely to avoid or disconnect from such suppliers during the period after the earthquake. Case studies also suggest that economic actors may strive to create parallel links with the suppliers of their suppliers with the aim of bypassing intermediaries (Tallontire 2000). From an analytical perspective, the avoidance of suppliers with too many independent sources and the creation of shortcuts to bypass intermediaries both empirically manifest as minimizing the number of firms at distance two in longitudinal networks. Both of these tendencies also lead to clustering.

As a competing hypothesis to that discussed immediately above, firms might prefer suppliers with diverse sources that cannot be directly accessed, and intermediaries may add value and thus tend not to be bypassed by direct trading and by forming redundant links (Bailey and Bakos 1997).

3. Methods

3.1 Data

This study focuses on the largest firms in the Japanese economy. Of the over one million incorporated firms in Japan, we selected the 500 largest firms in terms of annual sales reported in 2010. The sample ranges from manufacturers to financial institutions and retailers. The sales of these 500 companies amount to approximately one-third of national sales (Tokyo Shoko Research 2010, Table 1). Economic research on interfirm interactions appears to typically focus on samples of firms within the same industry, but we did not limit this sample to a specific industry because effective supply chain management requires partnerships and strategic alliances with stakeholders and intermediaries across sectors (Cooper et al. 1997, Ellram and Cooper 1990). Moreover, “horizontal” *keiretsu* linkages among firms in different industries are considered to be particularly important for the functioning of the Japanese economy (Lincoln and Gerlach 2004). These interindustry links are known to provide support to firms in need during difficult economic periods (Lincoln and Gerlach 2004). From the perspective of vulnerability to disasters, interindustrial linkages are crucial: the failure of an electricity, transportation, or communication services provider may disrupt the operations of groups of otherwise disconnected manufacturers or retailers.

The chosen sample size is large enough to include interconnected firms from a variety of industries and regions, but it still allows for the necessary analytic assumption that any actor can reasonably evaluate any other actor in the selection of network partners. This assumption would be less plausible with larger samples and would thus make the modeling of network evolution less realistic. (Incidentally, “500” is also a popular cut-off point in rankings of major corporations, e.g., S&P 500, Fortune 500, or Financial Times 500.)

The selected firms’ representatives were interviewed face to face about their transaction partners by Tokyo Shoko Research agency. The first wave of data gathering was undertaken between March 2010 and March 2011. The second wave of data gathering was undertaken between March 2011 and March 2012. The time between the two surveys was 12 months or more for 98% of the companies. In this paper, we refer to the data collected from the first wave as “2010 data” and the data collected from the second wave as “2011 data”. The informants were asked to name up to 24 of their main suppliers or buyers of goods or services. No other details about the interactions (such as the volumes of the transactions) were requested. Links to companies outside the top 500 firms are not considered in the present analysis.

Most of the companies in the sample have headquarters in the Tokyo Metropolitan Region (334) or its vicinity (24 firms have headquarters in Kanagawa, Chiba, Kawasaki, and Saitama). The second most popular location is Osaka (53). The remainder of the companies are scattered around Japan. Only four of the top 500 firms have headquarters in Tohoku region prefectures, which was the region that suffered direct physical damage from the Great East Japan Earthquake and tsunami. We found no relevant changes for these companies for this period (except for one link, all these companies maintained the same number of suppliers and clients in both years and their aggregate sales changed by only 1.5% between the two years); therefore, we do not treat these firms in any special way in the analysis.

Addresses of all headquarters were converted to geographical coordinates (using a service provided by Center for Spatial Information Science, University of Tokyo) from which the straight physical distance between each firm was calculated. The locations of the sample firms’ branches and plants are not known, which is a limitation of this study.

[[Table 1 about here]]

3.2 Stochastic actor-oriented modeling

After describing the structure and spatial distribution of the interfirm networks in 2010 and 2011, we analyze the microprocesses that lead to the observed macro network structures. Network interdependencies regarding the formation of economic interaction structures can be quantified via stochastic actor-oriented models while controlling for the possible effects of distance. Stochastic actor-oriented models are statistical parametric models for evolving networks (Ripley et al. 2012, Snijders et al. 2013). The technical details of this approach may be found in the appendix and in the cited works of T. A. B Snijders and his colleagues (Snijders 2001, Steglich et al. 2010, Snijders et al. 2010). This modeling approach enables us to uncover firms’ preferences in selecting their suppliers.

We assume that firms choose their suppliers to maximize their utility. Therefore, we code the observed network data for the model input such that links are directed from clients to suppliers. Furthermore, stochastic actor-oriented models are based on the assumption that actors may consider any of the other actors in the entire network to be their potential partners; this assumption seems reasonable given the limited sample of major players in the economy. The models are constructed such that firms may choose their suppliers (i.e., their outgoing network ties) based on their individual characteristics (such as firm size or industry type), their pair-wise characteristics (such as physical distance), and endogenous network characteristics (such as the number of mutual partners with a potential supplier) (Table 2). The goal of the simulation in this study was to estimate the direction and statistical significance of these effects for the log odds of the creation and maintenance of supply-purchase links between pairs of firms in the period around the Great East Japan Earthquake.

Using methods developed by Lospinoso and Snijders (2011), we tested the goodness of fit of the model on the overall fundamental network characteristics that were not explicitly modeled by any of the included micro-effects (specifically, the degree distribution, geodesic distance distribution, and triad census). Guided by our hypotheses, we searched by trial and error for a model specification with an acceptable fit. We aimed for the simulations to reproduce the fundamental network characteristics such that the observed statistics were within their 90% confidence intervals. The meaning of the effects in the final model is explained in Table 2. The fit of the models is discussed in detail in the appendix.

To estimate the log odds of an interfirm trade link in the presented models, we use the straight physical distance in the log form, which closely corresponds to the most commonly used functional form of distance in gravity models for estimating economic and social interactions (Preciado et al. 2012, Daraganova et al. 2012, Koskinen and Lomi 2013, Wilson 1967, Bergstrand and Egger 2007, Woo-Sung et al. 2008, Anderson 1979). The marginal costs of business interactions are likely to decrease with distance as the main mode of transport and its speed changes (walking to the next street block, train ride to another city, or air travel to another island; see Wilkerson 2013). The logarithmic transformation also has desirable properties, particularly considering the centralized headquarters' locations and highly skewed distribution of distances among them. Most partners are located within 10 km from one another, but a nonnegligible number of ties span hundreds of kilometers (Table 3).

[[Table 2 about here]]

[[Table 3 about here]]

4. Results

4.1 Descriptive results

The stability of the relations among Japanese firms even during this presumably turbulent economic period is remarkable. Although there was a sufficient amount of micro-level change in the observed networks to allow for statistical modeling with a limited number of effects (Table 4), the networks in 2010 and 2011 are almost indistinguishable in their aggregate characteristics. In both years, the average number of links per firm is approximately 4.6, and the average local clustering coefficient (i.e., the proportion of partners of each firm that are also partners with one another, calculated on an undirected network) is 0.16. This level of clustering is almost ten times higher than the expected level of clustering for a network of the same density with independent links. Furthermore, the median numbers of clients and suppliers in each industry (Table 1) and skewed degree distributions (Table 4, Figure 2) remain nearly unchanged.

Figure 1 shows the network of economic interactions on a map of Japan, and Table 3 quantitatively illustrates the extreme extent of geographical concentration of the headquarters of the largest Japanese companies. Half of the headquarters for the top 500 firms are located within a 4.3 km radius of the most centrally located firm in Tokyo. Most of the top 500 firms are located more than 968 km from the most remote firm.

As a result, most links are short in geographical distance. In both years, one-half of trading partners had headquarters within 10 km from one another. (The most proximate trading partners are located in the same block; the average is approximately 160 km; and the most distant partners trade between the northeast and southwest corners of the main island of Honshu and are over 1000 km apart; Table 3.) The relation between geographical and network centrality is not straightforward. For example, the headquarters of the largest financial and medical institutions agglomerate in the center of Tokyo close to individual customers and public institutions. However, most of these institutions do not have trading links with other top 500 corporations. Additionally, firms providing “professional services” (e.g., recruitment or advertisement) and entertainment are geographically central but peripheral in the network of interactions among major firms (Table 1).

Large energy firms are idiosyncratic. In contrast to other sectors, the energy sector in Japan is highly geographically decentralized, and the headquarters of major firms in the energy sector do not agglomerate in the capital region (Figure 1; Table 1). The energy firms in the sample include electric power firms and gas firms, and these firms have a notably high number of connections to other firms. They are not only among the main suppliers of many large firms (which is explainable by the importance of energy for industrial production) but also important clients of numerous other firms. Because of their distinct geographical and network characteristics, we pay special attention to energy firms in the main statistical analysis.

Figure 3 displays the 1-step and 2-step neighborhoods of an energy company. Interindustrial links, which are neglected in network studies on single industries, can be observed in this image. Although we do not have data related to the types of goods and services “flowing” through these links, these flows likely relate to the procurement of construction services to build facilities and the purchase of equipment and fuel from manufacturers, general contractors, and trading companies. On the client side, these links may relate to the distribution of energy to factories, construction sites, or offices. The failure or success of such an energy firm would affect major firms from diverse sectors both upstream and downstream.

[[Figure 1 about here]]

[[Figure 2 about here]]

[[Table 3 about here]]

[[Table 4 about here]]

4.2 Estimation results

In this section, the effects of network interdependencies on the formation of trade structures are assessed by using stochastic actor-oriented models. First, we present a model in which we control for the general network density and include the effects of distance and firm size, as proxied by sales (Model 1 in Table 5).

The distance between headquarters does not have a clear impact on links between energy firms and nonenergy firms. As discussed above, energy firms have headquarters attached to their regions of origin, whereas nonenergy firms tend to concentrate in the largest urban agglomerations. However, the distance between headquarters has a significantly negative relationship on with the probability of links between pairs of nonenergy firms (which form the vast majority of links) and the probability of links between pairs of energy firms.

To illustrate the relative strength of the coefficient estimates for distance (-0.324) and firm size (0.186), let us consider a firm that chooses between suppliers A and B. The firm would choose either A or B with a similar probability if the distance to A was half of that to B but if B was three times the size of A, ceteris paribus.[1]

In Model 2, we add endogenous network effects, which improve the fit of the model (Model 2 in Table 5; Appendix). The addition of these network interdependencies weakens the distance effect below the threshold of significance for this dataset with a limited amount of network change. The tendency of energy firms to reach more suppliers during this period also becomes insignificant under this model.

The following section reports the implications of the estimation results for the research hypotheses.

Hypothesis 1: Two firms may be both suppliers and client to one another. Reciprocity drives the formation of trading networks, and firms are more likely to buy goods and services from partners that buy goods and services from them.

Hypothesis 2: Firms prefer suppliers when they have clients in common with one another. (See the positively significant effect of transitive mediated triplets in Table 5.)

Hypothesis 3: When supplier size is controlled for, popular suppliers that are shared by many firms are

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[1] Both distance and size are included in the model in their logarithmic form. Two options have identical expected utility if

(Distance to A / Distance to B) ^ (0.324 / 0.186) = (Size A / Size B) particularly sought out (expressed by the positively significant indegree popularity effect).

Hypothesis 4: Firms attempt to minimize (not necessarily purposely) the number of independent suppliers that supply their suppliers (expressed by the negatively significant “number of actors at distance two effect”).

After endogenous effects are accounted for, the effect of client size becomes negatively significant. This effect is negatively correlated with the transitive mediated triplets (r = -0.35) and positively correlated with the number of actors at distance two (r = 0.20). This association with effects representing network closure (the latter effect inversely) suggests that smaller companies in the sample are particularly constrained by the existing clique structures of companies.

5. Ties that bind: discussion and conclusion

Major Japanese firms agglomerate their headquarters in space. The descriptive and estimation results jointly suggest that endogenous network processes operating on the clustered network structure that was formed among the spatially concentrated firms in the network sustain short links within network clusters and discourage the creation of long links to outsiders.

These results provide empirical evidence that trade links are not statistically independent, which is an assumption that is commonly made in regression analyses on trade. The confirmed tendency toward bidirectional trade and the formation of loops suggests that “supply chains” are not simply connected chains of firms through which goods flow from one side to the other. The observed creation of company cliques, loops, and bidirectional trade links may be motivated by a collective identity and a mutual exchange of favors among groups of long-term associates (Lincoln and Gerlach 2004).

We find no evidence that the tendencies toward clustering and centralization and the prominence of energy companies are unique to this period around the Great East Japan Earthquake. Clustering, and degree distribution skewness have not increased after the disaster (Table 1, Table 4). Instead, the already highly uneven popularity of suppliers and the clustered nature of the original economic network were sustained by the endogenous micromechanisms. Although hundreds of links changed during the observed period (Table 4), new link creation and old link dissolution tended to maintain the original macro network patterns. Firms tended to form alliances within the same groups and with established and prominent firms.

Sharing suppliers is considered to be an important driver of industrial agglomeration (Rosenthal and Strange 2001, Amiti and Cameron 2007, Puga 2010). Major Japanese companies prefer to “share” suppliers with many other firms and prefer suppliers that also share their suppliers within the group over independent sources outside the trusted company clique. The observed tendencies suggest that links are likely to be created among actors and in parts of the network in which there are links already.

The resulting locally dense network structures may promote group identity, foster generalized trust, and lower transaction costs. Membership in such groups also provides access to inside information (Kim and Nofsinger 2005). However, such partnerships may be difficult to reconfigure in times of need (Granovetter 2005). The identified mechanism sustains the status quo of the established groups with advantageous positions in the existing network and may limit the diversity of available resources and information among Japanese firms, which may be a source of vulnerability in a rapidly changing environment. These findings echo the findings of Lincoln and Gerlach (2002) that the largest Japanese manufacturing firms are embedded in network structures that offer only limited degrees of freedom.

It has been suggested that new firms are important for the revitalization of the Japanese economy (Motohashi 2008). However, without policies facilitating new firm entry, new actors and outsiders face an uphill battle in an environment that is characterized by networks of long-term relationships and preferences for established groups and well-recognized firms.

These tendencies combined with the extreme geographical clustering of the largest headquarters may be a source of vulnerability to natural disasters for Japanese firms. Mega-suppliers or entire industrial clusters might be damaged if a disaster hits a main urban center in Japan, such as Tokyo, which lies on a major earthquake fault (Sato et al. 2005).

Energy firms are an exception. In contrast to major firms in other sectors, the headquarters of major energy firms are distributed across all the regions of Japan. Supporting the development of business centers in other vital sectors outside Tokyo is also worth consideration. However, under the current network conditions in Japan, most major firms would be unlikely to accept the cost of formal and informal interactions over longer distances with firms and governmental institutions in Tokyo (Lincoln and Gerlach 2004), unless a critical mass of industrial headquarters and institutions are attracted to new locations.

These uncovered interfirm and interindustry network and geographical mechanisms may or may not be unique to Japan. There remains a need for comparative studies of network evolution in the literature; with increasingly available panel data on interfirm interactions and methods for analysis of such data, comparisons with the present results should become possible in the future.

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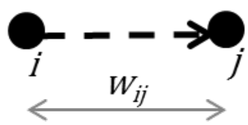
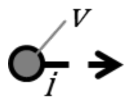
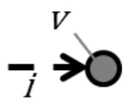
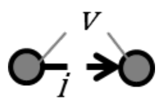
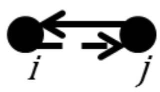
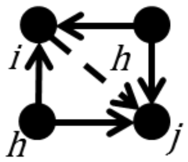
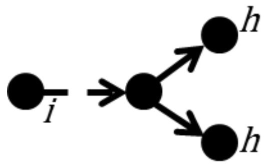
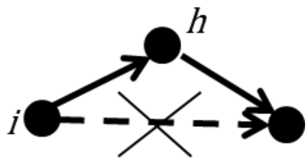
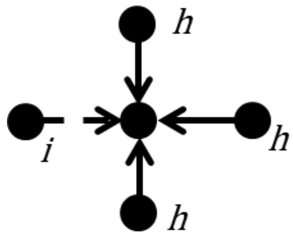
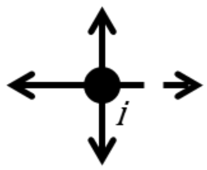
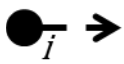
Tables

Table 1 – Description of the top 500 firms by broad industrial categories. Values for 2010 are presented above the values for 2011, and the values for 2011 are in italics. All statistics (except for N) are median values for firms in each category. Remoteness is the median geographical distance to the headquarters of all top 500 companies.

			Median firm statistics			
		N	Number of clients	Number of suppliers	Remoteness [km]	Sales ['000 Yen]
Construction	2010	22	5.5	4.5	7.2	3.91E+08
	2011		*5*	*4*		*4.04E+08*
Energy		13	6	8	305.1	1.03E+09
			6	*9*		*1.12E+09*
Finance		56	0	0	5.2	6.70E+08
			0	*0*		*6.94E+08*
ICT		20	4	4.5	5.3	4.26E+08
			4	*6*		*4.30E+08*
Manufacturing		161	6	4	7.3	4.92E+08
			5	*4*		*5.27E+08*
Medical care and welfare		8	0	0	5.0	1.55E+09
			0	*0*		*1.63E+09*
Mining		2	4	2	4.4	3.17E+08
			4	*3*		*4.49E+08*
Other services		15	1	1	21.7	3.29E+08
			1	1		3.46E+08
Personal services and entertainment		9	0	1	7.7	4.07E+08
			0	*1*		*3.56E+08*
Professional and technical services		15	2	3	4.7	3.90E+08
			2	*2*		*3.28E+08*
Real estate		21	2	5	5.3	4.76E+08
			2	*5*		*4.27E+08*
Retail		139	3	5	8.0	4.58E+08
			3	*5*		*4.89E+08*
Transport and postal		19	2	4	5.2	7.96E+08
			2	*4*		*8.26E+08*

Table 2 - Formulas for $s_{ki}(x)$ selection effects in network x for ego i and alters j, other actors h, and actors' attributes v. w_{ij} is (the natural logarithm of) the distance between i and j. Arrows point from clients to suppliers; dashed arrows signify trading relationships that are likely to be created and maintained if the effect is positive.

Hypothesis Effect name	Mathematical formula	Graphical representation
Spatial effects		
Dyadic physical distance	$\sum_j x_{ij}(w_{ij} - mean\,(w_{ij}))$	
Effects of firms' characteristics v on trade		
Client's attributes	$\sum_j x_{ij} v_i$	
Supplier's attributes	$\sum_j x_{ij} v_j$	
Similarity of an attribute	$\sum_j x_{ij}(sim_{ij}^{v} - \overline{sim^{v}})$	
Matching on an attribute	$\sum_j x_{ij} I\{v_{i=}v_j\}$ $\begin{cases} I\{v_{i=}v_j\} = 1 \\ 0 \end{cases}$	
Endogenous trade network interdependencies		
Hypothesis 1 Reciprocity	$\sum_j x_{ij} x_{ji}$	

Hypothesis 2		
Transitive mediated triplets	$\sum_{j,h} x_{ji} x_{ih} x_{jh}$	
Hypothesis 3		
Number of actors at distance two	$\#[\mathrm{j} \mid x_{ij} = 0, max(x_{ih} x_{hj}) > 0]$	 
Hypothesis 4		
Indegree popularity (sqrt)	$\sum_{j} x_{ij} \sqrt{\sum_{h} x_{hj}}$	
Control for network density		
Outdegree	$\sum_{j} x_{ij}$	
Control for firms that do not receive any supplies		
Truncated outdegree	$min(x_{i+}, c); c = 1$	

Note: x_{ij} = 1 if there is a directed tie from i to j and 0 otherwise

[b] $\overline{sim^{v}}$ is the mean of all similarity scores, which are defined as $sim_{ij}^{v} = \frac{\Delta - |v_i - v_j|}{\Delta}$

with $\Delta = max|v_i - v_j|$

Table 3 – The sales of the top 500 firms and the spatial distribution of their headquarters and their partners.

	Minimum	Median	Mean	Maximum
Sales in 2010 ('000 Yen)	$2.5*10^8$	$5.0*10^8$	$9.3*10^8$	$2.0*10^{10}$
Log of sales in 2010	19.3	20.0	20.2	23.7
Distance distribution among all pairs of top 500 firms [km]	0.1	26.3	195.0	1592.0
Log of distance among firms	-3.0	3.3	3.6	7.4
Median distance to all firms [km]	4.3	6.7	122.9	965.9
Trade link length distribution [km]				
2010	0.0	9.6	157.0	1267.0
2011	0.0	9.8	159.1	1267.0
Firms' median trade link length [km]				
2010	0.0	7.6	129.2	968.3
2011	0.0	7.5	127.0	968.3

Table 4 – Network density and network change

Overall network characteristics	2010	2011
Network density	0.009	0.009
Mean degree	4.63	4.62
Outdegree skewness	1.91	1.82
Indegree skewness	3.23	3.12
Number of links	2317	2255
Mean local clustering	016	0.16
Missing fraction	0.00	0.02

Link changes between 2011 and 2012	
Preserved relationships	2120
Number of changed relationships	305
New trading relationships	135
Abandoned relationships	170
Jaccard index	0.87
Ordered pairs of firms without a link in both years	241117
Missing	5958 (2%)

Table 5 – Stochastic actor-oriented model estimating the log odds of creating and maintaining a link.

	Parameter estimates (Standard errors)	
	(1) Independent links	(2) Interdependent links
Firm characteristics and geography		
Dyadic physical distance	0.254	0.176
[log km]	(0.165)	(0.158)
Client's size	-0.149	-0.279**
[log of sales in thousands of Yen]	(0.143)	(0.126)
Supplier's size	0.186**	0.251**
[log of sales in thousands of Yen]	(0.089)	(0.119)
Size similarity	0.187	-0.167
	(0.469)	(0.528)
Client is an energy firm	2.681***	1.403
	(0.655)	(0.651)
Supplier is an energy firm	1.716***	1.709***
	(0.539)	(0.548)
Link between two energy firms	2.066***	1.296*
or two nonenergy firms	(0.614)	(0.663)
Interaction of	-0.324*	-0.225
link between two energy firms or two	(0.166)	(0.161)
nonenergy firms & distance [log km]		
Network interdependencies		
Reciprocity		1.371***
		(0.311)
Transitive mediated triplets		0.247***
		(0.088)
Number of actors at distance two		-0.201***
		(0.033)
Indegree popularity		0.680***
[sqrt]		(0.092)
Outdegree	-4.808***	-4.965***
	(0.599)	(0.658)
Truncated outdegree		-2.310***
		(0.527)

Statistical significance levels: *10%, **5%, ***1%.

Figures

Figure 1 – Geographical distribution of trading links among the largest 500 companies in Japan in 2010 and 2011. Dashed lines represent links that were reported in only one of the two years. Red nodes depict energy firms. (Nodes depicting nonenergy firms and all links are semitransparent and thus are more visible in regions in which their geographical density is high.)

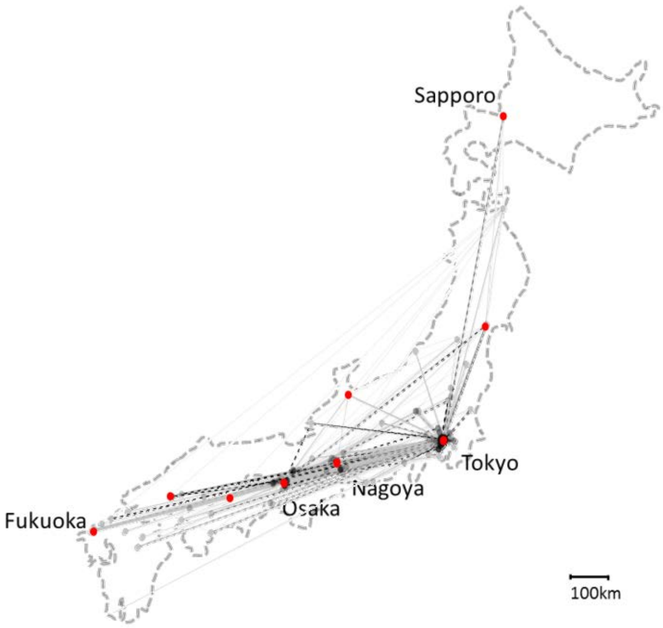


Figure 2 – Distribution of clients and suppliers among the top 500 firms.

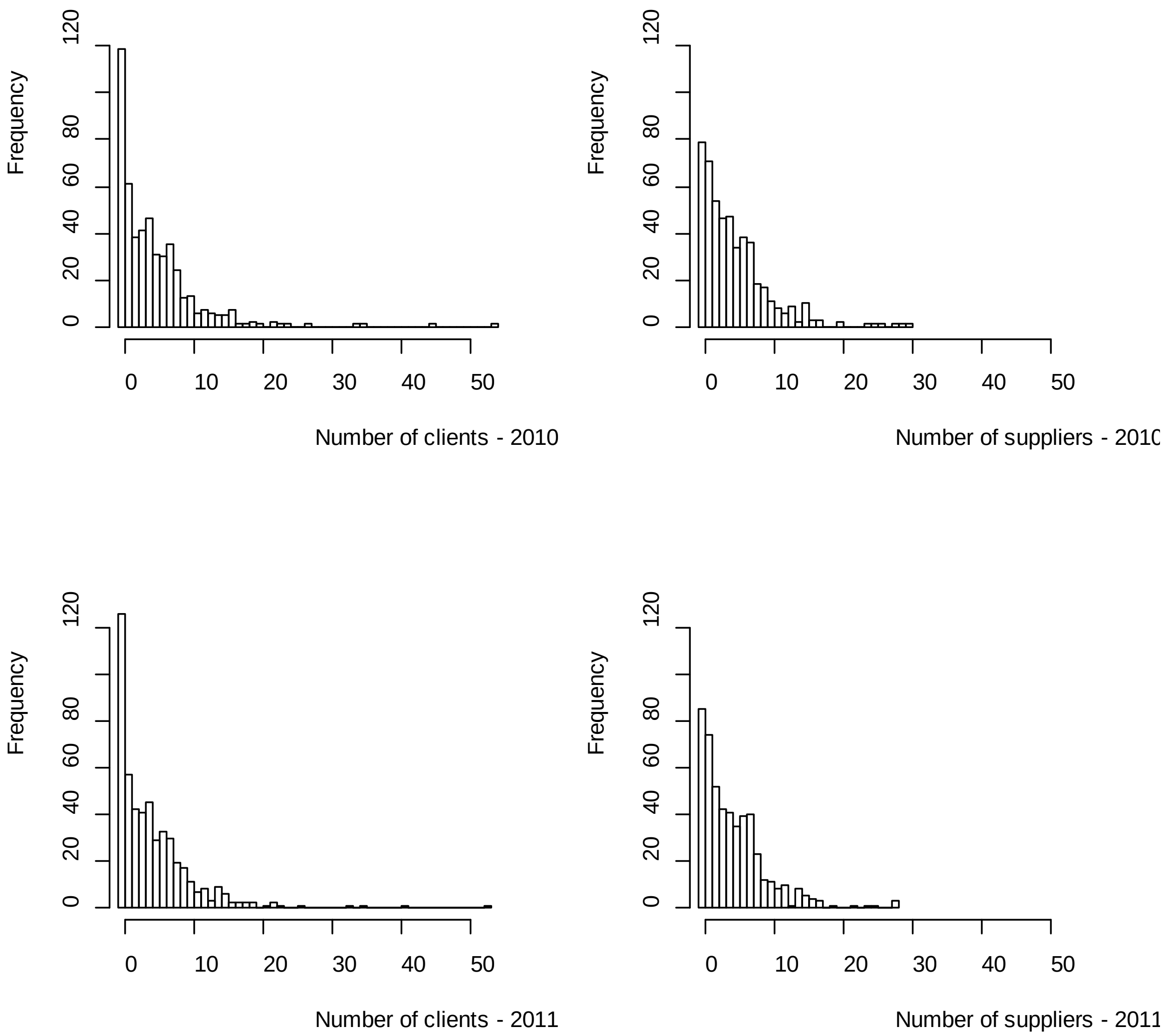
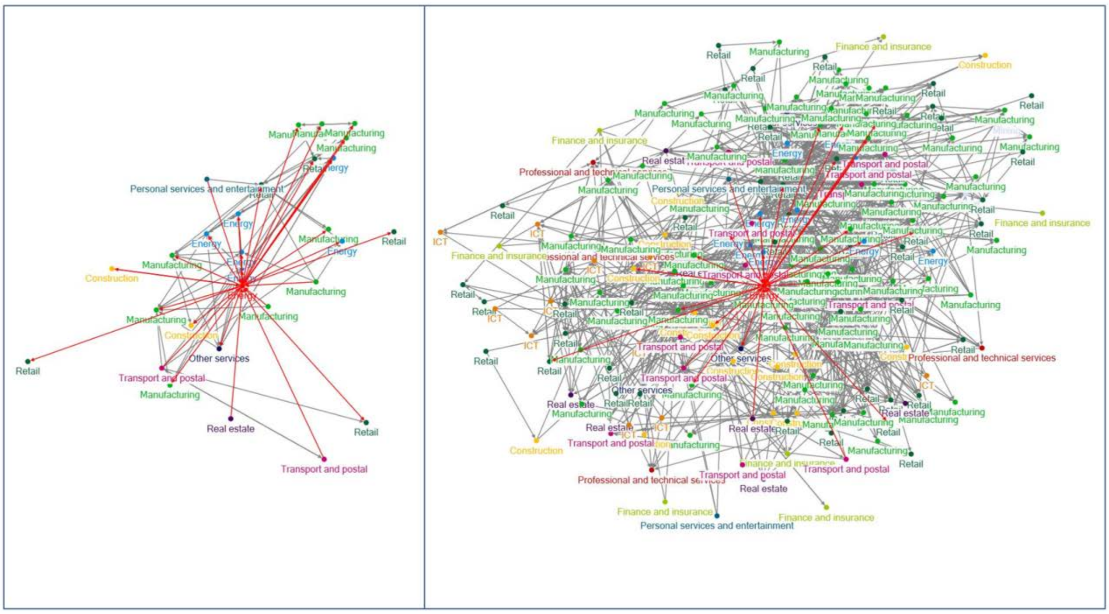


Figure 3 – One-step (left) and two-step (right) network neighborhoods of one energy firm within the top 500 firm network. Red lines indicate direct links of the firm to its suppliers and clients; node labels and their colors indicate the industrial sector of each firm.



Appendix

This appendix explains the method of stochastic actor-based modeling for network evolution. The model conditions on the first observation and tests hypothetical drivers of the evolution of the network evolution, which is treated as a continuous-time Markov chain of single trading link changes between observations.

Between the observations, each firm may receive one or more opportunities in a random order to change its suppliers represented by its outgoing ties. The model includes ‘rate effects’ that regulates how often actors receive an opportunity to modify their outgoing ties. These rate effects depend on the number of observed changes. Only one actor acts at a time, and coordination is not allowed.

Each firm chooses its suppliers to maximize its utility. Utility is expressed, as in generalized linear models, as a combination of hypothetically relevant network features $f_i(\beta, x) = \sum_k \beta_k s_{ki}(x)$. The utility function quantifies the desirability of each possible next state of the network x among the fixed set of actors from the viewpoint of actor i. A random component with a standard Gumbel distribution is added to the evaluation function. This procedure is included to respect the stochastic character of network evolution, which is a result of influences that are unrepresented by nodal or dyadic variables and of measurement errors. Thus, the actor does not necessarily choose the state with the highest utility, but such a choice is most likely. When a firm receives an opportunity to change its suppliers, the options are to create one new tie, delete one existing tie, or do nothing.

Each effect s_{ki} in the model corresponds to possible reasons why an actor might wish to change a tie or a behavior. These effects express the firm’s supply chain management tendencies. The explanations and mathematical formulas of effects s_{ki} are presented in Table 2.

The goal of the simulation is to estimate the relative weights β_k for the statistics s_{ki}. Parameter estimates can be used to compare how attractive are various supply chain configurations while controlling for other exogenous and endogenous effects. The signs of β_k indicate the preferred directions of network change, and their relative magnitudes can be interpreted similarly to parameters of multinomial logistic regression models in terms of the log-probabilities of changes among which the actors can choose.

The estimation was executed in SIENA package version 4 in R (Ripley et al. 2012). The method of moments, which depends on thousands of iterative computer simulations of the change process (Snijders 2001), is used to estimate the parameters β_k that enable the reproduction of trading network evolution between 2011 and 2012. There is one target statistic for each estimated effect (for example, the number of ties in the network corresponds to the outdegree effect, the number of reciprocated ties corresponds to the reciprocity effect, and the amount of change in network corresponds to the rate function). The presented models all converged with *T*-ratios, quantifying the deviations between the simulated and the observed values of the target statistics, between -0.1 and 0.1, which indicates an excellent model convergence (Ripley et al. 2012). In the final stage of the simulation, the standard errors of the estimated parameters are computed by the finite difference method, based on the sensitivity of the target statistics to β_k.

The diagrams below indicate the goodness of fit of the three presented models in terms of indegree distribution, outdegree distribution, geodesic distance distribution, and triadic census using methods developed by Lospinoso and Snijders (2011).

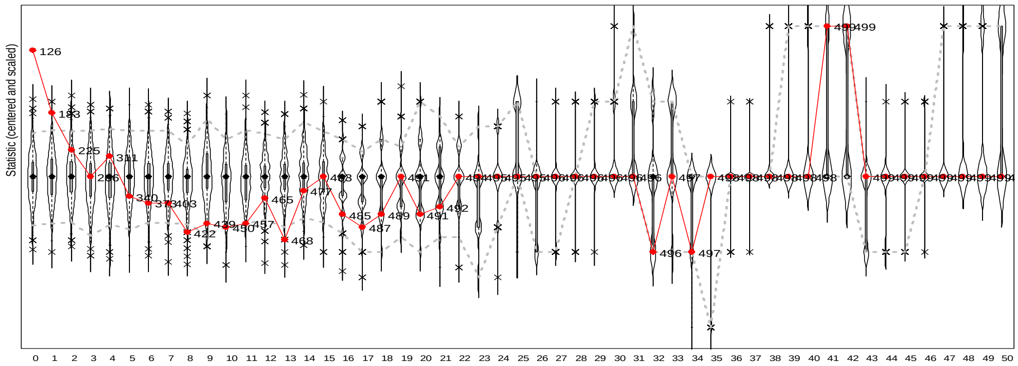
The violin plots (Hintze and Nelson 1998) represent the kernel density distribution of the statistic and the red lines depict the cumulative distribution of the observed values. The violins are not smooth for less frequent higher degree nodes because the density plots approximate distribution of a small number of discretely distributed values (Ripley et al. 2013).

Because the values for different statistics within each plot vary widely, each violin is scaled and centered to maximize the visibility of the plot. The dotted grey lines designate a point-wise 90%relative frequency band for the simulated data. The fit is considered acceptable if the observed values (red lines) fall within this region. However, the goal is not necessarily to match the model exactly on every single statistic which can be highly irregular. Such approach would require over-fitting the model to all incidental lone observations or errors in the data and necessitate addition of theoretically irrelevant effects.

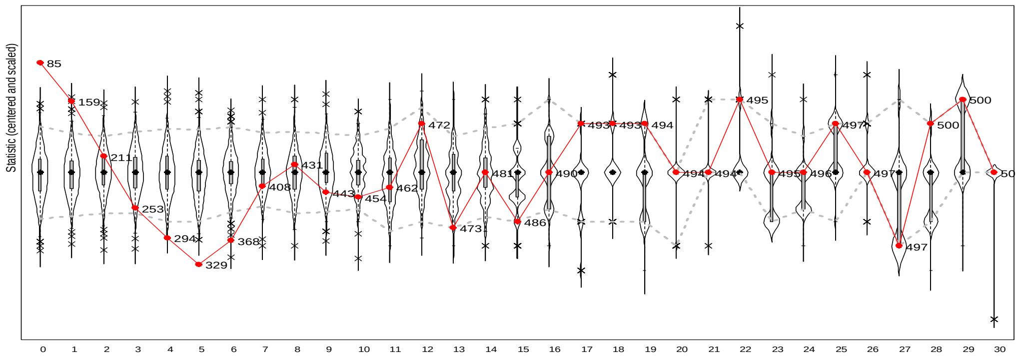
Standard labeling is used for the classes of the triad census (Wasserman and Faust 1994).

Model 1 – Independent links

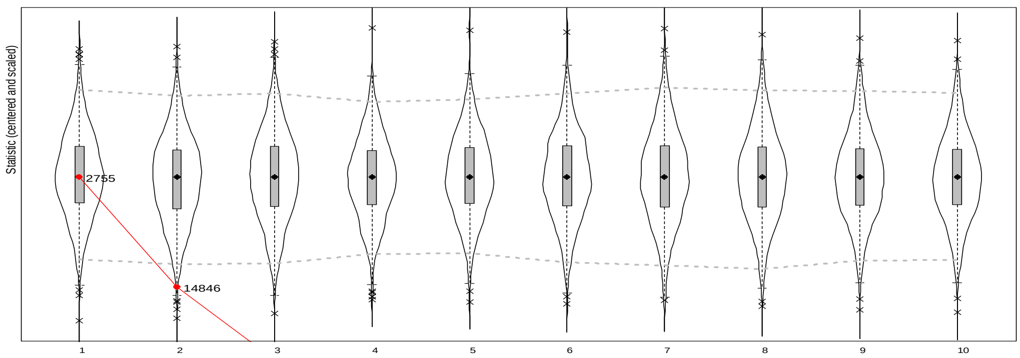
Indegree distribution



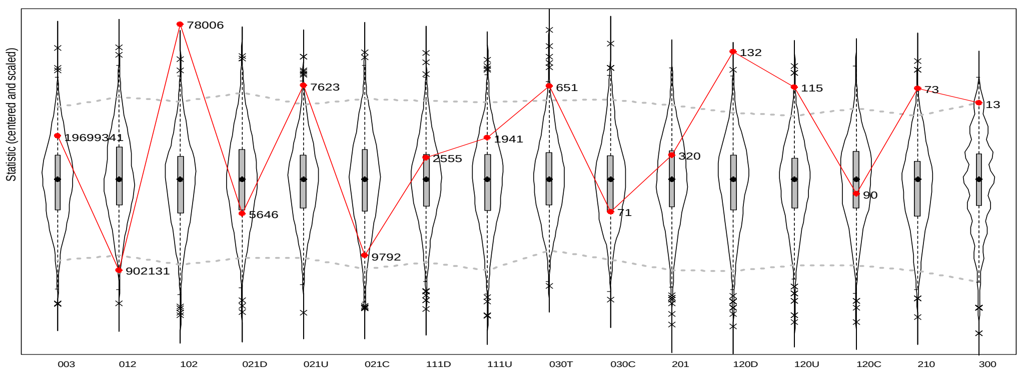
Outdegree distribution



Geodesic distribution

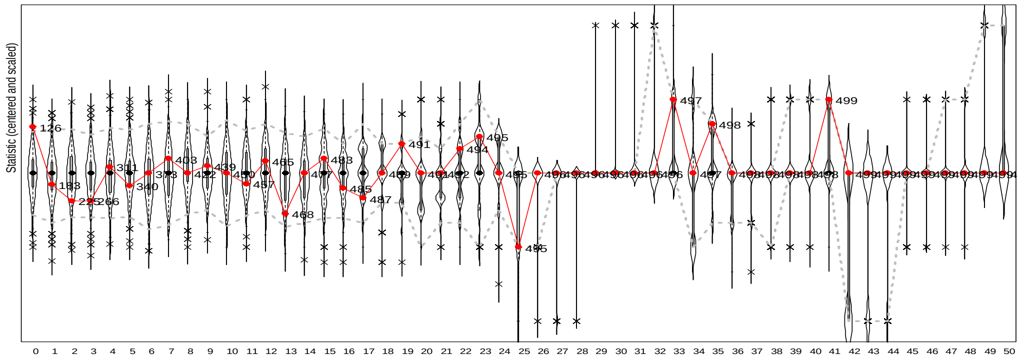


Triad census

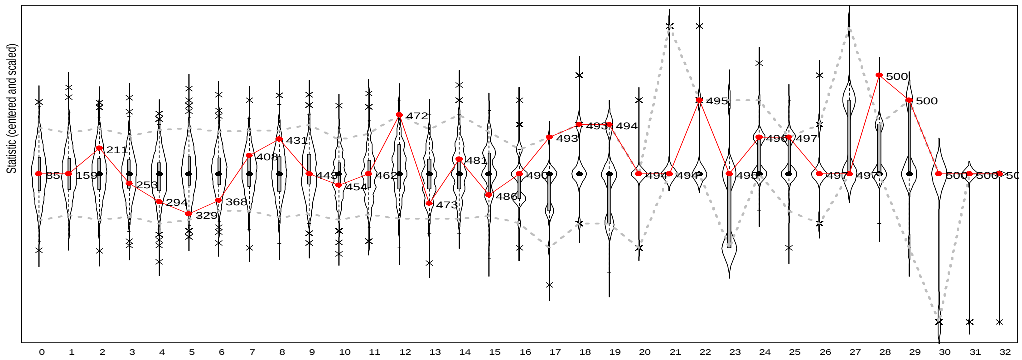


Model 2 – Interdependent links

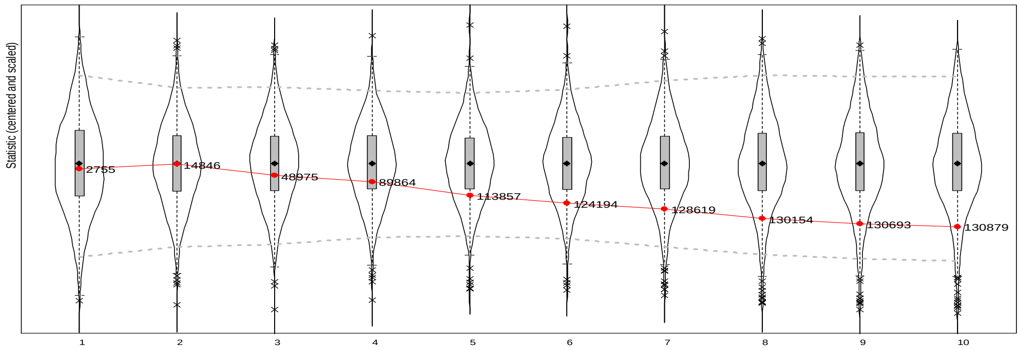
Indegree distribution



Outdegree distribution



Geodesic distribution



Triad census