Network Science (2023), 1–20
doi:10.1017/nws.2023.19

RESEARCH ARTICLE

Business transactions and ownership ties between firms

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Action Editor: Dr. Paolo Pin

Abstract
In this study, we investigate the creation and persistence of interfirm ties in a large-scale business transaction network. Business transaction relations (firms buying or selling products or services to each other) are driven by economic motives, but because trust is essential to business relationships, the social connections of owners or the geographical proximity of firms can also influence their development. However, studying the formation of interfirm business transaction ties on a large scale is rare, because of the significant data demand. The business transaction and the ownership networks of Hungarian firms are constructed from two administrative datasets for 2016 and 2017. We show that direct or indirect connections in this two-layered network, including open triads in the business network, contribute to both the creation and persistence of business transaction ties. For our estimations, we utilize log-linear models and emphasize their efficiency in predicting links in such large networks. We contribute to the literature by presenting different patterns of business connections in a nationwide multilayer interfirm network.

Keywords: transaction network; ownership network; multilayer network; network motifs; tie creation; tie persistence

1. Introduction

Economic production happens through the interaction of firms. Studying these interfirm interactions—such as transactions of firms buying or selling products or services to another firm—allows us to understand production processes (Atalay et al., 2011; McNerney et al., 2022), supply chain mechanisms (Arora & Brintrup, 2021; Todo et al., 2016), or economic shock propagation (Diem et al., 2021; Inoue & Todo, 2019; Pálovics et al., 2021).

The web of relationships between companies is essential for markets, as they convey information, resources, and knowledge within a social structure. Before the millennium, studies on business networks were mostly preoccupied with the buyer and supplier relationships of a handful of firms and mainly took an ego-network perspective (see Provan, 1993). However, the availability of large-scale datasets on firm-to-firm interactions enables researchers to analyze the complex structures of these networks (see Fujiwara & Aoyama, 2010; Atalay et al., 2011). Nodes of such networks represent companies and linkages between them indicate a business transaction, such as buying or selling a product.

We will refer to this network, which represents firms buying products or services from each other, as "business transaction networks" to distinguish it from the very close concepts of "production network," which often refers to the same network, but with separate layers for each specific product (e.g. Diem et al., 2021), and from "supply chain networks," which often refers to the same network, but with only one specific direction (e.g. downstream) from the perspective of the focal firm (e.g. Arora & Brintrup, 2021).

Business transaction networks have noteworthy features. Their degree distribution is highly unequal and is similar to scale-free networks (Fujiwara & Aoyama, 2010; Jaeheon & Sang, 2016; Mizuno et al., 2014; Ohnishi et al., 2009). As firm size and market strategy determines buyer and supplier connections, larger companies with a diverse product portfolio have more business transaction ties. The geographic proximity of firms is another strong predictor of business ties (Bernard et al., 2019), as establishing and maintaining business connections is easier and cheaper over short distances. Therefore, productive firms tend to have more distant business partners than less productive ones (Bernard et al., 2019; Todo et al., 2016), which also relates to the fact that they outsource more intermediate products to developing countries (Antras & Helpman, 2004). Furthermore, business ties of firms are largely influenced by the industry they belong to. Instead of horizontal, intra-industry connections, business transaction networks tend to show a strong hierarchy (Kichikawa et al., 2019) driven by supply chains of production, however, the strength of this hierarchy varies by industry (Luo et al., 2012).

While previous works provided evidence on the structural features, geography, industrial hierarchy, and position-related outcomes of business networks, we still have a limited understanding of the underlying mechanisms that drive transaction network tie formation between firms. In other words, we know less about features that support the observation of business network ties between companies. Therefore, this study takes a novel perspective to explore the drivers of tie creation and persistence in interfirm business networks. By doing so, we contribute to the literature on network formation in the following ways.

First, we take a multilayer network approach (Kivelä et al., 2014) considering ownership relations and business transaction relations as two layers of connections between firms and studying the influence of co-ownership relations on business ties. Ownership ties signal power, influence, and trust between firms (Takes et al., 2018). We expect that ownership significantly enhances business tie formation and promotes reduced environmental uncertainty and predictable circumstances based on control and mutual learning.

Second, to assess the importance of multilayer network features on business tie formation, we focus on network motifs (Ohnishi et al., 2010). Network motifs are small subgraph patterns that occur significantly more frequently than random chance, and as such, they carry information about the underlying mechanisms of the system (Alon, 2007). So far, studies on transaction network motifs showed that open, V-shaped triads are relatively frequent, while transitive triads are relatively sparse in business transaction networks (Borsos & Stancsics, 2020; Ohnishi et al., 2010). In particular, we analyze network motif configurations to reveal the effect of direct and indirect co-ownership and transaction linkages on the formation of business transaction ties.

Third, we separately test the mechanisms of business tie creation and tie persistence. The distinction is important, because the motivations, related costs, constraints, and uncertainties may be different for creating and persisting relationships (Juhász & Lengyel, 2018; Wilson, 1995; Zerbini & Castaldo, 2007).

Fourth, to test the influence of geography, industrial similarity, and co-ownership through multi-level network motifs on business tie formation, we use log-linear models. In contrast to classic regression models on tie formation or simulation-based methods like ERGMs or SAOMs (Block et al., 2019; Broekel et al., 2014), log-linear models are fast and efficient to assess the relationship between the presence of links and different categorical factors even in large networks as they analyze associations between nominal variables in contingency tables.

Our approach is also related to studies on the prediction of relationships in transaction networks. These include link prediction using external information such as text in the news (Wichmann et al., 2020), telecommunication events (Reisch et al., 2021), the information available from the (incomplete) transaction network, such as the specific products produced by firms and potential partners (Brintrup et al, 2018), or the network structure of the neighborhood of

https://doi.org/10.1017/nws.2023.19 Published online by Cambridge University Press

the potential partners (Kosasih and Brintrup, 2022).We contribute to this literature by testing the contribution of specific configurations within the direct neighborhood of the predicted links. It is not our aim to assess the causality of these relationships, that could be done with proper econometric or casual machine learning methods. However, we utilize the dynamic aspect of networks and test the correlations between network configurations and the creation and persistence of connections in the business transaction network to better understand the micro-level building blocks of a nationwide economic network.

Our results, based on the Hungarian value-added tax (VAT) records, indicate that business transactions are more likely to be created and persisted between firms with ownership ties, which might be attributed to ownership networks reducing uncertainty. Furthermore, we find that indirect links in this multilayer network also increase the probability of creating and maintaining business transactions, which provides inputs for further studies on link prediction in business networks.

We proceed as follows. In Section 2, we summarize the literature about mechanisms that can influence the creation and persistence of business transaction ties and present the differences in economic and social motivations. Based on this theoretical framework, we formulate our hypotheses. Section 3 introduces the data source, data management, and applied methodologies, including details about network construction and estimation strategies. In Section 4, we present and discuss our empirical results. The paper concludes with a discussion that highlights our contribution to the social and economic network literature and outlines limitations and future research possibilities.

2. Formation of business transaction ties

2.1 Pure economic motivations

Analyzing business transaction networks is an emerging field, and it is tempting to use the well-established measures and concepts of social network analysis to explain business ties. Social networks usually have a high level of transitivity, as friends of friends are likely to be friends, and they tend to be reciprocal, meaning that social connections reflect mutual interest (Snijders, 2011). Homophily is another key driving force, as social relations are more likely between similar entities (McPherson et al., 2001; Rivera et al., 2010).

Homophily can be defined similarly for companies as for people. This suggests that firms similar in size, productivity, technology used, or other characteristics are more likely to trade with each other. However, the motivations that generate business transactions and social connections are fundamentally different. Buying products or services is driven by the principle of substitution and complementarity. Therefore, firms that are similar in terms of their products would rather be competitors instead of partners (Brintrup et al., 2018). Alternatively, if the products of two firms are complements, their buyers will be more likely to purchase from both of them. This complementarity, however, results in V-shape open triangles or square-like structures (of two buyers and two producers) instead of closed triads. In this sense, transaction networks are rather similar to functional networks, e.g. protein networks, with the overrepresentation of even paths (Brintrup et al., 2018, Mattsson et al., 2021) than to social networks.

2.2 Social ties and economic interaction

Besides the illustration of the difference between social and business networks, a large body of literature shows a crucial influence of embeddedness in social structures on economic activity. An important dimension of embeddedness is trust, as "*any business operation can be broken into a multilayered structure of principal-agent relations, each involving high levels of risk and uncertainty*" (Nee & Opper, 2015, p. 160). In a supplier-buyer context, such risks are potential losses due

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to deviance from timely delivery, fulfilling an urgent order in the case of a shortage of resources, or issues of quality (Uzzi, 1997; Perry, 2012; Nee & Opper, 2015).

Information on trustworthiness is accordingly exchanged among buyers and suppliers in small businesses (Murthy & Paul, 2017), and the subsequent reputation of the partner is in fact the single most important factor for choosing the supplier of a key input (Nee & Opper, 2015). Network structure, therefore, is also related to trust, because having common partners (indirect relationships) creates the opportunity for control by imposing sanctions (tarnishing one's reputation), and for learning about potential partners (Granovetter, 1985; Jackson et al., 2012). Consequently, network closure is strongly associated with trust among businessmen both for Western and for Chinese entrepreneurs (Burt & Burzynska, 2017). However, the relationships that support trust are not necessarily pure transactions, but most likely more complex social connections of interacting and exchanging information. In dynamic multiplex (or multilayer) networks, non-cooperative behavior could lead to spontaneous symmetry breaking in cooperation levels across the layers (Takács et al., 2021). Structural closure of relationships correspondingly also correlates with having multiple layers of relationships with business partners (Burt & Opper, 2017; Uzzi, 1997).

Trust in business may arise from personal friendships, shared values, or ethnicity (Kremel et al., 2014; Murthy & Paul, 2017; Sofer & Schnell, 2017), but can emerge in networks of control and power such as interlocked directorates (Mizruchi, 1996; Connelly et al, 2011). Consequently, to understand the mechanisms of tie formation in business transaction networks, we have to consider the embeddedness of firms in other relational structures. In this respect, we focus on ownership ties hereby defined as co-ownership connections of firms.

Ownership ties are social connections that signal high influence, as they represent the most direct control over corporate decision-making (Glattfelder & Battiston, 2009; Kogut & Walker, 2001; Mizruchi, 1996; Takes et al., 2018; Vitali et al., 2011). Thus, ownership relations represent a power of control that can limit the potential opportunistic behavior of partners. Furthermore, common ownership of the parties involved eliminates the economic motivation for opportunistic behavior, as it would harm the economic interests of the group as a whole. In addition to direct control, co-ownership relationships are considered a communication structure advancing the reproduction of existing beliefs and the diffusion of new ideas (Burris, 2005; Carroll et al., 2010; Mizruchi, 1996). Consequently, ownership relations are a crucial source of information exchange (Hillman & Dalziel, 2003), and as such, they improve the legitimation and reputation of firms (Galaskiewicz, 1985) and enhance the firms' cooptation of environmental uncertainty.

2.3 Drivers of tie creation and tie persistence

Studying the dynamics of interfirm connections, previous studies highlighted that the underlying motivations to establish new ties and to maintain connections can involve different costs, constraints, and uncertainties (Wilson, 1995; Zerbini & Castaldo, 2007); thus, that drivers of tie creation and tie persistence may differ. Zerbini and Castaldo (2007) argue that the creation of business relationships is based on economic advantages, but they also require trust and collaborative behavior. Later, social connections stabilize the relationship, allowing its expansion. In the long run, persistence of business ties mainly depends on the quality of social exchanges and cooperation. Wilson (1995) argues that reputation, trust, and performance are key criteria for selecting partners, while structural bonds, commitment, and cooperation are important for the persistence of relationships.

However, these underlying mechanisms are hardly observable in our case; thus, we can build our hypotheses on observable indicators related to them. These are shared ties that may contribute to reputation and trust but also to social exchange and commitment. Consequently, we can argue that shared ties may facilitate both tie formation and persistence in business relationships, similarly as in the case of research collaboration studied by Dahlander & McFarland (2013).

From a geographic perspective, interfirm business transactions between distant locations are associated with higher trade costs, as a result of increased transportation costs (Krugman, 1991). In addition, geographic proximity eases communication with business partners. Despite the development of IT solutions that support communication over long distances, face-to-face interactions remained important in developing trust and valuable social connections that channel information and knowledge (Jones, 2007; Leamer & Storper, 2014). Personal interactions between individuals inside supply chains were shown to improve firm performance, as they increase firms' opportunity to find a good supplier and to work efficiently with their existing suppliers (Bernard et al., 2019). Therefore, we formulate the following two hypotheses to test the role of geographic proximity in business tie formation:

H1a: The creation of business transaction ties is more likely between geographically proximate firms.

H1b: The persistence of business transaction ties is more likely between geographically proximate firms.

While geographic proximity enhances both business ties and social network connections, industrial similarity of companies may influence business ties differently. As industrial classification is based on product similarity, firms within the same industry are more likely to be competitors, and business connections between them are less likely. This results in heterogeneous business transaction ties between companies in terms of industries (Fujiwara & Aoyama, 2010).

Relatedness of industries refers to the fact that industries are not identical, but share commonalities in a technological sense (Frenken et al., 2007; Hidalgo, 2021). Relatedness facilitates information and knowledge sharing as firms can easily understand each other based on their close knowledge basis and similar capabilities (Brennecke & Rank, 2017, 2016), yet they are different enough to be interested in cooperation (Broekel & Brachert, 2015; Nooteboom, 2000). In the context of business transaction ties, we can expect that firms in related industries face lower levels of uncertainty for new tie creation as they have a better understanding of the capabilities and production processes of the other. Moreover, relatedness can reduce the costs to strengthen connections through repeated interactions. Accordingly, we formulate the following two hypotheses:

H2a: The creation of business transaction ties is more likely between firms in related industries.

H2b: The persistence of business transaction ties is more likely between firms in related industries.

Direct ownership ties between firms represent a power of direct control between firms, and as such, it also mitigates the economic motivations for opportunistic behavior. Therefore, we expect that direct ownership through individual co-ownership ties is increasing the likelihood of both business transaction tie creation and persistence.

H3a: The creation of business transaction ties is more likely between firms directly connected by co-ownership ties.

H3b: The persistence of business transaction ties is more likely between firms directly connected by co-ownership ties.

To highlight the importance of more complex forms of relational embeddedness, we argue that indirect relationships between firms also facilitate the development of business connections. Three different network motifs of indirect contact are possible to consider in our multiplex network structure: (1) an indirect ownership relation, (2) an indirect transaction relation, and (3) a "mixed" transaction-ownership indirect connection (see Table 1).

Indirect ownership ties exist between firms, in case they are not connected by owners directly, but both firms are connected to a third intermediary. These common owners do not need to be the same people; the intermediary firm may have more owners, of which one owns one of the

Figure 1. Properties of firms in our sample based on 2016 data.
Note: By "all firms," we mean allcompanies operating in Hungary as joint stock companies, limited liability companies, and limitedpartnerships with less than 50 owners. "Final sample" refers to the subset of firms that have at least oneownership tie and positive revenue in one of the years observed and have also been successfully linked tothe business transaction data.

potential partners, and the other owns the other potential partner. In this case, we assume that our arguments about the lack of motivations for opportunistic behavior in case of direct ownership (H3a and H3b) are transitive over the indirect ownership relations. Thus, we expect that:

H4.1a Indirect ownership ties facilitate the creation of direct business transaction ties.

H4.1b Indirect ownership ties facilitate the persistence of direct business transaction ties.

Indirect transaction ties represent the emergence of triads in the transaction networks, which are shown to be relatively scarce due to the hierarchical nature of value chains (Kichikawa et al., 2019; Luo et al., 2012). However, there are still instances, when they easily appear, for example, when a supplier and a buyer in manufacturing may rely on a common partner providing business services to them, or they may sell their products to a common wholesale company. We also argued that transaction relationships are essential sources of business information and trust (e.g. Murthy and Paul, 2017), therefore we suggest the following two hypotheses:

H4.2a Indirect business transaction ties facilitate the creation of direct business transaction ties.

H4.2b Indirect business transaction ties facilitate the persistence of direct business transaction ties.

Through indirect mixed ties, we aim to capture the role of indirect connections in multiplex settings on direct business transactions. In case of firm A has a transaction tie with firm B, and firm B has a common owner with firm C, we investigate whether the creation and persistence of a transaction link (triadic closure) between firm A and firm C are facilitated by the mixed relations in this V-shape triad. In such cases, ownership relations transmit reliable information on the quality of work of the potential partner (from firm B to firm C about firm A), but it also represents a power of control. If the partner does not meet the expectations, it risks losing both prospective and existing business partners. To test such mechanisms behind business tie formation, we formulate the following two hypotheses:

H4.3a Indirect mixed (transaction-ownership) ties facilitate the creation of direct business transaction ties.

H4.3b Indirect mixed (transaction-ownership) ties facilitate the persistence of direct business transaction ties.

3. Data and methods

3.1 Data sources and network construction

To explore the drivers of business tie formation in a large-scale interfirm network, we combine two key data sources. Ownership information on companies is obtained from the firm-level OPTEN database. OPTEN is a Hungarian data provider company that offers annual information and statistics for companies registered in Hungary, including basic financial information, locations, and owners.

We map the business transactions of firms through VAT reports collected by the National Tax and Customs Administration of Hungary. Firms were obliged to report all their transactions in case the VAT content of their transactions exceeds 1 million HUF in the given year. Therefore, the database in practice should cover all transactions where the yearly pretax value exceeds 3.7 million HUF (ca 10,000 EUR) (except those few activities that are exempt from VAT). The dataset is anonymized and has no reference to the actual products or services exchanged between companies, but it is connected to the firm-level balance sheet panel database by the Central Statistical Office of Hungary. Access to the database is available in the research room run by the Databank of ELKH CERS. The co-ownership ties of firms were linked to the transaction database in this facility.

In the analysis, we only consider companies with a maximum of 50 registered owners that operate in the forms of a joint stock company (Rt. in Hungary), a limited liability company (Kft. in Hungary), or a limited partnership (Bt. in Hungary). These rules exclude associations, foundations, and other less common forms of organization that usually involve many owners.

As a key aim of our research is to model the influence of co-ownership-related connections on business transactions over time, we face a dilemma of how to treat the firms that do not have any ownership connections, given that having ownership connections at all may be a cofounder of the examined relationships. Regarding this concern, in our baseline analysis, we concentrate only on those firms that are observed in the ownership network and drop all firms that do not have any ownership connections in any of the two years. This way we exclude the cofounder, but limit the validity of the result to this specific sample. Next, to check the validity of the results, we extend the analysis by running it on the full sample of firms. A further concern is that ownership connections represent two types that potentially embody different mechanisms: firms that are owned by the same persons (82% of connections), and firms having direct shares of other firms (18% of connections). In our study, we utilize both types in the baseline models, but run a robustness check on the impact of excluding direct holdings from the sample. Furthermore, we dropped those firms from our data that reported zero net revenue in both observed years. After these restrictions, we have information on ownership and business transaction ties for 33,919 firms (in 2016 and 2017 together). Figure 1 illustrates the diversity of all firms and the resulting final (baseline) sample in terms of size and industries. The final (baseline) sample shows similar distribution with respect to firm size, but in terms of industries, it does not include firms from the financial services sector.

Figure 2 illustrates the degree distribution in the co-ownership network and the business transaction network (only between firms in the final sample) for 2016 and 2017. Given our network construction method, the minimum degree in the ownership network is 1 and only the minority of firms have more than 10 connections. The same set of companies are less connected in the transaction network; however, transaction ties are more concentrated than the ties in the ownership network. The degree distribution of both networks appears to be relatively stable over time.

https://doi.org/10.1017/nws.2023.19 Published online by Cambridge University Press

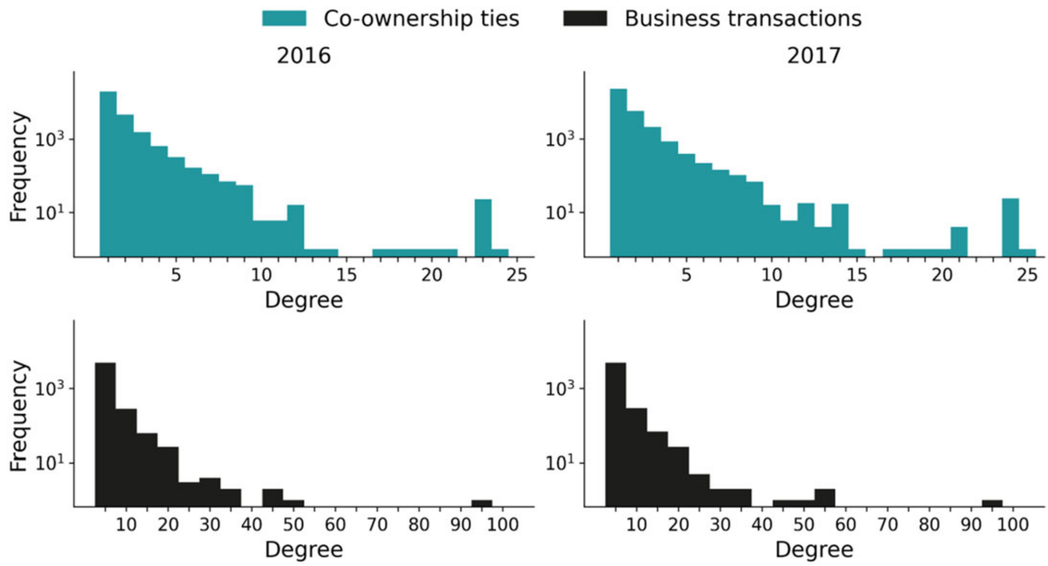

Figure 2. Distribution of ownership ties and business transactions.
Note: The business transaction network is limited to the set of companies present in the ownership network in 2016 or 2017.

SI1 in the Supplementary Information provides descriptive statistics on the number of nodes and edges in the full ownership and transaction networks, and their overlap and stability.

3.2 Motifs and variables

To model the influence of network structural patterns on interfirm business transactions, we focus on a set of network motifs (Takes et al., 2018). As illustrated in Table 1, we model whether transaction ties in 2017 (dashed red lines) develop or sustain between dyads of firms (blue dots) depending on the different multilayer settings that are observed in 2016.

It is important to note that we consider both networks in an undirected setting. Accounting for directionality in the transaction network itself would increase the number of possible motifs from four to twelve. However, these configurations do not differ from our theoretical considerations.

Table 1 also presents the number of observations and the relative frequencies of these motifs for both tie creation and tie persistence. Considering tie creation, only a small portion of firm dyads are connected through such motifs, given the large number of possible links in the network. Given that only a smaller fraction of firms are linked through business transactions in 2016, the relative frequencies of our motifs are higher in the case of tie persistence. The similar table on the observed number and relative frequency of motifs on the sample of all firms is included in Table SI2 in the Supplementary Information.

In addition to network structural features, we consider the influence of geographic proximity and industry similarity on the creation and persistence of interfirm business transactions. As our modeling approach requires dichotomized measures, we use the variable "same city" (1/0) to consider the co-location of firms at the level of cities. More precisely, the same city is based on the common zip codes of companies.

With respect to industries, the "same industry" dummy variable indicates that the main activity of the two companies is the same at the 4-digit NACE code level. In this case, two companies work

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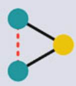
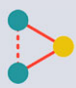
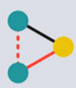
Table 1. Multi-level motifs to understand transaction tie formation

2016	2017	Motif name	Observed	Relative frequency
Motifs behind tie creation				
		Direct ownership	19,826	0.003%
		Indirect ownership	9,572	0.002%
		Indirect transaction	412,251	0.071%
		Indirect mixed	18,416	0.003%
Motifs behind tie persistence				
		Direct ownership	1,313	20.81%
		Indirect ownership	230	3.65%
		Indirect transaction	2,839	45.01%
		Indirect mixed	1,071	16.98%

Notes: The panel "behind tie creation" counts the motifs for all possible pairs of nodes where no transaction edge was observed in 2016, and relative frequency compares these figures to the number of possible pairs of nodes where no transaction edge was observed. The panel "behind tie persistence" counts motifs for dyads with an existing business edge in 2016, and relative frequency compares this number to the number of existing transactions in 2016.

ownership tie
existing transaction tie
predicted transaction tie

in the same area of production and are assumed to be technologically similar. "Related industry" is a dummy variable indicating that the first two digits of the focal firms' main activities are identical. This measure assumes that companies do not operate in the same, but in technologically close or related industries, which makes connections easier to create and maintain. These industrial similarity measures are simplified versions of other relatedness metrics reviewed by Content and Frenken (2016).

Supplementary Information SI3 provides further descriptives on the geographic distribution of companies and illustrates the distance of interfirm ties in detail. The observed co-ownership ties and business transactions across industries are illustrated in Supplementary Information SI4.

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3.3 Estimation strategy

We aim to understand the determinants behind the creation and persistence of business transaction ties. Social network researchers have developed sophisticated models such as ERGMs and SAOMs (Lusher et al., 2013; Snijders, 2011) that are readily available for estimating the structural and node-level factors that predict link formation. However, a distinctive asset of our study is the access to nationwide data that results in big networks (33,919 nodes) even after the limitations of the sample, which makes the estimation of these models unfeasible (Block et al., 2019). Therefore, we opt to use a simple dyad-level modeling approach for the entire network, with a dependent variable on the presence of links between two firms, and with independent variables on the multilayer motifs, industrial similarity, and geographic proximity. By including the multilayer motifs, we control for triadic effects in the networks. At the same time, we disregard higher-order effects that could have been included, e.g. in a SAOM, which might cause our estimates to be biased upwards.

Our dependent variable is a binary variable $T_{ij,t+1} = 1$, in case the business transaction tie between two firms (i and j) is present in time $t+1$, and $T_{ij,t+1} = 0$ if the tie is not observed. We model tie creation and tie persistence separately and the following two equations illustrate our model settings.

$$\mathrm{pr}(T_{ij,t+1} = 1 | T_{ijt} = 0) = \beta_1 \mathrm{SC}_{ijt} + \beta_2 \mathrm{Rel}_{ijt} + \beta_3 \mathrm{SI}_{ijt} + \beta_4 \mathrm{DO}_{ijt} + \beta_5 \mathrm{IO}_{ijt} + \beta_6 \mathrm{IT}_{ijt} + \beta_7 \mathrm{IM}_{ijt} \tag{1}$$

$$\mathrm{pr}(T_{ij,t+1} = 1 | T_{ijt} = 1) = \beta_1 \mathrm{SC}_{ijt} + \beta_2 \mathrm{Rel}_{ijt} + \beta_3 \mathrm{SI}_{ijt} + \beta_4 \mathrm{DO}_{ijt} + \beta_5 \mathrm{IO}_{ijt} + \beta_6 \mathrm{IT}_{ijt} + \beta_7 \mathrm{IM}_{ijt} \tag{2}$$

where SC_{ijt} indicates whether firm i and j are in the same city, Rel_{ijt} represents the relatedness of firms i and j, and SI_{ijt} indicates whether firms operate in the same industry. DO_{ijt} stands for the direct ownership connection between firm i and j, IO_{ijt} represents indirect ownership relations between firms, IT_{ijt} stands for indirect transaction ties, and IM_{ijt} indicates whether firm i and j are connected through indirect, mixed ownership-transaction relations. The model setting of equation (2) focuses on transaction ties that were present in the previous period. However, the estimation of equation (1) requires considering all the potential connections between companies, which is approximately 575 million possible connections in the baseline sample (and nearly 13 billion in case of the sample of all firms). Thus, instead of the apparent logistic regression approach, we propose the use of log-linear models to make the estimation faster and easier.

Log-linear models are used to analyze associations between nominal variables. They estimate the cell frequencies in contingency tables using the interactions of the defining variables. If we specify a log-linear model with two-way interactions, it directly corresponds to a logistic regression model (Von Eye et al., 2012). Its parameters (log odds ratios) are also interpreted similarly to logit regressions. We profit on the feature of log-linear models that the estimation uses a table, with the size (number of cells) being only the combination of the categories of the examined variables (144 observations in our case) that is independent of the size of the network itself. Therefore, it is much more efficient than running a logit regression on the dataset with all possible connections (575 million observations in our case).

We estimate the models described in equations (1) and (2) on the creation and persistence of business transaction ties in a stepwise manner. First, we estimate a null model, with only adding the parameters of geography (SC_{ij}) and industrial similarity (Rel_{ij}, SI_{ij}). Next, we add our parameter that represents direct (ownership) relation (DO_{ij}). Finally, we complement the model by adding the indirect network structure parameters (IO_{ij}, IT_{ij}, IM_{ij}). In each case, we add these variables as main effects, together with all their two-way interactions. Thus, equation (3) describes our full log-linear model.

$$\log\left(\hat{m}\right) = \lambda + \lambda^{\mathrm{T}} + \lambda^{\mathrm{DO}} + \lambda^{\mathrm{IO}} + \lambda^{\mathrm{IM}} + \lambda^{\mathrm{IT}} + \lambda^{\mathrm{Rel}} + \lambda^{\mathrm{SI}} + \lambda^{\mathrm{SC}} + \lambda^{\mathrm{T\#DO}} + \lambda^{\mathrm{T\#IO}} + \lambda^{\mathrm{T\#IM}}$$
$$+ \lambda^{\mathrm{T\#IT}} + \lambda^{\mathrm{T\#Rel}} + \lambda^{\mathrm{T\#SI}} + \lambda^{\mathrm{T\#SC}} + \lambda^{\mathrm{DO\#IM}} + \lambda^{\mathrm{DO\#IT}} + \lambda^{\mathrm{DO\#Rel}} + \lambda^{\mathrm{DO\#SI}} + \lambda^{\mathrm{DO\#SC}}$$
$$+ \lambda^{\mathrm{IO\#IM}} + \lambda^{\mathrm{IO\#IT}} + \lambda^{\mathrm{IO\#Rel}} + \lambda^{\mathrm{IO\#SI}} + \lambda^{\mathrm{IO\#SC}} + \lambda^{\mathrm{IM\#IT}} + \lambda^{\mathrm{IM\#Rel}} + \lambda^{\mathrm{IM\#SI}} + \lambda^{\mathrm{IM\#SC}}$$
$$+ \lambda^{\mathrm{IT\#Rel}} + \lambda^{\mathrm{IT\#SI}} + \lambda^{\mathrm{IT\#SC}} + \lambda^{\mathrm{Rel\#SC}} + \lambda^{\mathrm{SI\#SC}} \quad (3)$$

The parameters that describe the influence of the variables on the creation and persistence of ties are the interaction terms with the transaction relationship "T": T#DO, T#IO, T#IM, T#IT, T#Rel, T#SI, and T#SC.

Nevertheless, to check the validity of our results we estimate equations (1) and (2) in a logistic regression framework as well. This is possible only on a 10% sample of all possible nodes in case of tie creation and on the full sample in case of tie persistence. Our robustness checks with logistic regressions also enable us to control for observed characteristics of firms that are expected to be related to transaction patterns based on previous studies: size, size difference, and productivity of firms. This is not feasible in the log-linear approach as these are not categorical covariates.

Beyond testing our hypotheses directly, we extend the above model with three-way interactions. This may enable us to understand how the different mechanisms contribute to predicting business transactions. A positive interaction may indicate that two mechanisms amplify each other (complementarity), while a negative one may signify a supplementary relationship. Log-linear models are usually evaluated based on $\chi 2$ statistics (Benedetti & Brown, 1978; Rudas, 2018). A decrease in the $\chi 2$ statistics can be used to evaluate improvement in model fit, and when this decreases to a nonsignificant level, it suggests that the predictions based on the parameters do not significantly differ from the observed distribution of the table anymore. We will evaluate the possibility of this extension based on this statistic.

4. Results

4.1 Creation of business ties

To identify factors behind business transaction tie formation, we use different log-linear model settings. We begin by focusing on new business tie formation and present a null model (Model 1 in Table 2) with variables only on the geographic proximity and industrial similarity of firms. We include network structural effects stepwise. First, we control for the influence of direct ownership ties between firms (Model 2), then we assess the importance of indirect connections on new direct business transactions (Model 3). Chi-square test of Model 3 indicates that the predicted distribution of observations still significantly differs from the observed distribution, therefore, the addition of further effects is desirable to improve the predicting power of our model. Accordingly, we add all three-way interaction effects to the model (see Table 2 Model 4). The significant likelihood-ratio test supports the improved predictive power of this model compared to the previous one. Therefore, we consider this model as our preferred specification for new business tie creation for testing our hypotheses. The chi-square test of this last model is still significant, suggesting that even further terms could have been added to the model. We do not follow this lead as adding further effects would make the interpretation of the results overly complicated. Moreover, the decreased deviance of the model together with the decreased degrees of freedom suggests that this model is also close to the statistical capacity of prediction.

The two-way effects of "business tie creation" with all other variables describe the extent to which the presence of the motifs is associated with new business tie creation. These are the coefficients shown in Table 2 in terms of log odds. Thus, the parameter of the same city variable in Model 4 indicates that the probability of new business tie creation is by $e^{3.452} = 31.6$ times increased, if two firms are located in the same city. Results indicate that operating in the same city

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Table 2. Key coefficients of log-linear models on new business tie creation

	Model (1)	Model (2)	Model (3)	Model (4)
Business tie creation x				
Same city	4.094***	2.914***	2.276***	3.452***
	(0.047)	(0.077)	(0.093)	(0.076)
Related industry	0.602***	0.427***	0.232***	0.322***
	(0.082)	(0.083)	(0.084)	(0.119)
Same industry	1.162***	0.341***	0.018	0.777***
	(0.106)	(0.110)	(0.111)	(0.167)
Direct ownership		5.697***	5.465***	7.795***
		(0.092)	(0.120)	(0.122)
Indirect ownership			4.199***	6.197***
			(0.177)	(0.277)
Indirect transaction			6.011***	6.343***
			(0.043)	(0.045)
Indirect mixed			−1.992***	6.224***
			(0.106)	(0.186)
Model statistics				
Deviance	2.85E + 09	2.38E + 09	11,475.7	380.4
d.f.	134	129	109	65
p-value (LR test)		0.000	0.000	0.000
p-value (Chi2 test)	0.000	0.000	0.000	0.000

Source: Authors' own construction.
Notes: Parameters of log-linear models, standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and in related industries increases the probability of business tie creation corresponding to H1a and H2a, respectively. The variable same industry is also positive and significant in our best, final model (Model 4) on new business tie creation. This suggests that physical proximity and similar industrial knowledge support the development of new business connections.

Direct ownership is related to an increased probability of new business tie formation in all model specifications, confirming H3a. Further, we also find such a positive relationship for indirect ownership connections, corresponding to H4.1a. This suggests that ownership ties are influential for business development. Furthermore, the effects of these motifs are higher by an order of magnitude than the effects of geography and industrial similarity. Indirect transaction ties also increase the likelihood of new tie formation in line with H4.2a suggesting that embeddedness in the business network enhances further connections. In Model 4, we also observe that firms indirectly connected through mixed ownership and transaction ties are more likely to create new business connections as expected in H4.3a. Logistic regression estimates corresponding to models 1–3 that were run on a 10% sample as robustness check leads to similar conclusions, even after controlling for size and productivity effects (see SI5 in Supplementary Information).

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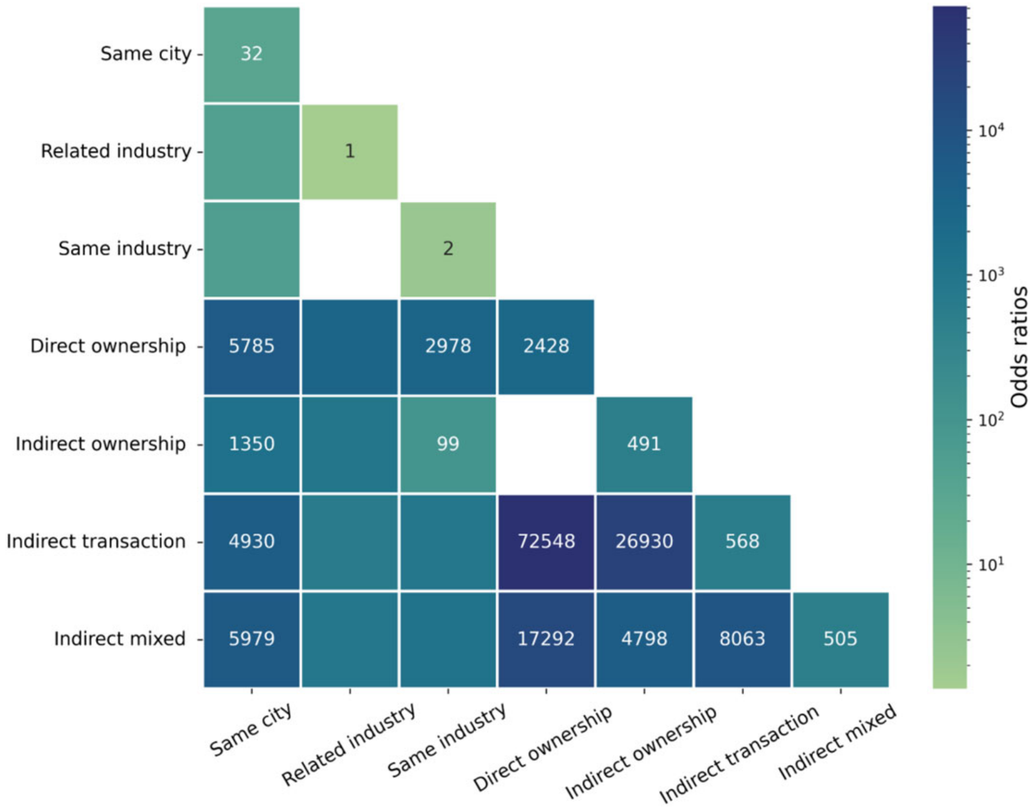

Figure 3. Odds ratios calculated from the significant parameters of the three-way interaction model on tie creation.
Notes: Colors correspond to the predicted probabilities calculated from the main effects and interaction effects of model 4 in Table 2. The underlying interaction coefficients are listed in Supplementary Information SI 6. The predicted probabilities are displayed numerically only in cells, where both the corresponding main effects and the interaction effects are statistically significant.

Running the models on the full sample of all firms produces highly similar results. The significance and magnitude of all coefficients are similar to the ones we get from the baseline sample, except the parameter "related industry" turns insignificant in Model 4 on the full sample (see SI6 in Supplementary Information).

Including three-way interactions to our final, preferred model enables us to evaluate the combination of effects on new business tie creation, such as how the effects of geographic proximity or industrial similarity add on each other in predicting business transactions. These coefficients are listed in the non-diagonal cells of the table in SI7, where the diagonal repeats the two-way effects from Table 2 Model 4. All significant non-diagonal elements are negative, indicating a "diminishing return" on the examined effects. Running the models on a limited sample, excluding direct holdings from ownership relations, we get similar results (presented in SI8)

Figure 3 illustrates the odds ratios calculated from our final model. Cells can be understood as if no other effect is present, being in the same city is associated with a 32-fold increase in the probability of business tie creation. If no other effect is present, having common owners is associated with a 2428-fold increase in the probability of tie creation. Having common owners *and* being in the same city together is associated with a 5785-fold increase in the probability of business tie creation. The heatmap suggests that the probability to create a new business tie is the highest in case two firms are connected across multiple network layers, namely they have direct

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Table 3. Key coefficients of log-linear models on tie business tie persistence

	Model (5)	Model (6)	Model (7)	Model (8)
Business tie x				
Same city	0.558***	0.282***	0.226***	0.507***
	(0.061)	(0.070)	(0.074)	(0.123)
Related industry	0.245***	0.228***	0.108	0.151
	(0.081)	(0.082)	(0.084)	(0.142)
Same industry	0.135	0.098	0.107	0.173
	(0.103)	(0.104)	(0.106)	(0.186)
Direct ownership		0.592***	0.699***	0.691***
		(0.074)	(0.078)	(0.139)
Indirect ownership			0.566***	1.025***
			(0.152)	(0.337)
Indirect transaction			0.655***	0.756***
			(0.055)	(0.071)
Indirect mixed			0.287***	0.444***
			(0.076)	(0.166)
Model statistics				
Deviance	11984	9905	276.0	111.9
d.f.	134	129	109	65
p-value (LR test)		0.000	0.000	0.000
p-value (Chi2 test)	0.000	0.000	0.000	0.0002

Notes: Parameters of log-linear models, standard errors in parentheses, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

ownership and indirect transaction ties. These very high odds ratios occur because the baseline probability of engaging in business transactions between two random non-connected firms is very low; it is around e^{-13} (see the constant term in SI5), which is 2.26×10^{-6}. Thus, even these high odds ratios of the indirect connections only elevate this probability to around one percent.

Odds ratios are not presented numerically in the cells of Figure 3 if the interaction effects are not significant. We observe that there are significant negative interactions between (1) the different motifs representing network connections, and (2) between geographic proximity and the network connections. However, there is no such interaction between the industry variables and the indirect network motifs. This suggests a supplementary relationship (e.g. in providing trust) between indirect relations and physical closeness and between the different types of indirect relationships.

4.2. *Persistence of business ties*

Coefficients from log-linear models on the persistence of business transaction ties are presented in Table 3. The structure of the models is identical to our models on tie creation. First, we present a null model (Model 5 in Table 3) with variables only on the geographic proximity and industrial similarity of firms. We include direct and indirect network structural effects stepwise in Models 6 and 7. To improve the predicting power of our models, we include three-way interactions in our final setting (see Model 8 of Table 3).

The results indicate that firms in the same city are more likely to maintain their business connections, as expected according to H1b. Related or identical industry profiles, however, do not significantly influence the maintenance of connections; thus, we cannot confirm H2b. These suggest that geographic proximity matters both for tie creation and persistence, while industrial similarity only influences the creation of new business ties.

Direct and indirect ownership ties between firms support the persistence of business transactions, according to H3.b and H4.1b. Coefficients for indirect transaction ties corresponding to H4.2b are positive and significant for all model settings, meaning that embeddedness in business transaction networks supports tie persistence. Indirect mixed ties increase the likelihood to maintain business connections between firms, too, as expected in H4.3b.

It is important to note that effect sizes are much smaller than the ones observed in the context of business tie creation. The parameters of the logistic regression equivalents of models 5–7 provide identical estimates to the second digit, underlining that the two specifications are mathematically equivalent (see SI9 in Supplementary Information). Results also remain stable if excluding direct holdings from the ownership network (see SI10). Considering the full sample, we also got similar coefficients both in terms of magnitude and significance related to the examined motifs. However, on the full sample also the industry-related variables turn significant (and their magnitude also increases), which confirms H2b on this full sample (see SI11).

Despite the chi-squared test of the three-way interaction model (Model 8 of Table 3) suggests that including further parameters (four-way interactions), most of the coefficients of the three-way interactions are not significant themselves. However, when significant, they tend to be negative, suggesting if one of these parameters is already present, the positive effect of the second one decreases (Table 3). Figure 4 illustrates the odds ratios calculated from the significant three-way interactions.

5. Discussion

Uncovering the drivers of network tie formation is key to understanding the evolution of social and economic systems. In this paper, we uniquely build on a social network approach to study the drivers of tie formation in a rather functional business transaction network. Specifically, we combine large-scale interfirm business transaction data with information on the industry profile, location, and owners of companies to identify factors that support the creation and persistence of business ties. Based on this novel perspective and the extensive dataset, our findings contribute to the literature on social and economic networks in multiple ways.

First, by integrating the literature on co-ownership networks (Takes et al., 2018) and transaction networks (Atalay et al., 2011; Diem et al., 2021; Hazama & Uesugi, 2017; Pálovics et al., 2021) we demonstrate that ownership connections strongly predict business relationships. In particular, we show that direct and indirect ownership ties between companies largely increase the likelihood that firms create and maintain business relationships. A potential explanation for this finding could be the reduced uncertainty ownership ties tend to imply through influence and trust between firms (Takes et al., 2018). Second, we contribute to the long discussion on network embeddedness (Granovetter, 1985; Uzzi, 1997) by illustrating that cohesive network structure in the business transaction and ownership networks influence the decisions and business development of companies. By employing several multiplex network motifs, the relevant finding shows that companies more embedded in networks of transactions and ownership ties are more likely to create and maintain their business activity over time. As all the tested network motifs supported

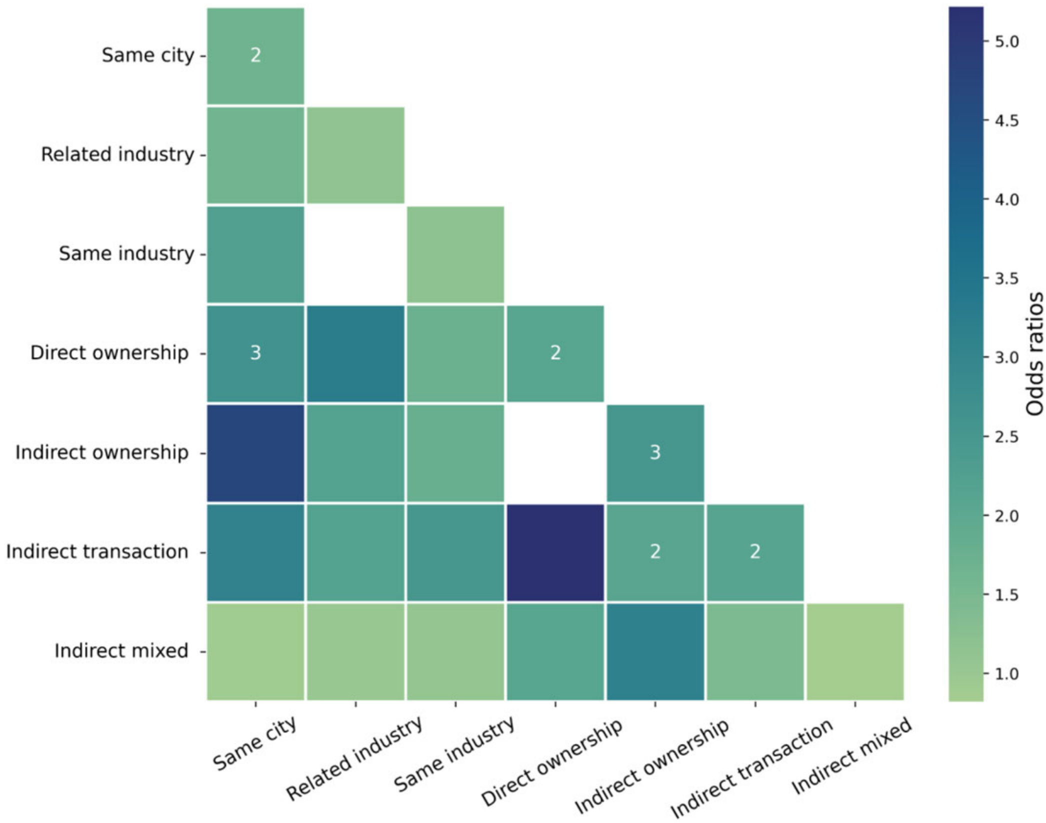

Figure 4. Odds ratios calculated from the significant parameters of the three-way interaction model on tie persistence. *Notes*: Colors correspond to the predicted probabilities calculated from the main effects and interaction effects of model 8 in Table 3. The underlying interaction coefficients are listed in Supplementary Information SI 8. The predicted probabilities are displayed numerically only in cells, where both the corresponding main effects and the interaction effects are statistically significant.

the creation and persistence of business transaction ties, our work demonstrates that embeddedness in and across network layers has a significant role in business connections. Moreover, when we compare the coefficients of indirect ties to direct ownership ties, we find similar magnitudes, suggesting that trust created by embeddedness has a similarly strong impact as direct control. In addition, we show that the different indirect relations together with physical co-location contribute to business relationships in a supplementary way, while the industry structure is a rather independent contributor.

Third, this paper also contributes to the growing literature on relatedness (Hidalgo, 2021) by showing that firms in related industries are more likely to establish business ties. At the same time, industrial similarity does not influence the reappearance of transactions. Additionally, in line with the literature (Bernard et al., 2019), we present that the geographic proximity of firms supports both the creation and persistence of new business links.

Our paper is not without limitations. Although relationship maintenance does not have a widely accepted definition, and in line with Zerbini and Castaldo (2007) we consider tie persistence as repeated transactions between firms, our measurement is relatively shallow, as we define persistence by having at least one transaction occurring in the next year. Observing repeated transactions on a large pool of firms of all types possibly includes mechanisms like repeatedly choosing the same product from the market without further commitments. This is a significant difference from what tie persistence means in supplier networks of technology-intensive industries between firms and their key suppliers. Therefore, further research would be needed to uncover forces that support the long-term dedication of companies toward their buyers and suppliers. Studying such processes over a longer period would also allow more precise measurement of new tie creation, as re-established connections over multiple years would be possible to identify and distinguish from once-established and persistent relations.

In this paper, we also illustrate the usability of log-linear models on network tie formation. Given that the estimation table these models use is independent of the size of the network, they can be handy for simple link prediction tasks in very large networks. Besides their clear benefit of being efficient estimations for large-scale network patterns, they do not allow us to account for actor decisions and the influence of network, dyad, and node-level factors on tie formation at the same time (Block et al., 2019). This potential extension of our work presents itself as a promising future research avenue. Furthermore, we tested the robustness of our results in the logistic regression framework by controlling a few apparent factors contributing to the development of business relationships, such as the size and productivity of firms. However, we cannot exclude that unobserved factors bias our estimates, or ultimately they cause the observed correlations.

As the theoretical foundation of this paper applies to business transaction ties in general without distinguishing between buyer and supplier relations, we operate with undirected, unweighted network structures. Besides the usage of directed and weighted ties would significantly increase the number of possible motifs to be tested, it would also enable us to consider the strength of buyer-supplier relationships. This scenario could open fruitful research directions to uncover the consequences of mergers and acquisitions on business transaction networks.

In short, our work contributes to the understanding of network tie formation in complex socioeconomic systems. Based on the social network perspective and combining two large-scale administrative datasets, we focus on business transaction ties and co-ownership relations as proxies of control and information. We integrate these relations in network motifs to uncover the role of multilayer network ties in the creation and maintenance of business relationships. We demonstrate that both direct and indirect ties in our multilayer network predict the creation and maintenance of economic transactions, as well as geographic and industrial proximity. We hope that our work inspires more research analyzing multilayer relations to understand complex socioeconomic phenomena.

Acknowledgements. We appreciate the comments and suggestions by Tom Broekel and the participants of the GCEG Conference in Dublin, 2022.

Competing interests. None.

Funding. Work of László Lőrincz was supported by the Bolyai Scholarship of the Hungarian Academy of Sciences. Sándor Juhász's work was supported by the European Union's Marie Skłodowska-Curie Postdoctoral Fellowship Programme (SUPPED, grant number 101062606).

Data availability statement. The data supporting this study are VAT tax records of individual firms that cannot be publicly disclosed by law. They are available for research purposes at the research room facility of the Hungarian Statistical Office operated by the Databank of the Centre for Economic and Regional Studies (only on-site). More information/Inquiries https://adatbank.krtk.mta.hu/en/kutatoszoba/, adatbank@krtk.mta.hu.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/nws.2023.19

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Cite this article: Lőrincz L., Juhász S. and O. Szabó R. Business transactions and ownership ties between firms. *Network Science*. https://doi.org/10.1017/nws.2023.19