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Modeling interprovincial migration in China using dual mechanism ERGM: toward resilient and sustainable mobility

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Understanding the dynamics of internal migration is essential for promoting regional resilience and sustainable development. This study applies a weighted Exponential Random Graph Model (ERGM) to investigate the structural and functional evolution of China's interprovincial migration networks in 2000, 2010, and 2020. By integrating embeddedness, information cascades, resource endowments, proximity, and emergence theory, the analysis reveals the dual influence of endogenous and exogenous mechanisms. Results highlight that information cascades are a significant endogenous mechanism influencing migration outcomes. Specifically, mutual and popularity cascades are positively correlate with migration network formation, while transitive cascades exhibit an inhibitory effect. Exogenous drivers, including favorable economic, educational, healthcare, ecological attributes, cultural similarity, and geographic proximity, consistently facilitate migration flows. The interprovincial migration networks have shifted from a "core-periphery clusters" to a pattern of "key agglomeration and regional balance." The dominance of endogenous mechanisms underscores the self-reinforcing nature of migration systems. These findings provide critical insights for designing evidence-based policies that address regional inequality, enhance human mobility infrastructure, and foster sustainable and inclusive internal migration systems.

KEYWORDS

migration networks, resilience, ecological attributes, exponential random graph model, endogenous and exogenous drivers

1 Introduction

Migration implicitly conveys dynamic information about a region's attractiveness, spatial reach, influence intensity, and stability. It serves as a crucial medium for understanding spatial characteristics such as regional resilience (Zhang et al., 2024; Sun et al., 2023). In China, the scale of migration has expanded markedly, from 42.42 million in 2000 to 124 million in 2020, paralleling the evolution of its market economy. Notably, despite the complexity of the socio-economic environment, these large-scale migrants have not led to disorder. Rather, migrants have self-organized into relatively stable, multi-polar networks centered around economically developed provinces (Zhou and Liu, 2023). Understanding the emergence and evolution of such ordered migration systems requires analytical depth beyond descriptive patterns. Traditional migration theories, such as the classical push-pull model (Bogue, 1959), view migration decisions as shaped by adverse conditions in origin areas ("push" factors) and attractive opportunities in destination areas ("pull" factors). Lee (1966) further introduced the role of intervening obstacles (e.g., cost, distance) and individual characteristics into the decision-making framework. However, this model offers only a limited account of migrant agency and overlooks collective decision-making processes within households (De Haas, 2010; Carling and Collins, 2018). Neoclassical migration theory attempts to bridge macro- and micro-level explanations. At the macro level, it links interregional wage differentials to migration patterns and suggests that migration reduces such disparities (Todaro and Smith, 2020). At the micro level, it conceptualizes migration as the outcome of rational decision-making, where individuals migrate if expected benefits exceed costs (Borjas, 2017). Yet, recent studies emphasize that decisions are frequently influenced by household strategies and social networks rather than individual utility alone (Massey et al., 2020; Czaika and Reinprecht, 2022). Furthermore, migration decisions are rarely based on exact cost–benefit calculations; instead, relative income perceptions shaped by comparisons with reference groups often play a key role (Stark and Bloom, 1985; Stark and Taylor, 1991).

Emergence typically manifests as a transformative process from lower-level to higher-level structures, and from micro-level components to macro-level networks (Hedstrom and Swedberg, 1998). This concept has attracted considerable attention across disciplines, including philosophy, biology, economics, and sociology, with research consistently confirming that "continuous small-scale changes eventually lead to the phenomenon of emergence" (Barabasi and Albert, 1999). A comprehensive understanding of emergence is essential for reconstructing the complete process of system development (Plowman et al., 2007). From this perspective, existing migration theories exhibit two notable shortcomings. First, whether adopting an "economic-dominant" or "noneconomic-dominant" explanation, these theories tend to resort to superficial attribution and fail to reveal the true process by which systematic migration networks emerge from dispersed individual movements. Second, current migration theories lack a logically consistent analytical framework. Often grounded in single-disciplinary approaches, they fail to systematically examine the phenomenon, leading to inevitable disciplinary limitations. Holland (1998) argues that emergence results from continuous interactions between agents and their internal and external environments, which then generate entirely new system-level properties. Therefore, a thorough understanding of the causes of migration requires simultaneous attention to the interactive rules that exist between migrants and their environments—that is, elucidating the endogenous and exogenous mechanisms underpinning the emergence of migration.

Research shows that economic level, spatial distance, population density, and social culture significantly affect migration decisions (Huang and Yang, 2020; Yang et al., 2020). However, most studies focus primarily on attribute data and rarely consider interpersonal connections. Some have used relational data, highlights the influences of economic networks, living comfort, and levels of interprovincial migration (Pu et al., 2018). Yet, these studies typically emphasize exogenous factors from a static perspective, neglecting endogenous mechanisms that drive migration evolution from local interaction to broader patterns. Notably, accounting for endogenous mechanisms reduces the apparent impact of exogenous attributes. Jang and Yang (2024) demonstrated that international trade exhibits strong path dependence, with endogenous mechanisms, such as node reciprocity, preferential attachment, and shared partner effects, serving as key drivers of evolution. Endogenous mechanisms are, therefore, pivotal in shaping and transforming network ties to drive macro-level changes in network structures through repeated local interactions (Pan, 2018). Similarly, in migration networks, information transmission channels are established between regions through various forms of migration. Migrants tend to abandon their market insights and follow others' behaviors, triggering an information cascade (Akbari, 2021; Somerville, 2015). The existence of an information cascade within the whole network has been demonstrated through the construction of a migrant worker network, and the transition from partial quantitative changes to overall qualitative transformations in migration has been explored (Ren et al., 2021). Thus, migration networks cannot be explained solely based on exogenous factors; endogenous mechanisms, such as information cascade, play an equally critical role. Conventional migration studies pay less attention to the endogenous mechanism underlaying migration dynamics and are unable to capture the intrinsic emergent mechanism. To address this gap, the exponential random graph model (ERGM) reveals how micro-level endogenous configurations lead to the emergence of macro-level network structures. Moreover, ERGM enables the simultaneous incorporation of both attribute (exogenous) and relational (endogenous) variables, enabling a comprehensive framework for analyzing migration networks (Lusher et al., 2013). The present study employs a weighted ERGM to analyze China's interprovincial migration networks using census data from 2000, 2010, and 2020. The study focuses on three central questions: (i) Does the migration network exhibit information cascade phenomena? (ii) Is information cascade a critical endogenous mechanism underlying the emergence of migration? (iii) Which endogenous drives complement the emergence of migration networks?

This study offers three key contributions. Firstly, it empirically demonstrates the existence of information cascades in population mobility across spatio-temporal dimensions, and addressing the limitations of push-pull theory that emphasize exogenous factors. Second, it proposes a novel analytical framework integrating ERGM with theories of information cascades, resource endowment, and spatial proximity, thereby capturing both endogenous and exogenous drivers of migration. Third, the study reconceptualize migration as a dynamic, self-organizing process, highlighting how localized individual decisions aggregately evolve into complex, stable macro-structures within migration theories.

2 Theoretical framework

2.1 Social networks and embeddedness

The socioeconomic system is a network comprising various types of social actors (such as individuals, groups, organizations, or nations) and the relationships between them. According to the social network perspective, each actor and their actions are embedded within social networks, and the degree and structure of this embeddedness vary over time and across space. Concerning specific actions, actors may both exhibit subjective initiative and be constrained by social norms. Therefore, it is unreasonable to view actors as either entirely rational individuals or as fully constrained by social norms (Granovetter, 1985). The social network is not only a channel connecting social actors but is also a conduit for the flow of social resources. In terms of interprovincial migration, different provinces and the migrants moving between them collectively form an interprovincial migration network. The movement of migrants between provinces is not solely determined by a province's attributes but is also shaped by its migrant relationships with other provinces; i.e., the network structure. In an interprovincial migration network, the micro-level decision-making processes of individual interdependent actors are embedded within the macro-level interprovincial relationships. In turn, this embeddedness influences actors' micro-level migration behavior, which is continuously supported and reinforced by bidirectional feedback (Sharifnia and Saghaei, 2022).

2.2 Social networks and endogenous mechanisms

Information cascades provide a new endogenous perspective for explaining the underlying drivers of migration. American scholar Sunstein (2009) first proposed the concept of information cascades in his book Rumors, describing a phenomenon in social networks. When people faced with incomplete information, rely on the observed actions of others. To achieve certain goals, they may ignore their own knowledge and instead imitate the behavior of preceding individuals. Information cascades act as a mechanism to reinforce the spread of rumors within networks. Kuran and Sunstein (1999) proposed the concept of "reputational cascade," whereby actors lacking sufficient information tend to adopt the opinions of higher-reputation individuals to gain social approval. When information and reputational cascades occur on a large scale and reinforce one another, the repeated dissemination of certain information or viewpoints increases the likelihood of others following the followers (Kuran and Sunstein, 1999). Empirical studies have confirmed the presence of an information cascade in international trade and innovation cooperation networks characterized by reciprocity, convergence, and brokerage (Zhou et al., 2016; Setayesh et al., 2022). In migration networks, incomplete information or comparative advantages often lead to mutual migration between provinces (Joohyun et al., 2019). Economically developed regions, such as the Yangtze River Delta and the Pearl River Delta, tend to attract migrants from other provinces, forming "prestige." Over time, a small number of provinces become highly influential hubs, connecting with many others in the migration network. These well-connected provinces have a major influence on the migration decisions of subsequent actors (Furkan and Mathias, 2021; Koskinen et al., 2023). Structural holes also exist in migration networks. Provinces occupying "bridging" or "core" positions have a greater capacity to attract labor resources than those in "non-bridging" or "non-core" positions (Burt, 1992). As information becomes more accessible over time, migrants increasingly prefer direct migration to relying on intermediate provinces as transit hubs, leading to one-step migration (Meng et al., 2023). Information cascade offers a novel perspective from which to understand the mechanisms underlying migration.

2.3 Social networks and exogenous mechanisms

The exogenous drivers of social networks include actor attributes and contextual factors. In terms of actor attributes, although individuals are the primary agents of migration, their micro-level decisions are inevitably influenced by the resource endowments of the regions they are embedded in, a relationship that has been confirmed by numerous studies. Ren et al.'s (2017) study on inter-city networks induced by migrant worker flows found that a concentration of migrant workers in developed cities does not always result in higher wages. Most existing studies focus primarily on the structural relationships within networks and often overlook the role of node attributes. In migration networks, the relative comparative advantages of origins and destinations exert a major effect on migration outcomes (Ren and Wang, 2025). These comparative advantages are reflected in resource endowments, such as economic scale, foreign investment, industrial structure, the number of hospitals and clinics, and green space (Li et al., 2023). Integrating node resource endowments into migration network research helps address the current limitations in the field.

In terms of contextual factors, multidimensional proximity is a crucial concept in social networks. For example, the spatial proximity between two parties involved in a transaction can reduce costs and mitigate risks (Liu et al., 2020). Proximity encompasses multiple dimensions, such as institutional, cultural, social, and geographical proximity. Multidimensional proximity has been recognized as a key factor influencing migration. For example, geographical proximity reduces travel time and transportation costs (Lu and Zhang, 2019), reduce barriers to obtaining destination-related information (Li, 2009), increases opportunities for reuniting with family and friends, and alleviates psychological costs, thereby promoting migration (Schwartz, 1973). Similarly, when origins and destinations share cultural similarities, such as being part of the same dialect region or religious community, the proximity in identity, acquaintance network, and value systems reduces uncertainty and opportunism during the migration process, increasing migration frequency (Wang and Li, 2019). Thus, integrating social networks with multidimensional proximity offers greater explanatory power when attempting to understand migration mechanisms.

2.4 Social network exponential random graph theory

As a meta-theory, ERGMT suggests that social systems emerge from the interplay of network self-organization, actor attributes, and external context (Lusher et al., 2013). Migration research, however, often focuses on destination choices through an exogenous perspective (Sheng, 2018; Zeng et al., 2023). Recently, some researchers have utilized ERGM to study migration in China (Shi et al., 2022; Zhao et al., 2024), primarily to examine endogenous and exogenous factors influencing migration, contributing to a deeper understanding of migration processes. However, many studies have focused solely on the application of the model and have often relied on single-type migration datasets, consequently lacking in-depth theoretical exploration (Wang et al., 2025). ERGM uses partial network configurations as key explanatory variables, incorporating the concepts of embeddedness, information cascade, and node resource endowments, as well as multidimensional proximity between nodes. ERGM skillfully integrates the idea of emergence, capturing the mechanism by which local configurations give rise to whole network structures—whether in single-time-point or multi-time-point ERGM applications—reflecting network evolution dynamics. This study integrates embeddedness theory, information cascade theory, resource endowment theory, multidimensional proximity theory, and ET into the framework of the social network ERGMT, forming a theoretical model for analyzing the intrinsic mechanisms of interprovincial migration in China.

3 Materials and methods

3.1 Network construction

This study utilized data from the China Population Censuses of 2000, 2010, and 2020, covering all 31 provincial-level administrative regions (Table 1) across the country (excluding Hong Kong, Macau, and Taiwan). Other indicators were sourced from the China Statistics Press and Google Maps. Based on the long-form data of "current residence and residence five years ago," interprovincial migration matrices were constructed for the three-time points to analyze migration network evolution characteristics and mechanisms. The total sample sizes of interprovincial migrants in 2000, 2010, and 2020 were 3,228,213, 5,489,191, and 5,083,191, respectively. To further explore the evolutionary mechanisms of migration across different economic regions, we selected the key regions of the Yangtze River Economic Belt (YtREB), Yellow River Economic Belt (YREB), and Belt and Road Economic Belt (BREB). Specifically, the YtREB includes 11 provinces: Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan, and Guizhou; the BREB comprises 18 provinces: Liaoning, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, Jilin, Heilongjiang, Inner Mongolia, Guangxi, Chongqing, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang; the YREB includes 11 provinces: Beijing, Tianjin, Hebei, Shandong, Shanxi, Henan, Qinghai, Gansu, Ningxia, Inner Mongolia, and Shaanxi. Table 1 illustrates the scale of migration within each region. Nationally, interprovincial migration has followed an inverted "U-shaped" trend, first increasing and then decreasing. Regionally, migration in the YREB and BREB increased steadily, while the trend in the YtREB aligned with the national pattern.

Provinces are represented by nodes (or vertices), and migration relations between provinces are denoted by the ties (or edges) that connect the nodes. Three directed and weighted interprovincial migration networks were constructed, represented by 31 × 31 matrices W_{ij}, as shown in Equation 1. In these matrices, the "rows" represent the number of people migrating from a given province to other provinces, while the "columns" represent the number of people migrating into a given province from other provinces. The diagonal elements, which represent the number of intraprovincial migrations, are set to 0 as they are not the focus of this study.

$$W_{ij} = \begin{bmatrix} 0 & a_{1,2} & \cdots & a_{1,j} & \cdots & a_{1,31} \\ a_{2,1} & 0 & \cdots & a_{2,j} & \cdots & a_{2,31} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ a_{i,1} & a_{i,2} & \cdots & 0 & \cdots & a_{i,31} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ a_{31,1} & a_{31,2} & \cdots & a_{31,j} & \cdots & 0 \end{bmatrix} \quad (1)$$

To analyze the information cascade, a Top1 network was constructed following the approach of Hisakado and Mori (2016). The rules were as follows: based on the original interprovincial migration network, the migration tie with the largest flow between each pair of provinces was retained as the edge in the Top1 network, while all other edges were set to zero. Top2 networks were also constructed to verify the robustness of the information cascade. The rules were as follows: based on the original interprovincial migration network, the largest and second-largest migration ties were retained as edges in the Top2 network, while all other edges were set to zero. The network construction approach proposed by Pan et al. (2018) and Liu et al. (2021) was adopted for utilizing weighted ERGM to analyze the mechanisms influencing interprovincial migration. Based on the original interprovincial migration network, the Top10 migration flows from each province to other provinces were retained as edges, while all other edges were set to zero. This process produced three new whole networks, ensuring the representativeness of the samples. The whole network's construction rules effectively reflect the relative equality of provinces within the migration network, avoiding the estimation bias of endogenous structural effects caused by neglecting nodes with small scales but high participation. According to the statistics, the migrants in the whole network account for 80–90% of the total sample, ensuring good sample representativeness. The resulting weighted network accurately captures the relative importance of interprovincial bilateral migration ties and meets the requirements of the weighted ERGM.

3.2 Information cascade verification methods

To verify the presence of information cascade in the interprovincial migration network, this study applied the theoretical model adopted by Zhou et al. (2016) (Figure 1). The method involved calculating the frequency of each triad configuration in the Top1 network and compared these with the triads shown in Figure 1. Information cascade was verified if triads corresponding to Figure 1 were present (non-zero) while all other triads were absent (zero). Subsequent analysis of Top2 networks assessed robustness by examining whether these triads remained prevalent and constituted a high proportion of

TABLE 1 Interprovincial migration patterns in China for 2000, 2010, and 2020.

Years	Nationwide (31 provinces)	YtREB (11 provinces)	YREB (11 provinces)	BREB (18 provinces)
2000	3,228,213	2,054,739	660,335	969,717
2010	5,489,391	3,164,090	1,421,832	1,715,081
2020	5,083,191	2,541,777	1,469,716	2,071,769

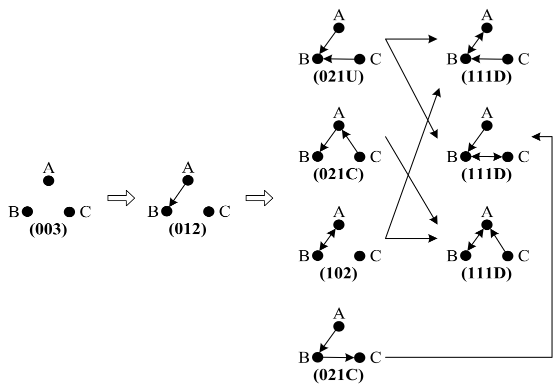


FIGURE 1
Information cascade model (Zhou et al., 2016).

all triad configurations. Triad counts were computed using UCINET software.

3.3 Weighted ERGM and configuration specification

ERGM is used to model the formation and evolution processes of ties and can be applied to binary and weighted networks. Since the interprovincial migration network is a weighted network, this study adopted the weighted ERGM, which enhances the model's explanatory power (Krivitsky, 2012). The expression for the weighted ERGM is shown in Equation 2

$$\Pr\left(Y=y\right)=\frac{1}{k}\exp\left\{\sum\nolimits_{A}\theta_{A}g_{A}\left(y\right)\right\} \tag{2}$$

where Y is a random variable representing the potential weighted ties in the migration network, and y is the observed value of Y. θ_A denotes the model parameters for the configurations, and g_A (y) represents the network statistics, including structural configurations, actor configurations, and exogenous contextual configurations. k is a normalization function ensuring that the distribution sums to 1, thereby constraining the probabilities within the range of 0–1. The configuration specification for the weighted network primarily depends on the type of distribution observed in the actual network. Since the values of ties in the interprovincial migration network are non-negative integers and exhibit over-dispersion, a binomial distribution is chosen as the reference distribution for the weighted ERGM (Pilny and Atouba, 2018).

Table 2 illustrates the configurations of the weighted ERGM. Endogenous factors in the interprovincial migration network mainly include configurations such as edges, mutual, popularity, and transitive. A transitive configuration comprises two types of triads: 021C and 111D. Since low-order network structures are nested within higher-order configurations, the 111D triad was selected to represent a transitive configuration.

Exogenous configurations include actor attributes and network covariate configurations. Actor attribute configurations capture the link between provincial resource endowments (e.g., economy, education, healthcare, and ecology), with migration. Following Wang et al. (2023) and Shi et al. (2025), this study uses the regional gross domestic product (GDP), university students per 100,000 people, average practicing physicians per hospital, and population-weighted PM2.5 concentration as indicators of these dimensions. Data for these indicators were averaged over the periods 1996–2000, 2006–2010, and 2016–2020. Network covariate configurations were measured using "whether two provinces belong to the same dialect region" and "the geographical distance between provincial capitals." The classification of dialect regions was primarily based on the "Large Dictionary of Chinese Dialects," which identifies the dialect regions of the capital of 31 provinces. If two provinces belonged to the same dialect region, the value of their tie was set to 1; otherwise, it was set to 0. Geographical distance was measured using the actual railway distance between provincial capitals.

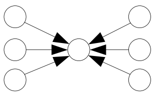
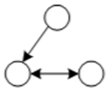
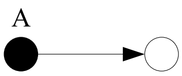
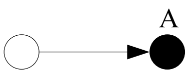
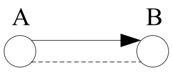
4 Results and discussion

4.1 Evolutionary trends of the interprovincial migration network

The evolution of the interprovincial migration networks is depicted in Figure 2. To differentiate the network structures of different regions, YtREB, YREB, and BREB are depicted in blue, yellow, and pink, respectively. If a province belongs to two or three economic belts, its node color in the diagram is determined by the first color assigned during the drawing process. Overall, interprovincial migration evolution exhibits a "one core, multiple sub-cores" network structure, with Guangdong as the core and Jiangsu, Beijing, Zhejiang, and Shanghai as sub-cores. This highlights Guangdong's enduring role as the leading hub for aggregation within the migration network, and the steadily increasing capacity of Jiangsu, Zhejiang, and Shanghai to attract migrant populations. From the perspective of traditional regional divisions, the core areas of the migration network are concentrated in the eastern provinces, while the central and western provinces remain on the periphery. This pattern reflects the migration preference toward key hubs "Beijing, Shanghai, and Guangzhou." In the three major economic belts, intra-regional clusters are evident: "Shanghai-Jiangsu-Zhejiang-Anhui" in YtREB, "Beijing-Tianjin-Shandong" in YREB, and "Guangdong-Guangxi-Shaanxi" in BREB. Among these, YtREB exhibits significantly higher flows and network connectivity compared with the other two economic belts. Specifically, it demonstrates a migration structure led by the eastern Yangtze River Delta, supported by the central region (Anhui-Hubei), and anchored in the western region (Sichuan-Chongqing). This reflects an evolving migration pattern characterized by both concentrated agglomeration and regional balance.

The Top1 interprovincial migration networks are depicted in Figure 3. Overall, the Top1 network exhibits a structural pattern characterized primarily by a star shape with tree-like supplements, forming three migration subgroups with one large and two smaller clusters. In the Guangdong-dominated migration subnetworks, "core-periphery" structures are particularly prominent. Additionally, the migration ties between provinces exhibit strong path dependence, with geographic proximity a key factor in the network's development into three distinct subnetworks. From the

TABLE 2 Weighted ERGM configurations and connotations.

Configurations		Graphical representation	Connotations
Network Self-organization (Endogenous configurations)	Weighted edge (Sum)		Similar to the intercept term of the regression model.
	Mutual		The number of provinces pairs with mutual migration. It is used to test whether there is a complementary advantage effect in inter-provincial migration.
	Popularity (Nodeicovar)		The number of configurations of migration flow from other provinces to a certain province that is at the center. It is used to test whether there is a preference attachment effect in inter-provincial migration.
	Transitive (Transitiveweights)		The number of configurations that one province receives migrants from the other two provinces, while the population of the province also migrates to one of the provinces. It is used to test whether there is a structural hole effect in inter-provincial migration networks.
Actor attributes (Exogenous configuration)	Destination economic, education, medical, and pollution levels (Nodeocov)		The number of configurations that the population of provinces with certain exogenous attributes, e.g., economic, education, medical, and pollution levels, migrates to other provinces.
	Origin economic, education, medical, and pollution levels (Nodeicov)		The number of configurations that provinces with certain exogenous attributes, e.g., economic, education, medical, and pollution levels, receive migrants from other provinces.
Network covariate (Exogenous configurations)	Geographical distance, cultural homophily (Edgecov)		The number of configurations that the population of geographically or dialectically adjacent provinces migrates from one province to another.

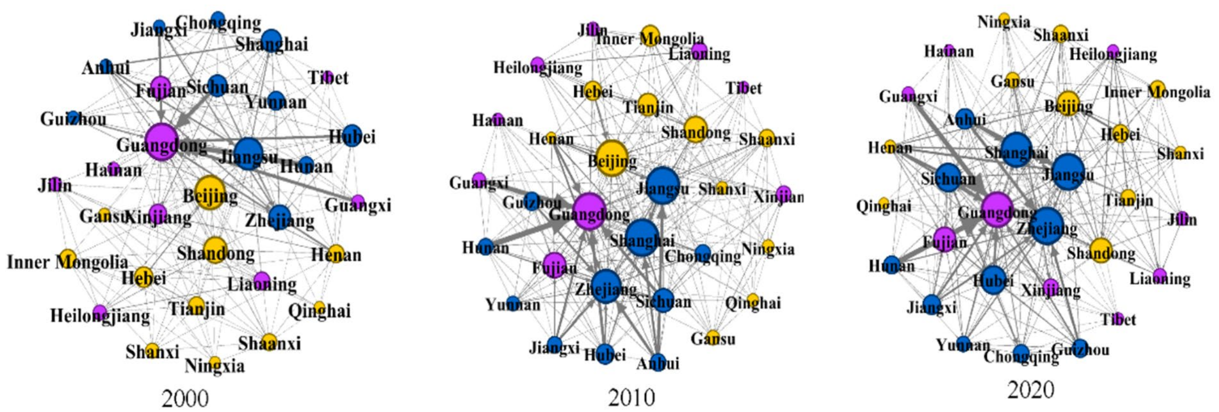


FIGURE 2
National interprovincial migration networks.

regional perspective, the eastern provinces' population attraction effect was relatively weak in 2000, with cross-regional migration primarily concentrated among neighboring provinces. As policies evolved, migration patterns shifted predominantly from the central and western regions to the eastern region, with this structure remaining relatively stable. From the perspective of the three major economic belts, there was no significant migration connectivity between them in 2000. However, the network connectivity among the three gradually improved with the advancement of regional coordinated development and the establishment of economic belt policies. The YtREB developed localized flows primarily centered on Shanghai-Zhejiang-Jiangsu-Anhui, while the YREB exhibited an instar-shaped pattern centered on Beijing. Similarly, the BREB evolved into a spatial structure with Guangdong as the primary and Xinjiang as the secondary center. This reflects the influence of economic policies on migration, exhibiting a clear temporal effect. The YtREB, YREB, and BREB cover all provinces, with each province's functional roles becoming increasingly defined. Consequently, this form of migration, driven by economic belts, demonstrates localized labor factor circulation among the provinces, in turn facilitating the broader domestic economic circulation.

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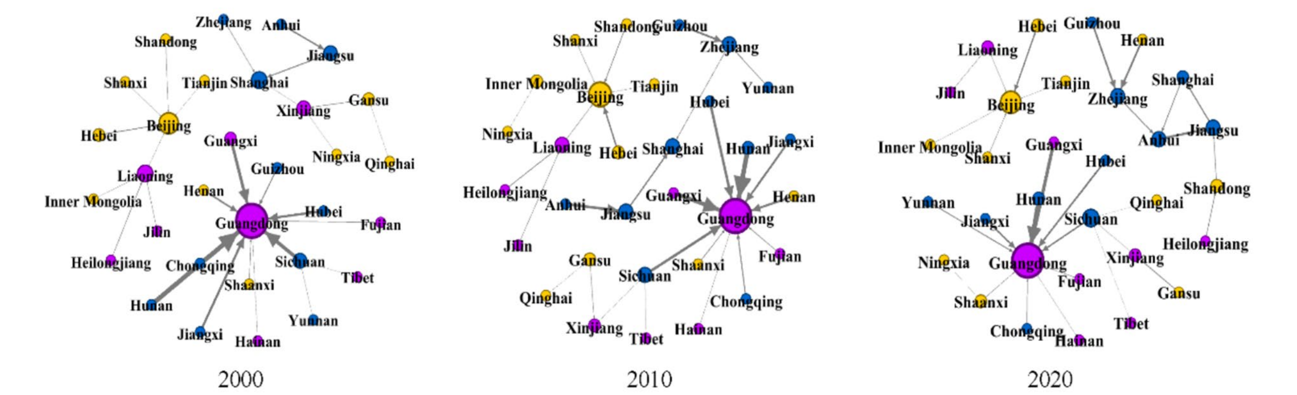

FIGURE 3
Interprovincial migration networks based on the largest migration flows.

4.2 Information cascade

4.2.1 Top1 network information cascade

The number of triads in the Top1 interprovincial migration network for the three major economic belts and nationwide Tables 3, 4, indicates that these triads align with those in the information cascade model (Figure 4) and confirms the existence of information cascade in the interprovincial migration network. Notably, there are 16 types of triads in directed networks, and this table only provides triads and numbers with non-zero triad numbers.

As shown in Table 3, the Top1 interprovincial migration network reflects a general pattern whereby the more complex the triad, the fewer its occurrences. Triad 102 represents mutual migration between two provinces, demonstrating stability. As shown in Figure 2, such mutual migration primarily occurs between provinces like "Beijing-Hebei," "Jiangsu-Shanghai," and "Guangdong-Guangxi." This mutual migration manifests primarily in two respects: underdeveloped provinces promote economic development in developed provinces by exporting a large amount of labor, while developed provinces provide technical talent to drive industrial upgrading or structural integration in underdeveloped regions. It also encompasses labor demand arising from comparative industrial advantages between developed provinces. Geographic proximity facilitates mutual migrations, contributing to a relatively balanced state of regional migration. Triad 021U represents the outflow provinces' preference for attaching to highly aggregated inflow provinces. For instance, Guangdong has consistently remained at the core of the network with a prominent leading effect, and the clustering migration phenomenon has not changed over time. Beijing demonstrates strong regional influence, continuously covering north and northeast China, while the Yangtze River Delta region tends to favor small-scale clustered development with a relatively concentrated radiation range. Other triad configurations, such as 021C, represent provinces that are both rich in labor resources and highly attractive within the migration network. For example, in the "Guizhou-Zhejiang-Shanghai" migration chain, Zhejiang serves as a province that not only attracts migrant inflows from Guizhou but also provides the labor resources Shanghai needs. Triad 111D is the highest-ranking triad configuration in this migration network, encompassing the structural characteristics of all other triads.

TABLE 3 Information cascade for national interprovincial migration.

Triads	2000	2010	2020
003	3,765	3,757	3,728
012	578	593	649
102	70	71	45
021 U	57	49	48
021C	8	9	12
111D	17	16	13

The triad configurations of the Top1 migration network for the three major economic belts have been provided in Table 4. The results demonstrate that, overall, for the BREB, the more complex the configuration, the fewer its occurrences. For the YtREB and YREB, the number of triads initially decreases before increasing sharply for triad 021U. From the perspective of network structure evolution, migration relationships in the YREB have shifted from being "reciprocity-dominated with convergence as a supplement" to "convergence-dominated with reciprocity as a supplement." In the BREB, mutual migration first decreases and then increases, while convergence exhibits an opposite trend, initially increasing and then decreasing. In the YtREB, mutual migration first decreases and then increases while convergence continues to grow steadily. The clustering effects of developed provinces in the YtREB and YREB have become increasingly prominent, reflecting the growing leading roles and influence of the Yangtze River Delta and Beijing-Tianjin-Hebei regions with the implementation and advancement of regional economic belt policies. In the BREB, officially established as a policy in 2013, a significant increase in reciprocal relationships can be observed, along with enhanced complementarity of regional advantages and strengthened regional cooperation.

4.2.2 Robustness of information cascade

Table 5 presents the triad configurations and frequencies in the Top2 network. To assess the robustness of the information cascade, the occurrence of the six triad configurations in the Top2 network is compared with those generated by the cascade model. The results reveal that the Top2 interprovincial migration network's triads for the three major economic belts and nationwide include the six triad

TABLE 4 Information cascade for interprovincial migration in the three major economic belts.

Triads	YtREB			YREB			BREB		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
003	95	105	99	94	93	105	475	587	612
012	43	23	35	47	50	28	160	177	143
102	14	7	11	14	4	2	27	25	41
021U	2	21	22	3	9	21	8	13	9
021C	7	7	7	3	4	2	6	7	4
111D	2	2	2	4	5	7	4	7	7

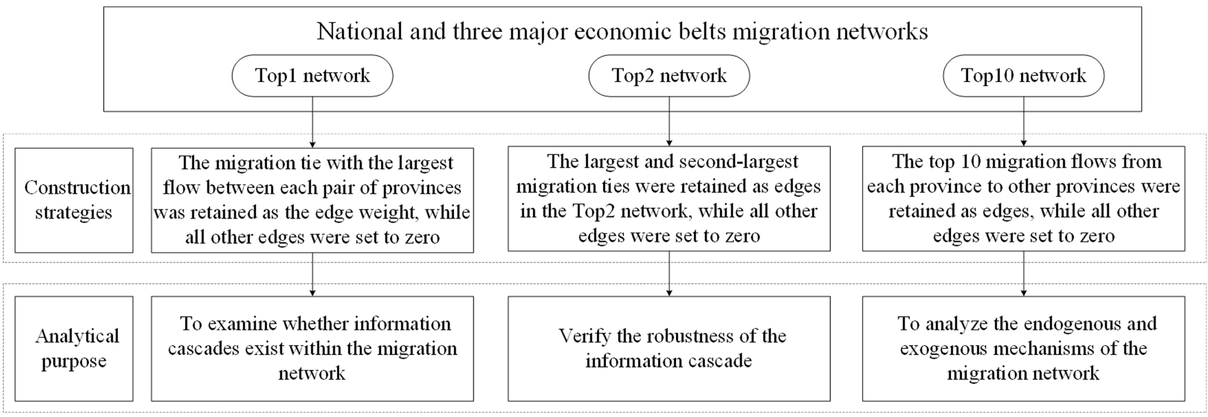

FIGURE 4
Network construction strategies and analytical purpose.

configurations hypothesized by the information cascade model. Additionally, three new triad configurations, 021D, 111U, and 030T, appear due to each node emitting two ties.

Table 5 indicate that the existence of an information cascade in the interprovincial migration networks, demonstrating strong temporal stability and spatial universality. Additionally, under conditions of incomplete information, migrants tend to observe and imitate the migration behaviors of other provinces, resulting in clustered migration patterns. Information cascade plays an increasingly important role as interprovincial migration increases. For example, in the nationwide interprovincial migration network, there were 4,469 information cascade triads in 2000, accounting for 99.42% of the total triads in the network. Similarly, the corresponding proportions were 99.48% in 2010 and 98.89% in 2020, confirming the robustness of the information cascade in interprovincial migration.

4.3 The evolution mechanisms of migration networks

4.3.1 Nationwide interprovincial migration network

Similar to traditional regression models, ERGM tests the significance of configurations using the t-statistic, where $p < 0.05$ indicates significance. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to measure the fit of the actual network, to evaluate the ERGM's validity. Typically, BIC is larger than AIC, and the smaller the values of both metrics, the better the model fit and the stronger the model's explanatory power (Kashima et al., 2013).

Table 6 presents the weighted ERGM fitting results for the nationwide interprovincial migration network. From the perspective of endogenous mechanisms, mutual and popularity cascades significantly and positively promote migration, with their effects remaining stable over time. On one hand, because of the substantial differences in resource endowments and economic structures across provinces, migrants weigh the costs and benefits of migration. Provinces leverage their comparative advantages, and the information cascade effect of migration behavior facilitates bidirectional labor flows between them. This mutual migration provides reference information for subsequent migrants, inadvertently reducing information uncertainty and objectively promoting the reallocation of labor resources across provinces. On the other hand, popularity exhibits a clear preference attachment impact, whereby provinces receiving a large inflow of migrants tend to attract even more migrants due to their "reputation effect." Additionally, the parameters estimated for transitive configurations are either insignificant or significantly negative, indicating that this structure is not an endogenous mechanism driving the emergence of the networks.

From the perspective of exogenous mechanisms, higher economic, healthcare, and educational levels in the destination provinces contribute significantly to the formation of interprovincial migration ties, reflecting destination provinces' "pull effect" on migration. In addition, over time, poorer ecological conditions in the destination

TABLE 5 Robustness of information cascades in interprovincial migration.

Triads	Nationwide			YtREB			YREB			BREB		
	2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
003	3,144	3,164	3,158	59	69	64	48	51	45	434	450	438
012	979	951	960	54	33	34	62	55	66	243	210	237
102	145	115	166	10	3	15	18	10	12	80	60	31
021D	11	6	14	1	1	3	2	2	2	4	3	4
021U	118	161	107	17	38	22	11	17	11	21	53	62
021C	39	30	28	2	1	8	8	11	12	11	9	19
111D	44	51	52	18	16	15	9	12	10	18	22	20
111U	6	1	2	2	1	2	2	2	1	2	3	2
030T	9	16	8	2	1	2	5	5	6	3	4	3

TABLE 6 Weighted ERGM simulation for nationwide interprovincial migration.

Configurations	2000		2010		2020	
	Model 1	Model2	Model3	Model4	Model5	Model6
Edge	−1.0253*** (0.0483)	−1.9249* (0.8613)	−1.0810*** (0.0077)	−2.3150** (0.784)	−0.9536* (0.3496)	−2.3210*** (0.0819)
Mutual	—	1.8989*** (0.3276)	—	1.8590*** (0.3097)	—	1.2580*** (0.3092)
Popularity	—	0.1512*** (0.0533)	—	0.2409*** (0.0522)	—	0.3998*** (0.0459)
Transitive	—	0.1951 (0.1277)	—	0.2041 (0.1245)	—	−0.3365*** (0.0800)
Destination economic level	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0009*** (0.0001)	0.0004* (0.0002)	0.0004*** (0.0000)	0.0001 (0.0001)
Origin economic level	0.0005 (0.0006)	−0.0002** (0.0001)	0.0000 (0.0001)	−0.0005*** (0.0001)	−0.0000 (0.0001)	−0.0000 (0.0001)
Destination medical level	0.0007 (0.0033)	0.0041 (0.0034)	0.0009** (0.0003)	0.0047*** (0.0006)	0.0094** (0.0031)	0.0005 (0.0030)
Origin medical level	−0.0057 (0.0037)	−0.0067* (0.0032)	−0.0056 (0.0035)	−0.0066* (0.0033)	0.0016 (0.0033)	−0.0001 (0.0036)
Destination education level	0.0018*** (0.0002)	0.0013*** (0.0003)	0.0008*** (0.0002)	0.0005* (0.0002)	0.0004* (0.0002)	−0.0001 (0.0002)
Origin education level	0.0004 (0.0002)	−0.0004 (0.0003)	0.0002 (0.0002)	−0.0001 (0.0018)	−0.0002 (0.0002)	−0.0001 (0.0002)
Destination pollution level	−0.0114 (0.0123)	0.0079 (0.0135)	−0.0059 (0.0036)	0.0112 (0.0077)	−0.0618*** (0.0107)	−0.0181* (0.0091)
Origin pollution level	−0.0440*** (0.0127)	−0.0252 (0.0134)	−0.0244*** (0.0072)	−0.0196* (0.0079)	−0.0122 (0.0098)	−0.0001 (0.0002)
Cultural homophily network	1.0010* (0.3962)	0.4596 (0.3767)	1.0070* (0.4128)	0.4565 (0.3969)	1.4410*** (0.3098)	1.4790*** (0.2986)
Spatial distance network	−0.0018*** (0.0002)	−0.0016*** (0.0002)	−0.0016*** (0.0002)	−0.0015*** (0.0002)	−0.0016*** (0.0002)	−0.0017*** (0.0002)
AIC	−1,922	−1,945	−1,908	−1,960	−1,935	−2,036
BIC	−1,869	−1,877	−1,855	−1,893	−1,881	−1,969

Where ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Values in parentheses represent standard errors.

provinces, indicated by higher PM2.5 concentrations, have become increasingly detrimental to migration. With respect to geographical factors, the estimated parameter for spatial distance is significantly negative, indicating that migration costs remain a major constraint. Under the constraint of transportation costs, proximity between provinces is more likely to facilitate migration. Cultural similarity has a significant positive impact on the formation of migration ties, suggesting that migration is more likely to occur between provinces with fewer cultural differences. This is because dialects, as cultural symbols of a region, can evoke cultural resonance among individuals (Gao and Lin, 2018), better-facilitating migrants' integration into new environments. It is worth noting that the marginal effects of exogenous variables generally decrease with the progressive addition of endogenous variables to the model. In Models 5 and 6, the significance of economic and healthcare levels declines after including information cascade variables. This suggests that local endogenous mechanisms can weaken migration reliance on exogenous factors (Shi et al., 2022).

4.3.2 Migration network of the three major economic belts

The weighted ERGM regression results for the interprovincial migration network of the three major economic belts (Table 7) reveal distinct structural patterns and influencing factors within each belt. The results show that endogenous and exogenous mechanisms significantly influence the formation and evolution of regional migration ties. Specifically, (1) Over time, mutual configurations have a significant positive effect on migration ties within the YtREB and BREB but exert a negative or insignificant effect on migration ties in the YREB. This may be attributed to the differentiated industrial layouts and the implementation of related policies in the YtREB and BREB, which promote more active migration. In contrast, the YREB is constrained by natural conditions such as poor navigability, making mutual migration between eastern, central, and western provinces less conducive to promoting migration in general (Zheng, 2016). (2) Popularity configurations have a positive effect across the three economic belts, indicating that the provinces within them experience significant migrant inflows. This highlights the importance of the preference attachment effect in the evolution of interprovincial migration networks. It is worth noting that the macro-level networks emerging from the convergent configurations constitute the mechanism underlying the previously observed "core-periphery" structure or the pattern characterized by "star-shaped with tree-like supplements." (3) The coefficients for transitive configuration are mostly negative or insignificant, indicating that transitive configuration also has a suppressive effect on migration within the three major economic belts.

The effects of exogenous mechanisms within the three major economic belts are largely consistent with those observed nationwide. Over time, spatial distance has little impact on migration network formation in the YtREB, while having a significantly negative effect on the migration networks of the YREB and BREB. This finding indicates that migration in the YtREB is less constrained by distance. Possible reasons for this include the region's high level of economic coordination, reduced institutional barriers to labor mobility, and well-developed transportation infrastructure, all of which help overcome spatial restrictions on migration. In contrast, the YREB and BREB require further improvements in terms of economic coordination and transportation infrastructure. The relatively small AIC and BIC values displayed in Tables 6**,** 7 indicate that the model demonstrates good convergence.

Depending on the research objective, ERGM can be specified simultaneously or hierarchically to account for endogenous and exogenous factors (Lehmann and White, 2024). This study adopts a hierarchical specification for the national dataset and a simultaneous specification for time specific datasets. This dual approach enables comparison of endogenous and exogenous effects (Table 6) and assesses how exogenous effects vary when controlling for endogenous structures (Table 7).

The aforementioned discussion provides a new theoretical perspective on migration and highlights endogenous mechanisms where reciprocal and convergent cascades significantly promote migration. The aforementioned discussion provides a new theoretical perspective on migration and highlights endogenous mechanisms where reciprocal and convergent cascades significantly promote migration. This aligns partly with dual labor market and neoclassical micro migration theories. Regional labor markets offer potential incentives for reciprocal exchanges among migrants. Although secondary labor markets are characterized by disadvantages such as employment instability, low wages, limited welfare, and limited career prospects, their low barriers to entry and the potential for quick returns provide abundant employment opportunities for migrant workers. In contrast, primary labor markets, leveraging advantages such as job stability, high income, generous benefits, and promising career development prospects, tend to selectively attract highly skilled migrants. Additionally, with the advancement of household registration reforms and regional coordinated development strategies, institutional barriers that once hindered migrants' access to primary labor markets have gradually been removed (Sumption, 2025). Information cascades transmit regional labor market advantages among migrants through bidirectional labor flow. Simultaneously, migrants' preferential for increasing returns and minimizing risks, amid socioeconomic complexity and limited information, drives preferential attachment behavior (Todaro, 1969; Williams and Baláž, 2012). To cope with these challenges, migrants tend to seek the locations offering the greatest opportunities, showing a preference for information disseminated from core cities within migration networks, thus maximizing the value of equivalent human capital investments. The regression results for exogenous mechanisms are largely consistent with the classical push-pull theory (Lee, 1966). The favorable characteristics of destination areas, such as better economic conditions, ecological environment, healthcare, and education, act as pull forces by improving migrant living conditions. Meanwhile, adverse socioeconomic conditions in origin areas function as push forces. In addition, cultural similarity and geographical proximity lower migration barriers. Comparative analysis shows destination pull forces have a stronger influence on migration than origin push factors, further suggests the primacy of destination socioeconomic conditions in shaping interprovincial migration in China.

Table 6 indicates that many exogenous variables lose significance when both endogenous and exogenous mechanisms are considered together (Windzio, 2018). According to cumulative causation theory, as the ties between origin and destination areas stabilize over time, other factors gradually lose relevance, and relational connections become the fundamental force driving migration (Massey, 1990). The present study extends this view: the greater explanatory power of endogenous mechanisms than exogenous factors does not imply that the latter have become unimportant, but rather reflects the outcome of their dynamic interplay (cooperation, competition, and mutual transformation). The underlying reason is that migration is an open, evolving, and adaptive complex system. On the one hand, migration networks exhibit complexity, characterized by the presence of numerous autonomous decision-making agents, thereby displaying

TABLE 7 Weighted ERGM simulation for interprovincial migration in the three major economic belts.

Configurations	YtREB			YREB			BREB		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Edge	−3.2860** (0.1245)	−2.7740* (1.3490)	−2.4940*** (0.2359)	−1.6591*** (0.4183)	−2.4160*** (0.2573)	−1.152*** (0.1902)	−1.3620** (0.4861)	−2.2918*** (0.2194)	−4.120** (1.416)
Mutual	0.8781 (0.6601)	0.8042* (0.3733)	1.1445* (0.5425)	−0.5621 (0.6482)	−1.7610* (0.8195)	−0.6614 (0.6524)	1.390 (0.8643)	1.1610* (0.5199)	0.4340 (0.4675)
Popularity	0.8381* (0.2225)	0.5806*** (0.1533)	0.5918* (0.2515)	0.3607** (0.1349)	0.1906 (0.1700)	0.3272** (0.1241)	0.6058** (0.2031)	0.6803** (0.2969)	1.2153* (0.6244)
Transitive	−0.006 (0.077)	−0.7705* (0.3691)	−1.158*** (0.3193)	−0.2865 (0.2141)	−0.5343* (0.2224)	−0.2768 (0.2147)	−0.1647 (0.1673)	−0.5958*** (0.1489)	−0.8317*** (0.1534)
Destination economic level	0.0005* (0.0002)	0.0001 (0.0001)	0.0001** (0.0000)	0.0001 (0.0001)	0.0002*** (0.0000)	0.0003*** (0.0001)	0.0002 (0.0002)	0.0002** (0.0000)	0.0005** (0.0002)
Origin economic level	0.0001 (0.0002)	0.0002 (0.0003)	0.0000 (0.0002)	0.0002 (0.0002)	0.0000 (0.0001)	0.0000 (0.0002)	0.0000 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)
Destination medical level	0.0186 (0.0104)	−0.0038 (0.0138)	0.0011 (0.0089)	0.0094 (0.0125)	0.0038 (0.0114)	0.0155 (0.0105)	0.0132* (0.0006)	0.0041 (0.0055)	0.0010* (0.0004)
Origin medical level	−0.0057 (0.0131)	0.0042 (0.0093)	0.0049 (0.0078)	−0.0089 (0.0127)	−0.0073 (0.0181)	0.0076 (0.0117)	−0.0014 (0.0062)	−0.0026 (0.0060)	0.0116 (0.0541)
Destination education level	−0.0003 (0.0006)	0.0006 (0.0007)	0.0013 (0.0009)	0.0012* (0.0006)	0.0022*** (0.0005)	0.0003*** (0.0001)	0.0015* (0.0006)	0.0012** (0.0004)	−0.0003 (0.0004)
Origin education level	0.0008 (0.0010)	0.0001 (0.0005)	−0.0004 (0.0008)	−0.0007 (0.006)	0.0000 (0.0005)	0.0001 (0.0004)	−0.0011* (0.0005)	0.0002 (0.0003)	−0.0002 (0.0003)
Destination pollution level	−0.2198*** (0.0590)	−0.0133 (0.0228)	−0.2149** (0.0669)	−0.0338 (0.0264)	−0.0746** (0.0260)	−0.0388*** (0.0023)	−0.0892** (0.0272)	−0.0230 (0.0144)	0.0443 (0.0246)
Origin pollution level	−0.0406 (0.0511)	−0.0144 (0.0229)	−0.0355 (0.0404)	−0.0610 (0.0362)	−0.0176 (0.0267)	−0.0331 (0.0306)	−0.0568* (0.0243)	−0.0268* (0.0134)	0.0149 (0.0189)
Cultural homophily network	0.9895 (0.5215)	0.8557* (0.4173)	0.8925* (0.4493)	1.9299** (0.6701)	0.6150 (0.5428)	1.1440* (0.5174)	1.975*** (0.4473)	0.6606 (0.4298)	1.2970** (0.4539)
Spatial distance network	−0.0024*** (0.0005)	0.0072 (0.0049)	−0.0027 (0.0107)	−0.0042*** (0.0009)	−0.0038*** (0.0009)	−0.0033*** (0.0009)	−0.0021*** (0.0003)	−0.0016*** (0.0003)	−0.0010*** (0.0002)
AIC	−123.1	−114.4	−162.5	−123.9	−164.7	−133.1	−697.3	−645.1	−668.8
BIC	−85.31	−76.59	−121.9	−86.06	−126.9	−95.3	−645.2	−593	−616.6

Where ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Values in parentheses represent standard errors.

self-organizing properties (Barbrook-Johnson and Carrick, 2022) such as reciprocal, convergent, and transitive cascades. Conversely, the formation and expansion of any system, from its inception to large-scale development, are inevitably influenced by external environmental factors. Sole reliance on internal information by migrants may lead to the emergence of an "information cocoon," characterized by information homogeneity, limited perspectives, and potential group polarization, ultimately limiting adaptive decision-making and system resilience. External environmental factors mitigate such blind spots by regulating and guiding the spontaneity of self-organization (Miao, 2020). Therefore, in the migration process, information cascades are subject to external constraints such as resource endowments and multidimensional proximities. Through dynamic competition and collaboration among various subsystems, new features of reciprocity and convergence gradually emerge, ultimately driving the migration system from disorder toward order.

The empirical analysis of interprovincial migration networks across the three major economic belts provides strong support for the theoretical arguments proposed in this study. As detailed in Table 7, both reciprocal and convergent cascades configurations significantly promote migration dynamics within the YtREB, with the influence of reciprocal cascades showing a marked increase over time. In contrast, the YREB and the BREB primarily exhibit trends characterized by convergent cascades. This difference can be explained by the fact that the YtREB initiated development earlier; the combination of regional development disparities and the push-pull dynamics formed through individual information cascades fostered the emergence of reciprocal and convergent features in the migration network. As network ties stabilized over time, and with the recent implementation of the "Yangtze River Delta Regional Integration" strategy, regional disparities have gradually diminished, leading to the establishment of reciprocal connections as the dominant force in migration flows (Wu et al., 2025). Conversely, the BREB and the YREB developed later and still exhibit pronounced regional disparities. In these contexts, core provinces exert stronger pull effects on migration (Huang et al., 2025), reinforcing convergence-driven migration patterns. This study proposes a theoretical framework for analyzing migration and reveals the emergent mechanisms underlying the formation of interprovincial migration networks. The findings have practical insights for managing and guiding orderly population flow in line with regional development goals. However, certain limitations remain unexplored. For instance, the selection and specification of network configurations, while informed by existing literature, may not fully capture the complexity of migration behaviors. Second, the current ERGM framework does not incorporate institutional and policy-driven factors (e.g., household registration systems or regional integration agreements), which may significantly influence migration decisions. Thus, future research should aim to refine configuration selection and explore the integration of institutional dynamics into ERGM-based analyses to enhance the explanatory power of migration network models.

5 Conclusions and policy implications

This study presents a comprehensive framework that integrates embeddedness, information cascade, resource endowments, proximity, and emergence theory within a ERGM to analyze the mechanisms driving interprovincial migration in China over the years 2000, 2010, and 2020. The results reveal a structural shift toward a "key agglomeration and regional balance" migration pattern, with significant outflows from central and western regions and consistent inflows to the eastern region. Migration networks exhibit a hierarchical core-periphery structure, particularly centered around Guangdong, forming a star-shaped pattern with peripheral provinces. The Top1 interprovincial migration network exhibits a "primarily star-shaped with tree-like supplements" pattern, with the Guangdong-dominated migration cluster exhibiting a distinct "core-periphery" structure. Second, information cascade is widely observed in the interprovincial migration networks, characterized by mutual, popularity (reputational), and transitive cascades. Three distinct types of information cascades (mutual, popularity, and transitive) are validated as key endogenous mechanisms. Mutual and popularity cascades positively influence migration network formation, while transitive cascades show a negative association with exogenous mechanisms such as economic, healthcare, educational, and ecological factors in destination regions along with cultural similarity and geographic proximity, also promote migration. However, endogenous mechanisms exert a greater impact than exogenous ones, indicating a self-reinforcing dynamic in migration flows. Regional variation across China's three major economic belts (YREB, YtREB, and BREB) results in differing migration dynamics.

This study underscores that migration resilience from the dynamic interplay between socio-economic shocks and self-organizing network structure. Migration systems adapt through information exchange, enabling responses to resource disparities, institutional constraints, and labor market volatility. Consequently, regional governance must shift from rigid controls to facilitating information flows, subsystem coordination, and adaptive mobility. To address entrenched regional disparities, especially popularity-driven migration to eastern regions, interregional coordination, market efficiency, and reduced migration costs are essential. In YREB and BREB, strategies should focus on consolidating economic clusters, enhancing transportation and housing, ensuring inclusive public services, and deploying digital platforms for real-time mobility monitoring and strategic planning.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

BW: Conceptualization, Writing – original draft, Writing – review & editing, Formal analysis, Data curation. YR: Investigation, Project administration, Conceptualization, Writing – review & editing, Validation, Funding acquisition, Supervision. HD: Conceptualization, Validation, Writing – review & editing, Investigation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

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