



Analysis of Innovation Consortium Network Evolution and Impact Mechanisms

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Abstract. Innovation consortia enhance national innovation systems and core-tech breakthroughs. Analysis of National Science Award networks (2012-2020) via SIENA reveals: (1) Spiral evolution with size/stage variation; (2) Structural balance, openness, subject size, cross-industry capability, and innovation drive dynamics; (3) Partner selection favors: high-low connectivity pairing, innovative-innovative clustering, specialist-generalist collaboration. Network properties and entity attributes co-shape ecosystems.

Keywords: Innovation consortium; Network evolution; Social network analysis; SIENA model

1 Introduction

Amid intensifying global tech competition, China's innovation consortium—led by enterprises, supported by universities/research institutes—emerges as a key model^[1]. It effectively resolves industry-academia-research collaboration bottlenecks, accelerates original technology creation/scenario-based application, and addresses issues like low enterprise innovation motivation and insufficient industrial focus^[2], enabling deep industry-university-research integration. Innovation consortia break disciplinary barriers to drive cross-disciplinary breakthroughs and innovative achievements^[3]. They elevate China's scientific-technological advancement and socioeconomic growth, while requiring continuous organizational refinement to adapt to evolving market/technical demands^[4].

Current innovation consortium research focuses on construction processes^{[5][6]}, dynamics^[7], network characteristics^[8], and evolutionary factors. Direct studies on innovation consortium network evolution remain limited. However, conceptual overlaps with collaborative innovation and industry-university-research cooperation offer valuable research perspectives from related fields. Hernan et al. (2003) found subject size increases consortium formation likelihood^[9]; Faro et al. (2023) demonstrated multidisciplinary collaboration enhances knowledge integration/consortium stability^[10]; Li et al.

(2024) identified network closure promotes evolution^[11]; Guo & Xie (2021) showed node openness boosts network formation^[12]; Peng (2015) established innovation capability advantages in partner selection^[13].

While existing studies focus on innovation consortia construction paths and network characterization, research combining network structure and subject attributes to explain evolutionary drivers remains scarce. Understanding innovation consortium network development requires analyzing evolutionary factors and revealing cooperation motivations. To address this gap, we analyze National Science Award consortium networks using: (1) Social Network Analysis to map evolutionary trajectories; (2) SIENA modeling quantifying impacts of structural balance, cooperation openness, subject size, multidisciplinary capacity, and innovation capability. This reveals cooperative decision-making mechanisms and partner selection foundations amid global tech competition.

2 Research Hypothesis

Innovation consortium network evolution is driven by structural (e.g., balance effect) and subject traits (e.g., openness, size, cross-industry collaboration, innovation capability), with combined influence examined.

2.1 Structural Balance Effect

Structural balance effect reflects network closure through triadic patterns: balanced when shared partners connect (i-j-k triad), promoting group solidarity via cooperative tie reinforcement^[14].

H1: In innovation consortium networks, structural balance effect contribute to network evolution.

2.2 Openness to Collaboration

Cooperation openness (external engagement willingness measured by breadth/width) critically influences network evolution, knowledge flow, innovation capability, and performance^{[15][16]}. Collaboration breadth (partner diversity via network connections) enables resource-integrated relationship-building^[17]. Broad-breadth subjects expand partnerships for competitive knowledge acquisition, while breadth disparity drives peripheral-to-core attraction and specialized capability access. High-depth subjects prioritize long-term strategic relationships through sustained investment, signifying value creation beyond transactional ties. While maintaining existing deep partnerships, they pursue new opportunities to acquire knowledge/technology/resources for sustained competitiveness and innovation^[18]. Therefore, this paper proposes:

H2: In the network of innovation consortium, subjects with a wide range of cooperation tend to form cooperative partnerships.

H3: In innovation consortium networks, cooperative ties are more likely to form amongst subjects with vastly different scopes of cooperation.

H4: In the network of innovation consortium, subjects with a high level of cooperation form cooperative partnerships.

2.3 Subject Size

Large subject size enhances an innovation consortium's overall capability through greater resource integration and R&D investment, driving technological innovation^[19]. These subjects also facilitate cooperation due to financial/technical strength. By collaborating, they access new knowledge/technology to improve offerings, respond to market shifts, and sustain competitiveness. Thus, this paper proposes:

H5: In a network of innovation consortium, subjects with large subject sizes form cooperative ties.

2.4 Multi-industry Cooperation

Cross-industry cooperation capacity reflects subjects' ability to integrate heterogeneous knowledge and reconcile paradigm conflicts. Strong-capacity subjects demonstrate: multi-industry cooperation capacity, motivation to build partnerships for professional/market advancement, and innovation through resource sharing. A bidirectional attraction mechanism exists: high-capacity subjects seek specialized partners to reduce integration risks in complex technologies, while low-capacity (but deep-expertise) subjects require architectural platforms for technological leapfrogging. Therefore, this paper proposes:

H6: In the network of innovation consortium, persons with a strong cross-industry cooperation capacity are more likely to form cooperative partnerships.

H7: In the network of innovation consortium, persons with significant disparities in cross-industry cooperation ability form cooperative relationships.

2.5 Innovation Capacity

Innovation capability drives consortium formation, operation, and outcomes as a core competitive factor^[20]. Strong innovators leverage leading technologies and external partnerships to access knowledge/resources, enhancing innovation through cost-sharing and efficiency gains^[21]. Synergies emerge when subjects of similar capability collaborate, accelerating R&D and improving output quality via knowledge spillovers. While low-capability subjects typically partner with peers, exceptions occur when unique technical barriers exist. Thus:

H8: In the innovation consortium network, people with significant innovation aptitude likely to form cooperative ties.

H9: In the innovation consortium network, people with slight disparities in invention capacity form cooperative interactions.

3 Methods

3.1 Data

Based on the available data, we obtained information on the National Science and Technology Progress Award program from the Ministry of Science and Technology of the People's Republic of China's official website (https://www.most.gov.cn/ztl_all/rdzt/). Because this data is only available until 2020, this report chose 2012-2020 as the study period. The National Science and Technology Progress Award program exemplifies the fundamental qualities of an innovation consortium and is dedicated to completing large scientific and technical research initiatives^[8]. As a result, the National Science and Technology Progress Award program is selected to build the innovation consortium network. Collect subject size information from Tianyancha's official website. Collect patent data from Wisdom Bud's official website.

3.2 Variables

3.2.1. Dependent Variables.

The dependent variable comprises three-stage collaboration matrices from National Science Award projects. Data processing involved: (1) standardizing completion unit names (2012-2020) and classifying entities (universities, institutes, enterprises, government) per Han et al. (2018) coding; (2) identifying enterprise-led innovation consortia (≥ 2 units) yielding 253 projects.

3.2.2 Independent Variables.

Table 1. Variable Selection and Measurement Methods

Network Effects	Variables	Measurements	hypothesis
Network	density	$\sum_j x_{ij}$	-
Structure	balance	$\sum_{j=1}^n x_{ij} \sum_{\substack{h=1 \\ h \neq i, j}}^n (b_0 - x_{ih} - x_{jh})$	H1
Characteristics	Breadth of cooperation-ego	Degree of nodes with deduplicated edges	H2
	Breadth of cooperation-sim	Degree of Nodes with Non-Deduplicated Edges/Breadth of cooperation	H3
	Depth of cooperation - ego	Degree of Nodes with Non-Deduplicated Edges/Breadth of cooperation	H4
Network Entity Characteristics	Scale-ego	Enterprise staff size and school type	H5
	Cross - industry cooperation ability - ego	Number of cooperative industries	H6
	Cross - industry cooperation ability -sim	Number of cooperative industries	H7
	Innovative capacity-ego	Number of patent authorizations	H8
	Innovative capacity-sim	Number of patent authorizations	H9

Independent variables include: (1) Subject size - enterprises measured by employee count, universities/research institutions classified by research scale (research/research-teaching/teaching-research/teaching); (2) Cross-industry ability & cooperation openness - derived from dependent variable data; (3) Field distribution - measured by industry entries in National Science and Technology Progress Award projects; (4) Innovation capacity - quantified using authorized patent counts (application-year basis) from PatSnap database. Table 1 summarizes the measurement methods for all variables.

Siena model analyzes structural (density, balance) and node attribute (cooperation breadth/depth, subject size, multi-disciplinary cooperation, innovation capacity) effects on consortium networks.

3.3 Model

This study employs the SIENA model to analyze innovation consortium network evolution and its formation mechanisms. Based on the Stochastic Actor Model (SAOM) with Markovian assumptions—where connection changes depend solely on the current network state—it simulates actor decisions (influenced by network structure, actor attributes, and peer characteristics) through iterative simulations of cross-wave network dynamics^[22]. This study focuses on two attribute effects: (1) Ego effect - positive estimates imply nodes with high attribute values form more ties; (2) Similarity effect - positive estimates indicate nodes with similar attribute values are more likely to collaborate.

4 Analysis and Results

4.1 Evolutionary Dynamics of Innovation Consortium Networks

The 2012-2020 period is divided into three phases to construct innovation consortium networks using National Science and Technology Award data; network parameters are shown in Table 2.

Table 2. Overall Characteristics of the National Science and Technology Progress Award Cooperation Network, 2012–2020

particular year	2012-2014	2015-2017	2018-2020
network node	433	447	339
total number of relationships	1795	2243	1457
clustering factor	0.967	0.997	0.995
network density	0.0192	0.0232	0.0254
average distance	4.316	3.852	3.623
Degree Centralization	0.0306	0.0658	0.0448
Betweenness Centralization	0.1652	0.293	0.2021

The examination of the parameters in the table reveals that the network of innovation consortium exhibits the following dynamics across the three stages of evolution:

(1) High clustering coefficients (>0.9) across stages indicate multiple stable communities enabling local collaboration. Decreasing average distance ($4.316 \rightarrow 3.623$) demonstrates improved efficiency. Combined short path length and high clustering confirm small-world characteristics.

(2) Network density ($0.0192 \rightarrow 0.0254$) indicates strengthening partnerships. Decreasing average distance enables faster resource/information flow. Despite growth, overall low density reveals significant untapped collaboration potential.

(3) Network interaction depth/quality improved, enhancing stability. Centralization metrics (Degree/Betweenness) rose then fell but remained higher in stage 3 vs. stage 1 (Table 2), indicating evolved quality-focused collaboration.

Stage 1 low Degree/Betweenness Centralization indicates distributed connections without dominant nodes and evolving decentralized intermediary influence. Stage 2 increased centralization shows key nodes emerging as bridges centralizing resource flows and enabling cross-subject cooperation. Stage 3 centralization declines but exceeds initial levels, signaling optimized quality-focused ties through pruning inefficient connections, yielding adaptable/mature cooperation dynamics (Table 2).

4.2 Examination of the Evolutionary Mechanisms Within Innovation Consortium Networks

4.2.1. Simulation Procedure.

SIENA estimation: (1) Initial fixed parameters for derivative matrix; (2) Iterative sub-stages (precision to sub-stages) with hundreds of simulations per sub-stage—adjusting parameters upward/downward when simulated statistics fall below/exceed observed values until mean deviation 0; (3) Final covariance/derivative matrix computation for standard errors (Snijders et al., 2010).

4.2.2. Create a Vertical Network Matrix.

To ensure accuracy, core subjects (≥ 2 annual projects) were selected, yielding 68 subjects and 188 projects for longitudinal analysis, addressing limited depth from sporadic participants. Three 68×68 binary matrices (2012–2020 phases) track core subjects' co-project relationships (1=cooperation, 0=none), constructed via Excel macros.

4.2.3. Discussion of Results.

The SIENA model analyzes structural balance, cooperation openness, subject size, multidisciplinary cooperation, and innovation capacity effects on innovation consortium network evolution via RSiena (R), examining ego/similarity effects.

After 2926 iterations, model converged (t-ratios <0.1 , max $0.16 < 0.25$; minimal covariance off-diagonals confirm reliability). Valid results (Table 3) enable network evolution analysis.

Table 3. Simulation results

parameters	parameter estimation	standard deviation	t Ratio
Rate T1-T2	1.437	0.191	-
Rate T2-T3	0.609	0.071	-
density	-1.102***	0.130	0.0511
Balance	0.261***	0.039	0.0614
Breadth of cooperation-ego	0.211**	0.071	-0.0225
Breadth of cooperation-sim	-2.452***	0.652	0.026
Depth of cooperation - ego	-0.938*	0.405	-0.0225
Scale-ego	0.818***	0.178	0.0438
Cross - industry cooperation ability - ego	-0.264	0.255	-0.0348
Cross - industry cooperation ability - sim	-1.537**	0.562	0.0502
Innovative capacity-ego	0.002**	0.001	-0.0546
Innovative capacity-sim	4.662**	1.439	0.0817

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$

All t-ratio < 0.09

Maximum convergence ratio 0.16

The simulation findings in Table 3 are examined, and the following study conclusions are drawn:

(1) Balance effect significantly positive ($\beta = 0.261$, $p < 0.001$) supports H1. Structural balance promotes network closure and resilience through enhanced cooperation, resource sharing, and adaptation capacity. (2) Cooperative openness impact: Breadth: Ego effect positive ($\beta = 0.211$, $p < 0.01$) supports H2 (high-degree nodes form new connections); Sim effect negative ($\beta = -2.452$, $p < 0.001$) supports H3 (strategic selection of low-degree partners). Broad-cooperation subjects enable resource integration/risk diversification; narrow-cooperation subjects offer specialized expertise. Depth: Ego effect negative ($\beta = -0.938$, $p < 0.05$) rejects H4—strong existing ties persist over new partnerships. This approach benefits individual consortia (cost reduction/innovation acceleration) but inhibits overall network evolution. (3) Subject size impact: Ego effect significantly positive ($\beta = 0.818$, $p < 0.001$) supports H5: large subjects leverage resources for complementary partnerships and risk reduction. (4) Multi-industry cooperation impact: Ego effect insignificant rejects H6 (no active edge formation); Sim effect negative ($\beta = -1.537$, $p < 0.01$) supports H7: connections favor large capability gaps, driven by low-capability specialists seeking high-capability partners for integration efficiency. (5) Innovation capability impact: Ego effect positive ($\beta = 0.002$, $p < 0.01$) supports H8 (high-innovation subjects form ties); Sim effect positive ($\beta = 4.662$, $p < 0.01$) supports H9: minor capability differences enable synergy through efficient knowledge transfer and complementary resources.

5 Conclusion

Innovation consortia represent China's innovation model enabling industry-academia-research integration and tech industrialization. Analysis of 2012-2020 National Science Award networks reveals: (1) Key metrics (density/clustering/distance/centrality) show cooperative ties, improved quality, and spiraling evolution; (2) Structural balance enhances stability/resilience; Node attributes significantly impact evolution—breadth/size/innovation drive new connections while depth/cross-industry capability sustain existing ties; (3) Partner selection favors: existing collaborators, high-low connectivity pairing, innovation capability matching, and specialist-generalist collaboration.

To address low network density: (1) Expand cross-industry partnerships through open innovation with academia/research institutes/startups; (2) Integrate knowledge/technology to break barriers, access new resources, and develop markets. Subject-specific optimization: (a) Broad-cooperation subjects: Strategic partner selection with focused resource allocation; (b) Large-scale subjects: Build open innovation ecosystems through network governance; (c) High-innovation subjects: Lead joint R&D for technology transfer and cross-industry business models. Refined partnership strategies: (i) Broad-breadth → narrow-breadth partners with clear goals/resource support; (ii) Domain specialists → cross-industry capable partners for complementary synergy; (iii) High-innovation → peer collaborators with IP-sharing frameworks for accelerated commercialization. Existing partners should deepen alliances through resource-sharing networks.

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