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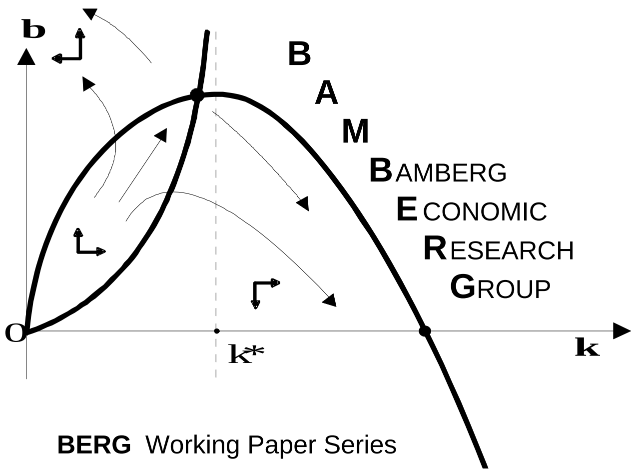

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Topology and formation of production input interlinkages: evidence from Japanese microdata

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Abstract

Recent studies emphasize the role of the network structure of production input interlinkages for a wide range of economic outcomes including shock propagation and the emergence of aggregate fluctuations. In most of these studies the input-output architecture is fixed and exogenously given and relatively little work has considered its evolution and the underlying mechanism of network formation. Here we provide evidence on the evolution of production input interlinkages on the most granular level of economic activity, building on a diverse set of more than 80,000 companies sampled across nearly all industries of the Japanese economy. We review the main empirical properties of the Japanese production network level and find that these features are remarkably stable over time. To estimate the mechanism of supplier selection inducing this stability, we employ a stochastic actor-oriented model that sidesteps the econometric problem of mutual dependencies inherent to networked environments. Building on this approach, we find that topological features of the network such as the geodesic distance between the firms and their current number of relationships are a main driver of network dynamics in subsequent periods, and are quantitatively more important than selection based on productivity.

Keywords: Production network, customer-supplier network, network formation, stochastic actor-oriented model
JEL classification: L14, D57, D22, L23, R15

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1. Introduction

The last years have seen a growing interest in the structure of production input interlinkages at different levels of aggregation.[1] Examples of situations in which these connections matter for economic outcomes are innovation and the diffusion of technologies (Conley and Udry, 2010; Choi et al., 2010), the propagation of natural disasters, bankruptcies and other forms of idiosyncratic shocks (Acemoglu et al., 2015; Barrot and Sauvagnat, 2016; Carvalho et al., 2017), international business cycle comovement (di Giovanni et al., 2014; Shea, 2002), and the emergence of cross-country differences in aggregate productivity (Ciccone, 2002). Especially the recent macroeconomic literature stresses the role of input-output relationships for the emergence of aggregate fluctuations (see e.g., Acemoglu et al., 2012, 2017; di Giovanni et al., 2017). On the most granular level of economic activity, the production network reflects customer-supplier relationships between interacting firms and hence the network evolves dynamically contingent on firms' decisions to choose their business partners. Here we employ microdata on Japanese companies to analyze the topology and evolution of these relationships over the period 2011-2016 and to quantitatively assess the role of alternative mechanisms of supplier selection shaping these dynamics in an endogenous production network.

We review a set of stylized facts of firm-level input-output interlinkages in Japan to motivate our interest in the underlying mechanism of network formation. Consistent with empirical results in the extant literature (see e.g. Carvalho and Tahbaz-Salehi, 2019, for a recent survey), we find that the Japanese customer-supplier network is extremely sparse. Yet approximately 95 percent of firms in our sample are either directly or indirectly connected through supply-chain relationships. Considering potential explanations for this high level of connectivity, we find that the distribution of business partners across firms is asymmetric. The distributions of both in- and out-degrees are skewed and leptokurtic with tails at least close to a power law and diverging second moments, testifying to the presence of hubs or general purpose technologies that considerably reduce the path length between firms, which turns out to be less than five steps for the largest strongly connected component. In such a "small-world" populated by granular firms, firm-level shocks can spread within and across sectors which foreshadows significant implications for macroeconomic fluctuations, as it has been forcefully argued by Gabaix (2011), Acemoglu et al. (2012) and subsequent studies. While the major characteristics of production networks have been documented in previous work, the major novelty and contribution here is to show that various key properties such as the degree distributions, connectivity patterns, shortest paths between companies as well as centrality measures or Domar weights, which have been identified as crucial determinants of the transmission of idiosyncratic shocks and the emergence of macroeconomic fluctuations, are remarkably stable over time. We consider this as an apparently non-trivial observation given that nearly 40 percent of individual input-output relationships change during the sample period, suggesting that the underlying process governing the formation of customer-supplier relationships exhibits a deeper regularity and structure that conserves these features over time. Therefore, after reviewing these characteristics, we turn to the empirical estimation of the network formation process and investigate firms' motivation to change their partners.

However, as pointed out by Jackson et al. (2017) and de Paula (2017) in their recent surveys, the estimation of network processes poses several challenges to the empirical researcher that render the application of standard econometric tools inappropriate.[2] In empirical models of network formation, the probably most fundamental problem pertains to the mutual dependence between

[1] Throughout the study we use the terms production input interlinkages, production network, customer-supplier network, and input-output network interchangeably.

[2] For an unweighted network, logit or probit regressions would be obvious candidates for an empirical model.

network structure and tie formation. As an example, consider the case where popular suppliers with many customers face a higher probability to be selected as a counterparty. The latter implies that the probability of two firms to establish a new relationship depends on existing connections to other companies, which violates the assumption of independent observations inherent to standard econometric models and may thus lead to biased estimation results and incorrect inference. Alternatively, one might think of a situation where a firm's decision to establish or terminate a business relationship changes the path length between two firms, which might feedback on the network formation process, as predicted by recent theoretical contributions in the field.

Against this background, our second contribution is methodological. We sidestep this econometric problem using a stochastic actor-oriented model (SAOM). The class of stochastic actor-oriented models has been popularized in the literature on social networks by Snijders (1996). In the same field, these models have been applied to the analysis of various types of network processes, ranging from advice relations in organizations (Agneessens and Wittek, 2012) to smoking behavior in school and within friendship networks (An, 2015; Mercken et al., 2010), the formation of peer relationships among pre-school childen (Schaefer et al., 2010), and the assimilation of norms and attitudes in social networks (de Klepper et al., 2010). In economics, Finger and Lux (2017) employ the SAOM to study counterparty selection in the Italian interbank money market. More closely related to our investigation, Balland et al. (2013) and Balland (2012) study collaboration in interfirm networks. However, their work focuses on highly specific sectors (global video game and navigation satellite system industry) with relatively small samples consisting of merely a few hundreds of firms to warrant computational tractability, implying that their results are not representative of the dynamics of an economy-wide production network.[3] In this paper, we employ the SAOM to analyze tie formation in a large-scale production network that consists of approximately 80,000 private and publicly traded Japanese companies operating in a diverse set of industries between 2011 and 2016. Hence, compared to intra- or intersectoral studies of input-output relationships in the extant literature, this article investigates the dynamics of economy-wide production input interlinkages on the most granular level of economic activity. Based on our empirical network model, we find that selection on productivity and other dimensions of firm performance plays only a minor role for the formation of input-output relationships, while topological features of the production network such as the actual number of counterparties and geodesic distance are quantitatively more important for the evolution of the network in subsequent periods, which might be motivated with the relatively stronger impact of reputation, trust, and the diffusion of private information on the network formation process.

Our investigation relates to different strands of the literature. First and foremost, we provide a framework to test recent theorizing on endogenous production networks. After all, this literature suggests that preferential attachment, differences in productivity across firms as well as network distance between potential counterparties are important mechanisms of network formation, without providing a quantitative assessment of the relative strength of these effects. In a relatively early contribution to this recent field of research, Atalay et al. (2011) stress the role of the well-known "rich get richer" mechanism to explain the skewed degree distribution observed in real-world production networks. Their statistical model combines random rewiring after the birth and death of companies with preferential attachment. A different tack is taken by Oberfield (2018) who presents a model where firms differing in productivity produce an output good using labor and one intermediate input. To select their supplier, firms consider both the match-specific productivity and the cost of the associated input that is a function of the supplier's efficiency

[3]In empirical network models such as the SAOM the computational burden of the estimation routine is significant. We use the K and Oakforest-PACS supercomputers to run our algorithm on a considerably larger sample than in previous work. To the best of our knowledge, our study is quite unique in this respect.

in producing that good. He shows that the optimal decisions of individual entrepreneurs on the most cost-effective technique lead to the endogenous emergence of star suppliers selling their good to many customers. Oberfield also investigates the presence of matching patterns in firm attributes and reports that there is a positive correlation between the size of a customer and its supplier. In a similar vein, Taschereau-Dumouchel (2017) considers a model in which a social planner maximizes the welfare of a representative household arising from the consumption of aggregate output. As the output rises with productivity, the social planner has an incentive to operate highly productive firms and companies whose operations increase the productivity of other firms. Consequently, the planner organizes production activity in clusters around very productive firms. Since more output also requires more labor, the model predicts that firms with many counterparties are also large in terms of size. Acemoglu and Azar (2017) construct a general equilibrium model in which each product can be produced by combining labor and a set of intermediate inputs. They show that a positive technology shock to a firm does not only lead to a price reduction but also increases the density of the network because the initial drop in unit costs and output price triggers a series of second and higher order price effects, leading to input diffusion and a general decline in prices. Finally, Gualdi and Mandel (2016) explain the emergence of scale-free production networks in a model with monopolistically competitive firms. In their model, link formation depends on the price of intermediate goods which decreases with productivity that is a function of the number of suppliers that are sourced by the firm. Hence, their model predicts a hierarchical network structure where links are directed first and foremost towards firms that source their inputs from many suppliers. Finally, Carvalho and Voigtländer (2015) stress the importance of network proximity for the evolution of input-output relationships. Building on a dynamic network formation model proposed by Jackson and Rogers (2007), they propose a mechanism according to which firms are more likely to develop new linkages to other firms in their suppliers' network neighborhood, which might be explained with technological similarity, spatial distance and the tendency for coagglomeration, or the diffusion of (private) information. Here we argue that our empirical model of tie formation is a valuable tool to assess the empirical relevance of the alternative mechanisms proposed in this literature.

Our paper also relates to the literature on the estimation of network processes. In this research field, the class of exponential random graph models (ERGM) received growing attention in recent years as a tool to describe network structures arising from local processes (Christakis et al., 2010; Chandrasekhar and Jackson, 2014).[4] However, the ERGM methodology is subject to several problems that hinder its application in large scale networks. First, exact computation of the normalization constant that is required to obtain properly defined probability measures is practically unfeasible due to the large number of network configurations that are consistent with a given number of nodes.[5] Second, ERGMs are subject to identification problems because standard MCMC or fixed density estimation techniques with improved convergence properties cannot warrant uniqueness of the estimated parameters, not even in large samples (Chandrasekhar and Jackson, 2014). Very recently, Mele (2017) demonstrated that ERGMs are subject to identification problems when the network process incorporates non-negative network externalities (e.g. preferential attachment), for which we find strong empirical support in our data. Unlike ERGMs,

[4]These papers describe the connection between ERGMs and strategic network formation models. It is shown that, under some mild assumptions, a network formation game converges to a unique stationary distribution of possible network configurations. For an introduction to ERGMs, see, for example, Lusher et al. (2012).

[5]To bypass this statistical problem, one might resort to Markov Chain Monte Carlo (MCMC) simulations to obtain an approximation of the network probability distribution (Snijders, 2002). Yet MCMC samplers exhibit a slow convergence speed, implying that the huge computational complexity of ERGMs limits their application in large networks.

the SAOM does neither rely on a single snapshot of the network for parameter estimation, nor does it assume the existence of a unique equilibrium distribution of network configurations that would require the computation of a normalizing constant. Instead, the SAOM incorporates the information from at least two waves of observations, generating additional heterogeneity of network statistics that can be exploited for parameter estimation, which makes this model less prone to convergence problems and thus renders the SAOM as a promising alternative in the empirical literature on the modeling of network processes.

The remainder of this article is organized as follows. Section 2 describes the data before we discuss the main properties of the Japanese production network and their stability in section 3. Section 4 presents the empirical framework and estimates the network formation process using the SAOM, while section 5 summarizes and concludes.

2. Data

Our analysis builds on firm microdata compiled by Tokyo Shoko Research (TSR) Ltd., a private market research and credit reporting agency in Japan. The TSR dataset surveys Japanese companies operating in virtually all industries of the economy across the years 2006, 2011, 2012, 2014, as well as 2016, and includes information on major accounting variables and customer-supplier relationships between those firms. The raw data are filtered according to several criteria. First, due to a considerable amount of missing sectors and a significantly smaller number of firms compared to later years the magnitude of which appears difficult to explain with the entry and exit behavior of markets, we omit observations from 2006 and focus on the period 2011-2016. Moreover, we exclude firms with an annual sales revenue less than one billion Japanese yen to improve the robustness of our results and to reduce the computation time of the estimation algorithm. Finally, we omit firms in sectors that appear inappropriate for studying the formation of production input interlinkages due to the nature of their operations or peculiarities in the regulatory environment.[6] Specifically, these include entities (with two-digit Japan Standard Industrial Classification (JSIC) codes in parentheses) operating in the divisions agriculture and forestry (01-04), electricity, gas, heat supply and water (33-36), finance and insurance (62-67), scientific research, professional and technical services (71-74), education and learning support (81-82), medical, healthcare and welfare services (83-85), and all subsequent sectors (86-99). The final sample includes more than 80,000 firms which are heterogenous in terms of size, S, ranging from small/medium-sized companies to large publicly traded corporations listed at the Tokyo Stock Exchange, and thus provide a comprehensive view on customer-supplier relationships within the Japanese economy. To describe the distribution of firm size for the present sample of companies, we report descriptive statistics of sales revenue including the tail index of a fitted Pareto distribution in Table 1. The estimates of the power law exponent hover around unity and hence testify to Zipf's law, implying that a firm of rank n in the power law tail has a size proportional to $1/n$ (see, e.g., Axtell, 2001; Gabaix, 2009). Overall, these results firmly corroborate that our sample is sufficiently well balanced in terms of the composition of firms and includes the largest and thus economically most crucial (or "granular") entities in the Japanese economy (Gabaix, 2011).

For all firms in the sample, the TSR dataset provides information on the identity of each firm's most important customers and suppliers (up to 24 entities in each category) in terms of

[6]These include, for example, utilities that occupy a quasi-monopoly within the region in which they operate. As we are interested in the mechanism shaping the selection of suppliers, we decided to completely exclude this subset of companies.

Table 1: Descriptive statistics of the firm size distribution.

Year	Firms	Mean	SD	10th.	90th.	N_{tail}	$\hat{\zeta}$
2011	84730	10.69	86.42	1.12	13.74	9815	1.000 (0.010)
2012	83158	11.13	92.42	1.12	14.37	8813	1.005 (0.011)
2014	85533	11.60	111.45	1.12	14.73	9127	1.001 (0.010)
2016	86447	11.54	99.80	1.12	14.76	9432	0.995 (0.010)

Note: Firm size is measured in terms of sales revenue (in billion yen). Estimation of the tail index ζ in $P(S > s) \sim s^{-\zeta}$ for firm size S is carried out using the method proposed by Clauset et al. (2009), i.e. we employ the maximum likelihood method with an endogenous cut-off. N_{tail} quantifies the number of firms with size above that threshold. The latter is estimated from the data by minimizing the distance between the empirical and the power-law distribution, measured in terms of the Kolmogorov-Smirnov statistic. Standard errors are given in parentheses.

sales revenue.[7] These data enable us to construct a panel of binary network data indicating which firms are trading intermediate inputs with each other. More formally, the structure of these production relationships at time t is represented by a binary $N \times N$ adjacency matrix $\mathbf{y}(t)$, where $y_{ij} = 1$ if firm $i = 1, \ldots, N$ is a customer of firm $j = 1, \ldots, N$ and $y_{ij} = 0$ otherwise for all companies $i \neq j$.[8] Additionally, the dataset contains information from the accounting books as well as several non-financial firm characteristics such as, for example, the number of employees, the firm's address, and the year of foundation, which enable us to characterize the firms in our sample in terms of their financial and organizational characteristics.

3. Topology of production input interlinkages

To guide our model of network formation, we begin our analysis by reviewing the main stylized facts of production input interlinkages. Most of these facts are known from previous work (e.g. Carvalho, 2014; Acemoglu et al., 2012; Carvalho and Tahbaz-Salehi, 2019), yet most analyses in the extant literature build on input-output tables subject to a higher level of aggregation, e.g. sector-level data provided by the US Bureau of Economic Analysis, while we provide more granular firm-level evidence. Among the few exceptions considering information on the level of individual firms, see for example Bernard et al. (2019), who employ the same data as we do, or Mizuno et al. (2014), also with a focus on Japan.

The features considered below are static properties that cannot provide information on the evolution of the production network and the process of tie formation on the firm-level. Hence, as a first step towards a more dynamic perspective, and to scrutinize the effect of local tie formation on the aggregate features of the production network, the focus of this section lies on the evolution of these properties over time. A key finding of our analysis is that the macroscopic network properties are remarkably stable. The nature and stability of these characteristics evokes the fundamental question about the underlying mechanism governing the formation of network

[7]Notice that despite this limitation of the data we can identify more than 24 relationships per firm by combining the information provided by different entities.

[8]Here entries y_{ij} represent the flow of money from company i to j as a compensation for the delivery of intermediate inputs from j to i.

Table 2: Descriptive statistics of the degree distributions.

Year	Total	Mean	SD	10th.	90th.	N_{tail}	$\hat{\zeta}$
Panel A: in-degree							
2011	663314	7.83	24.61	0	14	1335	1.441 (0.039)
2012	667701	8.03	24.61	0	15	1509	1.443 (0.037)
2014	694646	8.12	24.00	0	15	1402	1.472 (0.039)
2016	711529	8.23	23.69	0	15	1346	1.467 (0.040)
Panel B: out-degree							
2011	663314	7.83	27.82	1	12	1288	1.371 (0.038)
2012	667701	8.03	28.09	1	13	1343	1.373 (0.037)
2014	694646	8.12	28.21	1	13	1407	1.384 (0.037)
2016	711529	8.23	28.56	1	13	1341	1.387 (0.038)

Note: The table shows (from left to right): total number of ties, mean, standard deviation, 10th. percentile, 90th. percentile, number of firms in the power law tail, and the fitted tail index of a Pareto distribution. Estimation of this tail index builds on the method proposed by Clauset et al. (2009), i.e. we employ the maximum likelihood method with an endogenous cut-off. N_{tail} quantifies the number of firms with a degree above that threshold. The latter is determined by minimizing the distance between the empirical and the power-law distribution, measured in terms of the Kolmogorov-Smirnov statistic. Standard errors are given in parentheses.

ties, which we will turn to in section 4. We start out with two of the most fundamental static characteristics of network structure, namely density and degree distribution.

3.1. Network density and degree distribution

Considering the summary statistics in Table 2, the customer-supplier network is extremely sparse. Depending on the year under consideration, our sample consists of 83,000-86,000 companies which form a production network with approximately 663,000-711,000 customer-supplier relationships, the number of which exhibits a steady upward trend over time. The pertinent network density, which is defined as the actual number of network ties divided by $N(N-1)$, has an order of magnitude of 10^{-5}, implying that around 0.01 percent of the maximum number of relationships actually exist.[9] Consistent with this sparseness of the production network, the vast majority of firms have very few upstream and downstream relationships to other companies. According to the definition of network ties given in section 2, the number of suppliers of firm i is given by its out-degree

$$d_i^{out} = \sum_j y_{ij}, \tag{1}$$

while the in-degree

$$d_i^{in} = \sum_j y_{ji} \tag{2}$$

[9] $N(N-1)$ is the maximum number of ties in a directed network with N nodes.

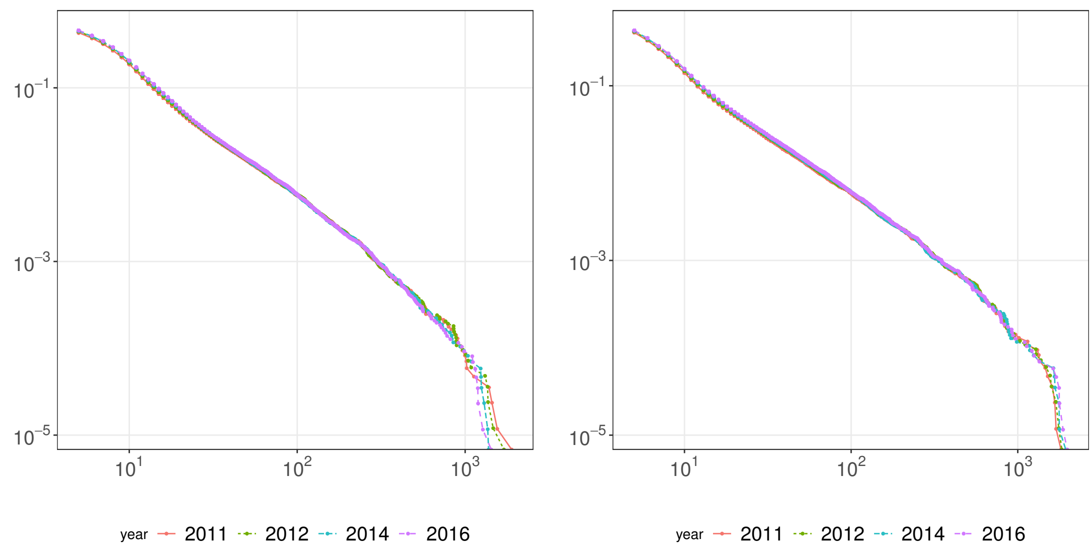

Figure 1: Counter-cumulative distribution (CCDF) function of in- and out-degrees. The left (right) panel shows the CCDF of in- (out-) degrees on double-logarithmic scale for different years.

reflects the number of its customers. The average values of (1) and (2) vary between 7 and 8, and even the 90th. percentiles of the two degree distributions do never exceed 15, implying that the vast majority of firms are connected to a relatively small number of customers and suppliers. Yet, like the firm size distribution, the empirical degree distributions are right-skewed and exhibit seizable excess kurtosis, and thus deviate significantly from a Binomial or Poisson distribution that would prevail under a completely random network formation mechanism. The heavy tail of the out-degree distribution implies that some companies serve as a hub in the network and hence acquire a disproportionate amount of customers, while the fat-tailed distribution of in-degrees illustrates that several firms rely on a very large number of inputs. In 2016, for instance, the largest in-degree (out-degree) is $1,431$ ($1,983$), which exceeds the corresponding average degree by three orders of magnitude. Visual inspection of the empirical counter-cumulative distribution function (CCDF) of in- and out-degrees in Figure 1 confirms that the two distributions exhibit heavy tails and are approximately scale-free, as indicated by the nearly linear shape on double-logarithmic scale over a wide range of observations. Estimates of the Pareto tail index, reported in Table 2, lie in the close vicinity of $1.3 - 1.4$ and exhibit only little fluctuations over time. Hence we find that both the functional form and the parametrization of the in- and out-degree distribution are remarkably stable across all years.

3.2. Connectivity

While in- and out-degree characterize a single node and thus capture a local network property, they do not capture the rich global structure of the production network. To better understand the aggregate network topology, we investigate patterns of network connectivity which have a pronounced impact on the speed of information diffusion and shock propagation in the production network. To this end we consider two measures: weak and strong connectivity. While weak connectivity neglects the direction of links and thus only requires that any two nodes belonging to a common subgraph are connected, strong connectivity additionally incorporates the information

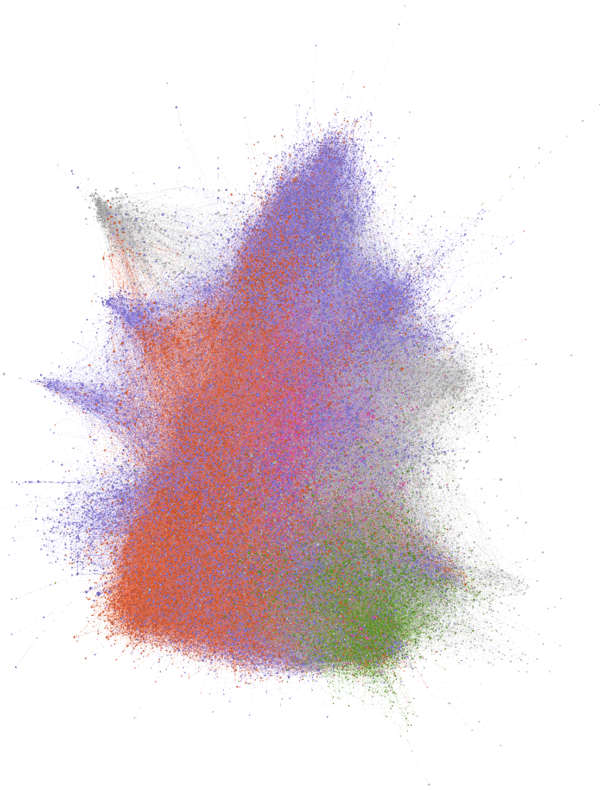

Figure 2: Snapshot of the largest weakly connected component in the Japanese customer-supplier network in 2016. For visual clarity, only firms with sales larger than three billion yen are shown. Nodes colored in purple, orange, and green represent firms operating in the three largest business divisions in the sample. We distinguish purple: retail & wholesale, orange: manufacturing, and green: construction. Firms operating in all remaining sectors are graphically illustrated in gray.

on the direction of links and thus requires that every node can be reached on a directed path from any other node in the subgraph. The latter gives rise to a loop structure where there exist directed paths from i to j and from j to i, implying that firm i is both an indirect supplier and an indirect customer of firm j, which facilitates both the upstream and downstream propagation of shocks within the network. Neglecting the direction of links in the first step of the analysis, we find that the largest weakly connected component (WCC), graphically illustrated in Figure 2 for the year 2016, contains more than 95 percent of all firms, which is remarkable in light of the sparseness of the production network. Similarly, the largest strongly connected component (SCC) includes about 72% percent of all companies. The time series plot of the relative size of WCC and SCC, graphically illustrated in the left panel of Figure 3, firmly corroborates the robustness of these results over time. A corollary of this observation is that, due to the presence of hubs or general purpose technologies that connect the vast majority of firms in the economy, the average network distance between firms is small relative to the overall size of the production network. The right panel of Figure 3 shows the distribution of shortest paths for the SCC, illustrating that firms are connected on a (directed) path of less than five steps on average. Like the degree distributions and the relative sizes of WCC and SCC, this feature of the production

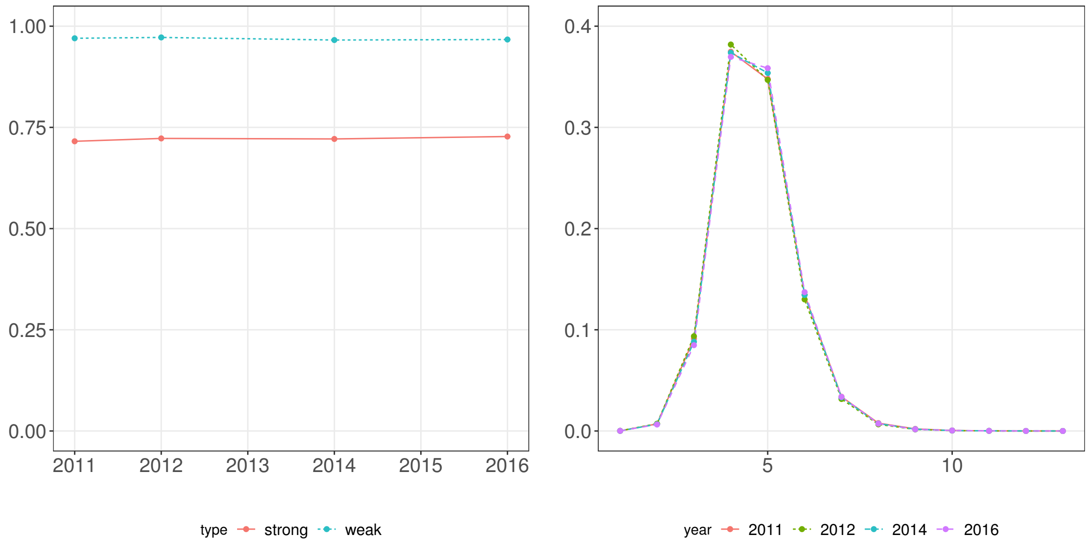

Figure 3: Relative size of WCC and SCC (left) and distribution of shortest paths between firms belonging to the SCC (right) for different years of the sample period. The average shortest paths are 4.66, 4.63, 4.66, and 4.68 for the years 2011, 2012, 2014, and 2016, respectively.

network is equally stable over time.

3.3. Network structure and macroeconomic implications: Domar weights

The recent macroeconomic literature stresses the role of production input interlinkages for shock propagation and suggests that idiosyncratic shocks to firms or disaggregated sectors may have a defining effect on aggregate fluctuations. Whether these shocks wash out in the aggregate due to the law of large numbers or are amplified and thus have macroeconomic implications depends on the structure of input-output relationships, particularly on the asymmetry of the distribution of first and higher order connections. To quantify the role of network structure on macroeconomic fluctuations, we employ the framework proposed by Acemoglu et al. (2012) where these first and higher order effects are captured by Domar weights or, put differently, the influence vector.

These authors show that in the competitive equilibrium the logarithm of real value added

$$y \equiv \log(\text{GDP}) = \mathbf{v}'\boldsymbol{\varepsilon} \tag{3}$$

is given by the sum of idiosyncratic shocks, $\boldsymbol{\varepsilon}$, multiplied with Domar weights

$$\mathbf{v} \equiv \frac{\alpha}{N}[\mathbf{I} - (1-\alpha)\mathbf{W}']^{-1}\mathbf{1}, \tag{4}$$

where $\mathbf{I}$ is the $N \times N$ identity matrix, $\mathbf{1}$ is a $N \times 1$ vector of ones, α is the labor share, and $[\mathbf{I} - (1-\alpha)\mathbf{W}']^{-1}$ denotes the Leontief inverse. The latter incorporates the matrix of production input interlinkages $\mathbf{W}$ with entries w_{ij}, which denote the share of good j in the total intermediate input use of firm i. Since the amount of transaction volumes is not available in our data, we

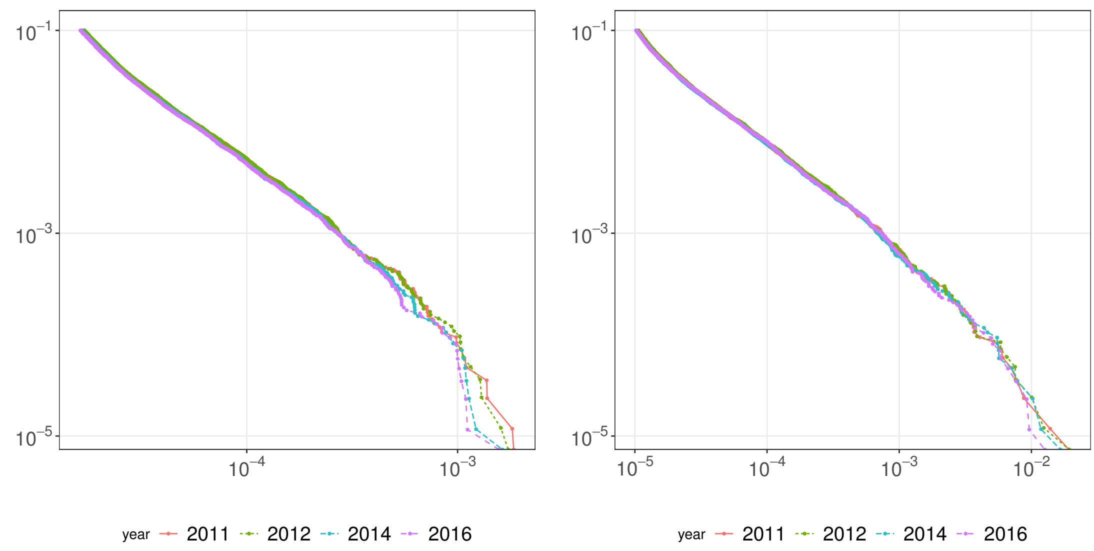

Figure 4: Distribution of Domar weights assuming equal (left) and size-dependent (right) input shares. In all calculations we assume a fixed labor share equal to $\alpha = 0.45$.

consider two hypothesized weights: equal weights, denoted by w_{ij}^e, and weights proportional to the size of suppliers, w_{ij}^s. Specifically, equal weights are defined as

$$w_{ij}^e \equiv \frac{y_{ij}}{\sum_j y_{ij}}, \tag{5}$$

where the denominator $\sum_j y_{ij}$ quantifies the number of firm i's suppliers. Thus, this weight is constant and equal to $1/\sum_j y_{ij}$ for all firms j that are suppliers of company i. As an additional robustness check, we also consider size-dependent weights given by

$$w_{ij}^s \equiv \frac{y_{ij} s_j}{\sum_j y_{ij} s_j}, \tag{6}$$

which increase in the sales revenue s_j of supplier j.[10] By definition, both weights add up to one for all i.

Figure 4 illustrates the CCDF of the implied Domar weights for the empirical structure of firm-level production input interlinkages, distinguishing between the two hypothesized weighting schemes $\mathbf{W}^e$ and $\mathbf{W}^s$. Again, we observe a right-skewed and heavy-tailed distribution that manifest itself in an approximately linear shape when plotted on double-logarithmic scale. The pertinent tail exponents of a fitted Pareto distribution for the four different years are reported in Table 3. They hover around 1.5 (1.0) for equal (size-dependent) weights and are fairly stable over the years, testifying to a robust distributional regularity that implies a significant number of highly influential firms which disproportionally contribute to aggregate fluctuations. For example, considering $\mathbf{W}^s$, the largest Domar weight across all firms is 0.0126 for 2016, implying

[10]The idea is borrowed from gravity-type models of world trade which establish a relationship between trade volume as well as size and distance.

Table 3: Descriptive statistics of the distribution of Domar weights.

Year	Mean	SD	v_{max}	N_{tail}	$\hat{\zeta}$
Panel A: equal weights ($\mathbf{W}^e$)					
2011	1.113×10^{-5}	2.34×10^{-5}	0.00185	2216	1.483 (0.031)
2012	1.137×10^{-5}	2.33×10^{-5}	0.00174	2668	1.522 (0.029)
2014	1.099×10^{-5}	2.15×10^{-5}	0.00163	2636	1.529 (0.030)
2016	1.088×10^{-5}	2.09×10^{-5}	0.00157	2733	1.544 (0.030)
Panel B: size-dependent weights ($\mathbf{W}^s$)					
2011	1.124×10^{-5}	1.15×10^{-4}	0.0192	2595	0.997 (0.020)
2012	1.148×10^{-5}	1.16×10^{-4}	0.0193	2477	0.997 (0.020)
2014	1.110×10^{-5}	1.09×10^{-4}	0.0166	2717	0.998 (0.019)
2016	1.099×10^{-5}	0.97×10^{-4}	0.0126	2676	1.000 (0.019)

Note: The table shows (from left to right): mean, standard deviation, maximum, number of firms in the power law tail, and the fitted tail index of a Pareto distribution. Estimation of this tail index builds on the method proposed by Clauset et al. (2009), i.e. we employ the maximum likelihood method with an endogenous cut-off. N_{tail} quantifies the number of firms with a weight above that threshold. The latter is determined by minimizing the distance between the empirical and the power-law distribution, measured in terms of the Kolmogorov-Smirnov statistic. Standard errors are given in parentheses.

Table 4: Frequency of tie changes for different time intervals.

	2011–2012	2012–2014	2014–2016	2011–2016
Jaccard index	0.871	0.774	0.822	0.616

Note: To quantify the frequency of changes in network ties, we use the Jaccard index defined as $J_{t_0-t_1} = N_{11}/(N_{01} + N_{10} + N_{11})$, where N_{11} is the number of network ties that are present in both years t_0 and t_1, N_{01} is the number of newly created ties in t_1, and N_{10} denotes the number of deleted ties in the same year.

that an individual shock of 10 percent to this single firm induces a $0.0126 \times 10\% = 0.126$ percent increase of the Japanese GDP. Most importantly, as suggested by Figure 4 and the estimates of the tail index in Table 3, also the influence vector exhibits a remarkable stability over time. In other words, though the weight v_i of a single firm i in $\mathbf{v}$ may vary over time, this aggregate feature of the customer-supplier network remains nearly unchanged.

3.4. Persistence of network ties

It might be tempting to explain the observed stability of macroscopic network properties with the persistence of individual network ties. Yet, as we will subsequently show, individual relationships are subject to perpetual and comprehensive fluctuations. A straightforward measure of the persistence of ties is the Jaccard index which measures the fraction of stable relationships from one snapshot of the network to the next realization. The realizations of this measure, reported in Table 4, confirm that a substantial number of relationships are added or dissolved within the sample period. Over the entire interval 2011-2016, the Jaccard index is $J_{2011-2016} = 0.616$, suggesting that nearly 40 percent of all firm relationships are either newly created or disappear within a period of merely 6 years. Within the shorter periods 2012-2014 and 2014-2016, respectively, approximately 20 percent of all ties are updated. Therefore, at the level of individual relationships, it seems fair to say that the network of production input interlinkages is by no means stable, but that there is sufficient variation of these relationships over time. At the same time, however, the stability of aggregate features of network structure suggests the presence of a deeper regularity and structure in the tie formation mechanism that preserves these properties over time. We will turn to the empirical estimation of this mechanism in the following section.

4. Tie formation in an endogenous production network

This section considers the mechanism of network formation. To this end, we set up a stochastic actor-oriented model (SAOM) that enables us to assess the significance of the alternative mechanisms of tie formation proposed in the extant literature.

4.1. An empirical model of network formation

In the SAOM, we consider a set of N firms, each of which is characterized in terms of M different attributes such as its size or age, summarized in the vector $\mathbf{x}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,M})$ for $i = 1, \ldots, N$. Let $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N)'$ denote a $N \times M$ matrix collecting the individual characteristics $\mathbf{x}_i$ of all firms in the sample.

To produce their output, these firms may demand intermediates supplied by other firms. Formally, the structure of these input-output relationships is represented by the binary adjacency matrix $\mathbf{y}(t)$ with dimension $N \times N$, where $y_{ij} = 1$ if firm i is a customer of firm j and $y_{ij} = 0$ otherwise for all $i \neq j$. The structure of this network is observed at two points in time, t_0 and $t_1 > t_0$, yielding two waves of customer-supplier relationships that are denoted by $\mathbf{y}(t_0)$ and $\mathbf{y}(t_1)$. Time t between these two observations is continuous.

In the SAOM, the network $\mathbf{y}(t)$ observed in period t is interpreted as a state of the stochastic process governing the evolution of the network between the initial realization $\mathbf{y}(t_0)$ and the final configuration $\mathbf{y}(t_1)$. The model approaches this transition from the perspective of individual firms (actors) which have the opportunity to add, dissolve, or keep ties according to their individual preferences.[11] To this end, the time interval between t_0 and t_1 is split into a sequence of micro steps at each of which the following three actions take place. (i) A waiting time τ_i is drawn for each firm i and the firm with the smallest τ_i gets the opportunity to change one tie. (ii) The selected firm changes or keeps one of its ties according to its individual preferences. Then, the network $\mathbf{y}(t)$ is updated. (iii) Time t is incremented by τ_i. This sequence of steps is repeated until time t reaches the endpoint t_1. At this point, the algorithm stops and the simulation of the model is compared to the empirical network configuration.

The process of tie formation is determined by two main components. The first component, called rate function, controls the waiting time τ_i, i.e., the frequency of changes, while the so-called objective function describes the firm's preferences with respect to the selection of its counterparties. We discuss these two functions in more detail below.

4.1.1. Frequency of tie changes

The frequency of tie changes for firm i is determined by its rate function $\rho_i(\mathbf{y}, \mathbf{x})$. Specifically, for each firm i, a waiting time τ_i is drawn from the exponential distribution

$$P(\tau_i > s) = \exp(-\rho_i(\mathbf{y}, \mathbf{x})s) \tag{7}$$

[11] Unlike the exponential random graph model, the stochastic actor-oriented model does not impose the notion of an equilibrium configuration of network structure.

which is the only distribution that is memoryless and thus warrants a Markov process. To account for activity differences between firms, the rate function

$$\rho_i(\mathbf{y}, \mathbf{x}) \equiv \rho + \sum_k \theta_k^\rho s_{i,k}(\mathbf{y}, \mathbf{x}) \tag{8}$$

depends on individual firm attributes, $\mathbf{x}$, and the current network topology, $\mathbf{y}$, via a set of canonical statistics, $s_{i,k}(\mathbf{y}, \mathbf{x})$, where ρ is a constant, and θ_k^ρ is a coefficient that measures the impact of the k-th canonical statistic on the change frequency. These canonical statistics are chosen by the researcher depending on theory and the implied hypotheses. For example, if one aims to test the hypothesis that firms with many suppliers change their counterparties more frequently, the corresponding network measure to be included as a canonical statistic is the out-degree and the related coefficient θ_k^ρ has a positive sign under this hypothesis.

A major advantage of the SAOM is that $\mathbf{y}$ is updated after every iteration. Hence the SAOM incorporates the permanent feedback of network structure on the dynamics of tie formation, which would otherwise be ignored in standard econometric models such as probit or logit regressions.

4.1.2. Supplier selection

Firms that are selected during the simulation have the opportunity to change their suppliers according to their individual preferences. This implies that a firm may either choose an additional supplier, terminate an existing business relationship with its vendor, or simply leave the current set of relationships unchanged. These preferences are operationalized with an objective function

$$V_i(\mathbf{y}, \mathbf{y}', \mathbf{x}) \equiv f_i(\mathbf{y}, \mathbf{y}', \mathbf{x}) + \epsilon_i(\mathbf{y}, \mathbf{y}', \mathbf{x}), \tag{9}$$

where $f_i(\mathbf{y}, \mathbf{y}', \mathbf{x})$ is a deterministic part reflecting the current state of the network, $\mathbf{y}$, and the new network configuration, $\mathbf{y}'$, which would materialize after the decision of firm i. Since at maximum one tie is allowed to change per micro time step, $\mathbf{y}'$ is either equal to $\mathbf{y}$ or different from $\mathbf{y}$ in exactly one element of $\{y_{ij}\}_{j=1,\ldots,N}$.

Like in the rate function, the impact of firm attributes and the network structure is captured by a set of canonical statistics, $s_{i,k}(\mathbf{y}, \mathbf{y}', \mathbf{x})$, i.e. we have

$$f_i(\mathbf{y}, \mathbf{y}', \mathbf{x}) \equiv \sum_k \theta_k^V s_{i,k}(\mathbf{y}, \mathbf{y}', \mathbf{x}). \tag{10}$$

For each statistic, the coefficient θ_k^V reflects the strength of the pertinent effect in the selection process. The second term of (9), $\epsilon_i(\mathbf{y}, \mathbf{y}', \mathbf{x})$, denotes an unobservable i.i.d. shock that is drawn from a Type I extreme value (or Gumbel) distribution. Under this assumption, the transition probability can be written in multinomial logit form (McFadden, 1974)

$$P(\mathbf{y} \to \mathbf{y}') = \frac{\exp(f_i(\mathbf{y}, \mathbf{y}', \mathbf{x}))}{\sum_{\mathbf{y}''} \exp(f_i(\mathbf{y}, \mathbf{y}'', \mathbf{x}))}, \tag{11}$$

where the sum runs over all feasible network states, $\mathbf{y}''$, that may result from firm i's choice.[12]

When choosing $\mathbf{y}'$, firms are assumed to select their suppliers such that the objective function in (9) is maximized. That is, firms are supposed to select that network $\mathbf{y}'$ from the set of feasible

[12]In economics, a very similar type of behavioral modeling is known as stochastic best-response dynamics (see, e.g. Mele, 2017).

network configurations, $\mathbf{y}''$, which yields the highest score of V_i. In this sense, the objective function can be interpreted as a measure of satisfaction with the actual network configuration.

Some points deserve further explanation. First, the SAOM assumes that merely current realizations of firm characteristics and the network topology are relevant for the future evolution of the network, implying that the stochastic process governing $\mathbf{y}_t$ is a continuous time Markov chain. In particular, when making its choice on the change of a network tie at a micro time step, each firm neglects the potential feedback from the likely reactions of other firms. Hence, according to Steglich et al. (2010), firms' behavior in the model is largely consistent with the notion of myopic rationality in the spirit of Luce (1959). However, this assumption is less restrictive than it seems first because other firms have the opportunity to react on every change of network ties in subsequent iterations of the algorithm. Second, like in the rate function, all canonical statistics involving network metrics are updated after every micro step and firms adjust their information sets accordingly. In this way, we take into account that every change of network ties affects the behavior of other players in subsequent rounds. Finally, we assume that outgoing ties are controlled by the sender, i.e. customers select their suppliers and the latter have no opportunity to reject a customer.

4.1.3. Calibration

To determine $\boldsymbol{\theta} = \{\boldsymbol{\theta}^\rho, \boldsymbol{\theta}^V\}$, where $\boldsymbol{\theta}^\rho$ and $\boldsymbol{\theta}^V$ are vectors of coefficients pertaining to the canonical statistics in the rate and objective function, respectively, we use the method of simulated moments (for an application of this method in the context of SAOMs, see, e.g., Snijders, 2001). Hence, the parameter estimates $\hat{\boldsymbol{\theta}}$ must satisfy the moment equation

$$E_{\hat{\boldsymbol{\theta}}}[S_k(\mathbf{y}(t_0), \mathbf{y}(t_1), \mathbf{x}) \mid \mathbf{y}(t_0), \mathbf{x}] = S_k^{obs} \quad \forall k, \tag{12}$$

where the left-hand side is the expectation of the (global) network statistic S_k across all simulations given the estimated parameters $\hat{\boldsymbol{\theta}}$, and the right-hand side is the empirical realization of that statistic S_k^{obs}. Our choice of S_k is an aggregate version of the individual statistic $s_{i,k}$, i.e. $S_k = \sum_i s_{i,k}$, which serves to evaluate the goodness of fit on the network-wide level. For example, if the relevant statistic in the objective function is the out-degree $\sum_j y_{ij}$, the corresponding aggregate measure is the number of ties in the entire network, i.e. $S_k = \sum_i \sum_j y_{ij}$.[13]

[13] Calculation of the expectation in (12) for given parameters builds on Monte Carlo simulations. That is, we repeatedly simulate the process $\mathbf{y}(t)$ for $t_0 \leq t \leq t_1$ given $\mathbf{y}(t_0)$ and $\mathbf{x}$ as initial conditions, and take the mean of the aggregate statistic over the simulation runs. Finding the solution to (12) draws on an iterative procedure called the stochastic approximation technique (Kushner and Yin, 2003). According to this algorithm, a distribution of simulated statistics is generated based on a set of starting values of the parameters. Then, we compute the average across these statistics and compare it to the sample realization. Based on the deviation between the two, the coefficients are adjusted according to

$$\hat{\boldsymbol{\theta}}_{n+1} = \hat{\boldsymbol{\theta}}_n - \boldsymbol{\alpha}_n \mathbf{D}_n^{-1} \left(\frac{1}{N^{sim}} \sum_{i=1}^{N^{sim}} \mathbf{S}_{\hat{\boldsymbol{\theta}}_n, i}^{sim} - \mathbf{S}^{obs} \right), \tag{13}$$

where $\mathbf{D}_n$ is (an approximation to) the matrix of partial derivatives of the aggregate statistics with respect to $\boldsymbol{\theta}$ evaluated at $\hat{\boldsymbol{\theta}}_n$, $\boldsymbol{\alpha}_n$ denotes a series of positive numbers converging to zero, $\mathbf{S}_{\hat{\boldsymbol{\theta}}_n}^{sim}$ are simulated statistics created with the parameter vector $\hat{\boldsymbol{\theta}}_n$, and N^{sim} specifies the number of simulation runs. In our computation, we set $N^{sim} = 512$. Standard errors are obtained from Monte Carlo simulations and application of the delta method. First, we approximate the covariance matrix of the aggregate statistics, $\Sigma_{\hat{\boldsymbol{\theta}}}(\mathbf{S})$, by simulations given the estimates $\hat{\boldsymbol{\theta}}$. Then, we inversely transform it by the derivative of $\mathbf{S}$ with respect to $\boldsymbol{\theta}$ (denoted by $\mathbf{D}$), i.e.

$$\mathrm{cov}_{\hat{\boldsymbol{\theta}}} = \mathbf{D}^{-1} \Sigma_{\hat{\boldsymbol{\theta}}}(\mathbf{S}) (\mathbf{D}^{-1})^T, \tag{14}$$

where $\mathbf{D}$ is estimated by simulations.

Table 5: Model specification.

Effect	Canonical statistic	Hypothesis
Panel A: rate function		
Out-degree	$\log(\sum_j y_{ij})$	Large diversified firms change their suppliers more frequently.
Log(age)	$x_j - \bar{x}$	Young firms change their suppliers more frequently.
Panel B: objective function		
Out-degree density	$\sum_j y_{ij}$	Tendency to have ties.
Log(sales) activity	$\sum_j y_{ij}(x_i - \bar{x})$	Large firms have many suppliers.
Productivity popularity	$\sum_j y_{ij}(x_j - \bar{x})$	Firms select productive suppliers.
Growth popularity	$\sum_j y_{ij}(x_j - \bar{x})$	Firms select growing suppliers.
Profitability popularity	$\sum_j y_{ij}(x_j - \bar{x})$	Firms select profitable suppliers.
Log(sales) popularity	$\sum_j y_{ij}(x_j - \bar{x})$	Firms select large suppliers.
In-degree popularity	$\sum_j y_{ij} \log(\sum_k y_{kj})$	Firms select popular suppliers.
Log(size) homophily	$\sum_j y_{ij}\lvert x_j - x_i\rvert$	Firms select suppliers of (dis)similar size.
Technological similarity	$\sum_j y_{ij} I_{\{x_j = x_i\}}$	Firms select suppliers operating in the same sector.
Geographical distance	$\sum_j y_{ij} g_{dis}(i,j)$	Firms select suppliers at close geographical distance.
Reciprocity	$\sum_j I_{\{y_{ij} y_{ji} = 1\}}$	Firms select their customers as suppliers.
Supplier of supplier	$\sum_j I_{\{\exists k,\ y_{ik} y_{kj} = 1\}}$	Firms select the suppliers of their direct suppliers.
Customer of customer	$\sum_j I_{\{\exists k,\ y_{jk} y_{ki} = 1\}}$	Firms select the customers of their direct customers.

Note: In most cases we consider the realization of the covariate, x, from its sectoral average, $\bar{x}$. Sectors are defined on the 2-digit JSIC level.

4.2. Model specification

It remains to determine the canonical statistics in the rate and objective function. As summarized in Table 5, in the rate function we include the actual number of suppliers of a firm, measured in terms of (the logarithm of) its out-degree. The rationale of the hypothesized degree dependence is that large firms tend to have more suppliers (Bernard et al., 2019), and are more diversified than small firms on average (e.g. Castaldi et al., 2006; Bottazzi and Secchi, 2006), suggesting that change opportunities should arrive more frequently for these firms. Moreover, we include (the logarithm of) firm age to check if young firms, which have not yet built up stable business relationships, tend to change their suppliers more often than older firms.

In the objective function, we consider the following variables reflecting the three main hypotheses prevalent in the extant theoretical work on endogenous production networks: (i) supplier's productivity (Gualdi and Mandel, 2016; Acemoglu and Azar, 2017; Oberfield, 2018; Taschereau-Dumouchel, 2017), (ii) preferential attachment (Atalay et al., 2011), and (iii) geodesic distance between the firms (Carvalho and Voigtländer, 2015). One economic rationale for the relevance of the productivity effect is that high productivity may result in cost advantages that allow the firm to offer lower prices compared to less efficient suppliers, thereby attracting more customers in the competitive process. To capture this effect, we consider the ratio of the firm's sales to the number of employees as a proxy of labor productivity, along with alternative performance indicators like the growth rate of sales and profitability, measured in terms of the return to total assets, as additional controls. As an alternative mechanism, the importance of the number of existing clients for the acquisition of additional customers has been discussed in the literature to explain the emergence of heavily skewed degree distributions, akin to the seminal preferential attachment mechanism introduced by Barabási and Albert (1999) and Albert and

Barabási (2000). Selecting a popular supplier with a central position in the network provides access to the broad knowledge base of that supplier and its cooperation partners, thereby increasing the supplier's attractiveness in the production network. Also, when information regarding the quality and reliability of potential partners and their products is scarce, and thus collecting and assessing this information is costly, selection rules based on popularity and reputation might be considered as a favored heuristic compared to perhaps more elaborated yet more expensive screening routines (Müller et al., 2014). We thus include the number of customers, measured in terms of the in-degree, in the objective function. Last but not least, Carvalho and Voigtländer (2015) argue an alternative mechanism according to which the geodesic distance between two firms is a major determinant of supplier selection. According to this view, an indirect supplier which is two steps away from the customer exhibits a higher probability to be selected than a company that is more distant in the network, which might be motivated with innovation processes and the diffusion of technologies or with search and informational frictions according to which firms can obtain information on potential partners through existing relationships to their immediate suppliers. Hence, we include a dummy variable that equals one if a potential supplier j already delivers inputs to an existing supplier k of a firm i and zero otherwise.[14] To check the validity of this interpretation, we also include a dummy variable that equals one if a potential supplier is the customer of an existing customer of a firm and zero otherwise. According to the information diffusion argument, the supplier-of-supplier dummy should have more explanatory power as only the former pattern warrants the flow of information from the potential supplier to the demanding firm.

In addition to these main effects, we include a set of additional variables into the objective function. First, we consider the density or out-degree effect which captures the overall tendency of firms to form relationships to other companies. The latter constitutes a standard effect in the SAOM literature. Given that the empirical customer-supplier network is extremely sparse, a negative coefficient is expected, reflecting capacity constraints in the accumulation of connections. Second, the notion of network proximity might be related to geographical distance or technological similarity, as noticed by Carvalho and Voigtländer (2015). Hence we follow their empirical strategy and control for the geographical distance between the firms measured in terms of latitude and longitude. Since the transportation costs increase with the distance between the two firms, a negative coefficient is expected. Moreover, to check if network proximity essentially measures the same or a distinctively different effect than technological similarity, we include a dummy variable that equals one if the two firms operate in the same industry as measured on the 4-digit JSIC classification level. Third, we consider the effect of firm size (measured in terms of sales revenue) on firms' willingness to form additional relationships as well as on the popularity of a potential supplier that might be selected. We also consider the difference in size between the customer and supplier and test whether firms belonging to different size classes are connected to each other with higher probability, which might be explained with the firm's preference to work with less-connected downstream firms because of product specialization and long-term contracting issues, as argued in (Atalay et al., 2011). Fourth, we control for technological complementarities by restricting the set of sectors in which customers search for new potential suppliers. For example, a firm that has suppliers operating in the sectors A and B in the initial network configuration and suppliers from the sectors B and C in the final network

[14] Carvalho and Voigtländer (2015) consider a path of length two. As we seek to test their theoretical prediction, we follow this suggestion and consider firms that are directly connected to the current suppliers as potential new candidates.

Table 6: Descriptive statistics of explanatory variables for 2014–2016.

	Mean	SD	10th.	90th.
Panel A: all firms (83,812 firms)				
Log(age)	3.541	0.599	2.708	4.143
Log(sales)	1.142	1.088	0.113	2.622
Labor productivity	0.000	0.818	−0.908	0.985
Growth rate	−0.018	0.269	−0.246	0.193
Profit rate	0.011	0.158	−0.013	0.048
Panel B: manufacturing (22,706 firms)				
Log(age)	3.680	0.556	2.944	4.174
Log(sales)	1.214	1.148	0.126	2.773
Labor productivity	0.000	0.708	−0.793	0.860
Growth rate	−0.026	0.263	−0.274	0.210
Profit rate	0.012	0.081	−0.025	0.058

Note: We report (from left to right): mean, standard deviation, 10th. percentile, and 90th. percentile of the respective explanatory variable.

configuration is supposed to select suppliers from the union of sectors, i.e. A, B, and C.[15] Table 6 summarizes the descriptive statistics of the covariates.

4.3. Results

We estimate the SAOM for the three time intervals 2011–2012, 2012–2014 and 2014–2016, where all covariates in $\mathbf{x}$ are evaluated at the beginning of each period, i.e. in 2011 for the first interval, in 2012 for the second and so on. For each of these periods, we report the parameter estimates $\hat{\boldsymbol{\theta}} = \left\{\hat{\boldsymbol{\theta}}^{\rho}, \hat{\boldsymbol{\theta}}^{V}\right\}$ for the full sample (approximately 80,000 companies) and for the manufacturing industries (about 22,000 firms) in Tables 7-8. To assess and compare the strength of the different effects, the two tables also report the pertinent odd ratios which quantify the increase in the selection probability when the respective variable increases by one standard deviation.

Considering the two statistics incorporated in the rate function, the out-degree effect is positive, while the coefficient of firm age has a negative sign in all periods, implying that firms with many suppliers and young firms face a higher frequency of tie changes on average. Both effects are statistically significant at the 1 percent level. In case of the age statistic, one possible explanation of the negative effect is that young firms have not yet build up stable business partnerships with other firms and thus tend to change their suppliers more frequently than older firms. At the same time, the positive coefficient of the out-degree effect implies that the arrival of change opportunities is proportional to the current number of suppliers.

In the objective function, consistent with our hypotheses, the coefficients of out-degree density and geological distance are negative and statistically significant at the 1 percent level. The large negative estimate of the density coefficient reflects the sparseness of the customer-supplier network, while the negative estimate of geological distance suggests that firms at close geographic distance tend to form clusters, consistent with theories of industrial agglomeration that date back to Marshall (1920). Moreover, the fitted coefficient of the size homophily effect indicates that

[15]This procedure has the additional advantage of reducing the estimation time of the SAOM because we can restrict the search for new suppliers to a smaller subset of firms.

Table 7: Estimated coefficients for the full sample.

	2011-2012		2012-2014		2014-2016	
	Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio
Panel A: rate function						
Rate	0.114 (0.001)		0.219 (0.001)		0.177 (0.001)	
Out-degree density	1.069 *** (0.001)	2.519	1.074 *** (0.001)	2.528	1.049 *** (0.001)	2.521
Log(age)	−0.182*** (0.006)	0.897	−0.187*** (0.004)	0.894	−0.185*** (0.005)	0.895
Panel B: objective function						
Out-degree density	−3.600*** (0.013)		−3.587*** (0.010)		−3.667*** (0.014)	
Log(sales) activity	0.024 *** (0.003)	1.026	0.009 *** (0.002)	1.010	0.014 *** (0.002)	1.015
Productivity popularity	−0.145*** (0.006)	0.895	−0.111*** (0.005)	0.920	−0.123*** (0.005)	0.910
Growth rate popularity	0.464 *** (0.022)	1.096	0.343 *** (0.018)	1.060	0.317 *** (0.025)	1.052
Profitability popularity	−0.508*** (0.116)	0.983	0.435 *** (0.095)	1.014	0.926 *** (0.088)	1.032
Log(sales) popularity	0.030 *** (0.004)	1.033	0.029 *** (0.003)	1.032	0.013 *** (0.003)	1.015
In-degree popularity	0.460 *** (0.005)	1.624	0.412 *** (0.004)	1.545	0.441 *** (0.004)	1.598
Log(sales) homophily	0.115 *** (0.003)	1.284	0.101 *** (0.002)	1.248	0.106 *** (0.002)	1.264
Technological similarity	0.171 *** (0.019)	1.186	0.192 *** (0.017)	1.212	0.207 *** (0.018)	1.230
Geographical distance	−0.147*** (0.001)	0.532	−0.142*** (0.001)	0.545	−0.154*** (0.001)	0.517
Reciprocity	1.515 *** (0.031)	4.551	1.384 *** (0.021)	3.992	1.423 *** (0.025)	4.151
Supplier of supplier	1.468 *** (0.014)	4.339	1.621 *** (0.011)	5.059	1.541 *** (0.011)	4.669
Customer of customer	0.554 *** (0.025)	1.739	0.689 *** (0.018)	1.991	0.570 *** (0.019)	1.768
Number of firms	83386		80685		83812	

Note: Standard errors are reported in parentheses. Odd ratios are computed as the exponential of the product of standard error and the estimated coefficient. ***,**, and * indicate statistical significance at the 10%, 5%, and 1% level, respectively.

there is a certain tendency of large firms to connect to small companies (and vice versa). This result may speak in favor of a core-periphery structure according to which small firms in the periphery form ties primarily to large corporations in the dense core. Further, it lends empirical support to the argument of Atalay et al. (2011) that product specialization and long-term contracting issues reward tight connections between vertically connected companies belonging to different brackets of the firm size distribution. The positive coefficient of the size activity effect further suggests that large corporations are more active than small firms in the sense that they are eager to accumulate additional relationships.

Considering the three main economic hypotheses, the network-related effects, i.e., measures of geodesic distance and in-degree popularity, are statistically significantly at the 1 percent level and have the hypothesized sign across all samples, which testifies to the robustness of our estimation results. The estimated coefficients of in-degree popularity firmly corroborate that popular firms with many customers are primarily selected as counterparties, suggesting

Table 8: Estimated coefficients for firms in the manufacturing sectors.

	2011-2012		2012-2014		2014-2016	
	Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio
Panel A: rate function						
Rate	0.098 (0.002)		0.213 (0.003)		0.168 (0.003)	
Out-degree density	1.073 *** (0.003)	2.526	1.050 *** (0.003)	2.486	1.001 *** (0.004)	2.389
Log(age)	−0.166*** (0.018)	0.912	−0.161*** (0.012)	0.913	−0.083*** (0.015)	0.956
Panel B: objective function						
Out-degree density	−3.004*** (0.044)		−2.959*** (0.025)		−3.038*** (0.031)	
Log(sales) activity	−0.026*** (0.008)	0.971	−0.008 (0.005)	0.991	−0.022*** (0.006)	0.975
Productivity popularity	−0.015 (0.019)	0.990	−0.101*** (0.015)	0.937	−0.129*** (0.017)	0.920
Growth rate popularity	0.045 (0.052)	1.009	0.327 *** (0.045)	1.057	0.335 *** (0.067)	1.047
Profitability popularity	0.379 (0.361)	1.016	1.003 *** (0.242)	1.038	−0.583*** (0.218)	0.979
Log(sales) popularity	0.018 * (0.010)	1.021	0.060 *** (0.007)	1.072	0.043 *** (0.008)	1.051
In-degree popularity	0.456 *** (0.014)	1.519	0.414 *** (0.009)	1.459	0.445 *** (0.011)	1.507
Log(sales) homophily	0.108 *** (0.008)	1.281	0.059 *** (0.005)	1.146	0.083 *** (0.006)	1.213
Technological similarity	0.084 * (0.046)	1.087	0.092 *** (0.034)	1.096	0.138 *** (0.041)	1.148
Geographical distance	−0.115*** (0.004)	0.610	−0.115*** (0.003)	0.611	−0.103*** (0.003)	0.643
Reciprocity	1.701 *** (0.069)	5.478	1.600 *** (0.044)	4.955	1.310 *** (0.053)	3.708
Supplier of supplier	1.133 *** (0.034)	3.105	1.220 *** (0.026)	3.388	1.118 *** (0.034)	3.058
Customer of customer	0.590 *** (0.052)	1.804	0.634 *** (0.046)	1.885	0.555 *** (0.054)	1.743
Firms	22809		22412		22208	

Note: Standard errors are reported in parentheses. Odd ratios are computed as the exponential of the product of standard error and the estimated coefficient. ***,**, and * indicate statistical significance at the 10%, 5%, and 1% level, respectively.

the presence of hierarchical structures in the production network, particularly when considered jointly with the size activity and size homophily effects. The estimated coefficients of the two dummies pertaining to geodesic distance imply that the search for new suppliers occurs primarily in the direct (network) neighborhood of current business partners. Consistent with the results obtained by Carvalho and Voigtländer (2015) for US data, we find that geodesic distance is highly significant even after controlling for geographical distance and technological similarity, implying that this effect can be neither explained with the clustering in a specific industry or local area nor with the technological similarity of the two firms. What reflects favorably on the idea of information diffusion is the estimated coefficient of the supplier of supplier dummy relative to the customer of customer dummy. A firm that is the actual supplier of a firm looking for a new supplier and, at the same time, the actual customer of the potential supplier, has information about the latter regarding the quality of its product since it uses this intermediate input in the production process. Thus, also the firm looking for a new supplier has access to this information because it uses the product incorporating the intermediate good of the potential supplier. As this is not the case for the alternative triadic structure, the smaller coefficient of the customer of customer dummy seems consistent with this interpretation.

Unlike the network-related metrics, the interpretation of the productivity effect and the remaining performance indicators is ambiguous. The coefficient of labor productivity is negative, while the coefficients of growth rate and return on assets are (mostly) positive. One might be concerned that these variables capture related aspects of firm performance and thus should be considered jointly to obtain a coherent view on the role of performance on supplier selection. Yet our main argument here is that the size of all three effects as measured by the odd ratios is much smaller compared to the impact of network-related metrics, which firmly suggest that the effect of productivity and other dimensions of supplier's performance on network dynamics is weaker than predicted by extant theories of endogenous production networks. Instead, both the preferential attachment mechanism as well as geodesic distance are quantitatively more important, testifying to the high relevance of current network structure for the evolution of the production network in subsequent periods.

In a first version of this paper, we have also experimented with more elaborated measures of productivity, e.g. a proxy of total factor productivity (TFP) that was derived under the assumption of a Cobb-Douglas production function with constant returns to scale technology, using aggregate data on sectoral labor and capital shares provided by the Japanese Ministry of Finance. Unfortunately, the detailed accounting information necessary for the computation of TFP is only available for 2014 in our dataset. Given this limitation of the data, we would have to restrict the analysis to the single time interval 2014-2016. Alternatively, maintaining the consideration of three distinct periods as a way to check the robustness of our findings, one would have to assume that productivity is constant over time and that its realization in 2014 is a reasonable approximation of its realization in the earlier years 2011 and 2012. Using this measure of TFP, and dropping both the growth rate of sales and the return on assets as alternative measures of performance, we obtain a positive coefficient of the productivity indicator, as predicted in the theories of endogenous production networks and perhaps more consistent with the economic intuition. Yet, most importantly, the result that geodesic distance, preferential attachment and other metrics of network structure are quantitatively more important than selection based on productivity differentials is invariant to the choice of the productivity measure. To emphasize the validity of our findings across time, we therefore decided to report the results for a simpler measure of labor productivity which can be computed for all years.

4.4. Goodness of fit

In this section we check whether our fitted model of network formation can reproduce the main stylized facts of the empirical data. Since the macroscopic properties of the production network are largely stable over time and the SAOM models the evolution of network ties conditional on the initial network configuration, our focus lies on assessing the model's ability to maintain these features. One should bear in mind, however, that our sample consists of more than 80,000 firms which is much larger than the samples analyzed in previous work, hence facilitating the identification of deviations between the data and the model. Yet it appears instructive to investigate how much of the process of network formation can be explained with our stylized model. At the same time, systematic deviations from the overall trend provide equally valuable information as they might indicate the presence of additional effects shaping the evolution of production input interlinkages, which may guide future theoretical work in the field.

To assess the goodness of fit of the model, we simulate 1,000 realizations of the network at the end-point in 2016, conditional on the first wave of observations in 2011, and compare the simulated realizations of the pertinent statistics to their empirical counterparts. Among these

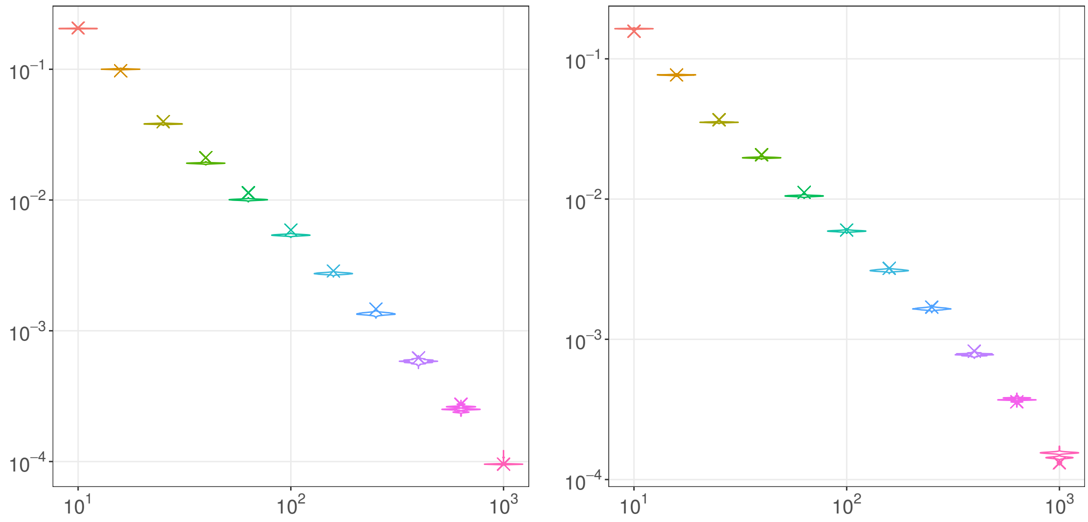

Figure 5: Violin plots for the distribution of in-degrees (left panel) and out-degrees (right panel) for 1,000 simulations of the network formation model. × represents the values of the empirical distribution.

statistics, we consider the distributions of in- and out-degrees, the relative size of the weakly and strongly connected components, and the distribution of Domar weights.[16] Figure 5 reports the empirical distributions of in- and out-degrees. It shows that the model maintains the heavy tails, and fits the respective percentiles of the empirical degree distributions to a reasonable degree of accuracy. In Figure 6 we plot the corresponding connectivity measures. In general, the model reproduces the high connectivity of the network, yet it consistently underestimates the size of the weakly and strongly connected components. We take this to imply that there might be additional forces contributing to high connectivity that remain unexplained by the included effects. Figure 7 reports the results for the distribution of Domar weights under the two alternative hypotheses on the weights of links. The distribution emerging under the assumption of equal weights is relatively close to its empirical counterpart, while we obtain a somewhat poorer fit for the size-dependent weights that manifests itself in an underestimation of the thickness of the Pareto tails. A potential explanation of this deviation is that input shares are not proportional to the size of the supplying firm, or that there is a mutual relationship between firm size and the number of links which is not captured by the model.

Since the estimation of the SAOM is based on the evolution of the empirical network, it is meaningful to confirm that our model is able to reproduce key patterns of network dynamics. The most fundamental measure is the change of node degrees over two consecutive network realizations. Therefore, we consider the difference of degrees between 2014 and 2016 and plot the distribution of these changes across all firms. Then we compare this distribution to its theoretical counterpart that is obtained from simulations.[17] Figure 8 illustrates the empirical

[16]Here we omit the distribution of shortest paths due to the tremendous computational effort imposed by the search algorithm that rises with the number of simulation runs in the Monte Carlo study.

[17]We merely show the distribution for the period 2014-2016 and confirm that the results for other periods are nearly identical. This material is available upon request.

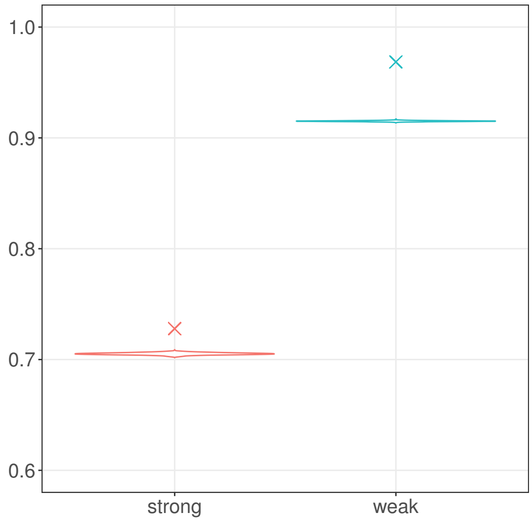

Figure 6: Violin plots for the relative size of WCC and SCC for 1,000 simulations of the network formation model. × represents the empirical values.

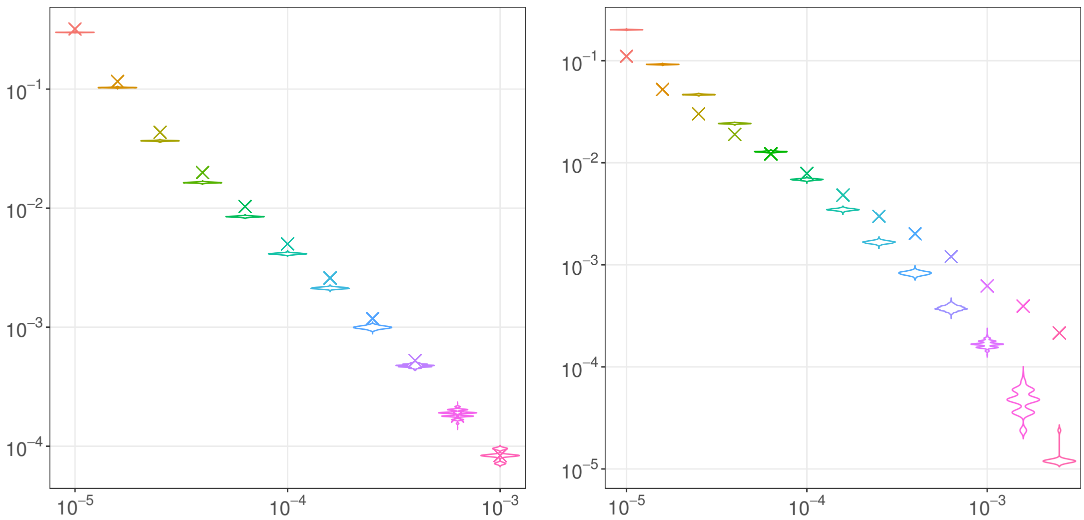

Figure 7: Violin plots for the distribution of Domar weights for 1,000 simulations of the model. The difference between the left and right panel is the weighting scheme. We distinguish $\mathbf{W}^e$ (left panel) and $\mathbf{W}^s$ (right panel). × represents the values of the empirical distribution.

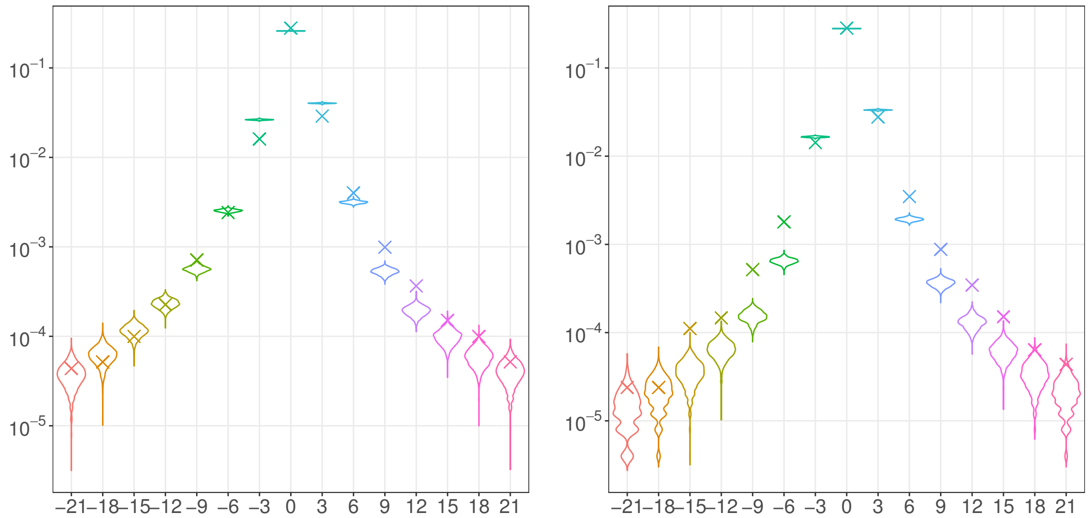

Figure 8: Violin plots for the distribution of the change in in-degrees (left panel) and out-degrees (right panel) for 1,000 simulations of the model. × represents the values of the empirical distribution.

distribution, superimposed with the violin plots of different percentiles of the pertinent simulated distribution. As nearly 80% of network ties remain unchanged within a period of two years, the empirical density is peaked around 0, and our model is consistent with this regularity. Deviations between the empirical distribution and its theoretical counterpart can be observed for some parts of the distribution, particularly for the number of suppliers as measured by the out-degree. The model tends to systematically underestimate the change of out-degrees, even more so for positive changes.

In light of these results, we conclude that the network dynamics implied by the mechanisms proposed in the theoretical literature are largely consistent with the statistical features of the empirical network, yet there seem to exist additional (unknown) mechanisms that further contribute to an increase in connectivity and a change of degrees and which make the hubs even more influential in terms of their macroeconomic impact.

5. Concluding remarks

Considering the Japanese case, this paper shows that a large scale input-output network describing production input interlinkages between firms is subject to considerable change of individual relationships on the micro level, yet exhibits robust properties on a higher level of aggregation that are largely independent of these idiosyncratic fluctuations. Some of these properties have been identified as crucial determinants of shock propagation and macroeconomic outcomes. Hence the remarkable stability of these aggregate properties testifies to their general importance even in a dynamically evolving environment.

To estimate the process of tie formation, we proposed an empirical model of network formation that enables us to assess the quantitative importance of several alternative mechanisms put forth in the theoretical debate. Hence, the present work is an important step to close the empirical gap in the relatively recent field of endogenous production networks. In this context the paper makes several contributions. First and foremost, to the best of our knowledge, it is the first piece of work which analyzes the evolution of a customer-supplier network using the SAOM methodology and big data. Therefore, we believe that the findings reported in this work provide valuable insights into the dynamics of economy-wide input-output relationships on the most granular level of economic activity, without restricting the level of analysis to small sub-samples or specific industries, thereby making the study prone to sample selection biases and thus hindering the generalization of the results to broader contexts. On the methodological side, our model building on the stochastic actor-oriented approach provides significant advantages relative to the ERGM and more standard econometric tools such as, for instance, logit or probit models, e.g. with respect to sample size and the endogeneity problem inherent to networked environments. Last but not least, the empirical estimation of the tie formation process provides some interesting and perhaps, in light of the theoretical literature, unexpected results. One is that the role of productivity for supplier selection is relatively weak compared to other effects pertaining to the network structure itself. At the same time, we obtain robust evidence for the general importance of topological features of the network, e.g. reflected by the geodesic distance between the companies in the production network or the current number of customers, for its evolution in subsequent periods. Regarding the economic interpretation of these effects, reputation as well as search and informational frictions strike us as potential explanations for these phenomena.

Our work provides at least two additional avenues for future research. Our experiments on the goodness of fit clearly suggest that the three main mechanisms of network evolution discussed in the theoretical debate are relevant but merely provide an incomplete picture of the real tie formation mechanism. Against this background, our quantitative view on the evolution of production input interlinkages should stimulate additional theoretical contributions seeking to improve the explanatory power of existing models. Moreover, the present empirical model could be extended to the even more general case where both the network and firm attributes change at the same time. It is, for example, conceivable that firm attributes and the network formation process mutually impinge on one another. In general, the SAOM methodology is flexible enough to take this into account, yet the additional computational complexity limits the application of this modeling approach in very large networks. Nevertheless, we believe that the present analysis constitutes a valuable first step towards a better understanding of the emerging dynamics in a customer-supplier network.

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