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September 16, 2026

Dear Professors Breza, Chandrasekhar, and Viviano:

I am writing to apply to the NBER Workshop on Network and Development Economics, to be held on December 5, 2026. I am a Ph.D. candidate in the Department of Economics at Oklahoma State University. My primary research interests include international economics, innovation, and applied microeconomics. My research focuses on how globalization, market incentives, and public policy shape technological change. Most recently, my work investigates the effect of foreign investment on cross-border innovative activity, with an emphasis on general network structure and the development status of network participants.

For consideration at the workshop, I am submitting my working paper, "The Effect of FDI on Innovation Networks: How the Development of Origin and Recipient Countries Influences Network Participation." In this paper, I investigate the impact of foreign investment on knowledge sourcing while accounting for the overall structure of the multilayer network and the economic development of participating countries. Our preliminary results indicate that development introduces substantial variation within our empirical setting, which we relate to absorptive capacity and the recipients' ability to leverage new sources of knowledge for future innovative activity.

The workshop would provide a valuable opportunity to receive feedback on this ongoing research and to further develop my use of empirical network methods within my broader research. I plan to incorporate network settings into subsequent projects on innovation and competition, and the methodological insights and feedback provided through the workshop would be invaluable as I continue to develop this broader research agenda.

If I am shortlisted for participation, Dr. Bidisha Lahiri, Associate Professor of Economics at Oklahoma State University, can provide a letter of recommendation in support of my application. She can be reached at bidisha.lahiri@okstate.edu. Thank you for your consideration. I would welcome the opportunity to participate in the workshop.

Sincerely,

Akseli DeBlieck
Ph.D. Candidate
Department of Economics
Oklahoma State University

AKSELI DEBLIECK

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Education

Oklahoma State University, Stillwater, OK
Ph.D., Economics, 2027 (Projected)

University of Arkansas, Fayetteville, AR
B.A. Economics, Biology, 2021

Research Fields

International Trade, Innovation Economics, Applied Microeconomics

Teaching Experience

Oklahoma State University 2022 – Present
Teaching Assistant

- **Graduate Courses**
  Managerial Economics (ECON 5113) – 19 Sections
- **Undergraduate Courses**
  Introduction to Macroeconomics (ECON 2203) – 3 Sections
  Managerial Economics (ECON 3023) – 8 Sections
  Money and Banking (ECON 3313) – 9 Sections

Leadership & Administrative Roles

Supervisor, P.E.T.E. Lab 2025 – Present
Department of Economics, Oklahoma State University

Publications

DeBlieck, A. and Lahiri, B., (2026). "From Hi-Tech Investment to Medium-Skill Employment: How FDI, Global Value Chains, and Intellectual Property Rights Shape Labor Markets." *Economic Modelling*, Vol. 163, p.107693.

- We study how U.S. outward foreign direct investment (FDI) across different stages of global value chains (GVC) affects host country labor market skill composition. We find that U.S. FDI increases skill intensity overall, while FDI in downstream and technologically complex industries shifts employment from high- to medium-skill employment. This heterogeneity suggests that U.S. firms retain skill-intensive tasks domestically while reallocating less skill-intensive roles within the production process abroad. We introduce a mechanism through which intellectual property rights (IPR) govern the magnitude of these effects. Host countries with high IPR mitigate the observed decline in high-skill employment.

Working Papers

"Competition and Innovation Strategies: How Heterogeneous Import Competition Shapes Firms' Choice across Exploratory and Incremental Innovation" - ***Job Market Paper***

- This paper studies how differences across the source of competition shape innovation strategies in U.S. manufacturing firms. We classify patents into incremental, mixed, and exploratory innovation and

find that competition from structurally dissimilar countries relative to U.S. manufacturing intensity encourages firms to shift toward incremental improvements and away from exploratory activity. These effects are strongest among firms with a broad product scope. The results show that the production structure of competitors shapes how firms reallocate innovation across strategies, beyond the effects of aggregate competitive pressure alone.

"The Effect of FDI on Innovation Networks: How the Development of Origin and Recipient Countries Influences Network Participation"

- This paper studies how foreign direct investment (FDI) reorganizes cross-border knowledge flows using a multilayer network approach which links FDI and cross-border patent citations across 85 countries and 31 industries. We find that FDI broadly strengthens existing knowledge network connections while selectively promoting the formation of such connections. FDI toward developing countries increases the probability of knowledge network formation. Our results describe how FDI reshapes the structure and allocation of international knowledge connections, while country-industry characteristics influence where new network connections are formed.

Honors and Awards

Outstanding Economics Graduate Student Award – 2026
Robberson Research Fellowship – 2026
Richard and Maxine Leftwich Distinguished Graduate Fellowship – 2026
Duck Woo Nam Distinguished Graduate Fellowship – 2025
Phillips Doctoral Dissertation Fellowship Award – 2025

Reviews and Refereeing

Applied Economics, Journal of African Economies, Journal of Economics and Finance, Cogent Economics and Finance

Presentations and Conferences

2026:

- Midwest Trade and Theory Conference (scheduled, Oct. 2026)
  - *Competition and Innovation Strategies: How Heterogeneous Import Competition Shapes Firms' Choice across Exploratory and Incremental Innovation*, ***Job Market Paper***
- Southern Economic Association Annual Meeting (scheduled, Nov. 2026)
  - *Competition and Innovation Strategies: How Heterogeneous Import Competition Shapes Firms' Choice across Exploratory and Incremental Innovation*, ***Job Market Paper***

2025:

- The Institute for the Study of Free Enterprise
- Annual Western Hemispheric Trade Conference
- Bridwell Institute for Economic Freedom Research (Graduate Student Colloquium)

2024:

- Southern Economic Association Annual Meeting
  - *From Hi-Tech Investment to Medium-Skill Employment: How FDI, Global Value Chains, and Intellectual Property Rights Shape Labor Markets*, with B. Lahiri.

Ph.D. Coursework

Completed:

- Mathematical Economics I
- Microeconomic Theory I/II
- Macroeconomic Theory I/II
- Econometrics I/II
- Time Series Econometrics
- International Trade
- Regional Economic Analysis and Policy
- International Finance
- Economic Development I/II
- Urban Economics

References

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Statement of Research Interests and Workshop Motivation

Akseli DeBlieck
Oklahoma State University

My research interests lie at the intersection of international economics, innovation, and applied microeconomics, with a particular focus on how international relationships shape the diffusion of knowledge. Most recently, my work has centered on knowledge network dynamics with an emphasis on how economic development and absorptive capacity affect the ability of participants to effectively implement new technologies and best practices. This work is especially interesting to me due to the role that differences in economic development can play in determining whether access to foreign knowledge translates into meaningful innovation and the adoption of new technologies.

My work examines these topics by studying how foreign direct investment influences the formation and intensity of international knowledge-network connections. Specifically, we leverage a multilayer network approach and distinguish between two distinct layers: the capital network layer and the knowledge network layer. Using a supra-adjacency matrix decomposition, we account for historical network structure, allowing us to characterize how participants are positioned across the joint capital and knowledge networks.

More broadly, my research agenda examines how international economic relationships affect innovation and knowledge transfer across heterogenous firms, industries, and countries. Network-based approaches have become increasingly relevant across my research. Since international competition, investment, and knowledge diffusion are inherently shaped by relationships among economic actors, network-based approaches provide a natural framework for accounting for the structure of these relationships.

I am particularly interested in attending the NBER Workshop on Network and Development Economics because my current research increasingly involves empirical questions for which network settings are a central component. I hope to leverage the workshop's combination of lectures and work-in-progress presentations to strengthen my understanding of empirical network methods and to receive feedback on the identification and interpretation of network relationships in my current work. The opportunity to discuss these questions with researchers working at the frontier of empirical network research would be particularly valuable as I continue to develop this project and my broader research agenda.

The Effect of FDI on Innovation Networks: How the Development of Origin and Recipient Countries Influences Network Participation[1]

Akseli DeBlieck[2]
September 15th, 2026

Abstract:

Given the increasingly collaborative nature of research captured by cross-border citations, how FDI shapes the organization of international knowledge flows remains an important but understudied question. Prior research shows that FDI promotes productivity growth and innovation through technology transfer and knowledge spillovers, but existing approaches largely treat innovation as country-level or bilateral outcome independent of the innovation and capital relations with the other partners, thus providing limited insight into how knowledge relationships are reorganized across countries. Using a multilayer network linking country-level FDI flows to industry-level cross-border patent citations across 85 countries and 31 industries from 2010–2019, we examine how FDI affects both the formation of innovation-network linkages and the allocation of innovative activity across existing connections. We find that FDI selectively influences the creation of new knowledge-network relationships while uniformly strengthening the intensity of existing innovation linkages. We further show that the effect of FDI on knowledge-network formation varies substantially across development pairings, with particularly large effects for some dyads involving developed recipient countries. These findings suggest that FDI reshapes the structure of global innovation networks by reallocating knowledge flows across countries, with network position and recipient absorptive capacity serving as key mechanisms governing the diffusion of foreign knowledge.

Keywords: FDI, knowledge spillovers, innovation networks, cross-border patent citations

JEL Codes: F23, O33, D85, F21, O19

[1] Preliminary draft. Results and discussion are subject to revision.

[2] Department of Economics, Oklahoma State University (akseli.deblieck@okstate.edu)

1. Introduction

Patent citations reveal not only who innovates, but also where innovators obtain the knowledge on which they build. A large literature uses patent citations to trace international knowledge flows and identify the direction of knowledge spillovers across firms, industries, and countries (Jaffe et al., 1993; Acemoglu et al., 2016; Liu and Ma, 2021). While foreign direct investment (FDI) is widely recognized as a channel for technology transfer and productivity spillovers (Aitken and Harrison, 1999; Javorcik, 2004; Branstetter, 2006), little is known about whether investment relationships influence the relative strength of those knowledge flows within the country's network of innovation connections. If multinational firms transmit technologies across borders, countries receiving investment from a particular source may become more likely to utilize and cite innovations originating from that source. Understanding whether FDI shapes the geography of knowledge diffusion is therefore an important and largely unanswered question. Our research represents a bridge between traditional citation-based bilateral knowledge spillovers analysis to modern network-based analyses of international innovation.

A large literature uses patent citations to measure the diffusion of knowledge across firms, industries, regions, and countries. The seminal work of Jaffe, Trajtenberg, and Henderson (1993) demonstrates that patent citations contain meaningful information about knowledge spillovers and can be used to trace the flow of ideas between innovators (Cai et al., 2022). Within this framework, a citation is interpreted as evidence that an inventor or firm has built upon previously developed knowledge. Patent citation networks provide a direct and observable measure of technological interdependence, allowing researchers to identify both where innovations are produced and where they are subsequently utilized. Building on this insight, studies such as Acemoglu et al. (2016) and Liu and Ma (2021) use citation-based networks to examine how innovation propagates through interconnected systems of countries and industries. By identifying both the origin and destination of knowledge flows, citation networks provide a particularly powerful lens through which to study global knowledge diffusion.

Globalization has dramatically expanded cross-border innovation activity. Firms increasingly patent in foreign markets both to protect intellectual property and to capitalize on international opportunities for learning and innovation. A large literature identifies foreign direct investment (FDI) as an important channel through which knowledge crosses borders. Early contributions by Aitken and Harrison (1999) and Javorcik (2004) show that foreign investment generates productivity spillovers in host economies, while subsequent work demonstrates that multinational enterprises transfer technologies, managerial practices, organizational knowledge, and production expertise across countries, contributing to innovation and productivity growth (Branstetter, 2006; Keller and Yeaple, 2009; Guadalupe et al., 2012).

These findings suggest that FDI influences where innovators obtain knowledge. Investment relationships create opportunities for learning, supplier interactions, labor mobility, and exposure to foreign technologies. If multinational firms transfer knowledge from source countries to foreign affiliates and local firms, innovators in recipient economies should become increasingly likely to build upon and cite technologies originating from those source countries. Consequently, FDI may shape both the volume of innovation as well as the direction of knowledge diffusion captured through cross-border patent citations.

Viewed through a network lens, this implies that international capital networks and international knowledge networks are fundamentally interconnected. Countries linked through investment relationships are more likely to exchange information, adopt common technologies, and participate in shared production systems. Over time, these interactions may alter the geography of innovation by changing which countries serve as important sources of knowledge relative to others. Stronger capital ties may therefore increase the relative importance of the investing country's patents within a recipient country's knowledge network, suggesting that capital and knowledge networks evolve jointly.

Despite substantial progress in both the FDI and innovation literatures, relatively little is known about how the organization of global capital networks shapes the organization of global knowledge networks. Most existing studies focus on whether FDI increases innovation or productivity in recipient economies. By contrast, the central question of this paper is whether the structure of the international capital network influences the structure of the international knowledge network. Understanding this relationship is essential for explaining how knowledge flows are allocated across countries and how international innovation networks evolve over time.

To address this question, we develop a multilayer network framework that jointly models capital flows and knowledge flows. Using bilateral FDI relationships to define a capital network and cross-border patent citations to define a knowledge network, we distinguish between two dimensions of international innovation linkages: the formation of new cross-border knowledge relationships and the strengthening of existing ones. This framework allows us to move beyond a purely bilateral perspective and examine how FDI and knowledge relationships between two countries evolve within the broader structure of interconnected global capital and knowledge networks.

The remainder of this paper is organized as follows. In section 2 we outline prior literature on knowledge networks and the effect of FDI on innovation. In section 3

2. Literature Review

The seminal contribution of Jaffe, Trajtenberg, and Henderson (1993) demonstrates that patent citations contain meaningful information about knowledge spillovers and can be used to trace the flow of ideas between innovators. Later work by Jaffe and Trajtenberg (2002) established patent citations as one of the most widely used empirical measures of knowledge diffusion and innovation linkages. Within this framework, citations provide evidence that an inventor or firm has built upon previously generated knowledge, allowing researchers to identify both the origins and destinations of technological ideas. Branstetter (2001) finds that knowledge spillovers remain concentrated within national boundaries despite increasing international integration, while Eaton and Kortum (1996) demonstrate that international patenting and innovation activity are closely linked to productivity differences across countries. More recently, citation-based measures have become a standard tool for identifying technological relationships and tracking global knowledge flows across countries, industries, and firms (Griffith et al., 2006; Acharya and Subramanian, 2009; Hsu et al., 2014; Cai et al., 2022). Collectively, this literature establishes cross-border patent citations as a direct and observable measure of international knowledge sourcing.

A parallel literature has studied international knowledge diffusion. Coe and Helpman (1995) show that foreign R&D stocks contribute to domestic productivity, suggesting that knowledge generated in one country can generate benefits elsewhere. Coe, Helpman, and Hoffmaister (1997) further demonstrate that these spillovers extend to developing economies, while Keller (2002) finds that international technology diffusion remains geographically localized despite increasing globalization. Keller's (2004) comprehensive review concludes that international technology diffusion constitutes a fundamental determinant of productivity growth and technological development.

As economic activity has become increasingly globalized, foreign direct investment (FDI) has emerged as an important channel through which technologies, production practices, and knowledge (Ahn et al.,2026) move across borders. A large literature documents the positive effects of foreign investment on productivity and innovation, with early contributions by Aitken and Harrison (1999) and Javorcik (2004) showing that foreign firms generate productivity spillovers in host economies. Subsequent research finds that these effects operate through both horizontal and vertical linkages, enhancing firm performance, technological adoption, and innovation (Haskel et al., 2007; Keller and Yeaple, 2009). A parallel literature identifies knowledge spillovers as a central mechanism underlying these gains (Keller, 2004; Branstetter, 2006; Keller, 2021). Through multinational activity, foreign investors transfer technologies, managerial know-how, organizational practices, and production expertise, allowing recipient firms to access and utilize knowledge developed abroad (Lee, 2006; Guadalupe et al., 2012). Branstetter (2006 provides direct evidence that multinational enterprises serve as vehicles for international knowledge transfer through foreign investment relationships.

Recent research increasingly recognizes that international investment relationships are embedded within broader networks rather than operating as isolated bilateral links. Countries compete for FDI, and multinational firms allocate investment across alternative host locations based on their relative attractiveness, making a network perspective particularly relevant for understanding global capital flows (Sultana and Turkina, 2020; Bettarelli and Resmini, 2022; Pan and Chong, 2023; Samani et al., 2026; DeBlieck and Lahiri, 2026). Rather than being determined solely by bilateral country characteristics, FDI outcomes reflect a country's position within a larger system of competing investment destinations and interconnected production relationships.

A parallel literature views knowledge diffusion as a network process in which innovation outcomes depend both on the stock of available knowledge and the structure of relationships linking countries, industries, and firms (Acemoglu et al., 2016; Liu and Ma, 2021). Research shows that network position, technological relatedness, connectivity, density, and tie strength all influence the creation and diffusion of knowledge (Cowan and Jonard, 2004; Fleming et al., 2007; Sorenson et al., 2006; Balland et al., 2019; Balland et al., 2020; Miguelez and Moreno, 2018; Moretti, 2021; Cai et al., 2022; LaBelle et al., 2023). Consequently, cross-border patent citations are increasingly accepted as components of a broader international knowledge network rather than as independent bilateral exchanges.

Similarly, a growing body of evidence suggests that knowledge transfer through FDI is the result of strategic decisions rather than a guaranteed outcome. Multinational firms allocate technologies across countries according to absorptive capacity, institutional quality, production-network relationships, and the relative attractiveness of competing hosts (Saggi, 2000; Glass and Saggi, 2002; Keller, 2004; Javorcik, 2004; Branstetter, 2006; Keller and Yeaple, 2009; Antràs and Chor, 2013; Correani et al., 2014; Adarov, 2021; Ahn et al., 2026; Barbosa et al., 2024). These findings suggest that capital and knowledge networks evolve jointly: investment relationships may influence both the volume of knowledge diffusion and its direction by altering the relative importance of foreign knowledge sources. As discussed above, literature on bilateral FDI and innovation, FDI-networks and innovation-networks have largely developed in parallel. Thus, relatively little is known about how the structure of the global capital network shapes the structure of the global knowledge network. Addressing this gap is the central objective of this paper.

Although foreign investment often embodies technologies and production practices developed elsewhere (Glass and Saggi, 2002), countries and industries differ in their ability to absorb and deploy this knowledge (Engelbrecht, 1997; Engelbrecht, 2002). Consequently, economies with stronger innovative capabilities and technological infrastructure tend to benefit more from foreign knowledge transfers (Kesidou and Romijn, 2008; Castellacci, 2011). Human capital, technological capabilities, institutional quality, and market structure all influence the magnitude of spillover effects (Sembenelli and Siotis, 2008; Bloom et al., 2013; He and Maskus, 2012; Ahn et al., 2026).

Our approach contributes to the growing literature on international innovation networks by demonstrating how capital flows influence both the magnitude of knowledge diffusion as well as the organization and direction of knowledge flows across countries and industries. In this paper, we build on these literatures by modeling FDI and knowledge spillovers within a multilayer global network. Rather than treating spillovers as reduced-form outcomes of FDI exposure, we explicitly examine how the structure of international capital networks shapes the structure of international knowledge networks. Following Kivelä et al. (2014), we represent investment and innovation relationships as interconnected network layers linking countries and industries. Further, by exploiting prior network structure to account for unobservable heterogeneity and endogenous sorting (Auerbach, 2022; Sheng, 2020), we provide a tractable specification for estimating global knowledge spillovers. By jointly studying capital and knowledge networks, we examine whether the structure of the global capital network actively shapes the geography of innovation.

3. Data and Variable Creation

3.1. Data Sources

We combine three complementary data sources to construct our multilayer network. International innovation activity is measured using the INPACT-S dataset developed by LaBelle et al. (2023), which contains patent applications and directional cross-border patent citations for 31 industries across 91 countries between 1980 and 2019. Measures of international capital flows are obtained from the IMF *Direct Investment Positions* database, which reports bilateral foreign direct investment (FDI) positions by counterpart economy between 2009 and 2025. Finally, development indicators and additional country-level controls are collected from the World Bank *World Development Indicators* database.
Because consistent bilateral FDI information is only available beginning in 2009, we restrict the analysis to the 2010–2019 period. Table 1 provides summary statistics for all variables used in the empirical analysis.

3.2. Network Structure

Our framework is built around a set of observable network nodes and network edges. Nodes are defined as country-industries at the 2-digit ISIC level, such that each country-industry i represents a unique observed node within the network. Network edges are defined as relationships between node i and a counterpart node j.

These relationships take two forms: capital flows through FDI and knowledge flows through cross-border patent citations. Importantly, network edges are directional. To preserve this directionality, each observation in our dataset represents a dyadic relationship between two nodes. Within the capital

network, node i is the recipient of investment originating from node j. Within the knowledge network, node i acts as the citing node while node j represents the source of knowledge embodied in previously filed patents. Conceptually, each node simultaneously participates in the international allocation of capital and the international diffusion of knowledge. Modeling both layers jointly allows us to examine whether the structure of international investment relationships influences the formation and intensity of international knowledge flows.

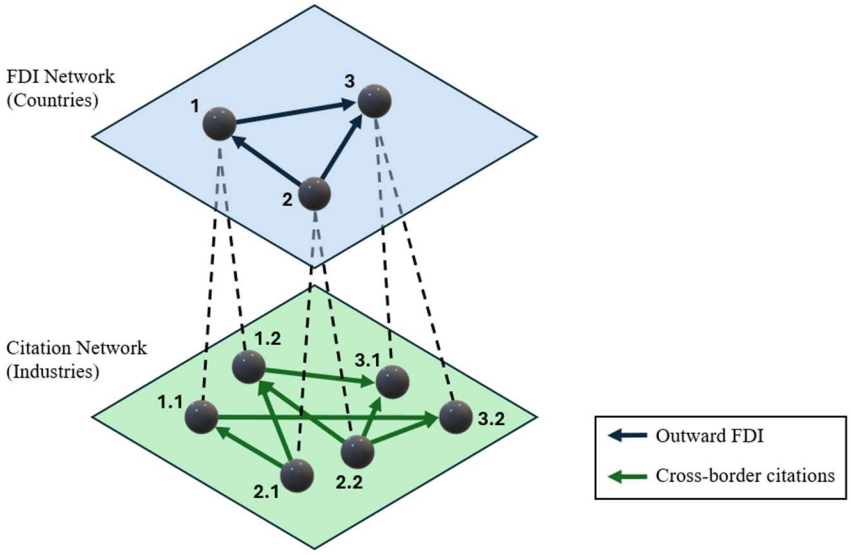


Figure 1: Multi-layer network visualization of FDI and cross-border citations. Industries are defined as subunits of countries. FDI connections (top) define relationships between countries (e.g. 1 & 2). Cross-border citations (bottom) define relationships between industries (e.g. 1.1 & 3.1) in different countries.

Incorporating network structure into empirical analysis introduces several identification challenges. Within network settings, node-level outcomes are often jointly determined by the behavior of interconnected participants, creating reflection problems and peer effects (Manski, 1993; Goldsmith-Pinkham and Imbens, 2013). Peer effects arise when the behavior of a node depends on the actions or characteristics of other nodes within the network, many of which may be unobservable. These challenges are amplified when considering network formation itself. Network links are often established intentionally by agents possessing unobserved characteristics, creating concerns regarding endogenous sorting and selection into networks. Even in static settings, unobservable heterogeneity and endogenous network formation complicate inference on network relationships (Graham, 2017). Recent methodological advances provide tools for addressing these concerns (Charbonneau, 2017; de Paula, 2017; de Paula, 2020; Auerbach, 2022), yet empirical applications remain relatively limited, particularly in global settings where multiple forms of interaction operate simultaneously.

In our analysis, identification is aided by the fact that FDI is observed at the country level while knowledge flows are observed at the country-industry level, reducing concerns that common industry-level shocks simultaneously determine both outcomes. In addition, we leverage lagged capital-network relationships, and controls for prior multilayer network structure using network-based measures of latent similarity. Defining both FDI and citation relationships as participation shares embeds each dyadic relationship within the broader network structure. As a result, the empirical analysis identifies whether changes in the relative importance of a particular investment partner are associated with changes in the relative importance of the corresponding knowledge partner. This approach reduces the influence of country size and aggregate trends and allows the analysis to focus on the reallocation of capital and knowledge flows across competing network relationships.

3.3. Dependent Variable: Innovation Network Participation

3.3.1. Intensity of Cross-Border Citation Centrality

To formalize the knowledge network layer following Acemoglu et al. (2016) and Liu and Ma (2021), we construct a measure of dyadic network participation.

$$y_{ij,t} = \frac{Cite_{ij,t}}{\sum_{j'} Cite_{ij',t}} \tag{1}$$

The participation of node i, $y_{ij,t}$, is defined as the ratio of citations made by node i to patents filed by node j relative to all citations made by node i. This measure captures the relative importance of knowledge originating from node j among all foreign knowledge sources available to node i.
Unlike conventional node-level centrality measures, equation (1) is an edge-level participation measure. Larger values indicate that knowledge originating from node j occupies a more important[3] position within the knowledge network of node i. While patent citations are recorded as outbound links from node i to node j, we interpret them as the absorption of knowledge by node i from the knowledge stock of node j. Each citation therefore represents the formal use of previously developed knowledge across international borders. Consequently, expression (1) measures how important a particular dyadic knowledge relationship is relative to all alternative knowledge relationships maintained by node i.

3.3.2. Creation of Cross-Border Citation Linkages

[3] For the remainder of this paper, we use the term 'importance' to interchangeably describe differences in the relative strength of knowledge network edges. This does not imply any other qualities of global knowledge or capital networks, however.

To study network formation, we define a binary indicator of meaningful knowledge-network connections. Specifically, $D_{ij,t} = 1$ when the citation count from node i to node j exceeds the 10th percentile of all positive cross-border citation flows in year t[4]. This threshold helps distinguish economically meaningful knowledge relationships from weak or sporadic citation activity while preserving the majority of observed cross-border knowledge flows.

3.4. Main Explanatory Variable: FDI Network Participation

To formalize the capital network layer, we define the participation of country c_i in the global capital network as the share of FDI received from country c_j relative to all foreign investment received by country c_i.

$$\omega^{FDI}_{c_j \to c_i, t-1} = \frac{FDI_{c_j \to c_i, t-1}}{\sum_{c_k \neq c_i} FDI_{c_k \to c_i, t-1}} \tag{2}$$

Equation (2) measures the relative importance of country j as a capital provider to country i. Similar to our citation participation measure, equation (2) captures network position rather than the absolute volume of activity. An increase in the FDI share of a particular source country necessarily implies a decline in the relative importance of alternative sources of foreign capital. Consequently, expression (2) should be interpreted as the proportion of total foreign capital inflows received by country $i$that originate from country j. This measure captures how investment relationships are allocated across partners within the broader global capital network.

3.5. Control Variable: Pre-Existing Multilayer Network Structure

Innovation networks do not form independently each period. Instead, they evolve from an existing global network structure. Countries occupying similar positions within international investment and innovation networks often share common characteristics, including technological sophistication, institutional quality, and historical economic relationships. Because these characteristics may simultaneously affect both FDI and knowledge flows, failing to account for existing network structure may bias inference. To address this concern, we construct a measure of multilayer network similarity motivated by the codegree methodology proposed by Auerbach (2022). Conceptually, this measure serves as a proxy for latent factors that influence both partner selection and knowledge diffusion.

Following Kivelä et al. (2014), each entity within a multilayer network can be represented as a node-layer tuple, allowing connections to occur both within and across network layers. These

[4] The 10th percentile threshold is calculated based on available data between 2009-2019.

relationships can be summarized using a supra-adjacency matrix, in which individual matrix blocks represent within-layer and cross-layer interactions.

$$S_t = \begin{pmatrix} A_{t-1}^F & I \\ I & A_{t-1}^C \end{pmatrix} \tag{3}$$

The matrix S_t combines information from both capital and knowledge networks while preserving cross-layer relationships between country and industry observations. Cross-layer connections ensure that each country-industry occupies a consistent position across the two network layers, allowing information from one layer to inform it's position in the other. We then compute: $M_t = S_t^2$ which captures second-order connectivity within the multilayer network. The resulting matrix reflects both direct and indirect relationships, allowing nodes to be compared based on their broader network neighborhoods.

Motivated by Auerbach (2022), we construct a codegree-based measure of multilayer network similarity. Codegree measures summarize the extent to which two nodes occupy similar positions within a network and share common direct and indirect connections. In our setting, the measure captures similarity in network position across both the capital and knowledge layers.

$$\delta_{ij,t-1}^{ML} = \frac{1}{1 + \left(\frac{1}{K_t}\left|\left|m_i - m_j\right|\right|^2\right)^{1/2}} \tag{4}$$

Intuitively, two nodes receive a large value of $\delta_{ij,t-1}^{ML}$when they share similar patterns across the same set of counterpart nodes. More specifically, any two nodes will be considered similar if they receive capital or cite counterpart nodes which belong to a shared set of neighbors. Conversely, nodes occupying very different positions within the global multilayer network in terms of direct and first-order indirect relationships receive small values. Any two nodes which share a relatively small set of counterpart nodes will then be considered less similar. The measure therefore captures an approximation of structural similarity between nodes and serves as a reduced-form proxy for otherwise unobservable characteristics influencing network formation.

Unlike Auerbach (2022), we include the codegree measure directly within our empirical specifications. Doing so allows us to account for persistent network structure while simultaneously examining how prior network similarity influences subsequent knowledge-network formation and intensity. More broadly, the inclusion of $\delta_{ij,t-1}^{ML}$helps mitigate omitted-variable concerns arising from endogenous partner selection and unobserved heterogeneity within the global network. To avoid mechanical correlation with contemporaneous outcomes, all network objects used in $S_t$are constructed -

using lagged information. Consequently, the matrix summarizes predetermined network structure rather than current-period outcomes.

4. Specification and Identification

Our empirical analysis examines whether the organization of the capital network influences the organization of the knowledge network. Specifically, we focus on two related outcomes. First, we investigate whether stronger capital-network ties increase the probability that new knowledge-network relationships. Second, we examine whether stronger capital-network ties increase the relative importance of existing knowledge-network connections. These two outcomes correspond to distinct dimensions of network dynamics. The first captures network formation, or whether knowledge links arise between previously weakly connected nodes. The second captures network intensity, or how knowledge flows are distributed across existing relationships. Under the hypothesis that FDI acts as a conduit for technology transfer, investment relationships should not only facilitate the creation of new knowledge connections but also increase the relative importance of knowledge obtained from investment-origin countries.

4.1. Network Formation

Our primary hypothesis is that stronger capital-network ties increase the likelihood that corresponding knowledge-network ties emerge and persist. If foreign investment facilitates the transfer of technologies, managerial practices, and production knowledge, then countries receiving a larger share of investment from a particular source should become more likely to cite patents originating from that source. To examine the creation of knowledge-network links, we estimate the probability that a meaningful citation relationship exists between nodes using the following baseline specification:

$$D_{ij,t} = \alpha + \theta_1 \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + X'_{ij,t}\beta + \lambda_{ij} + \eta_t + \varepsilon_{ij,t} \quad (5)$$

where $D_{ij,t}$indicates the presence of a knowledge-network edge between node i and node j, $\omega^{FDI}_{c_j \to c_i, t-1}$ measures the relative importance of the bilateral investment relationship, $\delta^{ML}_{ij,t-1}$ captures similarity in prior multilayer network positions, and $X_{ij,t}$ contains dyadic control variables. The term λ_{ij}captures persistent bilateral characteristics and unobserved dyadic factors, while η_t absorbs common time shocks.

The coefficient θ_1 measures the extent to which participation in the capital network influences knowledge-network formation. A positive estimate implies that countries receiving a larger share of investment from a particular origin become more likely to establish knowledge relationships with that

origin. In network terms, stronger capital-network ties increase the probability that corresponding knowledge-network ties emerge. Equivalently, θ_1 captures a reallocation of knowledge sourcing across potential foreign partners. A positive estimate indicates that an increase in the relative importance of an investment-origin country increases the relative importance of that country's knowledge base, leading recipient industries to utilize and cite technologies originating from that location more frequently.

The coefficient θ_2 captures the influence of prior multilayer network structure on subsequent knowledge-network outcomes. Since $\delta_{ij,t-1}^{ML}$ is an inverse distance measure, larger values indicate that nodes occupy similar positions within the joint capital and knowledge network, while smaller values indicate greater structural dissimilarity. Consequently, a negative estimate implies that nodes occupying dissimilar network positions are more likely to form and maintain knowledge relationships.

The expected sign of θ_2 is theoretically ambiguous. One possibility is that structurally similar nodes are more likely to exchange knowledge because they share comparable technological capabilities, institutional environments, or positions within the global innovation system. For example, advanced economies such as the United States and the United Kingdom may occupy similar positions in the multilayer network and benefit from mutual knowledge spillovers. In this case, larger values of $\delta_{ij,t-1}^{ML}$ would be associated with a higher likelihood of knowledge-network formation, implying a positive coefficient. This interpretation is consistent with network homophily, whereby nodes with similar characteristics and network positions are more likely to interact. At the same time, network similarity alone may not be sufficient to generate knowledge flows. Two developing economies, such as Malaysia and Vietnam, may occupy similar positions within the multilayer network and therefore exhibit large values of $\delta_{ij,t-1}^{ML}$, yet with limited likelihood of substantial knowledge exchange between them.

An alternative possibility is that knowledge flows arise primarily between structurally dissimilar nodes. For example, investment and knowledge transfer from the United States to a developing economy such as Indonesia may connect otherwise distant parts of the global network. In this case, knowledge relationships would be more likely to emerge between nodes with larger network distances, implying a positive coefficient and reflecting a bridging mechanism of network formation. Consequently, the estimated sign of θ_2 depends on whether network similarity primarily captures opportunities for knowledge exchange or reflects common constraints that limit the diffusion of knowledge across nodes.

4.2. Network Intensity

Whereas the network-formation specification focuses on the existence of knowledge relationships, the network-intensity specification focuses on their relative importance. The parameter estimates therefore reveal whether investment relationships influence the allocation of innovative activity across competing foreign knowledge sources. As a benchmark, we first consider the linear representation:

$$y_{ij,t} = \alpha + \theta_1 \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + X'_{ij,t}\beta + \lambda_{ij} + \eta_t + \varepsilon_{ij,t} \quad (6)$$

Equation (6) provides the linear analogue of the relationship of interest. However, because the dependent variable $y_{ij,t}$ is bounded between zero and one and represents a participation share within the knowledge network, a linear specification is not ideal for estimation. To accommodate the bounded nature of the dependent variable, we follow Papke and Wooldridge (1996, 2008) and estimate a fractional response model:

$$\mathbb{E}\left[y_{ij,t} \mid X_{ij,t}, \lambda_{ij} \right] = \mathrm{G}\left(\alpha + \theta_1 \, \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + X'_{ij,t}\beta + \delta' \overline{X_{ij}} + \eta_t \right) \quad (7)$$

where $y_{ij,t}$ measures the relative importance of the knowledge-network connection linking node i and node j. More specifically, it captures how central or important the edge between i and j is within node i's overall knowledge network relative to all alternative knowledge partners.

The function $G(\cdot)$ is the logistic link function mapping the linear index into the unit interval. This framework allows us to determine whether stronger capital-network ties increase the relative importance of corresponding knowledge-network connections. Conceptually, the specification tests whether FDI systematically redirects citation activity toward investment-origin countries. Because the analysis is conducted over a large global network, we employ a correlated random-effects approach through $\bar{X}_{ij}$, allowing us to account for time-invariant dyadic characteristics while maintaining computational feasibility. Average marginal effects are reported in Table 5.

4.3. Heterogeneity

We next examine whether the relationship between capital and knowledge networks varies across countries at different stages of development. Development status provides a natural proxy for absorptive capacity, as developed economies typically possess stronger innovation systems, larger stocks of human capital, and greater technological capabilities. Consequently, the ability to convert foreign investment into knowledge acquisition may differ substantially across country pairs. Let D denote the set of countries with GDP per capita greater than or equal to $13,000 USD. A country is classified as developed when $d_{c_i} \in \mathcal{D}$. We then define a set of indicators distinguishing interactions between developed and developing countries:

$$H^1_{ij,t} = 1\{d_{c_i,t} \in \mathcal{D}_t\} \times 1\{d_{c_j,t} \in \mathcal{D}_t\}$$
$$H^2_{ij,t} = 1\{d_{c_i,t} \in \mathcal{D}_t\} \times 1\{d_{c_j,t} \notin \mathcal{D}_t\}$$

$$H^3_{ij,t} = 1\{d_{c_i,t} \notin \mathcal{D}_t\} \times 1\{d_{c_j,t} \in \mathcal{D}_t\}$$
$$H^4_{ij,t} = 1\{d_{c_i,t} \notin \mathcal{D}_t\} \times 1\{d_{c_j,t} \notin \mathcal{D}_t\} \quad (8)$$

These indicators allow us to evaluate whether the effects of FDI differ across combinations of source and recipient development status. H1 and H4 represent indicators for similar node structure within a dyad between two developed nodes and two less developed nodes respectively. Here, both the capital network connections between FDI recipient and FDI origin nodes, and knowledge network connections between citation origin and citation recipient nodes represent network connections between two similar nodes in terms of economic development. Conversely, H2 and H3 represent dyads involving one developed node and another less developed node. In the case of H2, the observed node i is the developed node, and node j is less developed. Dyads characterized by H2 represent network relationships where a developed node cites a patent in and receives FDI from a less developed node. H3 mirrors this pattern in that dyads characterized by H3 represent connection where a less developed node cites a patent in and received FDI from a developed node.

Estimates associated with each dyad type should be interpreted in relative terms. For example, if an estimated coefficient associated with H1 is larger than H2, developed nodes are more likely to form connections with other nodes with a similar level of development. This means that developed nodes receive more FDI and cite the patents associated with other developed nodes more frequently than less developed nodes. The same holds for H3 and H4, such that a relatively large estimate attached to H3 indicates less developed nodes are more likely to form connections with more developed nodes[5].

Incorporating these interactions into the network formation specification yields:

$$D_{ij,t} = \alpha + \theta_1 \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + \theta'_{n+2}\left(\omega^{FDI}_{c_j \to c_i, t-1} \cdot H_{ij,t}\right) + \rho' H_{ij,t} + X'_{ij,t}\beta + \lambda_{ij} + \eta_t + \varepsilon_{ij,t} \quad (9)$$

where θ_{n+2} captures how the relationship between capital-network participation and knowledge-network formation varies across development groups. The total effect of capital-network participation for a given group is therefore given by $\theta_1 + \theta_{n+2}$.

Analogous specifications are estimated for knowledge-network intensity:

$$y_{ij,t} = \alpha + \theta_1 \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + \theta'_{n+2}\left(\omega^{FDI}_{c_j \to c_i, t-1} \cdot H_{ij,t}\right) + \rho' H_{ij,t} + X'_{ij,t}\beta + \lambda_{ij} + \eta_t + \varepsilon_{ij,t} \quad (10)$$

[5] The relative difference between magnitudes of H2 and H3 should be interpreted with caution. Since substantial structural differences may differentiate developed and developing countries, underlying terminal node (node j) structure is not inherently comparable. Comparison in this setting can only be made under the assumption that network behavior is similar between developed and developing nodes.

$$\mathbb{E}\left[y_{ij,t} \mid X_{ij,t}, \lambda_{ij} \right] \tag{11}$$
$$= \mathrm{G}\left(\alpha + \theta_1\, \omega^{FDI}_{c_j \to c_i, t-1} + \theta_2 \delta^{ML}_{ij,t-1} + \theta'_{n+2}\left(\omega^{FDI}_{c_j \to c_i, t-1} \cdot H_{ij,t}\right) + \rho' H_{ij,t} + X'_{ij,t}\beta + \delta' \overline{X_{\iota J}} + \eta_t\right)$$

In this setting, the coefficients θ_1 and θ_{n+2} describe how participation in the capital network translates into participation in the knowledge network. If stronger capital-network ties increase the relative importance of specific knowledge-network edges, the resulting network becomes more concentrated around particular knowledge sources. Conversely, a negative effect implies that knowledge sourcing becomes more dispersed, indicating that recipient industries draw knowledge from a broader set of foreign partners.

The coefficient on $\delta^{ML}_{ij,t-1}$ retains its interpretation as a measure of structural similarity. Negative estimates imply that knowledge relationships are more likely among nodes with otherwise common counterparts in the joint capital and knowledge network, whereas positive estimates suggest that knowledge exchange occurs across structurally distant parts of the network graph.

4.4. Identification

A key identification concern is the potential simultaneity between capital and knowledge network layers. We address this issue by utilizing a lagged capital-flow structure. The share of FDI at time *t-1* reflects investment decisions based on an earlier information set, whereas citation outcomes at time *t* capture realized knowledge flows. Under the assumption that contemporaneous innovation shocks are not fully anticipated by prior investment decisions, lagged FDI participation can be treated as predetermined with respect to observed innovation outcomes.

The difference in aggregation between capital and knowledge layers provides useful identifying variation. FDI is observed at the country level and therefore reflects broad investment relationships between economies, while patent citations are observed at the country-industry level and capture industry-specific knowledge sourcing decisions. This distinction reduces concerns that the estimated relationship is driven by common industry-level shocks affecting both capital and innovation outcomes simultaneously. At the same time, it allows us to examine how aggregate capital relationships influence the allocation of knowledge flows across individual industries.

Accordingly, standard errors are clustered at the source-recipient country-pair level, which corresponds to the level at which FDI participation is measured. This allows for arbitrary correlation in outcomes among industries exposed to the same bilateral investment relationship. As robustness checks,

we additionally report results using two-way clustering by source and recipient country, and clustering at the country-pair–industry level to accommodate alternative patterns of dependence in the error structure. More broadly, our estimates should be interpreted as conditional structural relationships between the organization of the capital network and the organization of the knowledge network rather than as fully causal treatment effects of FDI. The inclusion of lagged network measures, dyad effects, and multilayer codegree controls substantially reduce concerns related to simultaneity, endogenous partner selection, and persistent network heterogeneity.

Finally, both FDI and citation measures are defined as participation shares within their respective networks. This normalization embeds each dyadic relationship within the broader network structure, such that increases in the importance of one partner necessarily imply reductions in the relative importance of others. Consequently, the analysis identifies how changes in the relative importance of investing partners translate into changes in the relative importance of knowledge partners. This approach reduces the influence of country size and aggregate trends and allows the analysis to focus on the reallocation of capital and knowledge flows across competing network relationships. The resulting estimates should therefore be interpreted as reallocations within global capital and knowledge networks rather than changes in aggregate levels of investment or innovation.

5. Results

5.1. Baseline Results

Table 1. Summary Statistics – Dependent and Independent Variables

Variable Name (Normalized)	Mean	S.D.	Min.	Max.
$Form$	0.026	0.159	0.000	1.000
$y_{ij,t}$	0.006	0.031	0.000	1.000
$\omega^{FDI}_{c_j \to c_i, t-1}$	0.011	0.031	0.000	1.000
$H^1_{ij,t}$	0.735	0.441	0.000	1.000
$H^2_{ij,t}$	0.136	0.343	0.000	1.000
$H^3_{ij,t}$	0.115	0.319	0.000	1.000
$H^4_{ij,t}$	0.013	0.115	0.000	1.000
$\delta^{ML}_{ij,t-1}$	0.068	0.079	0.016	1.000
Intensity by Dyad Development				
$y_{ij,t} \times H^1_{ij}$	0.006	0.027	0.000	1.000
$y_{ij,t} \times H^2_{ij}$	0.015	0.055	0.000	1.000
$y_{ij,t} \times H^3_{ij}$	0.025	0.083	0.000	1.000
$y_{ij,t} \times H^4_{ij}$	0.074	0.155	0.000	1.000
Similarity by Dyad Development				
$\delta^{ML}_{ij,t-1} \times H^1_{ij,t}$	0.065	0.067	0.016	1.000
$\delta^{ML}_{ij,t-1} \times H^2_{ij,t}$	0.053	0.066	0.016	1.000
$\delta^{ML}_{ij,t-1} \times H^3_{ij,t}$	0.098	0.128	0.016	1.000
$\delta^{ML}_{ij,t-1} \times H^4_{ij,t}$	0.121	0.139	0.018	1.000
Observations (N)	2,579,917	-	-	-
Countries	85	-	-	-
Industries	31	-	-	-
Years	2010-2019	-	-	-

First, the formation of new knowledge network edges accounts for approximately 2.6 percent of all observations. Since our sample period is relatively modern, a substantial number of cross-border citations have already been formed globally, which explains the relatively small number of formation events between 2010-2019. Additionally, since knowledge flows are not constrained regionally, a substantial number of existing connections per observable node is expected, which helps explain the low average value of $y_{ij,t}$. Assuming a fixed or slow-moving number of cross-border citations, and increase in the number of existing connections for any node i will further decrease this value. On average, any connection to any node j represents approximately 0.6 percent of total knowledge flows available to node i.

Next, approximately 73.5 percent of all observable dyads can be characterized as relationships between two developed nodes, while only 6.8 percent of all dyads are relationships between two less developed nodes. While this is consistent with observable innovation and investment activity globally, it should be considered when interpreting our baseline results. Roughly 25 percent of all observations contain dyad level heterogeneity, where 13.6 percent of all dyads are characterized as a developed origin

and developing destination node, and 11.5 percent are characterized as a developing origin and developed destination node.

Finally, to aid in the interpretation of results containing similarity from equation (4) we include descriptive statistics for node similarity by dyad development parings. Within our sample, the similarity of two developed nodes is relatively small. This suggests that terminal node structure across observed developed nodes varies, such that developed nodes do not necessarily seek to make connections with the same set of counterparts nodes. Conversely, similarity between two less developed nodes (as indicated by H4) is relatively high on average, which suggests that unlike developed nodes, less developed countries are more likely to share connections with a similar set of neighbors. This baseline is consistent with the existence of innovative hubs, where many nodes within the overall knowledge network rely on the same large innovative nodes.

Variance in similarity scores is qualitatively determined more strongly by counterpart node development status, rather than an observed nodes own development status. Both H2 and H4 represent dyads with an observed node (developed and less developed respectively) is connected to a less developed counterpart. Here, the standard deviation of overall similarity is relatively high compared to dyads which involve a developed counterpart. This suggests that less developed nodes do not necessarily follow a similar approach in network participation, and that economic characteristics outside of development status alone are more likely to govern how connections are formed. This emphasizes our earlier argument, in that the relative effects of FDI on cross-border citations should not be interpreted as a global average, and rather through the lens of node specific characteristics. A direct comparison and a global outcome is therefore challenging to present within a network environment, and only comparable across nodes if a common behavioral assumption is maintained. Since this is generally unlikely within a global setting, we reserve interpretation across later results in relative terms subject to directionally. This necessitates the independent estimation and discussion of the effects of FDI on global innovation by dyad type.

Table 2: Formations of new cross-border patent citations connection: Overall Sample (Linear Probability Model)

	(1) $Form_{ij,t}$	(2) $Form_{ij,t}$	(3) $Form_{ij,t}$	(4) $Form_{ij,t}$
$\omega^{FDI}_{c_j \to c_i, t-1}$	0.170^{***}	0.195^{***}	0.203^{***}	0.094^{***}
	(0.009)	(0.009)	(0.009)	(0.017)
$\delta^{ML}_{ij,t-1}$	-	0.123^{***}	0.135^{***}	0.029^{**}
		(0.005)	(0.005)	(0.013)
Constant	0.039^{***}	0.032^{***}	0.031^{***}	0.035^{***}

	(0.000)	(0.000)	(0.000)	(0.001)
Controls	-	✓	✓	✓
Year-FE	-	-	✓	✓
Dyad-FE	-	-	-	✓
Observations	1041852	1041852	1041852	977124
R-squared	0.001	0.002	0.005	0.267

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $Form_{ij,t}$ describes the first observed cross-border citation activity from a focal node to its counterpart conditional on the lack of this activity in $t-1$. Sufficient activity for link formation is defined by a threshold of innovative activity above the 10th percentile globally.

Table 3: Formations of new cross-border patent citations connection: Overall Sample (Logit Average Marginal Effects) - Robustness

	(1) $Form_{ij,t}$	(2) $Form_{ij,t}$	(3) $Form_{ij,t}$
$\omega^{FDI}_{c_j \to c_i, t-1}$	0.104^{***}	0.116^{***}	0.130^{***}
	(0.004)	(0.004)	(0.004)
$\delta^{ML}_{ij,t-1}$	-	-	0.108^{***}
			(0.003)
Controls	-	-	✓
Year-FE	-	✓	✓
Observations	1041852	964362	964362

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $Form_{ij,t}$ describes the first observed cross-border citation activity from a focal node to its counterpart conditional on the lack of this activity in $t-1$. Sufficient activity for link formation is defined by a threshold of innovative activity above the 10th percentile globally.

Based on the results outlined in Table 2, the relative importance of FDI is associated with a modest increase in the probability of observing a new knowledge network connection. While the magnitude of this effect decreases when dyad fixed effects are introduced to the specification as shown in column (4), the effect remains positive and significant. Conceptually, as the intensity of inbound FDI increases for any observed node within the network, and conditional on the absence of a pre-existing knowledge network relationship, industries are more likely to form new connections through cross-border citations. In this setting, a sufficiently large transmission of knowledge embodied in the relative increase of FDI increases the likelihood that an FDI recipient begins to leverage a counterpart's existing knowledge base. While formation events are relatively rare within our empirical setting and represent less than 3% of all observations, enough of these events are associated with an increase in FDI exposure relative to all other sources. As industries can form knowledge connections freely with global counterparts, this association is suggestive of a dyad specific dynamic rather than an overall increase in innovation activity regardless of capital network relationships.

The coefficient associated with network similarity is also positive in this setting. While the general purpose of this measure is to capture prior network structure and how it may affect subsequent network dynamics, our results suggest that formation events are more likely to occur between two

relatively similar country-industries. As similarity within a dyad increases, this effect becomes more pronounced. Recall from the construction, that $\delta_{ij,t-1}^{ML}$ captures second order relationships within the network. If the similarity of two nodes is relatively high, both industries share a similar set of second order neighbors and occupy similar structural regions of the overall graph. This means that for an observed country-industry, its existing knowledge network defined by the direct sources of knowledge and the knowledge of their subsequent connections resembles that of the counterpart. Formation can thus be partially characterized as the ease with which an industry makes new connections, which is expected to be reasonably high when two nodes share similar connections and pre-existing patterns of knowledge acquisition.

Table 4: Cross-border citation intensity: Overall Sample (Fixed Effects Framework)

	(1) $y_{ij,t}$	(2) $y_{ij,t}$	(3) $y_{ij,t}$	(4) $y_{ij,t}$
$\omega_{c_j \to c_i, t-1}^{FDI}$	0.172***	0.164***	0.164***	0.034***
	(0.005)	(0.005)	(0.005)	(0.007)
$\delta_{ij,t-1}^{ML}$	-	-0.038***	-0.038***	-0.001***
		(0.001)	(0.001)	(0.000)
Constant	0.004***	0.006***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	-	✓	✓	✓
Year-FE	-	-	✓	✓
Dyad-FE	-	-	-	✓
Observations	1041852	1041852	1041852	977124
R-squared	0.048	0.055	0.055	0.655

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $y_{ij,t}$ describes the relative intensity of cross-border citations conditional on the existence of knowledge network connections greater than zero as indicated by a threshold of innovative activity at the 10th percentile globally.

Table 5: Cross-border citation intensity: Overall Sample (Fractional Response Average Marginal Effects) - Robustness

	(1) $Form_{ij,t}$	(2) $Form_{ij,t}$	(3) $Form_{ij,t}$
$\omega_{c_j \to c_i, t-1}^{FDI}$	0.031***	0.027***	0.027***
	(0.001)	(0.001)	(0.001)
$\delta_{ij,t-1}^{ML}$	-	-0.165***	-0.167***
		(0.002)	(0.002)
Controls	-	✓	✓
Year-FE	-	-	✓
Observations	1041852	1041852	1041852

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $y_{ij,t}$ describes the relative intensity of cross-border citations conditional on the existence of knowledge network connections greater than zero as indicated by a threshold of innovative activity at the 10th percentile globally.

Like network formation, the relative intensity of FDI is associated with the relative intensity of knowledge network connections. Based on the results outlined in Table 4, the intensity of any given connection measured through cross-border citations increases with FDI, suggesting that both layers of the network operate under similar conditions. The magnitude of these effects is relatively modest, and decreases substantially when dyad fixed effects are introduced to the specification.

Contrary to formation, however, pre-existing network similarity and structure is associated with a decrease in knowledge connection intensity. Similarity in this setting likely represents the amount of available knowledge for each observed node. Two knowledge bases which overlap may form new connections more easily but contain an intersection which introduces redundancy to the network. Based on the results of column (4), while the magnitude of this negative effect is small, innovative intensity concentrates away from connections which represent redundant information, and toward connections formed between two less similar nodes. This result also suggests selection occurs across layers within the network. Should the ease with which nodes form knowledge network connections and the intensity of those connections follow a similar pattern and direction, mechanical relationships would be more likely. This is not the case across our baseline results.

5.2. Heterogeneity based on Developmental status

Based on the results of Table 6, the effect of the relative intensity of FDI varies by dyad type. While the overall effect of FDI is positive across all types (columns (5-8)), the probability of new link formation is substantially higher when the observed focal node is developed, and the counterpart node is less developed (H2) compared to all other dyad types. In fact, relative to dyads with a less developed focal node, the probability of link formation when the FDI recipient country is developed is approximately 3-5x more likely. Across all dyad types however, the effect of similarity is consistent with our baseline results in that two nodes with a relatively high similarity across connected neighbors are more likely to form a new knowledge network linkage when one did not exist in the previous period.

When assessing the effect of each dyad type independently, new knowledge network connections are less likely to occur when both nodes are developed (H1). This in combination with how similarity affects intensity, supports our earlier interpretation about knowledge overlap, in that two nodes with similar knowledge bases introduce redundancy to the network at a higher rate than those with less closely related knowledge sources. The broader pattern presented in Table 6 should be interpreted through the lens of absorptive capacity. Countries with a high absorptive capacity can likely more readily implement technologies and best practices transmitted through FDI and begin incorporating this content into subsequent innovative activity relative to nodes with a lower absorptive capacity.

The results of Table 7 which assess the impact of FDI on knowledge network connection intensity, suggest that FDI is associated with a positive effect on intensity broadly across all development types. When estimating the effect of each dyad type independently (columns (1-4)), the relative intensity of FDI increases the intensity of directed cross-border citations. The magnitude of this effect is increased for dyads which involves a less developed focal node (H3 and H4). Interactions provide a similar pattern.

Relative to the overall network, the effect associated with dyads which contain two developed nodes (H1) is negative, while H2-H4 are positive. Overall, these results suggest that heterogeneity across development levels primarily affects the strength of the overall effect rather than its direction. Similar to our baseline specification, the relationship between the capital and knowledge network layers is positive regarding overall intensity.

Additionally, the effect of prior network structure as captured through similarity, matches our baseline results. Similarity is associated with a decrease in intensity across all development pairings, which suggests that knowledge sourcing becomes concentrated across connections which do not share a relatively large set of overlapping second order connections. As previously, a possible interpretation is that less developed nodes rely on similar sources of knowledge to bolster existing technological know-how while developed focal nodes can allocate innovative activity toward differentiated sources of knowledge, and more freely explore previously less impactful regions of the global knowledge network.

Table 6: Heterogeneity in formation of Cross border citation relation. (LPM)

	Subsample analyses of heterogeneity				Interaction terms to capture heterogeneity			
	H1	H2	H3	H4	H1	H2	H3	H4
$\omega^{FDI}_{c_j \to c_i, t-1}$	0.203***	0.604***	0.137***	0.271**	0.148***	0.199***	0.199***	0.194***
	(0.011)	(0.111)	(0.016)	(0.118)	(0.015)	(0.009)	(0.011)	(0.009)
$\delta^{ML}_{ij,t-1}$	0.119***	0.125***	0.184***	0.239***	0.125***	0.117***	0.133***	0.123***
	(0.005)	(0.012)	(0.023)	(0.054)	(0.005)	(0.005)	(0.005)	(0.005)
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	0.057***	-	-	-
					(0.019)			
H^1	-	-	-	-	-0.016***	-	-	-
					(0.001)			
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	0.402***	-	-
						(0.111)		
H^2	-	-	-	-	-	0.014***	-	-
						(0.001)		
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	-	-0.066***	-
							(0.020)	
H^3	-	-	-	-	-	-	0.015***	-
							(0.001)	
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	-	-	0.076
								(0.118)
H^4	-	-	-	-	-	-	-	0.019***
								(0.003)
Constant	0.030***	0.044***	0.043***	0.042***	0.045***	0.031***	0.030***	0.032***
	(0.000)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	852375	77512	106119	5846	1041852	1041852	1041852	1041852
R-squared	0.002	0.003	0.002	0.009	0.003	0.002	0.002	0.002

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $Form_{ij,t}$ describes the first observed cross-border citation activity from a focal node to its counterpart conditional on the lack of this activity in $t-1$. Sufficient activity for link formation is defined by a threshold of innovative activity above the 10th percentile globally. Columns (1-4) present results using a linear probability model on samples by dyad development pairing (e.g. column (1) sample includes dyads where both nodes are developed (H1)) Columns (5-8) introduce interactions based on dyad development indicator (H1-H4).

Table 7: Heterogeneity in Intensity of Cross border citation relation. (Linear estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$	$y_{ij,t}$
$\omega^{FDI}_{c_j \to c_i, t-1}$	0.141***	0.304***	0.177***	1.097***	0.202***	0.162***	0.148***	0.162***
	(0.006)	(0.054)	(0.011)	(0.271)	(0.010)	(0.005)	(0.006)	(0.005)
$\delta^{ML}_{ij,t-1}$	-0.041***	-0.004***	-0.105***	0.018**	-0.038***	-0.038***	-0.037***	-0.039***
	(0.001)	(0.000)	(0.004)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-0.061***	-	-	-
					(0.011)			
H^1	-	-	-	-	-0.001***	-	-	-
					(0.000)			
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	0.134**	-	-
						(0.054)		
H^2	-	-	-	-	-	-0.002***	-	-
						(0.000)		
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	-	0.034***	-
							(0.012)	
H^3	-	-	-	-	-	-	0.003***	-
							(0.000)	
$\omega^{FDI}_{c_j \to c_i, t-1} \times H^1$	-	-	-	-	-	-	-	0.261***
								(0.059)
H^4	-	-	-	-	-	-	-	0.002***
								(0.000)
Constant	0.030***	0.044***	0.043***	0.042***	0.045***	0.031***	0.030***	0.032***
	(0.000)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	852375	77512	106119	4287	1041852	1041852	1041852	1041852
R-squared	0.043	0.079	0.066	0.589	0.057	0.055	0.057	0.056

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the dyad level. $y_{ij,t}$ describes the relative intensity of cross-border citations conditional on the existence of knowledge network connections greater than zero as indicated by a threshold of innovative activity at the 10th percentile globally. Columns (1-4) present results using samples by dyad development pairing (e.g. column (1) sample includes dyads where both nodes are developed (H1)). Columns (5-8) introduce interactions based on dyad development indicator (H1-H4)

6. Conclusions and Policy Implications

We investigate the effect of FDI on knowledge networks by characterizing the capital network formed by international investment relationships and the knowledge network formed by cross-border patent citations as distinct layers within the same multilayer network. We construct a measure of network similarity using a supra-adjacency matrix to account for prior network structure. Finally, we address heterogeneity within the capital and knowledge network layers using development status to better understand how these relationships vary across countries.

Our preliminary results find that FDI supports both the formation of new knowledge network relationships and increases the relative importance of existing relationships between the FDI recipient and FDI origin countries. After accounting for prior network structure, link formation is more likely between nodes with similar sets second-order network relationships. Conversely, network similarity is associated with decreased intensity along existing knowledge-network connections. Together, these results suggest that common network structure may facilitate the formation of new relationships while knowledge sourcing shifts toward less redundant sources of information.

The effect of FDI on knowledge-network formation varies substantially across development pairings, with particularly large effects for some dyads involving developed recipient nodes. Conversely, the effect of FDI on the intensity of existing knowledge-network connections is generally larger for dyads involving less developed focal nodes. These results suggest that development status primarily affects the magnitude and allocation of responses to FDI rather than the overall direction.

We plan to extend this project by strengthening identification and by introducing a mechanism analysis based on absorptive capacity. A central endogeneity concern within our empirical setting arises from the source of FDI fluctuations. Although our current framework uses lagged information and prior network structure, we cannot assert that changes in FDI reflect economic conditions which do not affect subsequent innovative activity. Therefore, we seek additional variation in FDI that can strengthen identification. We also plan to directly measure absorptive capacity to investigate the heterogeneity discussed above, as countries and industries better positioned to implement knowledge and technologies embodied in FDI may respond differently to increased foreign investment.

References

Acemoglu, D., Akcigit, U., & Kerr, W. (2016). Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, 30(1), 273–335. https://doi.org/10.1086/685961

Acharya, V. V., & Subramanian, K. V. (2009). Bankruptcy codes and innovation. *The Review of Financial Studies*, *22*(12), 4949-4988.

Ahn, J., Kim, C., Li, N., & Manera, A. (2026). Knowledge diffusion through FDI: Worldwide firm-level evidence. *Journal of International Economics*, 104205. https://doi.org/10.1016/j.jinteco.2025.104205

Aitken, B. J., & Harrison, A. E. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. *American Economic Review*, 89(3), 605–618. https://doi.org/10.1257/aer.89.3.605

Adarov, A. (2021). *Interactions between global value chains and foreign direct investment: A network approach* (No. 204). wiiw Working Paper.

Amiti, M., & Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. *American Economic Review*, 97(5), 1611–1638. https://doi.org/10.1257/aer.97.5.1611

Antràs, P. (2020). *De-globalisation? Global value chains in the post-COVID-19 age* (NBER Working Paper No. 28115).

Antràs, P., & Chor, D. (2013). Organizing the global value chain. *Econometrica*, 81(6), 2127–2204. https://doi.org/10.3982/ECTA10813

Arora, A., Belenzon, S., & Sheer, L. (2021). Knowledge spillovers and corporate investment in scientific research. *American Economic Review*, 111(3), 871–898. https://doi.org/10.1257/aer.20171742

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, 86(3), 630–640.

Auerbach, E. (2022). Testing for differences in stochastic network structure. *Econometrica*, 90(3), 1205–1223. https://doi.org/10.3982/ECTA18624

Balland, P.-A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies*, 53(9), 1252–1268.https://doi.org/10.1080/00343404.2018.1437900

Balland, P.-A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P. A., Rigby, D. L., & Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3), 248–254. https://doi.org/10.1038/s41562-019-0803-3

Barbosa, S., Sáiz, P., & Zofío, J. L. (2024). The emergence and historical evolution of innovation networks: On the factors promoting and hampering patent collaboration in technological lagging economies. *Research Policy*, 53(5), 104990. https://doi.org/10.1016/j.respol.2024.104990

Bettarelli, L., & Resmini, L. (2022). The determinants of FDI: A new network-based approach. *Applied Economics*, 54(45), 5257-5272.

Bloom, N., Schankerman, M. and Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. *Econometrica*, *81*(4), pp.1347-1393.

Branstetter, L. G. (2001). Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the U.S. and Japan. *Journal of International Economics*, 53(1), 53–79. https://doi.org/10.1016/S0022-1996(00)00069-4

Branstetter, L. G. (2006). Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. *Journal of International Economics*, 68(2), 325–344. https://doi.org/10.1016/j.jinteco.2005.06.006

Branstetter, L. G., Fisman, R., & Foley, C. F. (2006). Do stronger intellectual property rights increase international technology transfer? Empirical evidence from U.S. firm-level panel data. *Quarterly Journal of Economics*, 121(1), 321–349. https://doi.org/10.1162/qjec.2006.121.1.321

Cai, J., Li, N., & Santacreu, A. M. (2022). Knowledge diffusion, trade, and innovation across countries and sectors. *American Economic Journal: Macroeconomics*, 14(1), 104–145. https://doi.org/10.1257/mac.20180398

Castellacci, F. (2011). Closing the technology gap? *Review of Development Economics*, 15(1), 180–197. https://doi.org/10.1111/j.1467-9361.2010.00593.x

Charbonneau, K. B. (2017). Multiple fixed effects in binary response panel data models. *Econometrics Journal*, 20(3), S1–S13. https://doi.org/10.1111/ectj.12093

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, 39(5), 859–887. https://doi.org/10.1016/0014-2921(94)00100-E

Coe, D. T., Helpman, E., & Hoffmaister, A. W. (1997). North–South R&D spillovers. *Economic Journal*, 107(440), 134–149. https://doi.org/10.1111/1468-0297.00146

Correani, L., Garofalo, G., & Pugliesi, S. (2014). R&D cooperation in regular networks with endogenous absorptive capacity. *Review of Network Economics*, 13(2), 191–226. https://doi.org/10.1515/rne-2014-0011

Cowan, R., & Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8), 1557–1575. https://doi.org/10.1016/j.jedc.2003.04.002

de Paula, Á. (2020). Econometric models of network formation. *Annual Review of Economics*, 12, 775–799. https://doi.org/10.1146/annurev-economics-081919-021021

de Paula, Á. (2017). Econometrics of network models. In *Advances in Economics and Econometrics: Theory and Applications*, Eleventh World Congress (pp. 268-323). Cambridge: Cambridge University Press.

DeBlieck, A., & Lahiri, B. (2026). From Hi-Tech Investment to Medium-Skill Employment: How FDI, Global Value Chains, and Intellectual Property Rights Shape Labor Markets. *Economic Modelling*, 107693.

Eaton, J., & Kortum, S. (1996). Trade in ideas: Patenting and productivity in the OECD. *Journal of International Economics*, 40(3–4), 251–278. https://doi.org/10.1016/0022-1996(95)01407-1

Engelbrecht, H. J. (1997). International R&D spillovers, human capital and productivity in OECD economies. *European Economic Review*, 41(8), 1479–1488. https://doi.org/10.1016/S0014-2921(97)00012-3

Engelbrecht, H. J. (2002). Human capital and international knowledge spillovers in TFP growth of a sample of developing countries. *Applied Economics*, 34(7), 831–841. https://doi.org/10.1080/00036840110058919

Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3), 443–475. https://doi.org/10.2189/asqu.52.3.443

Glass, A. J., & Saggi, K. (2002). Multinational firms and technology transfer. *Scandinavian Journal of Economics*, 104(4), 495–513. https://doi.org/10.1111/1467-9442.00308

Goldsmith-Pinkham, P., & Imbens, G. W. (2013). Social networks and the identification of peer effects. *Journal of Business & Economic Statistics*, 31(3), 253–264. https://doi.org/10.1080/07350015.2013.801251

Graham, B. S. (2017). An econometric model of network formation with degree heterogeneity. *Econometrica*, 85(4), 1033–1063. https://doi.org/10.3982/ECTA14042

Griffith, R., Harrison, R., & Van Reenen, J. (2006). How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technology sourcing. *American Economic Review*, *96*(5), 1859-1875.

Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics*, 94, S29–S47. https://doi.org/10.2307/3440244

Guadalupe, M., Kuzmina, O., & Thomas, C. (2012). Innovation and foreign ownership. *American Economic Review*, 102(7), 3594–3627. https://doi.org/10.1257/aer.102.7.3594

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER Patent Citation Data File: Lessons, insights and methodological tools* (NBER Working Paper No. 8498).

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to R&D. In *Handbook of the Economics of Innovation* (Vol. 2, pp. 1033–1082). Elsevier. https://doi.org/10.1016/S0169-7218(10)02008-3

Haskel, J. E., Pereira, S. C., & Slaughter, M. J. (2007). Does inward foreign direct investment boost the productivity of domestic firms? *Review of Economics and Statistics*, 89(3), 482–496. https://doi.org/10.1162/rest.89.3.482

He, Y., & Maskus, K. E. (2012). Southern innovation and reverse knowledge spillovers: A dynamic FDI model. *International Economic Review*, 53(1), 279–302. https://doi.org/10.1111/j.1468-2354.2011.00683.x

Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of financial economics*, *112*(1), 116-135.

Jaffe, A. B., Henderson, R., & Trajtenberg, M. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3), 577–598. https://doi.org/10.2307/2118401

Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, Citations, and Innovations: A Window on the Knowledge Economy*. MIT Press.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? *American Economic Review*, 94(3), 605–627. https://doi.org/10.1257/0002828041464605

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review*, 92(1), 120–142. https://doi.org/10.1257/000282802760015630

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3), 752–782. https://doi.org/10.1257/0022051042177685

Keller, W. (2021). *Knowledge spillovers, trade, and FDI* (NBER Working Paper No. 28739). https://doi.org/10.3386/w28739

Keller, W., & Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth. *Review of Economics and Statistics*, 91(4), 821–831. https://doi.org/10.1162/rest.91.4.821

Kesidou, E., & Romijn, H. (2008). Do local knowledge spillovers matter for development? *World Development*, 36(10), 2004–2028. https://doi.org/10.1016/j.worlddev.2007.10.003

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., & Porter, M. A. (2014). Multilayer networks. *Journal of Complex Networks*, 2(3), 203–271. https://doi.org/10.1093/comnet/cnu016

König, M. D., Liu, X., & Zenou, Y. (2019). R&D networks: Theory, empirics, and policy implications. *Review of Economics and Statistics*, 101(3), 476–491. https://doi.org/10.1162/rest_a_00766

LaBelle, J., Martinez-Zarzoso, I., Santacreu, A. M., & Yotov, Y. V. (2023). *Cross-border patenting, globalization, and development* (CESifo Working Paper No. 10850). CESifo.

Lee, G. (2006). The effectiveness of international knowledge spillover channels. *European Economic Review*, 50(8), 2075–2088.https://doi.org/10.1016/j.euroecorev.2005.10.004

Liu, E., & Ma, S. (2021). *Innovation networks and R&D allocation* (NBER Working Paper No. 29607). https://doi.org/10.3386/w29607

Maggioni, M. A., & Uberti, T. E. (2009). Knowledge networks across Europe: Which distance matters? *Annals of Regional Science*, 43(3), 691–720.https://doi.org/10.1007/s00168-008-0250-7

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, 60(3), 531–542. https://doi.org/10.2307/2298123

Miguelez, E., & Moreno, R. (2018). Relatedness, external linkages and regional innovation in Europe. *Regional Studies*, 52(5), 688–701. https://doi.org/10.1080/00343404.2017.1282606

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, 111(10), 3328–3375.https://doi.org/10.1257/aer.20191277

Pan, S., & Chong, Z. (2023). Effects of FDI on trade among countries along the Belt and Road: A network perspective. *The Journal of International Trade & Economic Development*, 32(1), 84-103.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11(6), 619–632. https://doi.org/10.1002/(SICI)1099-1255(199611)11:6

Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*, 145(1–2), 121–133. https://doi.org/10.1016/j.jeconom.2008.05.009

Saggi, K. (2000). *Trade, foreign direct investment, and international technology transfer: A survey*. World Bank Policy Research Working Paper No. 2349.

Samani, H. A., Pour, A. S. F., Zare, M. H., & Shabani, Z. D. (2026). Investigating the Structure and Policy Implications of the Global FDI Network. *Journal of Economic Integration*, 41(2), 235-272.

Sembenelli, A., & Siotis, G. (2008). Foreign direct investment and mark-up dynamics: Evidence from Spanish firms. *Journal of International Economics*, 76(1), 107–115. https://doi.org/10.1016/j.jinteco.2008.03.005

Sheng, S. (2020). A structural econometric analysis of network formation games through subnetworks. *Econometrica*, 88(5), 1829–1858.https://doi.org/10.3982/ECTA13707

Sorenson, O., Rivkin, J. W., & Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, 35(7), 994–1017.https://doi.org/10.1016/j.respol.2006.05.002

Sultana, N., & Turkina, E. (2020). Foreign direct investment, technological advancement, and absorptive capacity: A network analysis. *International Business Review*, *29*(2), 101668.