Multi-Polar Evolution of Global Inventive Talent Flow Network
—An Endogenous Migration Model and Empirical Analysis

Zheng Jianghuai[1,2], Sun Dongqing[*2], Dai Wei[3], Shi Lei[1,4]

[1] *Yangtze River Delta Economics and Social Development Research Center, Nanjing University, Nanjing, China*
[2] *School of Economics, Nanjing University*
[3] *School of International Economics and Business, Nanjing University of Finance and Economics (NUFE), Nanjing, China*
[4] *School of Economics, Nanjing University of Finance and Economics (NUFE)*

Abstract: *The global clustering of inventive talent shapes innovation capacity and drives economic growth. For China, this process is especially crucial in sustaining its development momentum. This paper draws on data from the EPO Worldwide Patent Statistical Database (PATSTAT) to extract global inventive talent mobility information and analyzes the spatial structural evolution of the global inventive talent flow network. The study finds that this network is undergoing a multi-polar transformation, characterized by the rising importance of a few central countries—such as the United States, Germany, and China—and the increasing marginalization of many peripheral countries. In response to this typical phenomenon, the paper constructs an endogenous migration model and conducts empirical testing using the Temporal Exponential Random Graph Model (TERGM). The results reveal several endogenous mechanisms driving global inventive talent flows, including reciprocity, path dependence, convergence effects, transitivity, and cyclic structures, all of which contribute to the network's multi-polar trend. In addition, differences in regional industrial structures significantly influence talent mobility choices and are a decisive factor in the formation of poles within the multi-polar landscape. Based on these findings, it is suggested that efforts be made to foster two-way channels for talent exchange between China and other global innovation hubs, in order to enhance international collaboration and knowledge flow. We should aim to reduce the migration costs and institutional barriers faced by R&D personnel, thereby encouraging greater mobility of high-skilled talent. Furthermore, the government is advised to strategically leverage regional strengths in high-tech industries as a lever to capture competitive advantages in emerging technologies and products, ultimately strengthening the country's position in the global innovation landscape.*

Keywords: *Inventive talent flow network; multipolarity; spatial structural evolution; regional industrial structure disparities; temporal exponential random graph model (TERGM)*
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[*] CONTACT: Sun Dongqing, e-mail: dg21020041@smail.nju.edu.cn.

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1. Introduction and Literature Review

As China shifts from a phase of high-speed growth to one of high-quality development, its growth model must transition from being primarily driven by factor inputs and capital investment to being increasingly propelled by innovation. During the factor- and investment-driven stage, China's population flows followed the Lewis model, characterized by labor migration from rural to urban areas and from agriculture to industry, thereby enabling more efficient utilization of capital. However, in the context of innovation-driven development—where the transfer of surplus rural labor to industrial sectors has largely been completed—China's economic growth increasingly relies on the movement of talent both within and across sectors. Such talent flows foster agglomeration, enhancing the effectiveness of R&D investment. As technological innovation becomes a key engine of China's economic advancement, the role of inventive talent has grown ever more vital in sustaining and accelerating this transformation.

Compared to general labor, inventive talent demonstrates significantly higher global mobility. Docquier & Rapoport (2012) note that emigration rates for individuals with PhDs and researchers are 2.2 to 5.3 times higher than those for individuals without higher education. Moreover, compared to native-born inventors, immigrant inventors tend to earn lower wages while exhibiting higher productivity (Akcigit, 2017). With the increasing globalization of inventive talent flows, scholars have begun to adopt a network-based perspective to examine international mobility patterns, identifying substantial knowledge externalities within global talent flow networks (Moretti, 2004; Winters, 2014). The inflow of inventive talent not only strengthens the receiving country's stock of human capital and knowledge (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010), but also contributes positively to knowledge diffusion in the sending countries (Miguelez, 2020). Highly skilled individuals serve as critical conduits of transnational knowledge transfer (Breschi et al., 2010, 2017; Kerr et al., 2016), playing a vital role in driving economic growth by facilitating technological change (Miguelez and Morrison, 2022) and enhancing total factor productivity (Chiswick, 2011). As shown in Figure 1, there is a "γ-shaped" relationship between a country's economic size (measured by the logarithm of GDP) and its centrality in the global inventive talent flow network[1].

The relationship between a country's economic size and its centrality in the global inventive talent flow network varies depending on the scale of the economy. For countries with relatively small economies, there is no significant correlation between economic size and network centrality, suggesting that becoming a global hub for inventive talent is not a critical factor for economic expansion at this stage. However, for countries with larger economies, a clear positive correlation emerges—indicating that occupying a central position in the global talent flow network becomes a necessary condition for attaining global economic leadership. These findings highlight that becoming a pivotal node in the global inventive talent network is a key step for China to achieve sustained economic growth under the innovation-driven development model.

As President Xi Jinping emphasized in the Report to the 20th National Congress of the Communist Party of China: "We will accelerate the development of world-class talent centers and innovation hubs, promote the rational and coordinated regional distribution of talent, and strive to build a competitive advantage in the global talent arena." In the context of globalization, building a talent-strong nation requires not only enhancing the domestic capacity to cultivate inventive talent, but also establishing China as a global center and high ground for talent—an apex node in the international talent flow network. This strategic positioning will enable China to attract greater flows of international talent, knowledge, and technology, and such agglomeration of innovation resources will inevitably translate

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[1] The global inventive talent flow network is constructed using data from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT), which will be described in greater detail in the following sections. Network centrality is measured using the PageRank algorithm, with the specific methodology also detailed later in the text.

into significant growth effects. Therefore, becoming a global talent hub is an essential pathway for China to advance innovation-driven development. Studying the global network of inventive talent flows and its evolving spatial structure is of great importance in the current era.

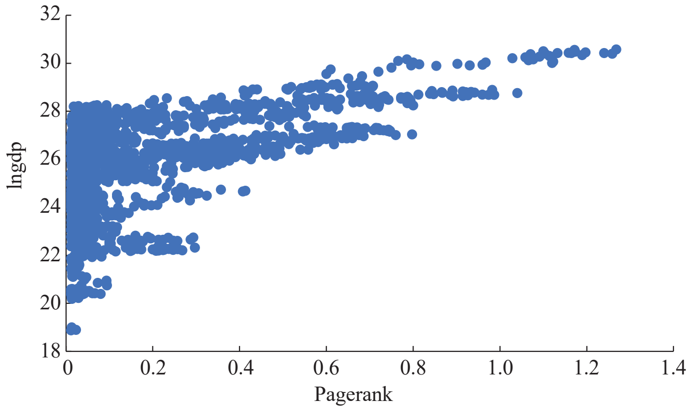

Figure 1: Scatter Plot of National Economic Size and Global Inventive Talent Flow Network Centrality, 1990-2017

Research on international talent mobility has evolved from a "zero-sum game" framework to the concept of brain circulation. Before the 21st century, scholars primarily adopted the diaspora and brain drain paradigms to analyze talent flows (Miyagiwa, 1991; Carrington & Detragiache, 1998). During this period, the prevailing view was that brain drain hindered economic development and technological progress in source countries, undermining residents' welfare (Bhagwati & Hamada, 1974; Grossman & Helpman, 1993), while simultaneously contributing to human capital accumulation and long-term economic growth in destination countries (Miyagiwa, 1991). However, with the emergence of new mobility patterns under globalization—specifically, the phenomenon of "brain circulation"—traditional brain drain theories have proven insufficient. In response, economists have begun analyzing brain circulation models, such as Lee and Kim's (2010) study of return migration between South Korea and the United States.

Scholars have also explored whether brain drain can yield positive effects. For instance, Chen & Yuan (2004) suggest that the outflow of talent from developing countries can promote scientific, technological, and economic exchanges with developed nations. Similarly, Saxenian (2005) notes that engineers from China and India working in Silicon Valley have, upon returning home, contributed to the development of their domestic information technology industries. In examining patterns of international talent mobility, much of the existing literature builds on Heberle's (1938) "push-pull" model, which contends that talent migration is driven by a combination of factors in both origin and destination countries. Subsequent studies have analyzed the determinants of talent flows from multiple perspectives, including economic conditions and wage differentials (Beaverstock, 1991), household registration systems (Song et al., 2022), urban livability (Glaeser et al., 2001; Florida, 2019), and political factors (Csedő, 2008; Peixoto, 2001), among others.

Research on global talent flows reveals increasingly complex patterns, more diverse drivers, and a wider range of impacts—making it increasingly difficult to analyze international talent mobility from a single perspective. This highlights the importance of examining the movement of inventive talent through a network-based lens. As many scholars have argued, networks that facilitate knowledge exchange both within and across regions are key sources of innovation and economic growth (Huggins & Izushi, 2007; Huggins & Johnston, 2009). With the growing availability and refinement of statistical data, recent studies have begun to describe and analyze talent mobility from a network perspective, with particular attention to the "center-periphery" structure of inventive talent flows. For example, Hou (2019) characterizes global student mobility as having a "pyramidal structure" and a distinct geographic pattern of movement "from East to West and South to North," reflecting distinctive core-periphery features. Similarly, Wang (2022), analyzing talent mobility data across 15 major countries between 1990 and 2012, found that a significant share of global talent flows occurs among a small group of developed countries (such as the United States, the United Kingdom, and France), while most other countries exhibit relatively limited flows. Within China, Jin et al. (2021) analyzed the inter-provincial migration of high-level scientific talent and found that the movement of highly cited scientists is concentrated in a few provinces, notably Beijing, Shanghai, Jiangsu, Zhejiang, Anhui, and Sichuan.

A review of existing research reveals a paucity of studies exploring global talent flows from a complex network perspective. Although some have examined the "center-periphery" structure of global talent flow networks, these works often suffer from limitations such as small country samples or a narrow regional scope, and they generally lack theoretical explanations for the structural characteristics and their evolutionary dynamics. In contrast, this study not only analyzes the dynamic evolution of the global inventive talent flow network and identifies its trend toward multi-polarity, but also constructs an endogenous migration model that offers a theoretical explanation for this shift. In doing so, it fills important gaps in the current literature on inventive talent flow networks.

2. Spatial Structural Changes in Global Inventive Talent Flow

2.1 Changes in the Scale and Structure of Global Inventive Talent Flow

This study derives global inventive talent flow data[2] from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT), analyzing trends from 1980 to 2015. Key observations include: (1) The volume and geographic scope of global inventive talent flows expanded significantly since 1980, peaking in 2010 before declining. This post-2010 reduction may stem from increased trade and regional protectionism, which have curtailed talent mobility, alongside diminished technological complementarity due to localized technological agglomeration (Zheng et al., 2022). (2) Inventive talent flows are concentrated among a few countries—primarily the United States, Germany, Japan, and China—and exhibit two-way patterns. (3) China's role in global inventive talent flows has grown markedly, with flows between China and other countries, particularly the United States, becoming central to the network. Before 2000, talent exchanges were dominated by the United States with Germany and Japan. By 2015, however, China's talent flows accounted for 30.7% of the global total, second only to the United States at 59.9%, with China-US flows comprising 16.4% of the global network.

2.2 Evolution of the Central Structure in Global Inventive Talent Flows

Following the analysis of the global inventive talent flow network's scale and structure, this section seeks to further identify the central roles played by individual countries within the network. A higher level of centrality indicates that a country functions as a key hub for talent mobility, playing a pivotal role in both knowledge dissemination and technological diffusion.

Network centrality measures the extent of a node's direct and indirect connections, as well as its influence within the network. It is a critical structural metric. In the context of global inventive

[2] The data used in this study comes from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT), which contains patent records from more than 100 countries and organizations. The database includes detailed information such as application, publication, and grant dates; IPC classifications; technological fields; and data on applicants and inventors, covering the period from 1893 to 2018. This paper traces the mobility of inventive talent by examining changes in the organizations associated with inventors across different patent applications. A movement of talent is identified when the enterprise or country listed in an inventor's patent application differs from those in the inventor's applications filed in other years.

talent flows, greater centrality signifies a country's more prominent and influential position. Common indicators of centrality include degree centrality, closeness centrality, and PageRank. This study adopts the PageRank algorithm, developed by Brin and Page (1998), to evaluate the centrality of countries within the global inventive talent flow network. The calculation method is shown in Equation (1):

$$PR(A)=\frac{1-d}{N}+d\frac{\sum_{i\in n(A)}PR(T_i)/C(i)}{C(i)} \tag{1}$$

In the above equation, $PR(A)$ denotes the PageRank value of country A, which reflects its centrality in the global inventive talent flow network. The damping factor (d) is typically set to 0.85. N represents the total number of countries in the network, $PR(T_i)$ indicates the PageRank value of country i, and $C(i)$ represents the total flow of inventive talent into country i from other countries.

Based on the PageRank values calculated for countries from 1980 to 2015, this study identifies the top ten countries by centrality in the years 1980, 1990, 2000, 2005, 2010, and 2015, as shown in Table 1.

Table 1: Top Ten Economies Ranked by PageRank, 1980-2015

Rank	1980	1985	1990	1995	2000	2005	2010	2015
1	Germany	Germany	US	US	US	US	US	US
2	US	US	Switzerland	UK	Germany	Germany	Germany	Germany
3	Netherlands	UK	Germany	France	UK	Japan	UK	China
4	Switzerland	France	UK	Japan	Netherlands	UK	Japan	Switzerland
5	UK	Sweden	Japan	Germany	Sweden	Switzerland	Switzerland	UK
6	Japan	Switzerland	Netherlands	Switzerland	Japan	China	China	France
7	France	Japan	Sweden	Netherlands	Switzerland	Netherlands	France	Japan
8	Sweden	Italy	France	Sweden	France	Sweden	Netherlands	Netherlands
9	Denmark	Netherlands	Canada	Italy	Italy	Canada	Israel	Sweden
10	Austria	Luxembourg	Italy	Canada	Canada	Belgium	Sweden	Canada

An analysis of the evolution of global inventive talent flow centers, as presented in Table 1, reveals two key trends since 1980: (1) Geographical Shift from Europe to North America to Asia. Since 1980, the global centers of inventive talent flows have undergone a notable geographical shift. In the 1980s, Europe—particularly Germany—played a central role in the global talent flow network. After 1990, the core hub of the global talent network underwent a regional transition from Europe to North America, with the U.S. surpassing Germany to attain the highest PageRank value. Since the early 21st century, Asia has gained increasing prominence, with both Japan and China significantly improving their centrality within the network. (2) Geographic Diffusion to Neighboring Regions. The rise of a region in the global inventive talent network often contributes to the advancement of innovation capacity in its neighboring areas. For example, after the United States became the central hub in 1990, Canada—its immediate neighbor—also saw a notable rise in its position within the network.

2.3 Shifts in the Network Structure of Global Inventive Talent Flows

To characterize the structure of the global inventive talent flow network, this study computes key network metrics for 1980-2015 and visualizes node clustering[3].

[3] Due to space limitations, the calculation methods for the network structure indicators are not detailed in the main text and are available upon request.

The results, presented in Table 2, highlight the network's multipolar structure, with the following features: In this small-world network, most countries lack direct connections but are linked through a few central hubs, whose influence has grown over time. From 1980 to 2015, the network diameter decreased from 6 to 4, and the average path length dropped from 2.56 to 2.15, indicating that by 2015, any country could connect to another via approximately two intermediaries, consistent with small-world properties. However, the network exhibits a high average clustering coefficient (around 0.5) and low density (around 0.1), reflecting significant clustering alongside a sparse structure. Talent flows are predominantly facilitated by a few central countries, while peripheral countries rarely connect directly with each other. Additionally, the network's modularity index has declined since 1980, signaling increasing integration across the network.

Table 2: Descriptive Statistics of the Inventive Talent Flow Network, 1980-2015

	1980	1985	1990	1995	2000	2005	2010	2015
Network diameter	6	5	5	5	4	4	4	4
Network density	0.101	0.099	0.088	0.096	0.099	0.098	0.112	0.092
Average clustering coefficient	0.276	0.336	0.348	0.467	0.501	0.443	0.501	0.416
Modularity index	0.243	0.268	0.195	0.041	0.033	0.015	0.014	0.026

To visually depict the structural evolution of the global inventive talent flow network, this study employs Gephi software with the ForceAtlas2 layout algorithm to create network diagrams for 1985 and 2015, presented in Figure 2. Node size reflects a country's PageRank value, edges represent talent flows between countries, and nodes of the same color denote communities identified by the Fast Unfolding algorithm.

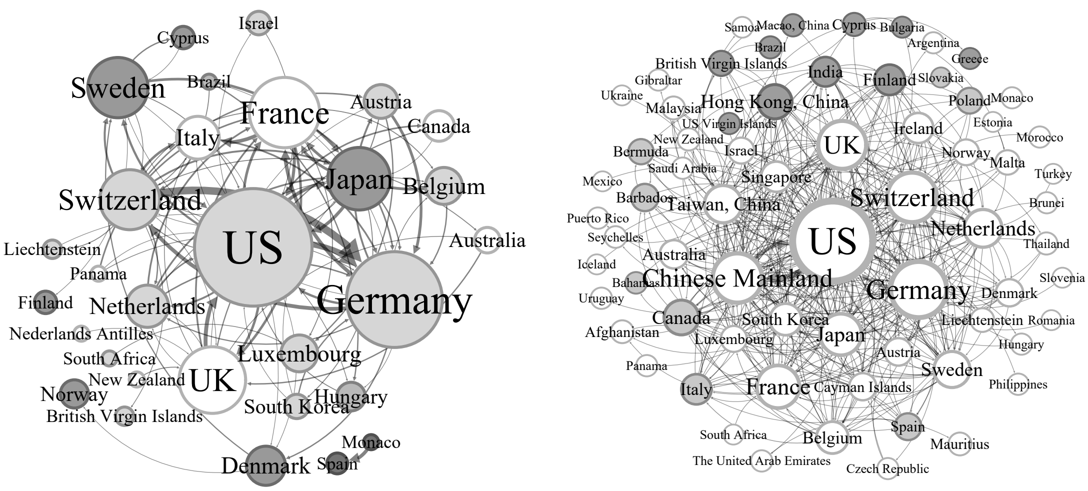

Figure 2: Visualization and Clustering of the Global Inventive Talent Flow Network in 1985 and 2015

Analysis based on Figure 2 reveals two key structural characteristics of the global inventive talent flow network, both of which align with a broader trend toward multipolarity: (1) Increasing Global Integration. As shown in Table 2, the modularity index of the global inventive talent flow network has significantly declined and has remained at a relatively low level. This indicates a shift from a regional to a global "center-periphery" network structure. In 1985, the network could be divided into several distinct "regional clusters." By 2015, however, the colors of the nodes had become more uniform in Figure 2, suggesting that previously fragmented national networks have formed closer connections and integrated into a cohesive global network. Regional inventive talent flow networks have largely disappeared. (2) Centralized Agglomeration. The global inventive talent flow network has become increasingly concentrated around a small number of central countries. In 1985, the clustering effect was less evident: while there were strong innovation linkages between central countries such as the US and Germany, notable connections also existed among peripheral countries—for instance, between Hungary and Brazil, or Monaco and Spain. By 2015, however, the degree of network agglomeration had increased significantly, with complex connections concentrated primarily among major hubs such as the US, Germany, Japan, and China. Many other countries had ties to only a single hub country, placing them on the periphery of the global inventive talent flow network.

2.4 Multipolar Transformation of the Spatial Structure in the Global Inventive Talent Flow Network

Based on the analysis of spatial structural changes in global inventive talent flows presented in this chapter, several key conclusions can be drawn: (1) Inventive talent flows are primarily concentrated among a small number of countries and often exhibit two-way patterns. (2) China's position within the global inventive talent flow network has steadily strengthened, establishing it as a key hub. (3) At the same time, the network has evolved toward greater integration and central agglomeration, with countries increasingly embedded within a unified global system. Talent flows are becoming more concentrated among a few central nations. These findings further illustrate the multipolar transformation of the global inventive talent flow network. Talent mobility is increasingly dominated by a limited group of central countries—such as the United States, Germany, China, Switzerland, and the United Kingdom—while talent exchanges among peripheral countries have become increasingly sparse. This pattern underscores the rising dominance of a few core hubs in shaping the global landscape of inventive talent flows.

Notably, the spatial structure of the global inventive talent flow network has undergone a multi-polar evolution, distinctly characterized by a transition from an "apolar" to a "multi-polar" configuration. This contrasts with the economic multi-polarization process, which typically evolves from "bi-polarity" to "multi-polarity," as exemplified by the period following the collapse of the Soviet Union. To underscore this difference between the spatial multi-polarization of the global inventive talent network and that of the global economy, this study separately calculates the CR_1 and CR_5 indicators[4] using GDP and

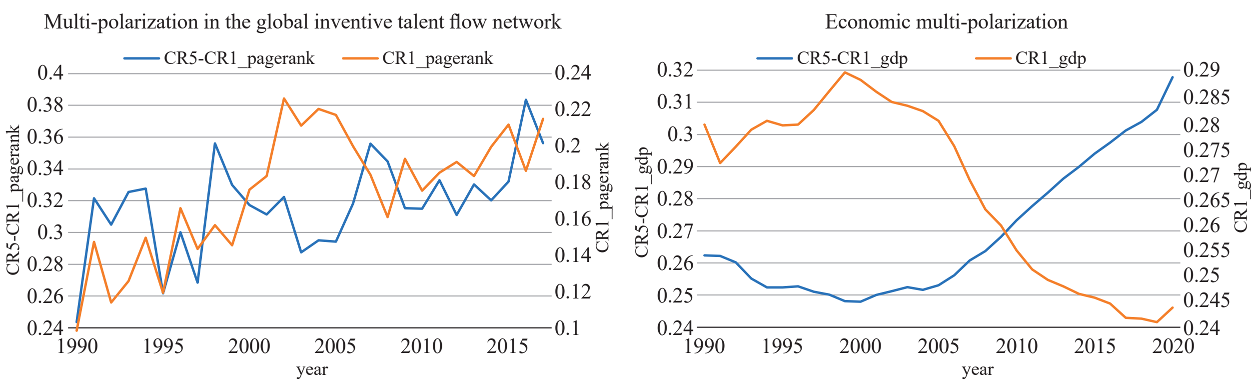

Figure 3: Comparison of Multi-polarization in the Global Inventive Talent Flow Network and Economic Multi-polarization

[4] The concentration ratio, CR_n, serves as an indicator of concentration levels. For example, when applied to GDP, CR_n represents the proportion of top five countries in global GDP.

PageRank values for sample countries from 1990 to 2018. Based on these calculations, we derive two indicators: the market share of the top-ranked country (CR_1) and the combined market share of the second- to fifth-ranked countries (CR_5-CR_1). These findings are presented in Figure 3.

Since 1990, economic multi-polarization has been marked by a declining GDP share of the top-ranked country (the US) and a rising share among the next leading countries (second to fifth-ranked). This reflects a relative decline of the dominant economy alongside the ascent of emerging ones. Conversely, the multi-polarization of the global inventive talent flow network follows a distinct pattern, with both the top-ranked country (the US) and the next leading countries (second to fifth-ranked) experiencing a simultaneous increase in PageRank share. This trend underscores the growing dominance of a few central countries (e.g., the US, Germany, China) in the network, while most peripheral countries become increasingly marginalized.

3. Endogenous Migration Model of Inventive Talent Flow

This section constructs an endogenous migration model to describe the flow of inventive talent. By analyzing the migration decisions between two countries and among three countries, it captures the endogenous mechanisms driving the movement of inventive professionals, while also considering differences in industrial structures. This framework helps explain the multipolar transformation in the spatial distribution of global inventive talent observed in the previous section.

3.1 Two-Country R&D Personnel Migration Model

This study assumes that R&D personnel face migration costs when relocating across national borders. Specifically, when researchers from country i migrate to country j, they incur a transitional cost C_{ij}, which is shaped by a variety of factors. For instance, geographical distance affects the financial burden of relocation; linguistic and cultural proximity influence how easily foreign researchers can integrate into local society and engage in knowledge exchange with domestic inventors; and the host country's institutional support for incoming talent affects their ability to adapt to the local research environment. Therefore, migration costs include not only transportation expenses but also the costs of learning the host country's language and adjusting to its cultural norms, legal systems, and research infrastructure.

In the context of a two-country model, this study puts forward the first hypothesis by taking into account the characteristics of migration costs: as R&D personnel move from country i to country j, the migration costs between the two countries (C^{ij} and C^{ji}) are expected to decrease. This is because a larger flow of personnel tends to reduce transportation costs between the two countries. Furthermore, interactions between R&D personnel from countries i and j help establish cross-regional interpersonal networks, which enhance mutual understanding and facilitate further mobility, thereby reducing migration costs. In support of this, Massey (1990) argues that the reduction in migration costs is often driven by the expansion of interpersonal networks.

This section explores the flow of R&D personnel between two countries, A and B, representing a developing country and a developed country, respectively. Drawing on the frameworks of Kwok & Leland (1982) and Chen (2015), we set out the assumptions regarding the R&D labor markets in both countries. In Country A (a developing country), the R&D labor market is imperfect and cannot determine wages based on individuals' actual abilities. Instead, R&D personnel are classified into two categories—ordinary researchers and high-skilled researchers with human capital—based on past experience and observable characteristics. Correspondingly, they are offered two types of wages, w_1 and w_2, where $w_1 << w_2$. In contrast, Country B (a developed country) is assumed to employ only high-skilled R&D personnel, with wages following a distribution $F(w, I)$. Consistent with standard assumptions in one-way search theory, we treat wage offers as exogenously given due to short-term wage rigidity. This assumption is justified as the study focuses on the migration decisions of R&D personnel rather than long-term labor market equilibrium. The distribution of intellectual ability among R&D personnel is assumed to be the same in both countries, uniformly distributed over the interval [0,1]. Each individual is assumed to have full knowledge of their own ability level I.

Building on these assumptions, this study analyzes R&D personnel flows in the two-country scenario through a two-stage framework.

3.1.1 Migration decision of R&D personnel in country A

First Stage: Decision to Migrate from Country A to Country B

In the first stage, R&D personnel in Country A face two options: either remain in Country A or migrate to Country B. If they choose to stay in Country A, their total utility is given by: $\frac{w_1}{1-\beta}$, where β is the discount factor, and w_1 represents the wage earned per period in Country A. If they decide to migrate to Country B, they will not receive any income in the current period and must bear a migration cost. However, during this period, they will acquire the human capital necessary to qualify for R&D positions in Country B. In the following period, after gaining new technological knowledge and enhancing their human capital, the migrated personnel can secure a research position in Country B with a wage denoted by w. The wage w follows a cumulative distribution function $F(w,I)$, where $\frac{\partial F(w,I)}{\partial I}<0$. It implies that R&D personnel with higher ability are more likely to obtain a higher-paying position. At this stage, the individual can choose to accept the offered wage or reject it and continue searching for a better opportunity in the next period. Accordingly, the expected future income for an R&D personnel with ability I who chooses to migrate to Country B can be expressed as shown in Equation (2).

$$V=\beta E(V(w',I))-C_{AB} \tag{2}$$

Here, $E(V(w',I))$ denotes the expected income of R&D personnel in the next period after migrating to Country B, and C_{AB} represents the migration cost incurred in the current period for the move to Country B.

$$V_B(w,I)=Max\left\{\frac{w}{1-\beta}, \beta\int_0^H V_B(w',I)\,dF(w',I)\right\} \tag{3}$$

Equation (3) models the R&D personnel's decision to either accept a job offer or reject it and continue searching in the next period. Here, $\frac{w}{1-\beta}$ represents the expected benefit of accepting the job, while $\beta\int_0^H V_B(w',I)\,dF(w',I)$ denotes the expected benefit of rejecting the job and continuing the search in the next period.

From Equation (3), the reservation wage $\overline{w}_B$ can be derived, as presented in Equation (4):

$$\frac{\overline{w}_B}{1-\beta}=\beta\int_0^H V_B(w,I)\,dF(w,I)\Big\} \tag{4}$$

At the reservation wage $\overline{w}_B$, R&D personnel are indifferent between accepting a job offer and rejecting it to continue searching. Substituting Equation (4) into Equation (2) yields Equation (5):

$$V(w,I)=\frac{\overline{w}_B(I)}{1-\beta}-C_{AB} \tag{5}$$

Thus, when R&D personnel in Country A decide whether to migrate to Country B, they compare the total utility of remaining in Country A, $\frac{w_1}{1-\beta}$, with the expected utility of migrating to Country B, $\frac{\overline{w}_B(I)}{1-\beta}-C_A^{AB}$. If $w_1>\overline{w}_B(1)-(1-\beta)C_{AB}$, no brain drain occurs in Country A. If $w_1<\overline{w}_B(0)-(1-\beta)C_{AB}$, all R&D personnel will migrate from Country A to Country B, leading to brain drain. If $\overline{w}_B(0)-(1-\beta)C_{AB}<w_1<\overline{w}_B(1)-(1-\beta)C_{AB}$, only personnel with ability above I_A^* will migrate from Country A to Country B, resulting in brain drain, where $I_A^*=\overline{w}_B^{\,-1}(w_1+(1-\beta)C_{AB})$.

Second Stage: Decision of R&D Personnel from Country A in Country B on Returning to Country A

After migrating to Country B and acquiring human capital, R&D personnel from Country A can either seek employment in Country B or return to work in Country A. If the R&D personnel choose to work in Country B, their expected future benefit is $V=\beta\int_0^H V_B(w,I)\,dF(w,I)=\frac{\overline{w}_B(I)}{1-\beta}$. If they choose to return to Country A, they can leverage the human capital gained through their learning in Country B to earn a high wage w_2, equivalent to the high-skill R&D personnel wages offered in Country A. However, this return involves a migration cost C_{BA}. Thus, if they decide to return to Country A, their expected future benefit becomes $\frac{w_2}{1-\beta}-C_{BA}$.

Comparison of Benefits for R&D Personnel: Returning to Country A vs. Staying in Country B

R&D personnel compare the expected benefit of returning to Country A, $\frac{w_2}{1-\beta}-C_{BA}$, with the expected benefit of staying in Country B to seek work, $\frac{\overline{w}(I)}{1-\beta}$.

If $w_2>\overline{w}_B(1)+(1-\beta)C_{BA}$, all R&D personnel seeking work in Country B will return to Country A.

If $w_2<\overline{w}_B(0)+(1-\beta)C_{BA}$, no R&D personnel will return to Country A.

If $\overline{w}_B(0)+(1-\beta)C_{BA}<w_2<\overline{w}_B(1)+(1-\beta)C_{BA}$, then among the migrants, R&D personnel with lower ability will return to Country A, while those with higher ability will stay in Country B $I_{A'}^{*}=\overline{w}_B^{\,-1}(w_2-(1-\beta)C_{BA})$.

Based on this analysis, among R&D personnel who initially migrated from Country A to Country B, those with ability I satisfying $\overline{w}_B^{\,-1}(w_1+(1-\beta)C_{BA})<I<\overline{w}_B^{\,-1}(w_2-(1-\beta)C_{BA})$ will return to Country A, while those with ability $I>\overline{w}_B^{\,-1}(w_2-(1-\beta)C_{BA})$ will remain in Country B to continue their job search.

3.1.2 Migration decision of R&D personnel in Country B

This section examines the migration decisions of R&D personnel in Country B. R&D personnel in Country B have two options in their job search: migrate to Country A or stay in Country B to seek work.

If R&D personnel in Country B choose to migrate to Country A, they must pay the migration cost C_{BA} from Country B to Country A in the current period. Since R&D personnel in Country B possess human capital, they can earn a wage w_2 in Country A, resulting in a total expected benefit of $\frac{w_2}{1-\beta}-C_{BA}$. If they choose to stay in Country B to seek work, their expected benefit is $\frac{\overline{w}_B(I)}{1-\beta}$. Therefore, R&D personnel in Country B initially opt to stay in Country B to seek work.

When deciding whether to migrate to Country A, R&D personnel in Country B compare the total expected benefit of staying in Country B, $\frac{\overline{w}(I)}{1-\beta}-U_B$, with the total expected benefit of migrating to Country A, $\frac{w_2}{1-\beta}-C_{BA}$.

If $w_2>\overline{w}_B(1)+(1-\beta)C_{BA}$, all R&D personnel in Country B will migrate to Country A.

If $w_2<\overline{w}_B(0)+(1-\beta)C_{BA}$, there will be no talent outflow from Country B.

At the threshold $\overline{w}_B(0)+(1-\beta)C_{BA}<w_2<\overline{w}_B(1)+(1-\beta)C_{BA}$, R&D personnel with ability below $I_B^{*}=\overline{w}_B^{\,-1}(w_2-(1-\beta)C_{BA})$ will migrate to Country A, while those with ability above I_B^{*} will stay in Country B to continue seeking work.

3.2 Endogenous Mechanism Analysis of R&D Personnel Migration

Using the theoretical model constructed in this paper, we analyze the endogenous mechanism of global talent flow.

When Country A has R&D personnel flowing into Country B, it not only strengthens ties between Countries A and B and lowers transportation costs but also enables R&D personnel in Country B to better understand the language, culture, institutions, and other aspects of Country A. This leads to a decrease in C_{BA}. Previous analysis showed that R&D personnel with ability below $\overline{w}_B^{-1}(w_2-(1-\beta)C_{BA})$ will return from Country B to Country A. Therefore, as C_{BA} decreases, the scale of R&D personnel returning from Country B to Country A will significantly increase. Comprehensive analysis reveals that the inflow of R&D personnel from Country A to Country B promotes the outflow from Country B to Country A through two channels: first, a portion of the R&D personnel in Country B will choose to return; second, it reduces the migration cost for R&D personnel in Country B to move to Country A, thereby increasing the flow from Country B to Country A. Additionally, Li & Yang (2016) noted that talent inflow often accompanies talent outflow, as evidenced by the simultaneous changes in the scale of cross-border outflow and return flow of Chinese scientific researchers from 1968 to 2018. Based on this, we propose Hypothesis 1.

Hypothesis 1: There is a reciprocal benefit effect in the flow of R&D personnel between countries: the flow from Country A to Country B facilitates the flow from Country B to Country A.

The model assumes that as R&D personnel flow from Country i to Country j, the migration cost C_{ij} between these countries decreases. Consequently, the current inflow of R&D personnel from Country A to Country B reduces the migration cost between Countries A and B. This leads to a lower migration cost for R&D personnel moving from Country A to Country B in the next period, i.e., $C_{AB}(t+1)<C_{AB}(t)$. As a result, $\overline{w}_B^{-1}(w_1+(1-\beta)C_{AB})$ decreases, indicating that the current inflow of R&D personnel from Country A to Country B promotes future inflows from Country A to Country B, exhibiting path-dependent characteristics. Based on this, we propose Hypothesis 2.

Hypothesis 2: There is a path-dependent effect in the flow of R&D personnel between countries: the current flow from Country A to Country B facilitates increased flow from Country A to Country B in the next period.

This section further explores whether the flow of R&D talent within international networks exhibits characteristics such as cyclical structures and the Matthew effect. Given that endogenous mechanisms like cyclical structures, transitive structures, and the Matthew effect occur across multiple nodes, this paper proposes a second assumption regarding migration costs in a multi-country context: migration costs exhibit externalities. Specifically, the inflow of talent from Country i to Country j not only reduces the migration costs between i and j, but also lowers the migration costs for talent moving from other countries to j. This feature is widely observed in real-world international talent flows. As R&D personnel from Country i migrate to Country j, Country j tends to improve its evaluation systems, security frameworks, and training mechanisms for overseas talent from i. These improvements, although initially designed for talent from i, are typically adaptable to researchers from other countries as well, thereby reducing migration costs for talent inflows from various countries to j.

This paper explores a three-country scenario to investigate the presence of cyclical structures, the Matthew effect, and other characteristics in the flow of R&D talent. Consider three countries, A, B, and C, where Country A represents developing country, as mentioned earlier, and Countries B and C are developed nations. The ability distribution of R&D personnel in Countries A, B, and C is assumed to be uniform, with I ranging between $[0,1]$.

Matthew Effect: When R&D personnel from Country B flow to Country C, the externality of migration costs leads the inflow from Country B to Country C to not only reduce the migration costs between Countries B and C, but also lower the migration costs for R&D personnel from Country A to Country C. Consequently, $\overline{w}_C(I)-(1-\beta)C_{AC}$ increases, driving more R&D personnel from Country A to flow to Country C than to Country B. Based on this, the paper proposes Hypothesis 3.

Hypothesis 3: The flow of R&D personnel exhibits the Matthew effect — “the strong get stronger, the weak get weaker” — meaning that researchers tend to migrate to countries that already attract a large inflow of R&D talent from other nations.

Transitive and Cyclical Structures: When R&D personnel move from Country A to Country B and then from Country B to Country C, this reflects a transitive mobility pattern where researchers flow sequentially from A to B and subsequently to C. According to Li & Yang (2021), among 39,569 Chinese scientific researchers with cross-border mobility experience, 5,248 followed such a mobility path. This transitive flow facilitates interaction between researchers from Countries A and C, which helps reduce migration costs between the two countries and increases the expected returns for researchers moving from A to C, $\overline{w}_C(I)-(1-\beta)C_{AC}$, as well as for those moving from C to A, $\frac{w_2}{1-\beta}-C_{CA}$. This dynamic, in turn, promotes the two-way flow of R&D personnel between A and C. Based on this reasoning, this paper proposes Hypothesis 4.

Hypothesis 4: The cross-border flow of R&D personnel exhibits both transitive and cyclical structures[5].

By synthesizing the theoretical mechanisms underlying Hypotheses 1 through 4, it becomes evident that the endogenous dynamics of global inventive talent mobility give rise to a self-reinforcing spatial structure. This structure progressively amplifies the role of central countries within the global talent flow network, resulting in the agglomeration of a few core countries and the marginalization of the majority of peripheral ones. This process, in turn, drives the trend toward multipolarization. Therefore, the endogenous mechanism of inventive talent migration constitutes the foundation for the emergence of a multipolar global landscape.

3.3 Two-Country R&D Personnel Migration Model Considering Industrial Structure Differences

Based on the previous analysis, the flow of R&D personnel is expected to occur primarily between developing and developed countries with significant economic disparities. However, the stylized facts discussed earlier reveal that the main movement of inventive talent actually takes place between developed countries and is characterized by two-way flows. This dynamic positions these countries as pivotal nodes—or poles—in the global inventive talent flow network. To explain the emergence of these poles in the context of the multi-polar evolution of the global talent flow network, it is necessary to further consider the specific characteristics of R&D personnel. Unlike ordinary labor, R&D personnel are highly specialized, and their migration tends to occur within the same industry. Therefore, differences in industrial structure between countries must be taken into account when analyzing their migration patterns. In this section, we incorporate differences in industrial structure to explore the flow of R&D personnel. Assume that Countries B and C are both developed economies with similar overall economic size, and that each country has only two industries, denoted as Industry *a* and Industry *b*. As the scale of an industry increases, it accommodates a wider variety of R&D roles, which in turn leads to a broader wage distribution. The following discussion provides theoretical derivations for two scenarios: one where the industrial structures of the two countries are identical, and another where structural differences exist.

3.3.1 Identical industrial structures between two countries

When the industrial structures of Countries B and C are identical, the wage distribution within both countries is the same, uniformly ranging between $[0, H]$. In this case, the wage function satisfies $\overline{w}_B(I)=\overline{w}_C(I)$.

For R&D personnel in Country B, the expected return from searching for a job domestically is $\frac{\overline{w}_B}{1-\beta}$, while the expected return from migrating to Country C is $\frac{\overline{w}_C}{1-\beta}-C_{BC}$. Given the condition, $\overline{w}_B>\overline{w}_C-(1-\beta)C_{BC}$,

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[5] A transitive structure refers to the flow of R&D personnel from Country *i* to Country *j*, and then from Country *j* to Country *k*, which in turn promotes the flow of R&D personnel from Country *i* to Country *k*. A cyclical structure refers to the flow of R&D personnel from Country *i* to Country *j*, and then from Country *j* to Country *k*, which encourages the flow of R&D personnel from Country *k* back to Country *i*.

which holds for all $\forall I\in[0,1]$, R&D personnel in Country B will have no incentive to migrate to Country C. By the same logic, R&D personnel in Country C will not choose to migrate to Country B. As a result, there will be no flow of R&D personnel between the two countries.

In conclusion, when the industrial structures of developed Countries B and C are identical, there will be no mutual talent migration between them.

3.2.2 Heterogeneous industrial structures between two countries

In case of heterogeneous industrial structures of Countries B and C, assume that Industry *a* is larger in Country C, while Industry *b* is larger in Country B. This section focuses on analyzing the talent flow in Industry *a* between Countries B and C. When Industry *a* has a larger scale in Country C, this implies a greater variety of R&D roles and a wider wage distribution. Specifically, if the wage distribution range for Industry *a* in Country B is $[0, H]$, then the corresponding range in Country C is $[0, H+h](h>0)$. For the sake of simplifying the model, this paper assumes that the wage distribution shapes for Industry *a* in both Countries B and C are identical. Since the objective of this section is to explore how differences in industrial structure affect the flow of R&D personnel, this assumption does not influence the conclusions of the model. Under this framework, the probability of an R&D worker obtaining a specific wage depends on the relative wage rather than the absolute wage. Accordingly, the wage distribution for R&D personnel in Industry *a* is denoted as $F(w,I)(w\in[0,H])$ in Country B and $F(w\frac{H}{H+h},I)(w\in[0,H+h])$ in Country C. The reservation wage for Industry *a* in Country C is determined as shown in Equation (6).

$$\frac{\overline{w}_C}{1-\beta}=\beta\int_0^{H+h}V_C(w,I)\,dF(w\frac{H}{H+h},I) \tag{6}$$

For R&D personnel in Country B, the expected benefit of staying in Country B is $\frac{\overline{w}(I)}{1-\beta}$, while the expected benefit of migrating to Country C is $\frac{\overline{w}_C}{1-\beta}-C_{BC}$. The reservation wage and the expected wage obtained by R&D personnel are positively correlated. If the expected wage, $\int_0^H wdF(w,I)$, is higher, the corresponding reservation wage $\overline{w}$ also increases. Consequently, $\int_0^{H+h}wdF(w\frac{H}{H+h},I)$ grows with larger h. Thus, for R&D personnel with the same ability level, the difference in expected wages between Countries C and B, $\overline{w}_C-\overline{w}_B>0$, and $\overline{w}_C-\overline{w}_B$ increases with h.

Additionally, this paper examines the difference in reservation wages for R&D personnel with varying ability levels. Assuming $I_1>I_2$, the difference in expected wages for these two types of R&D personnel is given by Equation (7):

$$\int_0^{H+h}wdF\left(w\frac{H}{H+h},I_1\right)-\int_0^{H+h}wdF\left(w\frac{H}{H+h},I_2\right) \tag{7}$$

Let $G\left(w\frac{H}{H+h}\right)=F\left(w\frac{H}{H+h},I_1\right)-F\left(w\frac{H}{H+h},I_2\right)$. Since $I_1>I_2$ and $\frac{\partial F(w,I)}{\partial I}<0$, it follows that $G(w\frac{H}{H+h})\leq 0$. Further, Equation (7) can be transformed as follows: $\int_0^{H+h}wdG\left(w\frac{H}{H+h}\right)=\left[wG\left(w\frac{H}{H+h}\right)\right]_0^{H+h}-\int_0^{H+h}G\left(w\frac{H}{H+h}\right)dw$. Given $G(H)=0$, Equation (7) can ultimately be simplified into the form of Equation (8):

$$-\int_0^{H+h}G\left(w\frac{H}{H+h}\right)dw \tag{8}$$

Taking the derivative of $-\int_0^{H+h}G\left(w\frac{H}{H+h}\right)dw$ with respect to h, we obtain:

$\frac{\partial-\int_0^{H+h}G\left(w\frac{H}{H+h}\right)dw}{\partial h}=-\int_0^{H+h}\frac{\partial G}{\partial h}dw-G(H)=\int_0^{H+h}\frac{\partial G}{\partial h}dw$. Since $\frac{\partial G}{\partial h}=-\frac{H}{(H+h)^2}\times\frac{\partial G}{\partial w}<0$, $G(H)=0$, it follows that $\frac{\partial-\int_0^{H+h}G\left(w\frac{H}{H+h}\right)dw}{\partial h}$ is greater than 0.

Based on this analysis, a larger h leads to a greater difference in reservation wages between high-ability and low-ability R&D personnel, i.e., $\frac{\partial[\overline{w}_C(I_1,h)-\overline{w}_C(I_2,h)]}{\partial h}>0$. Therefore, when $\overline{w}_C(1,h)-\overline{w}_B(1)<(1-\beta)C_{BC}$, there is no R&D personnel flow. When $\overline{w}_C(0,h)-\overline{w}_B(0)>(1-\beta)C_{BC}$, all R&D personnel flow to Country C. When $\overline{w}_C(0,h)-\overline{w}_B(0)<(1-\beta)C_{BC}$ and $\overline{w}_C(1,h)-\overline{w}_B(1)>(1-\beta)C_{BC}$, there exists an I^* such that when $\overline{w}_C(I^*,h)-\overline{w}_B(I^*)=(1-\beta)C_{BC}$, R&D personnel with ability greater than I^* migrate from Country B to Country C, resulting in a brain drain.

When R&D personnel in Industry *a* flow from Country B to Country C, a corresponding flow of R&D personnel in Industry *b* tends to occur from Country C to Country B. This ultimately results in a two-way exchange of R&D talent between the two countries. This finding suggests that in developed countries, when a particular industry is relatively small in scale and lacks competitiveness, R&D personnel are likely to migrate to other developed countries where that industry holds a competitive advantage. At the same time, industries in which their home country is strong will attract R&D talent from other developed countries. This dynamic leads to a substantial two-way flow of R&D personnel among developed nations. Overall, this conclusion provides a theoretical explanation for the two-way nature of talent flows observed between central countries.

In summary, when developed Countries B and C have identical industrial structures, there is no flow of R&D personnel between them. However, when their industrial structures differ, as noted earlier, and the conditions $\overline{w}_C(0,h)-\overline{w}_B(0)<(1-\beta)C_{BC}$ and $\overline{w}_C(1,h)-\overline{w}_B(1)>(1-\beta)C_{BC}$ hold, there exists an I^* such that $\overline{w}_C(I^*,h)-\overline{w}_B(I^*)=(1-\beta)C_{BC}$. Consequently, R&D personnel with ability greater than I^* migrate from Country B to Country C, leading to a brain drain. Furthermore, since $\overline{w}_C(I,h)-\overline{w}_B(I)$ increases with h, a larger h reduces I^*, thereby expanding the ability range of R&D personnel who migrate and increasing the scale of R&D personnel flow. Thus, differences in industrial structure promote the flow of R&D personnel between countries. Based on this, we propose Hypothesis 5:

Hypothesis 5: Differences in industrial structures between countries influence the migration choices of R&D personnel, with greater similarity in industrial structures being negatively correlated with the flow of R&D personnel.

The theoretical mechanism behind Hypothesis 5 suggests that the scale of R&D personnel flow between countries increases as the differences in their industrial structures expand. Countries with a larger number of highly differentiated industries are able to establish talent flow connections across a broader range of sectors with other nations. The strengthening of these connections through the movement of inventive talent brings new knowledge and technologies, positioning such countries as central hubs—or "poles"—within the global inventive talent flow network. In contrast, countries with fewer and less differentiated industries have only a limited number of sectors capable of forming talent flow links with other nations. As a result, they can attract talent only within a narrow range of industries and rely on the innovation generated in these few sectors to support economic development, ultimately positioning them on the periphery of the global inventive talent flow network. Therefore, differences in regional industrial structure serve as a decisive factor in the formation of poles during the process of global multi-polarization.

4. Empirical Analysis

4.1 Data Source

After data screening and processing, this study selects data from 42 countries for the period 2000-2014 for empirical analysis. Collectively, these 42 countries represented 78% of global GDP in 2014—a sufficiently large share to ensure high representativeness. The data on inventive talent flow networks are sourced from the European Patent Office's PATSTAT database. Country-level attributes, such as GDP per capita and R&D expenditure ratio, are drawn from the World Bank database. Industrial structure similarity derives from input-output data published by WIOD. Geographic distance, linguistic proximity, and colonial ties are obtained from the CEPII distance database. The decision to focus exclusively on post-2000 data for inventive talent flow networks is based on two considerations. First, if the time span is too broad, the underlying mechanisms of talent flow may undergo significant changes. By concentrating on the evolution of global inventive talent networks since 2000, the findings are better positioned to inform projections about future global innovation dynamics. Second, the data used for TERGM models cannot contain missing values, and a substantial portion of pre-2000 data—such as R&D expenditure ratios and human capital indicators—are incomplete for many countries. Limiting the dataset to the period after 2000 helps ensure data completeness and reliability.

4.2 Model Construction

This study employs the Temporal Exponential Random Graph Model (TERGM) to analyze the formation mechanisms of the global inventive talent flow network. TERGM, proposed by Hanneke (2010), is an extension of the Exponential Random Graph Model (ERGM) and has emerged as a widely adopted method in recent network analysis research (Liu et al., 2021; Cranmer et al., 2014). Compared to traditional regression approaches, TERGM relaxes the independence assumption and allows for the integration of various types of micro-level network configurations to estimate their influence on the formation and evolution of networks (Lusher et al., 2012). This makes it possible to examine both the endogenous and exogenous mechanisms that shape network structures. In contrast to ERGM, TERGM incorporates the temporal dimension, enabling the analysis of dynamic changes in network patterns over time. This provides a more comprehensive framework for exploring the endogenous mechanisms driving the evolution of networks.

The TERGM method models a sequence of network sets $G_t=(V_t, E_t)$, where V_t represents the nodes in the network at time t, and E_t denotes the edges. The network at time t is represented by N_t. It is assumed that N_t follows a k-order Markov distribution, meaning the network structure at time t depends on the network structures from time t-k to t-1, as expressed in Equation (9):

$$P(N^t|N^{t-k},\ldots N^{t-1},\theta)=\frac{exp(\theta^T h(N^t,N^{t-1},\ldots,N^{t-k}))}{c(\theta,N^{t-k},\ldots,N^{t-1})} \tag{9}$$

Let P denote the conditional probability of the formation of the network structure N^t, where c is a constant, h represents the network attributes, and θ denotes the parameters associated with these attributes. The joint probability distribution of a k-order Markov random field network is given by Equation (10).

$$P(N^{k+1},\ldots,N^t|N^1\ldots N^{t-1},\theta)=\frac{exp(\theta^T h(N^t,N^{t-1},\ldots,N^{t-k}))}{c(\theta,N^{t-k},\ldots,N^{t-1})} \tag{10}$$

To elucidate the evolution mechanism of the global inventor talent flow network, this study builds on the paper's theoretical assumptions by examining endogenous mechanisms and cross-country differences in industrial structure, while also incorporating other common exogenous variables. A temporal exponential random graph model (TERGM), as presented in Equation (11), is developed. Within the TERGM framework, endogenous mechanisms are categorized into structural and temporal effects, whereas cross-country industrial structure differences and other exogenous variables are classified as exogenous mechanisms, further divided into attribute effects and attribute networks.

$$\begin{gathered} P(N^t|N^{t-k},\ldots N^{t-1},\theta)=\frac{1}{c}exp(\theta_0\, edges+\theta_1\, mutual+\theta_2\, ttriple+\theta_3\, criple+\theta_4\, gwidegree+ \\ \theta_5\, transitiveties+\theta_6\, delrecip+\theta_7\, stability+\theta_{s1}\, lngdp+\theta_{s2}\, lnpergdp+\theta_{s3}\, growth+\theta_{s4}\, rd+ \\ \theta_{s5}\, tfp+\theta_{r1}\, lngdp+\theta_{r2}\, lngdpper+\theta_{r3}\, growth+\theta_{r4}\, rd+\theta_{r5}\, tfp+\theta_d\, lndist+\theta_l\, language+\theta_c\, clon) \end{gathered} \tag{11}$$

The variables in Equation (11) and their corresponding explanations are presented in Table 3.

Table 3: Key Variables and Their Definitions

		Variable name	Variable description	Explanation
Endogenous mechanism	Structural Effects	*edges*	Number of edges	The number of edges in the network, reflecting the network's density.
		mutual	Reciprocity	The tendency for talent flows to form mutual relationships through interactive exchanges.
		ttriple	Cyclicality	Talent flow from *i* to *j* and *j* to *k* promotes talent flow from *k* to *i*.
		ctriple	Transitivity	Talent flow from *i* to *j* and *j* to *k* promotes talent flow from *i* to *k*.
		gwesp	Convergence effect	Countries (regions) with more talent inflows tend to attract even more talent inflows.
	Temporal Effects	*delrecip*	Delayed reciprocity effect	Whether one-way talent flow in the previous period leads to reverse talent flow in the next period.
		stability	Path dependence effect	Whether talent flow in the previous period will persist into the next period.
Exogenous mechanism	Attribute Effects	*lngdp*	Economic scale of sender	Logarithm of the sender's GDP (measured in constant 2010 USD).
			Economic scale of receiver	Logarithm of the receiver's GDP (measured in constant 2010 USD).
		lnpergdp	Economic level of sender	Logarithm of the sender's GDP per capita (measured in constant 2010 USD).
			Economic level of receiver	Logarithm of the receiver's GDP per capita (measured in constant 2010 USD).
		growth	Economic growth of sender	Economic growth rate of the sending country (region).
			Economic growth of receiver	Economic growth rate of the receiving country (region).
		rd	Sender's R&D intensity	R&D expenditure as a proportion of GDP in the sending country (region).
			Receiver's R&D intensity	R&D expenditure as a proportion of GDP in the receiving country (region).
		tfp	Sender's TFP level	Total Factor Productivity (TFP) level of the sending country (region).
			Receiver's TFP level	Total Factor Productivity (TFP) level of the receiving country (region).
	Attribute Networks	*ind*	Industrial structure similarity	Measures the similarity of industrial structures between two countries, using the structural similarity coefficient introduced by UNIDO in 1979.[6]
		lndist	Geographic distance matrix	Logarithmic value of the geographic distance between the capitals (or centers) of two countries (regions).
		lang	Language proximity matrix	Whether two countries (regions) speak the same language (1 = Yes, 0 = No).
		clon	Colonial relationship matrix	Whether there was a colonial relationship between two countries (regions) (1 = Yes, 0 = No).

4.3 Empirical Results

The results of the TERGM-based analysis examining the formation mechanism of the global inventor talent flow network are presented in Table 4. Specifically, Model 1 includes only the structural effects within the endogenous mechanism; Model 2 incorporates the complete endogenous mechanism; Model 3 combines the endogenous mechanism with exogenous attribute variables; Model 4 includes only the exogenous mechanism; and Model 5 integrates both endogenous and exogenous mechanisms.

[6] This index was proposed in 1979 by the International Industrial Research Center of the United Nations Industrial Development Organization (UNIDO) to measure the similarity of industrial structures between countries. The formula is: $S_{ij}=\frac{\sum_{i=1}^{n}X_{ik}X_{jk}}{\sqrt{\sum_{k=1}^{n}X_{ik}^{2}\sum_{k=1}^{n}X_{jk}^{2}}}$, where X_{ik} represents the proportion of industry k in country i, and X_{jk} represents the proportion of industry k in country j.

Table 4: Empirical Results of the Evolution Mechanism of the Inventor Talent Flow Network[7]

	Variable name	Model 1	Model 2	Model 3	Model 4	Model 5
Structural effects	*edges*	-3.657*** (0.031)	-3.090*** (0.058)	-18.857*** (0.955)		-21.149*** (1.197)
	mutual	2.041*** (0.067)	1.402*** (0.093)	1.311*** (0.091)		1.216*** (0.086)
	ttriple	0.106*** (0.008)	0.074*** (0.007)	0.041*** (0.008)		0.041*** (0.008)
	criple	0.059** (0.026)	0.040 (0.025)	0.054** (0.026)		0.054** (0.026)
	gwideg	-0. 426*** (0.134)	-0.501*** (0.147)	-0.657*** (0.185)		-0.603*** (0.197)
Time effects	*delrecip*		1.133*** (0.108)	1.031*** (0.103)		0.930*** (0.097)
	stability		0.619*** (0.030)	0.532*** (0.031)		0.480*** (0.030)
Attribute networks	*ind*				-1.571*** (0.293)	-0.582*** (0.188)
	lndist				-0.473*** (0.017)	-0.306*** (0.019)
	language				1.778*** (0.059)	0.416*** (0.113)
	clon				0.563*** (0.084)	0. 602*** (0.167)

The regression results presented in Table 4 reveal that the combined influence of endogenous and exogenous mechanisms significantly shapes the formation of the global inventor talent flow network.

Among them, the structural effects within the endogenous mechanism play a pivotal role in the network's evolution. In Model 5, the coefficient for *mutual* is 1.22 and statistically significant, indicating strong reciprocity in the flow of inventor talent between countries (or regions). Specifically, when there is an inflow of inventor talent from Country A to Country B, talent from Country B is likewise more likely to flow to Country A, suggesting a "two-way flow" rather than a purely one-way pattern. The coefficients for *ttriple* and *ctriple* are both positive and statistically significant in Model 5, with *ctriple* (0.05) slightly exceeding *ttriple*. This finding suggests that, compared to a hierarchical structure, the global inventor talent flow network is more characterized by a circular "talent circulation" structure. In other words, when there is an existing flow of talent from Country A → Country B → Country C, it is more likely that talent will flow from Country C back to Country A rather than directly from Country A to Country C. Moreover, the coefficient for *gwesp* is negative and passes the 1% significance test, indicating the presence of a significant "Matthew Effect" within the network. Inventor talent tends to concentrate in countries (or regions) that already attract a high volume of inflows, reinforcing a centralized dynamic where "the strong get stronger, and the weak get weaker."

Temporal effects within the endogenous mechanism also play a significant role. In Model 5, the coefficient for *delrecip* is significantly positive, indicating the presence of delayed reciprocity in global inventor talent flows. Specifically, even if an inflow of inventor talent from Country A to Country B in

[7] Due to space limitations, the empirical results of the attribute effects and the corresponding analysis are not presented in the main text but are available upon request

the current period does not immediately trigger a reverse flow from Country B back to Country A, the reciprocal effect tends to persist and manifest in subsequent periods. When considered alongside the structural effect of *mutual*, these results suggest that the "two-way flow" characteristic of inventor talent is not only significant within the same period but also across periods, highlighting it as a fundamental mechanism in the global talent mobility network. Moreover, countries (or regions) with high inflows of inventor talent often experience high outflows as well. This phenomenon can be attributed to the fact that outward talent flows help strengthen international innovation linkages and establish communication bridges for advanced technologies, which, in turn, enhance the country's ability to attract further inflows of inventor talent from abroad. Additionally, the coefficient for *stability* in Model 5 is 0.48 and statistically significant, underscoring the path-dependent nature of global inventor talent flows. Rather than dissipating, established talent flow pathways are likely to persist into subsequent periods. Taken together, these empirical findings provide strong support for Hypotheses 1 through 4.

The coefficients of the attribute networks within the exogenous mechanism are consistent with our theoretical hypotheses. In Model 5, the coefficient for *ind* is -0.582 and statistically significant at the 1% level, indicating that greater similarity in industrial structures between countries exerts a negative influence on the flow of inventor talent, thereby supporting Hypothesis 5. In addition, the coefficients for *lndist*, *lang*, and *clon* are significant, with values of -0.306, 0.416, and 0.602, respectively. These results suggest that shorter geographical distances, as well as linguistic and cultural similarities, contribute positively to the mobility of inventor talent. Moreover, the negative coefficient for *lndist* underscores the inverse relationship between migration costs and inventor talent flows, which is fully aligned with the predictions of our theoretical model.

4.4 Robustness Checks

To ensure the reliability of the empirical results derived from the TERGM model, we conducted both goodness-of-fit tests and the following robustness checks: (1) Alternative Estimation Methods: To address potential issues such as outliers or extreme values that may arise in TERGM model estimation, we re-estimated the model using the Markov Chain Monte Carlo Maximum Likelihood Estimation (Leifeld et al., 2018) and the logit model. (2) Alternative Dependent Variable: Given that the original dependent variable is a binary indicator (0–1) representing the presence or absence of inventor talent flows between countries, we replaced it with a continuous variable reflecting the actual number of inventor talent flows. The model was then re-estimated using the OLS method to ensure that the research conclusions are not sensitive to changes in data format[8]. The estimation results show that the endogenous mechanisms remain statistically significant across different estimation methods, and the corresponding coefficients exhibit only minor variations. Likewise, when the dependent variable was switched from a binary indicator to the actual number of inventor talent flows, the effects of international migration costs and industrial structure similarity on inventor talent mobility remained consistent. These results provide robust support for the theoretical hypotheses proposed in this study, confirming the stability and reliability of the conclusions.

4.5 Heterogeneity Analysis

The flow of inventor talent varies considerably across industrial sectors, with talent mobility tending to concentrate in medium-high and high-technology industries. To explore the formation mechanisms of the global inventor talent flow network from the perspective of industrial heterogeneity, this study focuses on the manufacturing sector, which is further classified into low-technology, medium-

[8] Due to space constraints, the results of the goodness-of-fit tests and robustness checks are not reported here but are available upon request.

low technology, medium-high technology, and high-technology industries[9,10]. The analysis yields the following key insights: In low-technology and medium-low technology industries, the evolution of inventor talent flow networks is more strongly influenced by exogenous factors such as economic development level, R&D intensity, total factor productivity (TFP), geographical distance, and language similarity. In contrast, medium-high technology and high-technology industries are more significantly shaped by endogenous mechanisms, displaying significant effects of reciprocity, agglomeration, delayed reciprocity, and path dependence.

A possible explanation for this distinction is that innovation activities in medium-high and high-technology industries tend to be more complex, with higher knowledge barriers and greater differences in innovation environments between countries. In such sectors, cross-border inventor talent flows promote knowledge exchange, which helps reduce migration costs and further amplifies the influence of endogenous mechanisms on network evolution. Overall, these findings also suggest that the global inventor talent flow network within medium-high and high-technology industries is more likely to exhibit multi-polarization characteristics, reflecting a concentrated yet highly interconnected structure of talent mobility in advanced technological sectors.

5. Conclusions and Policy Recommendations

This study draws on global inventor mobility data extracted from the EPO Worldwide Patent Statistical Database (PATSTAT) to reveal the evolving multi-polar structure of the global inventor talent flow network. The findings show that inventor flows are increasingly concentrated among a handful of core countries — including the US, Germany, China, Switzerland, and the UK — while inventor mobility between peripheral nations continues to weaken. As a result, these central countries are becoming increasingly important within the global network. To explain this trend, we construct an endogenous migration model and apply a Temporal Exponential Random Graph Model (TERGM) to empirically test its underlying mechanisms. The results demonstrate that endogenous dynamics in inventor migration are the driving force behind this multi-polarization. These self-reinforcing mechanisms strengthen the centrality of key countries, accelerating the consolidation of a multi-polar global structure.

The study also identifies differences in regional industrial structures as a decisive factor in the emergence of these poles. Countries with heterogeneous and competitive industrial foundations are more likely to forge and sustain strong inventor mobility ties, allowing them to continuously replenish and upgrade their innovation capabilities. This dynamic positions such countries as pivotal nodes — or poles — in the global inventor talent flow network. Ultimately, the findings highlight a necessary stage in innovation-driven development. In this phase, regions with lower migration barriers and greater technological and industrial heterogeneity become magnets for talent, knowledge, and technology. Through the clustering of inventive talent, these regions achieve the concentration of innovation resources, enhance their innovation-driven growth capacity, and generate long-term economic gains.

Based on the above conclusions, this paper offers the following policy recommendations:

(1) Recognize the reciprocal and circular nature of global inventor talent flows. It is important to develop a nuanced understanding of inventor mobility, which often follows diverse patterns — including movements from lower-tier to higher-tier regions, from higher-tier to lower-tier regions, and cyclical flows — rather than a simple one-way "brain drain." Talent outflow should be viewed not merely as a loss but as an opportunity to strengthen international research collaboration, build innovation networks,

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[9] Due to space constraints, the detailed results of the heterogeneity analysis are not presented here but are available upon request.

[10] The industry classification in this study follows the OECD's *Science, Technology and Industry Scoreboard* (2001), which categorizes manufacturing industries into four groups—high-technology, medium-high technology, medium-low technology, and low-technology—based on R&D intensity within the production process.

and promote future talent inflows through reciprocity and circulation.

(2) Prioritize knowledge exchange and two-way talent flows with central innovation countries. Governments and research institutions should deepen cooperation with global innovation hubs such as the United States, Germany, and Japan. When designing and implementing foreign talent recruitment policies, special attention should be given to attracting skilled individuals from these core countries, as such connections not only raise the quality of domestic research but also help expand networks to include peripheral nations through established links with these centers.

(3) Lower barriers to researcher mobility through optimized R&D investment and system alignment. To enhance global competitiveness, efforts should be made to reduce the institutional and financial costs associated with cross-border researcher mobility. Aligning domestic research evaluation systems and innovation environments with those of leading countries will make it easier for talent to move and collaborate, positioning China as a vital node in the global inventor talent network.

(4) Accelerate the development of high-tech industries to secure long-term economic growth. Governments and industry leaders should focus on mastering core technologies and scaling up competitive high-tech sectors supported by complete industrial chains. Compared to other innovation leaders such as the United States, Japan, and Germany, China should actively pursue strategies that increase the share of high-tech industries in the economy, ensuring sustained momentum for technological and economic advancement. CE

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