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Exploring the dynamics of the disaggregated intercity corporate network in the Yangtze River Delta, China: a relational event approach

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Abstract

There has been a proliferation of studies trying to explain the driving forces behind the formation and evolution of intercity corporate networks. Previous approaches, however, require the input of aggregated data such as the connectivities of cities, a static network or a few discrete-time network snapshots. This may potentially cause the loss of information on the microscopic dynamics in corporate networks. In this paper, we explore the use of an approach invoking relational event models (REM), which has the advantage of being able to directly process continuously recorded disaggregated data on the establishment of each office. This allows for a more fine-grained analysis of the dynamics underlying the formation of the network. To demonstrate its potential in this research field, this paper applies REM to explain the temporal dynamics of the intercity corporate network in the Yangtze River Delta region of China. The result shows that there are preferential attachment and persistence effects in the evolution of the network, and this alongside the impact of several city covariates. Nonetheless, REM relies on event history and cannot model the forward-looking process in firms' location choice. The lack of detailed information regarding the date of the establishment of offices also poses a challenge to the application of REM in the study of corporate networks. We also conclude that it may be fruitful to apply REM to other forms of intercity networks, especially those significantly affected by event histories, such as commuting and knowledge networks.

Keywords Intercity corporate networks · Relational event models · Disaggregated data · Dynamics · Yangtze River Delta

JEL Classification JE1 · KE2

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1 Introduction

There has been growing academic interest in the study of intercity networks (e.g. Pažitka and Wójcik 2021; Taylor 2001). These networks come in a variety of forms, including corporate networks, transportation networks, migration networks and knowledge networks. Corporate networks, in particular, have been extensively studied, because they explicitly focus on some of the key agents in the formulation of intercity networks at various scales (Alderson and Beckfield 2004; Frost and Podkorytova 2018; Zhao et al. 2017). There is now a well-developed conceptual, methodological and empirical literature dealing with intercity corporate networks, much of which primarily focuses on describing network structures and their changes (Derudder and Taylor 2016, 2020). Meanwhile, more recently there has also been a proliferation of explanatory studies, which attempt to reveal the driving forces behind the evolution of these networks. These driving forces can be divided into two main categories.

The first category focuses on node attributes such as city factors. Since corporate networks are usually studied by considering firms' existence in different cities, the location factors (such as the population and GDP of a city) affecting firms' location choice are key driving forces behind the formation of corporate networks. They have been extensively examined in empirical research (Orozco Pereira and Derudder 2010; Zhang et al. 2019). In addition, firm heterogeneity (represented by factors such as size and sector) also have an impact on firms' location strategies (Liu et al. 2015; Neal et al. 2019).

The second category focuses on local network structures/configurations. The reason why they have an impact on the network formation is that the connections within a network are interdependent (Broekel et al. 2014). In a corporate network, this implies that a city-dyad can be affected by other city-dyads, just like a firm-city connection can be affected by other firm-city connections. A typical example of a local structure is a "star structure" (Alderson and Beckfield 2004; Liu et al. 2015), formed by processes of preferential attachment (Barabasi and Albert 1999). In such cases, new cities entering an intercity corporate network prefer to be connected with cities that are already well connected, or newly established offices tend to be located in cities with many existing offices.

Several approaches investigating the impact of these driving forces have been employed in empirical studies, including multivariate regression models (Orozco Pereira and Derudder 2010), multiple regression quadratic assignment procedures (MRQAP) (Zhang et al. 2019), exponential random graph models (ERGM) (Liu et al. 2015) and stochastic actor-oriented models (SAOM) (Liu et al. 2013). ERGM and SAOM stand out here because they can handle both local network structures and node attributes. However, there is a third type of explanatory models that is able to analyse local network structures and node attributes (Vu et al. 2015): relational event models (REM) (Butts 2008). To date, such models have not yet been used in research on intercity corporate networks, possibly because they were initially designed for analysing interpersonal interactions rather than firm activities, while the data they require are not always readily available.

Compared with the above approaches, one of the innovations of REM is the use of continuously recorded disaggregated event data, rather than discrete-time network snapshots (Vu et al. 2015) or aggregated static networks. This allows for fine-grained modelling of the network, i.e. based on the establishment of each office thus making it possible to investigate the microscopic dynamics underlying the network.

Against this backdrop, this paper aims to demonstrate the potential of REM for the study of intercity corporate networks, using the example of the evolution of such networks in the Yangtze Delta, China. The remainder of this paper is organized as follows. Previous approaches to the analysis of the evolution of intercity corporate networks are reviewed in the next section. Section three then presents a brief overview of REM and discusses its applicability to intercity corporate networks. This is followed by an overview of our case study and data analysis. We then give a brief description of the network structure and present our hypotheses and model specifications in the fifth section. The sixth and seventh sections contain the empirical results and a discussion, respectively, which are followed by the conclusions.

2 Literature review: explanatory models for studying intercity corporate networks

A range of approaches to the modelling of intercity networks can be found in current literature, such as the stochastic degree sequence model developed by Neal (2017), the extended Barabasi-Albert model proposed by Vinciguerra et al. (2010), and exponential random graph models (Liu et al. 2015). However, some of them focus more on backbone extraction, prediction, etc. rather than the explanation of the dynamics underlying intercity networks. In the below discussion, we focus on the main explanatory models.

2.1 Multivariate regression models

The earliest empirical studies studying dynamics of intercity corporate networks primarily relied on straightforward multivariate regression (MR) models. In their study on change in global intercity corporate networks between 2000 and 2004, Taylor and Aranya (2008) adopt a regression model to investigate the effect of capital cities on the cities' changing connectivities. Orozco Pereira and Derudder (2010) employ a similar method, but take into account more city factors such as pupil to teacher ratio and phone cost. In addition to these longitudinal studies, such models have been applied to cross-sectional data. For example, Jacobs et al. (2011) use negative binomial regression models to examine the impact of GDP per capita, population, etc. on the corporate connectivity of cities. However, these studies focus on cities' connectivity at the nodal level (cities) rather than on the dyadic level (intercity connections). This is partly because, although operationally possible, such models are not well suited to process network data: the underlying assumption that the observations

are independent of each other conflict with interdependencies being at the core of networks.

2.2 Multiple regression quadratic assignment procedure

To directly explain connections between cities, it is possible to apply a multiple regression quadratic assignment procedure (MRQAP), which is a combination of quadratic assignment procedure (QAP) and OLS/logistic regression. It solves the problem of interdependencies among connections by comparing regression statistics to the distribution of these statistics generated from row/column permutations of variables (Broekel et al. 2014). A recent example of its application can be found in the work of Zhang et al. (2019), who use MRQAP to identify the determinants of three intercity networks (including a corporate network) in the Yangtze River Delta, in which city-dyad connectivities feature as dependent variables. However, MRQAP is limited by failing to handle local structures, node attributes and longitudinal data (Broekel et al. 2014).

2.3 Exponential random graph models

Unlike the above approaches, exponential random graph models (ERGM) and its longitudinal extension into temporal exponential random graph models (TERGM) are specifically used to investigate how local structures affect network formation, and this alongside other factors such as node attributes (Sohn et al. 2019). It assumes that there are many possible network structures for a given number of nodes, and the observed network is treated as one of these (Hazir and Autant-Bernard 2014). ERGM finds a model of network formation that maximizes the likelihood of observing this network. These models are based on exponential graphs (see Broekel et al. 2014), and the parameters are estimated by a process of generation and optimization until the model converges. An example of this approach can be found in the work of Liu et al. (2015), who use ERGM to investigate the driving forces underlying global intercity connections created in the office networks of producer services firms in 2010, considering five local structures and two city factors. Another example is Broekel and Bednarz (2018), who apply a two-mode separable TERGM to study the formation and dissolution of links in an R&D network. The major difficulty with ERGM is that the models sometimes fail to achieve convergence in the parameter estimation (Broekel et al. 2014; Dai et al. 2016).

2.4 Stochastic actor-oriented models

Like ERGMs, Stochastic actor-oriented models (SAOMs) allow for an investigation of both local structures and node attributes based on longitudinal data. As agent-based models, SAOMs assume that actors try to maximize their utility by changing their connections with other actors, based on their knowledge of the network configuration and resulting in the evolution of the network (Snijders 1996). An example of its application is Liu et al. (2013), who use SAOM to investigate

changes in global intercity connections created in the office networks of producer services firms from 2000 to 2010. It has also been applied to study the joint dynamics of intercity corporate and Internet networks (Liu 2014). The difficulty of applying SAOM lies mainly in its requirement of a clear-cut conceptualisation and interpretation of actors and their behaviours (Dai et al. 2016).

3 Summary

While the above-reviewed approaches are collectively invaluable for examining the driving forces underlying intercity corporate networks, a common limitation is their failure in continuously changing intercity connections (i.e. changes in the network because of the establishment or closure of each office) into aggregated cross-sections. Multivariate regression models have the highest degree of aggregation, using the connectivities of cities as dependent variables. MRQAP has a lower degree of aggregation, as it uses one static network as the dependent variable. The degree of aggregation of ERGM and SAOM is also lower, as they focus on the change among several snapshots of a dynamic network, but this still involves collapsing fine-grained temporal data into discrete-time network cross-sections (Vu et al. 2015).

This kind of data aggregation may cause the loss of information on the microscopic dynamics in corporate networks. Figure 1 presents a simplified illustration of this problem, using the intercity corporate network in the Yangtze River Delta region as an example. The first row is highly aggregated data, only showing the connectivities of cities, while the information on intercity connections and their evolutions is lost through data aggregation. The second row disaggregates the connectivities of cities into city-dyad connections, which constitutes a static network. This can be used to investigate the influencing factors of the connections, but it suffers from the difficulty of understanding the dynamics underlying its evolution. The third row further disaggregates the static network into a few discrete-time snapshots that shows the change of the network among several time points. However, it fails to provide more fine-grained information on what happens between two snapshots. This makes it challenging to uncover more microscopic dynamics underlying the corporate network.

Relational event models allow to capitalise on the information contained in the disaggregation of the snapshots into continuously recorded events by investigating the microscopic dynamics of the network based directly on the establishment of each office. This can minimize the loss of information. For example, event 2 in the last row of Fig. 1 may have been, to some extent, influenced by event 1. Such a relationship can only be revealed with greater detail and reliability using continuously recorded event data, which contains the time order of these events. Since relational event models, introduced in the next section, allow for such a fine-grained analysis of the microscopic dynamics, we propose to employ this approach to the study on intercity corporate networks when the above data are available.
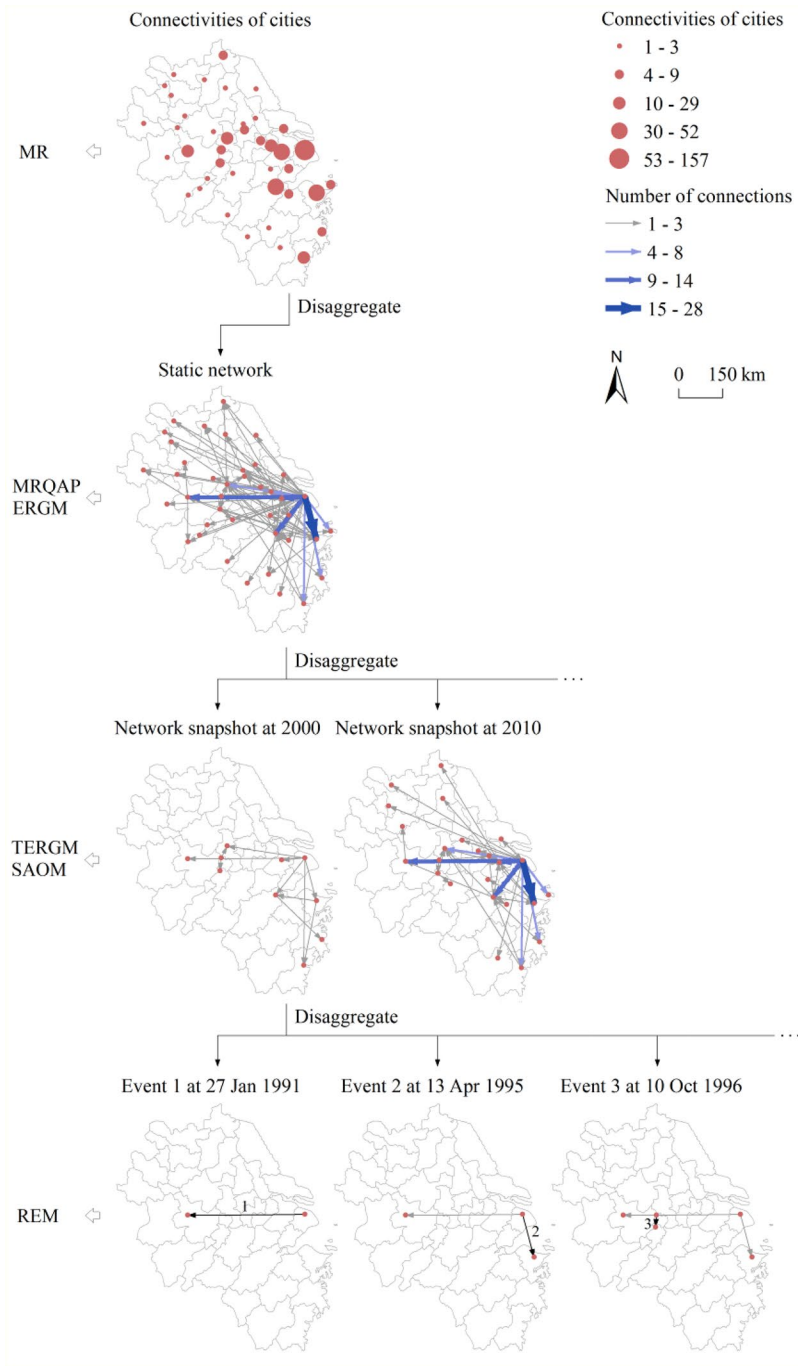
Fig. 1 An illustration of the data aggregation in modelling intercity networks (using the corporate network in the Yangtze River Delta region as an example). MR multivariate regression model, MRQAP multiple regression quadratic assignment procedure, ERGM exponential random graph models, TERGM temporal exponential random graph models, SAOM stochastic actor-oriented models, REM relational event models

4 Relational event models and their applicability to intercity corporate networks

4.1 An overview of relational event models

Relational event models (REM) were first proposed by Butts (2008). It is a behaviour-oriented and agent-based model that draws upon event history analysis. The central element of a REM is the relational event (or known as 'action'), which refers to a discrete event created by an actor (the 'sender') and directed toward one or more targets (the 'receivers'). Each action is defined as $a = (i, j, k, t)$, where i is the sender, j is the receiver, k is the action type, and t is the time of the event. A REM assumes that actions occur independently and are conditional on the realized history of previous actions, sometimes along with a series of covariates. The realized history of action a_i at time t is expressed as $A_t = \{a_i : \tau(a_i) \leq t\}$, which contains all actions taken on or before time t.

The modelling can be based on either the exact times or the order of events. For the latter, the likelihood of A_t is defined as (see Butts 2008):

$$p(A_t | \theta) = \prod_{i=1}^{M} \left[\frac{\lambda_{a_i A_{\tau(a_{i-1})} \theta}}{\sum_{a' \in \mathbb{A}\left(A_{\tau(a_i)}\right)} \lambda_{a' A_{\tau(a_{i-1})} \theta}} \right] \tag{1}$$

where M is the number of realized events in A_t; $\mathbb{A}$ is the support set, i.e. the set of all sender/receiver/type combinations that are possible at time t; and $\lambda_{aA_t \theta}$ is the abbreviated notation of the rate function given by:

$$\lambda_{aA_t \theta} = \lambda\left(s(a), r(a), c(a), X_a, A_t, \theta\right) = \exp\left[\lambda_0 + \theta^T u\left(s(a), r(a), c(a), X_a, A_t\right)\right] \tag{2}$$

where $s(a)$ is the sender, $r(a)$ is the receiver, $c(a)$ is the event type, and X_a is covariate. θ is a vector of parameters of the above statistics and needs to be estimated.

The first advantage of REM is its focus on disaggregated events rather than aggregate connections between senders and receivers (Tranmer et al. 2015). Accordingly, its input data are a set of continuous observations of events, rather than single complete networks or the connectivities of dyads/nodes. This prevents the loss of information on the dynamics of the networks resulting from data aggregation (Vu et al. 2015). Additionally, as in the case of SAOM, REM can only be applied to engage in longitudinal analysis, which allows for an investigation of the temporal dynamics underlying intercity corporate networks. Finally, REM can handle both network effects (such as persistence effect and preferential attachment; see Butts 2008) and covariates (such as the attributes of senders).

Because of these potential advantages, REM has been applied to a wide range of research themes, including interpersonal radio communications (Butts 2008), online political discussions (Liang 2014), animal social networks (Tranmer et al. 2015), interhospital patient transfers (Vu et al. 2017), characters and plots in movie scripts (Chao et al. 2019), etc. However, its potential in examining the driving forces behind intercity corporate networks has not yet been explored.

4.2 Applicability of relational event models to intercity corporate networks

Before applying REM to intercity corporate networks, its applicability to such networks needs to be scrutinized. Here, we will focus on two questions. First, is the central element of REM (i.e. the action from a sender to a receiver) compatible with the key process underlying intercity corporate networks? Second, is the assumption of REM consistent with the formation of corporate networks?

The central element of REM is relational events. Its conceptualization is largely based on the observation of human activities, especially those among individuals, and previous empirical research focuses mainly on this aspect (Butts 2008; Schecter et al. 2018). Meanwhile, collective entities, sets of individuals, or even inanimate objects can also be treated as senders or receivers (Butts 2008), which is testified by the proliferation of the empirical literature using REMs. The most obvious example is the work of Vu et al. (2017), who treat hospitals as senders and receivers in studying interhospital patient transfer. Similarly, Chao et al. (2019) consider human characters as senders and non-human plots as receivers in their study of movie scripts. It is therefore possible to apply REM to intercity corporate networks by either treating cities as both senders and receivers or treating firms as senders and cities as receivers (cf. Liu et al. 2013). For example, the formation of an intercity connection can be regarded as an action from the city where a firm is headquartered to the city where a subsidiary has been established (Alderson and Beckfield 2004).

The assumption of REM is that past history creates the context for present action, and the occurrence of an event alters the context (Butts 2008). Such dependence on event history also applies to intercity corporate networks, as a firm's location choice is significantly affected by the routines it has built up in the past (see Boschma and Frenken 2006) and the location strategies of other firms. For example, when a firm already has offices in a city and has accumulated considerable experience and social capital by operating locally (Iurkov and Benito 2018), the force of inertia may lead the firm to continue establishing offices in the city to further exploit the local market. Another example is that to follow clients (Hoyler, 2011), to imitate competitors or leading firms (Lieberman and Asaba 2006), or to exploit agglomeration effects, a firm may choose locations according to the location strategies of other firms.

Nonetheless, the formation of corporate networks is also affected by factors other than event histories. Some of them cannot be modelled by REM, and thus should be handled carefully. Butts (2008) has outlined three types of these factors and two of them need to be scrutinized here.[1]

First, it is assumed that current events are not subject to the influences of the realization of future events (Butts 2008). This implies that the establishment of an office should not be affected by the establishment of either this firm's or other firms' future offices. An obvious example is the representative offices of multinational enterprises in foreign cities. They are usually established when a firm plans to establish a larger

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[1] The other factor is third-variable effects, but they can be controlled by employing them as covariates (Butts, 2008). Therefore, these effects are not the main constraints on applying REM to intercity corporate networks.

office in a city but needs a representative office to pave the way, which may include publicity, building relationships with local firms, and early-stage market research on suppliers and customers. Although this practice may contradict the assumption of REM, it is not a major concern in our empirical study that focuses on Fortune China 500 firms in the Yangtze River Delta (see section four), as representative offices are often used in international business expansion (Luo 1999) rather than commonly used by large domestic firms.

Second, it is also assumed that current events are not subject to the influences of the non-occurrence of other events since the last realized event. This is common for "systems in which actors are strategically oriented, able to engage in significant forward-looking behaviour, and have substantial time for observation and reflection" (Butts 2008, p. 160), as these actors can evaluate and compare various possible circumstances (that do eventually not occur) before making decisions. Firms' location choice often involves such evaluation and comparison of possible locations,[2] which may appear to be inconsistent with the assumption. However, this may not be a serious problem for the following reasons. First, Butts (2008) holds that this may be less of a problem than might be feared, as forward-looking behaviour is usually limited. For some firms, the location choice may rely more on the decision-makers' personal experiences or preferences with bounded rationality (Collinson and Houlden 2005) than on a rational evaluation and comparison of all possible locations. This may be especially true when the information is incomplete and when formal decision-making is too time-consuming in a rapidly changing market. Second, Butts (2008) points out that systems for which behaviour is strongly impacted by past events may be well-approximated by REM despite some influences from the non-occurrence of other events. Since firms' location choice are strongly affected by event history (as discussed), REM may still be useful here. However, how much of the driving forces can be revealed depends on the extent to which the networks are affected by event histories and covariate, and thus may vary across different datasets.

Overall, REM seems to be applicable to intercity corporate networks. Although there are some inconsistencies, they may at most reduce the accuracy of models[3] but do not undermine the usefulness of REM in explaining (at least some of) the driving forces behind these networks. In the following sections, we use the example of the Yangtze River Delta to demonstrate its potential.

5 Study area and data

5.1 Study area

We take the Yangtze River Delta (YRD) in China as our study area (Fig. 2). According to the *Outline of the Regional Integration Development Plan of the Yangtze*

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[2] In this case, the situation that firms have not established offices in cities other than the selected location can be considered as "the non-occurrence of other events".

[3] This may be a problem for prediction, but we are only interested in the explanation here.
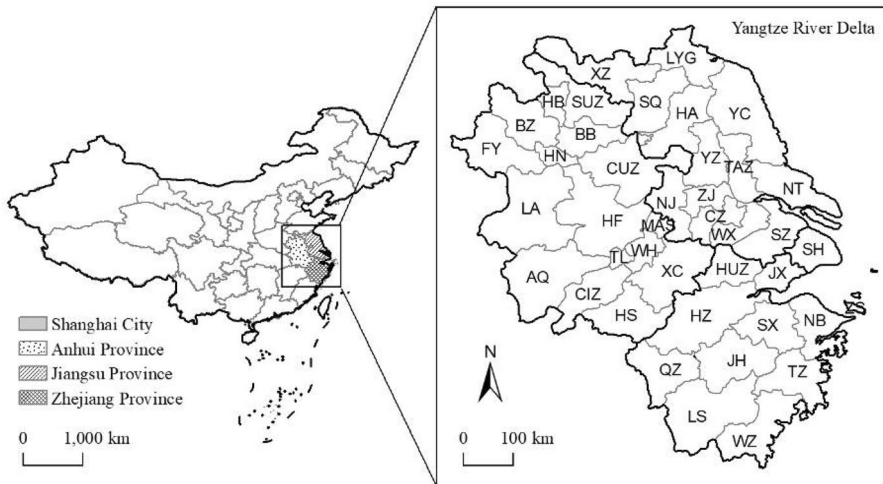
Fig. 2 The Yangtze River Delta region and its location in China. City codes are as follows. AQ Anqing, BB Bengbu, BZ Bozhou, CZ Changzhou, CIZ Chizhou, CUZ Chuzhou, FY Fuyang, HZ Hangzhou, HF Hefei, HUZ Huzhou, HA Huai'an, HB Huaibei, HN Huainan, HS Huangshan, JX Jiaxing, JH Jinhua, LS Lishui, LYG Lianyungang, LA Lu'an, MAS Ma'anshan, NJ Nanjing, NT Nantong, NB Ningbo, QZ Quzhou, SH Shanghai, SQ Suqian, SX Shaoxing, SZ Suzhou, SUZ Suuzhou, TZ Taizhou, TAZ Taaizhou, TL Tongling, WZ Wenzhou, WX Wuxi, WH Wuhu, XZ Xuzhou, XC Xuancheng, YC Yancheng, YZ Yangzhou, ZJ Zhenjiang, ZS Zhoushan

River Delta issued in 2019, there are a total of 41 cities in the region: Shanghai, a province-level city, and a further 40 cities in Jiangsu Province, Zhejiang Province and Anhui Province. The YRD is one of the most globalized and economically developed regions in China and is characterized by strong connections among its cities. Although the region covers only 2.1% of China's landmass, it is home to more than one-tenth of its population and one-fifth of its economic output. Meanwhile, its share of foreign trade, foreign direct investment and outbound investment stand at respectively 37, 39 and 29% of the national total.[4] The region's cities are strongly interconnected by various transport networks with a density of 1.14 km/km^2 against the national average of 0.51 in 2015 (Cao et al. 2018).

The intercity networks in the YRD region have received much attention in the literature, not only including a focus on corporate networks (Zhao et al. 2017) but also infrastructure networks (Dai et al. 2016), mobility networks (Zhang et al. 2018), knowledge networks (Li and Phelps 2016), etc. Some studies have investigated the driving forces behind the intercity corporate networks in this region. For example, by comparing the functional polycentricity in the corporate networks of the Yangtze and Pearl River Deltas, Zhao et al. (2017) point out that the transformations of these networks are affected by the size of the areas as well as international trade and political systems. Another example is Zhang et al. (2019), who identify the main

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[4] See *Outline of the Regional Integration Development Plan of the Yangtze River Delta.*

Table 1 The strategy of assigning service values

Score	Types of offices
4	Headquarters
3	Regional/provincial headquarters
2	Large offices, e.g. prefecture-level branches
1	Offices in a smaller size or is functionally less important, e.g. county-level branches, research institutes and factories
0	No presence

determinants of the corporate network in the region, focusing on GDP, administrative borders and administrative ranks.

However, the work of Zhao et al. (2017) is based on a qualitative analysis without quantitative testing. Zhang et al. (2019), on the other hand, focus only on cross-sectional rather than longitudinal analysis, which makes it difficult to grasp the temporal dynamics of the network. Additionally, neither of them pays attention to local networks structures. A REM allows exploring the temporal dynamics of the intercity corporate network in this region in more detail.

5.2 Data

To create the corporate network, we used the spatial distribution data of the offices owned by Fortune China 500 firms. In parallel with Fortune Global 500 that focuses on the world's 500 largest firms, this report was published by Fortune China and lists the 500 Chinese firms with the highest revenue in 2019. These firms cover a range of sectors such as wholesale and manufacturing. As opposed to focusing on a few advanced producer services (APS) sectors (Taylor 2001), this list may be more appropriate for investigating the intercity networks at the regional scale. The reason is that some APS sectors are highly geographically concentrated in China (Zhao et al. 2015), with much fewer offices in some small and medium-sized cities. Thus Fortune China 500 firms may therefore better capture the connectivities of these smaller cities in the YRD region than APS firms.

The primary data source was *Qichamao* (qichamao.com). We chose this database for two reasons. First, it covers more than 160 million firms in China,[5] including all firms in Fortune China 500, with various types of information such as the firms' size, sectors, locations, offices, etc. Second, despite being a commercial database maintained by Shenzhen Qichabao Data Technology Co., Ltd., its data are reliable since they were garnered from several official databases such as the National Enterprise Credit Information Publicity System and the database of the National Intellectual Property Administration.

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[5] While there are millions of firms in the database, most of them are small and have no offices in cities other than the place where they are headquartered. Therefore, we only focus on Fortune China 500 firms in this study.

Table 2 An overview of summary statistics of the data

Statistics	Value
Number of cities	40
Number of firms	79
Number of offices or events	708
With service value being 4	79
With service value being 3	40
With service value being 2	277
With service value being 1	312
Located in the same city as the headquarter	470
Located in a different city from the headquarter	238

The collected data include information on office names, address and date of registration.[6] According to the address, the firms' presence in the cities were recorded. The offices were assigned 'service values' from 0 to 4 (Table 1; cf. Derudder and Taylor 2018). This service value reflects the size of the office(s) of a firm in a city, and thus reveals the importance of a city within a firm's office network. Higher values reflect more important offices, with 0 suggesting there is no office and 4 suggesting the firm's headquarter is located in that city.

We use the approach proposed by Alderson and Beckfield (2004) to produce the intercity corporate network,[7] one of three major empirical models for approximating urban networks based on corporate networks (Liu and Derudder 2013). That is, when an office of a firm headquartered in city i is established in city j, there is a connection from i to j. Unlike the interlocking network model (INM) proposed by Taylor (2001), this approach creates a directed network that allows for the consideration of a range of network effects designed for directed networks (see Sect. 5.2) as well as the investigation of different impacts of sender covariates and receiver covariates. It is worth noting that some researchers also prefer to use two-mode networks with firms as senders and cities as receivers (e.g. Liu et al. 2013) rather than one-mode city-to-city networks to study intercity corporate networks. We nonetheless focus on one-mode networks, as the interpretation of results of two-mode network analysis is less intuitive (Liu and Derudder 2013) and may thus lead to confusion.

The end result was a set of continuous observations of city-dyad connection creations, which constituted a sample of 708 offices (i.e. the events of the establishment of offices) of 79 firms in 40 cities. Since we employed the approach proposed by Alderson and Beckfield (2004) and thus only focus on the firms whose headquarters

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[6] As opposed to Broekel and Bednarz (2018), who study both the formation and dissolution of links, we only considered link formation (i.e. the establishment of offices) in this study. This is because although the state of offices (e.g. opening, cancelled or revoked) can be found in the database, only around half of the offices that were cancelled or revoked have available information on the date of closing. By contrast, all offices have the information on the date of registration/establishment.

[7] This combines the service value used in the interlocking network model (Taylor, 2001) to measure the heterogeneity of offices.
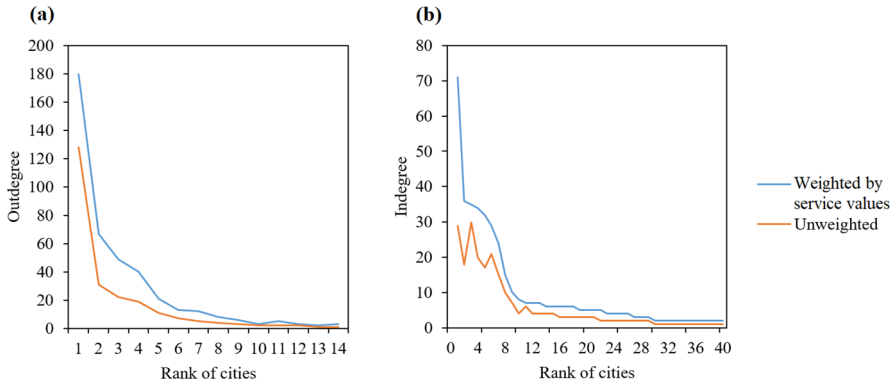
(a)

(b)

Fig. 3 Distribution of the outdegrees (**a**) and the indegrees (**b**) of cities

are located in the YRD region, the number of firms in the sample data is much smaller than 500. The number of cities is 40 rather than 41 because no office of these firms has been established in Bozhou City. The records in the sample were then sorted by the date of registration, with the earliest office located in a different city from its headquarter[8] established on May 27, 1991, and the latest on June 16, 2020. The summary statistics of the data are presented in Table 2.

The data on city attributes incorporate information about the province, administrative level, GDP and education. For the administrative level, all cities were scored 4 to 1, corresponding to four classes: province-level cities, sub-provincial cities, other provincial capital cities, and prefecture-level cities. As for education, we only focus on the number of higher education institutions, which include universities, colleges, higher and vocational schools. This along with GDP was collected from the City Statistical Yearbooks of China, whose values were then normalized between 0 and 1 before being entered into the model.

6 Modelling of the intercity corporate network

6.1 An overview of the network

Before presenting the hypotheses and model specification, Fig. 1 in Sect. 2.5 provides an overview of the network structure, with different degrees of aggregation, from which a few patterns can be observed.

First, the outdegree and indegree of cities are highly concentrated, which can be observed in both Figs. 1 and 3. Shanghai is the most connected city, with the outdegree being 128, which is much higher than the second-highest outdegree (31 of

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[8] The earliest office was established on May 16, 1982, and was located in Shanghai, as with its headquarter.

Hangzhou). Its weighted indegree is also the highest among the cities. This leads to a star structure in the network shown in the second row of Fig. 1. From this, it can be inferred that there may exist preferential attachment (Barabasi and Albert 1999): the already well-connected cities tend to be better-connected than other cities.

Also, some city pairs have very strong connections. The most obvious example is the connection from Shanghai to Ningbo, which is the undisputed dominant dyad. Shanghai→Hangzhou and Shanghai→Suzhou are also far more connected than other city-dyads. This phenomenon gives some evidence for the existence of persistence effects in the network. One possible reason is that firms from Shanghai may have accumulated considerable local knowledge (such as the knowledge about the local market) and social capital (such as the bond with local government and communities) in cities such as Ningbo, and thus may keep establishing new offices in these cities to better exploit the local market. Similarly, a reversed persistence effects can also be observed, such as the connection from Ningbo to Shanghai, which serves as the strongest link from Ningbo.

Another phenomenon is that cities with higher degrees generally have some common characteristics. For example, those with the highest degrees are mostly province-level cities, sub-provincial cities or provincial capitals, such as Shanghai, Ningbo and Hangzhou. Since these cities with higher administrative levels have greater power in administrative, fiscal and economic matters, as well as closer relationships with provincial or central governments (Ma 2005), they can attract more firms by, e.g. having higher administrative efficiency, providing some preferential benefits with the support of provincial or central governments,[9] etc. Also, many of them are cities with high GDP and many higher education institutions. The reason may be that higher GDP implies a larger market, which may be attractive for firms in sectors such as the consumer service industry. Universities and colleges, on the other hand, can provide a more educated workforce and thus impact the location choice of firms (Alañón-Pardo and Arauzo-Carod 2013). Furthermore, there are noticeable differences among cities in different provinces. For example, many cities in Anhui Province are less connected than cities in other provinces.

6.2 Hypotheses and model specification

While the above descriptions and their associated interpretations are tentative, they give some clues for model building. On this basis, and with particular reference to other empirical studies with the application of REM (Butts 2008; Vu et al. 2017) and on the dynamics of intercity networks (Liu et al. 2015; Zhang et al. 2019), we propose the following hypotheses.

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[9] Although capital cities normally are already popular with investors, while smaller cities often compete for potential investors with preferential benefits, the benefits a smaller city can offer are limited by its administrative power (see Ma, 2005). As a result, they usually attract firms by simply offering tax incentives or land with low rent, rather than, e.g. comprehensive industrial policies with the support of provincial governments, or massive infrastructure investment that is made possible by the fiscal power only a high-level city has.

Hypothesis 1: The network formation is influenced by effects such as preferential attachment, persistence effects and participation shifts. The participation shifts here includes the form AB-XB and AB-AY (cf. Butts, 2008). The former may represent the imitation among firms and the latter reflects the process of successively establishing offices in different cities by firms from the same city.

Hypothesis 2: The network formation is influenced by city factors including the province a city is located in, the city's administrative level, GDP, and higher education, as well as city-dyad factors including distance and provincial boundaries.

Hypothesis 3: Networks constituted by offices with different service values differ from each other in terms of their dynamics. This hypothesis aims to test the heterogeneity of offices. For example, offices with higher service values such as regional headquarters may prefer to be located in cities with higher GDP and administrative levels to better exploit the industrial policies and information that are available in these cities.

Following these hypotheses, we build the following six models. Model 1 is employed to test the network effects (Hypothesis 1) based on offices with service values greater than or equal to 3. Model 2 extends Model 1 by also considering city factors and city-dyad factors (Hypotheses 1 and 2). Model 3 and 4 have the same set of variables as Model 1 and 2, respectively, but they focus on the offices with service values greater than or equal to 2. Similarly, Model 5 and 6 are used to study the network constituted by offices with service values greater than or equal to 1. The statistics in the models are illustrated in Table 3. These models are estimated using the maximum likelihood estimation with the *relevent* package (Butts 2008) in R (R Core Team 2020) and evaluated using the Bayesian information criterion (BIC).

7 Results

Table 4 presents an overview of the estimated parameters. The following sets of results stand out. First, the four forms of preferential attachment can all be observed in Model 1, 3 and 5. However, when controlling for the covariates (Model 2, 4 and 6), only a positive effect of the form "in-in" can be observed in Model 6, while others either lose significance or reverse direction. This is consistent with what Butts (2008) observes: preferential attachment and individual-level heterogeneity substitute for one another to some extent. More specifically, many cities with high degrees are also province-level cities, sub-provincial cities or provincial capitals, usually having a higher GDP than other cities. These factors that are included in the covariates make the cities attractive to headquarters or other offices, and further lead to the self-accelerating process (Liu et al. 2015) in the formation of the network.

Second, the connections among cities are significantly persistent only for the form "out-out" in Model 1, 5 and 6. Given that this variable becomes insignificant in Model 2 after a set of covariates are considered, it can be concluded that such effect only exists with stability in the network constituted by all offices (i.e. Model 5 and 6). This is because offices with higher service values such as regional headquarters are in limited numbers, with large and separate service areas, e.g. the three regional headquarters of Haitong Securities Co., Ltd. that are located in Nanjing, Hangzhou

Table 3 Statistics in the models

Statistic	Event history	Realization	Explanation
Preferential attachment			
In–in			A city with a higher indegree is more likely to be a receiver
Out–out			A city with a higher outdegree is more likely to be a sender
In–out			A city with a higher indegree is more likely to be a sender
Out–in			A city with a higher outdegree is more likely to be a receiver
Persistence			
Out–out			Fraction of city i's past connections directed to city j affects i's future rate of sending to j
In–out			Fraction of city i's past connections from city j affects i's future rate of sending to j

Table 3 (continued)

Statistic	Event history	Realization	Explanation
Participation shifts			
AB-XB			City A sends to city B, then city X sends to city B
AB-AY			City A sends to city B and then to city Y
Sender covariates			The province a city is located in, the city's administrative level, GDP, and higher education
Receiver covariates			
Dyad covariates			Distance and provincial boundaries

Black lines are event histories, red dotted lines are possible events, and solid red lines are realized events

Table 4 Parameters for the relational event models

Statistics	Offices with service values ≥ 3		Offices with service values ≥ 2		Offices with service values ≥ 1	
	Model 1: Effects	Model 2: Effects and covariates	Model 3: Effects	Model 4: Effects and covariates	Model 5: Effects	Model 6: Effects and covariates
Preferential attachment						
In-in	3.948 (1.175)***	−1.792 (2.098)	7.434 (1.240)***	1.096 (1.759)	9.945 (1.031)***	3.644 (1.089)***
Out-out	5.950 (1.361)***	−1.933 (2.200)	7.740 (0.765)***	1.462 (1.580)	5.265 (0.281)***	−3.268 (1.017)***
In-out	3.216 (1.270)**	−6.423 (2.920)**	7.563 (1.076)***	2.116 (2.132)	11.633 (1.006)***	2.545 (1.616)
Out-in	6.115 (1.274)***	−0.717 (2.011)	4.382 (1.039)***	−3.922 (2.019)*	3.204 (0.522)***	−4.420 (1.026)***
Persistence						
Out-out	1.273 (0.669)*	0.560 (0.799)	−0.034 (0.762)	0.004 (0.703)	1.387 (0.557)**	1.442 (0.485)***
In-out	0.192 (0.657)	−0.793 (0.899)	0.757 (0.503)	0.583 (0.553)	0.088 (0.435)	0.666 (0.512)
Participation shifts						
AB-XB	0.759 (0.558)	0.327 (0.518)	−0.599 (0.536)	−0.834 (0.540)	−0.266 (0.402)	−0.437 (0.402)
AB-AY	0.950 (0.628)	0.473 (0.646)	0.876 (0.242)***	0.796 (0.243)***	0.793 (0.199)***	0.674 (0.191)***
Sender covariates						
Province		0.573 (0.274)**		0.269 (0.106)**		0.204 (0.109)*
Administrative level		1.366 (0.532)**		0.645 (0.248)***		0.611 (0.234)***
GDP		5.583 (2.058)***		1.111 (0.765)		4.868 (0.927)***
Education		−1.256 (1.921)		0.073 (0.890)		0.395 (0.798)
Receiver covariates						
Province		0.029 (0.333)		0.125 (0.089)		0.129 (0.073)*
Administrative level		−0.063 (1.015)		−0.173 (0.308)		0.262 (0.177)
GDP		0.173 (1.839)		2.146 (0.780)***		4.279 (0.695)***
Education		7.902 (3.168)**		2.884 (1.051)***		0.616 (0.612)
Dyad covariates						
Distance		0.849 (0.571)		−0.018 (0.231)		0.201 (0.183)
Provincial boundaries		−0.338 (0.611)		−0.204 (0.237)		−0.248 (0.197)

Table 4 (continued)

Statistics	Offices with service values ≥ 3		Offices with service values ≥ 2		Offices with service values ≥ 1	
	Model 1: Effects	Model 2: Effects and covariates	Model 3: Effects	Model 4: Effects and covariates	Model 5: Effects	Model 6: Effects and covariates
N	33	33	141	141	238	238
BIC	352.2973	308.023	1669.764	1650.116	2503.707	2402.14

Standard errors in parentheses

*significant at 0.1; **significant at 0.05; ***significant at 0.01

and Hefei, the provincial capitals of Jiangsu, Zhejiang and Anhui, respectively. Therefore, the connections constituted by them are less likely to be persistent among cities, which is especially true for the same firm. By contrast, as offices with lower service values have smaller service areas, they are more likely to be successively established in large numbers in the same city. This helps a firm to better exploit the local market and location-specific social capital, which are crucial for their profitability (Martynovich 2017). Moreover, the imitation of location choice among firms whose headquarters are located in the same city also leads to persistent connections among cities.

Third, as for participation shifts, only the form "AB-AY" is statistically significant in Model 3 to Model 6. This represents the process of successively establishing offices in different cities by firms from the same city, and reflect, to some extent, the rapid expansion of a firm. An example is China Eastern Airlines Co., Ltd., headquartered in Shanghai, which established a sales department in Hangzhou on January 8, 1997, and then another in Suzhou on February 16, 1997. The reason why the variable is insignificant in Model 1 and 2 may stem from the fact that the establishment of regional headquarters requires more resources and thus they cannot be rapidly set up in different cities.

Fourth, the addition of city covariates noticeably improves the accuracy of the models, as evidenced by the BIC of Model 2, 4, and 6 versus Model 1, 3 and 5, respectively. For sender covariates, prodvince and administrative level are statistically significant for the network with all thresholds (i.e. Model 2, 4 and 6), while GDP is only statistically significant for Model 2 and 6. By contrast, education is not significant in the different models. As for receiver covariates, a significant effect of province and GDP can still be observed, while administrative level loses its significance and education becomes significant in Model 2 and 4.

The effect of the province can be partly explained by the uneven administrative reform and economic development among provinces in the YRD. In the reform before 2000, many urban programmes (including policy incentives and power decentralization) were launched with a regional bias towards the coast (Li and Wu 2012). For instance, Shanghai received a massive tax return and reduction from the central government in the 1990s, which considerably facilitated its initial infrastructure investment (Li and Wu 2012). Developments zones under special policies and preferential treatments, such as the Pudong New Area and Shanghai Pilot Free Trade Zone, were also established to attract investment. This not only promotes the growth and expansion of the firms whose headquarters are located in these cities but also attract firms from other cities. By contrast, the reform and development in Anhui Province lagged far behind the coastal areas. As an illustration, there are only 17 national economic and technological development zones and high-tech industrial development zones in Anhui in 2018, while there are 43 in Jiangsu and 29 in Zhejiang.[10] Such uneven reform and development have led to different industrial policies, administrative efficiency and market size, which caused a significant difference among provinces.

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[10] Data source: The Audit Announcement Catalogue of China's Development Zones (2018 Edition).

GDP proxies the strength of the economy of a city, its internal potential market, and its purchasing power (Alañón-Pardo and Arauzo-Carod 2013). Therefore, by establishing offices in cities with high GDP, firms can be assumed to have more business opportunities thanks to the proximity to potential clients. This also helps to stimulate the growth and expansion of firms, as well as attracting firms from other cities. Meanwhile, cities with high GDP usually have more public revenue for improving public services and built environment. With better health care, education and public transportation, they can attract more firms by influencing employees' location choice, which is especially true for high-tech firms (Wu et al. 2019).

As for the administrative level, its significance as a sender covariate is largely because cities with higher administrative levels have greater power in administrative, fiscal and economic matters (Ma 2005). This allows them to promote the growth and expansion of firms by providing tax incentives, making special industrial policies, improving building environments and having higher administrative efficiency. Furthermore, some firms, especially state-owned enterprises (SOEs), have close bonds with local governments (Pan and Xia 2014), and sometimes influential leaders even rotate between provincial government posts and SOEs leadership. This helps these firms to obtain strong support from local governments. For example, Anhui Jianghuai Automobile Group Co., Ltd. witnessed a decrease in both sales and revenue in 2019, but with the subsidy of 1.117 billion RMB from the local government, it survived and even made a profit in that year.[11] Against this backdrop, the impact of the city governments' administrative level on the growth and expansion of these firms appears more evident.

The significant effect of the number of higher education institutions as a receiver covariate is consistent with some previous studies (e.g. Alañón-Pardo and Arauzo-Carod 2013). Universities and colleges provide a high-quality human resource environment with abundant skilled workers, which makes a city with many higher education institutions attractive to firms.

The estimated coefficients of the province and administrative level as sender covariates and education as a receiver covariate decrease from Model 2 to Model 4 and then to Model 6. This suggests that offices with higher service values are more affected by these factors. By contrast, GDP as a receiver covariate becomes statistically significant from Model 2 to Model 4, and its estimated coefficient increased from Model 2 to Model 6.

Finally, the results indicate that the two dyad covariates, distance and provincial boundaries, have no significant impact on the network formation. This finding is partly consistent with the work of Zhang et al. (2019), which suggests that the effect of distance on corporate network is relatively weak in comparison with other factors or other forms of networks in the YRD region.

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[11] Government subsidies have "rescued" Jianghuai Automobile Group, with profit in 2019 eventually exceed 100 million RMB (In Chinese). URL: https://www.qctt.cn/news/002_2791006.

8 Discussion

While the above results have demonstrated the potential of REM in the analysis of disaggregated events, longitudinal data and local network structures, they have also shown the challenges of using REM in studies on intercity corporate networks.

The first problem of REM is related to its assumptions. Since it is assumed that current events depend on the realized history of previous events, REM can only model the network by "looking back" and fails to provide insights into how the corporate network formation is affected by "looking forward" (e.g. the evaluation and comparison of possible locations). As forward-looking behaviour is common in locational decision-making, being unable to model this will certainly make the models less accurate.

Given this, it may be more appropriate to employ REM to model corporate networks when firms make locational decisions with limited information. In such a case, decision-makers can hardly have a rational evaluation of possible locations. Instead, they rely more on their personal experience (e.g. past locational decision-making) and the development trajectories of the firms (e.g. if the firms were embedded in one place or had been expanded to a large area). The location choice may also show a tendency of imitating other firms, especially firms in the same city or leading firms in the same sector, who are perceived as having similar or superior information (Lieberman and Asaba 2006). These factors can be easily modelled within the framework of REM. By contrast, it is more suitable to use SAOM to model firms' location choice with more complete information. In such a case, decision-makers can rationally evaluate and compare many (or all) possible locations and make decisions by maximizing the expected utility after the action (Snijders 1996).

Another problem of applying REM to study intercity corporate networks is often the lack of detailed information regarding the date of the establishment of offices. Although we have a reliable data source in this empirical study, such a problem may arise when investigating the corporate networks in some other regions or at other scales. For example, the GaWC datasets, widely used in studies of intercity corporate networks at the global scale, were collected from the website of each firm, with every website being different from others (Taylor 2004). Despite the presence of the date of establishment in some firms' websites, such information is not always available. In this context, researchers may need a telephone survey to collect this information, which poses a challenge to a broader application of REM in these studies.

9 Conclusion

The paper has been aimed to demonstrate the potential of REM in explaining the driving forces behind intercity corporate networks, using the example of the Yangtze River Delta. Compared with multiple regression, MRQAP, ERGM

and SAOM, which use connectivities of cities, a static network or discrete-time network snapshots as their input data, the most attractive feature of REM is that it can directly process continuously recorded disaggregated data, i.e. the time-ordered data on the establishment of each office. This allows for a more fine-grained analysis of the dynamics underlying the network.

The result suggests that there are significant preferential attachments, and this effect and the heterogeneity of cities substitute for one another to some extent. In addition, it can be observed that the connections among cities are significantly persistent, and the participation shift in the form of "AB-AY" can also be revealed in the result. As for city factors, province and GDP have significant impacts on both senders and receivers, while administrative level only affects senders and education only affects receivers. Also, neither distance nor provincial boundaries significantly influence the network. Finally, the networks constituted by offices with different service values differ from each other in terms of dynamics. For example, persistence effect and participation shifts play a less important role in the network produced by offices with higher service values, and the estimated coefficients of the province and administrative level as sender covariates and education as a receiver covariate decrease as more office with lower service values are included in the network.

The innovation and contribution of this work lie mainly in the use of disaggregated event data in studying intercity corporate networks. This not only minimizes the loss of information in comparison with the data used in previous studies but also allowing for the investigation of effects associated with these event-specific data (Vu et al. 2017), e.g. persistence effect and participation shifts.

Despite the advances that REM provides, this approach can only model the networks by "looking back" (i.e. based on event history) and is unable to provide insights into how the corporate networks are affected by firms' forward-looking behaviour (i.e. the evaluation and comparison of possible locations). Therefore, it is more appropriate to use REM to model corporate network when firms make locational decisions with limited information, which is more affected by event histories such as personal experiences, the development trajectories of the firms, etc. Another limitation is the lack of detailed information regarding the date of the establishment of offices. This poses a challenge as such information cannot be easily collected on firms' websites.

Additionally, a few further limitations of this study should be mentioned. First, this work is largely explorative and tentative, focusing mainly on the possibility and potential of employing REM in the analysis of intercity networks, and a more in-depth analysis of the microscopic dynamics of disaggregated intercity networks may be needed in future works. Second, our models at this stage have not taken into account the closing of offices due to the lack of data. Future research could compare the different microscopic dynamics of the establishment and closing of offices (see Broekel and Bednarz 2018) when the data required are available. Moreover, other forms of intercity networks can also be studied using REM, especially those depending heavily on event histories (i.e. impacted by habits, experiences, formed relationships, etc.), such as commute networks and knowledge networks. This may take full advantage of REM in modelling the history-related network dynamics.

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