International Sanctions and International Student Flows: A Network Econometrics Approach with Counterfactual Analysis *

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Abstract

International student flows are a critical component of global human capital accumulation. This paper investigates how the network of international sanctions disrupts these flows. To address the complex endogeneity inherent in network formation, we develop a theoretical model of the International Student Network (ISN) and estimate its dynamic evolution using panel data on international sanctions and student flows from 2000 to 2020 and a suite of advanced network econometric methods, including Exponential Random Graph Models (ERGM) and their structural variants. Our results reveal a significant deterrent effect: sanctions imposed by one country on another reduce the likelihood of student flow between them, with travel sanctions being the most effective. This effect is heterogeneous, stronger between countries with similar economic development levels and shorter geographical distances. Furthermore, we employ counterfactual simulations—specifically, removing U.S. sanctions on China—to quantify both the direct and indirect spillover effects of sanctions on the global network structure. Our analysis provides novel evidence on how geopolitical frictions shape the distribution of human capital across countries.

JEL classification: F22, F51, C45, C31

Keywords: International Student Flows; International Sanction Networks; Network Econometrics; Counterfactual Analysis

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1 Introduction

As the internationalization and globalization of talent accelerate (Marin and Verdier, 2012), the cross-border flow of high-quality human capital has emerged as a key driver of economic development and technological progress (Benhabib and Spiegel, 2005; Orefice et al., 2025; Spilimbergo, 2011), profoundly shaping the international political and economic landscape. Within these talent flows, international students constitute a critical component as talent reserves and future innovators. Their flows form a global knowledge network that exhibits a complex structure and a high degree of spatial alignment with international scientific collaboration.

It is widely recognized that a range of factors shape international student flows, including economic development, political relations, social and cultural links, geographic proximity, academic quality, and immigration policies. Among these, international relations exert a fundamental yet complex effect on student flows. However, comprehensively measuring international relations poses conceptual and empirical challenges, particularly regarding data availability. Prior studies often rely on co-membership in international intergovernmental organizations as a proxy for diplomatic affinity (Pevehouse et al., 2020; Vögtle and Windzio, 2016; Wallace and Singer, 1970).

International sanctions generally refer to coercive measures—including threats, restrictions, or punitive actions—imposed by one or more countries, or by international organizations, to compel a target country to comply with international norms or alter specific policies (Kaempfer and Lowenberg, 1988). As a prevalent and potent tool of diplomacy, sanctions aim to inflict economic costs on target states to induce political change (Felbermayr et al., 2020). Their use has become increasingly frequent since the turn of the 21st century, becoming a prominent instrument of non-military foreign policy, which reflects and shapes strategic disputes between countries (Felbermayr et al., 2020). Such sanctions may significantly disrupt student flows, particularly given the observed asymmetry between flow patterns and sanction directions. Whereas international students typically move from East to West and from South to North, sanctions are most frequently imposed by Western developed countries on Eastern or developing nations. This opposition suggests that sanctions likely counteract established mobility pathways, generating substantial inhibitory effects on international student flows.

International sanctions manifest in diverse forms, including unilateral, plurilateral, and multilateral sanctions; economic and non-economic sanctions; United States, European Union, and

United Nations sanctions; threat and actual sanctions (Afesorgbor, 2019; Kaempfer and Lowenberg, 1999; Levy, 1999). These heterogeneous sanctions exert a substantial effect across multiple domains such as economy, finance, trade, social welfare, and public well-being (Afesorgbor and Mahadevan, 2016; Neuenkirch and Neumeier, 2016; Peksen and Son, 2015). Yet, relatively little attention has been paid to the educational dimension, as the literature remains predominantly focused on the economic impacts of sanctions, with non-economic sanctions receiving scant scholarly attention (Kim et al., 2023; Prusa, 2008).

This paper starts from a macro perspective of international networks and builds upon a range of international migration theories to propose a theoretical model of the international student network (ISN) (Beine et al., 2018). We aim to explore the formation and evolution mechanisms of the ISN, emphasizing the role of its endogenous structures. We employ a suite of social network econometric models to empirically analyze the impact of international sanction networks on student flows, providing insights into how countries can leverage high-quality human capital flows to foster economic development amid the increasing normalization of international sanctions. Furthermore, we conduct counterfactual analysis to isolate both the direct and indirect spillover effects of sanctions, offering insights into their short- and long-run consequences.

Specifically, this paper is designed to address the following research questions: What are the static and dynamic evolutionary features of the ISN? Do its endogenous structures exhibit dynamic heterogeneity? How do the increment and decrement networks of international students evolve? Does the international sanction network exert a significant effect on the ISN? Do the effects on the ISN vary across different types of sanction networks, such as trade, financial, economic, and travel sanctions? Is the effect of the international sanction network moderated by factors such as GDP differences, geographical distance, and other national-level characteristics? Under a counterfactual scenario in which the U.S. removes all sanctions targeting China, would there be significant changes in student flows from China to the U.S., and in the overall structure of the ISN?

This paper contributes to the literature in several dimensions. We develop a theoretical model of International Student Network formation and evolution, and provide the first comprehensive empirical evidence on how international sanction networks—disaggregated into trade, financial, economic, and travel sanctions—affect international student flows. Our results uncover a novel and striking heterogeneity: travel sanctions have a significantly negative effect, while other economic sanctions show no statistically discernible effect. We further show that this effect is moderated by bilateral differences in GDP per capita and geographical distance. Methodologically, we are the first to apply Temporal Exponential Random Graph Models (TERGM) to this context, thereby explicitly accounting for the network's endogenous structure and time dynamics. We also leverage more recent techniques—Varying-Coefficient Exponential Random Graph Model (VCERGM) and Partially Separable Temporal Exponential Random Graph Model (PSTERGM)—to capture time-varying network topology and to separately model the formation and dissolution of the ISN. This allows for a more nuanced analysis of network dynamics than previously possible. We conclude with a counterfactual analysis that quantifies the direct and spillover effects of removing sanctions, providing causal evidence from a novel perspective.

The remainder of this paper will proceed as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical model and the econometric framework underpinning our analysis. Section 4 describes the data and examines the structural characteristics and stability of the ISN. Section 5 first details the empirical methodology, drawing on various network econometric estimators to identify determinants of student flows, and evaluates the heterogeneous effects of international sanctions—including trade, financial, economic, and travel sanctions—on the ISN. We also investigate the moderating roles of differences in GDP per capita and geographic distance in shaping the response of student flows to sanctions in the section 5. Section 6 presents a counterfactual analysis simulating the removal of U.S. sanctions targeting China. Section 7 concludes with a discussion of findings and policy implications.

2 Literature Review

The formation of international student flows is largely informed by theoretical frameworks derived from international migration theories, including the push-pull model, neoclassical economics, the new economics of migration (NELM), world systems theory, and new economic geography (NEG) (Sassen, 1988; Sjaastad, 1962). Empirical research has predominantly examined the push factors from countries of origin and pull factors from destination countries within the push-pull paradigm. Key determinants such as geographic distance, language proximity, and cost of living have been shown to significantly influence student flows, whereas tuition fees often exhibit limited explanatory power (Beine et al., 2014).

Specifically, both neoclassical economics and the NELM seek to explain student flows through the maximization of personal lifetime income and the diversification of household income risk, respectively (Stark and Bloom, 1985). Neoclassical economics frames international student flows as an investment decision: rational individuals choose to study abroad when the expected returns—primarily in the form of higher future earnings—outweigh the associated costs, thereby gaining access to higher-quality educational resources (Harris and Todaro, 1970). For instance, Beine et al. (2018) explicitly derives a migration equation from a human capital model combined with a random utility model (RUM) approach (McFadden, 1984). In their formulation, prospective students compare the present value of future earnings from studying at home versus abroad. If the income gain from abroad exceeds the combined costs of migration, tuition, and living expenses, the rational choice is to move to the destination that offers the highest net return. In contrast, the NELM framework posits that the decision to study abroad is often a household-level strategy aimed at minimizing income risks and stabilizing family welfare, rather than a purely individual utility-maximizing choice (Stark, 1991).

World system theory, on the other hand, emphasizes the role of structural inequality among nations, arguing that a country's position within the global order—shaped by its economic and political power—largely determines its role within international student flows (Chirot and Hall, 1982). Core countries with advanced economies and high-quality educational institutions attract students from peripheral countries, reinforcing a core–periphery structure in the ISN. Students from peripheral regions often seek advanced skills and knowledge in core countries, which in turn may contribute to the development of their home countries through knowledge transfer and remittances. On the other hand, the NEG framework highlights the interplay between individual agency and societal structures in migration decisions (Castles et al., 2005). Within this framework, historical ties—such as trade relationships and colonial links—between origin and destination countries are identified as significant factors shaping international student flow patterns.

Furthermore, cultural factors play a significant role in shaping the structure and evolution of the IS. Cross-cultural interactions among international students contribute considerably to the dynamic development of such networks (Taha and Cox, 2012). To systematically incorporate this dimension, we draw on world culture theory, which conceptualizes globalization as the diffusion of cultural and associative processes (Meyer et al., 1997). This perspective suggests that the expansion of international student flows is underpinned by ideals of "world citizenship," the pursuit of personal knowledge, and growing cosmopolitanism (Vertovec and Cohen, 2002). Consequently, when selecting destination countries, students often exhibit a preference for those that share social, cultural, and value systems similar to their home countries, such as countries with a common language (Schofer and Meyer, 2005).

Beyond these broad social, cultural, and value systems, a growing body of research emphasizes the role of social networks in shaping international student flows. Interpersonal connections can significantly reduce the information costs and perceived risks associated with studying abroad by providing credible information and support channels (Ding and Li, 2012). These network effects can reinforce—or occasionally bypass—traditional geographic, economic, political, and cultural channels.

Vögtle and Windzio (2016) provided empirical evidence on the formation of the ISN using ERGMs. Their study examined exogenous factors, including shared membership in international organizations, shaping the ISN, while also highlighting endogenous structural dependencies present at specific time points. However, their approach did not account for the dynamic evolution of the network. As the ISN evolves both spatially and temporally, emerging regional hubs exhibit flow patterns that increasingly diverge from traditional pathways. Between 2000 and 2010, the ISN remained relatively stable, with the United States, United Kingdom, France, and Germany consistently forming its core. In recent years, however, the number of international student flow pathways has expanded considerably, and the network's topology has shifted from a U.S.-centered single-core structure to a dual-core structure incorporating both the United States and China. Concomitantly, the geospatial pattern of the ISN is transitioning from the traditional "east-to-west and south-to-north" orientation toward a more regionalized architecture (Vögtle and Windzio, 2016). To capture these time-varying structural dynamics, our paper employs TERGMs.

Beyond the literature on international student flows, a closely related strand of research concerns the multidimensional effects of international sanctions. Existing literature demonstrates that sanctions exert broad influence across economic, financial, trade, political, and social domains (Afesorgbor and Mahadevan, 2016; Neuenkirch and Neumeier, 2016; Peksen and Son, 2015). Although the adverse effect of sanctions on student flows may appear intuitive, the mechanisms are in fact multidimensional. First, when a destination country becomes the target of sanctions, the resultant economic disruption—such as declining trade, financial instability, and increased economic volatility—often leads to rising prices and higher costs of living (Neuenkirch and Neumeier, 2015). Concurrently, sanctions may undermine democratic institutions, increase corruption, elevate the risk of military conflict, and foster broader societal instability (Oechslin, 2014). As living expenses rise and social conditions deteriorate, the attractiveness of the target country as a study destination diminishes. Second, sanctions are frequently accompanied by direct measures such as the expulsion of international students, bans on student visa applications, and the suspension of academic cooperation programs. These policies directly restrict educational flows and undermine the competitive openness of the higher education market. Furthermore, while economic sanctions, for example, trade or financial sanctions, may not immediately distort the study-abroad market, non-economic sanctions—such as travel sanctions—can directly impede student flows by limiting physical movement. For instance, Rezaee-Zavareh et al. (2016) shows that sanctions negatively affect academic and scientific activities by restricting opportunities for international collaboration and conference participation.

3 Theoretical Model and Econometric Framework

At the theoretical level, two complementary perspectives explain why students pursue higher education abroad. Educational and migration models focus primarily on the decision to study abroad, while other literature has concentrated on the choice of destination. Most studies employ country-level data and adopt a multi-origin framework. A key contribution of Beine et al. (2018) lies in their shift of analysis to universities as the unit of destination, offering a more granular understanding of student mobility patterns. Building on this approach, the theoretical model developed in this paper further extends the micro-founded analysis of destination choice within an international network environment.

As formalized in Beine et al. (2018), the utility that a student s from country o derives from studying at university u^d in destination country d is given by:

$$V^s_{o,d,u^d} = ln(\frac{(B(\frac{Q_{u^d}}{\bar{Q}_d})^{\beta_0} w_{u^d})^{\beta_1} A_d^{\gamma_1}}{\delta(CM_{o,d}, CS_{u^d}, CL_{u^d})}) + \epsilon^s_{o,d,u^d}, \tag{1}$$

where $CM_{o,d}$ denotes country-pair migration costs from o to d; CS_{u^d} represents education costs (tuition fees) at university u^d; CL_{u^d} is the cost of living in the city of u^d; A_d captures country-specific unpriced amenities in d; w_{u^d} denotes average earnings near u^d; Q_{u^d} and $\bar{Q}_d$ represent the education quality at university u^d and the average quality in country d, respectively; and ϵ^s_{o,d,u^d} is the idiosyncratic error term. Importantly, migration costs $CM_{o,d}$ consist of two components:

fixed costs C_o (origin-specific expenses of moving abroad) and variable costs $C_{o,d}$, which depend on dyadic factors including physical distance $d_{o,d}$, common official language $l_{o,d}$, and historical colonial links $col_{o,d}$.

Building on the work of Ding and Li (2012), this paper further incorporates the role of social networks in shaping migration costs. Specifically, the stock of prior international students from country o to d, denoted $R_{o,d}$, is expected to lower migration costs by fostering informational and social linkages. Similarly, the total number of students from both o and d who have studied in any common third country i, denoted $T_{o,i,d}$, may further reduce bilateral migration costs through shared academic and cultural experiences. In addition, international sanctions between o and d, denoted $S_{o,d}$, are introduced as a factor that distorts and increases migration costs, reflecting deteriorated bilateral relations.

Thus, the total factor cost ($\delta(CM_{o,d}, CS_{u^d}, CL_{u^d})$) is specified as follows:

$$\begin{aligned} ln(\delta(CM_{o,d}, CS_{u^d}, CL_{u^d})) = \gamma_2 ln(C_o) + \alpha_1 ln(d_{o,d}) + \alpha_2 ln(l_{o,d}) + \alpha_3 ln(col_{o,d}) \\ - \alpha_4 ln(R_{o,d}) - \alpha_5 ln(T_{o,i,d}) + \alpha_6 ln(S_{o,d}) + \beta_3 ln(CS_{u^d}) + \beta_4 ln(CL_{u^d}) \end{aligned} . \tag{2}$$

Therefore, I then have

$$V_{o,d}(Y_{o,d}) = -\alpha_1 ln(d_{o,d}) - \alpha_2 ln(l_{o,d}) - \alpha_3 ln(col_{o,d}) + \alpha_4 ln(R_{o,d}) + \alpha_5 ln(T_{o,i,d}) - \alpha_6 ln(S_{o,d}). \tag{3}$$

And the conditional probability of choosing country d, given the choice between staying or moving, is:

$$P_{o,d|h} = \frac{exp(V_{o,d}(Y_{o,d}) + (1-\lambda^u) ln(I^u(d,h)))}{exp(ln(\sum_{j=1}^{n_d} exp(V_{o,j}(Y_{o,j}) + (1-\lambda^u) ln(I^u(j,h)))))} \tag{4}$$

for any $j \neq d$, where

$$I^u(d,h) = \sum_{u=1}^{n_u^d} exp(\beta_2 ln(Q_{u^d}) + \beta_1 ln(w_{u^d}) - \beta_3 ln(CS_{u^d}) - \beta_4 ln(CL_{u^d})) \tag{5}$$

Therefore, the following partial effects can be derived from the model:

$$\frac{\partial P_{o,d|h}}{\partial R_{o,d}} = \frac{\alpha_4 P_{o,d|h}}{R_{o,d}} > 0, \quad \frac{\partial P_{o,d|h}}{\partial T_{o,i,d}} = \frac{\alpha_5 P_{o,d|h}}{T_{o,i,d}} > 0, \quad \frac{\partial P_{o,d|h}}{\partial S_{o,d}} = \frac{-\alpha_6 P_{o,d|h}}{S_{o,d}} < 0 \tag{6}$$

These results lead to the testable proposition of this paper:

Proposition 1. *The probability of student flows between countries o and d increases with the intensity of reciprocity ($R_{o,d}$) and transitivity ($T_{o,i,d}$) in the ISN, but decreases with the intensity of bilateral sanctions ($S_{o,d}$).*

This proposition implies that social network structures—captured by the stock of prior international students from country o to d (reciprocity) and the total number of students from both o and d who have studied in any common third country i (transitivity)—facilitate international student flows, whereas political-diplomatic friction in the form of sanctions inhibits them.

Therefore, this paper accounts for the endogenous structural properties of the ISN. Among these, edges constitute the fundamental building blocks of the network, while higher-order structures such as reciprocity and transitivity capture its endogenous clustering tendencies. In directed networks like the ISN, social ties frequently exhibit both reciprocity and transitivity (Hoff et al., 2002). Transitivity—often summarized by the adage "a friend of a friend is a friend"—can be represented geometrically in latent space models through triangle inequality constraints (McCormick and Zheng, 2015). Such closed triadic structures, commonly measured using the geometrically weighted edgewise shared partners (GWESP) statistic, indicate stable and cohesive subgroups. These structures serve as endogenous mechanisms that shape tie formation and foster network clustering (Giuliani, 2013). Empirical evidence confirms that transitive closure plays a key role in knowledge networks, supply chains, and international trade—mechanisms that support the formation and stability of relational ties. Within the ISN, Vögtle and Windzio (2016) identify significant and stable transitive patterns, where student flows from country i to k are facilitated by existing flows via $i \to j$ and $j \to k$. This tendency aligns with the small-world properties of the ISN, promoting tightly-knit communities. Reciprocity, another fundamental social mechanism, also underpins the topology of complex networks and reflects mutual exchange. The tendency for bilateral student flows has been empirically established in international education (Vögtle and Windzio, 2016) and is increasingly promoted through diplomatic channels, as exemplified by the Sino-Russian goal of reaching 100,000 exchanged students by 2020. Such initiatives highlight a shift away from earlier asymmetries in international student mobility toward more reciprocal flows, a pattern also reflected in global talent circulation models (OECD, 2008). The two core endogenous structures—transitivity and reciprocity—are illustrated in Figure 1.

The theoretical model for the formation and evolution of the ISN developed in this paper extends the framework of Gaonkar and Mele (2023) by incorporating a directed network structure and emphasizing distinct endogenous mechanisms. While Gaonkar and Mele (2023) focus on undirected networks with an emphasis on homophily and popularity, this analysis examines the directed ISN, prioritizing transitivity and reciprocity as key endogenous dependencies. To this end, the model further draws on the directed network formulation in Mele (2017).

The payoff function consists of both deterministic and stochastic components, consistent with the random utility framework (Heckman, 1978), which are specified additively. The model considers an economy comprising n countries, where each country i is characterized by a vector of observable attributes x_i—including GDP per capita, political stability, and the proportion of top universities. By integrating exogenous covariates with endogenous structures such as edges, transitivity, and reciprocity, the model offers a comprehensive analytical tool for understanding the formation and evolution of the ISN, providing valuable insights for both researchers and policymakers in international higher education.

The deterministic component of the payoff for country i, given a network configuration g and country attributes x, is defined as the sum of net benefits across all edges:

$$U_i(g, x; \theta) = \sum_{j=1}^{n} g_{ij} \left(a_0 + a_1 \cdot g_{ji} + a_2 \cdot t_{ij} \right), \tag{7}$$

where $t_{ij} = \sum_{k \neq i,j} \mathbf{1}\{g_{ik} \cdot g_{jk} = 1\}$ denotes the number of common partners between countries i and j—that is, the number of closed transitive triangles in the ISN in which both $i \to k$ and $j \to k$ are present. The parameter vector $\theta = (a_0, a_1, a_2)$ includes: a_0, the baseline payoff (or cost) of forming a link; a_1, the marginal payoff due to reciprocity; and a_2, the marginal payoff from transitivity.

From equation 7, the marginal payoff for country i from a directed edge to country j is:

$$MP_{ij} = a_0 + a_1 \cdot g_{ji} + a_2 \cdot \sum_{k \neq i,j} \mathbf{1}\{g_{ik} \cdot g_{jk} = 1\}. \tag{8}$$

The random component of the payoffs corresponds to a matching quality ϵ_{ij} between countries i and j. Thus, country i will form a directed edge to country j if and only if the sum of the marginal payoff and the matching quality is nonnegative:

$$g_{ij} = 1 \quad \text{if and only if} \quad MP_{ij} + \epsilon_{ij} \geq 0, \tag{9}$$

or equivalently,

$$U_i(g_{ij} = 1, g_{-ij}, x; \theta) + \epsilon_{g_{ij}=1} \geq U_i(g_{ij} = 0, g_{-ij}, x; \theta) + \epsilon_{g_{ij}=0}, \tag{9}$$

where g_{-ij} denotes the network configuration excluding the edge from i to j (i.e., the rest of the ISN).

I assume the matching quality ϵ_{ij} is independently and identically distributed (i.i.d.) according to a logistic distribution. The conditional probability that countries i and j form a directed edge from i to j is given by:

$$P(g_{ij} = 1 \mid g, x, \theta) = \frac{\exp(MP_{ij})}{1 + \exp(MP_{ij})}. \tag{10}$$

This conditional probability model satisfies the three key assumptions in Mele (2017). If this edge formation process is observed over a sufficiently long time horizon, the long-run probability of observing a particular ISN configuration g is:

$$\pi(g \mid x, \theta) = \frac{\exp(Q(g, x; \theta))}{c(\theta, x)}, \tag{11}$$

where $\theta = (a_0, a_1, a_2)$ is the parameter vector to be estimated, and $Q(g, x; \theta)$ represents the potential function:

$$Q(g, x; \theta) = a_0 \cdot \mathit{edges} + a_1 \cdot \mathit{reciprocity} + a_2 \cdot \mathit{transitivity}. \tag{12}$$

In the econometric specification, I incorporate a set of exogenous covariates to obtain the marginal benefit for country i from forming a directed edge to country j in the ISN:

$$\begin{aligned} MP_{ij} = {} & a_0 + a_1 \cdot g_{ji} + a_2 \cdot l_{ij} + \beta_1 |GDPper_i - GDPper_j| + \beta_2 |PS_i - PS_j| \\ & + \beta_3 GDPper_i + \beta_4 PS_i + \beta_5 TopUni_i + \beta_6 GDPper_j + \beta_7 PS_j + \beta_8 TopUni_j, \\ & + \gamma_1 samelanguage_{ij} + \gamma_2 distance_{ij} + \gamma_3 colonialrelation_{ij} + \gamma_4 sanction_{ij} \end{aligned} \tag{13}$$

where $GDPper_i$ is the per capita GDP of country i; PS_i is the political stability score of country i; $TopUni_i$ is the proportion of top-500 universities in country i; $samelanguage_{ij}$ indicates whether countries i and j share a common language; $distance_{ij}$ measures the geographical distance between countries i and j; $colonialrelation_{ij}$ indicates a historical colonial relationship; and $sanction_{ij}$ indicates whether country i has imposed sanctions on country j.

Within the framework of strategic network formation as proposed by Gaonkar and Mele (2023) and Mele (2017), the equilibrium of the ISN is characterized by an exponential random graph. This equilibrium can be empirically analyzed using econometric network models such as ERGM, TERGM, VCERGM, and PSTERGM, which yield parameter estimates with direct economic interpretations.

4 Network Structural Analysis

4.1 Static Network Structural Statistics of the ISN

As countries increasingly prioritize the cultivation of human capital and strategic investment in knowledge-based assets, the number of international students has risen dramatically in recent decades. Global international student enrollment grew from 0.108 million in 1950 to 2.173 million in 2001, further expanding to 4.788 million in 2015 and reaching 6.362 million by 2020 [1]. This growth has been accompanied by increasing connectivity and density within the ISN, reflecting its evolving role as a key infrastructure in global higher education and knowledge diffusion.

Due to variations in how countries define and classify international students, as well as differences in data collection and reporting standards, the data of Chinese international students used by this paper come from summary statistics published by the Department of International Cooperation and Exchange under the Ministry of Education of China, which explicitly exclude non-degree-seeking students. This helps mitigate measurement errors by excluding short-term training programs, non-degree research visits, and other forms of educational flow that are not intended to lead to the acquisition of formal academic qualifications.

To construct a representative ISN, we selected 174 countries as nodes after excluding nations with missing data or isolated across the observed period. This sample covers over 95% of global international student flow data. In line with conventional practice in ERGM analysis, we binarized the weighted network matrix by applying a threshold set at the 60th percentile of the distribution

[1] The data of international students come from the United Nations Educational, Scientific and Cultural Organization (UNESCO) database.

of international student counts across years. This step converts the valued adjacency matrix into a binary form, distinguishing substantively significant student flows from negligible ones.

From a static perspective, the ISN exhibits several key characteristics. First, the number of network edges shows a general upward trend, reaching an all-time peak in 2016. This period also includes noticeable fluctuations, with declines occurring between 2003–2005 and 2017–2020. You can see this in Figure 2. Accordingly, we divide the evolution of the ISN into four developmental stages: 2000–2002, 2003–2005, 2006–2016, and 2017–2020. Second, the ISN displays distinct structural properties, notably high transitivity and non-negligible reciprocity. From 2000 to 2020, the average transitivity—measuring the proportion of closed triangles among all possible triplets—was 53.15%, suggesting a strong tendency toward clustering and triadic closure. Over the same period, the average reciprocity—defined as the proportion of mutual dyads in this directed network—stood at 34.85%, reflecting substantial bidirectional student flows between country pairs. These descriptive patterns align closely with the theoretical model of the ISN introduced earlier. To capture these endogenous structural features empirically, we incorporate three types of endogenous effects—edges, GWESP, and reciprocity—in our ERGM, TERGM, VCERGM, and PSTERGM specifications.

Based on the trend characteristics shown in Figure 2, we selected five representative time points: 2000, 2003, 2005, 2016, and 2020. Table 1 reports descriptive statistics of key network metrics at these points, including the mean and standard deviation of node out-degree, eigenvector centrality, transitivity (clustering coefficient), and the diameter of the largest connected component.

Table 1: Descriptive Statistics of the International Student Network

	2000	2003	2005	2016	2020
Node out-degree	21.805	28.201	27.247	50.282	46.144
	(8.910)	(11.910)	(11.200)	(17.030)	(15.510)
Eigenvector centrality	0.060	0.062	0.061	0.066	0.065
	(0.050)	(0.040)	(0.040)	(0.040)	(0.390)
Cluster coefficient	0.411	0.486	0.468	0.632	0.619
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diameter	4.000	4.000	3.000	3.000	3.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	174	174	174	174	174

Note: Standard deviations are shown in parentheses. The table presents descriptive statistics of key network metrics for the ISN at five selected time points.

4.2 Dynamic Structural Stability Tests of the ISN

With economic globalization and the internationalization of education, the number of international students has grown rapidly, accompanied by substantial changes in flow patterns—shifting from a one-way flow from developing to developed countries toward a more reciprocal pattern of talent circulation between them (**?**). These shifts have led to significant spatiotemporal evolution in the global International Student Network (ISN), with the emergence of regional hubs indicating profound structural changes within the network (Chen and Barnett, 2000). We hypothesize that the ISN at different time points may be generated by distinct random graph processes, reflecting underlying structural differences. To test the dynamic stability of the network structure, we apply the method proposed by Auerbach (2022).

The null hypothesis of this test posits that the ISNs at two distinct time points are generated by the same random graph model, implying structural stability within the network—that is, no significant structural change exists. The first approach employs a regression-based test. For instance, when comparing network structures between time points τ_1 and τ_0, the dependent variable is a network statistic at τ_1, and the independent variable is the same statistic measured at τ_0. The regression model is specified as follows:

$$S(\tau_1) = \alpha_0 + \alpha_1 S(\tau_0) + \epsilon, \tag{14}$$

where a significant change in network structure corresponds to the statistical significance of coefficient α_1 (Banerjee et al., 2024). Table 2 reports significance tests for differences in three key network statistics: node out-degree, eigenvector centrality, and clustering coefficient. The results indicate statistically significant differences in node out-degree between 2000 and 2003, 2005 and 2016, and 2000 and 2020.

This paper further examines the structural stability of the network using a second methodological approach. Following a logic similar to the two-sample Kolmogorov–Smirnov test, we implement a randomization test procedure based on the $2 \to 2$ operator norm (Auerbach, 2022). Table 3 reports the p-values from this randomization test for six network statistics: the absolute difference in average degree, the mean squared difference in node degree, the mean squared difference in eigenvector centrality, the absolute difference in the clustering coefficient, the absolute difference in diameter, and the $T_{2\to 2}$ statistic itself. Overall, the results indicate that for nearly all pairs of time

Table 2: Regression-Based Tests for Structural Stability in the International Student Network

		Node out degree	Eigenvector centrality	Cluster coefficient
2000 vs. 2003	Intercept	21.805 (0.000)	0.060 (0.000)	0.814 (0.000)
	Parameter	6.397 (0.000)	0.002 (0.750)	-0.016 (0.502)
2003 vs. 2005	Intercept	28.201 (0.000)	0.062 (0.000)	0.798 (0.000)
	Parameter	-0.954 (0.441)	-0.001 (0.922)	0.021 (0.368)
2005 vs. 2016	Intercept	27.247 (0.000)	0.061 (0.000)	0.819 (0.000)
	Parameter	23.034 (0.000)	0.004 (0.322)	-0.021 (0.328)
2016 vs. 2020	Intercept	50.282 (0.000)	0.066 (0.000)	0.798 (0.000)
	Parameter	-4.138 (0.018)	-0.001 (0.885)	0.006 (0.762)
2000 vs. 2020	Intercept	21.805 (0.000)	0.060 (0.000)	0.814 (0.000)
	Parameter	24.339 (0.000)	0.005 (0.287)	-0.010 (0.648)

Note: Point estimated values are given outside parentheses and P-values in parentheses.

points, the international student network exhibits significant structural differences. Except for the difference in diameter—which may be consistent with a single underlying random graph model—all other statistics show significant variation across time. The randomization test based on the $T_{2\to 2}$ statistic in particular provides strong evidence against the null hypothesis of structural stability, confirming that the ISN displays significant time-varying characteristics.

Table 3: Randomization Test for Structural Stability of the International Student Network

	00 vs. 03	03 vs. 05	05 vs. 16	16 vs. 20	00 vs. 20
Average out-degree	0.002	0.002	0.002	0.002	0.002
Node out-degree	0.002	0.978	0.002	0.002	0.002
Eigenvector centrality	0.002	0.002	0.002	0.002	0.002
Cluster coefficient	0.002	0.002	0.002	0.002	0.002
Diameter	1.000	0.638	1.000	1.000	0.480
$2 \to 2$ norm	0.002	0.002	0.002	0.002	0.002

Note: This table presents p-values from randomization tests comparing network structures across different time periods. The tests are based on the $2 \to 2$ operator norm randomization test (Auerbach, 2022). Except for diameter differences, all statistics show significant structural changes between time points (p<0.05).

4.3 Structural Similarity Test of the ISN and the Sanction Network

Before conducting econometric analysis, we thoroughly assessed the structural similarities between the ISN and the international sanction network from both static and dynamic perspectives. Using static randomization tests and dynamic trend similarity analysis, we identified significant structural differences between the two networks, confirming that the same random graph process does not generate them. Moreover, dynamic metrics such as the number of edges, transitivity, and reciprocity evolved differently across the two networks. These consistent findings—from both static and dynamic tests—suggest an absence of common unobserved confounders between the ISN and the sanction network, thereby supporting the identification of causal effects in subsequent empirical models.

Data on international sanctions are sourced from the Global Sanctions Database (GSDB) (Felbermayr et al., 2020), which provides comprehensive coverage of bilateral, multilateral, and plurilateral sanctions globally (Kirilakha et al., 2021; Syropoulos et al., 2024). The database includes detailed information on various sanction types, such as trade, financial, and travel restrictions. The null hypothesis of the $T_{2\to 2}$ test posits that both networks are generated by the same random graph model. The results presented in Table 4 reject this hypothesis—all p-values indicate statistically significant structural differences between the networks, confirming that they do not share a common underlying stochastic structure.

Table 4: Randomization Test for Structural Differences Between Two International Networks

	2000	2003	2005	2016	2020
Average degree	0.002	0.002	0.002	0.002	0.002
Node degree	0.002	0.002	0.002	0.002	0.002
Eigenvector centrality	0.002	0.002	0.002	0.002	0.002
Cluster coefficient	0.002	0.002	0.002	0.002	0.002
Diameter	0.622	1.000	0.002	0.002	0.002
$2 \to 2$ norm	0.002	0.002	0.002	0.002	0.002

Note: This table presents p-values from randomization tests comparing the structure of the ISN and the international sanction network at five time points. The tests are based on the $2 \to 2$ operator norm randomization test (Auerbach, 2022). Lower p-values indicate stronger evidence against the null hypothesis that both networks share the same underlying structure.

We also performed dynamic structural similarity tests to examine whether the statistical properties of the two networks exhibited co-movement between 2000 and 2020. Drawing on time-series similarity assessment methods, we quantified the resemblance in evolutionary trends of edge number, transitivity, and reciprocity between the ISN and the international sanction network. Table 5 presents Pearson correlation coefficients, corresponding p-values, mean absolute percentage errors (MAPE), and Compression-based Dissimilarity Measures (CDM) for each of the three metrics. Figure 3 displays the optimal alignment paths between the time series derived from Dynamic Time Warping (DTW) for each network statistic.

The Pearson correlation and mean absolute percentage error (MAPE) were computed using point-by-point comparisons of the corresponding time series of network indices. Based on the resulting p-values, the number of edges and transitivity show co-directional movement (with signif-

Table 5: Dynamic Structural Similarity Tests of Two International Networks

	2000-2020 Time Period		
	Edge Number	Transitivity	Reciprocity
Pearson Correlation	0.749	0.766	0.163
	(0.000)	(0.000)	(0.480)
MAPE	0.588	0.513	0.595
CDM	0.829	0.784	0.798

Note: This table presents similarity measures between the ISN and the international sanction network over the period 2000-2020. Pearson correlation coefficients assess linear association (values in parentheses are p-values), MAPE measures prediction accuracy, and CDM quantifies informational divergence. Lower CDM values indicate greater similarity.

icantly positive correlation coefficients), while reciprocity does not exhibit a significant correlation. However, such pointwise comparisons lack flexibility in capturing similarity when time series are slightly misaligned. This limitation is effectively addressed by dynamic time warping (DTW) and compression-based dissimilarity measure (CDM). As illustrated in Figure 3, the slope of the best-matched alignment for all three statistics first increases and then decreases, indicating that the two networks followed broadly similar trends only around the years 2000 and 2020. CDM further quantifies the dissimilarity between the two networks across edge number, transitivity, and reciprocity, returning a minimum value as high as 0.784. These results collectively suggest that the evolutionary trends of the international student network and the sanction network are not similar between 2000 and 2020. This supports the absence of common unobserved confounders that might otherwise bias causal inference in subsequent empirical analysis.

5 Econometric Analysis

Based on the theoretical model and structural analysis of the ISN, we empirically analyze the impact of the international sanction network on the ISN using various network econometric methods, including QAP network regression, ERGM, TERGM, VCERGM, and PSTERGM.

It is essential to note that, within our econometric framework, international sanctions are treated as typical exogenous variables, consistent with the existing literature (Neuenkirch and Neumeier, 2015, 2016) which often utilize sanctions as policy shocks or quasi-experiments to identify their causal effects across various domains. Furthermore, given the considerable challenge in constructing comprehensive measures of international relations—which significantly affect international student flows—we employ international sanctions as an exogenous proxy that effectively captures core aspects of bilateral relations. This approach supports the assumption that endogeneity concerns are mitigated, thereby enhancing the validity and reliability of our network econometric model.

5.1 Benchmark Analysis

We begin by employing QAP regression to analyze the effect of the international sanction network on the ISN. This method is appropriate because the presence of a student flow tie between two countries depends not only on dyadic characteristics but also on the attributes of other countries and the broader network structure. Consequently, the observed network data are inherently interdependent, rendering traditional statistical inference invalid. QAP addresses this issue by preserving the network dependence structure during permutation-based significance testing.

QAP maintains the structure of the independent variable network constant, randomly permutes the rows and columns of the dependent variable network's adjacency matrix, and conducts inference by comparing the observed estimator against the distribution of estimators from the permuted networks. The model is specified as follows:

$$ISF_{ij} = \alpha_0 + \alpha_1 SANC_{ij} + X_{ij}\beta + u_{ij}, \tag{15}$$

where ISF_{ij} indicates the presence of international student flow from country i to country j, $SANC_{ij}$ indicates that country i imposes sanctions on country j, and the control variables X include the absolute difference in GDP per capita and the GDP per capita of the home country to measure economic development and living standards; the absolute difference in political stability and the home country's political stability, measured by the political stability socres of the World Governance Indicators (WGI); the education quality and academic level of the home country, represented by the proportion of top global universities; as well as geographical distance, colonial relations, and common language to account for spatial and cultural proximity between countries. Missing values for the proportion of top universities in 2000-2002 were imputed using a three-year simple moving average, where, for instance, the 2000 value was filled with the average of the 2003-2005 data.

The estimation results of the QAP model are presented in Table 6. Across all five time points, international sanctions are statistically significant at the 1% level, with an average coefficient of –0.1646. This implies that the presence of sanctions reduces the probability of student flows by approximately 16.46%. Most control variables also exhibit signs consistent with theoretical expectations, with several—including the proportion of top universities, geographical distance, and colonial relations—also significant at the 1% level. Taking 2020 as an example, which shows the best model fit: a larger income gap between countries is associated with a lower probability of student flows; higher GDP per capita in the home country similarly correlates with reduced outbound student flows. Conversely, a higher proportion of top universities in the home country—a proxy for education and research quality—increases the likelihood of attracting international students. Furthermore, geographical distance significantly inhibits student flows, while shared colonial ties facilitate them.

ERGM is an econometric method for statistical inference of social networks (Holland and Leinhardt, 1981; Wasserman and Pattison, 1996), which is more suitable for describing bilateral or multilateral relationships. Compared with the traditional regression model, ERGM and TERGM can not only reflect the impact of exogenous variables on the ISN but also effectively take into account the node attributes (national characteristics), bilateral attributes (the relationship between two countries), and multilateral attributes (the endogenous network structure of multiple countries) in the social network. The basic goal of ERGM is to construct a probability distribution that generates specific network structure features (Cranmer and Desmarais, 2011). The model is set as follows:

$$P(N, \boldsymbol{\theta}) = \frac{\exp\left\{\boldsymbol{\theta}' \mathbf{h}(N)\right\}}{\sum_{N^* \in \mathcal{N}} \exp\left\{\boldsymbol{\theta}' \mathbf{h}(N^*)\right\}}, \tag{16}$$

where $\boldsymbol{\theta}'$ is the parameter vector, N is the observed network and N_{ij} represents the flows of international students from country i to country j, $\mathbf{h}(N)$ is the statistics related to the network N, which mainly includes local endogenous network structure, exogenous network, node properties and bilateral properties. The variables of ERGM (and later TERGM) include international sanction, GDP per capita, political stability, proportion of top universities, geographical distance, colonial relations, and language, as well as various network structure variables and time statistics unique to TERGM. Under the framework of the ERGM general model, the social selection effect includes convergence, sender effect, and receiver effect. Based on the context of the ISN, the latter two are renamed as outflow country effect and inflow country effect, respectively, while the specific structure of the statistics remains unchanged.

Table 7 presents the ERGM estimation results for the five selected time points. Across all time periods, the coefficients for international sanctions are negative and statistically significant at the 0.001 level, indicating a strong inhibitory effect on international student flows. For instance, in 2000, the coefficient for international sanctions is -0.828, implying that the presence of a sanction reduces the odds of a student flow edge by approximately 56.2% (exp(-0.828) $\approx$ 0.438). The strongest negative effect is observed in 2003, while the weakest effect occurs in 2016. These results suggest that international sanctions significantly hinder the formation of educational flow connections between countries, thereby providing robust support for the core hypothesis of this paper.

ERGM can only analyze the cross-sectional network structure at a specific time point, whereas it cannot reflect the dynamic, time-varying characteristics of the network. We further adopt TERGM (Cranmer et al., 2020) to take the network observed in the past as conditions. TERGM models and analyzes the network observed at multiple time points. The probability distribution of the network probability for the t period is

$$P(N^t|N^{t-K},...,N^{t-1},\boldsymbol{\theta}) = \frac{\exp\left\{\boldsymbol{\theta}'\mathbf{h}(N^t,N^{t-1},...,N^{t-K})\right\}}{c(\boldsymbol{\theta},N^{t-K},...,N^{t-1})}. \tag{17}$$

Compared with ERGM, the international sanction coefficient $\boldsymbol{\theta}$ in TERGM measures the common inhibitory effect of the international sanction networks in the previous k period. Whenever the previous k period networks all increase an additional international sanction in the same direction relationship of studying abroad, then the conditional odds ratio of the ISN is $\exp(\theta)$. Pool the models' overall observation periods to obtain the pooled TERGM model:

$$P(N^{K+1},...,N^T|N^1,...,N^K,\boldsymbol{\theta}) = \prod_{t=K+1}^{T} P(N^t|N^{t-K},...,N^{t-1},\theta). \tag{18}$$

The network time interval is first set to 1 year. Therefore, there are 21 networks during the research period.

Simultaneously, considering the previously defined developmental stages, Table 8 presents the TERGM estimation results for the ISN spanning the entire period from 2000 to 2020, as well as across four distinct sub-periods. According to the TERGM results for the full period (2000–2020), the coefficient for international sanctions is negative and statistically significant at the 5% level, indicating that the sanction network exerts a significant inhibitory effect on the formation of the

ISN. This suggests that establishing a student flow edge from a sanctioning country to a sanctioned country is notably difficult. Furthermore, the time-varying effect of international sanctions is also significant at the 10% level, reflecting dynamic changes in its impact over time.

Regarding endogenous network effects, the significantly negative coefficient for edges and the significantly negative coefficient for GWESP collectively indicate that the ISN does not exhibit a strong tendency toward clustered or closed transitivity structures over the long term. In contrast, the significantly positive coefficient for reciprocity suggests that mutual student flows between countries are increasingly common. Additionally, the significantly positive coefficient for network stability indicates that the ISN has evolved stably throughout the period from 2000 to 2020.

To fully present the dynamic development of the international student network, the development time periods of the international student network are further divided into 2000-2002, 2003-2005, 2006-2016, 2017-2020, and then TERGM is used to analyze the influencing factors of the international student network during the four time periods. Since the time-varying impact of the international sanction network is only used in the longer time dimension, it is not included in the 2000-2002, 2003-2005, and 2017-2020 TERGM analysis, avoiding the possible collinearity.

From the empirical analysis results, it can be found that the international sanction coefficients in 2000-2002, 2003-2005, 2006-2016, and 2017-2020 are all significantly negative at the 10% significance level, indicating that the international sanction network has a significantly negative impact on the formation of the international student network. In the third time period, the time-varying impact of the international sanction network is significantly positive, indicating that the negative impact of the international sanction network on the ISN in this period is increasing over time. This is closely related to the world development trend in which economic globalization prevails and international relations become closer and closer.

To assess the endogenous mechanisms of the network, this study employs a series of empirical strategies and robustness checks. We first introduce GWESP, reciprocity, and their interaction into the model sequentially. Furthermore, we alter the temporal interval of the international student network to five years and switch the TERGM estimation method to Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC-MLE) (Leifeld et al., 2018) to further verify the robustness of the empirical findings. These specifications correspond to columns (2) through (5) in Table 9, respectively.

Compared to the baseline TERGM estimated for the full-period ISN (2000–2020), the estimates in columns (2)–(4) further confirm the robustness of the endogenous formation mechanisms—namely, transitivity and reciprocity. Meanwhile, the specification in column (5), which alters both the temporal interval and the estimation method, yields results highly consistent with the baseline, indicating that the core findings of this paper are robust.

As mentioned earlier, in the analysis framework of TERGM, the endogenous formation mechanisms of edges, transitivity, and reciprocity in the ISN between 2000 and 2020 are robust. Due to TERGM ignoring the heterogeneity of network structure, it cannot fully capture the time-varying patterns of network structure (Lee et al., 2020).

We further use the VCERGM method to characterize the heterogeneity of edges, transitivity, and reciprocity structures in a total of 21 ISNs from 2000 to 2020. Because TERGM can degenerate into a set of independent and identically distributed ERGM models, we compare the coefficients obtained from VCERGM analysis of the ISN with the corresponding coefficients obtained from cross-sectional ERGM analysis to better reflect the dynamic changes in the edges, transitivity, and reciprocity structures of the ISN.

From Figure 4, it can be visually observed that the coefficient fluctuation amplitude obtained from cross-sectional ERGM analysis is significantly higher than that of VCERGM, and the latter is also more effective in the calculation, which confirms conclusions obtained from simulation in Lee et al. (2020). We further found that the coefficient of edges remained negative but overall showed a continuously increasing trend (i.e., the absolute value of the coefficient decreased overall), indicating that the density of the ISN continued to increase, with only a slight decline in the N5-N7 and N18-N21 time progress stages, consistent with the descriptive statistics mentioned earlier. The coefficient of transitivity remains negative and relatively stable in most time stages (N3-N19), indicating that the ISN does not tend to form significant transitivity structures and closed trends. The existing closed transitivity triangles have been formed historically. The coefficient of reciprocity remains positive and shows an overall trend of increasing and then decreasing over time, indicating that the ISN tends to form a reciprocity structure of a two-way flow of students. The trend of reciprocity formation gradually increases in the early stage (N1-N4) and then declines in the later stage (N5-N21).

Based on a comprehensive understanding of the temporal heterogeneity of the endogenous structure in the ISN, we further analyze the dynamic evolution of the endogenous structure in the

ISN from a new perspective using PSTERGM.

Firstly, the ISNs are binary networks with values of 0 or 1. These networks are adjusted from the originally weighted networks by setting a threshold at the 60th percentile of the number of international students in different calendar years, which undoubtedly loses a lot of information about the flows of international students. Therefore, the PSTERGM model, which can be used to analyze dynamic valued networks, can fully utilize all the information in the research data and has obvious information advantages. Secondly, all previous models have only analyzed the dynamic endogenous structure of the ISN from the perspective of network formation, ignoring the importance of the persistence of endogenous structure in the dynamic network dimension. Therefore, PSTERGM analyzes the probability of new endogenous structure formation (incidence) and how long the old endogenous structure lasts (duration) by constructing intermediate increment networks and decrement networks ($N^{+,t}$ and $N^{-,t}$) based on the ideas of network formation and network dissolution (Kei et al., 2023).

To do this, we incorporate four endogenous structures, including edges, non-edges ($\Sigma_{ij}1(N_{ij} = 0) = n^2 - \Sigma_{ij}N_{ij}$), transitivity (closed transitive triangle), and reciprocity, into the originally weighted ISN in the PSTERGM model, resulting in a total of eight coefficients that can be divided into increment network coefficients and decrement network coefficients.

Table 10 illustrates that there are significant differences in the coefficients of edges between the increment and decrement networks, revealing new insights into the ISN. There are frequent instances of edge formation (i.e., international student flows), but these newly formed edges have a very short duration. The coefficients for non-edges were significantly positive, indicating that it is typical for there to be no edges between countries in the ISN, and when edges do form, they tend to last longer. The transitivity coefficient is significantly positive in both the increment and decrement networks, suggesting that the newly formed closed transitivity triangles in the ISN have a certain degree of duration. The reciprocity coefficient is significantly negative in the decrement network, indicating that the newly formed reciprocity structures in the ISN have a shorter duration.

5.2 Heterogeneity Analysis

The impact of economic sanctions (including trade sanctions and financial sanctions) and travel sanctions on the ISN may vary greatly. Trade sanctions, financial sanctions, and economic sanctions all mainly indirectly affect the flows of international students between countries from the macroeconomic dimension, through trade, financial stability, financial crisis, and exchange rate volatility to curb the flows of international students (Neuenkirch and Neumeier, 2015), that is, mainly through the economic factors under the framework of the "push-pull" model to affect international student flows.

Regarding non-economic travel sanctions, they have a direct impact on the flows of international students by restricting the movement of micro-objects in space. The negative effects are more significant compared to trade and financial sanctions. Currently, there is a lack of literature exploring the differences in the impact of travel sanctions and economic sanctions.

We further subdivide international sanctions, focusing on the difference in the impact of the international trade sanction network, the financial sanction network, the economic sanction network, and the travel sanction network on the ISN. Economic sanctions include trade sanctions and financial sanctions, so the data matrix of economic sanctions is the sum of the trade sanction matrix and the financial sanction matrix.

Based on the estimated TERGM for the period 2000-2020 (Table 11), we find that only travel sanctions exhibit a statistically significant effect at the 5% level, with a negative coefficient. The estimated coefficients for trade, financial, and economic sanctions are not statistically significant.

5.3 Mechanism Analysis

The difference in GDP per capita between countries serves as a proxy for disparities in economic development and cost of living. A larger GDP per capita gap reflects greater differentiation in economic conditions and living expenses, which inhibits international student flows. When the economic disparity between two countries is substantial, the economic disruptions and changes in living costs resulting from international sanctions are generally insufficient to alter the fundamental gap between them. Consequently, the negative effect of international sanctions on the ISN is attenuated by the pre-existing GDP per capita difference.

Proposition 2. *The negative effect of international sanctions on student mobility is moderated by the economic distance between countries. Specifically, a larger difference in GDP per capita attenuates the adverse impact of sanctions on the formation of student flow links.*

Geographical distance between countries is another significant negative factor influencing international student flows (Beine et al., 2014). Shorter distances facilitate student mobility, while greater distances reduce it, primarily due to increased transportation costs and reduced convenience for returning to the home country. Greater distance raises both the explicit financial costs and the implicit psychological costs—such as loneliness and homesickness—associated with studying abroad. According to theories of competition and liberalism, studying abroad is a rational decision based on cost-benefit analysis. As explicit and implicit costs rise, prospective students may opt for destinations closer to their home country to maximize the benefits of international education. International sanctions may negatively affect student flows by imposing additional external costs that disrupt free and competitive decision-making. These externally imposed costs may exhibit substitutability with the costs induced by geographical distance. Therefore, given the established negative effect of geographical distance on the formation of the ISN, the increased explicit and implicit costs associated with distance may partially suppress the external costs arising from international sanctions.

Proposition 3. *Geographical distance negatively moderates the effect of international sanctions on student flows. A greater distance between countries reduces the marginal inhibitory effect of sanctions on student mobility, as the costs associated with distance partially substitute for the costs imposed by sanctions.*

To test these hypotheses, we introduce interaction terms between international sanctions and both GDP per capita differences and geographical distance into the TERGM specification. To mitigate multicollinearity concerns, the matrices for these interaction terms are normalized and mean-centered before estimation.

Based on the empirical results in Table 12, the coefficient for international sanctions is significantly negative, consistent with the previous results. In contrast, the coefficients of the two interaction terms are both significantly positive. This suggests that both moderating variables weaken the negative effect of sanctions on international student flows. Specifically, a larger GDP per capita gap between countries reduces the inhibitory effect of sanctions on student flows, and a greater geographical distance similarly mitigates the negative impact. Furthermore, the coefficient of the interaction term involving GDP per capita difference is smaller than that of the term involving geographical distance, implying that the moderating effect of geographical distance is stronger than that of GDP per capita difference.

6 Counterfactual Analysis

Amid deepening strategic competition and tensions between China and the United States, the flow of international students and scientific collaboration between the two countries have faced substantial disruptions. Counterfactual analyses suggest that the U.S.–China trade war initiated in 2018 could prevent approximately 30,000 Chinese students from studying in the United States over the next decade (Khanna et al., 2025). Further exacerbating the situation, the U.S. has imposed restrictions on Chinese students pursuant to Presidential Proclamation 10043. Additionally, as of February 29, 2024, the renewal of the U.S.–China Science and Technology Agreement remains stalled. At the state level, Florida has prohibited the hiring of researchers from several countries, including China, contributing to a growing crisis in bilateral research cooperation. In 2021, U.S. universities awarded more than 8,000 doctoral degrees to Chinese students, accounting for roughly 32% of all international PhD recipients—making China and the U.S. each other's largest research partners. Terminating the U.S.–China science agreement would represent a consequential and misguided policy decision (Nature, 2024).

This paper proposes a novel methodological framework for network counterfactual analysis and employs it to rigorously examine the effects of U.S. sanctions targeting China on both bilateral student flows and the overall structure of the ISN. The econometric results indicate that international sanctions imposed by one country on another exert a significant inhibitory effect on the directionally corresponding flow of international students. Consequently, U.S. sanctions against China have substantially reduced the number of American students pursuing education in China. Furthermore, these sanctions may generate indirect spillover effects, influencing student flow between other countries within the global network.

As noted previously, coefficient estimates in the ERGM reflect the marginal effects of network statistics on the likelihood of edge formation in the ISN, thereby capturing primarily static, local effects—that is, the direct influence of sanctions on dyadic student flows. However, due to endogenous network structures and time-varying dependencies, sanctions may also indirectly affect student mobility between third countries and propagate throughout the network. These ripple effects, known as indirect or spillover effects, are not captured by conventional ERGM estimates but emerge through the interconnected and dynamic nature of the international student network.

Figure 5, incorporating the network endogenous structure of transitivity established in our model, visually demonstrates the mechanism of network spillover effects. Consider three national nodes (i, j, k) in the actual IStN during period t, where initially only a one-directional edge exists from i to j, and country j imposes international sanctions on both i and k. If the sanctions imposed by j on i and k are lifted, the probability of student flows from j to i and from j to k increases, thereby establishing new edges. This change represents the direct effect of sanctions. Subsequently, a reciprocity structure forms between i and j in the ISN. Although this endogenous structure does not propagate to other countries, it produces a spillover effect on the original probability of student flow from i to j. Moreover, due to the property of closed transitivity in triangular structures, the formation of the student flow relationship $i \to k$ is facilitated through the established paths $i \to j$ and $j \to k$.

In essence, this change represents an indirect spillover effect resulting from the sanctions. Such spillover effects may persist and propagate throughout the network until a new equilibrium is reached. It is important to note, however, that while the removal of sanctions increases the probability of international student flows, it does not guarantee the actual realization of such flows. Therefore, in our model, an edge in the ISN is assumed to form only when the predicted probability exceeds a predefined threshold.

Thus, to investigate both the direct and spillover effects of international sanctions, we extend the ERGM specification by applying an inverse logistic transformation, analogous to the framework commonly used in binary response models. This extension facilitates the derivation of change statistics and enables the computation of the predicted probability of an edge formation between any two nodes, given the estimated coefficients (Harris, 2013). Using these ERGM-based predicted probabilities, variations in edge formation likelihood can be assessed by constructing counterfactual scenarios in the absence of international sanctions. Guided by a predefined threshold for edge formation in the ISN, this counterfactual approach is employed within a causal inference framework to quantify direct and indirect spillover effects of sanctions on international student flows in both the short and long term.

The general procedure for our counterfactual analysis is as follows. Suppose the connection between countries i and j in the sanction network S changes from 1 to 0—that is, international sanctions between i and j are lifted—while all other exogenous variables remain unchanged. Using change statistics (Harris, 2013), we compute the updated probability of a student flow from i to j in the ISN, denoted $P^{(1)}(N_{ij} = 1)$. At this stage, the connection probabilities among all other country pairs remain unchanged. Let the observed ISN be $N^{(0)} = N$. We define a threshold ω such that if $P^{(1)}(N_{ij} = 1) \geq \omega$, the edge $i \to j$ is updated from 0 to 1, yielding $N^{(1)}$ with $N_{ij}^{(1)} = 1$. Using this updated network, we recalculate the change statistics and update the probabilities of all other edges. This process is repeated iteratively until the network either has no further structural changes (converges) or enters a cycle of structure (divergence). The final network allows us to quantify various causal effects: The short-term direct effect is defined as the change in connection probability from N_{ij} to $N_{ij}^{(1)}$. The long-term direct effect corresponds to the change from N_{ij} to $N_{ij}^{(n)}$. The short-term spillover effect is measured as the average change in connection probabilities from N_{-ij} to $N_{-ij}^{(2)}$ across all other country pairs. Similarly, the long-term spillover effect is given by the average change from N_{-ij} to $N_{-ij}^{(n)}$ over all non-focal dyads.

For illustrative purposes, the 2000 ERGM results serve as a baseline for counterfactual analysis, although the same methodology can be applied to any time point within the study period. A counterfactual approach is employed—following the iterative steps outlined above—to analyze the interplay between the ISN and the sanction network. Specifically, the short-term direct effects of international sanctions are examined by simulating a scenario in which all directed sanctions present in the year 2000 are simultaneously lifted. For each affected node pair (i, j), the original predicted probability of edge formation $P^{(0)}(N_{ij} = 1)$ is compared against the new probability $P^{(1)}(N_{ij} = 1)$ obtained immediately after removing sanction effects but before accounting for any network spillovers. The aggregate short-term direct effect is calculated as:

$$\frac{\Sigma_{(i,j)\in\{(i,j)|S_{ij}=1\}}[P^{(1)}(N_{ij} = 1) - P^{(0)}(N_{ij} = 1)]}{|\{(i, j)|S_{ij} = 1\}|}. \tag{19}$$

In our data, a total of 2,412 country pairs subject to directed sanctions are simultaneously affected. The results indicate that, in the absence of international sanctions, the predicted probability of international student flows would increase by an average of 0.66%. This implies that the presence of sanctions imposed by country i on country j reduces the probability of student flows from i to j by an average of 0.66%. This aggregate difference represents the overall short-term direct effect of international sanctions.

Subsequently, following the iterative procedure outlined above, a counterfactual analysis is conducted to measure both the direct and spillover effects resulting specifically from the removal of U.S. sanctions against China. The baseline predicted probability of U.S. students studying in

China is relatively low ($P^{(0)}(N_{ij} = 1) = 0.003$), which can be attributed to the United States' dominant position in global higher education and its comparative advantage in academic resources relative to China. Notably, no such flow was present in the original ISN. To ensure that the structural implications of sanction removal—particularly the potential formation of a new student flow between the U.S. and China—are fully captured, the formation threshold is set at the 20th percentile of the original predicted probabilities ($P^{(0)}(N_{\star\star} = 1)$) across all node pairs, ensuring that only substantively meaningful changes alter the network.

The counterfactual analysis converged to a stable cycle pattern with a period of 6 after the 15th iteration. The process revealed complex network dynamics, with considerable fluctuation in the number of updated node pairs and net edge changes across the initial iterations. As illustrated in Table 13, the network transitioned from an initial phase of volatility into a stable cycle, where the outcomes of iterations 16-21 exactly mirrored those of iterations 10-15, respectively.

Table 14 presents the direct and spillover effects of removing U.S. sanctions on China. In the short term, lifting these sanctions increases the probability of U.S. students studying in China by 0.39%, while it decreases the probability of Chinese students studying in the U.S. by 3.03% and reduces the average probability of international student flows among other country pairs by 0.03%. The latter reduction is consistent with the negative reciprocity coefficient estimated in the model. In the long term, both direct and spillover effects remain consistent with their short-term counterparts, a result attributable to the relatively low edge-formation threshold adopted in this simulation. Furthermore, in both the short and long term, the magnitude of the direct effect exceeds that of the indirect effect. This is expected, since the spillover mechanism in our model—as illustrated in Figure 5—operates only through transitivity and reciprocity, thus limiting the extent of secondary propagation.

7 Conclusions and Discussions

Through regression analysis and operator norm-based randomization tests, we identify significant time-varying structural characteristics in the International Student Network (ISN) across different time points. Using the CDM and DTW methods, we further detect divergent dynamic trends between the structural evolution of the ISN and the international sanction network. By employing ERGM, TERGM, and robustness checks, we examine both the endogenous formation mechanisms and exogenous influences on the ISN at five static time points, across four developmental stages, and over the entire period from 2000 to 2020. The results consistently show that international sanctions—as key measures of international relations—exert significant negative effects on the ISN, thereby validating the theoretical mechanisms proposed in this paper. Counterfactual analysis further corroborates both the direct and indirect spillover effects of international sanctions, underscoring their network-wide impact on international student flows.

Through disaggregated analysis of sanction types using TERGM, this study innovatively demonstrates that different forms of international sanctions—including trade, financial, economic, and travel sanctions—have heterogeneous effects on the ISN. Specifically, trade, financial, and economic sanctions show no significant impact, whereas travel sanctions exert a strong negative influence. This result highlights the pronounced effect of non-economic sanctions on student flows, aligning with the intuitive notion that travel restrictions directly hinder study abroad. It also contributes to the understudied area of non-economic sanctions, offering new perspectives for future research.

For the first time, we apply the VCERGM and PSTERGM models to comprehensively assess the dynamic evolution of the ISN's endogenous structures. Our findings reveal that between 2000 and 2020, the coefficients for edges and transitivity remain consistently negative, while reciprocity shows a persistently positive coefficient with a trend of initial increase followed by decline. Regarding the persistence of these endogenous structures, newly formed edges exhibit short duration, closed transitive triads demonstrate moderate persistence, and reciprocal structures show relatively shorter longevity.

We further incorporate interaction terms within the TERGM framework to explore nuanced pathways through which sanctions affect student flows. The results reveal significant negative moderating effects of GDP per capita differences and geographical distance on the relationship between sanction networks and the ISN. These findings provide policymakers with refined insights into the mechanisms through which sanctions influence student flows, supporting the design of targeted talent retention and international education policies.

In counterfactual analysis, we first examine a macro scenario where all international sanctions are lifted in 2000, revealing significant short-term direct effects. We then simulate the removal of U.S. sanctions against China to isolate both short- and long-term direct effects, as well as short- and long-term indirect spillover effects on U.S.-China student flows and the global ISN. The results indicate no significant difference between short- and long-term effects, and direct effects are consistently larger in magnitude than spillover effects.

Based on an international network perspective, this paper provides a comprehensive analysis of the formation mechanisms and specific influencing factors of the ISN, examining its spatiotemporal evolution and endogenous structural properties. These insights not only advance our understanding of the more complex global knowledge economy and international scientific collaboration networks underlying the ISN but also offer practical value for countries seeking to enhance their attractiveness to international students, optimize talent retention strategies, and strengthen long-term human capital and knowledge capital reserves through targeted policies and institutional mechanisms. Several policy recommendations emerge from our findings:

First, countries that aim to attract international students should refrain from imposing international travel sanctions. Our results indicate that while trade, financial, and economic sanctions show no significant effects on student flows, travel sanctions exhibit strong negative impacts. Thus, unlike economic sanctions, avoiding travel restrictions is crucial for maintaining and strengthening international student flows.

Second, when considering coercive measures against another country for political or economic reasons, the geographical distance between the countries should be taken into account. Sanctions imposed on distant countries have a weaker negative effect on student mobility than those on neighboring countries. From the perspective of international student attraction, therefore, implementing sanctions against geographically remote countries—while adopting alternative measures for nearby nations—can substantially mitigate the adverse effects on student flows.

Third, once a country becomes the target of sanctions, the conventional view that higher GDP per capita enhances attractiveness to international students may no longer hold—at least for students originating from sanctioning countries. We find that larger differences in GDP per capita between countries attenuate the negative effect of sanctions on student flows. Thus, if the sanctioning country has a higher GDP per capita than the sanctioned country, narrowing this economic gap may ironically strengthen the sanction's deterrent effect on student flows. Conversely, in the less common scenario where the sanctioned country has a higher GDP, further widening this gap through economic development could help attract more students from both the sanctioning country and third countries, leveraging improved material conditions and perceived opportunities.

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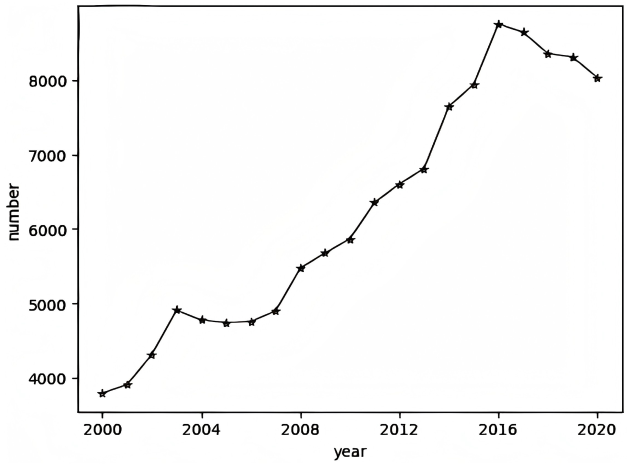
Figures and Tables

Figure 1: Network Endogenous Structures: Reciprocity (left) and Transitivity (right)

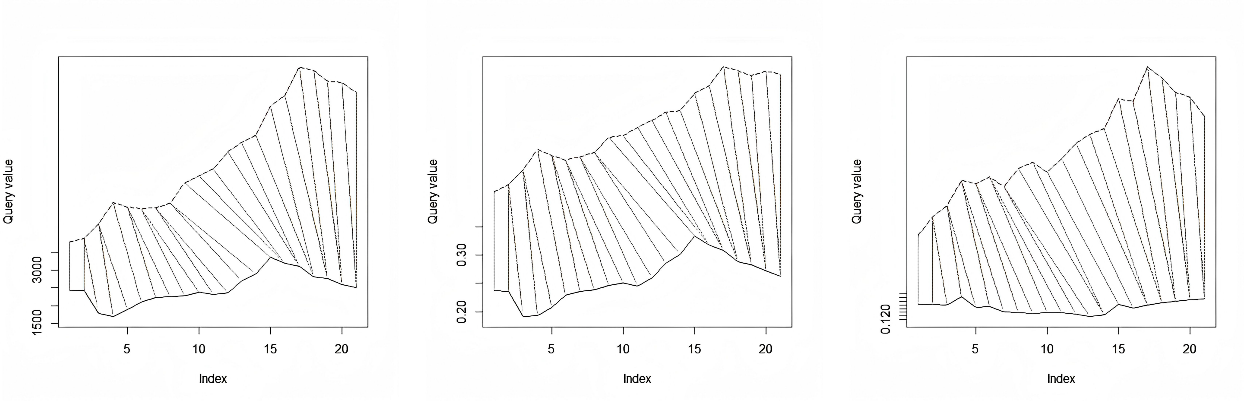
Note: This figure illustrates two fundamental endogenous structures—reciprocity (left) and transitivity (right)—that govern the formation and evolution of the International Student Network (ISN). Reciprocity refers to the mutual exchange of students between countries, reflecting a tendency toward balanced international educational partnerships. Transitivity, often measured by GWESP, represents the formation of closed triadic structures (e.g., student flows from $i \to j$ and $j \to k$, facilitating flow from $i \to k$), which promote clustered and stable communities within the network. Both mechanisms are well-established in social and knowledge networks (Giuliani, 2013; Hoff et al., 2002) and have been empirically validated in the context of student flows (Vögtle and Windzio, 2016). The presence of these structures indicates that the ISN exhibits properties of a small-world network, characterized by both local clustering and global connectivity.

Figure 2: Evolution of the International Student Network: Edge Number (2000-2020)



Note: We divide the evolution of the ISN into four developmental stages: 2000–2002, 2003–2005, 2006–2016, and 2017–2020.

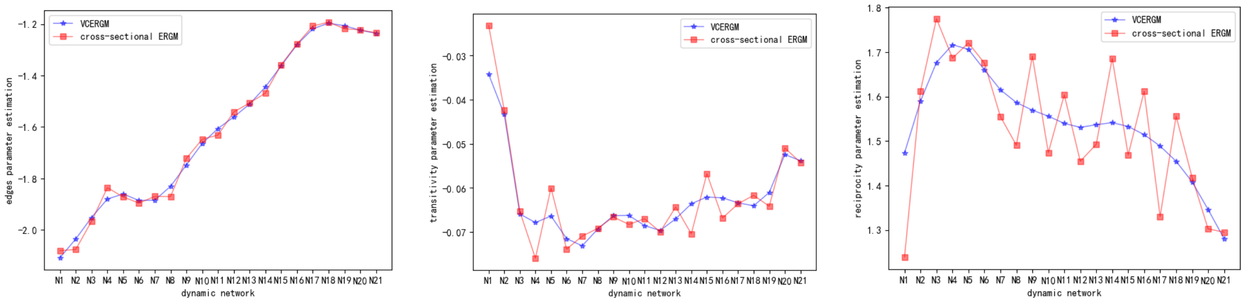
Figure 3: DTW Alignment Paths Between International Student and Sanction Networks



(a) Edge Number (b) Transitivity (c) Reciprocity

Note: This figure displays the optimal alignment paths between the time series derived from DTW for each network statistic. The slope of the best-matched alignment for all three statistics first increases and then decreases, indicating that the two networks followed broadly similar trends only around the years 2000 and 2020.

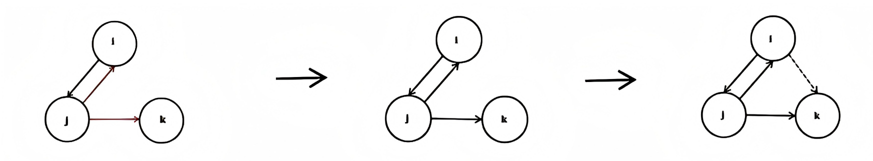
Figure 4: VCERGM Analysis: Dynamic coefficient of endogenous structures of ISNs (2000-2020)



(a) Edge Number (b) Transitivity (c) Reciprocity

Note: The figure shows the heterogeneity of edges, transitivity, and reciprocity structures in a total of 21 ISNs from 2000 to 2020. It compares the coefficients obtained from VCERGM analysis of the ISN with the corresponding coefficients obtained from cross-sectional ERGM analysis to better reflect the dynamic changes in the edges, transitivity, and reciprocity structures of the ISN.

Figure 5: Illumination: Network Spillover Effects of International Sanctions on the International Student Network



Note: Consider three national nodes (i, j, k) in the actual IStN during period t, where initially only a one-directional edge exists from i to j, and country j imposes international sanctions on both i and k. If the sanctions imposed by j on i and k are lifted, the probability of student flows from j to i and from j to k increases, thereby establishing new edges. This change represents the direct effect of sanctions. Subsequently, a reciprocity structure forms between i and j in the ISN. Although this endogenous structure does not propagate to other countries, it produces a spillover effect on the original probability of student flow from i to j. Moreover, due to the property of closed transitivity in triangular structures, the formation of the student flow relationship $i \to k$ is facilitated through the established paths $i \to j$ and $j \to k$.

Table 6: QAP Analysis: Impact of the International Sanction Network on Student Flows

	2000	2003	2005	2016	2020
International sanction	-0.128***	-0.163***	-0.153***	-0.185***	-0.194***
$\lvert GDPper_i - GDPper_j \rvert$	0.009	0.013	0.012	0.033***	0.034***
$\lvert PS_i - PS_j \rvert$	0.015*	0.000	-0.008	-0.014	-0.029**
$GDPper_i$	-0.008	-0.008*	-0.006	-0.010***	-0.008*
PS_i	-0.006*	-0.015***	-0.008**	-0.032***	-0.029***
$TopUni_i$	0.686***	1.164***	0.950***	1.614***	1.584***
Geographical distance	-0.110***	-0.151***	-0.139***	-0.148***	-0.211***
Colonial relation	0.383***	0.376***	0.373***	0.343***	0.312***
Language	-0.017	-0.011	-0.008	-0.064**	-0.041
Intercept	0.196***	0.270***	0.265***	0.879***	0.409***

Note: This table presents QAP regression coefficients estimating the effect of international sanctions and control variables on international student flows. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: ERGM Analysis: Impact of the International Sanction Network on Student Flows

	2000	2003	2005	2016	2020
International sanction	-0.828$^+$	-0.979$^+$	-0.739$^+$	-0.428$^+$	-0.582$^+$
Edges	-2.086$^+$	-1.659$^+$	-1.706$^+$	-1.325$^+$	-1.522$^+$
GWESP	0.230$^+$	0.109$^+$	0.100$^+$	-0.097$^+$	-0.128$^+$
Reciprocity	-1.453$^+$	0.074	0.062	2.211$^+$	2.219$^+$
$\|GDPper_i - GDPper_j\|$	-0.140$^+$	-0.162$^+$	-0.136$^+$	-0.079$^+$	-0.223$^+$
$\|PS_i - PS_j\|$	0.116***	0.055	-0.021	0.016	-0.072***
$GDPper_i$	-0.045$^+$	-0.041*	0.003	0.033	0.164$^+$
PS_i	-0.250$^+$	-0.331$^+$	-0.306$^+$	-0.310$^+$	-0.352$^+$
$TopUni_i$	0.313	2.951***	-1.327*	16.860$^+$	16.023$^+$
$GDPper_j$	0.147$^+$	0.214$^+$	0.151$^+$	0.304$^+$	0.551$^+$
PS_j	0.855$^+$	0.645$^+$	0.577$^+$	0.032	0.170$^+$
$TopUni_j$	4.079$^+$	3.614$^+$	43.668$^+$	129.685$^+$	25.030$^+$
Geographical distance	-0.701$^+$	-0.877$^+$	-1.055$^+$	-1.168$^+$	-1.312$^+$
Colonial relation	1.615$^+$	1.243$^+$	0.750$^+$	1.158$^+$	1.069$^+$
Language	-0.011	0.052	0.036	-0.245***	-0.126***

Note: This table presents ERGM coefficients estimating the effect of international sanctions and control variables on international student flows. $^+$, ***, **, and * are significant at the levels of 0.001, 0.01, 0.05, and 0.1, respectively.

Table 8: TERGM Analysis: Impact of the International Sanction Network on Student Flows

	2000-2020	2000-2002	2003-2005	2006-2016	2017-2020
International sanction	-0.718^{**}	-0.896^{**}	-0.626^{*}	-0.636^{*}	-0.528^{**}
Sanction × Time function	0.040^{*}			0.081^{*}	
Edges	-0.828^{+}	-0.978^{***}	-1.081^{+}	-0.812^{+}	-0.878^{+}
GWESP	-0.007^{+}	0.001	-0.002	-0.010^{+}	0.001
Reciprocity	0.600^{+}	0.815^{+}	0.515^{+}	0.681^{+}	0.438^{+}
Stability	2.226^{+}	2.330^{+}	2.275^{+}	2.197^{+}	2.177^{+}
$\lvert GDPper_i - GDPper_j \rvert$	-0.126^{+}	-0.142^{*}	-0.111^{+}	-0.129^{+}	-0.101^{+}
$\lvert PS_i - PS_j \rvert$	0.005	0.091	-0.010	0.036	-0.018
$GDPper_i$	0.036^{+}	0.043	-0.061^{+}	0.022^{***}	0.036^{***}
PS_i	-0.177^{+}	-0.173^{+}	-0.130^{+}	-0.180^{+}	-0.160^{+}
$TopUni_i$	3.367^{+}	5.165^{+}	2.526^{**}	3.497^{+}	3.658^{+}
$GDPper_j$	0.234^{+}	0.148^{+}	0.143^{***}	0.237^{+}	0.245^{+}
PS_j	0.278^{+}	0.678^{***}	0.315^{+}	0.299^{***}	0.096^{***}
$TopUni_j$	4.812^{*}	2.436^{+}	10.982	5.581^{*}	2.097
Geographical distance	-0.648^{+}	-0.719	-0.551^{+}	-0.632^{+}	-0.522^{+}
Colonial relation	0.605^{+}	0.774^{+}	0.661^{+}	0.552^{+}	0.497^{**}
Language	-0.090^{**}	-0.277	-0.079^{*}	-0.099^{**}	-0.143^{**}

Note: This table presents TERGM coefficients estimating the effect of international sanctions and control variables on international student flows. $^{+}$, ***, **, and * are significant at the levels of 0.001, 0.01, 0.05, and 0.1, respectively. Since the time-varying impact of the international sanction network is only used in the longer time dimension, it is not included in the 2000-2002, 2003-2005, and 2017-2020 TERGM analysis, avoiding the possible collinearity.

Table 9: TERGM Robust Analysis: Impact of the Sanction Network on Student Flows

	Baseline model	model 1	model 2	model 3	model 4
International sanction	-0.718**	-1.330^{+}	-1.140^{+}	-1.171^{+}	-0.658^{+}
Sanction × Time function	0.040*	0.085^{+}	0.067^{+}	0.069^{+}	0.080**
Edges	-0.828^{+}	-1.408^{+}	-1.576^{+}	-1.614^{+}	-0.718^{+}
GWESP	-0.007^{+}	-0.015^{+}		-0.012^{+}	-0.042^{+}
Reciprocity	0.600^{+}		1.063^{+}	1.006^{+}	0.742^{+}
Stability	2.226^{+}				1.451^{+}
$\|GDPper_i - GDPper_j\|$	-0.126^{+}	-0.255^{+}	-0.236^{+}	-0.226^{+}	-0.115^{+}
$\|PS_i - PS_j\|$	0.005	0.048***	0.031**	0.024*	-0.050**
$GDPper_i$	0.036^{+}	0.146^{+}	0.076^{+}	0.074^{+}	0.020**
PS_i	-0.177^{+}	-0.233^{+}	-0.300^{+}	-0.302^{+}	-0.215^{+}
$TopUni_i$	3.367^{+}	6.876^{+}	5.265^{+}	5.327^{+}	4.744^{+}
$GDPper_j$	0.234^{+}	0.397^{+}	0.388^{+}	0.380^{+}	0.259^{+}
PS_j	0.278^{+}	0.454^{+}	0.492^{+}	0.499^{+}	0.268^{+}
$TopUni_j$	4.812*	12.073***	11.467***	11.191***	7.787^{+}
Geographical distance	-0.648^{+}	-1.186^{+}	-1.064^{+}	-1.047^{+}	-0.760^{+}
Colonial relation	0.605^{+}	1.520^{+}	1.231^{+}	1.264^{+}	0.608^{+}
Language	-0.090**	-0.213^{+}	-0.192^{+}	-0.177^{+}	-0.087****

Note: This table presents TERGM robust coefficients estimating the effect of international sanctions and control variables on international student flows. $^{+}$, ***, **, and * are significant at the levels of 0.001, 0.01, 0.05, and 0.1, respectively. The estimates in columns (2)–(4) further confirm the robustness of the endogenous formation mechanisms—namely, transitivity and reciprocity. The specification in column (5) alters both the temporal interval and the estimation method.

Table 10: PTERGM Analysis: Parameter estimates for the increment and decrement network

	$N^{+,t}$	$N^{-,t}$
edges	**0.846**	**-5.689**
$\sum_{ij} N_{ij}$	(0.033)	(0.080)
non-edges	**6.388**	**8.180**
$\sum_{ij} 1(N_{ij} = 0) = n^2 - \sum_{ij} N_{ij}$	(0.110)	(0.114)
transitivity	**0.740**	**0.718**
$ATK_\lambda(N)$	(0.028)	(0.073)
reciprocity	0.005	**-0.049**
$\sum_{i<j} N_{ij} N_{ji}$	(0.009)	(0.016)

Note: The table presents the parameter estimates for the increment network and decrement network of the ISN, with the corresponding standard deviations in parentheses. Coefficients indicated in bold are statistically significant at the 0.05 level.

Table 11: TERGM Heterogeneity Analysis: Impact of Various Sanction Networks on Student Flows

	Trade	Financial	Economic	Travel
International sanction	-0.729	-0.740*	-0.466*	-0.946**
Sanction × Time function	0.061	0.044	0.032	0.057
Edges	-0.843^{+}	-0.841^{+}	-0.842^{+}	-0.835^{+}
GWESP	-0.007^{+}	-0.007^{+}	-0.007^{+}	-0.007^{+}
Reciprocity	0.600*	0.602^{+}	0.600^{+}	0.602^{+}
Stability	2.227^{+}	2.227^{+}	2.227^{+}	2.227^{+}
$\lvert GDPper_i - GDPper_j \rvert$	-0.127^{+}	-0.127^{+}	-0.127^{+}	-0.126^{+}
$\lvert PS_i - PS_j \rvert$	-0.003	-0.003	0.000	0.000
$GDPper_i$	0.037^{+}	0.037^{+}	0.037^{+}	0.037^{+}
PS_i	-0.183^{+}	-0.179^{+}	-0.181^{+}	-0.180^{+}
$TopUni_i$	2.903^{+}	3.065^{+}	3.002^{+}	2.939^{+}
$GDPper_j$	0.234^{+}	0.235^{+}	0.235^{+}	0.234^{+}
PS_j	0.292^{+}	0.283^{+}	0.287^{+}	0.285^{+}
$TopUni_j$	4.818*	4.797*	4.809*	4.798*
Geographical distance	-0.634^{+}	-0.639^{+}	-0.637^{+}	-0.642^{+}
Colonial relation	0.608^{+}	0.611^{+}	0.610^{+}	0.609^{+}
Language	-0.092**	-0.094**	-0.093**	-0.094**

Note: This table presents TERGM coefficients estimating the effects of various international sanctions on the ISN. $^{+}$, ***, **, and * are significant at the levels of 0.001, 0.01, 0.05, and 0.1, respectively. The results indicate that travel sanctions have the most consistently significant negative effect on the ISN.

Table 12: TERGM Mechanism Analysis: Impact of the Sanction Network on Student Flows

Variables name	Interaction term with GDP per capita difference	Interaction term with geographical distance
International sanction	-0.773***	-0.820***
Sanction × $[GDPper_i - GDPper_j]$	0.028***	
Sanction × Geographical distance		0.040**
Edges	-0.849^{+}	-0.846^{+}
GWESP	-0.007^{+}	-0.007^{+}
Reciprocity	0.604^{+}	0.606^{+}
Sanction × Time function	0.042*	0.042*
Stability	2.197^{+}	2.197^{+}
$[GDPper_i - GDPper_j]$	-0.111^{+}	-0.110^{+}
$PS_i - PS_j$	0.001	0.003
$GDPper_i$	0.033^{+}	0.033^{+}
PS_i	-0.179^{+}	-0.178^{+}
$TopUni_i$	3.050^{+}	2.842^{+}
$GDPper_j$	0.214^{+}	0.213^{+}
PS_j	0.269^{+}	0.266^{+}
$TopUni_j$	4.862*	4.862*
Geographical distance	-0.575^{+}	-0.578^{+}
Colonial relation	0.639^{+}	0.641^{+}
Language	-0.142^{+}	-0.142^{+}

Note: This table presents TERGM coefficients estimating the effects of the international sanctions and the interaction terms on the ISN. $^{+}$, ***, **, and * are significant at the levels of 0.001, 0.01, 0.05, and 0.1, respectively.

Table 13: Iteration Results and Emergent Cycle of the Counterfactual Analysis

Iteration	Updated Node Pairs	Net Edge Change
Initial Transient Phase		
1	–	–
2	413	+77
3	249	+71
4	223	-81
5	142	-36
6	312	+224
7	266	-264
8	186	+158
9	290	-20
Stable Cycle (Period = 6)		
10	227	-67
11	163	-9
12	156	+50
13	107	-107
14	181	+155
15	288	-20
16	(227)	(-67)
17	(163)	(-9)
18	(156)	(+50)
19	(107)	(-107)
20	(181)	(+155)
21	(288)	(-20)

Note: This table provides a complete breakdown of the network updates. Iteration 1 represents the initial removal of sanctions. Iterations 2-9 represent the initial transient phase before stabilization. The most substantial net increase in edges occurred in Iteration 6 (+224 edges). The most significant net decrease occurred in Iteration 7 (–264 edges). The simulation converged to a stable cycle with a period of 6, beginning at Iteration 10. The results for Iterations 16-21 are presented in parentheses to indicate that they are exact replicates of Iterations 10-15, confirming the cyclical equilibrium. Net edge change is calculated relative to the previous iteration's network state.

Table 14: Direct and Spillover Effects of Lifting U.S. Sanctions on China: Counterfactual Analysis

ISN Node Pair	Original Prob.	Direct Effect	Spillover Effect
		Prob. (Change)	Prob. (Change)
U.S. → China	0.0031	0.0070 (+0.0039)	–
China → U.S.	0.1717	–	0.1414 (-0.0303)
All Other Node Pairs	0.0307	–	0.0304 (-0.0003)

Note: This table presents the results of the counterfactual analysis analyzing the effects of lifting U.S. sanctions on China. The direct effect represents the change in probability for U.S. → China student flows, while spillover effects capture changes in reverse flows (China → U.S.) and flows between all other country pairs. All changes are expressed in probability units. Both short-term and long-term effects are identical due to the low formation threshold selected in our model configuration.