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Abstract

Using a statistical model of an evolving multiplex network, we study tie formation in global production chains within and across developed countries, their trade activities with developing economies in the intermediate goods market, and the mutual dependencies between these relationships. Our model approaches these dynamics from the perspective of individual nodes and thus identifies the driving forces behind the tie formation process. The empirical value of our approach is demonstrated by fitting the model to a panel data set from the OECD Inter-Country Input-Output Tables between 2005 and 2015. Based on these data, we find that (i) geography, two-sided heterogeneity of buyers and sellers, trade costs, as well as structural characteristics of the production network determine the formation of trade linkages between OECD country-sectors, (ii) some of these determinants have an asymmetric effect on import and export ties between OECD and non-OECD countries, and (iii) intra-OECD trade and import and export ties with non-OECD economies are mutually dependent.

JEL classifications: E23, F14, D57, R15
Keywords: trade network, network formation, stochastic actor-oriented model, multiplex dynamics, input-output analysis

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1 Introduction

The focus of trade research has shifted in recent years from the study of aggregate exchange between countries towards a more fine-grained analysis of domestic and international transactions data based on a network approach. This perspective accounts for the fact that production processes are organized in global production chains where downstream customers source intermediate inputs such as raw materials, parts, and supporting services from their domestic and foreign upstream suppliers and deliver their output to other producers before final products are sold in end consumer markets. The structure of these production chains was found to have implications for market structure, returns to input factors, and the gains from trade (Bernard and Moxnes, 2018). Moreover, it is also relevant for shock propagation and the explanation of aggregate fluctuations (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Carvalho, 2014; Chakrabarti, 2018), cross-country comovement in economic growth (Shea, 2002), and producers' performance (Bernard et al., 2019a).

Although input linkages reflect, to some extent, technological constraints, the structure of global production chains is not exogenously given but is instead subject to perpetual fluctuations.[1] Nonetheless, there has been a surprising lack of attention to the endogenous formation of global production chains and patterns of buyer-supplier matching until recently (see, e.g., Acemoglu and Azar, 2020; Atalay et al., 2011; Bernard et al., 2018; Carvalho and Voigtländer, 2014; Oberfield, 2018; Zou, 2019), particularly in empirical research. One likely reason for the scarcity of pertinent empirical work is the presence of network correlations, which violate the assumption of independent observations underlying standard regression models. The stochastic actor-oriented model (SAOM), originally developed by Snijders (1996, 2001) for one-mode networks and later extended by Koskinen and Edling (2012) and Snijders et al. (2013) to two-mode and multiplex networks, is a powerful alternative to regression analysis to estimate the process of

[1]This is certainly true for firm-level data, but it holds even at higher levels of aggregation (Mundt, 2021).

network formation.[2] It approaches network formation from the perspective of individual nodes and thus identifies the driving forces behind the tie formation process. The SAOM accounts for the endogeneity of network variables arising when the existence of a particular network tie predicts other ties in the network. Another advantage of the SAOM is its ability to cope with the interdependence of the network and individual outcomes (Snijders et al., 2007). In a recent paper, Mundt (2021) employs the SAOM to estimate the formation of input-output relationships in the European Union, finding that the production network and individual outcomes such as productivity or growth co-evolve and are interdependent. This finding has relevant macroeconomic implications because then idiosyncratic shocks are not only passively transmitted through the production network but are amplified by the change of the network after the shock.

The present paper complements this prior work in at least three directions. First, we considerably extend the scope of the analysis by studying the formation of input linkages within and across OECD countries, including economies in North and South America, Europe, and Asia-Pacific. Based on these data, we construct a one-mode network of intra-OECD trade and test a rich set of effects reflecting different dimensions of customer and supplier heterogeneity and country-level effects. We find that geography, the enforcement of free trade agreements (FTA), productivity, global market share, economic complexity, technological similarities and complementarities, as well as several structural network properties such as reciprocity and assortative as well as disassortative matching determine the formation of production chains in developed countries.

Second, we study two bipartite (or two-mode) networks reflecting OECD import and export activities with non-OECD economies in the market for intermediate inputs. This extension enables us to detect patterns in production relationships between developed high-income and developing countries that would remain undetected in the analysis of a global (one-mode) trade network consisting of OECD and non-OECD economies. Building on this extension, we obtain evidence for overlap in the preferences of OECD countries with respect to the selection of trading partners in developing economies, i.e.

[2]See Hermans (2021) for a recent overview of empirical applications in the field of economic geography and regional science.

OECD country-sectors which import from or export to the same non-OECD country-sectors tend to have more non-OECD trading partners in common. Moreover, our results further show that FTAs have an asymmetric effect on the formation of trade ties between OECD and non-OECD countries. Whereas FTAs stimulate the formation of export relationships from the OECD to non-OECD economies, they reduce OECD import relationships with non-OECD countries. Our analysis thus contributes to the debate on the economic benefits and drawbacks of FTAs for developing countries (see, e.g., Grundke and Moser, 2019; McQueen, 2002; Topalova, 2010).

Third, we study the joint evolution of the different networks to understand if intra-OECD trade and import and export ties with non-OECD economies are mutually dependent. Indeed, our results point to significant interaction effects in the tie formation process in the sense that common preferences of OECD countries with respect to their non-OECD import or export partners facilitate the creation of intra-OECD ties between the same country-sectors. Likewise, a trade relationship between two OECD country-sectors in the one-mode network promotes the formation of export and import relationships with the same non-OECD country-sectors. These findings would be consistent with knowledge spillovers in international trade predicting that importers and exporters learn from their peers. Another interesting aspect of our multiplex network analysis is that OECD import ties with country-sectors outside the OECD promote the creation of export ties with the same non-OECD country-sectors, but OECD export relationships do not lead to the formation of import ties. This asymmetric entrainment might reflect that non-OECD economies produce and sell primary goods to highly industrialized economies and then import finished goods from OECD countries, consistent with the core-periphery hypothesis.

Our study relates to the growing literature exploring global production chains (GVCs). Theoretical models of GVCs are variations of trade models with sequential production (Antràs and Chor, 2013; Costinot et al., 2013), aiming to explain the mechanisms behind the allocation of production to firms or countries (Alcacer and Delgado, 2016; Chor, 2019) and the geographical location of production stages in the presence of trade barriers (Antràs and De Gortari, 2020). Complementary to these theoretical studies, a growing body of empirical papers investigates the determinants and consequences of participating in GVCs (e.g., Adarov and Stehrer, 2021; Amador and Cabral, 2016; Piermartini and Rubinova, 2021) or focuses on the measurement of GVCs (Johnson, 2018). Relevant research topics in this field are the distribution of value added along GVCs (Baldwin and Ito, 2021; Timmer et al., 2014) and the measurement of the relative position of production units in GVCs (Antràs and Chor, 2018; Antràs et al., 2012). Our study contributes to this empirical literature by modeling the evolution of production chains and so provides an avenue for the identification of network formation mechanisms.

The remainder of this article is organized as follows. Section 2 introduces our data and explains the construction of the different networks. Section 3 lays out the empirical framework used for the estimation of tie formation and discusses the effects implemented in our model. Section 4 presents the estimation results, while Section 5 summarizes and concludes.

2 Data

Our analysis builds on several data sets. Network panel data on production input interlinkages are obtained from the OECD Inter-Country Input-Output (ICIO) tables (OECD, 2018a). These tables report transactions in intermediate goods and services across 36 ISIC Rev. 4 industries for 36 OECD and 28 non-OECD countries over the period 2005-2015, and also provide sector-level information on value added, gross output, and final demand for these countries. Hence, the unit of analysis in our study (i.e. a node in the network) is a country-sector such as, e.g., agriculture, forestry and fishing in Australia.[3] To describe these country-sectors in terms of their individual characteristics, we employ supplementary information on gross fixed capital formation and labor shares from the OECD Structural Analysis (STAN; OECD, 2018b,c) database. Information on

[3]Tables 5-6 in Appendix A.1 list the countries and sectors under consideration. Notice that our sample does not include Colombia and Costa Rica because they became OECD members after the end of our sample period, 2015.

the economic diversity of the different countries and free trade agreements are obtained from the Atlas of Economic Complexity (Hausmann et al., 2014) and the data set by Dür et al. (2014), respectively.

2.1 Network construction

From the input-output tables we construct eleven annual realizations of one-mode and two-mode networks. In the field of social network analysis, one-mode networks typically describe relationships between entities, whereas two-mode networks capture the association between these entities and certain activities or preferences. In our application, the one-mode network represents trade relationships between $N = 36 \times 36 = 1296$ OECD country-sectors. In the two bipartite networks, we distinguish two types of nodes: (i) industries in OECD countries and (ii) industries in non-OECD economies. The first two-mode network then describes the export preferences of OECD country-sectors into $K = 28 \times 36 = 1008$ non-OECD country-sectors, and the second two-mode network describes the preferences of OECD economies to import from non-OECD countries.

The three networks are formalized as binary adjacency matrices in the following way. Nodes in the one-mode network are connected by directed ties X_{ij} for $i, j = 1, \ldots, N$ $(i \neq j)$, where $X_{ij} = 1$ if OECD country-industry i buys intermediates from OECD country-industry j, and $X_{ij} = 0$ otherwise. The tie variables in the two bipartite networks are denoted by Y_{ip} (Z_{ip}), with $Y_{ip} = 1$ $(Z_{ip} = 1)$ if OECD country-sector i imports from (exports to) the non-OECD country-sector $p = 1, \ldots, K$, and $Y_{ip} = 0$ $(Z_{ip} = 0)$ otherwise.

The networks are observed at times $t_1, \ldots, t_M$, yielding $M = 11$ panel waves of observations $X(t_1), \ldots, X(t_M)$, $Y(t_1), \ldots Y(t_M)$, and $Z(t_1), \ldots Z(t_M)$, respectively. Following Carvalho (2014), we eliminate noise in the fluctuations of input-output relationships by deleting links that account for less than 1% of the country-sector's total input purchases used for total output. Figure 1 illustrates the emerging multiplex network of intra-OECD trade and the import and export activities of OECD countries with non-OECD economies.

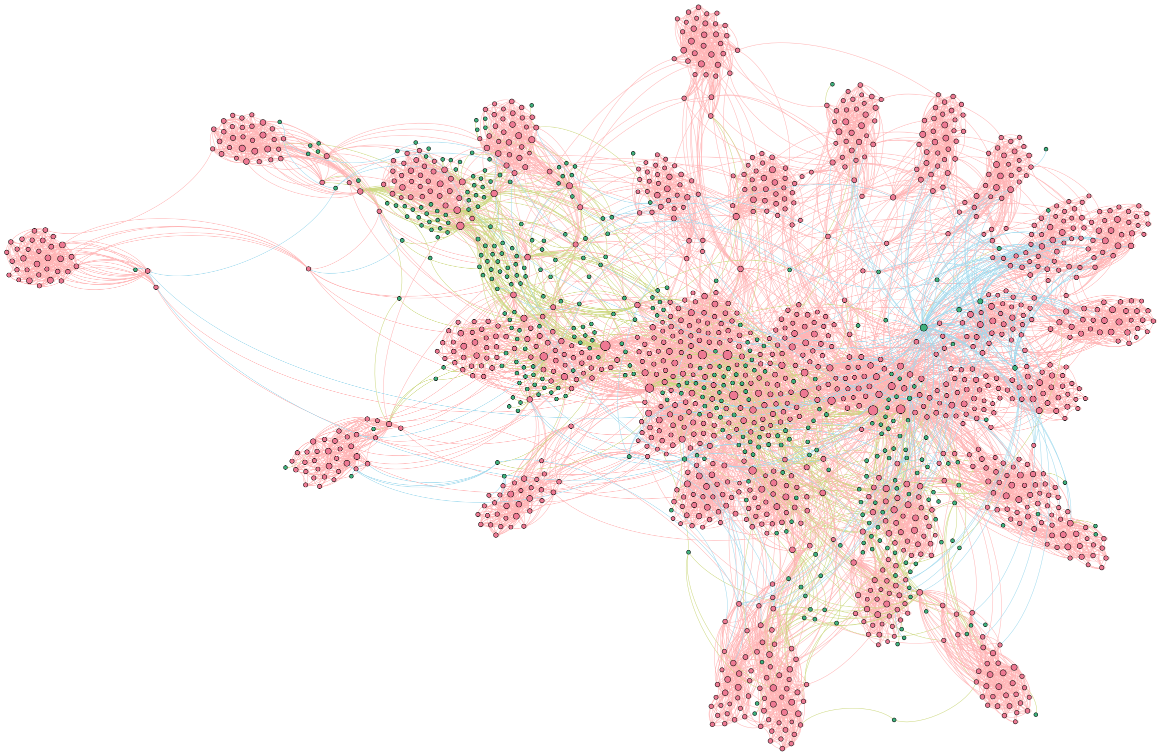


Figure 1: Network of trade relationships within the OECD and between OECD and non-OECD economies in 2015. Nodes represent country-sectors as described in the main text. Red nodes represent OECD countries, dark-green nodes stand for non-OECD countries. Red edges represent intra-OECD trade. Light-green edges illustrate export activities from OECD sectors to non-OECD sectors, whereas blue edges represent import activities of OECD industries with non-OECD industries. The size of a node is a function of its total degree, i.e. the number of its trade partners.

2.2 Descriptive statistics

Table 1 suggests that all three networks are sparse with a density below 1%.[4] A comparison of this statistic across networks further shows that the density is higher for the network of intra-OECD trade, which might be rationalized with the quality and effectiveness of institutions that reduce insecurity and transaction costs and thus stimulate the formation of trade ties within and across OECD economies (Anderson and Marcouiller, 2002). The degree statistics confirm these results because the average country-sector in the OECD has eight upstream or downstream relationships to other OECD

[4]Density is defined as the number of existing network ties to the maximum number of ties, given the size of the network. Previous studies confirmed the sparsity of production networks for different data (see, e.g., Carvalho (2014) for US firm-level data and Mundt (2021) for EU sectoral data).

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Intra-OECD trade											
Density (in %)	0.641	0.640	0.638	0.637	0.632	0.631	0.628	0.631	0.628	0.626	0.626
Average total degree	8.299	8.285	8.262	8.252	8.184	8.171	8.133	8.174	8.133	8.103	8.105
Number of ties	10756	10737	10707	10695	10606	10590	10541	10593	10540	10501	10504
OECD exports to non-OECD countries											
Density (in %)	0.071	0.074	0.074	0.072	0.060	0.067	0.069	0.071	0.066	0.063	0.061
Average out-degree	0.714	0.746	0.749	0.725	0.603	0.674	0.694	0.713	0.668	0.639	0.618
Number of ties	925	967	971	940	781	874	900	924	866	828	801
OECD imports from non-OECD countries											
Density (in %)	0.021	0.023	0.022	0.021	0.018	0.023	0.026	0.024	0.023	0.021	0.019
Average out-degree	0.213	0.231	0.217	0.216	0.183	0.228	0.262	0.242	0.231	0.211	0.191
Number of ties	276	299	281	280	237	295	339	314	300	273	248

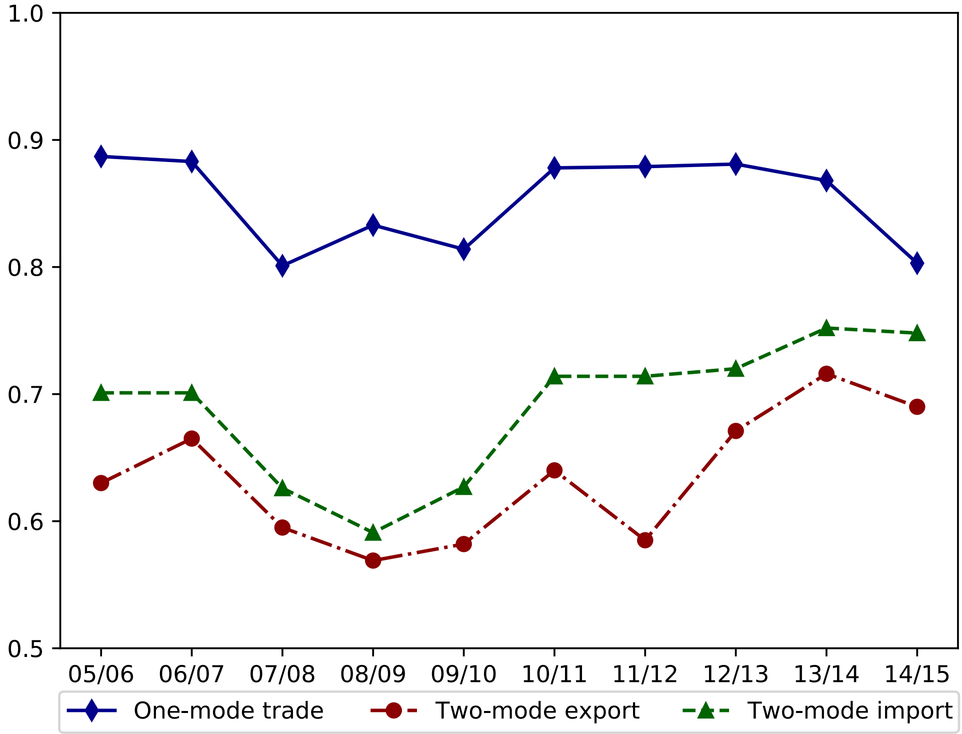
Table 1: Descriptive network statistics for the one-mode and the two bipartite networks. Density is defined as the number of existing ties to the maximum number of ties.

country-sectors, whereas OECD country-sectors have less than one import or export tie to non-OECD country-sectors on average.

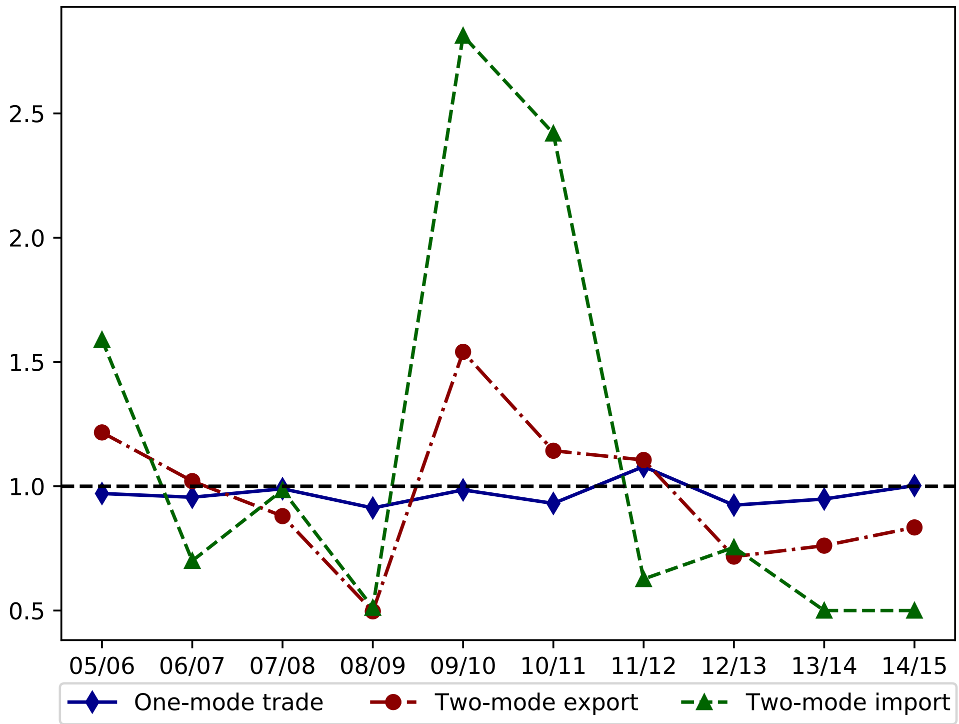
To quantify the (in-) stability of the networks over time, we consider two measures of network persistence in Figure 2.[5] Whereas the Jaccard index in panel (a) measures the percentage of stable relationships from one network panel wave to the next, the construction-to-destruction measure in panel (b) quantifies the ratio of created to dissolved network ties over two consecutive years. Both measures testify to fluctuations of trade relationships over time. Building on these statistics, we find that intra-OECD linkages are more persistent than ties between OECD countries and non-OECD economies. For example, the time series of the Jaccard index implies that 10-20% of all OECD trade relationships change from one year to the next, whereas the annual percentage change of ties between OECD and non-OECD countries amounts to 30-40%.[6] We also find that OECD export ties to non-OECD countries are more fluctuating than import relationships, a potential consequence of the relatively inelastic demand for raw materials

[5]Additional statistics measuring turnover and network persistence are provided in Appendix A.2.

[6]According to Ripley et al. (2011), a too high turnover may distort the estimation based on the SAOM because it violates the assumption of gradual network changes underlying the model. The authors recommend to apply the SAOM to networks with a Jaccard index larger than 0.3. Our descriptives confirm that all networks under consideration are clearly above that threshold.



(a) Jaccard index



(b) Construction-to-destruction ratio

Figure 2: Panel (a) shows the time evolution of the Jaccard index for the three networks. The Jaccard index is defined as $N_{11}/(N_{11} + N_{01} + N_{10})$, where N_{11} is the number of stable ties, N_{01} the number of newly created ties, and N_{10} denotes the number of dissolved relationships from one period to the next. Panel (b) illustrates the construction-to-destruction ratio, which measures the number of created ties relative to the number of dissolved relationships.

imported from non-OECD economies. Given these fluctuations of individual relationships, it seems worthwhile to conduct an empirical analysis of the tie formation process, which we will turn to next.

3 Model

To analyze the mechanisms of network formation, we employ a stochastic actor-oriented model (SAOM) in the spirit of Snijders et al. (2013). The model describes the multiplex dynamics of co-evolving networks, which allows us to study potential interdependencies between trade relationships within and across OECD countries and their preferences to export to or import from non-OECD countries. The SAOM is a micro-founded model that approaches network formation from the viewpoint of individual nodes.[7] These form new or dissolve existing ties, leading to incremental changes of the network over time. To simulate the evolution of the network, the SAOM splits the period between two network observations into a sequence of unobserved micro steps, assuming that the waiting time between two steps follows a Poisson process. At each of these micro steps, one node has the opportunity (but not the obligation) to change one tie variable based on its individual objective function. This may lead to the creation of a new tie, the elimination of an existing tie, or may leave the current network configuration unchanged.

In the model, two components describe the evolution of the network. The first component is the Poisson rate which determines the frequency of change opportunities. We simplify the model by assuming identical, constant Poisson rates for all actors in the respective network. The second component describes the change determination process. For each of the three different networks, individual preferences regarding these changes are expressed in a random utility function. For example, for the one mode network, we have

$$u_i^X(x, y, z, v) = f_i^X(x, y, z, v) + \epsilon_i, \tag{1}$$

[7] The SAOM provides a complementary view to the exponential random graph model (ERGM) introduced by Holland and Leinhardt (1981), which estimates the network formation mechanism from an aggregate optimization problem in which the network is created at once rather than link by link as in the SAOM (see Lusher et al., 2012; Robins et al., 2007, for an introduction to the ERGM).

where $f_i^X(x, y, z, v)$ is a deterministic evaluation function depending on network and covariate statistics, and ϵ_i are stochastic innovations drawn from a Gumbel distribution.[8] The evaluation function incorporates alternative mechanisms of network formation. For the one-mode network, the evaluation function of actor i reads

$$f_i^X(x, y, z, v) = \sum_k \beta_k^X e_{ki}^X(x, y, z, v), \tag{2}$$

representing a linear combination of effects $e^X(x, y, z, v)$, with running index k, which reflect the influence of the current network structure and node idiosyncrasies on network formation. Whereas the former is captured by the network variables x, y and z, the influence of the latter is captured by (exogenous) covariates v. The coefficients β_k^X measure the sign and strength of the different effects and are estimated from the data. We will explain our choice of the implemented effects in the next section.

3.1 Specification of the evaluation functions

By the type of the explanatory variable, we distinguish structural and covariate-related effects. Structural effects capture the influence of the current network structure, whereas effects based on individual and dyadic covariates reflect the influence of the characteristics of country-sectors (or pairs thereof) on the formation of trade relationships. We explain the different effects incorporated in our model in Sections 3.1.1-3.1.2 below (see Appendix A.3 for formal definitions).

3.1.1 One-mode network

The out-degree density effect is standard in the SAOM literature and is defined as the number of outgoing links of the focal node, reflecting the overall tendency of nodes to form network ties.[9] Another standard structural effect incorporated in our model is reciprocity, defined as the number of counterparties that maintain at the same time import and

[8] Identical functions can be defined for the two-mode networks. We omit them to simplify the exposition.

[9] Its role in the model is similar to that of an intercept in a regression model.

export relations with the focal country-sector, thereby accounting for bidirectional trade flows. Prior work suggests that reciprocated ties may originate in bargaining strategies as reciprocity is an effective means to elicit cooperation from trading partners (Rhodes, 1989).

Recent theoretical work on endogenous production networks argues that producers preferably select new trading partners from the suppliers of their current suppliers (e.g., Carvalho and Voigtländer, 2014; Chaney, 2014). To account for this phenomenon, we incorporate the transitive triplets effect. For the focal country-sector i, this effect is defined as the number of triadic relations in which i sources inputs from country-sectors j and k, and additionally j sources inputs from k. Thus a positive coefficient of the transitive triplets effect would indicate that country-sectors have a higher propensity to source inputs from other country-sectors if the latter already supply to a third country-sector that delivers to the first country-sector. Such tendencies for triadic closure can rationalized with the diffusion of innovation or search and informational frictions where producers use existing relationships to search for new trading partners.[10]

Pertinent literature further suggests that trade networks exhibit significant degree correlations between buyers and sellers (Bernard et al., 2019b, 2018; Squartini et al., 2011), which can be explained with heterogeneous productivity. Since it is easier for more efficient producers to bear the cost of establishing and maintaining a trade relationship, high productivity suppliers sell to more customers and their marginal customer is smaller and less productive than that of a low productive producer. The SAOM captures degree correlations through in-out and out-in-degree assortativity effects. A positive coefficient of out-in-degree assortativity would indicate that country-sectors with high out-degrees (many suppliers) exhibit a tendency to source inputs from country-sectors with high in-degrees (many customers). The in-out-degree assortativity, on the other hand, reflects the tendency of nodes with high in-degrees (many customers) to source from country-sectors with high out-degrees (many suppliers).

[10] In the literature on social networks, this mechanism is known as the "friends of friends become my friends" effect (Jackson and Rogers, 2007).

To investigate the influence of sector and country-level characteristics on the formation of trade relationships, we include effects based on individual and dyadic covariates. The technological similarity effect tests whether and how technological proximity influences the formation of network linkages. Under the hypothesis that technologically proximate inputs are more compatible, one may expect that similar production units are more likely to form ties. Our measure of technological similarity is the distance between ISIC Rev. 4 industry classification codes of two production units.

Recent work by Bernard et al. (2019a, 2018) emphasizes the role of customer-supplier heterogeneity in explaining the formation of trade relationships. Consequently, we study the influence of several idiosyncrasies on both the activity of a customer to search for new partners and the probability of a supplier to be selected as a counterparty. In the SAOM, the relevant mechanisms are called activity and popularity effects. The activity effect measures whether country-sectors with high realizations of the covariate v are more active in creating outgoing ties and thus have more suppliers. The popularity effect, on the other hand, measures whether high v country-sectors are more frequently selected as suppliers. As covariates for these activity and popularity effects, we include the output share of a country in the world market as a measure of size, productivity, and an index of the diversity of a country's economy.[11] Our measure of the former is the ratio of a country's output in a given sector to global output in that industry. Consideration of the output share popularity effect is consistent with research documenting that large suppliers have more customers (Bernard and Moxnes, 2018). It also conforms with evidence on the importance of preferential attachment for the evolution of real-world production networks (e.g., Atalay et al., 2011) because, for a given market size, output share popularity is equivalent to preferential attachment when changes in trade volume are caused by the extensive margin as in Melitz (2003). The rationale of the output

[11] To account for sectoral specificities in the explanatory variables, we measure the covariates as deviations from their sectoral average across all countries. For example, a positive parameter of the popularity effect then implies that country-sectors prefer sourcing inputs from country-sectors that are above the average in terms of the pertinent covariate, while country-sectors with realizations below the average are less attractive suppliers. Moreover, we transform continuous data into percentiles and replace the original observation with the number of each percentile. This procedure does not only improve the performance of the simulation algorithm, but also enables us to compare the estimated parameters across the effects.

share activity effect is that large country-sectors depend on more inputs and thus have more import relationships.

Trade theory also highlights the influence of production efficiency on the formation of trade links. For example, Lim (2018) argues that more productive producers form more links both upstream and downstream, matching with more potential customers and generating higher demand for intermediate inputs. In a similar vein, Bernard et al. (2019b) argue that outsourcing is costly and only the most productive producers can bear these costs of trade, leading to a situation where more productive producers have more suppliers. In the SAOM, this tendency is reflected in the productivity activity effect. At the same time, higher productivity implies lower cost of production, which should lead to lower prices and more export relationships (Gualdi and Mandel, 2016; McNerney et al., 2022; Oberfield, 2018). We test this hypothesis through the productivity popularity effect. Our measure of production efficiency is the change in total factor productivity (TFP) computed from

$$TFP_{i,t} = VA_{i,t}/(EMPN_{i,t}^{\alpha_{i,t}} \cdot CFC_{i,t}^{1-\alpha_{i,t}}), \tag{3}$$

where $VA_{i,t}$ represents value added, $EMPN_{i,t}$ denotes the number of employees, $CFC_{i,t}$ is the consumption of fixed capital, and $\alpha_{i,t}$ denotes the labor share.[12]

Hidalgo and Hausmann (2009) have shown that the availability of capabilities in a country is predictive of the complexity of its economy, the diversity and ubiquity of its output and its export vector. To account for such structural differences between the economies in our sample, we include economic complexity activity and popularity effects. The pertinent data come from the Atlas of Economic Complexity (Hausmann et al., 2014).

Trade linkages between country-sectors may also originate in input complementarities in production processes, arising when the manufacturing of goods requires specific

[12]Based on an comparison of alternative measures for different countries, Blades and Meyer-zu Schlochtern (1998) argue that consumption of fixed capital is the preferred measure of the capital stock.

combinations of non-substitutable inputs.[13] To account for this, we include the technological complementarity effect by constructing a dyadic indicator variable that turns one if a particular input is needed for the production of output in another industry, and zero otherwise. This variable is determined from the input-output data at the beginning of the sample period, 2005, by compiling, for each sector i, a list of other sectors $j \neq i$ that supply inputs to i. We call these sectors the technology set of industry i.

Consistent with classic gravity-type models of trade, we include an effect based on the geographical distance between the capitals of the different OECD and non-OECD countries as a proxy for transportation costs. Additionally, geographical distance has been associated with the diffusion of information in the matching process between buyers and sellers (Allen, 2014; Chaney, 2016), implying that the role of distance might reach beyond the classical transportation cost argument.

Finally, we also control for the existence of free-trade agreements (FTAs) between the different countries that reduce tariff and non-tariff barriers to trade and are supposed to stimulate the formation of trade linkages (Baier and Bergstrand, 2007). To this end, we count the number of existing free trade agreements (FTA) between countries.

3.1.2 Two-mode networks

In the two-mode networks, we incorporate the out-degree density as well as the 4-cycles effect as structural mechanisms. Whereas the meaning of the former is the same as in the one-mode network, the latter measures the tendency of overlap in preferences for the same non-OECD import or export partners among OECD country-sectors. Specifically, the 4-cycles effect tests the hypothesis that OECD country-sectors, which import from or export to the same non-OECD country-sectors, tend to have more non-OECD trading partners in common. One possible economic rationale for these peer effects in trade is that producers learn from the performance of their peers before undertaking risky investments in export markets, especially if self-discovery would entail high sunk costs

[13]For example, the production of steel requires iron ore, oxygen, and other minerals, which reduces the set of feasible backward connections of steel producers to a smaller subset of industries.

(Fernandes and Tang, 2014). Prior work documented learning effects and knowledge spillovers also for import decisions (Bisztray et al., 2018).

The activity effects for output share, economic complexity, and productivity as well as the dyadic covariate effects based on technological complementarity, geographic distance and FTAs are identical to those described in Section 3.1.1 for the one-mode network and are not repeated here.[14] Yet the consideration of two separate two-mode networks enables us to study their potentially asymmetric effect on developed countries' exports to and imports from developing economies, which adds a new perspective to the evolution of trade relationships.

3.1.3 Interaction effects

Finally, we address the question whether and how input ties between OECD countries have an influence on trade with non-OECD economies, and vice versa. To this end, we investigate the interaction between the one-mode and two-mode networks. Mechanisms to model interactions between different types of networks in the SAOM are agreement and entrainment effects. Agreement effects come in two different flavors. The one-mode tie from two-mode agreement effect tests whether two OECD country-sectors with the same non-OECD import or export partners are more likely to form intra-OECD trade links between each other. The one-mode tie leading to two-mode agreement effect captures the tendency that two OECD country-sectors with a trade relationship start to export into or import from the same non-OECD country-sectors. Last but not least, the entrainment effect tests if OECD imports from non-OECD country-sectors lead to exports into these country-sectors, and vice versa.

3.2 Estimation

The parameters of the model are estimated with the method of simulated moments using the RSiena program (Ripley et al., 2011). The simulation algorithm underlying

[14] An important difference between the one-mode and two-mode network is the absence of covariate-weighted popularity effects in the latter because merely nodes in the first mode are considered as actors, whereas nodes in the second mode represent preferences.

this program consists of three phases. The first phase assesses the sensitivity of the statistics used to evaluate convergence of the simulated networks to the empirical data (e.g., the total number of changed ties or the number of reciprocated relationships) with respect to the parameters. The second phase improves these provisional parameters in an iterative process. To this end, the program calculates the deviation of these moments from the observed values at the end of the observation period and adjusts the parameters using the Robbins-Monro algorithm (see, e.g., Kushner and Yin, 2003). The last phase tests whether the average statistics of a large number of network simulations are close enough to the target values.

4 Results

We estimate the model for the whole period 2005-2015 assuming constant parameters across the years. The pertinent t-statistics are less than 0.1 and the overall maximum convergence ratio is below 0.25, indicating good convergence of the simulation according to Snijders et al. (2010). To ease the exposition, we divide the discussion of the results into three parts. Section 4.1 discusses our findings pertaining to intra-OECD trade in the one-mode network, whereas Section 4.2 presents the results for the two-mode networks of trade relationships between OECD and non-OECD countries. Section 4.3 focuses on the multiplex dynamics of the different networks, investigating the mutual dependence between intra-OECD trade and import and export relationships with developing economies.

4.1 Formation of intra-OECD trade relationships

The results for the intra-OECD trade network in Table 2 point to a negative outdegree density effect, which suggests that establishing and maintaining trade relationships is costly and thus leads to a sparse network.[15] Reciprocity and transitivity are positive and statistically significant at the 1% level. The former shows that producers prefer to

[15]A positive density effect would imply a tendency to converge to a fully connected network.

Effect	Coefficient	Standard error
Network		
Outdegree density	-5.7285^{***}	0.0860
Reciprocity	0.6176^{***}	0.0329
Transitive triplets	0.4395^{***}	0.0061
Out-in degree assortativity	0.0585^{***}	0.0020
In-out degree assortativity	-0.0668^{***}	0.0034
Time-dependent individual covariates		
Output share activity	-0.0415^{***}	0.0053
Output share popularity	0.1330^{***}	0.0053
Productivity activity	0.0356^{***}	0.0056
Productivity popularity	0.0110^{***}	0.0044
Economic complexity activity	-0.0622^{***}	0.0049
Economic complexity popularity	0.0337^{***}	0.0045
Time-invariant dyadic covariates		
Technological similarity	1.2627^{***}	0.0456
Geographic distance	-0.2196^{***}	0.0076
Time-dependent dyadic covariates		
Technological complementarity	0.5395^{***}	0.0257
Free trade agreements	0.0571^{***}	0.0073

Table 2: Estimated coefficients for the one-mode network of intra-OECD trade. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

create mutual trade relations, i.e., exporting to a country-sector makes it more likely to also import intermediates from it, and that producers value maintaining such mutual relationships. Moreover, the observed tendency toward transitive closure supports recent theorizing on endogenous production networks arguing that producers acquire new trade relationships through their network of current contacts.

Our empirical analysis also testifies to significant degree correlations in global production chains. The in-outdegree assortativity effect is negative and significant at the 1% level. This means that country-sectors with few customers link, on average, to country-sectors with many suppliers, consistent with the theoretical prediction by Bernard et al. (2018). Moreover, the positive out-indegree assortativity implies that country-sectors with many suppliers form upstream relationships to country-sectors with many customers. These local mechanisms contribute to the emergence of a hierarchical core-periphery structure, where strongly connected production units in the core trade among themselves and with a large number of country-sectors in the periphery, which are well connected to the core but seldom trade with each other.

Size, productivity, and complexity might measure similar and thus correlated attributes of production units. Yet, our results do not confirm this intuition since the activity and popularity effects are highly significant for all three attributes, partly with opposing signs. In particular, we find that large country-sectors are more frequently selected as input providers, but are themselves less active in forming upstream ties. Excessively productive country-sectors are both more active and popular, yet the productivity popularity effect is relatively small. This confirms results in Mundt (2021) for EU data, and casts doubt on the dominant role of heterogeneity in productivity as a driver of network formation in theoretical studies. Our estimation further suggests that complex economies are less active in forming upstream relationships since the pertinent activity effect is significantly negative. At the same time, country-sectors that are more diverse in their economic capabilities are more frequently selected as suppliers because more downstream sectors depend on their inputs. Thus, economic complexity is not merely a crucial determinant for growth and prosperity, but also a relevant factor in the formation of production networks.

The two technology effects for similarity and complementarities in production functions are significantly positive and thus have the expected sign. The hypothesized influence of geography on trade is reflected in the negative distance effect, implying that the propensity to establish trade relationships declines with geographical distance. Finally, free trade agreements (FTA) foster the formation of input linkages between OECD countries as the pertinent FTA effect is significantly positive, though the strength of this effect is relatively small. One explanation is that barriers to trade are lower between OECD countries, which renders the influence of these agreements on the formation of trade relationships less important.

Effect	Activity	Coefficient	Standard error
Network			
Outdegree-density	Export	-19.3160^{***}	1.6272
	Import	-9.4588^{***}	0.5996
4-cycles	Export	0.2288^{***}	0.0109
	Import	0.1764^{***}	0.0112
Time-dependent dyadic covariates			
Technological complementarity	Export	6.9369^{***}	1.6275
	Import	2.7961^{***}	0.4125
Free trade agreements	Export	0.3014^{***}	0.0235
	Import	-0.2737^{***}	0.0965
Time-invariant dyadic covariates			
Geographical distance	Export	-0.2187^{***}	0.0148
	Import	-0.1857^{***}	0.0306
Time-dependent individual covariates			
Output share activity	Export	0.6713^{***}	0.0267
	Import	-0.0394	0.0294
Productivity activity	Export	-0.0519^{**}	0.0256
	Import	-0.0490	0.0472
Economic complexity activity	Export	0.0789^{***}	0.0182
	Import	-0.0868^{***}	0.0294

Table 3: Estimated coefficients for the two-mode networks. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

4.2 Formation of import and export ties with non-OECD countries

Next, we turn to the results for the two-mode networks in Table 3. Like the network of intra-OECD trade, the two bipartite networks of import and export activities with non-OECD countries exhibit negative outdegree density, a consequence of the sparsity of these networks. The new 4-cycles effect is significantly positive and thus testifies to peer effects in the formation of trade relationships. In the context of two-mode networks, this implies overlap in the preferences for the same non-OECD import and export partners, i.e. OECD country-sectors which import from or export to the same non-OECD country-sectors typically have more trade partners in common.

Whereas technological complementarity (positive) and geographical distance (negative) exhibit the same sign as in the one-mode network and impact symmetrically on imports and exports, FTAs have an asymmetric effect on the formation of trade relationships. On the one hand, FTAs lead to more export ties from OECD into non-OECD countries but, on the other hand, they have a negative effect on OECD imports from non-OECD economies. One explanation is that recent FTAs include product, labor and environmental standards, which may impose constraints on the access to international markets (see, e.g., Grundke and Moser, 2019; McGee and Yoon, 2003). Moreover, these regulations can reduce cost advantages of non-OECD exporters as the latter need to meet the higher standards, thereby reducing the import ties between OECD and non-OECD countries.[16] Compared to the network of intra-OECD trade, the estimated FTA effects are stronger for trade relationships between OECD and non-OECD countries, which likely originates in higher trade barriers between these countries.

Considering the different covariate effects, we find that large OECD country-sectors have more export relationships with non-OECD country-sectors, whereas the size effect on imports is insignificant. Our analysis further suggests that more complex economies have more export and fewer import ties with non-OECD countries and both effects are statistically significant at the 1% level. These results would be consistent with the hypothesis that mainly products produced in large, complex high-income economies in the core are exported to developing economies in the periphery, and that the dependence of OECD countries on imports of primary and less complex products from developing countries in the periphery declines with the economic complexity of the former. What is somehow unexpected is that disproportionately productive industries in OECD countries have fewer export ties to non-OECD countries, whereas the influence of productivity on imports is insignificant.

[16] Bernard and Dhingra (2016) report similar adverse effects of trade liberalization. Analyzing the consequences of the US-Colombia free trade agreement on firm-to-firm matching, they find that US exporters increased their average prices, reduced their export volume and the number of their import partners in the Colombian market.

Effect	Explanatory variable	Dependent variable	Coefficient	Standard error
Network				
One-mode tie from two-mode agreement	two-mode export	one-mode	0.3061***	0.0222
	two-mode import	one-mode	0.2130*	0.1173
One-mode tie leading to two-mode agreement	one-mode	two-mode export	1.3582***	0.0376
	one-mode	two-mode import	3.0373***	0.1176
Entrainment	two-mode import	two-mode export	3.3371***	0.5169
	two-mode export	two-mode import	1.2508	0.8891

Table 4: Estimated coefficients for the multiplex dynamics of the one-mode and two-mode network. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

4.3 Multiplex Dynamics

The estimation results for the joint evolution of the three networks in Table 4 testify to significant interaction effects between intra-OECD trade and trade between OECD and non-OECD countries. Specifically, agreement between OECD country-sectors to export to the same non-OECD country-sector promotes the creation of trade relationships between the same OECD country-sectors in the one-mode network. The same is true for imports, i.e. OECD countries importing from the same non-OECD countries exhibit a higher probability to establish a mutual trade relationship, though this effect is merely weakly significant.[17] We also find that intra-OECD trade ties have an effect on the formation of export and import ties with non-OECD economies. Both one-mode tie leading to two-mode agreement effects are significantly positive, which implies that the existence of a trade relationship between two OECD country-sectors in the one-mode network leads to more export or import ties with the same non-OECD country-sectors. We conjecture that learning effects as in Bisztray et al. (2018); Fernandes and Tang (2014) provide an explanation of these patterns.

Another interesting finding is the positive and highly significant entrainment effect for imports, which implies that OECD imports from non-OECD country-sectors

[17]In additional experiments, we analyzed whether similarity of OECD country-sectors with respect to their individual characteristics can explain the aforementioned agreement effects. To this end, we interact the latter with covariates. The one-mode tie from export agreement with same productivity is significant at the 1% level with a coefficient of 0.1435, whereas it is insignificant for complexity. Moreover, common import ties lead to intra-OECD trade especially when OECD country-sectors are similar with respect to their productivity (the pertinent coefficient 0.3427 is significant at the 10% level) and complexity (with a coefficient of 0.2945 that is significant at the 5% level).

promote the creation of export ties to the same non-OECD country-sectors. Perhaps somewhat surprisingly, however, OECD exports to non-OECD countries do not lead to more import ties with the latter. One possible interpretation of this asymmetry is that OECD countries maintain trade relationships with non-OECD countries especially in their upstream value chain activities to source basic inputs such as raw materials, and then sell (pre)finished goods back to these non-OECD countries. These patterns would be consistent with the dependency theory, predicting that resources flow from the periphery of developing countries to the core of highly industrialized countries (Kostoska et al., 2020). The fact that the same is not true for the entrainment effect from exports on imports reflects favorably on this interpretation.

5 Conclusions

This paper investigated the formation of trade linkages in global production chains. A key feature of our empirical model is its inherent actor-orientation. This implies that it approaches the evolution of global production chains from the perspective of individual nodes, assuming that network change originates in local change processes and their interactions. Our model thus helps to explain stylized facts of production networks based on the micro-mechanisms of network change. For example, the significant tendency toward transitive closure rationalizes clustering observed in empirical data (see, e.g., Chakraborty and Ikeda, 2020), which the pertinent theoretical literature in international trade typically ascribes to knowledge spillovers and learning. Moreover, the finding that large or more productive country-sectors are more popular and thus accumulate additional linkages over time provides an economic rationale on top of purely statistical explanations (see, e.g., Atalay et al., 2011) why empirical production networks have a small diameter and are well connected, colloquially summarized as the "small world property" (see, e.g., Carvalho, 2014). We also uncover mechanisms that lead to a core-periphery structure in the global production network, e.g, assortative and disassortative matching, entrainment, as well as size and complexity activity effects. Overall, our results point to a great deal of empirical regularity and structure in the tie formation process, which apparently lead to persistent structural features of the global production network in terms of, e.g., degree distribution, connectivity, and hierarchy.

An important aspect of the present work is the joint analysis of tie formation within OECD as well as between OECD and non-OECD countries in a dynamic multiplex network model. Building on this extension, we obtain several interesting and perhaps even unexpected findings. For example, our results suggest that free trade agreements have an asymmetric effect on the formation of trade linkages, increasing OECD countries' export ties but reducing import ties with non-OECD countries. This finding may support the view that the benefits from FTAs are unequally distributed between developed and developing countries (see, e.g., the discussion in McQueen, 2002), with the important qualification that our model predicts binary outcomes and thus cannot shed light on the intensive margin of trade. Our analysis also points to significant interaction effects between the different networks. For instance, we found strong empirical support for overlap in the preferences for non-OECD import and export partners among OECD countries. Common choices of two OECD countries with respect to their non-OECD trade partners even impact the probability of forming intra-OECD trade relationships between the same countries, and vice versa, testifying to some sort of mixed transitivity across networks that calls for a theoretical explanation.

A salient result of our empirical study is the relevance of peer effects in the evolution of global production chains. This means that the network structure of production itself, including interactions between different networks, is a major determinant of the tie formation process, and certainly requires further empirical and theoretical investigations. The SAOM is a good starting point to better understand these patterns of network formation, and the uncovered regularities could be integrated in theoretical models of global production chain formation.

A Appendix

A.1 Data

OECD countries	Code	Non-OECD countries	Code
Australia	AUS	Argentina	ARG
Austria	AUT	Brazil	BRA
Belgium	BEL	Brunei Darussalam	BRN
Canada	CAN	Bulgaria	BGR
Chile	CHL	Cambodia	KHM
Czech Republic	CZE	China	CHN
Denmark	DNK	Colombia	COL
Estonia	EST	Costa Rica	CRI
Finland	FIN	Croatia	HRV
France	FRA	Cyprus	CYP
Germany	DEU	India	IND
Greece	GRC	Indonesia	IDN
Hungary	HUN	Hong Kong	HKG
Iceland	ISL	Kazakhstan	KAZ
Ireland	IRL	Malaysia	MYS
Israel	ISR	Malta	MLT
Italy	ITA	Morocco	MAR
Japan	JPN	Peru	PER
Korea	KOR	Philippines	PHL
Latvia	LVA	Romania	ROU
Lithuania	LTU	Russia	RUS
Luxembourg	LUX	Saudi Arabia	SAU
Mexico	MEX	Singapore	SGP
Netherlands	NLD	South Africa	ZAF
New Zealand	NZL	Chinese Taipei	TWN
Norway	NOR	Thailand	THA
Poland	POL	Tunisia	TUN
Portugal	PRT	Vietnam	VNM
Slovak Republic	SVK		
Slovenia	SVN		
Spain	ESP		
Sweden	SWE		
Switzerland	CHE		
Turkey	TUR		
United Kingdom	GBR		
United States	USA		

Table 5: Countries in the OECD Inter-Country Input-Output (ICIO) Tables.

Industry	Code	ISIC Rev.4
Agriculture, forestry and fishing	D01T03	01-03
Mining and extraction of energy producing products	D05T06	05-06
Mining and quarrying of non-energy producing products	D07T08	07-08
Mining support service activities	D09	09
Food products, beverages and tobacco	D10T12	10-12
Textiles, wearing apparel, leather and related products	D13T15	13-15
Wood and products of wood and cork	D16	16
Paper products and printing	D17T18	17-18
Coke and refined petroleum products	D19	19
Chemicals and pharmaceutical products	D20T21	20-21
Rubber and plastic products	D22	22
Other non-metallic mineral products	D23	23
Basic metals	D24	24
Fabricated metal products	D25	25
Computer, electronic and optical products	D26	26
Electrical equipment	D27	27
Machinery and equipment, nec	D28	28
Motor vehicles, trailers and semi-trailers	D29	29
Other transport equipment	D30	30
Other manufacturing; repair and installation of machinery and equipment	D31T33	31-33
Electricity, gas, water supply, sewerage, waste and remediation services	D35T39	35-39
Construction	D41T43	41-43
Wholesale and retail trade; repair of motor vehicles	D45T47	45-47
Transportation and storage	D49T53	49-53
Accomodation and food services	D55T56	55-56
Publishing, audiovisual and broadcasting activities	D58T60	58-60
Telecommunications	D61	61
IT and other information services	D62T63	62-63
Financial and insurance activities	D64T66	64-66
Real estate activities	D68	68
Other business sector services	D69T82	69-82
Public admin. and defence; compulsory social security	D84	84
Education	D85	85
Human health and social work	D86T88	86-88
Arts, entertainment, recreation and other service activities	D90T96	90-96
Private households with employed persons	D97T98	97-98

Table 6: Industries in the OECD Inter-Country Input-Output (ICIO) Tables.

A.2 Network persistence

Years	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015
One-mode network										
$0 \Rightarrow 0$	1666932	1666934	1666435	1666696	1666633	1667069	1667072	1667084	1667059	1666670
$0 \Rightarrow 1$	632	649	1178	929	1081	661	707	643	721	1149
$1 \Rightarrow 0$	651	679	1190	1018	1097	710	655	696	760	1146
$1 \Rightarrow 1$	10105	10058	9517	9677	9509	9880	9886	9897	9780	9355
Hamming distance	1283	1328	2368	1947	2178	1371	1362	1339	1481	2295
Two-mode export network										
$0 \Rightarrow 0$	1305207	1305204	1305170	1305271	1305322	1305286	1305217	1305297	1305381	1305404
$0 \Rightarrow 1$	236	197	227	157	265	208	251	147	121	136
$1 \Rightarrow 0$	194	193	258	316	172	182	227	205	159	163
$1 \Rightarrow 1$	731	774	713	624	609	692	673	719	707	665
Hamming distance	430	390	485	473	437	390	478	352	280	299
Two-mode import network										
$0 \Rightarrow 0$	1306030	1306027	1306023	1306043	1306041	1305998	1305987	1306011	1306041	1306070
$0 \Rightarrow 1$	62	42	64	45	90	75	42	43	27	25
$1 \Rightarrow 0$	39	60	65	88	32	31	67	57	54	50
$1 \Rightarrow 1$	237	239	216	192	205	264	272	257	246	223
Hamming distance	101	102	129	133	122	106	109	100	81	75

Table 7: Change and persistence of network ties. $0 \Rightarrow 0$ counts the number of links that are absent (inactive) in both waves of network panel data. $0 \Rightarrow 1$ counts newly created trade links. $1 \Rightarrow 0$ counts dissolved trade links. $1 \Rightarrow 1$ is the number of trade relationships that persist over two consecutive years. The Hamming distance measures the number of links that differ between two consecutive waves, i.e. the sum of $0 \Rightarrow 1$ and $1 \Rightarrow 0$.

A.3 Effects

Level	Effect	Definition
Network		
Industry	Outdegree density	$\sum_j x_{ij}$
Industry	Reciprocity	$\sum_j x_{ij}x_{ji}$
Industry	Transitive triplets	$\sum_{j,h} x_{ij}x_{ih}x_{hj}$
Industry	Out-in degree assortativity	$\sum_j x_{ij}\sqrt{x_{i+}}\sqrt{x_{+j}}$
Industry	In-out degree assortativity	$\sum_j x_{ij}\sqrt{x_{+i}}\sqrt{x_{j+}}$
Time-invariant dyadic covariates		
Industry	Technological similarity	$\sum_j x_{ij}(sim_{ij}^v - \hat{sim}^v)$
Country	Geographical distance	$\sum_j x_{ij}v_{ij}$
Time-dependent individual covariates		
Industry	Output share activity	$v_i x_{i+}$
Industry	Output share popularity	$\sum_j x_{ij}v_j$
Industry	Productivity activity	$v_i x_{i+}$
Industry	Productivity popularity	$\sum_j x_{ij}v_j$
Country	Economic complexity activity	$v_i x_{i+}$
Country	Economic complexity popularity	$\sum_j x_{ij}v_j$
Time-dependent dyadic covariates		
Industry	Technological complementarity	$\sum_j x_{ij}v_{ij}$
Country	Free trade agreements	$\sum_j x_{ij}v_{ij}$

Table 8: Effects for the one-mode network of intra-OECD trade. Relationships between OECD country-sectors in the one-mode network are denoted by x_{ij}. v are covariates. Subscript "+" denotes summation over the pertinent index. In the definition of similarity effects, $\hat{sim}^v$ is the mean over all similarity scores, which are defined as $sim_{ij}^v = (\Delta - |v_i - v_j|/\Delta)$, with the support of the covariate $\Delta = \max_{ij} |v_i - v_j|$.

Level	Effect	Definition
Network		
Industry	Outdegree density	$\sum_p y_{ip}$, $\sum_p z_{ip}$
Industry	4-cycles	$\frac{1}{4}\sum_{p,k,h} y_{ip}y_{ik}y_{hp}y_{hk}$, $\frac{1}{4}\sum_{p,k,h} z_{ip}z_{ik}z_{hp}z_{hk}$
Time-dependent individual covariates		
Industry	Output share activity	$v_i y_{i+}$, $v_i z_{i+}$
Country	Economic complexity activity	$v_i y_{i+}$, $v_i y_{i+}$
Industry	Productivity activity	$v_i y_{i+}$, $v_i y_{i+}$
Time-invariant dyadic covariates		
Country	Geographic distance	$\sum_j y_{ij}v_{ij}$, $\sum_j z_{ij}v_{ij}$
Time-dependent dyadic covariates		
Industry	Technological complementarity	$\sum_j y_{ij}v_{ij}$, $\sum_j z_{ij}v_{ij}$
Country	Free trade agreements	$\sum_j y_{ij}v_{ij}$, $\sum_j z_{ij}v_{ij}$

Table 9: Effects for the two-mode networks. y_{ip} are OECD import relationships from non-OECD country-sectors, and z_{ip} are export ties from OECD into non-OECD country-sectors. v represent covariates. Subscript + denotes summation over the pertinent index.

Level	Effect	Definition
Multiplex network dynamics		
Industry	One-mode tie from two-mode agreement	$\sum_{j\neq h} x_{ij}y_{ih}y_{jh}$, $\sum_{j\neq h} x_{ij}z_{ih}z_{jh}$
Industry	One-mode tie leading to two-mode agreement	$\sum_{j\neq h} y_{ij}x_{ih}y_{hj}$, $\sum_{j\neq h} z_{ij}x_{ih}z_{hj}$
Industry	Entrainment	$\sum_j y_{ij}z_{ij}$

Table 10: Effects for the interaction of one-mode and two-mode networks. Relationships between OECD country-sectors in the one-mode network are denoted by x_{ij}. y_{ip} are OECD import relationships from non-OECD country-sectors, and z_{ip} are export ties from OECD into non-OECD country-sectors. v represent covariates.

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