Imitation, Innovation, and Technological Complexity: Foreign Knowledge Spillovers in China

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Preliminary and incomplete

Abstract

We study when foreign technology exposure becomes domestic innovation. Using matched Chinese firm-accounting, patent, and citation data from 2000–2009, we document three facts. Foreign firms' output and patent shares rose after WTO accession and later declined, but this reversal is concentrated in technologically simple industries. In complex industries, foreign leadership persists, especially among highly cited patents. Patent citations reveal a parallel transition: Chinese firms' reliance on foreign prior art is inverted-U-shaped in simple industries but remains persistent in complex industries. We develop a dynamic product-line model in which foreign firms choose whether to produce in China, trading off production and market-access benefits against imitation risk. Domestic firms choose imitation and innovation effort. Industry leakiness, quality gaps, and absorptive capacity determine whether exposure becomes catch-up. The model clarifies policy tradeoffs around global technology diffusion, FDI, intellectual-property protection, export controls, and emerging-market innovation strategies.

Keywords: knowledge spillovers, imitation, innovation, foreign direct investment, patents, China.

JEL codes: F23, O33, O34, L16.

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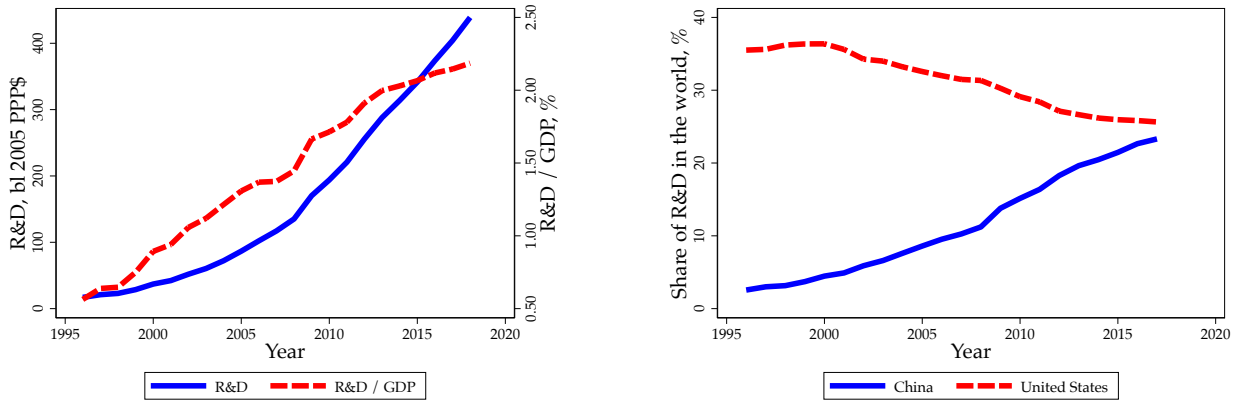
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1 Introduction

Foreign direct investment is a central channel for technology diffusion in emerging economies, but exposure is not the same as absorption. Multinational firms bring production methods, managerial practices, supplier standards, and patentable knowledge to host economies. For recipient countries, these flows can accelerate capability building and innovation. For frontier firms and their source countries, the same flows create an appropriability problem: local firms may learn, imitate, and eventually compete. This paper asks when foreign technology exposure becomes domestic innovation and when foreign technological leadership persists.

China provides a natural setting and an important test case for debates on global technology flows, intellectual-property protection, and frontier technology competition. China's WTO accession reshaped production, foreign investment, and export sophistication (Brandt et al., 2017). The edited volume *China's Growing Role in World Trade* provides broader evidence on China's integration into global markets (Feenstra and Wei, eds, 2010). During the same period, foreign multinationals expanded rapidly in Chinese manufacturing, while domestic firms experienced one of the largest innovation accelerations in modern economic history. R&D expenditures rose from 17 billion dollars in 1996 to more than 400 billion in 2017, and China's share of global R&D rose from 2.6 percent to 23.3 percent. Figure 1 summarizes this rise. Yet China's transition was highly uneven. Domestic firms became global competitors in some activities, including e-commerce, telecommunications equipment, and mobile payments, while foreign firms retained substantial leadership in industries such as semiconductors, pharmaceuticals, and advanced equipment. These contrasts suggest that foreign presence alone is not enough; the technological structure of the industry shapes whether exposure turns into catch-up.

Figure 1: Rising R&D in China



(a) R&D expenditures

(b) Share of global R&D

Notes: The left panel reports China's R&D expenditures in constant 2005 PPP dollars and as a share of GDP. The right panel reports China and U.S. shares of global R&D.

We study this question using matched firm-accounting, patent, and citation data for Chinese manufacturing. The data combine the Annual Survey of Industrial Enterprises (ASIE) with invention patents and backward citations from the Chinese National Intellectual Property Administration (CNIPA). The matched sample covers 27,343 manufacturing firms, 236,693 invention patents, and 464,072 backward citations over 2000–2009. The data allow us to measure both market outcomes, through output and ownership, and knowledge flows, through patent citations.

We document three facts. First, foreign firms' output and patent shares are hump-shaped. They rise sharply after WTO accession and fall after the mid-2000s. Second, this reversal is concentrated in technologically simple industries. In low-R&D industries, foreign shares rise and then fall; in high-R&D and technologically complex industries, foreign leadership persists. The contrast is especially stark among highly cited patents, where foreign firms retain a high share. Third, Chinese firms' reliance on foreign patent citations also follows an imitation-to-innovation pattern, but only in simple industries. Foreign citation reliance rises early in the sample and over the firm life cycle, then declines as firms accumulate domestic knowledge. In complex industries, reliance on foreign knowledge remains high.

We interpret these facts through a dynamic product-line model of FDI exposure, technology leakage, and domestic catch-up. The model builds on quality-ladder and imitation frameworks, but changes the source of imitation opportunities. In standard imitation models, firms search for or draw ideas from an external technology frontier. Here, the opportunity to imitate is endogenous to foreign firms' location decisions. A foreign leader chooses whether to produce in China. China production raises the foreign firm's payoff through lower costs,

market access, supplier depth, and local adaptation, but it also exposes the technology to domestic imitation. Chinese firms choose imitation effort in exposed foreign-led lines and innovation effort in neck-and-neck lines.

The central state variable is effective leakiness: the ease with which foreign exposure can be converted into domestic technological capability. Effective leakiness has an industry component, reflecting codifiability and technological complexity, and an absorptive-capacity component, reflecting human capital, accumulated domestic knowledge, and tools that reduce the cost of search, design, and recombination. Simple industries are intrinsically more leaky than complex industries, but the boundary is not fixed. As domestic knowledge and engineering depth accumulate, technologies that were initially difficult to absorb can become more imitable.

The model delivers three results. First, leakiness has a two-sided effect. It raises domestic learning conditional on foreign exposure, but it also discourages foreign firms from exposing their technologies in China. Second, a WTO-style rise in the attractiveness of China production can generate a hump in foreign leadership: foreign firms enter initially, but in leaky industries imitation and domestic innovation eventually erode foreign leadership. In tight industries, the erosion is slow and foreign leadership persists. Third, foreign citation reliance is inverted-U-shaped when foreign exposure initially generates imitation but accumulated domestic knowledge later supports indigenous innovation. The same mechanism generates persistent foreign reliance in complex industries. The model also clarifies why aggregate domestic patent-share growth can coexist with persistent foreign dominance among the most-cited patents. Complex industries remain harder to absorb at scale, producing fewer domestic patents, while each successful imitation or innovation event generates higher-quality knowledge. Together these forces predict the pattern in Figure 3: a falling aggregate foreign patent share alongside a stable foreign share among top-cited patents.

The model also clarifies policy tradeoffs that are central to emerging-market innovation strategy. Stronger intellectual-property protection reduces leakage risk and attracts foreign exposure, but it can slow domestic absorption conditional on exposure. Weak protection can accelerate learning when technologies are leaky, but it may discourage frontier firms from entering or from exposing their most valuable technologies. From a source-country perspective, decentralized FDI may be excessive when individual multinationals ignore how their entry raises the host country's industry-level absorptive capacity and future leakage risk faced by other foreign firms. From the host-country perspective, foreign entry may be insufficient because multinationals do not internalize domestic learning spillovers. These wedges are relevant for current debates on FDI policy, export controls, technology transfer, and industrial policy. They also connect to recent evidence from AI patents showing that

U.S. and Chinese innovation remain linked through cross-border citations, with Chinese AI inventors relying disproportionately on U.S. frontier knowledge (Fang et al., 2026).

The paper contributes to four literatures. First, it contributes to work on China's innovation surge, patent boom, and post-WTO reallocation. The edited volume *China's Growing Role in World Trade* documents China's expanding role in world trade and the changing organization of production around China's integration into global markets (Feenstra and Wei, eds, 2010). Hu and Jefferson (2009) and Hu et al. (2017) study the expansion and changing quality of Chinese patenting, while Fang et al. (2017) links intellectual-property protection to firm innovation. Brandt et al. (2017) study the effect of WTO accession on Chinese manufacturing firms, and Alder et al. (2016), Hsieh and Klenow (2009), and Song et al. (2011) provide broader evidence on China's growth, policy, and reallocation. Cong et al. (2020) survey the financing of entrepreneurship and innovation in China; our focus is the complementary technology-transfer channel. Closest in spirit, König et al. (2022) study the transition from imitation to innovation in Chinese R&D. Our contribution is to show, using firm-level patent citations matched to accounting data, that the transition is sharply sector-specific: foreign leadership erodes in simple industries but persists in complex ones.

Second, the paper contributes to the literature on international technology diffusion, FDI spillovers, and the geography of knowledge flows. Patent citations have long been used to trace knowledge spillovers (Jaffe et al., 1993). Keller (2004) surveys international technology diffusion, while MacGarvie (2006), Haruna et al. (2009), Shang et al. (2012), and Head et al. (2019) use trade, patent citations, or geography to study knowledge flows. Quantitative models of diffusion and innovation, including Santacreu (2015) and Cai et al. (2022), show how foreign technology adoption and domestic innovation jointly shape growth and comparative advantage across countries and sectors. For China, Hu et al. (2005), Ouyang and Fu (2012), Zhang (2017), Jiang et al. (2018), and Lin et al. (2020) study technology transfer through FDI, joint ventures, and foreign technology adoption; closely related, Choi et al. (2025) study multinational investment in China and the future competition created by technology transfer. Choi and Shim (2024) provide complementary evidence from Korea on the transition from foreign technology adoption to domestic innovation. Recent evidence on AI patents shows that frontier technologies continue to involve substantial cross-border knowledge flows between China and the United States (Fang et al., 2026). We add an industry-level mechanism: the same exposure to foreign knowledge has different consequences depending on technological complexity and domestic absorptive capacity. We also explicitly model the industry transition from imitation to innovation as a result of dynamic knowledge accumulation.

Third, the paper relates to theories of imitation, innovation, and endogenous growth.

Quality-ladder models such as Grossman and Helpman (1991) and Aghion and Howitt (1992) provide the leader-laggard logic of our product-line environment. Perla and Tonetti (2014), König et al. (2016), and Buera and Oberfield (2020) develop models in which imitation, search, and global idea diffusion shape productivity dynamics. The framework is designed to study a transition in foreign and domestic leadership rather than a balanced-growth path. Its key departure is that foreign firms choose whether to create the exposure from which imitation can occur.

Finally, the paper speaks to policy debates on intellectual-property rights, multinational activity, and technology transfer. Acemoglu and Akcigit (2012) show that IP policy affects innovation incentives through competition and appropriability. Helpman et al. (2004) study multinational location choices, and Branstetter (2006) provides evidence that FDI can transmit knowledge across borders. Our framework combines these forces: leakiness raises domestic learning conditional on exposure but discourages foreign firms from exposing their technologies. This two-sided effect is the central policy tradeoff.

The rest of the paper is organized as follows. Section 2 describes the data and measurement. Section 3 presents the empirical facts. Section 4 develops the model. Section 5 derives the analytical results. Section 6 presents a quantitative illustration. Section 7 discusses policy implications. Section 8 concludes.

2 Data and Measurement

This section describes the data and defines the empirical objects used in the analysis: foreign output shares, foreign patent shares, foreign citation reliance, and industry technological complexity.

2.1 Firm and patent data

Firm-level production data come from the Annual Survey of Industrial Enterprises (ASIE), administered by China's National Bureau of Statistics. The ASIE covers all state-owned enterprises and non-state firms with annual sales above five million RMB during our sample period. The survey contains balance-sheet and income-statement information, employment, output, industry codes, and registration type. We use registration type to classify firms as domestic or foreign. The ASIE has been widely used in studies of Chinese manufacturing, including Hsieh and Klenow (2009), Song et al. (2011), and Brandt et al. (2017). Brandt et al. (2014) discuss coverage and data quality in the NBS firm-level data.

Patent data come from CNIPA and cover the universe of granted patents since 1985.

We focus on invention patents, the Chinese counterpart to utility patents, because they require novelty and inventive step and are therefore better suited for studying technological innovation than utility models or design patents. CNIPA records application and grant dates, assignee names, inventor names, technology classes, and backward citations. We match patents to ASIE firms using harmonized assignee names, location, and registration type.

The final matched sample contains 27,343 manufacturing firms, 236,693 invention patents, and 464,072 backward citations between 2000 and 2009. Table 1 reports summary statistics for patenting Chinese firms in the matched sample.

Table 1: Summary Statistics for Matched ASIE–CNIPA Firms

	Mean	Std. Dev.	Min	Median	Max	Obs.
Average annual patents	3.661	5.966	0.500	2.000	43.000	17,561
Share of citations to foreigners	0.444	0.300	0.000	0.452	1.000	17,561
Years since first patent application	2.171	3.089	0.000	1.000	14.000	17,561
Output (million RMB)	851.0	2,866	5.0	114.7	21,828	14,133
Age	12.92	13.72	0.000	8.000	68.000	17,433
R&D intensity (%)	0.619	1.254	0.0295	0.257	9.842	17,561
Technological complexity	10.12	0.895	8.044	10.11	11.53	17,561

Notes: The table reports summary statistics for matched patenting firms. Average annual patents is the average annual count of granted invention patents over the years the firm appears in the matched sample. R&D intensity and technological complexity are industry-level, time-invariant measures. R&D intensity is the average R&D-to-sales ratio in the industry. Technological complexity follows Broekel (2019). Years since first patent application is computed using the full CNIPA history back to 1985, not only the 2000–2009 matched sample window.

2.2 Foreign knowledge reliance

We measure foreign knowledge reliance using backward patent citations. For each Chinese patenting firm, we compute the share of citations made to patents assigned to foreign assignees:

$$\text{Foreign Citation Share}_{it} = \frac{\text{Citations by Chinese firm } i \text{ to foreign patents in } t}{\text{All backward citations by Chinese firm } i \text{ in } t}. \quad (1)$$

The numerator includes citations to patents filed in China by foreign firms and citations to foreign patents outside China when these are listed as prior art. We also use variants excluding self-citations and variants normalized by the foreign patent share in the relevant industry-year or technology-year. The qualitative patterns are robust to these adjustments.

Patent citations are an imperfect measure of knowledge flows: they can reflect legal prior art, examiner practices, and changes in the availability of domestic patents. We therefore interpret citation shares as measures of knowledge reliance rather than direct causal estimates of learning. This interpretation is standard in the literature following Jaffe et al. (1993). The empirical analysis is designed to document a consistent set of facts that the model must rationalize.

2.3 Technological complexity

We measure industry heterogeneity in two ways. The main measure is R&D intensity, defined as the average R&D-to-sales ratio across firms in a four-digit industry using ASIE data for 2005–2007, the years in which R&D expenditures are available. Industries in the top decile of R&D intensity are classified as high-tech, and industries in the bottom decile are classified as low-tech.

The second measure is technological complexity, following Broekel (2019). This measure is based on the structural diversity of knowledge combinations in patenting. Intuitively, complex technologies require combining knowledge pieces that are less commonly recombined and therefore are harder to imitate or absorb. We map patent-level complexity to firms and industries and use the industry average. R&D intensity and technological complexity are positively correlated, but they capture distinct aspects of technological difficulty. Appendix A provides additional details, including top and bottom industries and the correlation between the two measures.

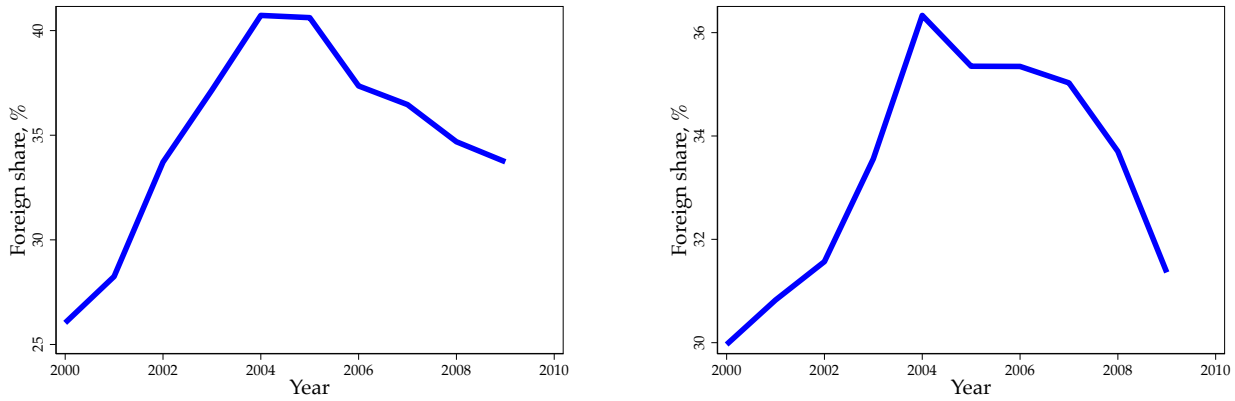
3 Empirical Facts

This section presents the empirical facts that discipline the model. We organize the evidence around three findings: foreign leadership is hump-shaped in the aggregate, the hump is concentrated in simple industries, and Chinese firms transition from relying on foreign to domestic knowledge only in those industries.

3.1 Fact 1: Foreign leadership is hump-shaped

Figure 2 plots foreign firms' shares of CNIPA invention patents and ASIE output in Chinese manufacturing. Both series rise rapidly in the early 2000s and decline after the mid-2000s. The timing is consistent with the idea that WTO accession increased the attractiveness of China for foreign firms, while domestic firms subsequently expanded their production and patenting.

Figure 2: Foreign Output and Patent Shares in Chinese Manufacturing



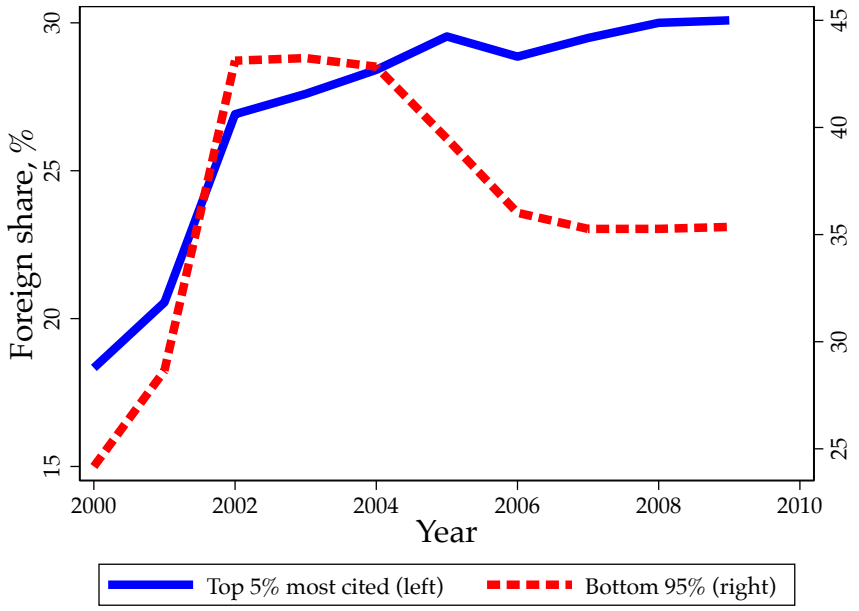
(a) Foreign patent share

(b) Foreign output share

Notes: Patent share is calculated using the stock of invention patents filed at CNIPA by foreign firms relative to all firms. Output share is calculated using ASIE firm output.

The aggregate decline in foreign shares does not mean that foreign firms lost leadership everywhere. Figure 3 separates patents by forward-citation quality. The erosion of foreign patent share is concentrated outside the top of the citation distribution. Among the top 5 percent most-cited patents, foreign firms retain a high and stable share. Thus domestic catch-up is strongest away from the frontier. This fact is important for the interpretation of China's innovation transition: domestic firms can expand patenting in technologically simpler activities while foreign firms remain central at the frontier. The model below accounts for this pattern by combining two forces. Complex technologies are harder to absorb at scale, so domestic patenting is limited in those lines. But when complex technologies are successfully imitated or improved upon, they generate higher-quality knowledge. Aggregate patent shares can therefore shift toward Chinese firms while the top of the citation distribution remains foreign-heavy.

Figure 3: Foreign Patent Share by Patent Quality

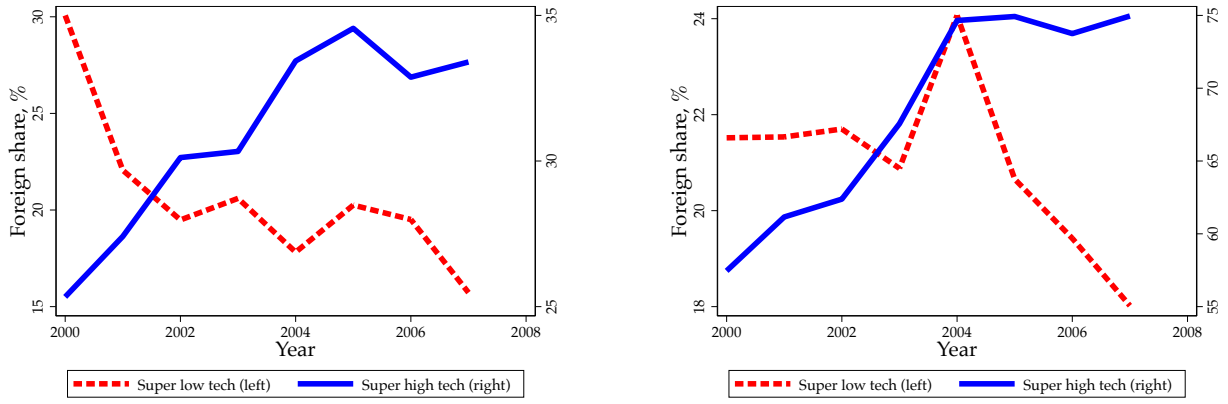


Notes: The figure reports foreign patent shares separately for patents in the top 5 percent of the forward-citation distribution and for the remaining patents, measured within technology class and application year.

3.2 Fact 2: The hump is concentrated in simple industries

Aggregate trends mask strong heterogeneity by technological difficulty. Figure 4 compares foreign patent and output shares in the top and bottom deciles of industry R&D intensity. In low-R&D industries, foreign shares rise and then fall sharply. In high-R&D industries, foreign shares rise and remain high. Thus, the aggregate decline in foreign leadership is driven by industries where technologies are more easily replicated or absorbed.

Figure 4: Foreign Shares in High- and Low-R&D Industries



(a) Foreign patent share

(b) Foreign output share

Notes: Industries are sorted by R&D intensity. The top decile is classified as high-R&D; the bottom decile is classified as low-R&D.

Table 2 confirms these patterns using industry-year regressions. The dependent variables are foreign output shares and foreign patent shares by industry-year. The regressions include industry fixed effects and interact a quadratic time trend with R&D intensity or technological complexity. The negative coefficient on the squared time trend captures the aggregate downturn in foreign shares. The positive interactions with R&D intensity and complexity imply that the downturn is weaker in more technologically difficult industries.

Table 2: Foreign Shares of Output and Patents by Industry Characteristics

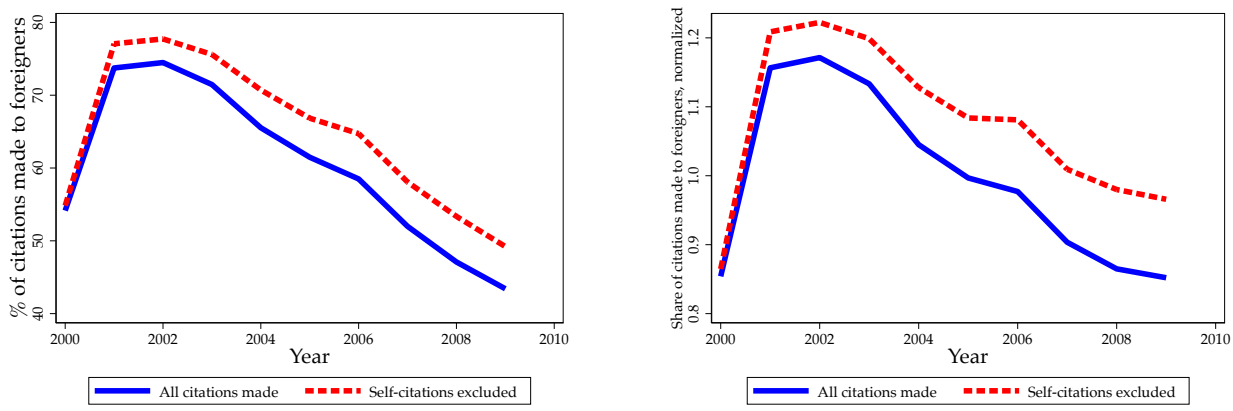
	Foreign output share		Foreign patent share	
	(1)	(2)	(3)	(4)
Year	13.66***	13.65***	5.227**	5.120**
	(1.073)	(1.074)	(2.428)	(2.424)
Year squared	-0.0034***	-0.0034***	-0.0013**	-0.0013**
	(0.0003)	(0.0003)	(0.0006)	(0.0006)
Year squared × R&D intensity	0.0634***		0.0850*	
	(0.0205)		(0.0454)	
Year squared × Technological complexity		0.0003**		0.0011***
		(0.0001)		(0.0003)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	3,318	3,318	3,140	3,140
R^2	0.896	0.896	0.726	0.727

Notes: The table estimates differential time trends in foreign output and patent shares across industries. R&D intensity and technological complexity are industry-level time-invariant measures. Standard errors in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

3.3 Fact 3: Foreign knowledge reliance declines only where imitation succeeds

The previous facts are about market and patent leadership. We next use citations to study the knowledge flows behind the transition. Figure 5 plots the share of citations by Chinese firms to foreign patents. The share rises sharply in the early 2000s and then falls. The pattern is robust to excluding self-citations and to normalizing by foreign patent availability. This suggests a transition from foreign-based learning to domestic knowledge accumulation.

Figure 5: Foreign Knowledge Reliance of Chinese Firms

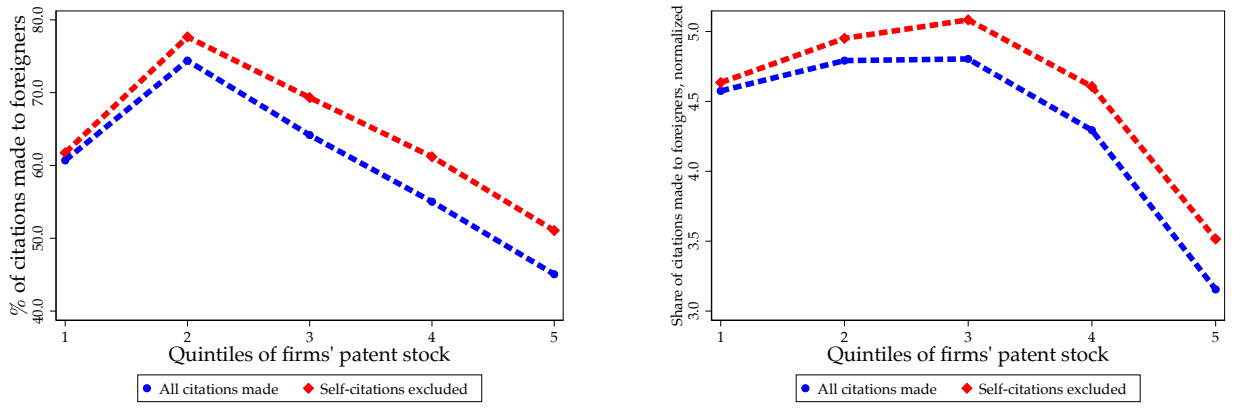


(a) Share of citations to foreigners (b) Normalized by foreign patent share

Notes: The figure reports the share of backward citations made by Chinese firms to foreign patents. The right panel normalizes by the foreign patent share in CNIPA.

Figure 6 shows the same transition over the firm life cycle. We sort firm-year observations by the firm's patent stock and plot foreign citation shares across quintiles. Young patenting firms rely heavily on foreign knowledge. Reliance peaks at intermediate levels of patenting experience and falls for mature patenting firms. This inverted-U remains after excluding self-citations and normalizing by the foreign patent share.

Figure 6: Foreign Knowledge Reliance over the Firm Life Cycle



(a) By patent-stock quintile (b) Normalized by foreign patent share

Notes: The figure plots the average share of citations made by Chinese firms to foreign patents as a function of firm patent-stock quintiles.

Table 3 uses within-firm variation to estimate the relationship between foreign citation reliance and firm life cycle. The dependent variable is the foreign citation share normalized by foreign patent availability. The level of life-cycle variables enters positively and the squared

term enters negatively, consistent with an inverted-U. The positive interaction between the squared term and R&D intensity shows that the decline is attenuated in high-R&D industries. In complex industries, the foreign citation share can remain increasing over the observed life cycle.

Table 3: Foreign Spillovers over the Firm Life Cycle: Heterogeneity by R&D Intensity

	Share of citations made to foreigners			
	(1)	(2)	(3)	(4)
Years since first patent	0.234***		0.330***	
	(0.0732)		(0.0789)	
Years since first patent, squared	-0.00708**		-0.0103***	
	(0.00331)		(0.00357)	
Years since first patent, squared × R&D intensity	0.00270**		0.00316**	
	(0.00136)		(0.00154)	
Patent stock		1.201***		1.339***
		(0.279)		(0.300)
Patent stock, squared		-2.431*		-2.479*
		(1.282)		(1.378)
Patent stock, squared × R&D intensity		1.185*		1.209*
		(0.634)		(0.681)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Excluding self-citations	No	No	Yes	Yes
Observations	17,561	17,561	17,340	17,340
R^2	0.829	0.829	0.832	0.833

Notes: The dependent variable is the share of citations by Chinese firms to foreign patents, normalized by the foreign patent share in the firm's industry-year. Patent stock is measured in thousands. Controls include firm and year fixed effects and the numbers of foreign and Chinese patent applications in the firm's four-digit industry-year. Standard errors in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

3.4 Summary of the facts

The evidence leaves three empirical patterns for the model to explain. First, foreign presence in Chinese manufacturing rises after WTO accession and then declines. This pattern suggests that foreign firms initially found China more attractive as a production and market location, but that the same exposure later created conditions for domestic catch-up. A model therefore needs an entry or exposure margin for foreign firms, rather than treating foreign technology

as an exogenous frontier available to Chinese firms.

Second, the reversal in foreign output and patent shares is concentrated in technologically simple industries. In complex industries, foreign firms retain leadership, especially among highly cited patents. This heterogeneity implies that exposure alone is not enough. The model must distinguish between the amount of foreign activity in China and the ease with which domestic firms can convert that activity into technological capability. We capture this distinction through industry-specific quality gaps and leakiness: complex industries have larger technological gaps but lower leakiness, while simple industries have smaller gaps but greater absorptive ease.

Third, patent citations show that Chinese firms' reliance on foreign knowledge is transitional only in the industries where domestic catch-up occurs. In simple industries, Chinese firms initially cite foreign patents heavily, but later rely more on domestic prior art. In complex industries, foreign citation reliance remains persistent. This pattern points to a dynamic mechanism in which foreign exposure first supports imitation, imitation builds domestic knowledge, and accumulated domestic knowledge later raises the productivity of domestic innovation.

The next section develops an innovation and imitation model that formalizes these forces. Foreign firms choose whether to expose technologies through production in China, trading off the benefits of China production against imitation risk. Chinese firms choose imitation effort in exposed foreign-led lines and innovation effort once they reach neck-and-neck competition. Industry leakiness, quality gaps, and accumulated domestic knowledge jointly determine whether foreign exposure becomes domestic catch-up. Thus the same mechanism generates the foreign-share hump, the cross-industry divergence, and the transition from foreign to domestic knowledge reliance.

4 A Model of FDI Exposure, Leakiness, and Domestic Catch-Up

We develop a dynamic product-line model of innovation and imitation to organize the empirical facts. The model is a tractable framework designed to isolate the mechanism linking foreign location decisions, technology leakage, domestic imitation, and the transition to indigenous innovation. The key departure from standard imitation models is that imitation opportunities are created by foreign firms' endogenous decision to expose technology through production in China, and by a product-line characteristic that we call leakiness.

The model has four building blocks. First, technological leadership is represented by a

quality gap within each product line; complex product lines have larger gaps and lower intrinsic leakiness. Second, foreign firms choose whether to produce particular product lines in China. China production raises flow payoffs but exposes the firm to imitation. Third, Chinese firms choose imitation effort in exposed foreign-led product lines and, if they catch up, the innovation effort after reaching a neck-and-neck state. Fourth, domestic knowledge accumulates from imitation and innovation, raising future innovation productivity and absorptive capacity.

4.1 Product lines and states

Time is continuous. A unit mass of product lines is partitioned into permanent industry types $\chi \in \{S, C\}$, where S denotes *simple/leaky* industries and C denotes *complex/tight* industries. In addition, product lines can be in one of three states over time:

$$F : \text{foreign leader, Chinese laggard,}$$
$$N : \text{neck-and-neck,}$$
$$D : \text{Chinese leader, foreign laggard.}$$

The industry type χ summarizes two technological primitives that are described in more detail below. The first is the *quality gap*, which measures the technological distance between the leader and the laggard in a product line. Complex industries have larger quality gaps: frontier firms are farther ahead, and catching up requires mastering a deeper set of capabilities. The second is intrinsic *leakiness*, which measures how easily foreign exposure can be converted into successful domestic imitation. Simple or leaky industries are those in which technologies are relatively codified, modular, or observable through production, so that foreign entry creates substantial learning opportunities for domestic firms. Complex or tight industries are those in which production depends more heavily on tacit know-how, specialized equipment, cumulative scientific knowledge, or tightly integrated design capabilities, so that exposure is less likely to translate into imitation.

4.2 Quality gaps, Cournot competition, and value gaps

Within each product line, firms compete in quality-adjusted effective units. Firm $i \in \{F, D\}$ produces physical output y_i with quality q_i. Effective output is $x_i = q_i y_i$, and inverse demand is

$$P = A - (x_F + x_D), \qquad A > 0. \tag{2}$$

Firm i has physical marginal cost $c > 0$ and quality-adjusted effective cost $\widetilde{c}_i = c/q_i$. A technological leader has higher quality and therefore lower effective cost, which maps into higher output and profits.

Quality gaps. In a foreign-led line, the foreign firm has quality $\sigma_\chi q$ and the Chinese firm has quality q, where $\sigma_\chi > 1$ measures the leader's quality advantage, or technological distance. In a Chinese-led line, the roles are reversed, and in a neck-and-neck line, both firms have quality q. We normalize $q = 1$. The quality gap σ_χ between a leader and the follower is the product-line counterpart of technological distance. We allow it to differ by industry type,

$$\sigma_C > \sigma_S > 1, \tag{3}$$

so complex industries feature deeper frontier gaps. We maintain $A > 2c$, which is sufficient for both firms to produce positive quantities in all three states.[1]

Flow profits. Solving the Cournot game in effective quantities gives the following state payoffs:

$$\pi_\chi^{\text{lead}} = \frac{[\sigma_\chi(A+c) - 2c]^2}{9\sigma_\chi^2}, \tag{4}$$

$$\pi_\chi^{\text{lag}} = \frac{[\sigma_\chi(A-2c) + c]^2}{9\sigma_\chi^2}, \tag{5}$$

$$\pi^N = \frac{(A-c)^2}{9}. \tag{6}$$

The leader earns π_χ^{lead}, the laggard earns π_χ^{lag}, and both firms earn π^N in the neck-and-neck state. Define the profit premia

$$\Delta\pi_\chi^{lead} \equiv \pi_\chi^{\text{lead}} - \pi^N = \frac{4c(\sigma_\chi - 1)(A\sigma_\chi - c)}{9\sigma_\chi^2} > 0, \tag{7}$$

$$\Delta\pi_\chi^{\text{lag}} \equiv \pi^N - \pi_\chi^{\text{lag}} = \frac{c(\sigma_\chi - 1)\left[2A\sigma_\chi - c(3\sigma_\chi - 1)\right]}{9\sigma_\chi^2} > 0. \tag{8}$$

Both premia vanish at $\sigma_\chi = 1$ and increase with the quality gap.

State transitions. The transition rates summarize what can happen in each product-line state. In a foreign-led line F, the Chinese firm is the technological laggard and can catch up

[1] The laggard's equilibrium effective quantity is $(A - 2c + c/\sigma_\chi)/3$. This is positive whenever $A > c(2 - 1/\sigma_\chi)$. Since $2 - 1/\sigma_\chi < 2$ for $\sigma_\chi > 1$, $A > 2c$ is sufficient.

through imitation; successful imitation moves the line from F to N at rate M. In a neck-and-neck line N, both firms can innovate. Chinese innovation moves the line from N to D at rate G^D, while foreign innovation moves it from N to F at rate G^F. In a Chinese-led line D, the foreign firm is the laggard and can regain leadership through leapfrogging innovation, which moves the line from D to F at rate L. Thus,

$$F \xrightarrow{M} N, \qquad N \xrightarrow{G^D} D, \qquad N \xrightarrow{G^F} F, \qquad D \xrightarrow{L} F.$$

For the purpose of deriving the value gaps below, we take M, G^D, G^F, and L as given transition hazards. The effort and exposure decisions introduced later determine these hazards endogenously.

Value gaps. Let $V_\chi^F, V_\chi^N, V_\chi^D$ denote the foreign firm's continuation values in foreign-led, neck-and-neck, and Chinese-led lines. Let $W_\chi^F, W_\chi^N, W_\chi^D$ denote the corresponding values of the Chinese firm. The model uses three gross continuation value gaps:

$$\Omega_\chi \equiv V_\chi^F - V_\chi^N, \tag{9}$$

$$\Delta_\chi^I \equiv W_\chi^N - W_\chi^F, \tag{10}$$

$$\Delta_\chi^D \equiv W_\chi^D - W_\chi^N. \tag{11}$$

The first is the foreign leader's loss due to imitation. The second is the Chinese laggard's gain from becoming neck-and-neck. The third is the Chinese firm's gain from becoming the leader. Appendix B derives these objects from the product-line HJB equations.

Lemma 1 (Product-line value gaps)**.** *Fix industry type χ and suppress time subscripts. For given state transition rates M, G^D, G^F, and L, define*

$$\mathcal{D} = r^2 + r(M + L + G^D + G^F) + G^D(L + M) + G^F L + LM > 0. \tag{12}$$

The value gaps are

$$\Omega_\chi = \frac{(r + G^D + L)\Delta\pi_\chi^{lead} + G^D\Delta\pi_\chi^{\text{lag}}}{\mathcal{D}}, \tag{13}$$

$$\Delta_\chi^I = \frac{G^D\Delta\pi_\chi^{lead} + (r + G^D + L)\Delta\pi_\chi^{\text{lag}}}{\mathcal{D}}, \tag{14}$$

$$\Delta_\chi^D = \frac{(r + G^F + M)\Delta\pi_\chi^{lead} + (G^F - L)\Delta\pi_\chi^{\text{lag}}}{\mathcal{D}}. \tag{15}$$

The gaps Ω_χ and Δ_χ^I are strictly positive for $A > 2c$ and $\sigma_\chi > 1$. The gap Δ_χ^D is strictly

positive under the sufficient condition $G^F \geq L$. Economically, this condition says that foreign innovation in contested neck-and-neck lines is at least as strong as foreign leapfrogging of Chinese-led lines, which is natural when the foreign firm's primary route back to leadership is innovation in lines where it remains technologically active.

The proof is provided in Appendix Section B.3.

The value gaps are determined by the static profit premia, the discount rate, and the transition rates that will be generated by imitation, innovation, and foreign leapfrogging. The model remains analytically transparent because the comparative statics below depend on the signs and local monotonicity of these gaps rather than on a full closed-form solution for the dynamic fixed point.

Corollary 1 (Quality gap and incentives)**.** *The foreign leader's loss from imitation Ω_χ and the Chinese laggard's imitation gain Δ_χ^I are increasing in the quality gap σ_χ. Under the sufficient condition $G^F \geq L$ (that is, foreign firms regain leadership more easily from the neck-and-neck state than from the Chinese-led state), the Chinese leadership gain Δ_χ^D is also increasing in σ_χ.*

The proof is provided in Appendix Section B.4.

The corollary isolates the role of quality gaps, or technological distance. A larger quality gap raises the value at stake in technological transitions: the Chinese laggard gains more from catching up, and the foreign leader loses more when imitation erodes its lead. These statements hold for given transition hazards and do not by themselves imply faster domestic catch-up. Actual catch-up also depends on how easily foreign exposure can be converted into imitation, which we introduce next as effective leakiness.

4.3 Foreign location choice, leakiness, and imitation

A foreign leader chooses whether to produce outside China or in China. Producing in China generates a line-specific flow benefit

$$b_j = B_{\chi t} + \varepsilon_j, \tag{16}$$

where $B_{\chi t}$ is the common China-production benefit for industry-χ lines at time t, which rises in a WTO-style shock, and ε_j is a line-specific component with cumulative distribution G and density g. The benefit $B_{\chi t}$ summarizes lower production costs, access to the Chinese market, local supply chains, scale, and local-demand adaptation. A WTO-style shock is represented as an increase in $B_{\chi t}$.

On the downside, producing in China also exposes the technology to imitation. Effective leakiness is

$$\lambda_{\chi t} = (1 - \phi_t)\bar{\lambda}_\chi a(H_t, K_{\chi t}, AI_t), \qquad \bar{\lambda}_S > \bar{\lambda}_C. \tag{17}$$

Here $\bar{\lambda}_\chi$ captures intrinsic codifiability or technological leakiness; ϕ_t captures intellectual-property enforcement or other protection against leakage; H_t is domestic human capital; $K_{\chi t}$ is accumulated domestic knowledge; and AI_t captures technologies that reduce search, design, simulation, and recombination costs. We assume

$$a_H > 0, \qquad a_K > 0, \qquad a_{AI} > 0. \tag{18}$$

Thus, effective leakiness is partly technological and partly determined by domestic absorptive capacity.

Chinese imitation effort. If a foreign leader produces in China, a Chinese laggard can choose an imitation effort $m \geq 0$ by paying imitation cost $\frac{\kappa_I}{2}m^2$. Imitation succeeds with hazard $\lambda_{\chi t} m$ and moves the line from F to N. The Chinese laggard solves

$$\max_{m \geq 0} \left\{ \lambda_{\chi t} m \Delta_\chi^I - \frac{\kappa_I}{2} m^2 \right\}. \tag{19}$$

The optimal imitation effort is:

$$m_{\chi t}^* = \frac{\lambda_{\chi t} \Delta_\chi^I}{\kappa_I}, \tag{20}$$

and the resulting imitation hazard is:

$$h_{\chi t}^I = \lambda_{\chi t} m_{\chi t}^* = \frac{\lambda_{\chi t}^2 \Delta_\chi^I}{\kappa_I}. \tag{21}$$

The foreign firm anticipates the imitation hazard. It produces in China if

$$b_j \geq \Omega_\chi h_{\chi t}^I. \tag{22}$$

This condition compares the flow benefit of China production to the expected flow loss from imitation: $h_{\chi t}^I$ is the per-period imitation hazard and Ω_χ is the value loss if imitation occurs. Therefore, the endogenous share of foreign-led lines exposed through China production is

$$x_{\chi t} = \Pr(b_j \geq \Omega_\chi h_{\chi t}^I) = 1 - G\left(\Omega_\chi h_{\chi t}^I - B_{\chi t}\right). \tag{23}$$

As a result, the aggregate transition rate from foreign leadership to neck-and-neck is

$$M_{\chi t} = x_{\chi t} h^I_{\chi t}. \tag{24}$$

Equations (21)–(24) show how quality gaps and leakiness interact. The quality gap σ_χ affects the imitation prize Δ^I_χ and the foreign leader's loss Ω_χ (Corollary 1). Effective leakiness $\lambda_{\chi t}$ determines how easily exposure is converted into successful imitation. Complex industries have larger quality gaps, which raise the prize from imitation, but lower intrinsic leakiness, which reduces the conditional arrival rate of imitation. Simple industries have smaller prizes but higher leakiness. Domestic catch-up is therefore concentrated in simple industries when the leakiness advantage dominates the larger imitation prize in complex industries.

4.4 Innovation in neck-and-neck lines

In neck-and-neck lines, both Chinese and foreign firms can innovate. Chinese firms are successful at innovation depending on their innovation effort n_D and innovation productivity $\xi^D_{\chi t}$, which increases with accumulated domestic knowledge: $\xi^D_{\chi t} = \xi^D_\chi(K_{\chi t})$, with $\frac{\partial \xi^D_\chi}{\partial K_{\chi t}} > 0$.

Innovation cost is $\frac{\kappa_D}{2} n_D^2$. Hence, Chinese firms solve:

$$\max_{n_D \geq 0} \left\{ \xi^D_{\chi t} n_D \Delta^D_\chi - \frac{\kappa_D}{2} n_D^2 \right\}. \tag{25}$$

The optimal effort is:

$$n^{D*}_{\chi t} = \frac{\xi^D_{\chi t} \Delta^D_\chi}{\kappa_D}, \tag{26}$$

while the resulting innovation hazard is:

$$G^D_{\chi t} = \xi^D_{\chi t} n^{D*}_{\chi t} = \frac{(\xi^D_{\chi t})^2 \Delta^D_\chi}{\kappa_D}. \tag{27}$$

Analogously, a foreign firm innovates with effort n^F and pays cost $\frac{\kappa_F}{2} n_F^2$. Innovation productivity is $\xi^F(\sigma_\chi)$, and we assume that $\xi^{F\prime}(\sigma) > 0$. This assumption ties the foreign frontier advantage to the same technological-distance parameter that governs the quality gap: the knowledge depth that creates a larger quality lead also supports stronger foreign recombination capacity in contested product lines.

The resulting foreign innovation hazard in neck-and-neck lines is:

$$G^F_{\chi t} = \xi^F(\sigma_\chi) n^{F*}_{\chi t} = \frac{[\xi^F(\sigma_\chi)]^2 \Omega_\chi}{\kappa_F}. \tag{28}$$

The foreign firm's gain from innovating in a neck-and-neck line is $V_\chi^F - V_\chi^N = \Omega_\chi$, the same value gap that governs the exposure decision in foreign-led lines.

Combining (28) with Corollary 1 implies that, holding other transition hazards fixed, the foreign innovation hazard $G_{\chi t}^F$ is increasing in the quality gap σ_χ. Larger quality gaps raise the foreign firm's value gain from innovation, Ω_χ, and higher σ_χ also raises foreign innovation productivity through $\xi^F(\sigma_\chi)$. Thus, complex industries give foreign firms a stronger innovation incentive in neck-and-neck lines.

4.5 Foreign leapfrogging of Chinese-led lines

In product lines led by Chinese firms, foreign firms can innovate to leapfrog leaders. Let $L_{\chi t}$ denote the transition rate from Chinese leadership to foreign leadership. For tractability and to keep the main mechanism focused, we let

$$L_{\chi t} = \ell_\chi x_{\chi t}, \qquad \ell_\chi > 0. \tag{29}$$

The dependence on $x_{\chi t}$ captures an exposure spillover: when more foreign-led type-χ lines are produced in China, foreign firms obtain more local information about suppliers, engineers, users, production practices, and domestic competitors, making it easier to identify and leapfrog Chinese-led lines. The linear specification is a transparent first-order representation of this exposure margin; Appendix B.5 derives the corresponding effort-based hazard and shows that the qualitative results only require $L_{\chi t}$ to be increasing in exposure.

4.6 Laws of motion

Let $f_\chi(t)$, $n_\chi(t)$, and $d_\chi(t)$ denote the shares of type-χ product lines in states F, N, and D, respectively. They satisfy

$$f_\chi(t) + n_\chi(t) + d_\chi(t) = 1. \tag{30}$$

For each industry type χ, product-line shares evolve according to

$$\dot{f}_\chi = L_{\chi t} d_\chi + G_{\chi t}^F n_\chi - M_{\chi t} f_\chi, \tag{31}$$

$$\dot{n}_\chi = M_{\chi t} f_\chi - (G_{\chi t}^D + G_{\chi t}^F) n_\chi, \tag{32}$$

$$\dot{d}_\chi = G_{\chi t}^D n_\chi - L_{\chi t} d_\chi. \tag{33}$$

Adding (31)–(33) gives $\dot{f}_\chi + \dot{n}_\chi + \dot{d}_\chi = 0$, so the total measure of type-χ product lines is fixed and the state shares continue to sum to one.

Domestic knowledge accumulates when Chinese firms successfully imitate foreign technologies or innovate in neck-and-neck lines. Let $\mu_I(\sigma_\chi)$ denote the increment to domestic knowledge from a successful imitation event, and let $\mu_N(\sigma_\chi)$ denote the increment from a successful domestic innovation event in a neck-and-neck line. We allow both increments to depend on the quality gap and assume $\mu_I'(\sigma) > 0$ and $\mu_N'(\sigma) > 0$: absorbing or improving a more complex technology generates a larger knowledge gain. Domestic knowledge then evolves according to

$$\dot{K}_{\chi t} = \mu_I(\sigma_\chi) M_{\chi t} f_\chi + \mu_N(\sigma_\chi) G^D_{\chi t} n_\chi - \delta K_{\chi t}. \tag{34}$$

The first term is knowledge accumulated through imitation of exposed foreign technologies. The second is knowledge accumulated through domestic innovation. The final term captures depreciation or obsolescence of domestic knowledge at rate δ.

4.7 Mapping to observables: patents, citations, and market shares

We map the model to the empirical objects as follows. First, the model-implied foreign output share is a weighted average of the shares of product lines in which the foreign firm leads, is neck-and-neck, or lags:

$$Y^F_{\chi t} = \omega_F f_{\chi t} + \omega_N n_{\chi t} + \omega_D d_{\chi t}, \qquad \omega_F > \omega_N > \omega_D. \tag{35}$$

The weights ω_F, ω_N, and ω_D denote the foreign firm's output share within a product line in states F, N, and D, respectively. The ordering follows from the Cournot equilibrium in Section 4.2: the foreign firm has the lowest effective cost and highest output share when it leads, an intermediate output share when firms are neck-and-neck, and the lowest output share when it is the laggard.

Next, we assume that successful innovation and imitation events can generate patents filed at the Chinese Patent Office. Let p_F denote the number of patents of a foreign firm that leads a product line, and let p_D denote the patenting intensity of a Chinese firm that leads a product line. Let p^F_N and p^D_N denote the number of patents associated with successful foreign and Chinese innovation in neck-and-neck lines, respectively. Finally, let p_E denote patents associated with foreign leapfrogging events, and let p_I denote patents associated with successful Chinese imitation events. Then foreign patenting is

$$P^F_{\chi t} = p_F f_\chi + p^F_N G^F_{\chi t} n_\chi + p_E L_{\chi t} d_\chi, \tag{36}$$

and Chinese patenting is

$$P_{\chi t}^{D} = p_D d_\chi + p_N^D G_{\chi t}^D n_\chi + p_I M_{\chi t} f_\chi. \tag{37}$$

The foreign patent share is $P_{\chi t}^F/(P_{\chi t}^F + P_{\chi t}^D)$.

Chinese patents cite foreign prior art when knowledge acquisition comes from foreign-based imitation and cite domestic prior art when innovation builds on domestic knowledge. The model-implied foreign citation share is therefore

$$R_{\chi t} = \frac{M_{\chi t} f_{\chi t}}{M_{\chi t} f_{\chi t} + G_{\chi t}^D n_{\chi t} + \rho K_{\chi t}}, \tag{38}$$

where $\rho > 0$ is the rate at which the domestic knowledge stock generates domestic-patent citations, capturing the probability that a domestic innovation builds on codified prior domestic art. This object is the model counterpart of the empirical foreign citation share.

Following the complexity-dependent knowledge accumulation in (34), we can define the patent quality. Define the knowledge-quality index of domestic patenting in industry χ as

$$Q_{\chi t} = \frac{\mu_I(\sigma_\chi) M_{\chi t} f_{\chi t} + \mu_N(\sigma_\chi) G_{\chi t}^D n_{\chi t}}{M_{\chi t} f_{\chi t} + G_{\chi t}^D n_{\chi t}}. \tag{39}$$

Then the following is true:

Corollary 2 (Citation quality and technological distance)**.** *Suppose $\mu_I'(\sigma) > 0$ and $\mu_N'(\sigma) > 0$. For any fixed composition of domestic patenting between imitation-based patents and innovation-based patents, $Q_{\chi t}$ is increasing in σ_χ. Hence patents produced in higher-gap product lines are predicted to have higher average forward-citation quality, even when such patents are less frequent.*

The quality index $Q_{\chi t}$ maps to the forward-citation quality of domestic patents. Together with persistent foreign leadership in complex industries, it explains why the top-citation tier can remain foreign-dominated even when aggregate domestic patenting expands.

5 Analytical Results

We now derive the main comparative statics. Proofs are in Appendix C. Lemma 1 establishes that the value gaps Ω_χ, Δ_χ^I, and Δ_χ^D are determined by product-market primitives and equilibrium transition rates. The propositions below analyze local responses of foreign exposure, imitation, and domestic innovation to changes in leakiness λ, IP enforcement ϕ, and

the China benefit B, evaluated around a current equilibrium. Equivalently, the direct exposure margin can be written as a conditional imitation hazard $h^I(\lambda)$ with $h^I_\lambda > 0$. Appendix B.6 shows how the value-gap block and the effort/exposure block can be closed as a recursive equilibrium fixed point. The quantitative illustration in Section 6 uses a reduced-form implementation that preserves the equilibrium monotonicities.

Proposition 1 (Foreign exposure is endogenous)**.** *The share of foreign-led lines exposed through China production is*

$$x_{\chi t} = 1 - G\left(\Omega_\chi h^I_{\chi t} - B_{\chi t}\right), \qquad h^I_{\chi t} = \frac{\lambda^2_{\chi t}\Delta^I_\chi}{\kappa_I}.$$

Then, holding the current value gaps $(\Omega_\chi, \Delta^I_\chi, \Delta^D_\chi)$ *fixed,* $\partial x_{\chi t}/\partial B_{\chi t} > 0$*,* $\partial x_{\chi t}/\partial \phi_t > 0$*, and* $\partial x_{\chi t}/\partial a(H_t, K_{\chi t}, AI_t) < 0$*.*

Proposition 1 formalizes the foreign firm's tradeoff. Foreign exposure rises when China production becomes more attractive and when IP protection reduces leakage risk. But, holding the China benefit and current value gaps fixed, higher domestic absorptive capacity discourages exposure because it raises the expected loss from imitation.

Proposition 2 (Leakiness has a two-sided effect)**.** *Let* $M_{\chi t} = x_{\chi t} h^I_{\chi t}$ *and suppress subscripts. Let* $h = h^I(\lambda)$*,* $x = 1 - G(\Omega h - B)$*, and* γ *be the density evaluated at* $\Omega h - B$*. Then*

$$\frac{\partial M}{\partial \lambda} = h'(\lambda)\left[x - \Omega h \gamma\right]. \tag{40}$$

Therefore total imitation rises with leakiness if and only if $x > \Omega h \gamma$*.*

This proposition is the core mechanism. Leakiness increases learning conditional on exposure, but it also reduces exposure by making foreign firms less willing to locate in China. Total learning can therefore be non-monotone in leakiness. This is the central difference between the model and frameworks in which imitation opportunities are exogenous.

Proposition 3 (IP protection has an ambiguous effect on domestic imitation)**.** *An increase in IP protection lowers effective leakiness and raises foreign exposure. Its effect on total domestic imitation* $M = xh$ *is ambiguous. In particular, if* $x > \Omega h \gamma$*, then* $\partial M/\partial \phi < 0$*; if* $x < \Omega h \gamma$*, then* $\partial M/\partial \phi > 0$*.*

IP protection attracts foreign firms by reducing the imitation risk they face. At the same time, it directly lowers leakage conditional on exposure. Which effect dominates depends on whether the economy is on the exposure-dominated or leakage-dominated part of the tradeoff.

When $x < \Omega h\gamma$, foreign exposure is highly sensitive to imitation risk, so stronger IP can raise total imitation by inducing enough additional exposure to offset the lower leakage rate conditional on exposure. When $x > \Omega h\gamma$, the exposure margin is less sensitive and the direct leakage-reduction effect dominates.

Proposition 4 (Steady-state foreign leadership)**.** *Fix K and hence hold transition rates M, G^D, G^F, and L fixed, all strictly positive. The stationary shares are*

$$f^* = \left[1 + \frac{M}{G^D + G^F} + \frac{G^D M}{L(G^D + G^F)}\right]^{-1}, \tag{41}$$

$$n^* = \frac{M}{G^D + G^F} f^*, \qquad d^* = \frac{G^D M}{L(G^D + G^F)} f^*. \tag{42}$$

Moreover, $\partial f^*/\partial M < 0$ and $\partial d^*/\partial M > 0$.

Holding other transition rates fixed, stronger domestic imitation reduces foreign leadership and increases domestic leadership. This is why the model predicts catch-up in simple industries when leakiness translates into imitation rather than deterring exposure completely.

Proposition 4 also clarifies why foreign leadership can persist in complex industries. Write

$$f^* = \left[1 + \frac{M}{G^D + G^F}\left(1 + \frac{G^D}{L}\right)\right]^{-1}.$$

Holding M, G^D, and L fixed, the bracketed term is decreasing in G^F, so f^* is increasing in G^F. Since the foreign innovation hazard in (28) rises with the quality gap σ_χ, complex industries have a stronger foreign recapture force. If, in addition, intrinsic leakiness differences imply $M_C < M_S$, the innovation and imitation channels reinforce each other: higher foreign innovation and lower domestic imitation both raise foreign leadership in complex industries. This cross-industry implication is conditional on the leakiness-dominance region characterized above.

Proposition 5 (A WTO-style shock can generate a foreign-share hump)**.** *Foreign leadership rises whenever*

$$L_{\chi t} d_{\chi t} + G^F_{\chi t} n_{\chi t} > M_{\chi t} f_{\chi t}, \tag{43}$$

and falls whenever

$$M_{\chi t} f_{\chi t} > L_{\chi t} d_{\chi t} + G^F_{\chi t} n_{\chi t}. \tag{44}$$

If (43) holds initially after a rise in $B_{\chi t}$ and (44) holds later, then foreign leadership is hump-shaped over the interval.

A WTO-style increase in the China benefit raises foreign exposure and foreign leadership initially. In leaky industries, imitation and domestic innovation can eventually dominate the inflows into foreign leadership. In tight industries, imitation remains weak and the downturn may not occur within the sample window.

Proposition 6 (Citation transition)**.** *Foreign citation reliance is*

$$R_{\chi t} = \frac{M_{\chi t} f_{\chi t}}{M_{\chi t} f_{\chi t} + G_{\chi t}^{D} n_{\chi t} + \rho K_{\chi t}}.$$

It is increasing in foreign-based imitation $M_{\chi t} f_{\chi t}$ and decreasing in domestic innovation $G_{\chi t}^{D} n_{\chi t}$ and domestic knowledge $K_{\chi t}$.

The model thus generates an imitation-to-innovation transition. In simple industries, foreign exposure initially raises foreign citation reliance. As domestic knowledge accumulates and domestic innovation becomes more productive, foreign reliance falls. In complex industries, low leakiness slows domestic knowledge accumulation, so foreign reliance remains persistent.

Proposition 7 (Human capital and AI shift effective leakiness)**.** *If $\lambda_{\chi t} = (1-\phi_t)\bar{\lambda}_{\chi} a(H_t, K_{\chi t}, AI_t)$ and $a_H, a_K, a_{AI} > 0$, then*

$$\frac{\partial \lambda_{\chi t}}{\partial H_t} > 0, \qquad \frac{\partial \lambda_{\chi t}}{\partial K_{\chi t}} > 0, \qquad \frac{\partial \lambda_{\chi t}}{\partial AI_t} > 0.$$

These forces raise conditional imitation but may reduce foreign exposure. Their effect on total imitation is governed by Proposition 2.

This result allows the model to speak to changes after the empirical window. Industries that appeared tight in the early 2000s can become more absorbable as China accumulates human capital, domestic knowledge, supplier depth, and AI-assisted search and design capabilities. At the same time, this raises the leakage risk perceived by foreign firms.

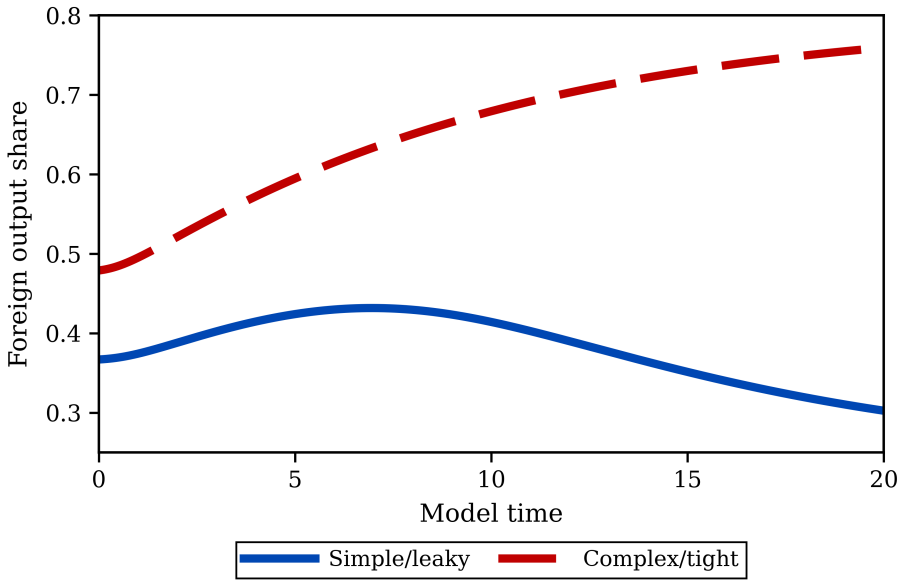
6 Quantitative Illustration

This section illustrates the transition dynamics of the model. The exercise is not a structural calibration and is not used for quantitative counterfactuals. Its purpose is to show that the mechanism in Sections 4 and 5 can jointly reproduce the qualitative patterns documented in Section 3: a foreign-share hump in simple industries, persistent foreign leadership in complex industries, and an inverted-U in foreign citation reliance only where imitation succeeds.

We simulate a simple/leaky industry and a complex/tight industry after a WTO-style increase in the China production benefit $B_{\chi t}$. The simple industry has higher intrinsic leakiness and a stronger response of absorptive capacity and domestic innovation productivity to accumulated knowledge. The complex industry has lower intrinsic leakiness, a larger quality gap, and stronger foreign innovation productivity through $\xi^F(\sigma_C) > \xi^F(\sigma_S)$. Although the per-event knowledge weights $\mu_I(\sigma_\chi)$ and $\mu_N(\sigma_\chi)$ are increasing in the quality gap, realized domestic knowledge accumulates faster in the simple industry because exposure is more readily converted into imitation and subsequent domestic innovation. Appendix F reports the full parameterization and algorithm.

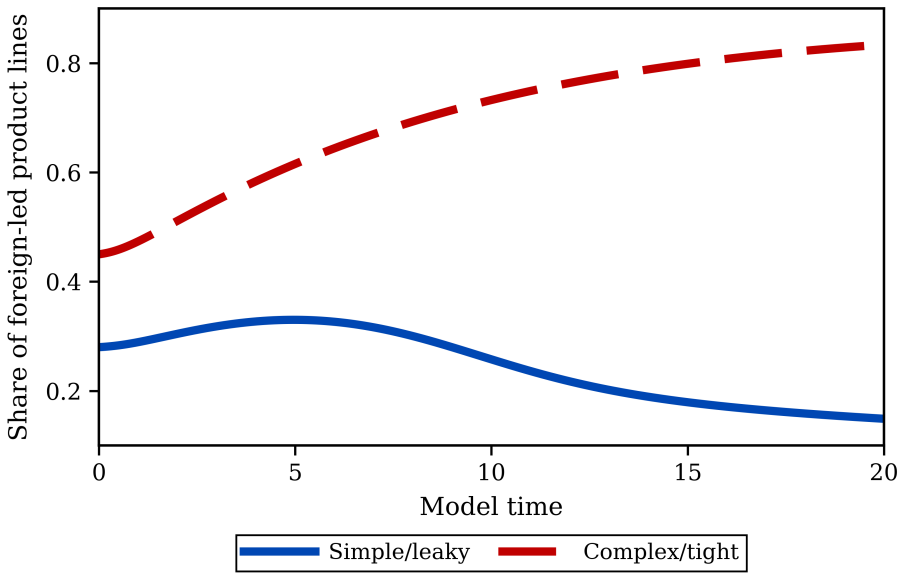
Figure 7 shows the model-implied foreign output share. In the simple industry, foreign output share rises at the beginning of the transition and later falls as imitation and domestic innovation erode foreign leadership. In the complex industry, foreign output share rises and remains high. Figure 8 shows the same force at the product-line level: foreign-led lines are eventually displaced in leaky industries but persist in tight industries.

Figure 7: Model Illustration: Foreign Output Share



Notes: The figure shows the simulated foreign output share for simple/leaky and complex/tight industries. The exercise is illustrative and is not a structural calibration.

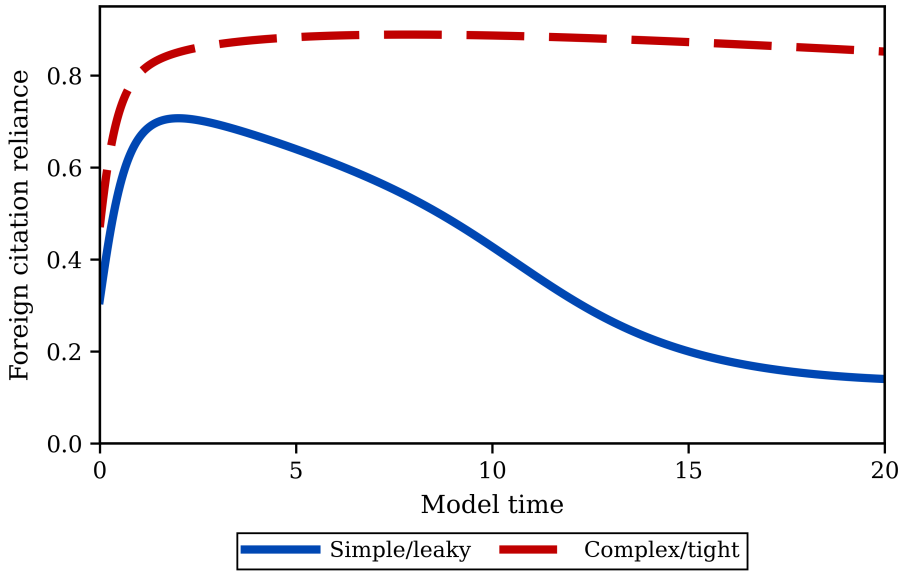
Figure 8: Model Illustration: Foreign-Led Product Lines



Notes: Foreign-led product lines rise after the China-benefit shock. In leaky industries, imitation and domestic innovation later reduce foreign leadership. In tight industries, foreign leadership persists.

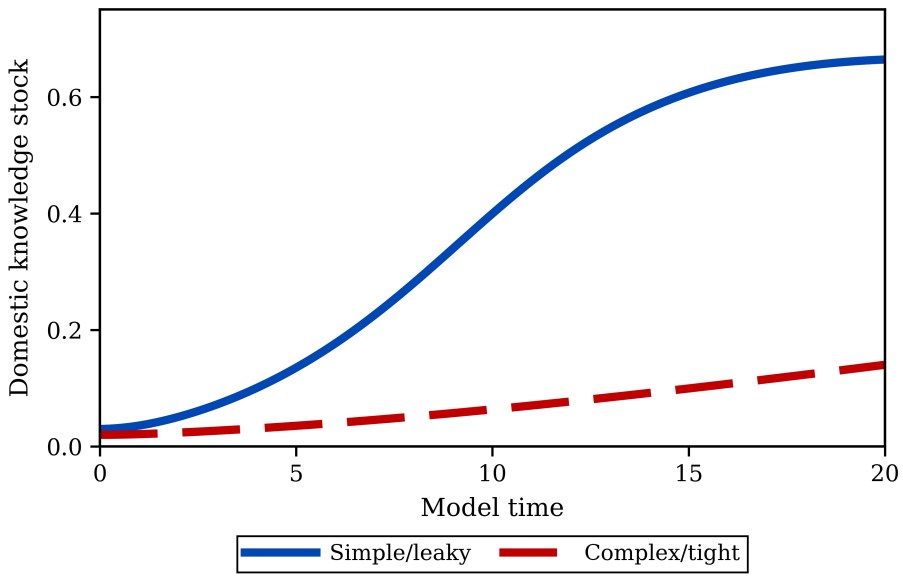
Figure 9 shows the model-implied foreign citation share. In the simple industry, foreign reliance is inverted-U-shaped. Foreign exposure raises imitation early in the transition, but domestic knowledge later becomes sufficiently important to support domestic-based innovation. In the complex industry, foreign reliance remains high because low leakiness limits the transition away from foreign prior art. Figure 10 shows the corresponding path of domestic knowledge.

Figure 9: Model Illustration: Foreign Citation Reliance



Notes: The model-implied foreign citation share is the ratio of foreign-based imitation to total domestic knowledge acquisition.

Figure 10: Model Illustration: Domestic Knowledge Accumulation



Notes: Domestic knowledge accumulates faster in leaky industries because foreign exposure is converted into imitation and then into domestic innovation.

The illustration highlights the model's central logic. Foreign entry creates exposure. Leakiness determines whether exposure becomes domestic knowledge. Domestic knowledge raises innovation productivity and shifts Chinese firms from foreign-based imitation to domestic-based innovation. The same mechanism accounts for the market-share facts and

the citation facts.

7 Policy Discussion

The model has implications for policies that affect multinational entry, intellectual-property protection, and technology transfer. The key lesson is that exposure and absorption are distinct margins. A policy that increases foreign exposure need not increase domestic learning, and a policy that facilitates domestic absorption can reduce foreign firms' willingness to expose technology.

7.1 IP protection

IP protection affects both sides of technology transfer. Stronger IP reduces effective leakiness and therefore raises foreign firms' willingness to produce, collaborate, or locate technology-intensive activities in China. At the same time, it reduces the rate at which Chinese firms absorb foreign knowledge conditional on exposure. Proposition 3 shows that the effect on total domestic imitation is ambiguous. The implication is that IP policy has sector-specific effects. In simple industries, where leakage is high, IP protection can strongly affect both foreign exposure and domestic absorption. In complex industries, where intrinsic leakiness is low, IP may primarily determine whether frontier firms are willing to expose advanced technologies at all.

7.2 Private and social incentives for foreign exposure

The baseline model treats each foreign firm as internalizing its own leakage risk. In practice, foreign entry can also raise industry-level domestic knowledge, which increases future absorptive capacity and the leakage risk faced by other foreign firms. A foreign firm does not internalize this effect. Let aggregate foreign exposure in industry χ be $X_{\chi t} = \int x_{j\chi t} dj$. If

$$\dot{K}_{\chi t} = \mu X_{\chi t} \lambda_{\chi t} - \delta K_{\chi t}, \tag{45}$$

and $\lambda_{\chi t}$ increases with $K_{\chi t}$, then one firm's entry raises future leakage risk for the industry. From the source-country perspective, decentralized FDI can be excessive because firms ignore the effect of their entry on other foreign firms' future losses. From the host-country perspective, foreign entry can be insufficient because foreign firms do not internalize the learning benefits generated for domestic firms.

This wedge is not needed to explain the empirical facts, but it clarifies why private

and social incentives for technology exposure may differ. It is directly relevant for debates about outbound investment screening, export controls, technology-transfer restrictions, and host-country FDI subsidies.

A related robustness issue is that the China benefit $B_{\chi t}$ may itself be larger in complex industries, because frontier products often have larger market-access and supply-chain returns. Appendix E shows that the imitation gap between simple and complex industries survives this extension whenever intrinsic leakiness differences are large enough. Thus the mechanism does not require complex industries to have low China benefits; it requires low leakiness to dominate any exposure advantage.

7.3 Changing technological boundaries

The empirical analysis focuses on 2000–2009, an early phase of China's transition. The model implies that the boundary between simple and complex technologies is not fixed. Human capital accumulation, domestic supplier depth, accumulated patent stocks, and tools for search, coding, simulation, and design can raise absorptive capacity. This can make technologies that were effectively tight in the early 2000s more leaky in later periods. At the same time, stronger absorptive capacity raises the leakage risk perceived by foreign firms and may reduce their willingness to expose frontier technologies.

Thus, the model does not imply that complex industries are permanently protected from catch-up. It implies that catch-up depends on the interaction between intrinsic complexity and domestic absorptive capacity. In the WTO-era data, domestic catch-up appears primarily in simple industries. As absorptive capacity rises, some initially complex industries may move closer to the leaky region, while foreign firms and source-country governments may respond by restricting exposure to frontier inputs.

8 Conclusion

Foreign exposure is not the same as technology transfer. Using matched firm, patent, and citation data from China, we show that foreign output and patent shares rose after WTO accession and later declined, but that the reversal was concentrated in technologically simple industries. In complex industries, foreign leadership persisted, especially among highly cited patents. Patent citations reveal a parallel knowledge transition: Chinese firms moved from foreign to domestic prior art only in sectors where imitation was feasible.

We develop a dynamic product-line model to organize these facts. Foreign firms choose whether to produce in China, trading off production and market-access benefits against

imitation risk. Domestic firms choose imitation and innovation effort. Industry leakiness, quality gaps, and domestic absorptive capacity govern whether exposure becomes domestic knowledge and domestic leadership. The model generates the foreign-share hump, the cross-industry divergence, the inverted-U in foreign citation reliance, and the coexistence of aggregate domestic patent-share growth with persistent foreign dominance among the most-cited patents.

The results speak to a broader issue in emerging-market innovation. Access to foreign technology is valuable, but the conversion of access into domestic capability depends on both the structure of the technology and the absorptive capacity of local firms. This distinction matters for policies governing FDI, intellectual-property protection, export controls, and industrial strategies in frontier technologies. Stronger protection can attract or preserve foreign exposure but slow domestic absorption; weaker protection can accelerate learning but discourage exposure by frontier firms. The effects are therefore sector-specific.

The central lesson is that global technology flows produce catch-up only when foreign exposure is paired with sufficiently leaky technologies and sufficiently strong domestic absorptive capacity. This helps explain why China caught up rapidly in some activities while foreign firms retained leadership in others, and why the path from imitation to innovation depends on the technological structure of the industry.

A Additional Data Details and Empirical Figures

A.1 Data construction

We harmonize assignee names using deterministic rules, including punctuation removal, corporate suffix standardization, simplified/traditional character harmonization, and location checks. When the same legal entity appears in multiple prefectures, we prioritize the majority location in ASIE employment and sales. An assignee is classified as foreign if it is a foreign-registered entity or a Chinese subsidiary controlled by a multinational. Ownership is frozen at first appearance in the panel.

A.2 R&D intensity and technological complexity

R&D intensity is the average ratio of R&D expenditures to sales in the industry over 2005–2007. Technological complexity follows Broekel (2019). Figure 11 shows the positive correlation between the two measures.

Figure 11: Correlation of R&D Intensity and Technological Complexity

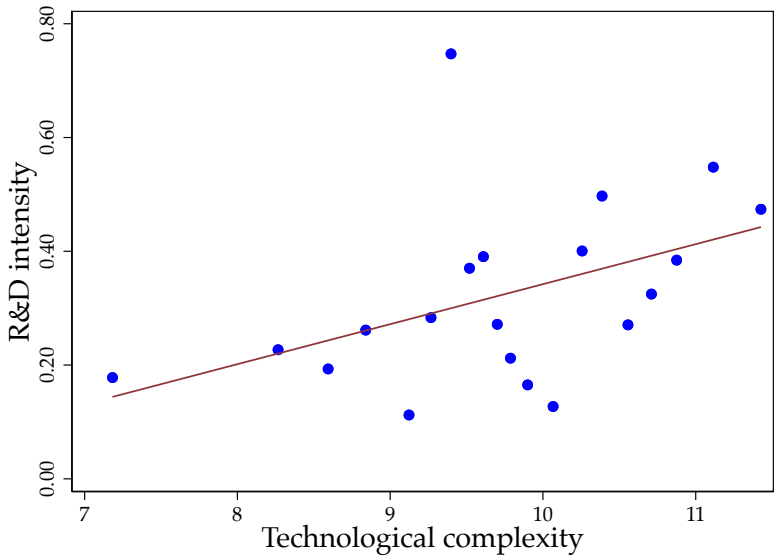


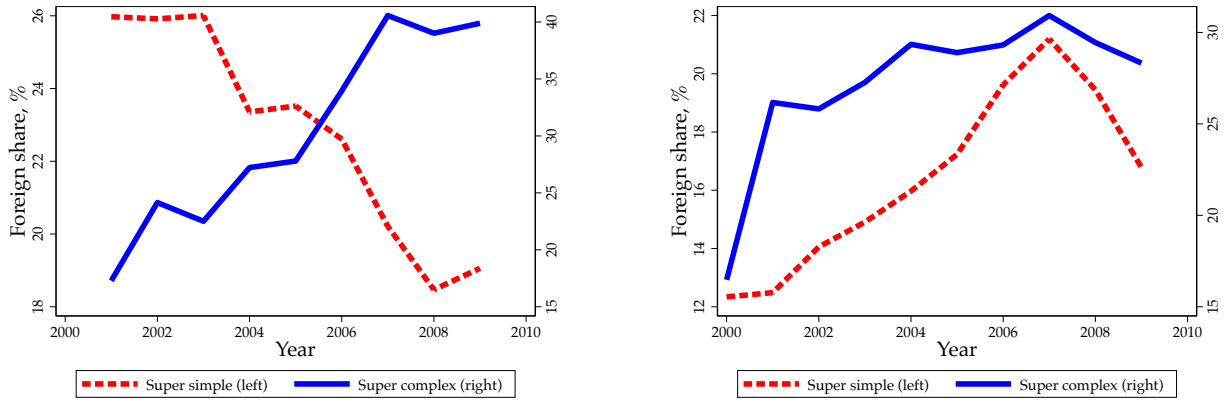
Table 4: Top and Bottom Industries by R&D Intensity and Complexity

	Top 3	Bottom 3
R&D intensity	biological and biochemical products; radar and supporting equipment; nuclear radiation processing	artificial board; tobacco redrying; coal products
Technological complexity	veterinary medicine; Chinese patent medicine; medicinal chemicals	bamboo and rattan furniture; musical instruments; hat making

A.3 Alternative complexity split

Figure 12 repeats the simple-versus-complex exercise using the technological-complexity measure instead of R&D intensity.

Figure 12: Foreign Shares in Super Complex and Super Simple Industries



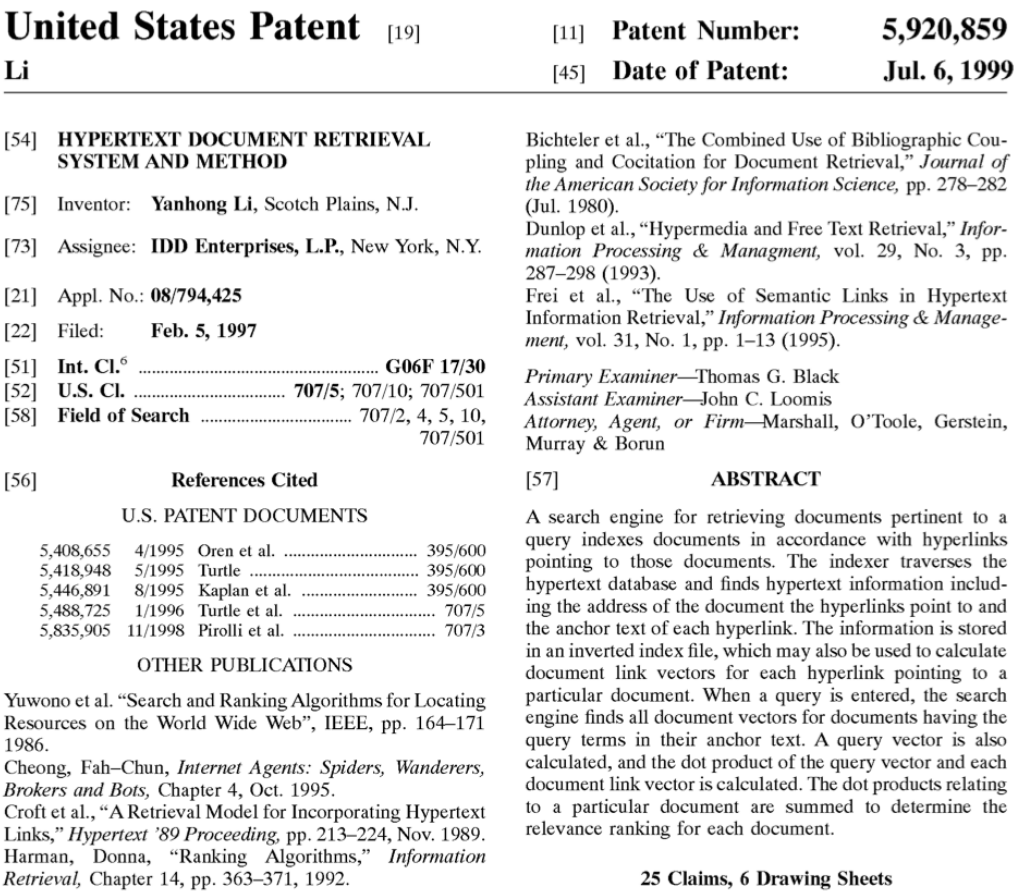
(a) Foreign patent share

(b) Foreign output share

A.4 Example of a citation trail

Figure 13 reproduces the front page of the Rankdex patent filed by Robin Li, later founder of Baidu. The cited prior art includes patents assigned to Apple, IBM, Xerox, and West Publishing. The example illustrates how patent citations can trace reliance on foreign knowledge.

Figure 13: Patent by Robin Li: Rankdex Search Algorithm



United States Patent [19]
Li

[11] **Patent Number: 5,920,859**
[45] **Date of Patent: Jul. 6, 1999**

[54] **HYPERTEXT DOCUMENT RETRIEVAL SYSTEM AND METHOD**

[75] Inventor: **Yanhong Li**, Scotch Plains, N.J.

[73] Assignee: **IDD Enterprises, L.P.**, New York, N.Y.

[21] Appl. No.: **08/794,425**

[22] Filed: **Feb. 5, 1997**

[51] **Int. Cl.**[6] **G06F 17/30**
[52] **U.S. Cl.** **707/5**; 707/10; 707/501
[58] **Field of Search** 707/2, 4, 5, 10, 707/501

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[57] **ABSTRACT**

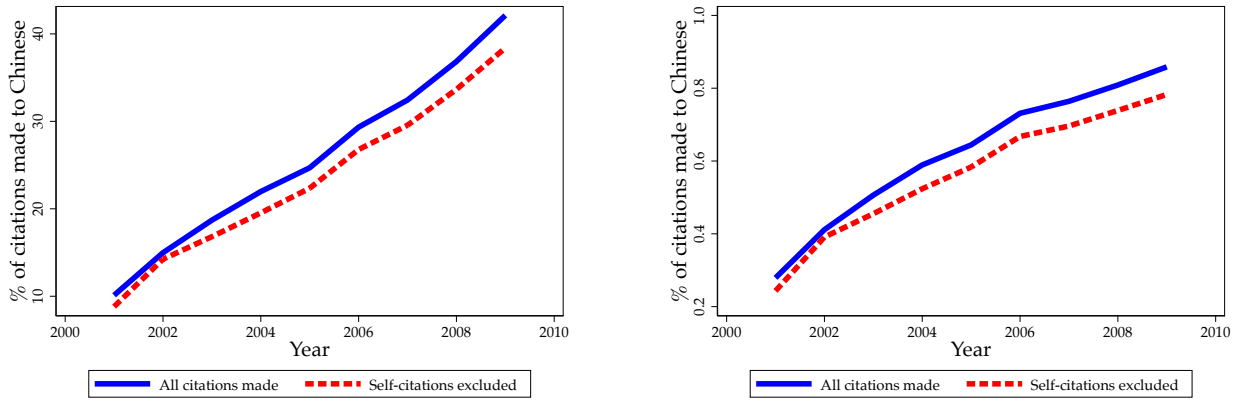
A search engine for retrieving documents pertinent to a query indexes documents in accordance with hyperlinks pointing to those documents. The indexer traverses the hypertext database and finds hypertext information including the address of the document the hyperlinks point to and the anchor text of each hyperlink. The information is stored in an inverted index file, which may also be used to calculate document link vectors for each hyperlink pointing to a particular document. When a query is entered, the search engine finds all document vectors for documents having the query terms in their anchor text. A query vector is also calculated, and the dot product of the query vector and each document link vector is calculated. The dot products relating to a particular document are summed to determine the relevance ranking for each document.

25 Claims, 6 Drawing Sheets

A.5 Knowledge flows from foreign firms to Chinese firms and back

The main text focuses on citations from Chinese firms to foreign patents. Figure 14 reports the reverse direction: citations by foreign firms operating in China to Chinese patents. The rise in this series is consistent with domestic knowledge becoming more relevant over time.

Figure 14: Citations Made by Foreign Firms to Chinese Firms



(a) Share of citations to Chinese firms

(b) Normalized by Chinese patent share

B Cournot Profits and Equilibrium Value Gaps

This appendix derives the product-line payoffs and the gross value gaps used in Section 4.2. The derivation has two purposes. First, it shows how the quality gap σ_χ maps into leader, laggard, and neck-and-neck flow profits. Second, it shows how the continuation value gaps Ω_χ, Δ^I_χ, and Δ^D_χ are generated by the same dynamic product-line environment.

Throughout the appendix, fix an industry type χ and suppress the subscript. The transition rates M, G^D, G^F, and L are treated as equilibrium hazards. The effort problems in the main text determine these hazards; the derivation here gives the gross continuation gains that enter those effort problems.

B.1 Quality gaps and flow profits

Normalize the base quality to one. In a leader-laggard state, the leader has quality $\sigma > 1$ and the laggard has quality one. Physical marginal cost is $c > 0$ for both firms. The leader's effective marginal cost is therefore c/σ, while the laggard's is c.

Consumers demand effective units. If firm i produces physical output y_i with quality q_i, effective output is $x_i = q_i y_i$. Inverse demand is

$$P = A - (x_F + x_D).$$

Profits can be written as

$$\pi_i = (P - \widetilde{c}_i)x_i, \qquad \widetilde{c}_i = \frac{c}{q_i}.$$

Thus the model is equivalent to standard Cournot competition in effective quantities with marginal costs $\widetilde{c}_i$. The first-order condition is

$$A - 2x_i - x_j - \widetilde{c}_i = 0.$$

Solving the two best responses gives

$$x_i^* = \frac{A - 2\widetilde{c}_i + \widetilde{c}_j}{3}, \qquad \pi_i^* = \frac{(A - 2\widetilde{c}_i + \widetilde{c}_j)^2}{9}.$$

Substituting $(\widetilde{c}_{\text{lead}}, \widetilde{c}_{\text{lag}}) = (c/\sigma, c)$ gives

$$\pi^{\text{lead}} = \frac{[\sigma(A + c) - 2c]^2}{9\sigma^2}, \tag{B.1}$$

$$\pi^{\text{lag}} = \frac{[\sigma(A - 2c) + c]^2}{9\sigma^2}, \tag{B.2}$$

$$\pi^N = \frac{(A - c)^2}{9}. \tag{B.3}$$

The leader earns π^{lead}, the laggard earns π^{lag}, and each firm earns π^N in the neck-and-neck state.

Define

$$\Delta\pi^{lead} \equiv \pi^{\text{lead}} - \pi^N = \frac{4c(\sigma - 1)(A\sigma - c)}{9\sigma^2}, \tag{B.4}$$

$$\Delta\pi^{\text{lag}} \equiv \pi^N - \pi^{\text{lag}} = \frac{c(\sigma - 1)[2A\sigma - c(3\sigma - 1)]}{9\sigma^2}. \tag{B.5}$$

Under $A > 2c$ and $\sigma > 1$, both premia are strictly positive.

B.2 HJB system

To describe HJB equations, we take the transition rates M, G^D, G^F, and L as given; the main text closes the model by making these hazards endogenous through effort and exposure choices. Let $r > 0$ be the discount rate. Let V^F, V^N, V^D denote the foreign firm's values in foreign-led, neck-and-neck, and Chinese-led lines. Let W^F, W^N, W^D denote the corresponding values for the Chinese firm.

The HJB equations for foreign firms are

$$rV^F = \pi^{\text{lead}} + M(V^N - V^F), \tag{B.6}$$
$$rV^N = \pi^N + G^D(V^D - V^N) + G^F(V^F - V^N), \tag{B.7}$$
$$rV^D = \pi^{\text{lag}} + L(V^F - V^D). \tag{B.8}$$

Here, M denotes the transition rate from the foreign-led state to the neck-and-neck state, driven by Chinese firms' imitation effort. The rates G^D and G^F denote the innovation hazards of Chinese and foreign firms, respectively, in the neck-and-neck state. Finally, L denotes the foreign firm's leapfrogging hazard in the Chinese-led state. Thus, when the foreign firm leads, Chinese firms can only catch up through imitation; when the Chinese firm leads, the foreign firm can regain leadership through innovation.

Similarly, for domestic firms, we have:

$$rW^F = \pi^{\text{lag}} + M(W^N - W^F), \tag{B.9}$$
$$rW^N = \pi^N + G^D(W^D - W^N) + G^F(W^F - W^N), \tag{B.10}$$
$$rW^D = \pi^{\text{lead}} + L(W^F - W^D). \tag{B.11}$$

B.3 Proof of Lemma 1

We repeat Lemma 1 that provides closed-form expressions for value gaps below:

Lemma (Product-line value gaps)**.** *Let*

$$\mathcal{D} = r^2 + r(M + L + G^D + G^F) + G^D(L + M) + G^F L + LM. \tag{B.12}$$

Since $r > 0$ and all transition rates are non-negative, $\mathcal{D} > 0$, so the value gaps are well-defined. Then

$$\Omega \equiv V^F - V^N = \frac{(r + G^D + L)\Delta\pi^{lead} + G^D\Delta\pi^{\text{lag}}}{\mathcal{D}}, \tag{B.13}$$
$$\Delta^I \equiv W^N - W^F = \frac{G^D\Delta\pi^{lead} + (r + G^D + L)\Delta\pi^{\text{lag}}}{\mathcal{D}}, \tag{B.14}$$
$$\Delta^D \equiv W^D - W^N = \frac{(r + G^F + M)\Delta\pi^{lead} + (G^F - L)\Delta\pi^{\text{lag}}}{\mathcal{D}}. \tag{B.15}$$

The gaps Ω and Δ^I are strictly positive under $A > 2c$ and $\sigma > 1$. The gap Δ^D is strictly positive under the sufficient condition $G^F \geq L$.

Proof. Solving the foreign-firm HJB system for (V^F, V^N, V^D) and taking the difference $V^F -$

V^N gives (B.13). Solving the domestic-firm HJB system for (W^F, W^N, W^D) and taking the differences $W^N - W^F$ and $W^D - W^N$ gives (B.14) and (B.15). The common determinant is $\mathcal{D}$. Positivity of Ω and Δ^I follows because $\Delta\pi > 0$, $\Delta\pi^{\text{lag}} > 0$, $r > 0$, and all transition rates are non-negative. For Δ^D, the first term in the numerator is strictly positive and the second is non-negative whenever $G^F \geq L$. □

B.4 Proof of Corollary 1

We repeat Corollary 1 for comparative statics with respect to quality gap below.

Corollary (Quality gap and incentives)**.** *For fixed transition rates, Ω and Δ^I are strictly increasing in σ. Under the sufficient condition $G^F \geq L$, Δ^D is also strictly increasing in σ.*

Proof. The profit premia satisfy

$$\frac{\partial \Delta\pi^{lead}}{\partial \sigma} = \frac{4c[\sigma(A+c) - 2c]}{9\sigma^3} > 0, \tag{B.16}$$

$$\frac{\partial \Delta\pi^{\text{lag}}}{\partial \sigma} = \frac{2c[\sigma(A-2c) + c]}{9\sigma^3} > 0, \tag{B.17}$$

where the inequalities use $A > 2c$ and $\sigma > 1$.

Equations (B.13) and (B.14) are positive linear combinations of $\Delta\pi^{lead}$ and $\Delta\pi^{\text{lag}}$ divided by the positive denominator $\mathcal{D}$. Hence (B.16)–(B.17) imply that both are increasing in σ. Equation (B.15) has a non-negative coefficient on $\Delta\pi^{\text{lag}}$ whenever $G^F \geq L$, so the same argument applies. □

B.5 Foreign leapfrogging: effort microfoundations

To microfound foreign firms' leapfrogging efforts, we model leapfrogging as a Poisson arrival process whose intensity depends on foreign effort and aggregate foreign exposure among type-χ product lines. The effort e is directed at a Chinese-led line. The exposure term $x_{\chi t}$ is the share of foreign-led type-χ lines that are produced in China. Thus, the specification allows for an exposure spillover: when foreign activity in China is broader within a technology type, foreign firms have better access to relevant suppliers, engineers, customers, production practices, and information about domestic competitors, making a given unit of leapfrogging effort more effective. The parameter ζ_χ governs the productivity of this effort. Hence, over a short interval $\mathrm{d}t$, the probability of successful leapfrogging is $\zeta_\chi x_{\chi t} e\,\mathrm{d}t + o(\mathrm{d}t)$.

Let us denote the foreign firm's gain from leapfrogging a Chinese-led line:

$$\Delta^E_\chi \equiv V^F_\chi - V^D_\chi > 0$$

The foreign firm solves

$$\max_{e\geq 0}\left\{\zeta_\chi x_{\chi t} e\Delta_\chi^E - \frac{\kappa_E}{2}e^2\right\}.$$

The optimal effort is

$$e_{\chi t}^* = \frac{\zeta_\chi x_{\chi t}\Delta_\chi^E}{\kappa_E},$$

and the leapfrogging hazard is

$$\zeta_\chi x_{\chi t} e_{\chi t}^* = \frac{(\zeta_\chi x_{\chi t})^2\Delta_\chi^E}{\kappa_E}.$$

The effort problem delivers a quadratic hazard in exposure because both the success technology and optimal effort scale with $x_{\chi t}$. The main text uses the linear representation $L_{\chi t} = \ell_\chi x_{\chi t}$ as a transparent first-order approximation to this increasing relationship and to keep the laws of motion analytically simple. None of the propositions relies on linearity; the results require only that foreign leapfrogging is weakly increasing in exposure, $L_x \geq 0$.

B.6 Recursive equilibrium with endogenous value gaps

The main text emphasizes local comparative statics around an equilibrium. This subsection makes explicit how the two blocks of the model can be closed as a recursive fixed point. The first block maps transition rates into gross operating-value gaps through the HJB system in Section B.2. The second block maps those value gaps back into transition rates through foreign exposure, imitation effort, and innovation effort.

For a fixed industry type χ and state variables $(K_{\chi t}, B_{\chi t}, \lambda_{\chi t})$, let

$$\Theta_\chi = (M_\chi, G_\chi^D, G_\chi^F, L_\chi) \tag{B.18}$$

denote the vector of transition rates. Given Θ_χ, Lemma 1 defines the gross operating-value gaps

$$\Gamma_\chi(\Theta_\chi;\sigma_\chi) = \left(\Omega_\chi(\Theta_\chi), \Delta_\chi^I(\Theta_\chi), \Delta_\chi^D(\Theta_\chi)\right). \tag{B.19}$$

These are gross operating-value gaps: they measure the product-market continuation gains from moving across product-line states. Effort costs are incurred by the research activities that generate the transitions and enter the hazard equations below; they are not included in the operating-value HJBs used to compute the prizes.

Given these value gaps, the effort and exposure choices in the main text imply a new

vector of transition rates. The conditional imitation hazard is

$$h_\chi^I(\Theta_\chi) = \frac{\lambda_{\chi t}^2 \Delta_\chi^I(\Theta_\chi)}{\kappa_I}. \tag{B.20}$$

The foreign exposure share is

$$x_\chi(\Theta_\chi) = 1 - G\left(\Omega_\chi(\Theta_\chi) h_\chi^I(\Theta_\chi) - B_{\chi t}\right). \tag{B.21}$$

Thus the implied imitation rate is

$$\widehat{M}_\chi(\Theta_\chi) = x_\chi(\Theta_\chi) h_\chi^I(\Theta_\chi). \tag{B.22}$$

Similarly, domestic and foreign innovation in neck-and-neck lines imply

$$\widehat{G}_\chi^D(\Theta_\chi) = \frac{\left[\xi_\chi^D(K_{\chi t})\right]^2 \Delta_\chi^D(\Theta_\chi)}{\kappa_D}, \tag{B.23}$$

$$\widehat{G}_\chi^F(\Theta_\chi) = \frac{\left[\xi^F(\sigma_\chi)\right]^2 \Omega_\chi(\Theta_\chi)}{\kappa_F}. \tag{B.24}$$

Finally, the main text uses the transparent exposure-based leapfrogging rate

$$\widehat{L}_\chi(\Theta_\chi) = \ell_\chi x_\chi(\Theta_\chi). \tag{B.25}$$

Section B.5 shows that this linear specification can be viewed as a first-order representation of an effort-based leapfrogging problem.

Define the mapping

$$\mathcal{T}_\chi(\Theta_\chi) = \left(\widehat{M}_\chi(\Theta_\chi), \widehat{G}_\chi^D(\Theta_\chi), \widehat{G}_\chi^F(\Theta_\chi), \widehat{L}_\chi(\Theta_\chi)\right). \tag{B.26}$$

A recursive equilibrium is a transition vector Θ_χ^* satisfying

$$\Theta_\chi^* = \mathcal{T}_\chi(\Theta_\chi^*). \tag{B.27}$$

Equilibrium therefore closes the loop between the value-gap block and the effort/exposure block: transition rates determine value gaps, and value gaps determine transition rates.

Existence follows from a standard fixed-point argument. Suppose effort choices are restricted to compact intervals $m \in [0, \bar{m}]$, $n_D \in [0, \bar{n}_D]$, $n_F \in [0, \bar{n}_F]$, and the leapfrogging effort in Section B.5 satisfies $e \in [0, \bar{e}]$. These bounds can be chosen arbitrarily large and are used only to rule out infinite hazards. The implied transition rates lie in a compact convex

set. On this set, the HJB formulas in Lemma 1 are continuous whenever the maintained positivity conditions hold. The effort rules and the exposure cutoff are continuous in the value gaps when the distribution G is continuous. Hence $\mathcal{T}_\chi$ is a continuous map from a compact convex set into itself. Brouwer's theorem implies that at least one recursive equilibrium exists.

We do not require uniqueness. The propositions in Section 5 characterize local forces around any recursive equilibrium satisfying the maintained positivity conditions. The numerical illustration in Section 6 does not solve this full fixed point at each date; instead, Appendix F uses a transparent reduced-form implementation of the same monotonic relationships to show the transition logic.

C Proofs

Proof of Proposition 1. Let

$$z_{\chi t} = \Omega_\chi h^I_{\chi t} - B_{\chi t}.$$

Then $x_{\chi t} = 1 - G(z_{\chi t})$. Since $g(z) > 0$,

$$\frac{\partial x}{\partial B} = g(z) > 0.$$

Next, $\lambda = (1-\phi)\bar{\lambda}a$, so

$$\frac{\partial \lambda}{\partial \phi} = -\bar{\lambda}a < 0.$$

Because $h^I(\lambda) = \lambda^2 \Delta^I / \kappa_I$,

$$\frac{\partial h^I}{\partial \lambda} = \frac{2\lambda \Delta^I}{\kappa_I} > 0.$$

Thus

$$\frac{\partial z}{\partial \phi} = \Omega \frac{\partial h^I}{\partial \lambda} \frac{\partial \lambda}{\partial \phi} < 0.$$

Since $\partial x/\partial z = -g(z) < 0$, it follows that $\partial x/\partial \phi > 0$. Similarly, $\partial \lambda/\partial a = (1-\phi)\bar{\lambda} > 0$, so $\partial z/\partial a > 0$ and $\partial x/\partial a < 0$. □

Proof of Proposition 2. Suppress industry and time subscripts. Let $h = h^I(\lambda)$ and $x = 1 - G(\Omega h - B)$. Then $M = xh$. Differentiating with respect to λ,

$$\frac{\partial M}{\partial \lambda} = xh' + hx_\lambda.$$

Since

$$x_\lambda = -\gamma \Omega h',$$

where Ω is treated as fixed, consistent with the local comparative-static interpretation, we obtain

$$\frac{\partial M}{\partial \lambda} = h' \left[x - \Omega h \gamma \right].$$

Because $h' > 0$, the sign is the sign of $x - \Omega h \gamma$. □

Proof of Proposition 3. By Proposition 2,

$$\frac{\partial M}{\partial \lambda} = h'(x - \Omega h \gamma).$$

Also $\partial \lambda / \partial \phi < 0$. Therefore

$$\frac{\partial M}{\partial \phi} = \frac{\partial M}{\partial \lambda} \frac{\partial \lambda}{\partial \phi}$$

has the opposite sign of $x - \Omega h \gamma$. The stated result follows. □

Proof of Proposition 4. At a stationary point,

$$\begin{aligned} 0 &= Ld + G^F n - Mf, \\ 0 &= Mf - (G^D + G^F) n, \\ 0 &= G^D n - Ld. \end{aligned}$$

From the second equation,

$$n = \frac{M}{G^D + G^F} f.$$

From the third equation,

$$d = \frac{G^D}{L} n = \frac{G^D M}{L(G^D + G^F)} f.$$

Using $f + n + d = 1$ yields

$$f \left[1 + \frac{M}{G^D + G^F} + \frac{G^D M}{L(G^D + G^F)} \right] = 1,$$

which proves (41) and (42). Let

$$\mathcal{A}_f = \frac{1}{G^D + G^F} + \frac{G^D}{L(G^D + G^F)} > 0.$$

Then $f^* = 1/(1 + \mathcal{A}_f M)$, so

$$\frac{\partial f^*}{\partial M} = -\frac{\mathcal{A}_f}{(1 + \mathcal{A}_f M)^2} < 0.$$

Let $\mathcal{B}_d = G^D/[L(G^D + G^F)] > 0$. Then $d^* = \mathcal{B}_d M/(1 + \mathcal{A}_f M)$, so

$$\frac{\partial d^*}{\partial M} = \frac{\mathcal{B}_d}{(1 + \mathcal{A}_f M)^2} > 0.$$

□

Proof of Proposition 5. From (31),

$$\dot{f}_\chi = L_{\chi t} d_\chi + G^F_{\chi t} n_\chi - M_{\chi t} f_\chi.$$

Thus $\dot{f}_\chi > 0$ if and only if (43) holds, and $\dot{f}_\chi < 0$ if and only if (44) holds. If the first inequality holds initially and the second holds later, continuity implies that $f_\chi(t)$ reaches an interior maximum over the interval. □

Proof of Proposition 6. Let $\mathcal{N}_R = Mf$ and $\mathcal{C}_R = G^D n + \rho K$, where the subscript R indicates that these objects refer to the citation-ratio numerator and denominator. Then $R = \mathcal{N}_R/(\mathcal{N}_R + \mathcal{C}_R)$. Hence

$$\frac{\partial R}{\partial \mathcal{N}_R} = \frac{\mathcal{C}_R}{(\mathcal{N}_R + \mathcal{C}_R)^2} > 0, \qquad \frac{\partial R}{\partial \mathcal{C}_R} = -\frac{\mathcal{N}_R}{(\mathcal{N}_R + \mathcal{C}_R)^2} < 0.$$

Because $\mathcal{C}_R$ is increasing in $G^D n$ and K, the result follows. □

Proof of Proposition 7. The result follows immediately from the definition $\lambda = (1-\phi)\bar{\lambda} a(H, K, AI)$ and the assumptions $a_H, a_K, a_{AI} > 0$. The effect on total imitation follows from Proposition 2 because total imitation is $M = xh$ and both x and h depend on λ. □

Proof of the foreign-innovation implication after Proposition 4. From (28),

$$G^F_\chi = \frac{[\xi^F(\sigma_\chi)]^2 \Omega_\chi}{\kappa_F}.$$

Differentiating with respect to σ_χ gives

$$\frac{\partial G^F_\chi}{\partial \sigma_\chi} = \frac{2\xi^F(\sigma_\chi)\xi^{F\prime}(\sigma_\chi)\Omega_\chi + [\xi^F(\sigma_\chi)]^2 \partial \Omega_\chi/\partial \sigma_\chi}{\kappa_F} > 0,$$

using $\xi^{F\prime}(\sigma) > 0$ and Corollary 1. From (41),

$$f^* = \left[1 + \frac{M}{G^D + G^F} + \frac{G^D M}{L(G^D + G^F)}\right]^{-1}.$$

The bracketed term is decreasing in G^F, so f^* is increasing in G^F. The stated implication follows.

Furthermore, Proposition 4 shows that $\partial f^*/\partial M < 0$. Under leakiness dominance, complex industries have lower domestic imitation M_χ, which provides a second reinforcing channel toward persistent foreign leadership. □

Proof of Corollary 2. Let

$$s^I_{\chi t} = \frac{M_{\chi t} f_\chi}{M_{\chi t} f_\chi + G^D_{\chi t} n_\chi} \in [0, 1].$$

Then (39) can be written as

$$Q_{\chi t} = \mu_I(\sigma_\chi) s^I_{\chi t} + \mu_N(\sigma_\chi)(1 - s^I_{\chi t}).$$

For fixed $s^I_{\chi t}$,

$$\frac{\partial Q_{\chi t}}{\partial \sigma_\chi} = \mu_I'(\sigma_\chi) s^I_{\chi t} + \mu_N'(\sigma_\chi)(1 - s^I_{\chi t}) > 0.$$

This proves the result.

Under leakiness dominance, $s^I_C < s^I_S$, so the complex industry places less weight on imitation-based domestic patents and more weight on innovation-based patents. Because $\mu_N(\sigma)$ is also increasing in σ, this composition effect reinforces the fixed-composition result. □

This fixed-composition result is conservative. In the model, composition is endogenous: under leakiness dominance, complex industries have lower imitation intensity and a larger share of domestic patents coming from innovation-based activity. Since $\mu_N(\sigma)$ also increases with σ, allowing the composition of domestic patenting to adjust strengthens the quality prediction.

D Strategic Externalities in Foreign Exposure

For clarity in this extension, we specialize absorptive capacity to $a(K_\chi)$, suppressing the H_t and AI_t arguments in equation (17). The results hold under the full specification.

This appendix formalizes the source-country externality discussed in Section 7.2. Let $X_\chi = \int x_{j\chi} \mathrm{d}j$ be aggregate foreign exposure in industry χ. Suppose domestic knowledge

evolves according to

$$\dot{K}_\chi = \mu X_\chi \lambda_\chi - \delta K_\chi, \tag{D.1}$$

and $\lambda_\chi = (1-\phi)\bar{\lambda}_\chi a(K_\chi)$ with $a_K > 0$. A foreign firm j enters if

$$b_j \geq \lambda_\chi \Omega_j.$$

The private firm internalizes its own leakage cost $\lambda_\chi \Omega_j$ but takes K_χ and hence λ_χ as given. A source-country planner that values the profits of all foreign firms also internalizes the effect of firm j's entry on K_χ and on future leakage costs for other firms.

The marginal external cost of exposure by firm j is locally

$$\mathcal{E}_j = \frac{\partial \lambda_\chi}{\partial K_\chi} \frac{\partial K_\chi}{\partial x_j} \sum_{k \neq j} x_k \Omega_k. \tag{D.2}$$

Under $a_K > 0$, $\partial \lambda_\chi / \partial K_\chi > 0$. From (D.1), $\partial K_\chi / \partial x_j > 0$ along the transition. Therefore $\mathcal{E}_j > 0$ whenever other exposed foreign firms have positive rents at risk. The source-country planner's cutoff includes this external cost:

$$b_j \geq \lambda_\chi \Omega_j + \mathcal{E}_j.$$

Thus decentralized foreign exposure can exceed the source-country preferred level. From the host-country perspective, the same force is a learning externality: foreign firms do not internalize the benefit their exposure creates for domestic knowledge accumulation.

E Extension: Industry-Specific China Benefits

The baseline model allows the common China benefit $B_{\chi t}$ to differ by industry. This appendix shows that the core imitation channel is robust when the China benefit increases with the quality gap. This case is relevant for frontier sectors: advanced products may have larger Chinese market-access benefits, deeper supplier complementarities, or stronger local-adaptation returns, even though they also carry larger leakage costs.

Let

$$B_{\chi t} = B_t + \beta \sigma_\chi, \qquad \beta \geq 0, \tag{E.1}$$

where B_t is a common China-production benefit and $\beta \sigma_\chi$ is the additional benefit of producing higher-gap technologies in China. The exposure share is

$$x_{\chi t} = 1 - G(z_{\chi t}), \qquad z_{\chi t} = \Omega_\chi h^I_{\chi t} - B_t - \beta \sigma_\chi. \tag{E.2}$$

A higher σ_χ has two opposing effects on exposure. It raises the deterrence term $\Omega_\chi h^I_{\chi t}$ because the foreign firm has more to lose and the Chinese firm has more to gain from imitation. It also raises the China benefit when $\beta > 0$. Therefore exposure to complex technologies can be lower or higher than exposure to simple technologies.

The implication for total imitation depends on exposure and conditional imitation. Since

$$M_{\chi t} = x_{\chi t} h^I_{\chi t} = x_{\chi t} \frac{\lambda^2_{\chi t} \Delta^I_\chi}{\kappa_I}, \tag{E.3}$$

Proposition E1 (Leakiness dominance with industry-specific China benefits). Complex industries have less total imitation than simple industries if and only if

$$\left(\frac{\lambda_{Ct}}{\lambda_{St}}\right)^2 < \frac{\Delta^I_S}{\Delta^I_C} \frac{x_{St}}{x_{Ct}}. \tag{E.4}$$

Condition (E.4) is a leakiness-dominance condition. It can hold even if $x_{Ct} > x_{St}$ because complex industries offer larger China benefits. What is required is that the lower intrinsic leakiness of complex technologies is strong enough to offset any exposure advantage. Under this condition, the cross-industry imitation gap is driven by absorption rather than by the amount of foreign activity. This is the empirically relevant case emphasized in the main text: high-R&D industries can attract foreign firms and still exhibit slower domestic catch-up.

Proof of Proposition E1. For each industry type,

$$M_{\chi t} = x_{\chi t} h^I_{\chi t} = x_{\chi t} \frac{\lambda^2_{\chi t} \Delta^I_\chi}{\kappa_I}.$$

Since κ_I is common across industries, $M_{Ct} < M_{St}$ if and only if

$$x_{Ct} \lambda^2_{Ct} \Delta^I_C < x_{St} \lambda^2_{St} \Delta^I_S.$$

Dividing by the positive term $x_{Ct} x_{St} \lambda^2_{St} \Delta^I_C$ gives

$$\left(\frac{\lambda_{Ct}}{\lambda_{St}}\right)^2 < \frac{\Delta^I_S}{\Delta^I_C} \frac{x_{St}}{x_{Ct}},$$

which is condition (E.4). □

F Simulation Details

This appendix reports the parameters and algorithm behind the illustrative transition in Section 6. The exercise is not a structural calibration. The parameters are chosen only to illustrate the mechanism emphasized in the paper: a common China-benefit shock raises foreign exposure, but domestic catch-up occurs primarily when exposure is paired with high leakiness and rising absorptive capacity.

The simulation uses the product-line laws of motion in (31)–(34). To keep the illustration transparent, the value gaps entering the imitation and exposure equations are parameterized as increasing functions of the quality gap:

$$\Omega_\chi = \Omega_0 + \Omega_\sigma(\sigma_\chi - 1), \tag{F.1}$$

$$\Delta^I_\chi = \Delta^I_0 + \Delta^I_\sigma(\sigma_\chi - 1). \tag{F.2}$$

This reduced-form parametrization preserves the monotonicity implied by Corollary 1 without solving the full fixed point for value gaps at each date. The resulting transition rates are

$$B_{\chi t} = B_0 + B^{shock}_\chi(1 - e^{-\psi_B t}), \tag{F.3}$$

$$\lambda_{\chi t} = (1-\phi)\bar{\lambda}_\chi \left[a_0 + a^\chi_K K_{\chi t} + a_T(1 - e^{-\psi_a t})\right], \tag{F.4}$$

The trend term $a_T(1 - e^{-\psi_a t})$ is a reduced-form representation of rising human capital and search/design technologies, corresponding to H_t and AI_t in equation (17) and Proposition 7.

$$h^I_{\chi t} = \frac{\lambda^2_{\chi t}\Delta^I_\chi}{\kappa_I}, \tag{F.5}$$

We parametrize the CDF $G(\cdot)$ as a logistic function with slope parameter s, which satisfies the smoothness assumptions used in Section 4.

$$x_{\chi t} = \left[1 + \exp\{-s(B_{\chi t} - \Omega_\chi h^I_{\chi t} - F_\chi)\}\right]^{-1}, \tag{F.6}$$

$$M_{\chi t} = x_{\chi t} h^I_{\chi t}, \tag{F.7}$$

$$G^D_{\chi t} = g^D_{0,\chi} + g^D_{K,\chi} K_{\chi t}, \tag{F.8}$$

$$G^F_{\chi t} = g^F_{0,\chi} + g^F_{x,\chi} x_{\chi t} + g^F_{\xi,\chi}\xi^F(\sigma_\chi), \tag{F.9}$$

$$L_{\chi t} = \ell_\chi x_{\chi t}. \tag{F.10}$$

Domestic knowledge evolves according to

$$\dot{K}_{\chi t} = \mu_I(\sigma_\chi) M_{\chi t} f_{\chi t} + \mu_N(\sigma_\chi) G^D_{\chi t} n_{\chi t} - \delta_{K,\chi} K_{\chi t}, \tag{F.11}$$

where

$$\mu_I(\sigma_\chi) = \mu_{I0} + \mu_{I\sigma}(\sigma_\chi - 1), \qquad \mu_N(\sigma_\chi) = \mu_{N0} + \mu_{N\sigma}(\sigma_\chi - 1). \tag{F.12}$$

Thus complex technologies generate larger knowledge increments conditional on successful absorption, but the realized accumulation of domestic knowledge can still be faster in simple industries because their higher leakiness generates many more imitation and innovation events.

Table 5 reports common parameters. Table 6 reports industry-specific parameters.

Table 5: Common Parameters in the Quantitative Illustration

Parameter	Description	Value
ϕ	IP protection / leakage barrier	0.25
B_0	Initial China benefit	-0.12
ψ_B	Speed of China-benefit shock	0.75
s	Logistic exposure slope	8.00
κ_I	Imitation effort cost parameter	1.00
Ω_0	Baseline foreign loss from imitation	0.85
Ω_σ	Quality-gap loading in Ω_χ	0.35
Δ^I_0	Baseline imitation gain	0.75
Δ^I_σ	Quality-gap loading in Δ^I_χ	0.50
a_0	Absorptive-capacity intercept	0.34
a_T	Absorptive-capacity trend loading	0.18
ψ_a	Speed of absorptive-capacity trend	0.08
ξ^F_0	Baseline foreign innovation productivity	0.30
ξ^F_σ	Quality-gap loading in $\xi^F(\sigma)$	0.20
μ_{I0}	Baseline imitation knowledge weight	1.25
$\mu_{I\sigma}$	Quality-gap loading in $\mu_I(\sigma)$	0.35
μ_{N0}	Baseline innovation knowledge weight	0.60
$\mu_{N\sigma}$	Quality-gap loading in $\mu_N(\sigma)$	0.20
$\omega_F, \omega_N, \omega_D$	Output-share weights	0.85, 0.50, 0.15

Table 6: Industry-Specific Parameters in the Quantitative Illustration

Parameter	Simple/leaky	Complex/tight
Quality gap, σ_χ	1.15	1.75
Intrinsic leakiness, $\bar{\lambda}_\chi$	0.88	0.24
China-benefit shock, B_χ^{shock}	0.52	0.60
Exposure fixed cost, F_χ	0.08	0.06
Initial foreign-led share, $f_\chi(0)$	0.28	0.45
Initial neck-and-neck share, $n_\chi(0)$	0.06	0.04
Initial domestic knowledge, $K_\chi(0)$	0.03	0.02
Knowledge loading in absorptive capacity, a_K^χ	1.20	0.25
Chinese innovation intercept, $g_{0,\chi}^D$	0.012	0.008
Chinese innovation slope, $g_{K,\chi}^D$	0.240	0.035
Foreign leapfrogging parameter, ℓ_χ	0.060	0.095
Foreign innovation intercept, $g_{0,\chi}^F$	0.014	0.028
Foreign innovation exposure loading, $g_{x,\chi}^F$	0.014	0.022
Foreign innovation productivity loading, $g_{\xi,\chi}^F$	0.010	0.018
Knowledge depreciation, $\delta_{K,\chi}$	0.045	0.030
Domestic-citation weight, ρ_χ	0.090	0.003

The sufficient condition $G^F \geq L$ in Corollary 1 is used only for the analytical value-gap comparative static. The illustrative simulation specifies $G_{\chi t}^D$, $G_{\chi t}^F$, and $L_{\chi t}$ directly and does not rely on that sufficient condition.

Starting from the initial shares in Table 6, we integrate the product-line laws of motion forward with a small time step. At each date, we compute the transition rates above, update $(f_{\chi t}, n_{\chi t}, d_{\chi t}, K_{\chi t})$, and then map the simulated states to observables using

$$Y_{\chi t}^F = \omega_F f_{\chi t} + \omega_N n_{\chi t} + \omega_D d_{\chi t}, \tag{F.13}$$

and

$$R_{\chi t} = \frac{M_{\chi t} f_{\chi t}}{M_{\chi t} f_{\chi t} + G_{\chi t}^D n_{\chi t} + \rho_\chi K_{\chi t}}. \tag{F.14}$$

The simulation produces the qualitative patterns reported in Section 6: a foreign-share hump and citation-reliance reversal in the simple industry, together with persistent foreign leadership and persistent foreign reliance in the complex industry.

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