Identifying FDI Knowledge Spillovers Using Innovation Networks: Evidence from China *

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Abstract

We examine knowledge spillovers along the innovation network, using detailed data on foreign direct investment (FDI) firms in China and global patent records. In particular, we construct a measure of FDI-embedded intermediate technology, using a *knowledge input–output (KIO) table* based on inter-field patent citations. Our results show that a 10% increase in FDI-embedded technology raises China's patent output by 7.9%. In comparison, the conventional production input–output (PIO) framework yields effects that are roughly half as large, and become statistically insignificant when PIO and KIO spillovers are considered jointly. Exploring the mechanisms, we find that FDI-embedded technology increases backward citations of source-country patents and technological similarity. These spillovers primarily occur through collaborative innovation rather than market transactions. Finally, spillovers are stronger when source countries have greater technological advantages and when technologies are more central to the innovation network.

Keywords: *FDI; knowledge spillover; innovation network*
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1 Introduction

Foreign direct investment (FDI) brings valuable capital and know-how to host countries, which is particularly important for developing countries with relatively backward technology. Consequently, whether and how FDI promotes technological progress in these countries has long been a central question to scholars and policy makers alike (Blomström and Kokko, 1998; Harrison and Rodríguez-Clare, 2010; Keller, 2021). However, knowledge spillovers can follow very different pathways than simply mirroring product flows. Conventional production-based input–output (**PIO**) measures, as often used in the existing literature,[1] might not fully reflect the knowledge linkages across sectors, limiting our understanding of the true spillover effects of FDI, leading to mixed and often contradictory evidence (Havranek and Irsova, 2011).[2] To identify knowledge spillovers more accurately, a new perspective that captures the structure of cross-sectoral linkages is necessary. The present paper attempts to take on this challenge. We examine how FDI knowledge spillovers propagate through the *innovation network*, rather than the production-based PIO linkages.

We argue that innovation networks, defined by knowledge dependencies across sectors, are a key channel for FDI-driven knowledge spillovers in host countries. A case from our sample clearly illustrates this mechanism. Appendix Table B1 reports the top 20 upstream sectors for the battery technology (H01M), based on both the innovation and production networks. The differences are notable. The innovation network (based on patent citation flows) shows that H01M draws heavily on upstream knowledge from fields such as H02J (electric power storage systems), C01B (non-metallic elements and compounds), B01J (catalytic processes and related apparatus), G01R (measuring electric variables), and G01N (material testing). In contrast, the production network identifies sectors such as C22C (metal alloys), B29C (plastic processing), and E06B (building elements), which have little direct relevance to H01M's technological progress. This comparison indicates that H01M's advancement depends primarily on upstream knowledge flows along technological trajectories rather than on material inputs in production. Thus, FDI in sectors such as energy storage, catalysis, and measurement, even without direct involvement in battery manufacturing, can shape the technological evolution of battery systems through innovation networks.

Our study examines the spillover effects of FDI-embedded intermediate technologies on innovation in China. China provides an ideal context for several reasons. First, since opening up in 1978, China has experienced sustained growth in FDI inflows and it is now

[1] This includes industry-level input–output linkages such as (Aitken and Harrison, 1999; Javorcik, 2004; Lu, Tao and Zhu, 2017), as well as firm-level supplier–customer relationships (Alfaro-Ureña, Manelici and Vasquez, 2022; Amiti, Duprez, Konings and Van Reenen, 2024).

[2] Early studies, such as Aitken and Harrison (1999) and Konings (2001), focus on horizontal spillovers within the same industry and often find negative effects. In contrast, Alvarez and López (2008) and Keller and Yeaple (2009) report positive impacts using data from Chile and the United States, respectively. Javorcik (2004) shifts the focus from horizontal to vertical spillovers and finds significant positive effects. Yet, even within vertical relationships, the magnitude of spillovers varies widely across upstream and downstream sectors.

among the world's top FDI destinations.[3] Second, China's innovation system has made great leaps. Before 1985, it had no formal patent regime; today, it rivals those of the U.S., Europe, and Japan.[4] Third, China offers comprehensive and accessible firm-level data of registrations and patents, making it possible to rigorously examine both the extent and the mechanisms of FDI-driven knowledge spillovers. Finally, China's accession to the World Trade Organization (WTO) brought a significant easing of FDI entry restrictions, providing a quasi-natural experiment for identifying the causal effects of FDI on innovation (Lu, Tao and Zhu, 2017; Eppinger and Ma, 2024; Liu, Qiu and Zhan, 2024).

We start by combining near-complete firm registration data on foreign-invested enterprises (FIEs) in China with global patent data and detailed Chinese patent records. In particular, we construct a technology-level measure of FDI-embedded intermediate technology. 'Intermediate technology' refers to knowledge embedded in upstream fields within the innovation network that supports downstream innovation activities, directly or indirectly. To measure knowledge flows, we employ observable indicators such as patent backward citations and technological similarity (Jaffe, Trajtenberg and Henderson, 1993), and construct a knowledge input–output (**KIO**) table from global patent citation data, following recent advances that map inter-field knowledge flows within innovation networks (Acemoglu, Akcigit and Kerr, 2016; Liu and Ma, 2021; Cai, Li and Santacreu, 2022; Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023; Davies, Kogler and Yang, 2023).[5]

We find that FDI-embedded intermediate technology significantly increases China's innovation output. Specifically, a 10% higher level of FDI-embedded intermediate technology in a given technology field leads to approximately 7.9% more granted invention patents in that field. In contrast, when relying on the PIO framework under a mirror specification, the effect size is nearly halved: the coefficient obtained from PIO spillovers (0.404) amounts to only about 51% of the KIO estimate (0.790). Moreover, once both channels are considered jointly, the estimated effects of PIO spillovers become much smaller and statistically insignificant, while the KIO effect remains strong and robust. These findings underscore that the benefits of FDI extend beyond production linkages, and are deeply embedded in the structural interconnections of the innovation network.

The findings withstand various robustness checks, including possible confounding factors, alternative measures of FDI-embedded intermediate technology, different innovation output metrics, and overseas patent counts, alleviating concerns over measurement and patent quality. Instrumental variable estimations remain stable across mapping thresholds, supporting the identification strategy. Our results are also robust to alternative estimation methods, exclusion of zero-patent values, and aggregation to broader technology

[3] Actual FDI utilization increased from $920 million in 1983 to over $100 billion annually since 2008 (source: Chinese National Bureau of Statistics, NBS).

[4] By the end of 2024, China held 4.756 million active domestic invention patents, becoming the first country to exceed 4 million. Source: Press conference on China's 2024 intellectual property progress, accessible at: https://www.gov.cn/lianbo/fabu/202501/content_6998991.htm.

[5] Since the seminal work of Jaffe, Trajtenberg and Henderson (1993), which uses backward citations to identify spatial knowledge spillovers, cross-border patent citations have been widely applied to trace international technology flows, advancing this literature significantly (MacGarvie, 2006; Nagaoka, Motohashi and Goto, 2010).

categories, confirming that FDI facilitates genuine technological knowledge spillovers.

Next, could the FDI-generated spillovers enhance Chinese firms' ability to learn from, absorb, and imitate foreign knowledge? We examine this mechanism through two complementary perspectives. First, we focus on explicit learning, captured by backward citations, and find that greater FDI-embedded intermediate technology from a foreign source significantly increases Chinese citations to that source's patents in the same field. This effect remains robust when aggregated to the technology level. Second, we analyze structural convergence in technological knowledge, and find that such FDI raises the technological similarity between China and the source country in the corresponding fields. It also increases China's technological similarity with innovation leaders, such as the U.S. Taken together, these results provide direct evidence of FDI knowledge spillovers.[6]

Further, we examine the specific channels of knowledge spillovers, which could be a significant empirical challenge (Javorcik, 2010). While the existing literature has focused on whether FDI generates knowledge spillovers, it offers limited insight into the underlying mechanisms and pathways. We classify the channels of FDI-induced knowledge flows into two types: market-based transfers (e.g., patent assignments, licensing) and interaction-based exchanges (e.g., joint patents). Using patent transaction and collaboration data from IncoPat, we find that FDI significantly increases patent assignments but not licensing, and it also significantly promotes collaborative innovation, with the effect persisting even after controlling for market-based transfers. These suggest that the observed knowledge spillovers are not solely driven by market-based technology transactions, highlighting the role of collaborative innovation in technological upgrading induced by FDI.

Finally, we test for heterogeneity by the technological advantages of the source country and the centrality of the recipient field in the global innovation network. Consistent with theory (Findlay, 1978; Liu and Ma, 2021), the effects are stronger for FDI from countries with a greater technological lead over China and in more central technology fields. These findings reinforce the idea that FDI facilitates knowledge spillovers primarily through the structure of the innovation network.

Our work contributes to several strands of literature. First, our study relates to the extensive empirical literature on FDI spillovers. Prior studies have largely examined whether FDI enhances host-country firms' productivity through horizontal (within-industry) and vertical (cross-industry) spillovers based on PIO linkages (Aitken and Harrison, 1999; Javorcik, 2004; Keller and Yeaple, 2009; Lu, Tao and Zhu, 2017; Alfaro-Ureña, Manelici and Vasquez, 2022; Gong, 2023; Amiti, Duprez, Konings and Van Reenen, 2024; Jiang, Keller, Qiu and Ridley, 2024; Olurotimi, Foltz and Traore, 2025).[7] While both channels are theoret-

[6] An alternative explanation is that openness improves the speed of knowledge transmission rather than spillovers arising from FDI technology. If that were the case, the lag time for knowledge diffusion from FDI source countries should fall. However, after controlling for industry characteristics and time-varying factors, we find that FDI-embedded intermediate technology has no significant effect on the lag in China's access to foreign knowledge. Therefore, changes in the speed of cross-border knowledge diffusion are not the main driver of our findings.

[7] The first empirical study of multinational corporations (MNCs) spillovers on host-country firm productivity dates back more than three decades (Caves, 1974), and the inquiry remains active (Barrios, Görg and Strobl, 2011). Horizontal spillovers, grounded in demonstration effects (Branstetter, 2001) and competition

ically plausible, evidence remains mixed. In China, provincial- or industry-level analyses generally find positive effects of FDI on technological progress (Cheung and Lin, 2004; Hu and Jefferson, 2009), though Lu, Tao and Zhu (2017) caution about potential negative impacts. More recent work highlights joint ventures as potential facilitators of knowledge transfer (Bai, Barwick, Cao and Li, 2020; Jiang, Keller, Qiu and Ridley, 2024; Ma and Zhang, 2024). We contribute to this literature by moving beyond traditional production networks to patent-based innovation networks. On this point, a closely related paper is Fons-Rosen, Kalemli-Ozcan, Sorensen, Villegas-Sanchez and Volosovych (2017), which incorporates technological structure into FDI spillover analysis by measuring technological closeness between domestic and foreign firms. Our paper constructs a directed and heterogeneous technology dependence network to capture FDI-induced international knowledge inflows, and provides direct evidence on both knowledge spillovers and learning processes in the host country.

Second, our research contributes to the literature on FDI and innovation by examining how foreign knowledge embedded in FDI diffuses across technology fields. Existing research has highlighted two main channels: competition, whereby FDI pressures domestic firms to innovate to maintain market position (e.g., Aghion, Blundell, Griffith, Howitt and Prantl, 2009), and knowledge spillovers, whereby foreign technologies are transferred to local firms (e.g., Chen, Jiang, Liang and Pan, 2022). Complementing this literature, we adopt a network-based perspective to trace FDI-induced international knowledge inflows to host countries and reveal the multiple channels (market-based transfers and interaction-based exchanges) through which cross-border knowledge transfer occurs.

Third, our study speaks to the literature on the drivers and micro-level mechanisms of international knowledge diffusion by highlighting the crucial role of FDI. While major technologies historically emerged in advanced countries and gradually spread to less developed countries (Comin and Hobijn, 2004), cross-border knowledge flows remain highly localized due to language barriers, institutional mismatches, and divergent patent systems (Jaffe, Trajtenberg and Henderson, 1993; Jaffe and Trajtenberg, 1999; Hegde, Herkenhoff and Zhu, 2023). The new growth theory underscores that openness through trade and investment enables countries to access a broader global knowledge base and sustain long-run growth (Grossman and Helpman, 1991; Coe and Helpman, 1995; Buera and Oberfield, 2020; Cai, Li and Santacreu, 2022), with multinational firms acting as key vehicles in overcoming cross-border barriers (Keller, 2021). We leverage comprehensive firm registration and patent data to identify how foreign knowledge embedded in FDI diffuses across technology fields within host-country innovation systems. Our analyses also confirm that developing countries benefit more from knowledge spillovers originating from technolog-

effects (Aitken and Harrison, 1999), are among the earliest mechanisms explored. However, as noted by Javorcik (2010), empirical evidence has long remained divided, partly because horizontal channels conflate learning with crowding-out effects, complicating identification. In contrast, Javorcik (2004) shifts attention to vertical spillovers, using industry-level PIO tables to examine how FDI exposure among upstream (suppliers) and downstream (buyers) firms relates to productivity. Her identification of backward linkages has become a benchmark for subsequent studies (e.g., Bajgar and Javorcik, 2020). However, this line of research often relies heavily on production linkages and typically constructs exposure measures only at the industry or regional level, limiting their capacity to capture knowledge diffusion at the technology level.

ically advanced countries (Findlay, 1978; Jiang, Keller, Qiu and Ridley, 2024).

Finally, we contribute to the growing literature on innovation networks, by integrating their role into the study of FDI-driven knowledge spillovers. Recent research underscores the need for a shift in perspective when analyzing such spillovers. Three features are particularly salient. (i) Technological progress is path-dependent, building on existing knowledge: fields with a richer stock of upstream knowledge tend to generate more downstream innovations (Acemoglu, Akcigit and Kerr, 2016). (ii) Knowledge spillovers are highly heterogeneous across sectors, with certain technologies contributing disproportionately to the broader innovation system (Cai and Li, 2018). (iii) The structure of innovation networks differs markedly from that of production networks, as the correlation between input–output relationships in production and those in knowledge is relatively weak (Liu and Ma, 2021; Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). This disconnect suggests that relying solely on PIO linkages may misidentify or underestimate FDI-induced knowledge spillovers. Building on this literature, our study extends the innovation network perspective to FDI, employing KIO tables (Liu and Ma, 2021; Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023; Davies, Kogler and Yang, 2023) to capture the heterogeneous interconnections across technologies and provide new evidence on how global knowledge embedded in FDI interacts with domestic innovation networks.

The remainder of the paper is structured as follows. Section 2 outlines the institutional background of China's FDI policy. Section 3 describes the data and key variables. Section 4 presents the empirical strategy, including the baseline model and instrumental variable approach. Section 5 reports the main results and key findings. Section 6 provides further evidence on the underlying mechanisms. Section 7 concludes.

2 Institutional Background

China's Reform and Opening-up in 1978 marked a major milestone in the country's integration into the global economy. In 1979, the enactment of the *Law of the People's Republic of China on Chinese-Foreign Equity Joint Ventures* formally established a legal framework for the entry of foreign capital. This was followed by the *Law on Wholly Foreign-Owned Enterprises* in 1986 and the *Law on Chinese-Foreign Contractual Joint Ventures* in 1988. Collectively known as the "Three FDI Laws," these regulations laid the legal foundation for different types of foreign invested enterprises (FIEs) and formed the institutional cornerstone of China's early FDI regime.

In this period, China began to experiment with foreign capital and gradually expanded its openness. In 1983, China's actual FDI inflows stood at just $920 million. By 1991, this figure had increased to $4.37 billion. In 1992, Deng Xiaoping's southern tour reaffirmed China's commitment to deepening reform and expanding openness, providing strong policy support for a surge in FDI inflows. That year, actual FDI reached $11.01 billion, representing an increase of more than 150% over the previous year and marking the first time China surpassed the $10 billion threshold. FDI inflows continued to grow, exceeding $27 billion by 1993 and maintaining a steady upward trend throughout the late 1990s.

China initially pursued FDI to address capital shortages. As domestic savings and foreign exchange reserves improved, the government gradually shifted its focus to attracting foreign technology. In 1995, the government introduced the *Catalogue for the Guidance of Foreign Investment Industries* (hereafter referred to as the "*Catalogue*") along with the *Provisional Regulations on Guiding the Direction of Foreign Investment*. These regulations classified industries open to foreign investment into four categories: encouraged, permitted, restricted, and prohibited. Projects involving high-tech or advanced technologies were designated as encouraged investments. Since 1998, actual inward FDI in high-tech industries has increased sixteenfold, reaching 23.5% of total FDI by 2018. Over 2,000 multinational corporations have established regional headquarters and R&D centers in China.[8]

We construct our instrumental variable using the 2002 revision of the *Catalogue*. In response to its WTO commitments, China pledged to further open its markets, making substantial concessions in areas such as tariff reductions and foreign investment access. In 2002, China overhauled the *Catalogue*, significantly loosening FDI restrictions across more than one-quarter of manufacturing industries (Liu, Qiu and Zhan, 2024). This was the first systematic revision of the *Catalogue* following China's WTO entry. Although there were subsequent revisions in 2004, 2007, 2011, 2015, and 2017, the 2002 update was a pivotal step in liberalization, sharply increasing FDI openness and triggering sustained growth in foreign investment inflows (Lu, Tao and Zhu, 2017). Over time, mainland China gradually emerged as one of the world's top FDI destinations. After a brief adjustment during the 2008 global financial crisis, China's actual FDI inflows stabilized above $100 billion annually.

A substantial body of anecdotal evidence suggests that FDI carrying intermediate technologies has generated meaningful knowledge spillovers for Chinese domestic firms. One example is ZEISS, a leading German supplier of optical and precision metrology technologies, which has had a significant spillover effect through its investment activities in China. Since the early 2000s, ZEISS has established multiple production and technical service centers across China. Although its primary business does not directly serve battery manufacturing (H01M), the company has strong technological capabilities in high-end inspection, precision imaging, and materials testing (G01N). ZEISS has continuously innovated in equipment such as X-ray microscopes, CT-based non-destructive testing systems, and 3D surface profilers, embedding German metrology standards into China's battery industry. These technologies provide battery firms, such as CATL (Contemporary Amperex Technology Co., Ltd.), with reliable tools for quality control and R&D support, facilitating the diffusion of intermediate technologies into domestic innovation processes.[9]

[8]Source: Special lecture series of the Standing Committee of the 13th National People's Congress, available at: http://www.npc.gov.cn/zgrdw/npc////xinwen/2019-02/20/content_2071908.htm.

[9]Source: https://d1ev.com/kol/209799.

3 Data and Variable Construction

3.1 Data

We draw on three main data sources: firm-level registration records of FIEs in China, global patent datasets, and detailed records of patent assignments, licensing agreements, and joint patent applications involving FIEs operating in China. Our empirical analysis covers the period from 1996 to 2016. This section provides a brief overview of the data, with further details on data processing available in Appendix A.

3.1.1 FIEs in China

Firm-level data on FIEs come from the Comprehensive Management Platform for Foreign Investment of the Chinese Ministry of Commerce (MOFCOM).[10] This dataset includes all registered FIEs listed on the platform prior to 2019, providing detailed information such as firm name, address, establishment date, industry classification, type of foreign investment, and ownership structure, along with the names of investors, their country or region of origin, investment amount, and currency. Under the regulatory framework, all FIEs established in China were required to register or obtain approval from local and central commerce departments.[11] The resulting data were consolidated by MOFCOM, making the FIE registration records in this study both authoritative and representative with strong institutional continuity. We validate our dataset against MOFCOM's official statistics on newly established FIEs (see Appendix Figure A1) and find that the two data sources closely align in trend over the 1990–2019 period.

We identify 824,565 FIEs established no later than 2019, involving FDI from 205 countries and regions across 1,364 four-digit China Industry Classification (CIC4) industries. Table 1 reports the geographic distribution of newly established FIEs in mainland China from 2000 to 2015. Hong Kong is the largest source, accounting for over 41.27% of all new FIEs, followed by Taiwan (10.52%), South Korea (9.79%), the United States (6.91%), and Japan (5.71%). Offshore financial centers, such as the British Virgin Islands and Samoa, also account for a significant proportion, reflecting the widespread use of tax avoidance strategies in FDI (Wei, 2000). To address potential bias from tax-motivated FDI routing, we control for the influence of offshore financial centers in our robustness checks.

Table 2 reports the industry distribution of newly established FIEs in mainland China during the same period. The top two sectors are "Other Professional Consulting and Sur-

[10] More information about the Comprehensive Management Platform for Foreign Investment (MOFCOM) is available at: https://wzzxbs.mofcom.gov.cn/.

[11] Since the issuance of the *Regulations on the Administration of Registration for Foreign Enterprises Engaged in Production and Business Activities within the Territory of China* in 1992, China has operated a centralized system for collecting and approving FDI information. This system is managed jointly by the national industrial and commercial registration system and MOFCOM (formerly the Ministry of Foreign Economic Relations and Trade). Prior to the implementation of the *Interim Measures for the Record-Filing Administration of the Establishment and Change of Foreign-Invested Enterprises* in 2016, FDI projects in China were subject to case-by-case approval, meaning that each project had to be submitted to and approved by the relevant authorities before proceeding.

Table 1: Geographic Distribution of Newly Established FIEs in Mainland China

Source	Number	Share
Hong Kong, China	177,796	41.27%
Taiwan, China	45,331	10.52%
South Korea	42,169	9.79%
United States	29,777	6.91%
Japan	24,594	5.71%
British Virgin Islands	19,517	4.53%
Singapore	12,033	2.79%
Samoa	7681	1.78%
Macao, China	7,296	1.69%
Canada	6,382	1.48%
Germany	5,396	1.25%
Australia	5,076	1.18%
United Kingdom	4,407	1.02%

Notes: Table 1 reports the distribution of source countries/regions for newly established FIEs in mainland China from 2000 to 2015. Each firm is assigned a unique source based on the location of its largest shareholder (Ma and Zhang, 2024). The cumulative share is calculated using the number of firms from each source. Only source countries/regions accounting for more than 1% of the total number of firms are reported.

Table 2: Industry Distribution of Newly Established FIEs in Mainland China

CIC4	Industry	Number	Share
7249	other professional consulting and surveying services	23,604	5.48%
1819	other woven apparel manufacturing	23,533	5.46%
5199	other unspecified wholesale trade	13,432	3.12%
7010	real estate development and operation	11,586	2.69%
6513	application software development	10,989	2.55%
3981	manufacture of resistors, capacitors, and inductors	10,653	2.47%
5179	wholesale of other machinery, equipment, and electronic products	10,338	2.40%
3670	manufacture of motor vehicle parts and accessories	7,148	1.66%
2929	manufacture of plastic parts and other plastic products	6,664	1.55%
7499	other unspecified professional and technical services	6,449	1.50%
5132	wholesale of apparel	6,024	1.40%
7243	socio-economic consulting services	5,942	1.38%
6299	other unspecified food and beverage services	5,469	1.27%
3990	manufacture of other electronic equipment	5,453	1.27%
3525	manufacture of moulds	4,888	1.13%
5146	wholesale of jewellery, handicrafts, and collectibles	4,586	1.06%

Notes: Table 2 reports the industry distribution of newly established FIEs in mainland China from 2000 to 2015. Industries are classified according to the four-digit CIC codes reported at the time of registration. The cumulative share is calculated based on the number of firms within each industry. Only industries accounting for more than 1% of total firms are reported.

veying Services" and "Other Woven Apparel Manufacturing," accounting for 5.48% and 5.46% of FIEs, respectively. Other significant industries include unspecified wholesale trade (3.12%), real estate development (2.69%), software development (2.55%), and electronic component manufacturing (2.47%). These data reveal that FDI flows not only into traditional manufacturing sectors, such as apparel, parts, and plastics, but also increasingly targets high-value-added services and high-tech manufacturing, including professional technical services, software development, and mold manufacturing. This industry-level distribution provides empirical support for our identification strategy, which focuses on FDI-induced knowledge spillovers across technology fields.

To link FDI industry information with patent-based technology fields, we use the *Reference Table for International Patent Classification (IPC) and National Economic Industry Classification (2018)*, published by the China National Intellectual Property Administration (CNIPA). This table enables us to map four-digit CIC industry codes (CIC4) to four-digit IPC technology codes (IPC4). Since a single industry may correspond to multiple technology fields, we adopt an equal-weight allocation approach in our baseline analysis. Specifically, for each CIC4–IPC4 mapping, we divide the FDI amount equally among all associated IPC4 codes. In other words, if a CIC4 code maps to N IPC4 codes, each receives $1/N$ of the FDI value. This approach effectively prevents double counting in the industry-to-technology conversion. To verify the robustness of our findings, we also apply an alternative full-assignment approach, where the entire FDI amount for each CIC4 industry is assigned to all its corresponding IPC4 technology fields. This allows us to test the consistency and stability of our results under different allocation approaches.

Appendix Table A1 reports the distribution of newly established FIEs across major IPC4 technology fields from 2000 to 2015. Leading fields include traditional labor-intensive manufacturing sectors such as food processing (A23L, 2.53%), outerwear (A41D, 2.39%), and shirts (A41B, 2.16%), alongside electronic component-related technologies like magnetic materials and inductors (H01F, 1.45%), capacitors and related devices (H01G, 1.43%), semiconductor devices (H01L, 1.37%), and electric motors (H02K, 1.27%). Comparing the technology distribution in Table A1 with the industry distribution in Table 2 shows a consistent and intuitive mapping. Leading industries like apparel manufacturing and wholesale, professional consulting, and electronic component manufacturing in Table 2 correspond to technology fields with high FDI investment in Table A1.

3.1.2 Global Patent Data

The global patent data are drawn from the Autumn 2023 release of the PATSTAT Global database. Developed by the European Patent Office (EPO), PATSTAT is currently the most comprehensive global patent statistics database available. It is widely used to measure innovation activity at the firm, country, and technology-field levels. PATSTAT contains patent information from over 100 countries and regions, covering bibliographic records, citation data, patent family information, inventors, applicants, technology classifications, and priority claims. These features make PATSTAT well suited for long-term, cross-country,

and cross-technology patentometric research. The Autumn 2023 edition used in this study is a snapshot covering the entire global stock of patents up to the end of July 2023. Using the global patent citation network and technology classifications, we construct a technology-level input–output table to measure the intermediate technology spillover pathways embedded in FDI. Accordingly, the PATSTAT database, with its broad coverage and high-quality citation data, serves as our primary data source for constructing subsequent variables.

We compile a base dataset comprising 92.3 million patent application IDs and 60.2 million DOCDB patent family IDs using patent applications filed up to 2022. To address duplicate filings across jurisdictions, we count applications using patent families as the statistical unit and rely on family-level citation data from PATSTAT to construct a citation network at the family level.[12] Given the substantial time lag in patent citations, the sample is restricted to patents filed between 1996 and 2016 that were granted within the observation period, along with their citation relationships. This yields a citation network comprising 6.49 million citing patent families and 5.92 million cited patent families.

3.1.3 Patent Transactions and Collaboration by FIEs in China

Data on patent assignments, licensing, and collaborative applications undertaken by FIEs in China are drawn from the Chinese patent records contained in the IncoPat Global Patent Database from 1985 to 2022. The IncoPat database compiles patent information from major countries and regions worldwide and includes all applications, assignments, and licensing records processed by the CNIPA. This dataset offers detailed, structured information, including applicant name, application number, filing date, publication number, grant date, main IPC class, assignor, assignee, assignment execution date, licensor, licensee, and licensing contract filing date.

Using a standardized data processing procedure, we identify 10,668 patent assignments from FIEs to non-FIEs, 1,138 patent licenses from FIEs to non-FIEs, and 44,885 joint applications filed by FIEs in collaboration with at least one non-FDI partner. While these reflect only measurable transactions, they offer micro-level evidence of how FIEs transfer technology and collaborate with Chinese entities. Figure 1 shows a clear upward trend from 1996 to 2016, especially in collaborative applications, which surged after 2005 and became the dominant channel for technology diffusion by FIEs.

[12]Since patents within the same family have identical substantive content, using patent families avoids double-counting when analyzing global innovation activity. Patent rights are territorial, so that a patent granted in one country or region is only valid within that jurisdiction. This territoriality leads applicants seeking protection in multiple jurisdictions to file separately in each one. The associated priority right system allows an application filed in one member state to serve as the basis for the priority of subsequent filings in other member states, thereby securing a time advantage for protection. The patent families used in this paper are defined as groups of identical patents filed in multiple countries or regions based on the same priority claim.

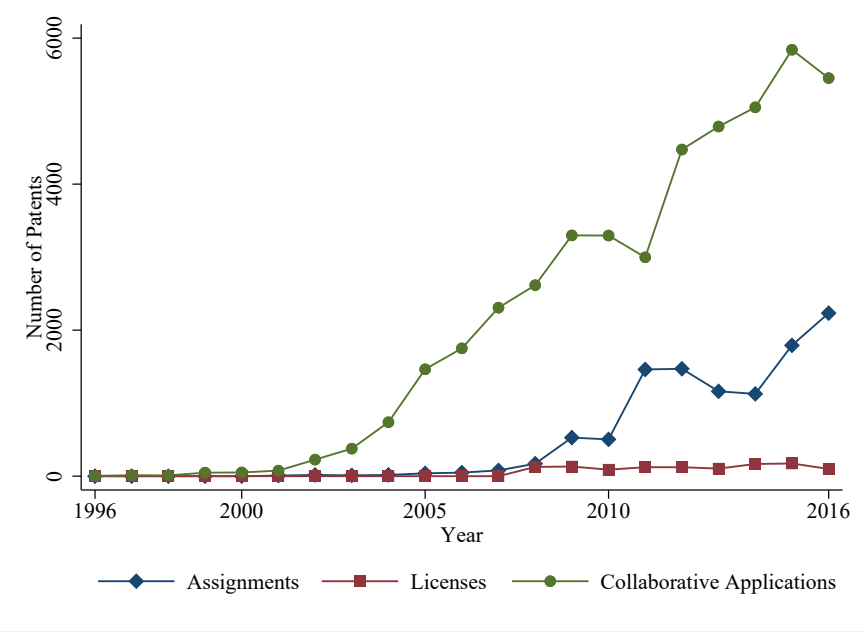


Figure 1: Patent Transactions and Collaboration by FIEs, 1996–2016

Notes: Figure 1 shows the annual number of patent assignments, licenses, and collaborative applications conducted by FIEs in China, 1996-2016. The horizontal axis represents the year, and the vertical axis represents the number of patents. The data include granted invention patents in China where the assignor is an FIE and the assignee is not (patent assignments), the licensor is an FIE and the licensee is not (patent licenses), and where the applicant is an FIE but not all co-applicants are FIEs (collaborative applications). Each patent is counted only once.

3.2 Variable Construction

To identify the potential cross-border knowledge spillover effects of FDI on Chinese innovation, we construct a measure of FDI-embedded intermediate technology based on the structure of the global innovation network. This variable captures the indirect stimulus that FDI exerts through cross-border technology flows. Focusing on the linkages among different technology fields, we first build a knowledge input-output (KIO) network using patent citations, and then integrate it into a unified framework with the scale of FDI inflows and the knowledge stock of the source country. This allows us to reveal how FDI serves as a carrier of foreign knowledge.

3.2.1 FDI-Embedded Intermediate Technology

We focus on FDI inflows into technology fields j that serve as intermediate input technologies for China's technology field i:

$$embtech_{it} = \sum_{j}(\omega_{ij} \sum_{c}(K_{cjt} FDI_{cjt})). \tag{1}$$

This equation for embedded technology comprises three elements: (1) Knowledge input–output linkages between technology fields (ω_{ij}): the share of citations from field i to field j in field i's total backward citations, capturing the importance of j to i and the

channels through which i absorbs FDI-induced knowledge spillovers. (2) FDI scale at the technology-field level (FDI_{cjt}): the amount of FDI from country c in year t flowing into China's technology field j. (3) Knowledge stock of the FDI source country at the technology-field level (K_{cjt}): the accumulated technological knowledge of country c in field j in year t.

This composite variable captures the knowledge content embedded in multinational firms operating in upstream technology fields through the lens of the innovation network. If field i depends more on certain fields j, and those fields attract larger FDI inflows from countries with greater technological accumulation in j, then the FDI entering i embodies richer intermediate technology.[13] If FDI serves as an effective channel for technology diffusion, investments with higher embedded intermediate technology should have a stronger positive impact on China's technological innovation.

The knowledge stock at the country–technology–year level is computed as:

$$K_{cjt} = (1-\delta)K_{cjt-1} + FwdCite_{cjt},$$

where $FwdCite_{cjt}$ denotes the five-year forward citation count for country c in technology field j in year t, and δ is the knowledge depreciation rate, set at 5% in the baseline (Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). For robustness, we test alternative specifications, including using patent application counts, setting δ to 15%, and approximating knowledge accumulation with 10-year cumulative forward citations (Hall, Jaffe and Trajtenberg, 2005; Gong, 2023). For each country–technology pair, the initial knowledge stock is set to $K_{cj1940} = FwdCite_{cj1940}/\delta$ in 1940. Given the long time span of the analysis, the choice of initial value has little impact on the computed knowledge stock.

3.2.2 Inter-sectoral Knowledge Input–output Linkages

Now we derive our core metric, by constructing a technological innovation network. Previous studies have commonly used patent citations as a proxy for knowledge flows (Jaffe, Trajtenberg and Henderson, 1993), and have developed an input–output analytical framework at the technology-field level (Acemoglu, Akcigit and Kerr, 2016; Liu and Ma, 2021; Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). Following Acemoglu, Akcigit and Kerr (2016), we use U.S. data in the global patent family citation dataset from 1996 to 2016 to calculate the proportion of citations that each technology field (at the IPC4 level) contributes to patents in other fields. This enables us to construct the KIO network across technology fields as follows:

$$\omega_{ij} = \frac{cite_{ij}}{\sum_k cite_{ik}}, \tag{2}$$

where i, j and k index technology fields. The numerator, $cite_{ij}$, represents the number of citations from field i to patents in field j. The denominator represents the total number of

[13] For example, if battery technology (H01M) depends heavily on upstream knowledge from material testing (G01N), and G01N receives significant FDI from countries with a strong knowledge base in that field (e.g., Germany), then the FDI flowing into H01M is considered to embed more intermediate technology.

backward citations made by field i. The resulting matrix, Ω, describes the KIO structure among technology fields, effectively representing the innovation network. Conceptually, this network reflects the extent to which the innovation output of field i depends on knowledge inputs from field j during the R&D process. Analogous to traditional PIO analysis, in which intermediate goods are used in production, the knowledge from other technology fields cited by a given field can be regarded as intermediate technology inputs.

In our baseline analysis, the KIO linkage is constructed using U.S. data, given the U.S. technological frontier position and its global representativeness. This approach captures the structural interdependencies between technologies while reducing endogeneity concerns that would arise if Chinese patent data were used for both independent and dependent variables. Appendix Figure B1 presents a heatmap of cross-field citation intensity. The darkest cells along the diagonal show that most fields rely heavily on knowledge from their own and adjacent fields. Vertically, some fields exhibit dense citations across multiple horizontal cells, indicating a broad, general-purpose technological base. Horizontally, certain fields show few citations, reflecting weak knowledge connections with other fields.

The structure of this innovation network is highly stable across both time and geography. Temporally, we divide the sample period by patent application year into three subperiods (1996–2006, 2001–2011, and 2006–2016) using global patent data and construct the corresponding knowledge input–output networks. Appendix Table B2 compares these subperiod networks with the full-period network (1996–2016), revealing strong stability over time, with correlation coefficients exceeding 0.9 in all cases. Geographically, we select the 10 countries (regions) with the highest patent output between 1996 and 2016 and construct separate networks for each based on patent application over the same period. Appendix Table B3 shows high cross-regional correlations. Using the global network as a benchmark, one sees that its correlation with China's network is the highest (0.95), followed by Japan, South Korea, Germany, the United States, France, Russia, the United Kingdom, Taiwan (China), and Canada—all above 0.82.[14]

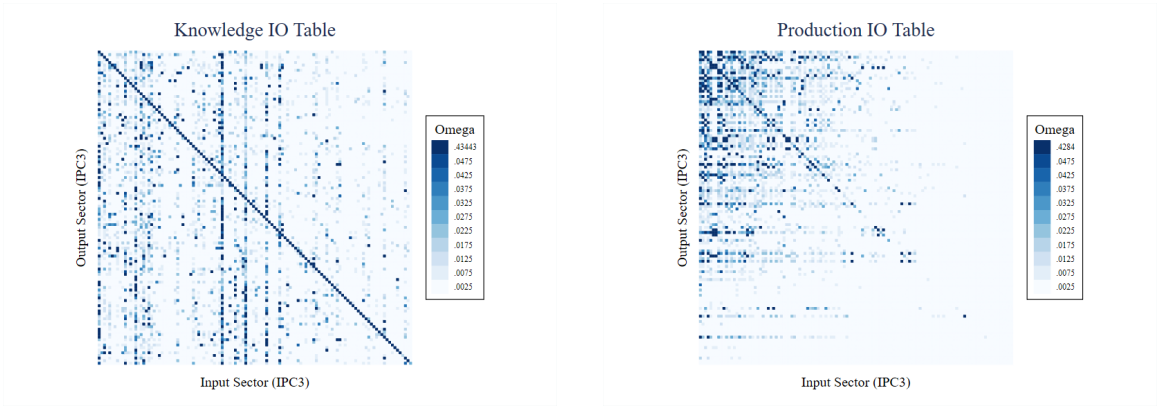
3.2.3 Innovation vs Production Networks

To compare the structures of technological and material inputs, we map the input–output relationships at the IPC3 level for both networks.[15] Figure 2 shows that the relative importance of the same input sector differs markedly between the innovation and production networks, highlighting the heterogeneity between knowledge and material input structures. This difference reflects the distinct resource demands of technological innovation versus product manufacturing.

In addition, by vertically summing all off-diagonal cells, we obtain the ranking of each input field's importance within the network (Table 3). The results again reveal substantial divergence between the two dimensions. In the innovation network, the most important

[14] Liu and Ma (2021) and Ayerst, Ibrahim, MacKenzie and Rachapalli (2023) also note that, compared with production networks, innovation networks exhibit higher cross-country comparability and temporal consistency, reflecting the structural stability of knowledge linkages.

[15] Results at the IPC4 level are provided in Figure B2 and Table B4.



(a) Innovation Network (b) Production Network

Figure 2: Innovation and Production Networks at IPC3 Level

Notes: Figure 2 presents IPC3-level heatmaps for both innovation and production networks. The horizontal axis represents input sectors, and the vertical axis represents output sectors. Each cell in the heatmap shows the share of knowledge or material from sector j used in sector i, with darker colors indicating higher shares. The knowledge input-output relationships are calculated based on U.S. patent citation data from global patents during 1996–2016. The production input-output relationships are derived from the 1997 input-output table provided by the U.S. Bureau of Economic Analysis (BEA) (Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). Sectors are ranked by their overall importance in the production network, calculated as the sum of contributions from all input sectors to downstream sectors (excluding diagonal cells).

Table 3: Top and Bottom Five Sectors by Importance (IPC3)

Innovation Network		Production Network	
IPC3	Description	IPC3	Description
Panel A: Top Five Industries			
A61	medical or veterinary science; hygiene	H01	basic electric elements
H01	basic electric elements	B21	mechanical working of metals without substantial removal; metal pressing
G06	computing; calculating; counting	A01	agriculture; forestry; animal husbandry; hunting; trapping; fishing
G01	measuring; testing	F41	weapons
B01	general physical or chemical methods or apparatus	B29	working of plastics
Panel B: Bottom Five Industries			
C13	sugar industry	B30	presses
B68	saddlery; upholstery	C40	combinatorial technology
G12	instruments	G03	photography; cinematography
B33	additive manufacturing	E03	water supply; sewerage
C14	skins; hides; pelts; leather	G12	instruments

Notes: Table 3 reports the five most and least important sectors under IPC3 classification in the input–output linkages for the innovation and production networks. The innovation network is derived from U.S. patent citation data in global patent records from 1996–2016, while the production network is based on the 1997 input–output table from the U.S. Bureau of Economic Analysis (BEA) (Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). Each sector's overall network importance is measured as the sum of its contributions to all downstream sectors, excluding diagonal cells. Only the top and bottom five sectors are reported for each network.

input fields represent foundational scientific and engineering technologies that are highly general-purpose and widely applicable across technological domains. In contrast, the production network is dominated by sectors closely tied to specific manufacturing processes and intermediate product inputs, reflecting the material input structure of production.

Taken together, these stylized facts suggest that studies relying solely on production-based input–output relationships to identify technological knowledge spillovers may be systematically biased. It is therefore necessary to re-identify and validate the cross-border spillover effects of FDI on host-country innovation using knowledge-based input–output relationships.

4 Empirical Strategy

4.1 Specification

We examine the impact of FDI-embedded intermediate technology on China's innovation output at the technology-field level, using the following specification:

$$\ln patnum_{it} = \alpha + \beta \ln embtech_{it-1} + \gamma Controls + \mu_i + \delta_t + \varepsilon_{it}, \tag{3}$$

where i denotes a technology field (IPC4), and t denotes the year. The dependent variable, $\ln patnum_{it}$, measures the innovation output of China's technology field i in year t, proxied by the log granted invention patents in that field. Patent data are widely used to measure innovation output, and granted patents are of higher quality and less noisy than patent applications, making them a more suitable indicator of innovative achievements (Griliches, 1990; Hall, Jaffe and Trajtenberg, 2005; Autor, Dorn, Hanson, Pisano and Shu, 2020). As robustness checks, we also employ two alternative measures of innovation performance at the technology-field level: the log forward citations ($\ln fwdcite$) and the log average forward citations per patent ($\ln fwdrate$).

The core explanatory variable, $\ln embtech_{it-1}$, refers to the log of FDI-embedded intermediate technology flow to China's technology field i in year $t-1$. We lag this variable by one year for two reasons. First, to mitigate endogeneity concerns arising from reverse causality, i.e., the possibility that domestic innovation could influence FDI inflows. Second, to account for potential time lags between foreign knowledge inflows and local absorption. μ_i and δ_t represent technology-field fixed effects and year fixed effects, respectively, controlling for time-invariant characteristics of technology fields and macroeconomic shocks that affect all fields uniformly. ε_{it} is the error term. The robust standard errors are clustered at the technology-field level.

$Controls$ is a vector of control variables, all lagged by one year to maintain consistency with the treatment of the core explanatory variable. We include key factors that may jointly influence both FDI inflows and China's innovation output: (1) Production-network knowledge spillovers ($\ln prodspill$), controlling for potential technology spillovers through the production dimension of the input–output network. This variable is constructed anal-

ogously to the core explanatory variable, but weighted by the PIO structure, thus capturing upstream and downstream linkages (Javorcik, 2004; Lu, Tao and Zhu, 2017). The PIO relationships are derived from the 1997 U.S. Input–Output Table provided by the Bureau of Economic Analysis (BEA). (2) Global technological trends ($\ln globalpat$), controlling for global developments in specific technology fields that may drive patent growth in China, thus avoiding the misattribution of patent surges in highly active fields to FDI inflows. This variable is measured as the log of the total global patent applications in each field (excluding China). (3) Technology-field imports ($\ln import$), controlling for the impact of imports on domestic technological innovation through channels such as learning-by-importing, competitive pressure, and the provision of advanced intermediate inputs (Amiti and Konings, 2007; Bloom, Draca and Van Reenen, 2016; Liu and Qiu, 2016). This variable is measured as the log import values at the technology-field level.[16]

FDI inflows can also alter the demand conditions of a technology field without necessarily generating the kind of cross-field knowledge spillovers that stimulate innovation. To disentangle these effects, the robustness analysis separately controls for intra-field FDI-embedded intermediate technology ($\ln embtechdiag$), capturing foreign technology flows originating and applied within the same field. This distinction allows us to isolate the spillover-driven component of FDI from the market-demand effect. Appendix Table A2 reports the summary statistics for all variables.

4.2 Instrumental Variable

The coefficient β captures the effect of intermediate technologies embedded in FDI on innovation output at the technology-field level in China. It relies on the assumption that, conditional on a set of control variables and fixed effects, the error term is uncorrelated with the core explanatory variable. Recall that the core explanatory variable, FDI-embedded intermediate technology, is constructed from three components: (1) the technological innovation network, (2) the scale of FDI inflows, and (3) the knowledge stock of the FDI source countries. The innovation network is primarily constructed from U.S. patent data. The knowledge stock of the source countries is mainly determined by their endowments and long-term accumulated technological advantages, which are relatively exogenous to China's innovation output. Therefore, potential endogeneity concerns mainly stem from the endogeneity of China's FDI inflows.

Specifically, endogeneity could arise from two primary sources: reverse causality and omitted variables. As China's innovation capacity improves, its domestic market attracts more high-tech, knowledge-intensive foreign firms, possibly leading to reverse causality, where innovation induces FDI inflows. Although lagging the core explanatory variable by one year partly mitigates this concern, it does not fully eliminate bias arising from innovation-driven FDI inflows. Second, omitted variables, such as economic growth, institutional reforms, or industrial policy adjustments, may influence both FDI inflows and

[16]Import data are sourced from the CEPII-BACI database and converted from the product level (HS6) to the technology-field level (IPC4) using the concordance provided by Lybbert and Zolas (2014).

innovation output simultaneously. These factors may encourage multinational firms to invest more in certain Chinese industries or regions, accelerating domestic firms' technological accumulation and biasing the estimates. To address potential biases from reverse causality and omitted variables, we employ an instrumental variable (IV) strategy.

4.2.1 Instrumental Variable Construction

Following Lu, Tao and Zhu (2017), we exploit the major revision of China's *Catalogue for the Guidance of Foreign Investment Industries* in 2002 as an exogenous shock to foreign market access, and use it to predict the scale of FDI inflows. Specifically, we estimate:

$$\ln FDI_{cjt} = \alpha + \beta \ln Shock_{jt} + \mu_{cj} + \delta_t + \varepsilon_{cjt}. \tag{4}$$

Here, the dependent variable is the amount of FDI from source country c into technology field j in year t. The core explanatory variable, $\ln Shock_{jt}$, is constructed from three components: (1) Treatment group indicator ($treat$): Based on the comparison between the 1997 and 2002 editions of the *Catalogue*, we set $treat = 1$ if foreign market access in a technology field was liberalized in 2002 (e.g., from "permitted" to "encouraged" category), and $treat = 0$ if it remained unchanged.[17] (2) Post-revision indicator ($post$): Since the revised *Catalogue* was announced in April 2002, we set $post = 0$ before 2002, $post = 1$ after 2002, and $post = 3/4$ in 2002 to reflect partial-year implementation. (3) Pre-existing outward investment capacity ($invest$): Because our FDI variable is defined at the country–sector–year level, while the *Catalogue* revision occurred at the industry level, we account for heterogeneity in source countries' outward investment capacities. We measure $invest_c$ as the average outward FDI from country c over the three years prior to the reform (1999–2001), using World Bank World Development Indicators data. This variable remains constant throughout the sample period and captures baseline differences in investment capacity across countries. The composite shock variable is then defined as:

$$Shock_{cjt} = treat_j \times post_t \times invest_c. \tag{5}$$

The coefficient on this triple interaction captures the differential change in FDI inflows to China between liberalized fields (treatment group) and unchanged fields (control group), before and after the 2002 *Catalogue* revision, conditional on a given level of outward investment capacity. The specification includes country $\times$ technology-field fixed effects (μ_{cj}) and year fixed effects (δ_t). The robust standard errors are clustered at the country level.

Since the policy change occurred at the industry level, whereas our analysis is conducted at the technology-field level, we construct treatment indicators through a concordance process. First, we map CIC4 codes from the 2002 edition to the 2017 edition using historical classification concordances. Then, we link CIC4 codes to IPC4 codes based on the *Reference Table between International Patent Classification and National Economic Industry*

[17] All possible changes in foreign investment access categories are listed in Appendix Table C1.

Classification (2018). When multiple CIC2002 codes correspond to a single CIC2017 code, we generate treatment indicators using two alternative approaches. Under the liberal approach, a CIC2017 code is assigned to the treatment group if any of its corresponding CIC2002 industries were directly affected by the policy. Under the conservative approach, a CIC2017 code is assigned to the treatment group only if all of its corresponding CIC2002 industries were affected.[18] These dual approaches allow us to capture potential uncertainty in the mapping process and assess the robustness of our results to classification ambiguities.

Next, when mapping from CIC2017 to IPC4 codes, a technology field is classified into the treatment group if more than 50% of its industry composition is directly affected by the policy. Otherwise, it is placed in the control group. The baseline analysis uses the liberal mapping approach combined with the 50% threshold. Robustness checks use the conservative mapping method and alternative threshold values to ensure that our results are not driven by arbitrary classification choices. This procedure enables precise alignment between industry-level policy shocks and technology-field-level FDI exposure.

Finally, using the predicted FDI values from Equation (4), we construct the instrumental variable for the core explanatory variable in Equation (1). This IV strategy ensures that our identification of FDI-embedded technology effects on innovation is driven by exogenous policy-induced variation rather than potential reverse causality.

$$IV_{it} = \sum_{j}(\omega_{ij} \sum_{c}(K_{cjt}\widehat{FDI}_{cjt})) \tag{6}$$

4.2.2 Instrumental Variable Validity

The validity of our instrumental variable depends on two key conditions. First, the relevance condition requires that the instrument be strongly correlated with the endogenous regressor. We assess this condition through the first-stage regression and report the F-statistic from the weak instrument test to demonstrate sufficient strength. Second, the orthogonality condition requires that the instrument be uncorrelated with the error term in the structural equation conditional on the control variables.

As previously mentioned, the potential endogeneity of the core explanatory variable primarily stems from reverse causality between China's FDI inflows and domestic innovation, as well as omitted variable bias. Our identification strategy isolates the exogenous component of FDI inflows by exploiting the 2002 revision of the *Catalogue*, which altered market access exogenously at the industry (and, by extension, technology field) level. This allows us to interpret the orthogonality condition in terms of the exogeneity of the policy-induced shock and provides a credible source of variation for causal inference.

We assess the exogeneity of the policy shock along three dimensions. First is the selection of reformed industries. The 2002 *Catalogue* revision was driven by China's WTO accession negotiations rather than sector-specific performance, which makes the designa-

[18]The liberal approach yields 187 CIC2017 treatment industries, compared to 174 under the conservative approach, indicating that the two methods differ only slightly.

tion of affected industries largely exogenous. As in Lu, Tao and Zhu (2017), we control for pre-reform (1998) sectoral characteristics at the technology-field level, including new product intensity, export intensity, number of firms, and average firm age, and interact them with year dummies. This flexible specification mitigates concerns that post-reform innovation trends could be driven by endogenous policy targeting.[19]

Second, we consider concurrent institutional reforms. Around 2002, China implemented other structural changes, such as state-owned enterprise (SOE) reform and trade liberalization, that could affect FDI inflows and innovation with heterogeneous effects across industries. We therefore include the following controls: (1) the interaction between the SOE share in each technology field in 2001 and year dummies, which capture the heterogeneous effects of SOE reform, and (2) China's 2001 import tariffs and the weighted average export tariffs imposed by China's trading partners, each of which is interacted with year dummies. The former captures the effects of import liberalization, and the latter reflects changes in export market access.[20]

Third is pre-reform comparability between the treatment and control groups. To verify parallel pre-reform trends in FDI inflows, we conduct an event study of the 2002 *Catalogue* revision. Specifically, we regress China's FDI at the country–technology–year level on the interaction between year dummies and the treatment group indicator. We use 1995, the first year in the FDI sample, as the baseline. The regression includes all aforementioned controls, as well as country $\times$ technology-field fixed effects and year fixed effects.

Figure 3 presents the results of this event study. The estimated coefficients of the interaction terms reveal no statistically significant differences in pre-reform FDI trends between the treatment and control groups, suggesting strong pre-trend comparability. After the reform, however, the coefficients become significantly positive, suggesting that the 2002 relaxation of foreign investment restrictions substantially increased FDI inflows into technology fields in the treatment group.

Table 4 reports the estimation results for Equation (4), which uses the 2002 revision of China's *Catalogue* as an exogenous policy shock to predict the scale of FDI inflows. Column 1 defines treated industries using the liberal approach with a 50% threshold; Column 2 adopts the conservative approach at the same threshold. Columns 3 and 4 explore alternative thresholds of 40% and 60%, respectively. All regressions control for country $\times$ technology-field fixed effects and year fixed effects, as well as interactions of pre-reform industry characteristics, tariff levels, and SOE share with year dummies, ensuring that the predicted FDI variation reflects the exogenous policy shock rather than other confounding factors. Across all specifications, the coefficients on the core explanatory variable remain significantly positive, confirming that the 2002 policy revision effectively predicts FDI inflows. The stability of the estimates across different treatment definitions and thresholds

[19] Data for sectoral characteristics are drawn from the Annual Survey of Industrial Enterprises (ASIE), classified by CIC4 codes. They are then converted to the technology-field level (IPC4) for consistency.

[20] Import tariff data are from Brandt, Van Biesebroeck, Wang and Zhang (2017), and export tariff data are from the World Integrated Trade Solution (WITS). Export tariffs are measured as the weighted average rate levied on Chinese exports by destination markets, with weights given by China's export values to those markets.

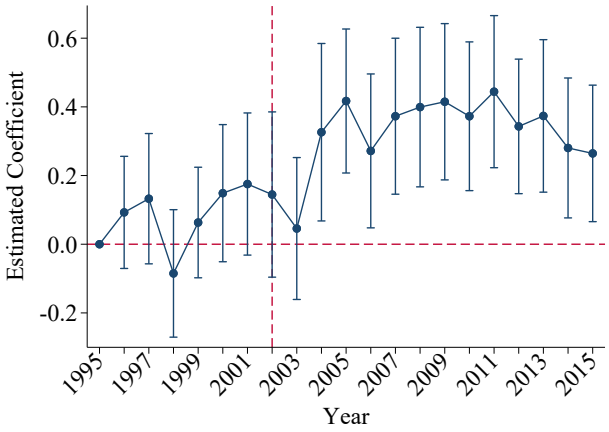


Figure 3: Event Study of the 2002 Foreign Investment Access Policy on China's FDI Inflows

Notes: Figure 3 presents the event study estimates of the 2002 revision of the *Catalogue for the Guidance of Foreign Investment Industries* on China's FDI inflows. The dependent variable is the log of FDI inflows at the country–technology–year level. The coefficients correspond to interactions between year dummies and the treatment group indicator, with 1995 (the first year of the FDI sample) as the baseline. The regression includes country × technology-field fixed effects and year fixed effects. Standard errors are clustered at the country level. The horizontal axis denotes years, and the vertical axis shows estimated coefficients. The vertical dashed line marks the 2002 policy revision, and the horizontal bars represent 95% confidence intervals.

Table 4: Estimation of FDI Inflows Predicted by the 2002 Foreign Investment Policy Shock

	(1) $\ln FDI$	(2) $\ln FDI$	(3) $\ln FDI$	(4) $\ln FDI$
$\ln Shock_lib_50$	0.010***			
	(0.002)			
$\ln Shock_con_50$		0.009***		
		(0.002)		
$\ln Shock_lib_40$			0.012***	
			(0.002)	
$\ln Shock_lib_60$				0.010***
				(0.002)
Country × Technology-field FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Observations	1,905,561	1,905,561	1,905,561	1,905,561
R^2	0.615	0.615	0.615	0.615

Notes: Table 4 reports the estimation results for China's FDI inflows on the exogenous policy shock derived from the 2002 revision of the *Catalogue*. Column 1 uses the liberal approach with a 50% threshold to define treated industries; Column 2 adopts the conservative approach at the same threshold. Columns 3 and 4 explore thresholds of 40% and 60%, respectively. All regressions include country × technology-field fixed effects and year fixed effects, as well as interactions of pre-reform industry characteristics, tariff levels, and SOE share with year dummies. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the country level are reported in parentheses.

demonstrates the robustness of the fitted values.

5 Empirical Results

5.1 Baseline Results

We begin by examining the effects of FDI-embedded intermediate technology on China's innovation output. Columns 1 to 3 in Table 5 report the OLS estimation results for Equation (3). Column 1 includes only technology-field (IPC4) fixed effects and year fixed effects, without additional controls. Column 2 adds controls for global technology trends ($\ln globalpat$), technology-field imports ($\ln import$), and the interactions between year dummies and industry characteristics, tariff levels, and the share of SOEs, thereby accounting for confounding from global patenting dynamics, broader openness, and policy reforms. Column 3 further incorporates production-network knowledge spillovers ($\ln prodspill$), allowing us to compare the role of embedded FDI technologies with alternative channels of spillovers. Across all three OLS specifications, the positive coefficients confirm a robust correlation between FDI-embedded technology and innovation output.

Table 5: The Effects of FDI-Embedded Technology on China's Innovation Output

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS First Stage	(5) 2SLS Second Stage
	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln embtech$	$\ln patnum$
$\ln embtech$	0.157***	0.152***	0.127***		0.790***
	(0.036)	(0.037)	(0.033)		(0.122)
$\ln prodspill$			0.123***	0.171***	-0.063
			(0.045)	(0.024)	(0.050)
$\ln globalpat$		0.402***	0.399***	-0.030***	0.380***
		(0.065)	(0.065)	(0.012)	(0.062)
$\ln import$		0.036	0.038	-0.006	0.045
		(0.037)	(0.037)	(0.010)	(0.035)
IV				1.299***	
				(0.058)	
Year FE	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$		Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$		Yes	Yes	Yes	Yes
SOE share $\times\delta_t$		Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390
KP-rk LM statistic					130.275
KP-rk F statistic					506.356

Notes: Table 5 reports the OLS and 2SLS estimates for the baseline specification. Column 1 includes only technology-field (IPC4) and year fixed effects, without additional controls. Column 2 adds controls for global technology trends ($\ln globalpat$), technology-field imports ($\ln import$), and interactions between year dummies and industry characteristics, tariff levels, and the share of SOEs. Column 3 further includes production-network knowledge spillovers ($\ln prodspill$). Column 4 presents the first-stage regression results of the instrumental-variable (IV) regression, while column 5 reports the second-stage results. The KP-rk LM and F statistics test for under-identification and weak instruments, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics, clustered at the technology-field level, are reported in parentheses.

Columns 4 and 5 of Table 5 report the 2SLS estimation results using our instrumental

variable, with both columns including the full set of controls and fixed effects. Column 4 presents the first-stage regression results, showing a strong positive relationship between the instrument and $\ln embtech$, thereby satisfying the relevance condition. The Kleibergen–Paap rk LM statistic rejects the null of under-identification, while the first-stage F-statistic (506.356) far exceeds the Stock–Yogo critical value, confirming that the instrument is both relevant and strong (Stock and Yogo, 2005). Column 5 reports the second-stage estimates. The results indicate that a 10% increase in FDI-embedded intermediate technology leads to an approximately 7.9% increase in granted invention patents in the corresponding technology field, an effect that is both economically sizable and statistically significant at the 1% level.[21]

This evidence aligns with the vertical spillover literature, such as Javorcik (2004) and Alfaro-Ureña, Manelici and Vasquez (2022), which views FDI not only as a source of production inputs but also as a conduit for cross-border knowledge transfer. Our findings also resonate with Ma and Zhang (2024), who document a positive association between cross-border knowledge flows and innovation output. Furthermore, the results contribute to the recent literature on innovation networks and the structure of knowledge dependence. Acemoglu, Akcigit and Kerr (2016) and Ayerst, Ibrahim, MacKenzie and Rachapalli (2023) emphasize that knowledge diffusion is shaped not only by production-network linkages but also by the input–output structure among technologies. Our findings suggest that the innovation-enhancing role of FDI in China operates precisely through such knowledge-based innovation networks. In other words, the benefits of FDI extend beyond production linkages or competitive pressures, and are deeply embedded in the structural interconnections of the innovation network.

5.2 Comparison with Traditional Production Networks

To further highlight the importance of knowledge spillovers based on innovation networks (KIO), we next compare them with estimates based on traditional production-based input–output (PIO) linkages. The intuition is straightforward: whereas KIO captures knowledge flows embedded in technological interdependencies, PIO reflects spillovers transmitted purely through material production linkages. If the latter were the dominant channel, the estimated effect of FDI should be comparable in magnitude across the two frameworks. Conversely, if innovation networks are more central, the effect of FDI-embedded technology would diminish sharply once attention is restricted to production network linkages.

Table 6 reports the corresponding OLS and 2SLS results using PIO linkages as the measure of knowledge spillovers. Columns 1 to 3 present the OLS estimates with progressively richer controls, while columns 4 to 6 report the 2SLS results.[22] In column 4, the coefficient on $\ln prodspill$ is 0.435 and highly significant, suggesting that when examined in isolation,

[21] The 2SLS coefficient is substantially larger than the OLS estimate. This may indicate that endogeneity biases the OLS results downward. In addition, Imbens and Angrist (1994) note that 2SLS estimates the Local Average Treatment Effect (LATE), while OLS recovers the average treatment effect for the full population. Thus, the 2SLS estimate can be larger than the OLS estimate.

[22] The first-stage estimates for the PIO spillover specifications are reported separately in Appendix Table E1.

PIO spillovers appear to have a strong positive effect on innovation. Column 5 introduces $\ln embtech$ as a control but instruments only $\ln prodspill$.[23] Under an otherwise identical specification, the coefficient from PIO linkages amounts to only about 51% of the KIO estimate (0.404 vs 0.790). In economic terms, a 10% increase in FDI-embedded technology is associated with only a 4% increase in invention patents when PIO spillovers are used, compared to an 7.9% increase under the KIO framework. This sharp contrast underscores how the production-network approach substantially understates the role of FDI. Finally, column 6 instruments both $\ln prodspill$ and $\ln embtech$, making the two channels directly comparable. The coefficient on $\ln embtech$ remains large and significant at 0.711. By contrast, the coefficient on $\ln prodspill$ collapses to 0.121 and becomes statistically insignificant.

Table 6: Estimates of Knowledge Spillovers Using Production Networks

	(1) OLS $\ln patnum$	(2) OLS $\ln patnum$	(3) OLS $\ln patnum$	(4) 2SLS $\ln patnum$	(5) 2SLS $\ln patnum$	(6) 2SLS $\ln patnum$
$\ln prodspill$	0.181***	0.159***	0.123***	0.435***	0.404***	0.121
	(0.047)	(0.049)	(0.045)	(0.111)	(0.112)	(0.109)
$\ln embtech$			0.127***		0.069**	0.711***
			(0.033)		(0.034)	(0.123)
$\ln globalpat$		0.403***	0.399***	0.393***	0.391***	0.376***
		(0.065)	(0.065)	(0.064)	(0.064)	(0.062)
$\ln import$		0.036	0.038	0.041	0.041	0.047
		(0.037)	(0.037)	(0.037)	(0.037)	(0.035)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$		Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$		Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$		Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390	12,390
KP-rk LM statistic				122.918	128.082	137.232
KP-rk F statistic				555.615	567.070	316.381

Notes: Table 6 reports the OLS and 2SLS estimates based on traditional production input–output linkages. Columns 1 to 3 present OLS estimates with progressively richer controls: Column 1 includes only fixed effects for year and technology field; Column 2 adds controls for global technology trends ($\ln globalpat$) and technology-field imports ($\ln import$), together with interactions of year dummies and industry characteristics, tariff levels, and SOE shares; Column 3 further includes innovation-network knowledge spillovers ($\ln embtech$). Columns 4 to 6 report the 2SLS estimates: Column 4 instruments $\ln prodspill$; Column 5 adds $\ln embtech$ as an additional control while still instrumenting only $\ln prodspill$; Column 6 simultaneously treats both $\ln prodspill$ and $\ln embtech$ as endogenous, each instrumented by its corresponding external instrument. The KP-rk LM and F statistics test for under-identification and weak instruments, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics, clustered at the technology-field level, are reported in parentheses.

The stepwise comparison reveals that when both channels are considered together, the production-network effect disappears, while the innovation-network effect remains robust

[23] Columns 5 of Table 5 and Table 6 are designed as mirror specifications. In the baseline setting, $\ln embtech$ is treated as endogenous and instrumented, with $\ln prodspill$ included as a control. In contrast, Table 6, column 5, instruments the latter and treats the former as a control. This symmetry ensures that the two estimates are directly comparable under otherwise identical model specifications.

and economically significant. Quantitatively, the estimated impact of FDI-embedded technology decreases modestly (by about 10%) relative to the baseline, while the contribution of production networks becomes effectively null. These suggest that analyses relying solely on PIO linkages would severely underestimate the true spillover effects of FDI.

5.3 Robustness Checks

We address potential concerns regarding confounding factors, the measurement of key variables, and the handling of patent data. Across all tests, our findings regarding the positive impact of FDI-embedded intermediate technology on China's innovation output remain robust.

5.3.1 Potential Confounding Factors

A potential concern in our analysis is that not all FDI inflows contribute equally to technological knowledge spillovers. First, FDI directed into the same technology field may primarily reflect local market demand, resource advantages, or policy incentives, rather than the transfer of new knowledge (Keller and Yeaple, 2009). Such demand-driven investment could indirectly affect domestic innovation through capacity expansion or competition (Aghion, Blundell, Griffith, Howitt and Prantl, 2009), potentially confounding our estimates of true knowledge spillovers. Second, a substantial portion of FDI is routed through offshore financial centers or tax havens (Wei, 2000; Luo, Luo and Zeng, 2022), which may involve round-tripping or purely financial flows with limited substantive R&D content. If unaccounted for, these flows could bias the measured effect of FDI on innovation.

To address these concerns, we conduct robustness checks by including controls for same-field FDI and FDI from identified tax havens. Same-field FDI is measured separately to isolate knowledge spillovers from market-driven inflows, while tax-haven FDI is distinguished using the OECD Tax Haven List (Bennedsen and Zeume, 2018).[24] Appendix Table D1 reports the results controlling for potential confounding factors. Appendix Table D2 further tests the robustness of our findings using alternative tax haven classifications. Across all specifications, the coefficient on cross-field FDI remains positive and statistically significant, while same-field and tax-haven FDI are generally small or insignificant. These results indicate that our main findings are not driven by market-demand effects or financial round-tripping, supporting the validity of our causal interpretation that FDI facilitates technological knowledge spillovers.

5.3.2 Other Robustness Checks

Alternative Measures of FDI-Embedded Intermediate Technology: Our measure of FDI-embedded intermediate technology combines three components, each of which could raise

[24] Appendix Table A3 lists countries and regions classified as tax havens based on five different sources. The baseline analysis relies on the OECD Tax Haven List. Robustness checks use four additional sources that are widely applied in the literature: the OECD Grey List (as of August 17, 2009), the "Stop Tax Haven Abuse Act" (which was not enacted), the classification by Hines and Rice (1994), and the Tax Information Exchange Agreement under the OECD Harmful Tax Practices framework.

measurement concerns, so here we conduct a series of checks to assess the robustness of our results. For ω_{ij}, we have already confirmed that the structure of the innovation network is stable across time and regions; For FDI_{cjt}, the baseline analysis converts industry-level (CIC4) FDI into technology-field (IPC4) values using equal-weight allocation to avoid double counting. To test sensitivity to this choice, we replace it with a full-allocation method (Appendix Table D3, columns 1 and 2); For K_{cjt}, the baseline uses forward citations with a 5% depreciation rate. We re-estimate the model using three alternatives: a 15% depreciation rate (Appendix Table D3, columns 3 and 4), citation counts within 10 years without depreciation (Appendix Table D3, columns 5 and 6), and patent applications with a 5% depreciation rate (Appendix Table D3, columns 7 and 8). Across all specifications, the effects remain similar to the baseline, indicating that our findings are not driven by a particular allocation rule or knowledge stock measure.

Alternative Measures of Innovation Output: In the baseline, China's innovation output is proxied by the log of granted invention patents. To show that our findings are not sensitive to the transformation or quality metric used, (i). we replace the log with the inverse hyperbolic sine (IHS) transformation of patent counts (Appendix Table D4, columns 1 and 2), which retains the scale-adjusting property of logs while accommodating zeros and small values (Bellemare and Wichman, 2020); (ii). We incorporate two quality-based measures: total forward citations (Appendix Table D4, columns 3 and 4) to capture aggregate knowledge impact, and average forward citations per patent (Appendix Table D4, columns 5 and 6) to control for output scale while reflecting per-patent quality.

A further concern is the potential "patent bubble" in China, as policy incentives and lenient examinations could spur a surge in low-quality filings in China (Hu, Zhang and Zhao, 2017). By contrast, Chinese patents filed in the U.S., Europe, and Japan—facing higher costs and stricter standards—generally have higher market value and technological content (Wei, Xie and Zhang, 2017). We therefore use overseas patent counts as the dependent variable (Appendix Table D4, columns 7 and 8). The positive and significant effect of FDI-embedded intermediate technology persists, reinforcing the robustness of our findings.

Instrumental Variable Robustness: We construct the instrumental variable using the 2002 revision of the *Catalogue*, which created exogenous cross-industry variation in FDI inflows. Since the policy is defined at the industry level, mapping to IPC4 technology fields involves judgment. To address this concern, we re-estimate the instrument by varying the mapping method (conservative vs. liberal) and the threshold for defining treatment groups. Three alternative specifications are considered: a conservative mapping with a 50% threshold, a relaxed 40% threshold (liberal), and a stricter 60% threshold (liberal). As shown in Appendix Table D5, the signs, magnitudes, and statistical significance of the coefficients remain stable across all variations, supporting the validity of our identification strategy.

Patent Data Concerns: We measure innovation output using patent counts at the IPC4 level. However, patent data pose concerns such as zeros, skewness, and aggregation sensitivity. For these we test robustness in three ways. First, we follow Chen and Roth (2023) and replace OLS with Poisson regression (Appendix Table D6, columns 1 and 2). Second, we exclude technology fields with zero patents (Appendix Table D6, columns 3 and 4). Third, we aggregate the data to IPC3 codes (Appendix Table D6, columns 5 and 6). In all cases, the positive effect of FDI knowledge spillovers on China's innovation remains robust.

6 Mechanism Analysis

In this section, we examine the mechanisms underlying FDI-induced knowledge spillovers. We first establish the presence of spillovers, distinguishing them from general effects of openness. We then investigate the specific channels through which knowledge diffuses, separating genuine interactive spillovers from market-mediated transfers. Finally, we examine heterogeneity across source countries and technology fields to identify the conditions under which these spillovers are most pronounced, providing a structured view of how innovation networks mediate cross-border knowledge flows.

6.1 Knowledge Spillover Effects

Our mechanism analysis focuses on two complementary channels: the technology absorption path and the technology convergence path. The logic is, if FDI-embedded intermediate technology generates knowledge spillovers, then it should improve China's capacity to learn from, absorb, and imitate foreign knowledge.

We identify these mechanisms from two perspectives. First, we examine the explicit learning behavior reflected in patent backward citations. Backward citations indicate the extent to which a new patent builds on existing knowledge during R&D, serving as a measure of knowledge absorption and technology learning (Jaffe, Trajtenberg and Henderson, 1993; Jaffe and Trajtenberg, 1999). We examine how intermediate technology embedded in FDI affects cross-border knowledge flows by using the number of citations that Chinese patents in each technology field make to foreign patents as the dependent variable.

We further refine the analysis to the country–technology-field level by constructing the number of backward citations that Chinese patents provide to patents from the FDI source country. If FDI entails genuine knowledge spillovers, an increase in intermediate technology inflows from a given source country to a specific Chinese technology field should lead to more citations to patents from that country. The regression specification is:

$$\ln backcite_{cit} = \alpha + \beta \ln embtech_{cit-1} + \gamma Controls + \mu_{ci} + \delta_{ct} + \varepsilon_{cit}, \tag{7}$$

where c, i, and t denote the source country, technology field (IPC4), and year. The dependent variable $backcite_{cit}$ measures citations from Chinese patents in field i to patents from

foreign country c in year t. The key explanatory variable $embtech_{cit-1}$ captures intermediate technology embedded in FDI from country c to field i in the previous year. Other controls are identical to the baseline analysis. We include country $\times$ technology-field fixed effects (μ_{ci}) and country $\times$ year fixed effects (δ_{ct}) to absorb unobserved heterogeneity at the country–technology-field level and macro-level fluctuations at the country–year level.

Columns 1 and 3 of Table 7 present the 2SLS estimates at the two aggregation levels, indicating increased FDI-embedded intermediate technology leads to more backward citations.[25] At the technology-field level, a 10% increase in embedded technology raises backward citations by roughly 10%, suggesting that domestic inventors actively learn from foreign knowledge brought by FDI. At the country–technology-field level, citations are concentrated toward patents originating from the FDI source country, indicating localized spillover effects. These results support the view that FDI facilitates foreign technology learning in the host country.

Table 7: Knowledge Spillover Effects: 2SLS Estimates

	(1)	(2)	(3)	(4)
	Technology-field level		Country–technology-field level	
	2SLS	2SLS	2SLS	2SLS
	$\ln backcite$	$proxy_US$	$\ln backcite$	$proxy$
$\ln embtech$	1.005***	0.090***	0.055***	0.027***
	(0.141)	(0.024)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Country $\times$ Technology-field FE			Yes	Yes
Country $\times$ Year FE			Yes	Yes
Observations	12,390	12,390	814,004	814,004
KP-rk LM statistic	130.275	130.275	19,796.605	5,060.318
KP-rk F statistic	506.356	506.356	18,754.878	7,932.231

Notes: Table 7 reports the 2SLS estimates of the knowledge spillover effects. Columns 1 and 2 present results at the technology-field level, and columns 3 and 4 at the country–technology-field level. Columns 1 and 3 use the number of foreign patents cited in Chinese patents' backward citations as the dependent variable, capturing knowledge absorption. Columns 2 and 4 use technological similarity between Chinese and foreign patents, capturing structural convergence. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technological trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as the interactions of industry characteristics, tariff levels, and SOE share with year dummies. Columns 1 and 2 include year and technology-field fixed effects, while columns 3 and 4 additionally include country $\times$ technology-field and country $\times$ year fixed effects. The KP-rk LM and F statistics test for underidentification and weak instruments, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

Second, we examine convergence in knowledge structures using technological similarity. Beyond point-to-point learning, knowledge spillovers may reshape the overall technological structure of domestic innovation. To capture this effect, we construct a patent-based technological similarity measure following Jaffe (1986) and Bloom, Schankerman

[25] The corresponding OLS estimates are reported in Appendix Table E2.

and Van Reenen (2013), computing the cosine similarity between China's and the FDI source country's patenting vectors within each IPC subclass (IPC4) across IPC main groups (5–7 digit level):

$$proxy_{cit} = \frac{\sum_{k \in i} patnum_{CNkt}\, patnum_{ckt}}{\sqrt{\left(\sum_{k \in i} patnum_{CNkt}^2\right)\left(\sum_{k \in i} patnum_{ckt}^2\right)}}, \tag{8}$$

where c, i, and t denote the source country, technology field (IPC4), and year, and k denotes the IPC main group within field i. $patnum_{CNkt}$ and $patnum_{ckt}$ are patent counts in main group k for China and source country c in year t, respectively. The resulting $proxy_{cit}$ measures the technological similarity between China and source country c in field i in year t. Higher values indicate greater technological convergence. We also compute the cosine similarity between China and the global technology frontier (U.S.) to assess whether FDI-induced spillovers enhance convergence toward the frontier.

Columns 2 and 4 of Table 7 report the regression results for technological similarity. The results show that FDI-embedded intermediate technology significantly increases technological similarity both with source countries and with frontier countries, implying FDI not only facilitates discrete learning events but also induces broader structural alignment in host-country innovation, supporting knowledge diffusion and technological upgrading.

Our findings align with Branstetter (2001), who demonstrate that FDI facilitates the transfer of knowledge from FIEs to host-country entities. In contrast to earlier studies that primarily focus on productivity gains (Javorcik, 2004; Fons-Rosen, Kalemli-Ozcan, Sorensen, Villegas-Sanchez and Volosovych, 2017), our mechanism analysis provides direct evidence of host-country learning behavior. Notably, the country–technology-field analysis reveals that FDI-induced spillovers are not diffused indiscriminately but exhibit clear dependencies on the source country and technology path, highlighting the role of multinational enterprises as critical conduits in global knowledge diffusion (Keller, 2021).

6.2 Alternative Explanation

While FDI is often argued to generate knowledge spillovers, some studies emphasize that cross-border knowledge diffusion depend not only on specific channels, but also on institutional environments and the efficiency of information dissemination (Jaffe, Trajtenberg and Henderson, 1993; Hegde, Herkenhoff and Zhu, 2023). In the present paper, the observed improvements in domestic innovation may result from general enhancements in China's access to global knowledge or faster overall knowledge diffusion, rather than from FDI per se. In other words, improvements in domestic innovation might reflect faster knowledge flows rather than the specific technological content carried by FDI.

To evaluate this possibility, we examine whether FDI-embedded intermediate technologies affect the speed of cross-border knowledge diffusion. Following Hegde, Herkenhoff and Zhu (2023), we measure diffusion speed as the average lag, in years, from the filing of a foreign patent to its first citation by a Chinese patent. If FDI indirectly promotes innovation through accelerated knowledge flows, countries and technology fields

with more FDI-embedded technologies should exhibit shorter citation lags.

Table 8 reports the results. Columns 1 and 2 present estimates at the technology-field level. Columns 3 and 4 extend the analysis to the country-technology-field level. After controlling for industry characteristics and time-varying factors, we find no significant effect of FDI-embedded intermediate technologies on the speed of cross-border knowledge diffusion in any specification. This indicates that even with an increase in FDI-embedded intermediate technologies, China does not acquire foreign knowledge more rapidly, suggesting that improvements in domestic innovation are unlikely to be driven by faster knowledge transmission. This aligns with Cotterlaz and Guillouzouic (2025), who show that since the 1980s, changes in the speed of cross-border knowledge flows have been limited.

Table 8: Speed of Cross-border Knowledge Diffusion

	(1)	(2)	(3)	(4)
	Technology-Field Level		Country–Technology-Field Level	
	OLS	2SLS	OLS	2SLS
	$\ln citationlag$	$\ln citationlag$	$\ln citationlag$	$\ln citationlag$
$\ln embtech$	-0.005	-0.000	-0.018	0.004
	(0.006)	(0.001)	(0.018)	(0.006)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Country $\times$ Technology-field FE			Yes	Yes
Country $\times$ Year FE			Yes	Yes
Observations	12,368	125,799	12,368	125,799
KP-rk LM statistic			131.758	4,799.415
KP-rk F statistic			553.241	4,444.512

Notes: Table 8 examines whether FDI-embedded intermediate technologies indirectly affect China's technological innovation by accelerating cross-border knowledge diffusion. The dependent variable is the average time interval (in years) from the application year of a foreign patent to its first forward citation by a Chinese patent, capturing the lag in cross-border knowledge diffusion. Columns 1 and 2 present estimates at the technology-field level, and columns 3 and 4 at the country–technology-field level. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as the interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Columns 1 and 2 include year and technology-field fixed effects, while columns 3 and 4 additionally include country $\times$ technology-field and country $\times$ year fixed effects. The KP-rk LM and F statistics test for under-identification and weak instruments, respectively. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

Overall, these findings weaken the plausibility of alternative explanations. Cross-border knowledge diffusion largely depends on specific economic linkages and technological ties rather than a general acceleration of global knowledge flows. Our empirical evidence therefore reinforces our main argument: FDI promotes domestic innovation primarily through direct technological channels—such as knowledge transfer, imitation, and structural integration—rather than by accelerating the overall pace of cross-border knowledge diffusion.

6.3 How Do Spillovers Occur?

Beyond establishing the presence of FDI-induced knowledge spillovers, it is essential to understand how they occur. While the literature has largely focused on whether FDI generates knowledge spillovers, it has paid little attention to identifying the specific pathways and mechanisms involved (Javorcik, 2010). Theory suggests two broad channels: (1) market-based technology transactions (Akcigit, Celik and Greenwood, 2016), such as patent assignments and licensing, where knowledge is codified and traded; and (2) interaction-based collaboration processes (Singh, 2005), such as co-application and R&D interactions between innovators, where knowledge is exchanged through collaboration. Accordingly, some observed spillovers may simply reflect market-mediated transfers rather than embedded knowledge spillovers (Keller, 2004; Bai, Barwick, Cao and Li, 2020).

To disentangle these channels, we construct three measures from the IncoPat database: (1) Technology transfer ($\ln transfer$): the number of FIE patents assigned to domestic entities, capturing property-rights-based transactions; (2) Technology licensing ($\ln license$): the number of FIE patents licensed to domestic entities, reflecting controlled, institution-dependent transactions; (3) Innovation collaboration ($\ln collaborate$): the number of patents jointly filed by FIEs and domestic entities, indicating interactive, R&D-based exchanges.[26] All measures are constructed at the IPC4–year level and are matched with our measure of embedded intermediate technology in FDI ($\ln embtech$).

Table 9 shows that FDI-embedded intermediate technology significantly increases technology transfers (column 1), indicating that FDI is associated with property-rights-based technology outflows.[27] This aligns with early evidence on the role of technology markets in facilitating knowledge diffusion (Arora, Fosfuri and Gambardella, 2001). However, the effect on licensing is insignificant (column 2), likely reflecting the dependence of licensing on institutional conditions, intellectual property protection, and complementary transaction mechanisms (Branstetter, Fisman and Foley, 2006), as well as the inherent limitations of licensing in a cross-border context. In contrast, FDI has a positive effect on innovation collaboration (column 3), which remains robust after controlling for transfers and licensing (column 4), suggesting that collaboration is an independent and substantive spillover channel. These results suggest that the greater the embedded technology in FDI, the more frequently FIEs engage in collaborative innovation with domestic innovators. Moreover, controlling for both market transactions in the baseline model (column 5) leaves the core spillover effect largely unchanged, indicating that market-based transfers alone cannot account for the observed knowledge gains.[28]

[26] Innovation collaboration is measured using joint patent applications between FDI and domestic entities, which do not include innovations carried out within joint ventures.

[27] The corresponding OLS estimates are reported in Appendix Table E3.

[28] We focus here on observable activities in patent markets and collaboration networks. In addition, FDI may generate spillovers through informal channels such as employee mobility or imitation. Due to data constraints, these channels are beyond the present scope but warrant further investigation through firm-level microdata or case studies in the future.

Table 9: Channels of Knowledge Spillover: 2SLS Estimates

	(1) 2SLS $\ln transfer$	(2) 2SLS $\ln license$	(3) 2SLS $\ln collaborate$	(4) 2SLS $\ln collaborate$	(5) 2SLS $\ln patnum$
$\ln embtech$	0.133**	-0.012	0.391***	0.334***	0.766***
	(0.060)	(0.024)	(0.087)	(0.061)	(0.118)
$\ln transfer$				0.458***	0.191***
				(0.027)	(0.023)
$\ln license$				0.342***	0.087**
				(0.059)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390
KP-rk LM statistic	130.275	130.275	130.275	130.944	130.944
KP-rk F statistic	506.356	506.356	506.356	511.182	511.182

Notes: Table 9 reports the effects of embedded intermediate technology in FDI on three channels of technology diffusion. Column 1 presents the results for technology transfer; Column 2 for technology licensing; Column 3 for collaborative innovation. Column 4 adds transfers and licensing as controls to test the independent effect of collaboration. Column 5 controls for technology market transactions (patent assignments and licensing) in the baseline model to test the robustness of our core findings. All regressions control for production network spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as the interactions of industry characteristics, tariff levels, and SOE share with year dummies. Fixed effects include year and technology-field levels. The KP-rk LM and F statistics test for under-identification and weak instruments, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

6.4 Heterogeneity Analysis

In this subsection, we explore the heterogeneity in the knowledge spillover effects of FDI, focusing on two dimensions: the technological advantage of the source countries and the centrality of the technology fields affected by FDI within the global innovation network.

6.4.1 Technological Gap

We examine whether the innovation effects of FDI-embedded technology depend on the technological lead of the source country. The technological gap ($techgap$) for source country c in technology field i is measured as:

$$techgap_{ci} = \frac{\sum_{k \in i} (patnum_{ck} - patnum_{CNk})}{n}, \tag{9}$$

where $patnum_{ck}$ ($patnum_{CNk}$) denotes the number of patents filed by country c (China) in the technology subclass (IPC subclass level) k at the start of the sample period (1985–1995), and n denotes the number of IPC subclasses within the IPC4 category i. For each IPC4 subclass, the measure takes the average difference between the initial patent counts of the FDI source country and China. Higher values indicate a stronger lead of the source country

over China, whereas a negative value ($techgap_{ci} < 0$) suggests that the source country is less advanced or even lags behind China.[29]

We rank the technological gaps between China and each source country by field. Then, we classify country–technology pairs into high-gap ($techgap$ above the 90th percentile) and low-gap ($techgap$ below the 10th percentile) groups. Suppose that cross-border knowledge spillovers from FDI are driven by the technological lead of the source country, then we would expect a significantly larger spillover effect in the high-gap group, where the source country has a pronounced technological lead.

Columns 1 and 2 of Table 10 present OLS and 2SLS estimates for this heterogeneity, showing that FDI from high-gap countries generates significantly larger increases in invention patents than FDI from low-gap countries, and the coefficient differences are statistically significant. This supports the "technology-advantage-driven spillover effect," consistent with the technology catch-up hypothesis. As Findlay (1978) noted, the intensity of cross-border knowledge flows tends to be proportional to the technological gap, as less advanced countries can accelerate their technological accumulation and innovation capability through interactions with advanced countries. Our results also align with Keller (2004), who emphasizes that diffusion is shaped by the technological advantage of the source and the absorptive capacity of the recipient.

These results also provide micro-level evidence of uneven international innovation diffusion. Technologically advanced sources have a greater capacity for knowledge export, and China, as a catching-up country, benefits disproportionately more from engagement with frontier countries, which is consistent with Coe and Helpman (1995). As Javorcik (2004) emphasizes, the impact of FDI on host industries depends on the type of investment and market structure. We further find that the technological gap itself is a critical factor in FDI-driven knowledge spillovers.

6.4.2 Innovation Centrality

Technological innovation does not occur in isolation, but unfolds within a highly interconnected knowledge network. Some technology fields occupy central positions, engaging in frequent cross-field knowledge exchanges, while others remain peripheral with limited diffusion channels.[30] Beyond the technological advantages of FDI source countries, it is important to ask whether the impact of FDI-induced spillovers varies with a field's position in the innovation network. To address this question, we introduce an indicator of innovation centrality to examine the role of network structure.

Following Liu and Ma (2021), we construct a patent citation matrix across technology fields and compute the left eigenvector associated with the unit eigenvalue as our measure

[29] The $techgap_{ci}$ distribution is highly right-skewed (skewness 42.68, kurtosis 2906.71), with a mean of -1.04 and standard deviation of 31.53. In most fields, gaps are small, while a few advanced countries maintain overwhelming leads (maximum 2991.51). The 10th percentile is -7.77 (low-gap group), and the 90th percentile is 0 (high-gap group). These statistics highlight the pronounced heterogeneity in technological gaps between China and FDI source countries.

[30] Liu and Ma (2021) argue that allocating more R&D resources to high-centrality fields can maximize long-term growth and welfare.

Table 10: Heterogeneity Analysis

	(1) OLS $\ln patnum$	(2) 2SLS $\ln patnum$	(3) OLS $\ln patnum$	(4) 2SLS $\ln patnum$
$\ln embtech_highgap$	0.106***	0.739***		
	(0.030)	(0.125)		
$\ln embtech_lowgap$	0.000	0.035		
	(0.021)	(0.083)		
$\ln embtech$			0.951***	2.152***
			(0.063)	(0.148)
$\ln embtech \times \ln centrality$			0.093***	0.186***
			(0.006)	(0.014)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390
KP-rk LM statistic		77.542		107.313
KP-rk F statistic		49.672		223.508
F-test for coefficient difference	8.840	18.282		
p-value	0.003	0.000		

Notes: Table 10 reports the heterogeneity analysis results. Columns 1 and 2 report regressions by the technological advantage of FDI source countries; Columns 3 and 4 focus on the innovation centrality of technology fields. Each pair of columns reports OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument concerns. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

of innovation centrality. In this setting, eigenvalues and eigenvectors capture the structural properties of the network, and the centrality vector reflects the steady-state distribution of knowledge flows. Higher centrality values indicate a more pivotal position in the diffusion network.[31]

To examine whether FDI-induced knowledge spillovers exhibit heterogeneous effects across the structure of the technological network, we introduce an interaction term between embedded intermediate technology in FDI and the innovation centrality of the technology field. Columns 3 and 4 of Table 10 show that the interaction term is significantly positive in both OLS and 2SLS estimates, indicating that the knowledge spillover effects is stronger in technology fields with higher innovation centrality. This finding is consistent with Liu and Ma (2021), who highlight that spillovers depend on the structural position of a field within the global innovation network. Core fields have denser cross-field knowl-

[31]The innovation centrality exhibits a markedly asymmetric distribution across technology fields (mean = 0.00159, maximum = 0.134), suggesting that most fields occupy peripheral positions in the network, while only a few hold core positions in the KIO structure. Appendix Table E4 ranks the top and bottom five IPC4 fields by centrality. The highest-ranking fields cluster in electronic information, biomedicine, and advanced manufacturing, which are areas with high spillover potential. The lowest-ranking fields are traditional, process-based industries with stable trajectories and limited cross-field interaction.

edge linkages and are thus better positioned to stimulate innovation in their own and related fields via network-based diffusion pathways when receiving external knowledge inputs, such as intermediate technology embedded in FDI.

Our results also corroborate the view of Acemoglu, Akcigit and Kerr (2016) and Cai and Li (2018) on the asymmetry of innovation networks. Specifically, they argue that innovation diffusion paths are not uniformly distributed, but rather shaped by locality and the heterogeneity of inter-sectoral linkages. These results expand our understanding of the mechanisms underlying FDI spillovers. While the traditional literature emphasizes vertical production linkages or industry-level connections as channels for FDI-induced knowledge spillovers (Javorcik, 2004; Alfaro-Ureña, Manelici and Vasquez, 2022), our empirical findings suggest that the internal technological structure of the *innovation network* plays a critical role.

7 Conclusions

In this paper we have examined the role of FDI as a channel for cross-border knowledge diffusion, using the global innovation network. Employing registration data of FIEs in China, matched with global patent information, we measure the intermediate technologies embedded in FDI and assess their impact on domestic innovation output at the technology-field level. The analysis shows that FDI-embedded technologies significantly enhance China's innovation performance: a 10% increase in embedded intermediate technologies is associated with an 7.9% rise in granted invention patents. In comparison, using traditional PIO linkages under a mirror specification produces much smaller and statistically insignificant effects once both channels are considered jointly, whereas the KIO effect remains robust.

Mechanism analysis suggests that these spillovers operate primarily through enhanced knowledge-borrowing from source countries—reflected in increased backward patent citations and greater technological similarity—rather than through accelerated diffusion speed. FDI also promotes collaborative innovation with domestic actors, and the effects are stronger for technologies from countries with a greater technological lead over China and for fields located at the core of the innovation network.

The findings contribute to the literature by highlighting the important role of innovation networks in shaping the effectiveness of FDI-induced spillovers, complementing the traditional focus on production linkages and market transactions. However, the analysis is limited to observable and traceable channels documented in patent data, leaving out informal or tacit mechanisms, such as labor mobility, technological imitation, and industrial training. Imitation and knowledge stealing are also out of the scope due to data availability. Future research could integrate firm-level data, exploit policy variations, and explore broader institutional determinants to deepen our understanding of how FDI shapes domestic innovation trajectories.

Observe also that our mechanism analysis relies on backward citations and technological similarity. Backward citations primarily capture explicit learning, or knowledge

sources formally acknowledged in patent documents, which are usually constrained by disclosure requirements and drafting practices. As a result, backward citations only partially reflect actual knowledge absorption. In practice, technology diffusion often involves tacit knowledge transfer, informal imitation, and collaborative innovation. These processes may not appear in citation records or patent filings, making them difficult to observe. Similarly, technological similarity between patent vectors only indirectly indicates convergence in knowledge structures. Consequently, the learning effects we identify should be interpreted as a lower bound of the broader knowledge-absorption processes at work. Nevertheless, the institutionalized and quantifiable nature of patent data makes it a robust entry point for examining cross-border technology flows arising from FDI.

References

Acemoglu, Daron, Ufuk Akcigit, and William R. Kerr. 2016. "Innovation Network." *Proceedings of the National Academy of Sciences*, 113(41): 11483–11488.

Aghion, Philippe, Richard Blundell, Rachel Griffith, Peter Howitt, and Susanne Prantl. 2009. "The Effects of Entry on Incumbent Innovation and Productivity." *The Review of Economics and Statistics*, 91(1): 20–32.

Aitken, Brian J., and Ann E. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review*, 89(3): 605–618.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood. 2016. "Buy, Keep, or Sell: Economic Growth and the Market for Ideas." *Econometrica*, 84(3): 943–984.

Alfaro-Ureña, Alonso, Isabela Manelici, and Jose P Vasquez. 2022. "The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages." *The Quarterly Journal of Economics*, 137(3): 1495–1552.

Alvarez, Roberto, and Ricardo A. López. 2008. "Entry and Exit in International Markets: Evidence from Chilean Data." *Review of International Economics*, 16(4): 692–708.

Amiti, Mary, and Jozef Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review*, 97(5): 1611–1638.

Amiti, Mary, Cédric Duprez, Jozef Konings, and John Van Reenen. 2024. "FDI and Superstar Spillovers: Evidence from Firm-To-Firm Transactions." *Journal of International Economics*, 152: 103972.

Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella. 2001. *Markets for Technology: The Economics of Innovation and Corporate Strategy.* The MIT Press.

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu. 2020. "Foreign Competition and Domestic Innovation: Evidence from US Patents." *American Economic Review: Insights*, 2(3): 357–374.

Ayerst, Stephen, Faisal Ibrahim, Gaelan MacKenzie, and Swapnika Rachapalli. 2023. "Trade and Diffusion of Embodied Technology: An Empirical Analysis." *Journal of Monetary Economics*, 137: 128–145.

Bai, Jie, Panle Jia Barwick, Shengmao Cao, and Shanjun Li. 2020. "Quid Pro Quo, Knowledge Spillover, and Industrial Quality Upgrading: Evidence from the Chinese Auto Industry." National Bureau of Economic Research Working Paper 27644.

Bajgar, Matej, and Beata Javorcik. 2020. "Climbing the Rungs of the Quality Ladder: FDI and Domestic Exporters in Romania." *The Economic Journal*, 130(628): 937–955.

Barrios, Salvador, Holger Görg, and Eric Strobl. 2011. "Spillovers Through Backward Linkages From Multinationals: Measurement Matters!" *European Economic Review*, 55(6): 862–875.

Bellemare, Marc F., and Casey J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics*, 82(1): 50–61.

Bennedsen, Morten, and Stefan Zeume. 2018. "Corporate Tax Havens and Transparency." *The Review of Financial Studies*, 31(4): 1221–1264.

Blomström, Magnus, and Ari Kokko. 1998. "Multinational Corporations and Spillovers." *Journal of Economic Surveys*, 12(3): 247–277.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica*, 81(4): 1347–1393.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *The Review of Economic Studies*, 83(1): 87–117.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Branstetter, Lee 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.

Branstetter, Lee G., Raymond Fisman, and C. Fritz Foley. 2006. "Do Stronger Intellectual Property Rights Increase International Technology Transfer? Empirical Evidence from U. S. Firm-Level Panel Data." *The Quarterly Journal of Economics*, 121(1): 321–349.

Buera, Francisco J., and Ezra Oberfield. 2020. "The Global Diffusion of Ideas." *Econometrica*, 88(1): 83–114.

Cai, Jie, and Nan Li. 2018. "Growth Through Inter-sectoral Knowledge Linkages." *The Review of Economic Studies*, 86(5): 1827–1866.

Cai, Jie, Nan Li, and Ana Maria Santacreu. 2022. "Knowledge Diffusion, Trade and Innovation across Countries and Sectors." *American Economic Journal: Macroeconomics*, 14(1): 104–145.

Caves, Richard E. 1974. "Multinational Firms, Competition, and Productivity in Host-Country Markets." *Economica*, 41(162): 176–193.

Chen, Jiafeng, and Jonathan Roth. 2023. "Logs with Zeros? Some Problems and Solutions." *The Quarterly Journal of Economics*, qjad054.

Chen, Yongmin, Haiwei Jiang, Yousha Liang, and Shiyuan Pan. 2022. "The Impact of Foreign Direct Investment on Innovation: Evidence from Patent Filings and Citations in China." *Journal of Comparative Economics*, 50(4): 917–945.

Cheung, Kui-yin, and Ping Lin. 2004. "Spillover Effects of FDI on Innovation in China: Evidence from the Provincial Data." *China Economic Review*, 15(1): 25–44.

Coe, David T., and Elhanan Helpman. 1995. "International R&D Spillovers." *European Economic Review*, 39(5): 859–887.

Comin, D., and B. Hobijn. 2004. "Cross-Country Technology Adoption: Making the Theories Face the Facts." *Journal of Monetary Economics*, 51(1): 39–83.

Cotterlaz, Pierre, and Arthur Guillouzouic. 2025. "The Percolation of Knowledge across Space." *Journal of International Economics*, 153: 104026.

Davies, Ronald B., Dieter Franz Kogler, and Guohao Yang. 2023. "Construction of a Global Knowledge Input-Output Table."

Eppinger, Peter, and Hong Ma. 2024. "Optimal Ownership and Firm Performance: An Analysis of China's FDI Liberalization." *The Review of Economics and Statistics*, 1–46.

Findlay, Ronald. 1978. "Relative Backwardness, Direct Foreign Investment, and the Transfer of Technology: A Simple Dynamic Model." *The Quarterly Journal of Economics*, 92(1): 1–16.

Fons-Rosen, Christian, Sebnem Kalemli-Ozcan, Bent E. Sorensen, Carolina Villegas-Sanchez, and Vadym Volosovych. 2017. "Foreign Investment and Domestic Productivity: Identifying Knowledge Spillovers and Competition Effects."

Gong, Robin Kaiji. 2023. "The Local Technology Spillovers of Multinational Firms." *Journal of International Economics*, 144: 103790.

Griliches, Zvi. 1990. "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature*, 28(4): 1661–1707.

Grossman, Gene M., and Elhanan Helpman. 1991. "Quality Ladders and Product Cycles." *The Quarterly Journal of Economics*, 106(2): 557–586.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. 2005. "Market Value and Patent Citations." *The RAND Journal of Economics*, 36(1): 16–38.

Harrison, Ann, and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In *Handbook of Development Economics*. Vol. 5 of *Handbooks in Economics*, , ed. Dani Rodrik and Mark Rosenzweig, 4039–4214. Elsevier.

Havranek, Tomas, and Zuzana Irsova. 2011. "Estimating Vertical Spillovers from FDI: Why Results Vary and What the True Effect Is." *Journal of International Economics*, 85(2): 234–244.

Hegde, Deepak, Kyle Herkenhoff, and Chenqi Zhu. 2023. "Patent Publication and Innovation." *Journal of Political Economy*, 131(7): 1845–1903.

Hines, Jr., James R., and Eric M. Rice. 1994. "Fiscal Paradise: Foreign Tax Havens and American Business." *The Quarterly Journal of Economics*, 109(1): 149–182.

Hu, Albert Guangzhou, and Gary H. Jefferson. 2009. "A Great Wall of Patents: What Is Behind China's Recent Patent Explosion?" *Journal of Development Economics*, 90(1): 57–68.

Hu, Albert G. Z., Peng Zhang, and Lijing Zhao. 2017. "China as Number One? Evidence from China's Most Recent Patenting Surge." *Journal of Development Economics*, 124: 107–119.

Imbens, Guido W., and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica*, 62(2): 467–475.

Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value." *The American Economic Review*, 76(5): 984–1001.

Jaffe, Adam B., and Manuel Trajtenberg. 1999. "International Knowledge Flows: Evidence from Patent Citations." *Economics of Innovation and New Technology*, 8(1-2): 105–136.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *The Quarterly Journal of Economics*, 108(3): 577–598.

Javorcik, Beata S. 2010. "Foreign Direct Investment and International Technology Transfer."

Javorcik, Beata Smarzynska. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages." *American Economic Review*, 94(3): 605–627.

Jiang, Kun, Wolfgang Keller, Larry D. Qiu, and William Ridley. 2024. "International Joint Ventures and Internal Technology Transfer vs. External Technology Spillovers: Evidence From China." *Journal of International Economics*, 150: 103939.

Keller, Wolfgang. 2004. "International Technology Diffusion." *Journal of Economic Literature*, 42(3): 752–782.

Keller, Wolfgang. 2021. "Knowledge Spillovers, Trade, and FDI."

Keller, Wolfgang, and Stephen R. Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm Level Evidence from the United States." *The Review of Economics and Statistics*, 91(4): 821–831.

Konings, Jozef. 2001. "The Effects of Foreign Direct Investment on Domestic Firms." *Economics of Transition*, 9(3): 619–633.

Liu, Ernest, and Song Ma. 2021. "Innovation Networks and Innovation Policy." National Bureau of Economic Research Working Paper 29607.

Liu, Qing, and Larry D. Qiu. 2016. "Intermediate Input Imports and Innovations: Evidence from Chinese Firms' Patent Filings." *Journal of International Economics*, 103: 166–183.

Liu, Qing, Larry D. Qiu, and Chaoqun Zhan. 2024. "FDI Inflows and Export Quality: Domestic Competition and Within-Firm Adjustment." *Journal of Development Economics*, 170: 103293.

Luo, Changyuan, Qin Luo, and Shuai Zeng. 2022. "Bilateral Tax Agreement and FDI Inflows: Evidence from Hong Kong Investment in Mainland China." *China Economic Review*, 73: 101788.

Lu, Yi, Zhigang Tao, and Lianming Zhu. 2017. "Identifying FDI Spillovers." *Journal of International Economics*, 107: 75–90.

Lybbert, Travis J., and Nikolas J. Zolas. 2014. "Getting Patents and Economic Data to Speak to Each Other: An 'Algorithmic Links with Probabilities' Approach for Joint Analyses of Patenting and Economic Activity." *Research Policy*, 43(3): 530–542.

MacGarvie, Megan. 2006. "Do Firms Learn from International Trade?" *The Review of Economics and Statistics*, 88(1): 46–60.

Ma, Xiao, and Yiran Zhang. 2024. "How Do Multinationals Impact China's Technology? The Role of Quid Pro Quo Policy and Technology Spillovers."

Nagaoka, Sadao, Kazuyuki Motohashi, and Akira Goto. 2010. "Patent Statistics as an Innovation Indicator." In *Handbook of the Economics of Innovation*. Vol. 2 of *Handbook of the Economics of Innovation, Volume 2*, , ed. Bronwyn H. Hall and Nathan Rosenberg, 1083–1127. North-Holland.

Olurotimi, Osaretin, Jeremy Foltz, and Nouhoum Traore. 2025. "FDI in Côte d'Ivoire: Are Local Firms Better Off?" *Journal of Development Economics*, 174: 103441.

Singh, Jasjit. 2005. "Collaborative Networks as Determinants of Knowledge Diffusion Patterns." *Management Science*, 51(5): 756–770.

Stock, James H., and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. , ed. Donald W. K. Andrews and James H. Stock, 80–108. Cambridge:Cambridge University Press.

Wei, Shang-Jin. 2000. "How Taxing Is Corruption on International Investors?" *The Review of Economics and Statistics*, 82(1): 1–11.

Wei, Shang-Jin, Zhuan Xie, and Xiaobo Zhang. 2017. "From "Made in China" to "Innovated in China": Necessity, Prospect, and Challenges." *Journal of Economic Perspectives*, 31(1): 49–70.

Online Appendix

A Data Processing Details

A.1 FIEs in China

We compare our sample data with publicly available records from the Ministry of Commerce (MOFCOM) on the number of newly established FIEs in China. The MOFCOM data are sourced from the Commerce Data Center.[1] The comparison results are shown in Figure A1. We find that the overall trends of newly established FIEs from 1990 to 2019 are highly consistent between the two datasets, indicating strong representativeness and reliability of our sample. In certain years (e.g., 1992–1994), MOFCOM statistics differ from our sample data, likely due to early-stage data collection biases such as underreporting or retroactive corrections; however, these discrepancies do not alter the overall trend conclusions.

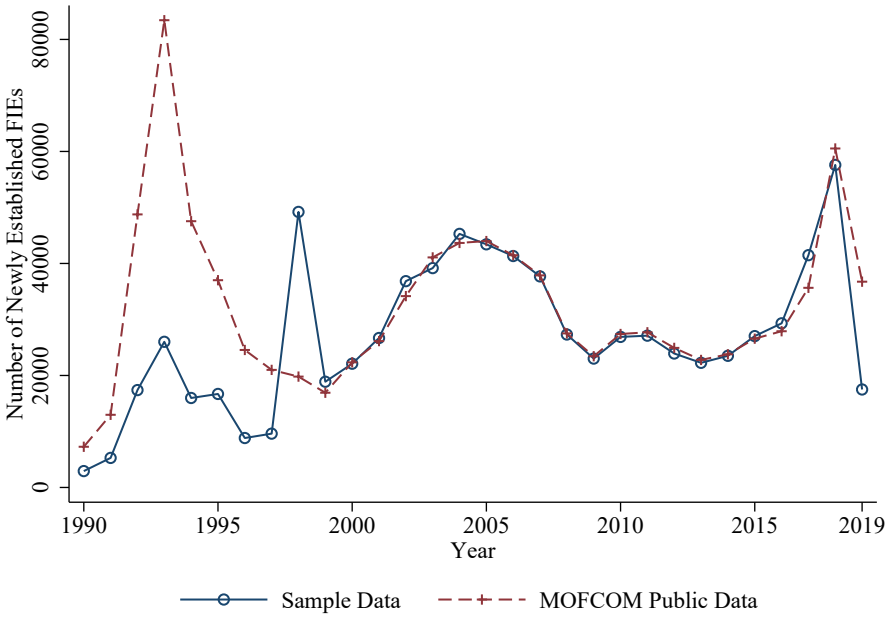


Figure A1: Data Comparison of Newly Established FIEs in China

Notes: Figure A1 presents the annual number of newly established FIEs in China from 1990 to 2019, comparing our sample data with official statistics released by the MOFCOM via the Commerce Data Center. The vertical axis represents the number of FIEs, and the horizontal axis represents the year.

We clean and process the FIE registration data as follows: First, we remove observations with missing establishment year, firm name, investment amount, or industry classification (CIC4 codes). Second, to ensure consistent matching and coding, we standardize the names of investment sources in the raw data using International Organization for Standardization (ISO) country codes published by the United Nations Statistics Division

[1]Source: https://data.mofcom.gov.cn/lywz/inmr.shtml

(UNSD). Third, we exclude firms that lacked any investment source information to guarantee the accuracy of subsequent investment allocation and source identification.

Following these procedures, the final dataset includes the registration information of 824,565 FIEs, all of which were established no later than 2019. These firms represent FDI from 205 source countries/regions and span 1,364 CIC4 industries. To ensure the comparability of multinational investment amounts, all figures are converted to U.S. dollars using Penn World Table 10.0 exchange rates. Finally, we aggregate the firm-level data to the country–industry–year level for empirical analysis. During this process, Chinese capital contributions are excluded, and only the actual foreign-invested amounts are retained to more accurately measure the intensity and industry distribution of foreign investment.

A.2 Global Patent Data

To ensure the quality and relevance of the data, the PATSTAT Global database was processed in six steps. (1) Patent applications are restricted to years up to 2022 to mitigate truncation from publication delays, as most are disclosed within 18 months. (2) Only invention patents are retained to better capture substantive technological innovation; utility models, design patents, and other types are excluded. (3) Patent records are de-duplicated following European Patent Office (EPO) guidelines, yielding 92.3 million application IDs and 60.2 million DOCDB family IDs. (4) Patent families are adopted as the statistical unit to address multiple filings of the same invention across jurisdictions; application counts are measured at the family level, with the earliest application date in each family representing its innovation timing. (5) Citation data are compiled at the family level to measure inter-technology knowledge flows, matching citing and cited families to build a network of 14.28 million citing and 15 million cited families. (6) To allow sufficient time for citation accumulation, only patents applied for between 1996 and 2016 and granted within the sample period are retained, producing a final citation network of 6.49 million citing and 5.92 million cited families.

A.3 Patent Transactions and Collaboration by FIEs in China

To identify the patent assignment, licensing, and collaborative application activities of FIEs in China, we construct corresponding measures from the IncoPat database and apply a unified data processing procedure. Using patent assignments as an example, the process is as follows.

First, sample selection. We extract all granted invention patents from the IncoPat database and retain records where the applicant type includes firms. For patents with multiple announcements, only the latest announcement is used as the reference record. Second, assignment record identification. All records with patent assignment activities are selected according to the assignment execution date. Observations with inconsistencies in the number of assignments, assignors, or assignees due to missing or structurally unmatched data are excluded. Third, identification of FIEs. A two-step name-matching procedure is applied to identify assignments in which the assignor is an FIE and the assignee

is a domestic Chinese entity. In the first step, abnormal symbols in company names are removed for initial matching. In the second step, unmatched samples are reprocessed by removing secondary terms such as "Province," "Autonomous Region," "City," "District," "County," "Limited," "Responsibility," "Shares," "Company," "Group," and "Factory" to improve matching accuracy. Fourth, variable construction. Based on firm type identification, we aggregate the number of patents assigned by FIEs to local Chinese firms at the IPC4 technology-field level, counting each patent assignment only once.

The same procedure is applied to patent licensing and collaborative applications with minor adjustments. For licensing, the licensor must be an FIE and the licensee a non-FIE. For collaborative applications, the applicant is an FIE and at least one co-applicant is a domestic (non-FIE) entity. This approach enables the systematic identification of micro-level channels for technology diffusion and collaboration between FIEs and domestic entities in China's patent activities.

In terms of patent assignments, 197,900 firm-type assignment records are identified, including 17,179 cases where the assignor is an FIE. Among these, 10,668 assignees are domestic Chinese entities, directly reflecting technology transfer from foreign firms to the host country. The five most concentrated technology fields are semiconductor devices (H01L, 1,356), electric digital data processing (G06F, 1,078), digital information transmission (H04L, 628), television systems (H04N, 373), and pharmaceutical formulations (A61K, 331), primarily in information and communication technology (ICT) and life sciences.

For patent licensing, FIEs act as licensors in 1,747 patents, with 1,138 licenses granted to non-FIEs. Although smaller in scale, licensing still reflects the diffusion of technological knowledge through contractual arrangements. The leading licensing fields are refrigeration equipment (F25D, 81), digital information transmission (H04L, 75), electric digital data processing (G06F, 60), chemical synthesis (C07D, 45), and pharmaceutical formulations (A61K, 41).

Collaborative applications represent the largest scale among the three channels. A total of 44,885 cooperative patents are identified in which the applicant is an FIE and at least one co-applicant is a domestic (non-FIE) entity. These patents reflect joint R&D and knowledge sharing between FIEs and domestic firms or research institutions, potentially fostering more advanced local technological capabilities. Collaboration is concentrated in electric digital data processing (G06F, 7,601), semiconductor devices (H01L, 3,456), digital information transmission (H04L, 2,334), electric circuit components (H05K, 1,584), and optical systems (G02F, 1,574).

A.4 Concordance

To integrate industry-level FDI data with technology-level patent data, we establish a concordance between the China Industry Classification (CIC4) and the International Patent Classification (IPC4). The procedure is as follows. First, patent data are classified according to the internationally recognized IPC system, and all records are consistently assigned to four-digit IPC codes (IPC4) following the official 2020 edition. Second, industry data are

categorized under China's National Economic Industry Classification (CIC) using its four-digit codes (CIC4), with the 2017 version serving as the baseline for FDI statistics. Third, the linkage between FDI industry information and patent technology fields is constructed using the *Reference Table between International Patent Classification and National Economic Industry Classification (2018)* published by the CNIPA, which provides the official mapping from CIC4 codes to IPC4 codes.

Through this mapping, we establish correspondences between 819 CIC4 industries and 634 IPC4 technology fields. This enables the construction of technology-level FDI variables for subsequent analysis. The resulting distribution of technology fields for newly established foreign-invested enterprises (FIEs) in China during 2000–2015 is presented in Table A1.

Table A1: Distribution of Technology Fields for Newly Established FIEs in China

IPC4	Technology Field	Amount	Share
A23L	foodstuffs; beverages; non-alcoholic drinks; preparation or treatment	30.978	2.53%
A41D	outerwear; protective clothing; accessories	29.192	2.39%
A41B	shirts; underwear; baby clothes; handkerchiefs	26.387	2.16%
E04F	building finishing works	19.124	1.56%
H01F	magnets; inductors; transformers; selection of magnetic materials	17.732	1.45%
H01G	capacitors; electrolytic capacitors; rectifiers; detectors; switches; photosensitive or thermosensitive devices	17.488	1.43%
H01L	semiconductor devices; electric solid-state devices	16.737	1.37%
C12N	microorganisms or enzymes; compositions thereof; propagation, preservation or maintenance of microorganisms; mutation or genetic engineering; culture media	16.122	1.32%
H02K	electric machines	15.566	1.27%
G06F	electric digital data processing	15.250	1.25%
H01M	methods or apparatus for directly converting chemical energy into electrical energy	15.127	1.24%
H01P	waveguides; resonators; transmission lines or other waveguide-type devices	14.728	1.20%
H01C	resistors	14.219	1.16%
C10L	fuels; natural gas; synthetic natural gas; liquefied petroleum gas, etc.	12.567	1.03%

Notes: Table A1 reports the distribution of technology fields for newly established FIEs in China during 2000–2015. The firms' CIC4 codes are mapped to IPC4 codes using the *Reference Table between International Patent Classification and National Economic Industry Classification (2018)* published by CNIPA. FDI scale in each technology field is measured by investment amount (in 100 million USD). Only technology fields with cumulative shares exceeding 1% are reported. To prevent double counting, when multiple technology fields correspond to the same industry, FDI amounts are evenly allocated.

A.5 Summary Statistics

Table A2: Summary Statistics

Variable	N	Mean	SD	Min	Max
Panel A: IPC4-year level					
ln $patnum$	12,390	3.120	2.078	0.000	10.107
ln $embtech$ (equal weight)	12,390	27.775	1.497	14.206	32.667
ln $prodspill$	12,390	24.288	2.394	14.358	32.312
ln $globalpat$	12,390	5.150	1.724	0.000	10.338
ln $import$	12,390	18.864	2.122	6.848	26.033
IV	12,390	12.025	0.970	8.751	15.860
ln $embtechup$	12,390	27.732	1.489	14.206	32.537
ln $embtechdiag$	12,390	18.973	6.695	0.000	32.645
ln $embtech_nothaven$	12,390	27.766	1.506	5.144	32.665
ln $embtech_haven$	12,390	22.368	2.005	0.000	27.978
ln $embtech$ (full assignment)	12,390	29.306	1.461	16.732	34.486
ln $embtech$ ($\delta = 15\%$)	12,390	27.221	1.490	12.460	32.121
ln $embtech$ (10-year fwd citations)	12,390	27.672	1.529	0.000	32.584
ln $embtech$ (patent counts)	12,390	26.263	1.282	13.902	30.430
$asinh_patnum$	12,390	3.644	2.268	0.000	10.800
ln $fwdcite$	12,390	2.933	2.478	0.000	11.164
ln $fwdrate$	12,390	0.556	0.449	0.000	3.970
ln $patnum_nonCNIPA$	12,390	0.543	0.877	0.000	6.048
ln $backcite$	12,390	2.839	2.355	0.000	10.387
$proxy_US$	12,390	0.591	0.347	0.000	1.000
ln $citationlag$	12,368	2.213	0.480	0.000	3.434
ln $transfer$	12,390	0.177	0.546	0.000	6.230
ln $license$	12,390	0.040	0.215	0.000	3.912
ln $collaborate$	12,390	0.467	0.938	0.000	7.073
ln $embtech_highgap$	12,390	27.765	1.514	0.000	32.664
ln $embtech_lowgap$	12,390	17.738	2.812	0.000	23.817
Panel B: IPC4 level					
new product intensity	590	0.093	0.065	0.000	0.460
export intensity	590	0.216	0.170	0.000	0.790
number of firms	590	310.421	267.363	9.000	2,438.620
average age of firms	590	16.057	4.543	5.300	39.656
$soeshare2001$	590	0.423	0.188	0.009	0.989
$tariff_input2001$	590	9.881	1.780	3.997	19.018
$tariff_output2001$	590	14.494	5.538	3.429	47.761
$weighted_tariff2001$	590	3.919	2.504	0.521	25.004
ln $centrality$	590	-8.249	2.068	-15.066	-2.008
Panel C: Country-IPC4-year level					
ln $patnum$	826,327	3.326	2.049	0.000	10.107
ln $embtech$ (equal weight)	826,327	13.295	6.174	0.001	32.595
IV	826,327	3.589	2.959	0.000	15.545
ln $backcite$	826,327	0.218	0.734	0.000	9.794
$proxy$	826,327	0.147	0.297	0.000	1.000
ln $citationlag$	130,316	2.149	0.564	0.000	3.296

Notes: Table A2 presents summary statistics for the main variables used in the analysis.

A.6 Tax Haven Lists

Table A3: Tax Haven Lists

Country/Region	ISO3	List 1	List 2	List 3	List 4	List 5
Andorra	AND	1	1	0	1	1
Anguilla	AIA	1	1	1	1	1
Antigua and Barbuda	ATG	1	1	1	1	1
Aruba	ABW	1	1	1	1	1
Bahamas	BHS	1	1	1	1	1
Bahrain	BHR	1	1	1	1	1
Barbados	BRB	1	0	1	1	1
Belize	BLZ	1	1	1	1	1
Bermuda	BMU	1	0	1	1	1
British Virgin Islands	VGB	1	1	1	1	1
Cayman Islands	CYM	1	1	1	1	1
Channel Islands	/	1	1	1	1	1
Cook Islands	COK	1	1	1	1	1
Costa Rica	CRI	1	1	1	0	1
Cyprus	CYP	1	0	1	1	0
Dominica	DMA	1	1	1	1	1
Gibraltar	GIB	1	1	1	1	1
Grenada	GRD	1	1	1	1	1
Guatemala	GTM	0	0	0	0	1
Hong Kong, China	HKG	1	0	1	1	0
Ireland	IRL	0	0	0	1	0
Isle of Man	IMN	1	0	1	1	1
Jordan	JOR	0	1	0	1	0
Lebanon	LBN	0	1	0	1	0
Liberia	LBR	1	1	1	1	1
Liechtenstein	LIE	1	1	1	1	1
Luxembourg	LUX	0	0	0	1	0
Macao, China	MAC	0	0	0	1	1
Maldives	MDV	1	1	0	1	0
Malta	MLT	1	0	1	1	0
Marshall Islands	MHL	1	1	0	1	1
Mauritius	MUS	1	0	0	0	1
Monaco	MCO	1	1	0	1	1
Montserrat	MSR	1	1	0	1	1
Nauru	NRU	1	1	1	0	0
Niue	NIU	1	1	0	0	0
Panama	PAN	1	1	1	1	1
Samoa	WSM	1	1	1	1	1
San Marino	SMR	1	0	0	1	1
Seychelles	SYC	1	0	0	1	1
Singapore	SGP	1	1	1	1	0
St. Kitts and Nevis	KNA	1	1	1	1	1
St. Lucia	LCA	1	1	1	1	1
St. Vincent and the Grenadines	VCT	1	1	1	1	1
Tonga	TON	1	1	0	0	0
Turks and Caicos Islands	TCA	1	1	1	1	1
U.S. Virgin Islands	VIR	1	0	0	1	0
Uruguay	URY	0	0	0	0	1
Vanuatu	VUT	1	1	0	1	1

Notes: Table A3 reports the classification of tax havens based on five widely used lists. List 1 refers to the original OECD Tax Haven List; List 2 is the OECD Grey List (as of August 17, 2009); List 3 corresponds to the "Stop Tax Haven Abuse Act" (not enacted); List 4 follows the classification by Hines and Rice (1994); List 5 covers jurisdictions identified by entering a Tax Information Exchange Agreement under the OECD Harmful Tax Practices framework. The data are obtained from Bennedsen and Zeume (2018).

B Innovation Network

Table B1: Top 20 Upstream Sectors of H01M in Innovation and Production Networks

	Innovation network			Production network		
Rank	IPC4	ω_{inno}	ω_{prod}	IPC4	ω_{inno}	ω_{prod}
1	H01M	0.579550	0.045174	C22C	0.002669	0.072780
2	H02J	0.035897	0.006763	H01M	0.579550	0.045174
3	C01B	0.021888	0.004080	H01L	0.013899	0.040953
4	B01J	0.016761	0.002328	E06B	0.000156	0.036607
5	H01G	0.015197	0.000338	B29C	0.004335	0.031982
6	G01R	0.014442	0.000851	C22F	0.000175	0.025564
7	H01L	0.013899	0.040953	B60C	0.000129	0.017677
8	C01G	0.013659	0.000970	B24D	0.000046	0.015207
9	B01D	0.012905	0.001370	B21B	0.000129	0.014121
10	G06F	0.011312	0.002186	C03B	0.000433	0.013560
11	C25B	0.008459	0.001096	B65D	0.001298	0.011656
12	C23C	0.008440	0.009303	C04B	0.005201	0.011279
13	H01B	0.007769	0.003998	B32B	0.007336	0.010661
14	G01N	0.007667	0.000009	B22F	0.002678	0.010589
15	A61N	0.007630	0.000000	B22D	0.000902	0.010164
16	B60K	0.007391	0.000010	C23C	0.008440	0.009303
17	B32B	0.007336	0.010661	F21V	0.000460	0.008833
18	B05D	0.007115	0.000102	F16B	0.000884	0.008791
19	B60L	0.005569	0.000346	F16L	0.000985	0.008300
20	C08J	0.005302	0.002963	B24B	0.000184	0.008053

Notes: Table B1 lists the top 20 upstream IPC4 technology fields for H01M (methods or apparatus for directly converting chemical energy into electrical energy, e.g., batteries) in both the innovation network and the production network. ω_{inno} and ω_{prod} represent the importance of the upstream sector for H01M under innovation network and production network, respectively. In the innovation network, upstream importance is measured by the share of forward patent citations from H01M to each IPC4 sector, indicating knowledge dependence. In the production network, upstream importance is measured by the share of intermediate input flows from each sector to H01M, reflecting physical input dependence. The comparison reveals substantial structural differences between knowledge flows and production linkages.

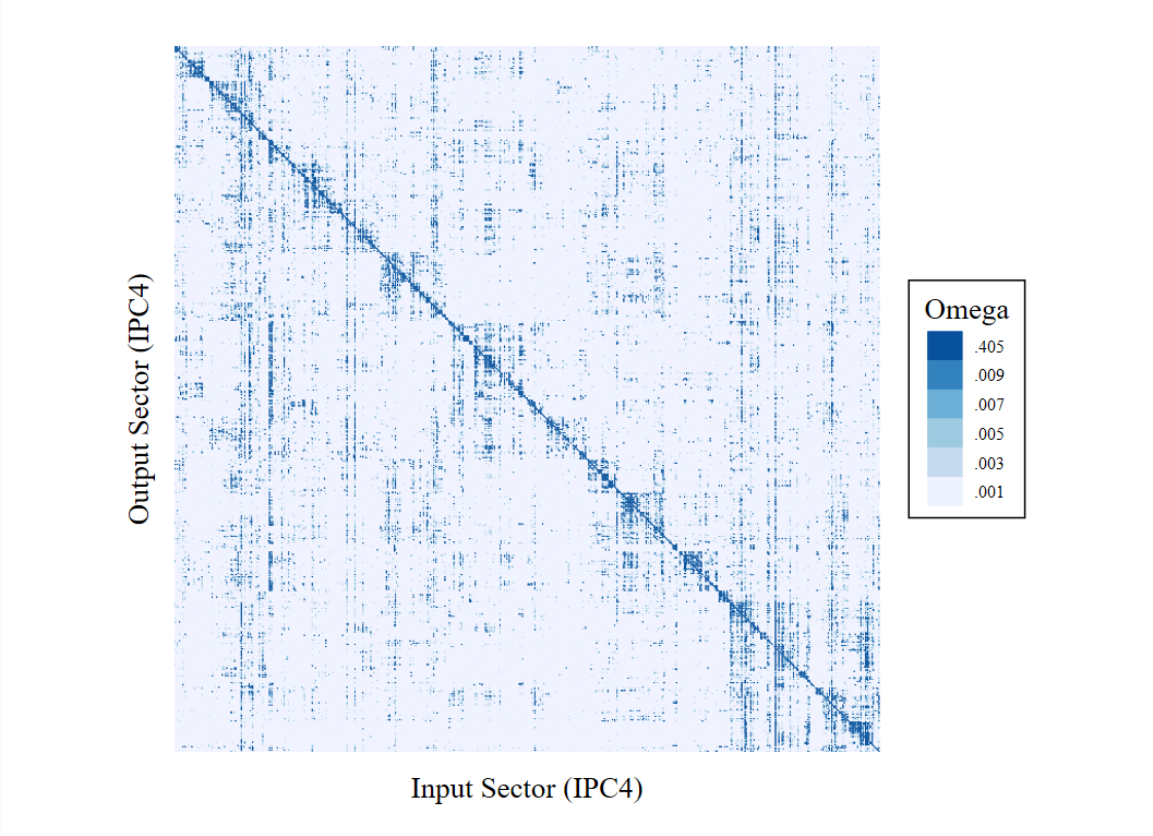


Figure B1: Innovation Network at IPC4 Level

Notes: Figure B1 presents a heatmap of citation intensity between technology fields, constructed from U.S. patent citation data (1996–2016) at the IPC4 level. The horizontal axis represents input sectors, and the vertical axis represents output sectors. Each cell in the heatmap shows the share of knowledge or material from sector j used in sector i, with darker colors indicating higher shares. Diagonal cells capture within-field knowledge flows, while off-diagonal cells represent cross-field flows.

Table B2: Stability of the Innovation Network over Sample Periods

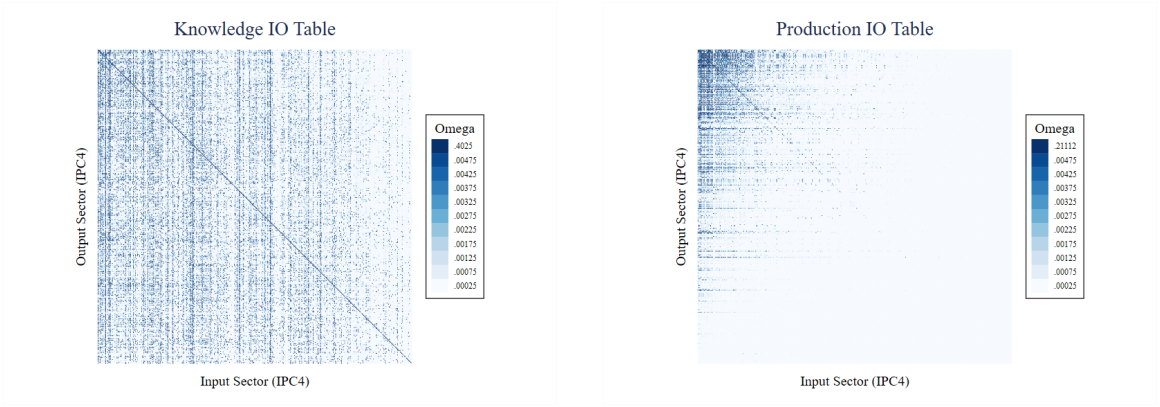
	1996–2016	1996–2006	2001–2011	2006–2016
1996–2016	1			
1996–2006	0.974	1		
2001–2011	0.987	0.971	1	
2006–2016	0.983	0.933	0.968	1

Notes: Table B2 reports the stability of the innovation network across different time periods. Based on global invention patent data from 1996 to 2016, the sample is evenly divided into three subperiods: 1996–2006, 2001–2011, and 2006–2016. Pearson correlation coefficients are calculated for the innovation network weights between these periods. All countries and regions in the sample are included in the calculation.

Table B3: Similarity of Innovation Networks Across Regions

	World	JP	CN	US	KR	RU	DE	TW	FR	GB	CA
World	1										
JP	0.950	1									
CN	0.956	0.939	1								
US	0.922	0.869	0.854	1							
KR	0.929	0.929	0.930	0.863	1						
RU	0.887	0.887	0.906	0.818	0.878	1					
DE	0.928	0.922	0.911	0.894	0.905	0.880	1				
TW	0.834	0.837	0.825	0.838	0.846	0.805	0.843	1			
FR	0.902	0.898	0.887	0.885	0.888	0.866	0.919	0.834	1		
GB	0.860	0.854	0.840	0.861	0.846	0.833	0.880	0.839	0.879	1	
CA	0.827	0.815	0.812	0.852	0.826	0.820	0.853	0.823	0.850	0.854	1

Notes: Table B3 presents the similarity of innovation networks across regions. We select the top 10 countries (regions) with the highest patent output during 1996–2016 and calculate the Pearson correlation coefficients of the innovation network weights at the country (region) level. All time periods within the sample are considered.



(a) Innovation Network (b) Production Network

Figure B2: Innovation and Production Networks at IPC4 Level

Notes: Figure B2 presents IPC4-level heatmaps for both innovation and production networks. The horizontal axis represents input sectors, and the vertical axis represents output sectors. Each cell in the heatmap shows the share of knowledge or material from sector j used in sector i, with darker colors indicating higher shares. The knowledge input-output relationships are calculated based on U.S. patent citation data from global patents during 1996–2016. The production input-output relationships are derived from the 1997 input-output table provided by the U.S. Bureau of Economic Analysis (BEA) (Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). Sectors are ranked by their overall importance in the production network, calculated as the sum of contributions from all input sectors to downstream sectors (excluding diagonal cells).

Table B4: Top and Bottom Five Sectors by Importance (IPC4)

Innovation Network		Production Network	
IPC4	Description	IPC4	Description
Panel A: Top Five Industries			
G06F	electric digital data processing	H01L	semiconductor devices; electric solid-state devices
H01L	semiconductor devices; electric solid-state devices	D04H	making textile fabrics
B01D	separation	D02G	yarn; threads; twisting
A61B	medical or veterinary diagnostics; diagnosis; surgery; identification	B60C	vehicle tyres
G01N	investigating or analyzing materials	B29C	shaping or joining of plastics
Panel B: Bottom Five Industries			
G21J	nuclear reactors	F15D	fluid dynamics; hydraulic engineering
C23D	coating metallic material; coating with metallic material	E03B	water supply
F17B	gas holders; gas storage	A01C	planting; sowing; fertilising
B29K	use of materials for shaping plastics	G16C	computational chemistry; cheminformatics
C10N	lubricating compositions	E01F	additional road equipment; traffic safety devices

Notes: Table B4 reports the five most and least important sectors under IPC4 classification in the input–output linkages for the innovation and production networks. The innovation network is derived from U.S. patent citation data in global patent records from 1996–2016, while the production network is based on the 1997 input–output table from the U.S. Bureau of Economic Analysis (BEA) (Ayerst, Ibrahim, MacKenzie and Rachapalli, 2023). Each sector's overall network importance is measured as the sum of its contributions to all downstream sectors, excluding diagonal cells. Only the top and bottom five sectors are reported for each network.

C Instrumental Variable

Table C1: Changes in China's Foreign Investment Access Categories from 1997 to 2002

			2002			
			(1) Supported Category	(2) Permitted Category	(3) Restricted Category	(4) Prohibited Category
1997	(1)	Supported Category	No change	Less welcome	Less welcome	Less welcome
	(2)	Permitted Category	More welcome	No change	Less welcome	Less welcome
	(3)	Restricted Category	More welcome	More welcome	No change	Less welcome
	(4)	Prohibited Category	More welcome	More welcome	More welcome	No change

Notes: Table C1 compares foreign investment access categories between the 1997 and 2002 editions of China's *Catalogue for the Guidance of Foreign Investment Industries*. Rows represent the 1997 category, and columns represent the 2002 category. "More welcome" indicates a shift toward a more liberal category (e.g., from "permitted" to "supported"), while "Less welcome" indicates a shift toward a more restrictive category. "No change" denotes that the category remained the same. The treatment group in our empirical analysis comprises technology fields moving to a more liberal category.

D Robustness Checks

Table D1: Controlling for Potential Confounding Factors

	(1)	(2)	(3)	(4)
	Same-field FDI		Tax-haven FDI	
	OLS	2SLS	OLS	2SLS
	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$
$\ln embtechup$	0.129***	0.880***		
	(0.033)	(0.121)		
$\ln embtechdiag$	0.010**	0.008*		
	(0.004)	(0.004)		
$\ln embtech_nothaven$			0.112***	0.777***
			(0.029)	(0.125)
$\ln embtech_haven$			0.030	-0.046
			(0.039)	(0.029)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390
KP-rk LM Statistic		124.990		74.444
KP-rk F Statistic		550.412		194.044

Notes: Table D1 reports presents robustness checks controlling for potential confounding factors. Columns 1 and 2 distinguish FDI within the same technology field, using $embtechup_{it} = \sum_{j\neq i}(\omega_{ij}\sum_c K_{cjt}FDI_{cjt})$ for cross-field spillovers and $embtechdiag_{it} = \omega_{ii}\sum_c K_{cjt}FDI_{cjt}$ for same-field FDI. Columns 3 and 4 distinguish FDI routed through tax havens, based on the OECD Tax Haven List. Each pair of columns reports OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument concerns. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

Table D2: Robustness Checks with Alternative Tax Haven Classifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	List 2		List 3		List 4		List 5	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	ln *patnum*	ln *patnum*	ln *patnum*	ln *patnum*	ln *patnum*	ln *patnum*	ln *patnum*	ln *patnum*
ln *embtech_nothaven*	0.125***	0.791***	0.112***	0.777***	0.111***	0.777***	0.123***	0.918***
	(0.033)	(0.123)	(0.029)	(0.125)	(0.029)	(0.125)	(0.029)	(0.141)
ln *embtech_haven*	0.015	-0.015	0.030	-0.046	0.032	-0.044	0.008	-0.078**
	(0.015)	(0.017)	(0.039)	(0.029)	(0.039)	(0.028)	(0.030)	(0.032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390	12,390	12,390	12,390
KP-rk LM statistic		130.774		74.439		73.803		120.857
KP-rk F statistic		507.933		194.057		193.376		370.384

Notes: Table D2 reports robustness checks using alternative tax haven classifications. Columns 1 to 8 replace the OECD original list with List 2 (OECD Grey List as of August 17, 2009), List 3 (Stop Tax Haven Abuse Act, not enacted), List 4 (classification by Hines and Rice (1994)), and List 5 (jurisdictions entering a Tax Information Exchange Agreement under the OECD Harmful Tax Practices framework). Each pair of columns presents OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers (ln *prodspill*), global technology trends (ln *globalpat*), and technology-field imports (ln *import*), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument concerns. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

Table D3: Alternative Measure of FDI-Embedded Intermediate Technology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Recalculated FDI Amount		Knowledge Depreciation Rate 15%		Citations within 10 Years		Based on Patent Applications	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$
$\ln embtech$	0.064*	0.958***	0.120***	0.736***	0.110***	0.625***	0.128***	0.629***
	(0.034)	(0.158)	(0.036)	(0.125)	(0.033)	(0.133)	(0.034)	(0.135)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390	12,390	12,390	12,390
KP-rk LM Statistic		109.369		66.988		22.534		147.777
KP-rk F Statistic		283.383		416.911		77.196		447.637

Notes: Table D3 reports robustness checks using alternative constructions of the FDI-embedded intermediate technology measure. Columns 1 and 2 recalculate FDI at the technology-field level using full allocation from CIC4 industries. Columns 3 and 4 apply a 15% knowledge depreciation rate. Columns 5 and 6 use citation counts within 10 years without depreciation. Columns 7 and 8 measure knowledge stock via patent applications with a 5% depreciation rate. Each pair of columns presents OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technological trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument issues. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

Table D4: Alternative Measure of Innovation Output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent Count (IHS)		Patent Citations		Average Citations per Patent		Overseas Patent Count	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	$asinh_patnum$	$asinh_patnum$	$\ln fwdcite$	$\ln fwdcite$	$\ln fwdrate$	$\ln fwdrate$	$\ln patnum$	$\ln patnum$
$\ln embtech$	0.131***	0.835***	0.133***	0.918***	0.004	0.078***	0.040**	0.315***
	(0.035)	(0.130)	(0.043)	(0.161)	(0.008)	(0.027)	(0.016)	(0.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390	12,390	12,390	12,390
KP-rk LM Statistic		130.275		130.275		130.275		130.275
KP-rk F Statistic		506.356		506.356		506.356		506.356

Notes: Table D4 reports robustness checks using alternative measures of innovation output. Columns 1 and 2 replace the log of patent counts with their inverse hyperbolic sine (IHS). Columns 3 and 4 use total patent citations. Columns 5 and 6 use average citations per patent. Columns 7 and 8 measure innovation by Chinese patent applications filed abroad. Each pair of columns reports OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technological trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument issues. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

Table D5: Instrumental Variable Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Conservative, 50%		Liberal, 40%		Liberal, 60%	
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
	$\ln embtech$	$\ln patnum$	$\ln embtech$	$\ln patnum$	$\ln embtech$	$\ln patnum$
$\ln embtech$		0.799***		0.828***		0.804***
		(0.125)		(0.125)		(0.124)
IV	1.274***		1.292***		1.233***	
	(0.059)		(0.066)		(0.053)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390	12,390
KP-rk LM Statistic		125.239		112.878		116.454
KP-rk F Statistic		466.449		386.937		532.640

Notes: Table D5 reports robustness checks for the instrumental variable. Columns 1 and 2 use a conservative mapping with a 50% threshold. Columns 3 and 4 adopt a relaxed 40% threshold (liberal approach). Columns 5 and 6 use a stricter 60% threshold (liberal approach). Each pair of columns reports first-stage and second-stage estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument issues. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

Table D6: Robustness to Patent Data Concerns

	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson Regression		Zero Counts		IPC3 Level	
	PPML	PPML-2SLS	OLS	2SLS	OLS	2SLS
	$patnum$	$patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$	$\ln patnum$
$\ln embtech$	0.082**	0.703***	0.151***	0.755***	0.102	0.581***
	(0.036)	(0.209)	(0.032)	(0.109)	(0.068)	(0.220)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,369	12,369	11,069	11,069	2,499	2,499
KP-rk LM Statistic				122.318		47.485
KP-rk F Statistic				387.797		99.475

Notes: Table D6 reports robustness checks for the treatment of patent data. Columns 1 and 2 replace OLS with Poisson regression, where "PPML-2SLS" implements a two-stage regression that is manually executed. Columns 3 and 4 exclude observations with zero patents. Columns 5 and 6 use IPC3-level aggregation. Each pair of columns reports OLS and 2SLS estimation results, respectively. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as interactions of industry characteristics, tariff levels, and SOE shares with year dummies. Fixed effects include year and technology-field levels. KP-rk LM and F statistics test for instrument identification and weak instrument concerns. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are t-statistics clustered at the technology-field level.

E Additional Results

Table E1: Estimates of Knowledge Spillovers Using Production Networks: First Stage

	(1) 2SLS First Stage $\ln prodspill$	(2) 2SLS First Stage $\ln prodspill$	(3) 2SLS First Stage $\ln prodspill$
IV_prod	1.430***	1.356***	1.392***
	(0.061)	(0.057)	(0.060)
IV_tech			0.107***
			(0.038)
$\ln embtech$		0.117***	
		(0.016)	
$\ln globalpat$	0.006	0.003	0.002
	(0.012)	(0.011)	(0.012)
$\ln import$	-0.020**	-0.018**	-0.020**
	(0.009)	(0.009)	(0.009)
Year FE	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes
Observations	12,390	12,390	12,390
R^2	0.986	0.986	0.986

Notes: Table E1 reports the first-stage regression results for the 2SLS specifications where production-network knowledge spillovers ($\ln prodspill$) are instrumented. Column 1 instruments $\ln prodspill$; Column 2 adds $\ln embtech$ as an additional control while still instrumenting only $\ln prodspill$; Column 3 simultaneously treats both $\ln prodspill$ and $\ln embtech$ as endogenous, each instrumented by its corresponding external instrument. All regressions control for year fixed effects, technology-field fixed effects, and interactions between year dummies and industry characteristics, tariff levels, and SOE shares. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

Table E2: Knowledge Spillover Effects: OLS estimates

	(1)	(2)	(3)	(4)
	Technology-field level		Country–technology-field level	
	OLS	OLS	OLS	OLS
	$\ln backcite$	$proxy_US$	$\ln backcite$	$proxy$
$\ln embtech$	0.132***	0.012	0.002***	0.002***
	(0.039)	(0.007)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes
Country $\times$ Technology-field FE			Yes	Yes
Country $\times$ Year FE			Yes	Yes
Observations	12,390	12,390	814,004	814,004
R^2	0.846	0.528	0.775	0.604

Notes: Table E2 reports the OLS estimates of the knowledge spillover effects. Columns 1 and 2 present results at the technology-field level, and columns 3 and 4 at the country–technology-field level. Columns 1 and 3 use the number of foreign patents cited in Chinese patents' backward citations as the dependent variable, capturing knowledge absorption. Columns 2 and 4 use technological similarity between Chinese and foreign patents, capturing structural convergence. All regressions control for production-network knowledge spillovers ($\ln prodspill$), global technological trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as the interactions of industry characteristics, tariff levels, and SOE share with year dummies. Columns 1 and 2 include year and technology-field fixed effects, while columns 3 and 4 additionally include country $\times$ technology-field and country $\times$ year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

Table E3: Channels of Knowledge Spillover: OLS estimates

	(1) OLS $\ln transfer$	(2) OLS $\ln license$	(3) OLS $\ln collaborate$	(4) OLS $\ln collaborate$	(5) OLS $\ln patnum$
$\ln embtech$	0.014	-0.011	0.054**	0.051***	0.125***
	(0.016)	(0.008)	(0.023)	(0.017)	(0.032)
$\ln transfer$				0.464***	0.203***
				(0.027)	(0.023)
$\ln license$				0.325***	0.050
				(0.058)	(0.032)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Technology-field FE	Yes	Yes	Yes	Yes	Yes
Industry characteristics $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
Tariff levels $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
SOE share $\times\delta_t$	Yes	Yes	Yes	Yes	Yes
Observations	12,390	12,390	12,390	12,390	12,390
R^2	0.410	0.187	0.625	0.681	0.916

Notes: Table E3 reports the OLS estimates of FDI technology diffusion channels. Column 1 presents the results for technology transfer; Column 2 for technology licensing; Column 3 for collaborative innovation. Column 4 adds transfers and licensing as controls to test the independent effect of collaboration. Column 5 controls for technology market transactions (patent assignments and licensing) in the baseline model to test the robustness of our core findings. All regressions control for production network spillovers ($\ln prodspill$), global technology trends ($\ln globalpat$), and technology-field imports ($\ln import$), as well as the interactions of industry characteristics, tariff levels, and SOE share with year dummies. Fixed effects include year and technology-field levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics clustered at the technology-field level are reported in parentheses.

Table E4: Top 5 and Bottom 5 Technology Fields by Centrality (IPC4)

IPC4	Description
Panel A: Top 5 Technology Fields by Centrality	
G06F	electric digital data processing
A61B	medical or veterinary diagnostics; diagnosis; surgery; identification
H01L	semiconductor devices; electric solid-state devices
H04L	transmission of digital information
A61F	medical devices and implants
Panel B: Bottom 5 Technology Fields by Centrality	
F24T	solar thermal energy systems
B41G	printing plate stamping
C10F	petroleum distillation
D06G	fabric treatment machinery
C14B	leather treatment

Notes: Table E4 presents the top and bottom five technology fields ranked by innovation network centrality under the IPC4 classification. Centrality is measured by the left eigenvector corresponding to the unit eigenvalue of the patent citation matrix across technology fields. The patent citation matrix is calculated based on U.S. patent citation data from global patents during 1996–2016. Only the five highest and lowest IPC4 fields are reported.