https://doi.org/10.17221/369/2024-AGRICECON

Structural characteristics and determinants of the patent collaboration network in China's agricultural sector

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Citation: Cheng X. (2025): Structural characteristics and determinants of the patent collaboration network in China's agricultural sector. Agric. Econ. – Czech, 71: 285–297.

Abstract: Drawing upon data on co-signed patents in China's agricultural sector between 2015 and 2022, this paper explores the structural characteristics and determinants of the patent collaboration network in agricultural technology involving universities (U), enterprises (E) and research institutes (R). The results of social network analysis (SNA) revealed that the patent collaboration network is expanding in scale, but innovators are sparsely connected to others. Although the subnetwork linked by enterprises is the largest, universities and research institutes are more likely to play roles as hubs and bridges in the network. Furthermore, quadratic assignment procedure (QAP) regression revealed that prior collaboration experience and geographical proximity are key factors that promote co-patenting in the agricultural sector. Compared with *U–U* partnerships, *E–E* and *E–R* partnerships are associated with decreased patent collaboration. In the agriculture and forestry industries, the *U–U* and *U–R* partnerships are most likely involved in co-patenting, followed by the *R–R* and *U–E* partnerships. In the animal husbandry and fishery industries, no significant difference was found between the partnerships of *U–U*, *R–R*, *U–E* and *U–R* in their collaborative propensity.

Keywords: Patents; collaborative innovation; agriculture; proximity; social network analysis

Agriculture plays a significant role in long-term growth and development. As early as the 1950s, China vowed to achieve the goal of agricultural modernisation. Over the past several decades, China has made a remarkable contribution to global food security. The output of grain and other staple agricultural products steadily increased. With less than 7% of the global cultivated land, China feeds more than 20% of the world's population (FAO 2024). China's agriculture has improved in terms of quality and efficiency. Amid rising productivity and economic development levels, China has seen steady decreases in the agricultural labour force as a share of the total workforce and agricultural value-added as a share of total GDP. In 2023, 24% of the labour force was engaged in the agriculture sector, and this sector contributed approximately 7% of GDP (NBS 2024). Progress in agricultural technology has injected vital forces into China's agricultural modernisation. In 2023, the contribution of scientific and technological progress to agriculture reached 63% (NBS 2024).

As a large agricultural producer, China has yet to qualify as an agricultural powerhouse in terms of agricultural sufficiency, competitiveness, innovation, and sustainability. To increase overall agricultural production capacity and achieve the goal of agricultural modernisation, China has long been dedicated to im-

Supported by the Chongqing Social Science Research Project (Grant No.2024NDQN035), the Humanities and Social Sciences Program of Chongqing Education Commission (Grant No. 23SKJD092), and the Chongqing Postdoctoral Science Foundation Project (Grant No.2021XM2007).

https://doi.org/10.17221/369/2024-AGRICECON

proving the agricultural research system. Universities and research institutes have been recognised as the major contributors to basic and applied research. Enterprises, especially leading enterprises, are engaged mainly in agricultural machinery and equipment, new product development and new modes of agricultural production. Moreover, the Chinese government places great emphasis on the establishment of collaborative innovation mechanisms, which can be seen in the 'No. 1 Central Document' and a series of other policies.

Research collaboration can be defined as the working together of researchers to achieve the common goal of producing new scientific knowledge, and it is created through interactions, the sharing of competences and resources, and effective communication (Melin and Persson 1996; Katz and Kawai 1997). Among the factors that motivate research collaboration are cost reduction by reaching economies of scale, expanding opportunities to access various sources, and inducing the creation and dissemination of new knowledge (Choe and Lee 2017). The topic of interorganisational collaboration has long been an area of interest to researchers and policy-makers based on empirical findings that interorganisational relationships have a direct influence on innovation performance. However, cooperation between universities, research institutes and enterprises may be hampered by difficulties in achieving strategic integration across independent organisations (Kharazmi and Dartoomi 2023).

The main research questions addressed by this paper are as follows: How did patent collaboration in China's agricultural sector develop over time? What role do innovators play within the collaboration network, and how has this role changed over time? How do the structures of collaboration networks differ from industry to industry? Which factors explain the formation of interorganisational collaboration? To characterise the evolution of patent collaboration, this paper applied social network analysis (SNA) to construct a patent collaboration network among universities, enterprises and research institutes in China, with a total of 27 597 co-assigned agricultural patents from 2015 to 2022. Furthermore, quadratic assignment procedure (QAP) regression is applied to explore the determinants of patent collaboration.

The main contribution of this study is threefold. First, this study can provide a clear understanding of the structure, characteristics and changes of patent collaboration networks in the agriculture, forestry, animal husbandry and fishery industries. Agricultural patent data were used to show the network structure of collaboration. However, existing studies have focused on the entire agricultural system or some specific technology fields and lack interindustry comparisons. In China, the agricultural sector consists of the agriculture industry, forestry industry, animal husbandry industry and fishery industry. This paper investigates similarities and differences in co-patenting across different agricultural industries, ensuring a more accurate depiction of the complex dynamics and heterogeneity within the data. Second, by examining collaboration over relational data, this study used QAP regression to empirically investigate how interorganisational factors are related to agricultural patent collaboration. It is important to understand network evolution from the perspective of relations. In the context of the patent collaboration network, the dependent variable of interest is the relational intensity of co-patenting between organisations. Compared with conventional regression approaches such as ordinary least square (OLS), the QAP method, which incorporates relational variables and considers their inherent interdependencies when assessing their statistical relevance, is superior for testing research hypotheses in models based on relational data. Third, this study helps in understanding the influence of proximity on interorganisational collaborative innovation. According to the theory of multidimensional proximity and the division of knowledge, social, geographical, and institutional relationships explain how networks and clusters emerge. Prior studies have underscored the proximity factors associated with interregional networks, but studies with a particular focus on interorganisational networks have not yet been carried out. This study addresses this gap by examining the pivotal role of proximity in co-patenting in the context of interorganisational networks. Proximity factors, including geographical proximity, prior collaboration experience and the types of organisation partnerships, have been identified.

Literature rewiev

Patent network analysis. The study of collaborative innovation has been carried out primarily by building a patent collaboration network and observing its structure and properties. Patent networks can be analysed at the country level (Liu et al. 2022), at the regional level (Hu et al. 2023) or the organisation level (Wang et al. 2023). With respect to agricultural patent collaboration in China, Li et al. (2018) argued that government-industry-university-research cooperation in the agricultural sector still needs to be improved. The results of Wang (2022) revealed that there are few

https://doi.org/10.17221/369/2024-AGRICECON

cooperative relationships between smart agriculture technology companies, but the overall network density is low. While Tey et al. (2024) provided evidence that during the last decade, the growth of patent applications in areas concerning precision agriculture was almost entirely attributable to China and the USA. Ma (2023) suggested that the collaborative innovation network in agricultural biotechnology could be characterised as small-world, scale-free and core-edge structures. Hu and Fu (2023) revealed that both internal and external factors contribute to the dynamics of collaborative networks in agricultural science and technology, which exhibit a sparse structure.

The exploration of patent collaboration networks has been a focal point for researchers, and several studies have investigated agricultural patent collaboration. However, most of the prior studies in the agriculture field have conducted overall analyses without accounting for the heterogeneity. It is imperative to offer a more nuanced analysis of the heterogeneity of the patent collaboration networks among agricultural industries.

Factors influencing patent collaboration. Various factors influence the formation and continuation of patent collaboration. Previous studies have stressed the importance of external environmental factors, such as public support (Gyamfi et al. 2024). Many works have focused on the influencing factors at the organisational level. Intraorganisational factors, such as knowledge management and organisational structure, are investigated as help or hindrance to collaborative innovation (Kharazmi and Dartoomi 2023). Notably, interorganisational factors also play a crucial role in determining cooperative behaviour. Among them, three main factors that can be used as proxies for proximity stand out.

Traditionally, in the analysis of geographical spillovers, different innovators need to be physically close to one another to ensure the success of collaboration. Geographical proximity allows frequent face-to-face contact, resulting in trust creation and efficient information transfer. As innovation increasingly becomes a topic of concern, a growing number of studies have investigated the role of various forms of proximity. The effects of nonspatial proximity dimensions have been emphasised. The work of Boschma (2005), which separates geographical, cognitive, organisational, social, and institutional proximity, is particularly influential. The central idea is that different forms of proximity reduce coordination costs in interactive knowledge creation. Li et al. (2021) showed that economic proximity, technological proximity, and social proximity are key factors that promote international green technological collaboration. Hansen (2015) investigated the relationships between geographical and nonspatial proximity dimensions in collaborative projects in the Danish cleantech industry, and support is generally found because geographical proximity facilitates nonspatial proximity. Geographical proximity facilitates nonspatial forms of proximity by developing a common institutional, social, and cultural setting. Therefore, a focus on geographical proximity leads to the following hypothesis:

H_1: The propensity of patent collaboration by a pair of innovators is positively influenced by their geographical proximity.

Second, prior experience is critical to the present and future of organisations. Scholars assert that prior collaboration experience has a positive effect on the centrality of the organisation in the network, which enhances the organisation's ability to recognise new opportunities and exploit external resources (Schiavone and Simoni 2016). Di Guardo and Harrigan (2016) suggested that alliances formed by experienced partners are more likely to produce inventions that effectively synthesise technological knowledge from more diverse domains. Therefore, an organisation with collaborative experience is likely to be a partner worthy of interest for other organisations. The question to be decided was whether the experienced organisation reiterates co-patents with partners with whom it has already collaborated in the past or finds new partners. The literature on open innovation often highlights the advantages of diversity in collaboration. Organisations may choose to diversify their collaboration partners to avoid the risk of being locked in a small number of relationships (Capaldo 2007). Conversely, some scholars have noted that trust and mutual understanding make existing relationships efficient to establish and easy to maintain. Repeated collaboration can reinforce the level of trust among participants, facilitating the reduction of transaction costs and the promotion of knowledge sharing (Anderson et al. 2022). In addition, frequent interactions among the same participants could favour mutual understanding of their different goals and cultures, reducing information asymmetries and the risk of opportunistic behaviours (Murgia 2021). Petruzzelli (2011) showed that prior ties between universities and firms have a positive effect on the value of joint innovations. For this reason, this article develops the following hypothesis:

H_2: The propensity of patent collaboration by a pair of innovators is positively influenced by their prior collaboration experience.

https://doi.org/10.17221/369/2024-AGRICECON

The type of innovator is another critical factor. The motivations of innovators to engage in cooperative activities can be complex and different. The knowledge-based theory recognises cooperation as a vital mechanism for innovators to acquire knowledge and fill their knowledge gaps (Van Beers and Zand 2014). Collaborative innovation with a diverse set of partners could help generate nonredundant information flows, stimulate meaningful debates, and pull together complementary resources, thereby leading to better innovation performance (Lo and Li 2018). Enterprises are keen to collaborate with universities and research institutes to access and leverage valuable resources such as star scientists and state-of-the-art research facilities. Technology commercialisation and curriculum development are the main motivations for universities to engage in collaborative innovation. Research institutes are devoted to facilitating the spillover and commercialisation of university research. Following this perspective, partnerships are more likely to be created between different types of innovators. However, coordination and transaction costs are significant barriers to collaboration, and not all transaction costs are the same for innovations within and across organisation types. Goals and objectives are profoundly different among particular types of organisations. Transaction costs related to searching, negotiation, contracting, and enforcement occur in cooperation with different partner types (Vivona et al. 2023). From a transaction cost perspective, innovators tend to cooperate with the same type to reduce cognitive distance. This is supported by Shin et al. (2022), who studied projects for reducing emissions from deforestation and forest degradation. Overall, previous studies provide mixed results on the question of how organisation types affect innovation partnerships, but the following hypothesis can be proposed:

H_3: The propensity of patent collaboration by a pair of innovators is influenced by their organisational type.

MATERIAL AND METHODS

Sample

The international patent classification codes for agriculture, forestry, animal husbandry and fishery industries can be identified on the basis of the 'Table of Correspondence between International Patent Classification and National Economic Industry Classification' issued by the China National Intellectual Property Administration. Data on co-assigned patents in the fields of agriculture, forestry, animal husbandry and fishery were retrieved and downloaded from the Patent Search and Analysis System database, which was developed by the China National Intellectual Property Administration. By exempting solely applied patents, only patent data that were jointly applied for by two or more organisations were adopted as the raw data. Among the co-assigned patents, those filed by individuals were filtered out, and only patents owned by two or more organisations (such as universities, enterprises, or research institutes) were retained. There is some time lag between application and publication. The average pendency period for the granting of patents is approximately 18 months in China (Li et al. 2021). For this reason, this paper focused on patent documents published between 2015 and 2022. The final database contained 27 597 co-assigned patents, which included 10 610 in agriculture, 11 172 in forestry, 2 641 in animal husbandry, and 3 174 in fishery. In the following analysis, the sample is split to compare the results for different industries.

Social network analysis

Social network analysis (SNA) is a method for modelling relationships between actors through nodes and links to identify network typologies and evolution. In this study, the nodes are innovators, and the links are the joint patents among them. The measures used to describe network properties in the agricultural sector can be divided according to the level of analysis: at the level of the network or the level of the nodes. Network-level measures are indices calculated for the whole network, such as size, density, average degree (AD), and average path length (APL). The number of network nodes and links can represent the scale of the network. Density is defined as the ratio between the actual number of links and the greatest possible number of links in the network. AD is the average of the number of links that are owned by all individual nodes in the network, which is able to explain the global connectivity of the network. The APL depicts the average number of nodes that should pass from one node to another in the network. Centrality is a general term that relates to measures of a node's position in the network. The most widely used methods are degree, betweenness and closeness centrality. Degree centrality measures the immediate adjacency and is computed as the number of edges incident on a given node. Betweenness centrality measures the extent to which a node lies between other nodes in the network and can be computed as the number of shortest paths that

https://doi.org/10.17221/369/2024-AGRICECON

go through a given node. Closeness centrality refers to the reciprocal of the gross distance between a given node and all other nodes.

Quadratic assignment procedure (QAP)

To identify the factors that influence the patent collaboration network in the agricultural sector, this paper applies QAP regression. For network dyadic data, it is difficult to apply OLS in the regression because of the lack of independence of dyadic observations. QAP is a method that uses nonparametric permutation and is useful for analysing dyadic datasets. In the QAP, rows and columns of the network matrices are permuted, and correlation coefficients between independent matrices and the dependent matrix are calculated. After repeating such permutations many times, a test statistic can be derived to test the null hypothesis of the regression. Essentially, the QAP allows one to determine the influence of one matrix on another, controlling for the effects of one or more covariate matrices.

This study used QAP regression to explore the impact of various factors on co-patenting relationships, as follows:

$$P = f(Dist, Exp, E-E,\ R-R,\ U-E,\ U-R,\ E-R) \quad (1)$$

where: the observed variables refer to the way in which the innovation unit i is related to the innovation unit j; the dependent variable matrix P – number of coassigned patents between innovators i and j in the agriculture, forestry, animal husbandry and fishery industries, respectively; the independent variables, $Dist$ – geographical proximity; Exp – prior collaboration experience and the types of organisation pairs in the respective industry; f – function

This paper examines the effect of geographical proximity on interorganisational collaboration in China. The geographical proximity denoted by the $Dist$ matrix indicates whether innovators i and j belong to the same province in China. First, a web crawling tool is used to scrape the postal code data for each innovator from the Postal Code Base website. Next, the first two characters of the postal code are used to identify the corresponding province. The element of the $Dist$ matrix equals 1 if these two innovators belong to the same province and 0 otherwise.

The prior collaboration experience, denoted as the Exp matrix, is the co-patenting relationship between innovators within the last 3 years. When P at time t is used as a dependent variable, the independent variable Exp is measured by the number of co-assigned patents previously developed by the pair of innovators in the time interval between $t-1$ and $t-3$.

Innovators can be classified into universities, enterprises, and research institutes, which are denoted by U, E, and R, respectively. The pairs of innovators i and j can be classified into one of six types: two universities ($U-U$), two enterprises ($E-E$), two research institutes ($R-R$), a university and an enterprise ($U-E$), a university and a research institute ($U-R$), and an enterprise and a research institute ($E-R$). Notably, comparisons of standardised regression coefficients are generally appropriate for examining the effects of different explanatory variables within a subgroup on a dependent variable. To compare the regression coefficients, some type of innovator pair would be omitted. This paper selects the university–university pair as the comparison group. For analytic convenience, the $U-U$ matrix is removed from the estimation model. The remaining five matrices are binary matrices. For example, the element of the $E-E$ matrix equals 1 if innovators i and j enterprises are both and 0 otherwise.

RESULTS AND DISCUSSION

Structural characteristics of the patent collaboration network in the agricultural sector

SNA can be implemented in UCINET 6.0 software. First, the basic indicators reflecting the network size and structure of the patent collaboration network in the agriculture, forestry, animal husbandry and fishery industries are shown in Table 1. The total number of nodes and links engaged in the network can indicate whether the network expands or shrinks over time. From 2015 to 2022, the number of innovators participating in agricultural technology cooperation rapidly increased. The patent collaboration network shows a continuous trend of expansion. This is also reflected in the increasing number of links.

A high-density value indicates that the network is dense and that the nodes are cohesive. A low-density value indicates a sparse network. Different patent collaboration networks in China's agricultural sector have low point density, which corresponds to a sparse network. In general, when the number of nodes increases, the density of the network tends to decrease. This also holds true in this study. The figure shows that the innovator in the networks is connected with approximately 1.2 other partners on average during the period 2015–2022, and the AD of these networks increases

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Table 1. Topological characteristics of the patent collaboration network

Year	Nodes	Links	Density	AD	APL	Nodes	Links	Density	AD	APL
	Agriculture					Forestry				
2015	585	618	0.002	1.227	1.868	613	655	0.002	1.279	2.014
2016	760	735	0.002	1.216	3.231	775	767	0.002	1.215	3.099
2017	944	852	0.001	1.235	1.981	1 012	946	0.001	1.275	3.197
2018	1 179	1 217	0.001	1.276	4.350	1 245	1 217	0.001	1.300	4.875
2019	1 415	1 445	0.001	1.299	2.517	1 438	1 416	0.001	1.313	3.331
2020	1 771	1 774	0.001	1.308	3.284	1 851	1 840	0.001	1.326	6.058
2021	1 933	1 916	0.001	1.334	6.972	2 068	1 996	0.001	1.344	7.463
2022	2 139	2 053	0.001	1.360	9.078	2 341	2 335	0.001	1.396	9.673
	Animal husbandry					Fishery				
2015	158	110	0.007	1.114	1.599	188	149	0.006	1.106	1.256
2016	227	173	0.005	1.110	1.393	250	218	0.005	1.160	1.399
2017	309	264	0.004	1.133	1.344	270	263	0.004	1.148	1.286
2018	353	277	0.003	1.133	1.332	354	309	0.003	1.175	1.466
2019	448	402	0.003	1.156	1.536	378	386	0.003	1.222	1.831
2020	490	451	0.002	1.163	1.461	603	549	0.002	1.217	2.126
2021	538	453	0.002	1.175	1.554	593	634	0.002	1.268	2.110
2022	636	511	0.002	1.198	1.945	696	666	0.002	1.296	3.230

AD – average degree; APL – average path lenght
Source: Own calculation

over time. The APL results show that most innovators are far from each other, and as time passes, they need more steps to reach another partner.

Table 2 shows the percentage differences between innovators in the networks. The enterprise accounts for the largest share of innovators. The enterprise plays a crucial role in the patent collaboration network. Research institutes are encouraged to build collaborative relationships with others, whereas there is a large decrease in the share of research institutes in the fishery industry. Fewer than 20% of innovators are universities, and this number is decreasing in the agriculture and forestry industries.

Nodes with a high degree of centrality have many connections and are central to the network. Table 3 presents the percentages of different types of innovators in the top 20% of nodes ranked by degree centrality. A large proportion of the central organisations of the network are enterprises. However, this happens mostly because of the large number of enterprises in the network. Compared with the proportions of different types of innovators in the network, a university, not enterprise, is more likely to occupy the central locations of the network. The share of universities in the top 20% of nodes in terms of degree centrality is significantly greater than the share in the entire network.

Table 4 presents the percentage of different types of innovators in the top 20% of nodes ranked by betweenness centrality. Considering that fewer than 20% of network nodes are universities, universities constitute

Table 2. Percentages of different types of innovators in the patent collaboration network

Year	Agriculture (%)			Forestry (%)			Animal husbandry (%)			Fishery (%)		
	U	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*
2015	18.6	52.0	29.4	17.8	48.3	33.9	15.2	52.5	32.3	16.5	45.2	38.3
2022	14.4	57.1	28.5	13.6	54.5	32.0	18.4	51.6	30.0	17.4	55.3	27.3

U – universities; *E* – enterprises; *R* – research institutes
Source: Own calculation

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Table 3. Percentages of different types of innovators in the top 20% of nodes ranked by degree centrality

Year	Agriculture (%)			Forestry (%)			Animal husbandry (%)			Fishery (%)		
	U	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*
2015	29.9	40.2	29.9	28.5	37.4	34.1	9.4	59.4	31.3	18.4	31.6	50.0
2022	26.4	43.0	30.6	25.4	39.7	34.8	30.7	43.3	26.0	26.6	43.2	30.2

U – universities; *E* – enterprises; *R* – research institutes
Source: Own calculation

approximately 30% of the top 20% of nodes ranked by betweenness centrality. There is a high probability that a university will play the role of the bridge that controls or facilitates research collaboration. Research institutes also play an important role in the network as a bridge for research collaboration and knowledge flows.

Nodes with high closeness centrality are well-connected and able to reach other nodes quickly. Table 5 shows the results of the closeness centrality analysis. The proportion of enterprises in the top 20% of nodes ranked by closeness centrality decreased compared with the proportion of enterprises in the network nodes. In contrast, universities and research institutes are more densely ranked. While enterprises have a high proportion of network nodes compared with universities and research institutes, the status of universities and research institutes in the network is higher than that of enterprises.

Our general observation is that the patent collaboration network in the agricultural sector is expanding in scale, but the overall network density is low. These findings resonate with those of prior studies (Wang 2022; Hu and Fu 2023). This paper contributes to the literature by providing an interindustry comparison, which reveals that there are more collaborative relationships in the forestry and agriculture industries than in the fishery and animal husbandry fishery industries. In China, the forestry industry accounts for less than 10% of the value of agricultural output (NBS 2024). Hence, it is urgent to promote collaborative innovation in China's agricultural sector, and it is also important to give attention to the quality of patents. We need to capture the economic value of patents. The results of the node-level analysis are in line with the findings of Choe and Lee (2017), who showed that while research institutes played a role as hubs and bridges in the network, universities gradually took their place. Choe and Lee (2017) targeted a network constructed by using joint patent application data from 75 major innovative actors in Korea. The work most closely related to this paper is that of Ma (2023), who finds that universities are more attractive to other innovators for carrying out collaborative innovation in China's agricultural biotechnology. While Ma (2023) noted that the dominant position of enterprises in the network has been significantly strengthened, this study found that, based on centrality measures, the status of enterprises in the network has decreased in most cases.

Main determinants of patent collaboration in the agricultural sector

This section provides empirical evidence on the effects of multiple variables on patent collaboration. By dividing the dataset into four groups, agriculture, forestry, animal husbandry and fishery, we can run the regression model separately for each industry. Table 6 presents the results of the QAP cross-sectional regression models of patent collaboration in the agriculture industry between 2015 and 2022. A low R-square value is common in cross-sectional studies with large sample sizes. Nevertheless, the model fits for each model are significant at the 0.001 level.

Table 4. Percentages of different types of innovators in the top 20% of nodes ranked by between centralities

Year	Agriculture (%)			Forestry (%)			Animal husbandry (%)			Fishery (%)		
	U	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*
2015	31.6	33.3	35.0	34.1	28.5	37.4	9.4	62.5	28.1	15.8	34.2	50.0
2022	31.3	32.0	36.7	31.0	26.5	42.5	37.0	30.7	32.3	31.7	33.8	34.5

U – universities; *E* – enterprises; *R* – research institutes
Source: Own calculation

https://doi.org/10.17221/369/2024-AGRICECON

Table 5. Percentages of different types of innovators in the top 20% of nodes ranked by closeness centrality

Year	Agriculture (%)			Forestry (%)			Animal husbandry (%)			Fishery (%)		
	U	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*	*U*	*E*	*R*
2015	22.2	56.4	21.4	17.9	47.2	35.0	3.1	68.8	28.1	10.5	34.2	55.3
2022	15.7	47.9	36.4	17.7	43.8	38.5	26.8	35.4	37.8	16.5	54.0	29.5

U – universities; *E* – enterprises; *R* – research institutes
Source: Own calculation

Hypothesis H_1 proposes that the propensity of collaborative innovation by a pair of innovators is positively influenced by their geographical proximity. Consistent with expectations and previous studies, the coefficients of geographical proximity, ranging from 2.980 to 3.152, are positive and statistically significant in all years, indicating that innovators belonging to the same administrative region are more likely to cooperate in agricultural innovation, which leads us to accept H_1. Geographical proximity is an important factor influencing patent collaboration. The relationship of belonging to the same province helps with face-to-face communication and the spread of tacit knowledge among organisations, hence favouring the emergence of collaborative innovation.

As shown in Table 6, the prior collaboration experience between two innovators is positively and significantly related to their current co-patenting behaviour. The regression coefficients range from 3.043 to 4.447. The results lead to a confirmation of H_2. The shared experience of co-patenting among innovators facilitates a climate of trust, and there is a propensity to reiterate collaboration. In other words, the rich get richer mechanism through preferential attachment exists in the collaborative innovation process.

Among the matrices for the five pairs of innovators, the coefficients of the *E*–*E* matrix are negative and statistically significant in all years, the coefficients of the *R*–*R* matrix are negative and significant in 2017

Table 6. Results of the quadratic assignment procedure regression analysis for the agriculture industry

Variable	2015	2016	2017	2018	2019	2020	2021	2022
Dist	3.094***	2.998***	3.152***	2.982***	3.023***	3.092***	2.980***	3.108***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp	3.578***	4.447***	3.642***	3.605***	4.066***	3.911***	3.561***	3.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
E–*E*	–0.462*	–0.495**	–0.830***	–0.772***	–1.131***	–1.113***	–1.047***	–1.323***
	(0.082)	(0.047)	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
R–*R*	0.055	–0.086	–0.276*	–0.156	–0.405**	–0.578**	–0.473**	–0.526***
	(0.501)	(0.258)	(0.091)	(0.173)	(0.039)	(0.012)	(0.013)	(0.002)
U–*E*	0.350	0.091	–0.132	–0.260*	–0.277*	–0.455**	–0.290**	–0.494***
	(0.278)	(0.464)	(0.172)	(0.091)	(0.072)	(0.022)	(0.046)	(0.002)
U–*R*	0.142	0.133	–0.072	0.027	–0.228	–0.155	–0.041	–0.113
	(0.419)	(0.411)	(0.248)	(0.497)	(0.108)	(0.122)	(0.241)	(0.174)
E–*R*	–0.269	–0.296*	–0.535**	-0.862***	–1.178***	–1.067***	–0.968***	–1.353***
	(0.148)	(0.099)	(0.018)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	–6.845	–6.983	–7.029	–7.046	–6.982	–7.204	–7.323	–7.145
R^2	0.057	0.058	0.059	0.045	0.046	0.055	0.046	0.046
N	170 820	288 420	445 096	694 431	1 000 405	1 567 335	1 867 278	2 286 591

*, **, ****P* < 0.1; 0.05; 0.01, respectively; One thousand permutations; numbers in each variable represent standardised coefficients; *P*-values in parentheses
Source: Own calculation

https://doi.org/10.17221/369/2024-AGRICECON

Table 7. Results of the quadratic assignment procedure regression analysis for the forestry industry

Variable	2015	2016	2017	2018	2019	2020	2021	2022
Dist	2.864***	2.914***	2.784***	2.924***	2.985***	2.951***	2.889***	2.985***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp	3.689***	4.413***	3.827***	3.541***	4.334***	3.536***	3.604***	3.524***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
E–E	–0.712**	–0.858**	–0.646**	-0.969***	–1.032***	–1.228***	–1.001***	–1.471***
	(0.036)	(0.014)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R–R	–0.296	–0.472**	–0.137	–0.494**	–0.498**	–0.756***	–0.509***	–0.865***
	(0.139)	(0.044)	(0.189)	(0.015)	(0.012)	(0.003)	(0.004)	(0.001)
U–E	–0.011	–0.510**	–0.001	–0.457**	–0.340**	–0.552***	–0.375**	–0.713***
	(0.436)	(0.038)	(0.506)	(0.027)	(0.039)	(0.006)	(0.017)	(0.001)
U–R	–0.137	–0.295	0.077	–0.239*	–0.081	–0.218*	–0.070	–0.138
	(0.256)	(0.112)	(0.399)	(0.091)	(0.236)	(0.083)	(0.213)	(0.174)
E–R	–0.560*	–0.920**	–0.434**	–1.156***	–1.119***	–1.356***	–1.099***	–1.636***
	(0.055)	(0.015)	(0.040)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	–6.465	–6.555	–7.029	–6.826	–7.047	–7.036	–7.350	–6.956
R^2	0.052	0.083	0.054	0.043	0.055	0.046	0.048	0.048
N	18 7578	299 925	511 566	774 390	1 033 203	1 712 175	2 137 278	2 738 970

*, **, ***P < 0.1; 0.05; 0.01, respectively; One thousand permutations; numbers in each variable represent standardised coefficients; P-values in parentheses
Source: Own calculation

and 2019–2022, the coefficients of the *U–E* matrix are negative and significant in 2018–2022, the coefficients of the *U–R* matrix are not statistically significant, and the coefficients of the *E–R* matrix have been negative and significant since 2016. They indicate that, the pairs of *U–U* and *U–R* have the highest propensity to collaborate, followed by *R–R* and *U–R*, whereas the collaborative propensities of *E–E* and *E–R* are the lowest. Given the number of links centred on universities, universities not only form *U–U* research collaborations but also have strong collaborative innovation relationships with research institutes and enterprises. When a research institute decides on a collaborative partner, the university is the most preferred type, and the enterprise is the least preferred. With respect to enterprises, the propensity to collaborate is significantly greater with universities than with research institutes or other enterprises. In brief, H_3 states that the propensity of collaborative innovation by a pair of innovators is influenced by organisational type, which is supported by the results.

The results for the forestry industry, shown in Table 7, are very similar to those reported for agriculture. Pairs of innovators belonging to the same administrative region are more likely to cooperate in forestry innovation. Pairs of innovators with prior successful collaborative relationships are more likely to have new collaborative innovation relationships added. Pairs of *U–U* and *U–R* have the greatest propensity to collaborate, whereas pairs of *E–E* and *E–R* have the least propensity to collaborate.

Table 8 presents the results of the QAP regression of patent collaboration in animal husbandry. A significant positive relationship occurred between geographical proximity and co-patenting. Cooperation with partners within a region is much more likely than cooperation with partners located outside the region. A positive and significant relationship occurred between prior collaboration and co-patenting in the present. Pairs of innovators who have been previously involved in innovation collaboration are more likely to develop more innovations. Compared with *U–U* partnerships, pairs of *E–E* partnerships are associated with decreased collaborative innovation, and pairs of *U–R* partnerships are also associated with decreased collaborative innovation. Between 2015 and 2022, the coefficients of *R–R* and *U–E* are significantly negative only in three years, and the negative coefficients of *U–R* are significant only in 2016. In 2018, there was a significant and positive coefficient for *R–R* and *U–R*.

https://doi.org/10.17221/369/2024-AGRICECON

Table 8. Results of the quadratic assignment procedure regression analysis for the animal husbandry industry

Variable	2015	2016	2017	2018	2019	2020	2021	2022
Dist	2.302***	2.301***	2.632***	2.793***	2.777***	2.647***	2.464***	2.636***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp	4.707***	19.348***	19.577***	4.910***	6.968***	6.231***	4.661***	2.806***
	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
E–E	–0.086	–0.769**	–0.073	0.449	-0.580**	–0.797**	–0.118	–0.468**
	(0.330)	(0.026)	(0.344)	(0.177)	(0.030)	(0.022)	(0.239)	(0.030)
R–R	0.081	–0.603*	–0.095	0.764*	–0.453*	–0.596*	0.221	–0.219
	(0.497)	(0.053)	(0.367)	(0.059)	(0.060)	(0.054)	(0.324)	(0.141)
U–E	–0.356	–0.527*	0.047	0.648	–0.514**	–0.761**	–0.021	–0.245
	(0.180)	(0.072)	(0.500)	(0.103)	(0.044)	(0.033)	(0.435)	(0.124)
U–R	–0.818	–0.870**	0.479	0.819*	–0.254	–0.343	0.412	0.066
	(0.101)	(0.039)	(0.195)	(0.077)	(0.158)	(0.126)	(0.191)	(0.447)
E–R	–0.288	–0.842**	–0.430	–0.052	–0.840**	–1.175***	–0.732**	–0.181***
	(0.182)	(0.022)	(0.103)	(0.376)	(0.015)	(0.008)	(0.044)	(0.001)
Intercept	–5.283	–5.242	–6.177	–6.929	–6.135	–5.974	–6.676	–6.537
R^2	0.090	0.088	0.112	0.085	0.098	0.100	0.102	0.052
N	12 403	25 651	47 586	62 128	10 0128	119 805	144 453	201 930

*, **, ****P* < 0.1; 0.05; 0.01, respectively; One thousand permutations; numbers in each variable represent standardised coefficients; *P*-values in parentheses
Source: Own calculation

Table 9. Results of the quadratic assignment procedure regression analysis for the fishery industry

Variable	2015	2016	2017	2018	2019	2020	2021	2022
Dist	2.227***	2.327***	2.306***	2.325***	2.433***	2.305***	2.126***	2.293***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exp	4.765***	7.560***	4.191***	3.806***	4.638***	4.791***	4.613***	3.461***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
E–E	–0.537*	–1.279**	–0.363	–0.093	–0.593*	–0.411*	–0.536*	–0.456*
	(0.081)	(0.023)	(0.123)	(0.286)	(0.055)	(0.073)	(0.058)	(0.051)
R–R	–0.027	–0.841**	0.030	0.103	–0.043	–0.066	0.011	0.058
	(0.417)	(0.041)	(0.475)	(0.496)	(0.418)	(0.312)	(0.503)	(0.481)
U–E	–0.243	–0.490	–0.074	0.101	–0.304	–0.287	–0.595*	–0.123
	(0.213)	(0.100)	(0.362)	(0.474)	(0.158)	(0.141)	(0.062)	(0.223)
U–R	–1.203**	–0.910**	–0.043	0.401	–0.011	0.361	0.085	0.345
	(0.033)	(0.046)	(0.434)	(0.282)	(0.457)	(0.221)	(0.454)	(0.177)
E–R	–0.316	–0.703**	–0.284	–0.092	–0.699**	–0.378*	–0.895**	–0.593**
	(0.148)	(0.039)	(0.168)	(0.282)	(0.045)	(0.084)	(0.025)	(0.028)
Intercept	–5.368	–5.170	–5.858	–6.304	–6.015	–6.562	–6.221	–6.671
R^2	0.066	0.086	0.077	0.075	0.106	0.064	0.103	0.073
N	17 578	31 125	36 315	62 481	71 253	18 1503	175 528	241 860

*, **, ****P* < 0.1; 0.05; 0.01, respectively; One thousand permutations; numbers in each variable represent standardised coefficients; *P*-values in parentheses
Source: Own calculation

https://doi.org/10.17221/369/2024-AGRICECON

The results do not support that pairs of *R–R*, *U–E* and *U–R* partnerships are associated with decreased collaborative innovation in animal husbandry.

The QAP regression results for the fishery industry are shown in Table 9. Geographical proximity and prior collaboration experience clearly play important roles in explaining co-patenting behaviour in the fishery industry. The coefficients of *E–R* and *E–R* are significantly negative in most years. Similar to the case of the animal husbandry industry, compared with *U–U* partnerships, pairs of *E–E* and *E–R* partnerships have negative effects on the number of co-assigned fishery patents. However, the negative coefficients are significant only in 2016 for *R–R*, significant in 2021 for *U–E*, and significant in 2015 and 2016 for *U–R*. No significant difference is found between the *U–U*, *R–R*, *U–E* and *U–R* in their propensity for collaborative innovation.

Our empirical results strongly support the hypotheses derived from the literature. The finding that geographical proximity promotes collaborative innovation is consistent with existing evidence (Li et al. 2021). As Petruzzelli (2011) argues, the existence of previous collaborations may promote the creation of an initial base of trust between partners. This paper complements Petruzzelli (2011) by providing a QAP regression using relational data. Notably, this paper allows better identification of the effect of organisation type on innovation partnerships across agricultural industries. The patent network analysis above implies that while the subnetwork linked by enterprises is the largest, the status of universities and research institutes in the network is higher than that of enterprises. These findings are consistent with the results obtained using the QAP regression. Universities are more attractive to other innovators for carrying out collaborative innovation, whereas enterprises are perceived as a less attractive choice. Prior studies have debated the effects of proximity and diversity on collaborative innovation (Lo and Li 2018; Shin et al. 2022). This study revealed that the type of organisation pair greatly influences the propensity for patent collaboration. For example, *U–U* partnerships and *U–R* partnerships are more likely to be involved in collaborative innovation than *E–E* and *E–R*.

CONCLUSION

Based on the data of China's agricultural patents jointly filed from 2015 to 2022, this paper applies SNA and QAP regression to explore the network structural characteristics and determinants of the co-patent network. The following conclusions can be drawn. First, the patent collaboration network in China's agricultural sector is expanding in scale, and an increasing number of innovators are actively involved in research collaboration, but they are sparsely connected to others. Second, the subnetwork linked by enterprises is the largest, and the subnetwork linked by universities is the smallest. Enterprises account for half of the innovators in the network, but some of them are crowded out to the periphery of the network. Universities and research institutes are more likely to play roles as hubs and bridges. Third, geographical proximity and prior collaboration experience are key factors that promote collaborative innovation in the agricultural sector. Fourth, compared with *U–U* partnerships, the pairs of *E–E* and *E–R* partnerships are associated with decreased co-patent. Universities are more attractive to other innovators for carrying out collaborative innovation, whereas enterprises are perceived as a less attractive choice. Fifth, in the agriculture and forestry industries, the pairs of *U–U* and *U–R* have the greatest propensity to collaborate, followed by *R–R* and *U–E*. In the animal husbandry and fishery industries, no significant difference was found between the pairs of *U–U*, *R–R*, *U–E* and *U–R* in their propensity for patent collaboration.

With respect to policy implications, this paper outlines the following recommendations. First, China has made great improvements in the development of agricultural research and technology, but the cooperative innovation network is far from complete or regular, and the width and depth of cooperation need to be improved. Organisations, especially enterprises, should adopt a more open attitude towards in-depth cooperation with more partners in the field of agricultural innovation. The government should foster a conducive innovation ecosystem by protecting intellectual property and patents and drafting technology standards. Second, universities and research institutes are quite active in collaborative innovation and make significant contributions to the regional innovation system. Therefore, universities and research institutes should prioritise the research of fundamental and frontier technologies. Faculty in universities should be encouraged to carry out more collaboration and innovation. The provision of government-sponsored research institutes and the quality of their research are vitally important issues. Third, considering that the rich get richer phenomenon is indeed present in the collaborative innovation network, the government should take effective measures to fos-

https://doi.org/10.17221/369/2024-AGRICECON

ter interactions between organisations. Moreover, potential resource redundancy caused by excessive cooperation should be managed. Fourth, the adoption of digital technologies, which can diminish the difficulties and risks of cross-regional collaboration, should be stressed as an important policy instrument. Fifth, in the process of implementing research collaboration policies, policy-makers should give attention to the industry differentiation of the structure of collaborative innovation networks and the organisations shaping collaborative innovation.

This study has several limitations that should be explored in future research. First, this paper targeted the network constructed by using co-assigned patent data. Patents are an imperfect proxy for innovation because not all innovations are patented in agriculture. If other relational data on innovative activities can be collected, we can obtain more accurate information about interorganisational collaborative relationships in agriculture. Moreover, this study is based only on the quantities of patents. There are significant differences in the quality of patents. Future studies could investigate research collaboration concerning patent quality. In addition, additional proximity factors, such as technological proximity, institutional proximity and cultural proximity, could be examined in future research to better understand the determinants of collaborative innovation.

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Received: September 30, 2024
Accepted: March 31, 2025
Published online: June 25, 2025