Human Capital Without Borders:
International Spillovers Through Return Migration

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Abstract

Human capital is increasingly accumulated in one country but utilized in another. We study the international returns to human-capital investment using return migration in China's biopharmaceutical industry. Linking individual employment histories to clinical innovation, we construct technology-specific measures of returnee expertise. Exploiting displacement events at foreign employers as an instrument, we find that a 10% increase in technology-specific returnee stock raises novel clinical trials by 6–8%. We further show that returnee-managed firms initiate more new drug projects, pursue different research opportunities, and secure venture financing earlier. These firms also remain responsive to subsequent advances at the U.S. innovation frontier, while the innovations they facilitate can re-enter the U.S. development pipeline through overseas clinical trials and international drug licensing. Our findings highlight how the returns to human-capital investment cross national borders, generating innovation in the utilization country while allowing benefits to flow back to the training country.

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1 Introduction

In the modern economy, there is a common separation between human capital accumulation and utilization due to the high mobility of skilled workers. More than 6 million students were enrolled in higher education outside their home countries in 2023,[1] with the United States as the largest destination. It hosted 1.1 million international students in 2023–24, including over half a million graduate students,[2] and international students accounted for 39% of all U.S. science and engineering doctorates in 2023.[3] Many of these students stay, but many do not. Roughly one quarter of scientifically active U.S.-trained STEM PhDs eventually leave the country (Shvadron et al. 2025), taking with them education and work experience acquired in the United States (Amanzadeh et al. 2024). This creates a large and growing stock of human capital accumulated in one country (the training country) but utilized in another (the utilization country).

Despite the flow of talent across borders, both the measurement and policy discussion of these returns have largely focused on benefits realized within the training country: wages, productivity, and knowledge spillovers where the training took place (Bernstein et al. 2022; Moretti 2004; Romer 1990; Shvadron et al. 2026). Once human capital crosses borders, this accounting is incomplete and ignores the international margin of the return to human-capital investment. In this paper, we study this *international spillover of human-capital investment*: whether human capital accumulated in the training country generates innovation in the utilization country. In addition, innovation produced in the utilization country by foreign-trained talent does not necessarily stay there. Through business collaborations and trade, part of it may flow back to the training country, so gains abroad are not simply leakage from its perspective. We therefore ask both how large the return abroad is and whether, and

1. See UNESCO, *Higher Education Global Trends Report* (2026), available at https://hepo.iesalc.unesco.org/pc/page/content/202606_HEPO_New/.

2. See Institute of International Education, *Open Doors 2024*, available at https://www.iie.org/news/us-hosts-more-than-1-1-million-intl-students-at-higher-education-institutions-all-time-high/.

3. See National Center for Science and Engineering Statistics, *Doctorate Recipients from U.S. Universities: 2023* (NSF 25-300), available at https://ncses.nsf.gov/pubs/nsf25300/report/u-s-doctorate-awards.

through what channels, it flows back.

Three obstacles make these questions challenging. First, measuring the international returns to human capital requires tracking individuals' education and employment histories across countries and linking them to subsequent innovation outcomes, often with limited observations of cross-border talent flows. Second, individuals trained in one country but working in another are selected: they may be more talented, better financed, or better connected than those trained domestically in the utilization country, so their innovation premium need not reflect human capital acquired in the training country. Third, the timing and technological direction of cross-border mobility are endogenous: scientists may move to fields that are about to grow in the utilization country for reasons unrelated to their training.

China's biopharmaceutical industry provides a particularly useful setting for confronting these obstacles. First, the large influx of internationally trained Chinese scientists and entrepreneurs (returnees) provides substantial variation in cross-border human capital flows. Second, biopharma's science-intensive nature and granular classification of drug development across diseases and modalities allow us to link specific knowledge accumulated in the training country to innovation outcomes in China. Third, the coexistence of returnees and domestically trained talent, together with variation in returnees' technological expertise and timing of return, provides a basis for distinguishing knowledge transfer from selection and endogenous sorting.

We combine global clinical-trial data from Citeline TrialTrove, individual education and employment histories from Revelio Labs, and company and financing records from PitchBook. These linked data allow us to identify returnees, trace their education and employment histories across countries, and characterize their employers' clinical-development portfolios by disease and drug modality. Our sample covers 1,608 Chinese biopharmaceutical firms and nearly 24,000 linked clinical trials, supporting analyses at both the firm and disease–modality levels. We observe not only whether individuals received training abroad but also the specific technological expertise to which they were exposed through their employers'

clinical-development activities. This allows us to construct a technology-specific measure of returnee human capital and examine its relationship with subsequent innovation in China.

Our analysis proceeds in four steps. First, we document the growing presence of returnees and their firm-level innovation premium. Returnee-managed firms account for 63.6% of our sample but conduct roughly 73% of all clinical trials and three-quarters of novel trials. Conditional on firm size, founding year, province, and venture backing, returnee-managed firms conduct 30.7% more trials than locally managed firms, with an 11.6–50.4% premium for novel trials depending on the measure. The premium is concentrated in frontier therapeutic areas, particularly oncology and gene therapy. These patterns highlight the importance of internationally accumulated human capital in China's clinical development.

Second, we estimate the international spillovers of human capital accumulated abroad on innovation in China. We link returnees' employment histories to their employers' clinical-trial portfolios to measure each returnee's technological expertise and construct a returnee stock, a weighted count of returnees, for each disease–modality field. We find that a larger returnee stock is associated with more clinical trials, especially novel trials, within these fields. To address endogenous return migration, we instrument returnee stock using displacement events at foreign employers, including layoffs, restructuring, and closures, weighted by their pre-event employment of Chinese professionals and disease–modality specialization. Consistent with the OLS findings, the IV estimates suggest that a one-standard-deviation increase in returnee stock raises novel trials by 15–20%.

Third, we examine the mechanisms through which internationally accumulated human capital contributes to innovation. We first focus on firms, where technological expertise is translated into drug development and resource allocation decisions. Returnee-managed firms initiate more new drug projects and pursue less mature clinical pipelines, consistent with exploring emerging opportunities rather than simply following established development paths. They also secure venture financing earlier. We then ask whether the returnee innovation premium reflects knowledge accumulated abroad before return or continued knowledge flows

from the foreign innovation frontier. We find that the returnee innovation premium does not diminish with firm age or time since return. Moreover, returnee-managed firms conduct more novel trials in diseases with greater U.S. clinical-trial activity after their managers return, a pattern not observed among locally managed firms. These findings suggest that returnees shape firms' innovation decisions and maintain lasting connections to the foreign innovation frontier.

Fourth, we examine whether innovation generated in the utilization country flows back to the training country. We focus on two channels: overseas clinical trials conducted by Chinese firms and the licensing of Chinese-developed drugs to foreign companies. Using the same disease–modality panel and instrument, we find that returnee stock promotes both activities. Relative to the baseline means, a 10% increase in returnee stock generates estimated effects equivalent to 60% more trials with foreign clinical sites and 56% more trials with U.S. sites. The corresponding effects on drug licensing to foreign and U.S. companies are approximately 25% each. These findings suggest that the innovation benefits of internationally accumulated human capital may also flow back to the training countries.

Our paper relates to three literatures. First, we contribute to research on the returns to human capital. A large literature examines the private returns to education and the broader effects of human capital on productivity and innovation within national borders (Akcigit et al. 2025; Andrews 2023; Bell et al. 2019; Card 1999; Ciccone and Peri 2006; Moretti 2004; Toivanen and Väänänen 2016). Recent work further documents the production of U.S. scientific human capital and its international mobility, highlighting the role of public investment and the departure of U.S.-trained scientists (Shvadron et al. 2025, 2026). We extend this literature by examining the innovation generated in countries that receive human capital trained elsewhere. This distinction matters because the returns to human-capital investment depend not only on how much human capital is produced, but also on where it is subsequently utilized. Our results show that part of the innovation return to scientific training is realized beyond the borders of the training country.

Second, we contribute to research on skilled migration and international knowledge diffusion. A large literature documents the contributions of skilled immigrants to innovation in receiving countries (Agrawal et al. 2011; Bernstein et al. 2022; Moser et al. 2014). A related literature examines how return migration transfers knowledge and contributes to productivity, entrepreneurship, and scientific activity in migrants' home countries (Amanzadeh et al. 2024; Bahar et al. 2024; Batista et al. 2025; Gibson and McKenzie 2014). We extend this literature by tracing how technology-specific human capital accumulated abroad shapes the direction and novelty of innovation in the returnees' home country. Rather than focusing solely on aggregate innovation outcomes, we show that returnees contribute to frontier drug development in fields aligned with their foreign expertise, and that returnee-managed firms remain responsive to subsequent advances at the U.S. innovation frontier. Our findings highlight how return migration can strengthen domestic innovation capabilities, not merely by transferring existing knowledge but also by shaping the pursuit of new technological opportunities.

Third, we contribute to the literature on the "flow back" of human-capital investment across country borders. Human capital may be geographically mobile, but its returns need not be geographically confined. Early studies examine how emigrants benefit their countries of origin through diaspora networks and knowledge remittances (Agrawal et al. 2011; Breschi et al. 2017; Fackler et al. 2020; Kerr 2008). Related work shows that mobile scientists and inventors continue to generate knowledge benefits for the places they leave behind (Kahn and MacGarvie 2016; Oettl and Agrawal 2008; Shvadron et al. 2025). While these studies primarily trace knowledge flows through citations, co-authorship, and co-patenting, we identify a distinct channel of flow back through downstream innovation and commercialization. Specifically, we show how U.S.-trained human capital contributes to drug innovation in China that subsequently reenters the U.S. development pipeline through clinical trials and

licensing. Our findings inform debates over federal research funding [4], visas for international students and scholars [5], and restrictions on U.S.–China biotechnology transactions. [6]

The remainder of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 documents the prevalence of returnees and their firm-level innovation premium. Section 4 examines the effects of technology-specific returnee human capital and presents our identification strategy. Section 5 investigates the mechanisms underlying these effects. Section 6 examines international linkages and aggregate contributions. Section 7 discusses the broader implications for international returns to human-capital investment.

2 Data and Variable Construction

2.1 Data

To study how human capital accumulated in the training country contributes to innovation in China, we assemble a new employee–firm–trial dataset linking clinical trials conducted by Chinese biopharmaceutical firms to employees' education and employment histories. We combine three data sources: clinical-trial records from Citeline TrialTrove, employee résumés from Revelio Labs, and company profiles from PitchBook.

The resulting dataset covers 1,608 Chinese biopharmaceutical firms and nearly 24,000

4. The FY2027 budget proposes cutting NSF funding by 55% and NIH funding by 12% (Harvard Office of Federal Relations, April 2026, https://ofr.harvard.edu/news/2026/04/president-trump-releases-fy27-budget-request). Our findings suggest that the benefits of U.S. scientific training may extend beyond domestic innovation.

5. In May 2025, the State Department announced plans to revoke visas of Chinese students in critical fields, and new international student enrollment fell 17% in fall 2025 (IIE, November 2025, https://www.iie.org/blog/four-things-to-know-about-the-fall-2025-snapshot/). Our findings highlight how restrictions on international talent mobility may affect the accumulation and cross-border transfer of scientific human capital.

6. The BIOSECURE Act restricts federal procurement from designated Chinese biotechnology firms, while proposed October 2026 investment rules would subject certain U.S. investments in Chinese biotechnology to screening (Axios, October 23, 2026, https://www.axios.com/2026/10/23/trump-china-biotech-restrictions). Our findings highlight international licensing as a channel through which innovation developed in China can benefit U.S. firms.

linked clinical trials. We organize the data at two main levels: a firm-level cross section and a disease–modality–year panel that captures variation in clinical development and returnee human capital across technologies and over time. We also construct firm–year, firm–disease–year, and firm–disease panels for additional analyses.

Citeline TrialTrove Database. Our clinical-trial data come from Citeline TrialTrove, a commercial database that compiles trial records from national registries, including ClinicalTrials.gov in the U.S. and the Chinese Clinical Trial Registry (ChiCTR), supplemented by sponsor announcements and other public filings. For each trial, we observe the drug under investigation and its mechanism of action, disease indication, development phase, start date, sponsoring organization and its headquarters location, and clinical-site locations, as well as detailed trial descriptions and study-design information. We link these records to our other data sources through the sponsoring firm.

Revelio Labs. Revelio Labs assembles individual résumés from a range of online sources, comparable in content to professional networking platforms such as LinkedIn, with broad coverage of white-collar employment. The data overrepresent management, business, and technology occupations and underrepresent sectors such as agriculture and manufacturing (Tambe 2026). We use Revelio to recover employees' education and employment histories. At the firm level, we identify top managers based on seniority and classify firms based on whether their managers received education abroad. At the disease–modality–year level, we track employees' foreign work experience and subsequent return to China to construct technology-specific returnee stocks.

PitchBook. PitchBook is among the most comprehensive databases of startups and venture-capital activity, with especially strong coverage since 2000 (Marx et al. 2026; Retterath and Braun 2020). It provides company- and individual-level profiles, including firm characteristics, top managers, and financing records, which we use to link firms to Revelio. We use

PitchBook to supplement top managers' education histories for firms with limited Revelio coverage, identify firms' founding years, and obtain venture-capital financing information. The financing records include the stage, date, and amount of each round. We classify firms as VC-backed if they have completed at least one Seed, Early-Stage, or Later-Stage VC round. Finally, we use PitchBook's founder records to validate our seniority-based top-manager classification and assess the sensitivity of our returnee-managed firm classification to alternative manager definitions.

Data Linkage. We link clinical trials to employees' education and employment histories through their sponsoring firms. We first identify each trial's sponsor in TrialTrove and match private, China-based sponsors to firms in Revelio and PitchBook using name normalization, fuzzy string matching, large-language-model verification, and manual review. We then link these firms to their employees and top managers, recovering their education and employment histories across countries. Of the 3,819 Chinese firms sponsoring 31,588 trials, we match 1,750 firms (45.8%) to Revelio or PitchBook. These matched firms account for 79.5% of all trials, reflecting their greater clinical-development activity. Among them, 1,608 firms (91.9%) have at least one top manager or early employee with observed education records, forming our firm-level regression sample. Additional details on the matching procedure are provided in Appendix A.1.

2.2 Variable Construction

Table 1 documents the summary statistics for key variables in our sample.

Trial novelty. We characterize firms' clinical-trial activity along two main dimensions: the total number of trials and the number of novel trials.

We measure trial novelty using three complementary measures that distinguish frontier R&D from incremental, "me-too" development. First, following Dranove et al. (2022), we construct a mechanism-of-action novelty index based on how frequently a drug's mechanism

has been explored in prior trials.[7] We classify a trial as high-novelty if its index is above the median for its start year.

Second, we apply a fine-tuned large language model to clinical-trial registry records to classify each drug as a new molecular entity, a novel combination, a new indication for an existing molecule, or a generic. We classify the first three categories as innovative, non-generic trials.

Third, we classify a trial as *first-in-China* if no earlier Chinese-firm trial has tested the same mechanism of action at the same or a more advanced phase. Each measure is defined at the trial level and aggregated into firm-level counts. On average, a firm conducts 7.0 high-novelty and 12.8 non-generic trials, while first-in-China trials are much rarer, averaging 0.56 per firm.

Returnee top managers and returnee-managed firms. For our firm-level analysis, we focus on top managers because their individual characteristics can shape firms' strategic decisions and resource allocation (Bertrand and Schoar 2003). We identify a firm's *top managers* as the five most senior employees with identifiable education records, using earlier join dates to break ties.[8] We classify educational institutions as Chinese, U.S., or other, where "Chinese" includes mainland China, Hong Kong, and Macau. A top manager is classified as a *returnee* if they hold at least one degree from a non-Chinese institution. A firm is *returnee-managed* if at least one of its top managers is a returnee, and *locally managed* otherwise. The indicator ReturneeManaged_i equals one for returnee-managed firms, which account for 63.6% of our sample. We also consider alternative definitions of top managers, including early employees (Choi et al. 2025), and distinguish foreign doctoral training from

7. Following Dranove et al. (2022), the novelty of trial i with mechanism $m(i)$ at phase $j(i)$ is

$$\text{Novelty}_i = \frac{1}{1 + \#\{\text{prior trials at phase } j(i) \text{ using mechanism } m(i)\}}.$$

This distinguishes drugs with rarely explored mechanisms from those relying on well-established pathways. We calculate the annual median using trials from all countries, benchmarking novelty against the global clinical-development frontier rather than country-specific baselines.

8. When a firm has no matched Revelio top managers, we use its PitchBook-listed top managers instead.

prior industry and academic employment experience.

Returnee stock. The main explanatory variable in our disease–modality–year analysis is the *returnee stock*, a weighted count of returnee employees associated with each disease–modality cell. We construct this measure from Chinese individuals[9] who worked at biopharmaceutical firms outside China and subsequently returned. An individual enters the stock in the year of their first employment in China following employment overseas.

We assign each returnee to disease–modality cells based on their employers' clinical-trial portfolios. Let N_{idmt} denote the cumulative number of trials in disease d and modality m associated with individual i's employers through year t. We include trials conducted by both Chinese and foreign employers, counting each employer's trials through year t if the individual is currently employed there, or through the end of their tenure if they have left. We normalize these counts across disease–modality cells and aggregate the resulting weights across returnees:

$$w_{idmt} = \frac{N_{idmt}}{\sum_{d',m'} N_{id'm't}}, \qquad \text{Stock}_{dmt} = \sum_{i:T_i \le t} w_{idmt},$$

where T_i is the year individual i returned to China. The weights sum to one across disease–modality cells for each individual with an observed employer trial portfolio. For example, a returnee whose employers conduct 80% of their trials in small-molecule oncology contributes 0.8 to the returnee stock in that disease–modality cell. The stock evolves as new returnees arrive and existing returnees' weights change with their employers' clinical-trial portfolios and job transitions.

In Appendix A.3, we examine two alternative measures using static weights. The first fixes the disease–modality weights at return based on foreign employers' pre-return trials. The second uses trial portfolios accumulated over each individual's entire career. We prefer

9. We classify an individual as Chinese if they have at least one education record from an institution in mainland China, Hong Kong, or Macau. For individuals without such a record, we use a large language model to infer Chinese origin from surnames and romanization conventions.

the dynamic measure because it captures changes in disease–modality exposure over time without incorporating future information.

Firm controls. For our firm-level cross-sectional analyses, we control for employee headcount and venture-capital backing, along with founding-year and headquarters-province fixed effects. Employee headcount is measured by the number of employees matched to each firm in Revelio, and for firms without matched employees, we use PitchBook's reported headcount. A firm is classified as *VC-backed* if it has completed at least one Seed, Early-Stage, or Later-Stage VC round in PitchBook. Employment is highly skewed: the median firm has approximately 20 employees, and the mean exceeds 110. The median founding year is 2005, and 33% of firms are VC-backed.

Disease–modality–year controls. The panel regressions include three controls at the disease–modality–year level. *Global trials* counts trials initiated in each disease–modality pair in year t by firms headquartered outside China, capturing scientific opportunities in the field. *Global cumulative trials* accumulates these trials through year $t-1$, proxying for the field's maturity. *Employee stock* measures the workforce allocated to each disease–modality combination. We construct it by allocating each sample firm's Revelio employee headcount in year t across disease–modality combinations based on its cumulative trial portfolio through year $t-1$, then summing across firms. This helps distinguish the contribution of returnee human capital from that of overall workforce size.

3 Returnees and Firm-Level Innovation

3.1 Descriptive Evidence

We begin by documenting three empirical facts about returnees in China's biopharmaceutical industry: (i) the growing presence of returnees in the workforce, (ii) the prevalence of re-

turnees in firm management, and (iii) the disproportionate contribution of returnee-managed firms to clinical development.

First, returnee employment has grown alongside the expansion of China's biopharmaceutical sector. Figure 1 tracks employment at the 1,608 sample firms from 2000 to 2025. Total employment rises from about 2,000 to 55,975 over this period, while the number of returnee employees grows from 143 to 9,493. The returnee share of the workforce more than doubles, from 7.0% in 2000 to a peak of 18.6% in 2021, and stands at 17.0% in 2025.[10]

Second, returnees are also prevalent in firm management, particularly at larger and younger firms. In our sample, 63.6% of firms have at least one top manager with foreign education. Figure A1 compares these returnee-managed firms with locally managed firms (those without foreign-educated top managers). Panel (a) shows that returnee-managed firms tend to have larger workforces, while locally managed firms are more concentrated among smaller firms. Panel (b) shows that returnee-managed firms are also younger, with founding years concentrated in the 2010s, whereas locally managed firms were mostly founded in the 1990s and early 2000s.

Third, returnee-managed firms account for a disproportionately large share of clinical development. Table A2 shows that returnee-managed firms, which account for 63.6% of the sample, sponsor 73.1% of the 23,957 unique trials. This share is higher still among innovative trials, at 74.8% of Dranove-novel trials, 76.6% of GPT-novel trials, and 77.9% of first-in-China trials. The pattern is most pronounced for first-in-China trials, suggesting that returnee-managed firms play an important role in introducing new mechanisms of action into Chinese clinical development.

3.2 Firm-Level Innovation Premium

The descriptive evidence shows that returnee-managed firms account for a disproportionate share of clinical innovation, but these firms also tend to be larger and younger. We next

10. The post-2021 decline in the measured returnee share may partly reflect reduced coverage of recent employment spells in Revelio after LinkedIn discontinued its localized service in China in 2021.

examine whether this firm-level innovation premium persists after controlling for observable firm characteristics.

Returnee-managed firms conduct more (novel) clinical trials. We begin with a firm-level cross-sectional comparison of returnee-managed and locally managed firms. For firm i, we estimate

$$Y_i = \beta\, \text{ReturneeManaged}_i + \gamma' X_i + \delta_{p(i)} + \theta_{f(i)} + \varepsilon_i, \tag{1}$$

where Y_i measures clinical-trial activity, including total and novel-trial counts. ReturneeManaged_i equals one if at least one of the firm's five most senior employees holds a degree from an institution outside China, and zero otherwise. X_i includes employee headcount and VC backing to account for differences in firm size and access to venture capital. Finally, $\delta_{p(i)}$ and $\theta_{f(i)}$ denote headquarters-province and founding-year fixed effects, which account for geographic differences and variation across founding cohorts. Standard errors are heteroskedasticity-robust. The coefficient β captures the conditional difference in clinical-trial activity between returnee-managed and locally managed firms, which we refer to as the firm-level innovation premium.

Given the non-negative and right-skewed trial counts, we estimate equation (1) using OLS on $\log(Y_i + 1)$ and Poisson pseudo-maximum-likelihood (PPML) on the untransformed counts. We report OLS estimates as the baseline and PPML as a robustness check.

Table 2 shows that returnee-managed firms conduct significantly more trials than locally managed firms. The coefficient of 0.268 in column 1 implies that, after controlling for firm size, VC backing, headquarters province, and founding year, returnee-managed firms conduct approximately 31% more trials than locally managed firms. We refer to this conditional difference as the firm-level innovation premium, which is statistically significant at the 1% level. The premium is 32% for Dranove-novel trials, 50% for GPT-novel trials, and 12% for first-in-China trials (columns 2–4), all significant at the 1% level. The premium for novel

trials suggests that returnee-managed firms not only conduct more trials but also pursue more innovative projects.

Broader Disease Coverage and Higher Within-Disease Novelty. The preceding results establish a firm-level innovation premium in novel trials. This premium may arise because returnee-managed firms conduct trials across more diseases or because they pursue more novel trials within the diseases they enter.

To distinguish these two margins, we first examine whether returnee-managed firms are more likely to conduct clinical trials in a given disease, capturing differences in the breadth of clinical development. We then focus on firms that have entered a disease and examine whether a larger share of their trials are novel. This allows us to distinguish broader disease participation from greater novelty within the same disease. We estimate disease entry using a logit model and within-disease novelty using a grouped binomial logit model.[11]

Table A3 shows positive differences along both margins. Returnee-managed firms are 0.85 percentage points more likely to enter a given disease than locally managed firms, compared with a baseline entry probability of 2.8%. Conditional on entry, returnee-managed firms have novelty rates that are 3.94 percentage points higher under the Dranove measure, 5.64 percentage points higher under the GPT measure (marginally significant), and 1.62 percentage points higher for first-in-China trials. These results suggest that the firm-level innovation premium reflects not only broader disease coverage but also greater novelty within the same diseases.

11. Specifically, we estimate disease entry across all firm–disease pairs using

$$\Pr(\text{Enter}_{id} = 1) = \Lambda\big(\beta\,\text{ReturneeManaged}_i + \gamma' X_i + \delta_{p(i)} + \theta_{f(i)}\big)\,,$$

where Enter_{id} equals one if firm i conducts at least one trial in disease d. Conditional on entry, we estimate

$$\text{logit}(\pi_{id}) = \alpha\,\text{ReturneeManaged}_i + \eta' X_i + \delta_{p(i)} + \theta_{f(i)} + \lambda_d,$$

where π_{id} is the share of novel trials among firm i's trials in disease d, and λ_d denotes disease fixed effects. Both specifications include the firm controls and fixed effects from equation (1), with additional disease fixed effects in the novelty specification.

3.3 Heterogeneity and Robustness

The firm-level innovation premium varies across therapeutic areas and with managers' foreign training and experience. The results are robust to alternative measures of returnee presence and estimation methods.

Heterogeneity across Therapeutic Areas. We re-estimate the baseline specification separately for ten therapeutic areas, using firm-level counts of total and novel trials (Figure 2). The innovation premium is strongest in oncology, metabolic and endocrine diseases, and gene therapy, with significant differences in total and novel trials across all three novelty measures. Effects elsewhere are generally weaker or insignificant. The concentration in oncology and gene therapy suggests a stronger premium in frontier, research-intensive areas (Barwick et al. 2026).[12]

Foreign Training and Professional Experience. Appendix Table A4 examines whether the firm-level innovation premium varies with top managers' foreign training and professional experience. Panel A adds an indicator for a foreign-PhD top manager to the baseline returnee-managed indicator, capturing the additional premium associated with doctoral training among returnee-managed firms. Firms with a foreign-PhD top manager conduct 32% more total trials and 44% more Dranove-novel trials than returnee-managed firms without one. Panel B replaces the returnee-managed indicator with two indicators for top managers' prior foreign industry and academic experience, included jointly. Foreign industry experience is associated with 26% more total trials and 28% more Dranove-novel trials, while foreign academic experience is associated with 32% and 43% more, respectively, controlling for the other experience channel.

12. Oncology accounts for about 30% of U.S. trials and the largest absolute increase in activity, while U.S. gene therapy trials roughly quadrupled between the early 2010s and early 2020s.

Alternative Measures of Returnee Presence. We consider two alternative measures using the baseline controls and fixed effects. First, motivated by Choi et al. (2025), we define returnee management based on whether at least one of the firm's five earliest observed employees received education abroad. Returnee-managed firms conduct 19% more total trials and 23% more Dranove-novel trials, both significant at the 1% level (Table A6). Second, using the share of foreign-educated employees in the firm's Revelio-matched workforce, a 10-percentage-point increase is associated with 1.6% more total trials, 2.3% more Dranove-novel trials, and 4.7% more GPT-novel trials (Table A7). These results are broadly consistent with the baseline findings, reinforcing the positive association between returnee presence and clinical innovation.

Poisson Pseudo-Maximum Likelihood (PPML). We also estimate the baseline specification using PPML on untransformed trial counts. Appendix Table A10 shows that returnee-managed firms conduct 43% more total trials, 52% more Dranove-novel trials, 48% more GPT-novel trials, and 85% more first-in-China trials than otherwise comparable locally managed firms. All estimates are statistically significant at the 5% level, with magnitudes for total and novel trials broadly comparable to the baseline OLS estimates, further supporting the robustness of the firm-level innovation premium.

4 Technology-Specific Human Capital and Innovation

4.1 Main Results: Returnee Human Capital and Innovation

The firm-level evidence establishes an innovation premium associated with returnee management, but does not directly measure the contribution of returnees' internationally accumulated human capital. Moreover, firm-level comparisons take firms and their research portfolios as given, although both may be shaped by returnee human capital. We therefore shift to the disease–modality–year level to examine whether a larger stock of returnees with

relevant technological expertise is associated with greater innovation in China.

Figure 3 provides initial evidence of this relationship. Each point represents a disease, comparing the change in returnee human capital between 2010 and 2025 with the change in average annual clinical-trial activity over the same period. The raw correlation is strongly positive, indicating that diseases attracting more returnee human capital also experienced greater growth in clinical trials. The estimated slope is 0.403 (s.e. 0.076), with a weighted R^2 of 0.70 for total trials, and the corresponding R^2 is 0.75 for Dranove-novel trials. The relationship remains positive after controlling for global trial activity, baseline conditions, and therapeutic-area fixed effects, with conditional slopes of 0.458 for total trials and 0.253 for Dranove-novel trials.

We next examine the relationship between technology-specific returnee human capital and clinical innovation within disease–modality level over time. For disease d, modality m, and year t, we estimate

$$\log(1 + n_{dmt}) = \beta \log(1 + \text{Stock}_{dmt}) + \gamma' X_{dmt} + \mu_{dm} + \delta_{dt} + \lambda_{mt} + \varepsilon_{dmt}, \tag{2}$$

where n_{dmt} counts clinical trials initiated by sample firms in disease d, modality m, and year t, measured separately for total trials and each of the three novelty measures. Stock_{dmt} measures the stock of returnees with expertise relevant to the corresponding disease–modality combination, as defined in Section 2.2. The controls X_{dmt} include contemporaneous global trial activity, cumulative global trials through $t-1$, and total employee stock, all measured at the disease–modality–year level and transformed as $\log(1+x)$.

Disease–modality fixed effects μ_{dm} account for persistent differences across technologies. Disease–year fixed effects δ_{dt} and modality–year fixed effects λ_{mt} absorb annual shocks common to each disease or modality. The coefficient β therefore captures the association between changes in returnee human capital and clinical innovation within the same technology, conditional on these controls and fixed effects. Standard errors are clustered at the disease–modality level.

Panel A of Table 3 shows a strong positive association between returnee human capital and clinical development. The coefficient of 0.587 for total trials implies that a 10% increase in returnee stock is associated with approximately 5.9% more trials, substantially larger than the corresponding association for total employee stock (0.088). The coefficients are also positive for Dranove-novel (0.401), GPT-novel (0.479), and first-in-China trials (0.045). These findings suggest that technology-specific returnee human capital is associated with both greater clinical development activity and more novel trials.

The association is not limited to returnee-managed firms. Table 4 estimates equation (2) separately for trials involving returnee-managed firms and those conducted exclusively by locally managed firms. The coefficients are positive for both groups, at 0.554 versus 0.282 for total trials, 0.365 versus 0.157 for Dranove-novel trials, and 0.462 versus 0.176 for GPT-novel trials. Although the OLS associations are stronger for returnee-managed firms, the positive estimates for locally managed firms are consistent with knowledge spillovers extending beyond firms directly employing returnees.

Additional analyses examine heterogeneity and robustness. Appendix Table A5 shows stronger associations for senior than junior returnees, consistent with the importance of accumulated experience and tacit knowledge. Both doctoral-trained and other returnees are positively associated with clinical trial activity, with a significantly stronger association for doctoral-trained returnees in Dranove-novel trials (0.421 versus 0.154). Appendix Tables A8 and A9 show that results remain positive and significant when returnee stock is constructed using fixed disease–modality weights based on either pre-return foreign-employer trials or employers' trial portfolios over the returnee's observed career. PPML estimates are broadly consistent with the baseline findings (Appendix Table A11).

4.2 Identification

The earlier section shows a positive association between returnee human capital and clinical innovation among both returnee-managed and locally managed firms. However, the estimates

may be upward biased if returnees sort into promising technologies or firms recruit them in anticipation of innovation opportunities. Conversely, returnees may target less-developed technologies in China, where gaps in domestic expertise create opportunities to apply knowledge acquired abroad, potentially biasing the estimates downward.

To address these endogeneity concerns, we exploit disruptions at foreign employers that may induce Chinese professionals to return independently of innovation opportunities in China. The resulting inflows should be larger in disease–modality combinations where affected employers previously employed more Chinese professionals and conducted a greater share of their clinical trials.

We hand-collect 118 displacement events at 89 multinational pharmaceutical, biotechnology, and contract research organization (CRO) employers between 2008 and 2023, including mass layoffs, post-merger restructuring, bankruptcies, and site closures. We construct a shift-share instrument for disease d, modality m, and year t:

$$Z_{dmt} = \sum_{f} \underbrace{N_{f,2007}\, w_{fdm,2007}}_{\text{Pre-event exposure}} \underbrace{\sum_{\tau=2008}^{t} D_{f\tau}}_{\text{Cumulative displacement shocks}},$$

where $N_{f,2007}$ is the number of ethnically Chinese professionals whose employment at foreign firm f began by the end of 2007, $w_{fdm,2007}$ is the share of the firm's pre-2008 clinical trials in disease–modality combination (d, m), and $D_{f\tau}$ indicates a displacement event at firm f in year τ. Both exposure measures are fixed before the event window, and Z_{dmt} is standardized to unit variance.

Our identification relies on displacement shocks at foreign employers that are plausibly independent of innovation opportunities in China (Borusyak et al. 2022). This is plausible because our sample firms accounted for only 0.6% of worldwide trials in the relevant diseases in 2008, making it unlikely that Chinese innovation prospects drove these foreign-employer disruptions. A potential violation of the exclusion restriction is that these shocks could also affect Chinese innovation through changes in global research activity. We mitigate this

concern by controlling for global trial activity and including disease–year and modality–year fixed effects to absorb broader technological shocks.

Figure 4 and the first-stage estimates in Panel B of Table 3 provide evidence for the displacement channel. Figure 4 shows no significant differential trends in returnee inflows across technologies with different exposure levels before 2008 ($F = 1.59$, $p = 0.13$), followed by larger inflows in more exposed technologies.[13][14] Consistent with this pattern, a one-standard-deviation increase in event exposure is associated with approximately 11% higher returnee stock, about two fifths of its within-technology variation (first-stage $F = 22.37$).

Panel B of Table 3 reports the 2SLS estimates. A 10% increase in instrumented returnee stock is associated with 9.2% more total trials, 7.6% more Dranove-novel trials, 6.0% more GPT-novel trials, and 0.6% more first-in-China trials. These estimates consistently exceed their OLS counterparts, suggesting that downward selection into less-developed technologies may dominate upward sorting into promising ones.

5 Mechanisms

Section 4 establishes that the accumulation of returnee human capital stimulates innovation in the corresponding disease–modality combinations. We now investigate the mechanisms underlying these effects in two steps. Specifically, we examine (i) how this human capital translates into innovation through firms' decisions, as firms are where knowledge is transformed into new drug projects, research priorities, and access to financing; and (ii) whether returnees serve as a bridge to the foreign innovation frontier, facilitating continued knowledge flows across countries rather than merely transferring knowledge accumulated abroad before their return.

13. We estimate $\log(1+\text{Inflow}_{dmt}) = \sum_{y \neq 2007} \theta_y \, s_{dm} \, \mathbf{1}[t = y] + \gamma' X_{dmt} + \mu_{dm} + \delta_{dt} + \lambda_{mt} + \varepsilon_{dmt}$, where s_{dm} is standardized total event exposure, with controls and fixed effects from equation (2); 2007 is the omitted year.

14. As a robustness check, we also examine the shocks directly at the employer level. Figure A3 shows that employment at affected employers begins falling in the announcement year and stabilizes 40–50% below the path of comparable never-treated sponsors within five years, with similar estimates across four staggered difference-in-differences estimators.

5.1 Firm Innovation and Resource Allocation

Section 3 documents a firm-level innovation premium associated with returnee management, while Section 4 links greater innovation to returnees' technology-specific expertise accumulated abroad. We now examine how this human capital may translate into innovation through firms' decisions. Specifically, we investigate three margins: new drug development, research direction, and access to financing.

New drug development. The firm-level returnee premium may reflect more trials of existing drugs rather than the development of new drug candidates. To distinguish these margins, we examine whether returnee-managed firms initiate more new drug projects. Using a panel of 1,607 firms from their founding year through 2025 (32,241 firm–year observations), we regress annual trial and new drug counts, transformed as $\log(1 + y)$, on returnee management. A new drug project is defined by the first trial of a given drug initiated by a firm. We control for VC backing, lagged employment, and year, founding-year, and province fixed effects, with standard errors clustered by firm.

Table 5 shows that returnee-managed firms initiate 6.5% more trials and 4.2% more new drug projects annually. These findings suggest that the returnee premium extends to the initiation of distinct drug candidates, rather than merely additional trials of existing drugs.

Research direction. Foreign experience may also shape which technological opportunities firms pursue, beyond the number of projects they initiate. We therefore examine whether returnee-managed firms select diseases with different prior research activity and stages of clinical development. For each trial–disease pair, we relate returnee management to the disease's prior trial activity, growth, late-phase share, and phase-advance index. The regressions use the same controls and fixed effects as above, weight each observation by the inverse of the number of diseases listed for the trial, and cluster standard errors by firm.

Table 6 shows no significant differences in prior global trial activity or growth, or in do-

mestic trial activity. Instead, returnee-managed firms target diseases with 13% more prior US trial activity but less mature clinical pipelines: the late-phase share is about 2 percentage points lower and the phase-advance index about 15% lower. These patterns are consistent with returnee managers identifying emerging research opportunities connected to US innovation rather than simply following established clinical pipelines.

Access to financing. Developing new drug candidates also requires substantial financial resources, and returnee management may facilitate access to external financing. Using PitchBook records, we examine annual VC financing, funding amounts, and the timing of firms' first VC rounds. The annual financing regressions control for lagged employment and prior clinical-development activity, including total, novel, and late-phase trials over the preceding three years, along with year, founding-year, and province fixed effects. The first-round timing regression controls for founding-year and province fixed effects.

Table 7 shows that returnee-managed firms are 1.3 percentage points more likely to receive VC financing annually, raise about 5% more funding, and secure their first round approximately 1.4 years earlier. The financing differences persist after controlling for prior clinical pipelines, suggesting that returnee management may facilitate access to capital beyond differences in observable innovation output.

5.2 Connection to the Foreign Frontier

Section 5.1 examines how returnee human capital shapes firms' development decisions, research priorities, and access to financing. We now ask whether these advantages reflect knowledge accumulated abroad before return or continued access to the foreign innovation frontier. Under a *static knowledge-stock mechanism*, returnees bring back expertise that may depreciate over time. Under a *dynamic knowledge-flow mechanism*, returnees maintain connections to foreign research and facilitate continued knowledge transfer. We examine how the returnee premium evolves with firm age and time since return, and whether returnee-managed firms

remain connected to subsequent U.S. innovation.

The premium builds with firm age. If the returnee advantage primarily reflects a depreciating stock of foreign knowledge, we would expect it to diminish as firms age. We test this using the firm–year panel, interacting returnee management with indicators for firm ages zero through twelve. The regressions control for employment, VC backing, and firm-age, year, and province fixed effects, with standard errors clustered by firm. Figure 5 shows that the premium grows rather than declines with firm age. The gaps in total, Dranove-novel, and GPT-novel trials are initially negative, turn positive around ages three to four, and reach approximately 4–9% by ages six to twelve. This pattern is inconsistent with a simple mechanism in which the benefits of foreign knowledge diminish as firms mature.

The premium does not fade with time since return. A more direct test of knowledge depreciation examines whether the returnee premium declines with the time elapsed between managers' return and firm founding. We divide this interval into seven cohorts and interact each with returnee management, using the baseline firm-level controls and fixed effects. Figure 6 shows no systematic decline in the premium as the interval increases. The advantage remains positive even for firms founded more than a decade after their managers' return, particularly for GPT-novel trials. Together, these two findings suggest that the returnee premium reflects durable advantages rather than knowledge that rapidly depreciates after return.

Knowledge flows from the US frontier. The persistence of the premium alone cannot distinguish durable knowledge accumulated before return from continued access to foreign innovation. We therefore examine whether returnee-managed firms' research portfolios are more closely associated with subsequent advances in the US innovation frontier. Using a firm–disease panel, we interact returnee management with US clinical-trial activity in the

corresponding disease following managers' return, including firm and disease fixed effects.[15] The interaction captures whether returnee-managed firms' innovation is more strongly associated with subsequent US research activity.

Table 8 shows that returnee-managed firms conduct disproportionately more novel trials in diseases with greater US innovation activity, while locally managed firms exhibit no comparable pattern. A doubling of US trial activity is associated with 13–15% more GPT-novel and 11–13% more Dranove-novel trials relative to their respective baseline means, with a smaller increase in total trials that is significant only at the 10% level in the five-to-ten-year window. These patterns persist when measuring US activity five to ten years after return. Together, the evidence is consistent with returnees serving as lasting bridges to the foreign innovation frontier, rather than merely transferring a fixed stock of knowledge when they return.

6 International Linkages and Aggregate Contributions

6.1 Flows Back to Foreign Markets

Returnee human capital may not only bring foreign knowledge into China but also connect Chinese innovation to foreign markets. This possibility matters for the international returns to human-capital investment, as innovations developed in China may also benefit the training countries where returnees acquired their human capital. Beyond the potential benefits to patients from drugs eventually approved in training countries, these innovations may also reach foreign markets before approval. We examine two channels: clinical trials with foreign sites and drug out-licensing to foreign companies.

Table 9 reports OLS and 2SLS estimates at the disease–modality–year level. Panel A counts trials initiated by Chinese biopharmaceutical firms in our sample with at least one

15. We estimate $\log(1+y_{id}) = \beta\,(\text{ReturneeManaged}_i \times \log(1+F_d)) + \phi_i + \lambda_d + \varepsilon_{id}$, where F_d measures US clinical-trial activity following managers' return, and ϕ_i and λ_d denote firm and disease fixed effects.

foreign clinical site, while Panel B counts drugs linked to these firms' trials and licensed to foreign companies. For each outcome, "World" includes all foreign destinations, including the United States, while "US" restricts attention to U.S. sites or licensees.

Panel A shows that a larger returnee stock is associated with more trials involving foreign clinical sites. The 2SLS estimates imply that a 10% increase in returnee stock corresponds to approximately 3.3% more trials with at least one foreign site (60% relative to the baseline mean) and 2.0% more trials with a US site (56% relative to the baseline mean), significant at the 1% and 5% levels, respectively.[16] Panel B shows a similar pattern for drug out-licensing. A 10% increase in returnee stock corresponds to approximately 1.1% more drugs licensed to foreign companies and 0.8% more drugs licensed to US companies (both about 25% relative to the baseline mean). Both 2SLS estimates are significant at the 1% level. The OLS estimates are also positive and significant across outcomes and destinations.

Together, these findings suggest that the benefits of returnee human capital may extend beyond China through overseas clinical trials and drug licensing. By connecting Chinese drug projects to further development and commercialization abroad, these activities provide channels through which the benefits of internationally accumulated human capital may flow back to the training countries.

6.2 Aggregate Magnitudes

To assess the aggregate magnitudes associated with returnee human capital in clinical development, we conduct two back-of-the-envelope exercises, reported in Table 10. The first translates the firm-level returnee premium into a share of observed trial activity, and the second uses technology-level estimates to assess the contribution of returnee accumulation to growth since 2000.

16. As with the knowledge-flow estimates in Table 8, we express each effect relative to the sample mean of the dependent variable, $\log(1+y)$. A 10% increase in returnee stock changes the dependent variable by $\hat{\beta}\ln(1.1)$, so the relative effect is $\hat{\beta}\ln(1.1)/\bar{\ell}$, where $\bar{\ell}$ is the mean reported in Table 9. For trials with a foreign site, this gives $0.331 \times \ln(1.1)/0.0526 \approx 60\%$.

Panel A isolates the additional trial activity associated with returnee-managed firms' innovation premium, rather than their total trial output. The raw shares in Table A2 reflect both this premium and the prevalence of returnee-managed firms. To separate the two, we apply the baseline coefficients of Table 2 and estimate how much lower aggregate trial activity would be if returnee-managed firms performed like otherwise similar locally managed firms, holding the number and composition of firms fixed. We estimate that returnee-managed firms conduct 4,119 more trials than under this counterfactual, equivalent to 17.2% of all trials in the sample. The corresponding excess amounts to 1,579 Dranove-novel trials (18.2%), 4,038 GPT-novel trials (25.7%), and 59 first-in-China trials (8.1%). The implied contribution is largest for GPT-novel trials, reaching about a quarter of the sample total.[17]

Panel B assesses the contribution of returnee human capital accumulated across technologies. We hold each disease–modality pair's returnee stock at its year-2000 level and use the 2SLS coefficients from Panel B of Table 3 to rescale observed trial activity, holding other determinants unchanged. We then sum the gap between observed and counterfactual trials over 2001–2025 and divide it by cumulative trial growth relative to the year-2000 level. The resulting shares are 84.9% for total trials, 81.0% for Dranove-novel trials, 71.5% for GPT-novel trials, and 10.2% for first-in-China trials.

7 Discussion

This paper examines how human capital accumulated in one country contributes to innovation in another, using return migration in China's biopharmaceutical industry as a setting. We find that returnee-managed firms conduct more clinical trials, particularly novel ones, and that technology-specific returnee human capital stimulates innovation in corresponding disease–modality fields. Our instrumental-variable estimates support a causal interpretation

17. For each outcome, we multiply the unique trial count of returnee-managed firms by $1 - e^{-\hat{\beta}}$, where $\hat{\beta}$ is the corresponding firm-level coefficient, an approximate proportional adjustment implied by the log specification.

of these spillovers. Returnee-managed firms also initiate more new drug projects, pursue emerging research opportunities, secure venture financing earlier, and maintain connections to the U.S. innovation frontier. Moreover, returnee human capital promotes overseas clinical trials and international drug licensing, creating channels through which innovation benefits may flow back to training countries. Together, these findings highlight both accumulated knowledge transfer and lasting international innovation linkages.

The country where human capital is accumulated is not necessarily where its returns are realized. Evaluating education and scientific training solely through domestic outcomes may therefore overlook substantial international benefits. For utilization countries, return migration can strengthen domestic innovation capacity. For training countries, skilled emigration need not represent a complete loss, as innovations developed abroad may generate benefits through international research and product markets. The relevant policy question is thus not simply whether skilled workers stay or leave, but how their mobility shapes the creation and distribution of innovation benefits across borders.

Our study also suggests directions for future research. First, measuring the full international returns to human capital requires quantifying benefits flowing back to training countries through licensing, collaboration, and trade. Second, further work could distinguish knowledge embodied in returning workers from continued knowledge flows through international networks. Finally, examining how these effects vary with utilization countries' absorptive capacity, financing, and technological development would help identify when and where international human-capital spillovers are most valuable.

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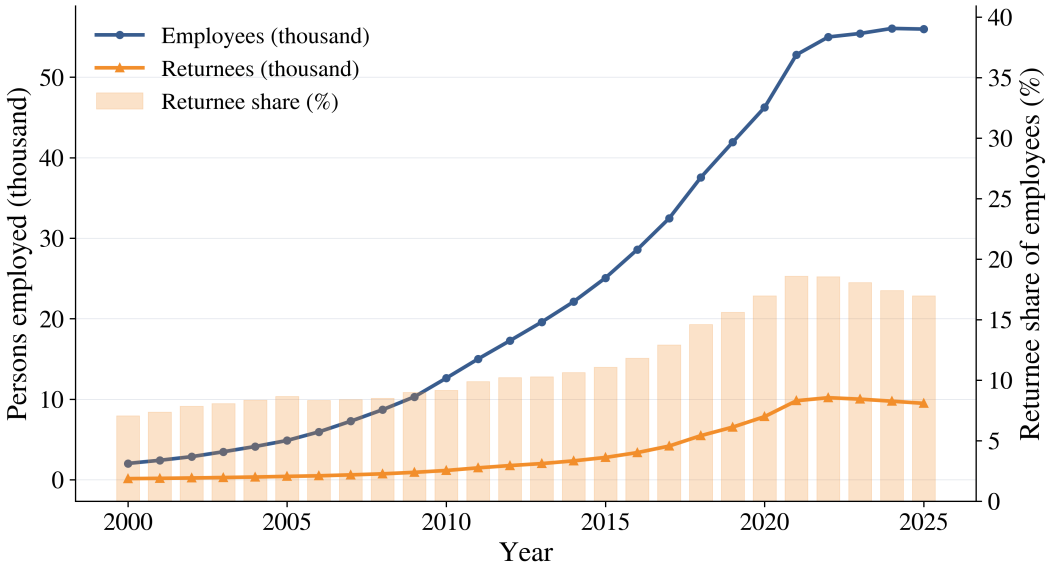
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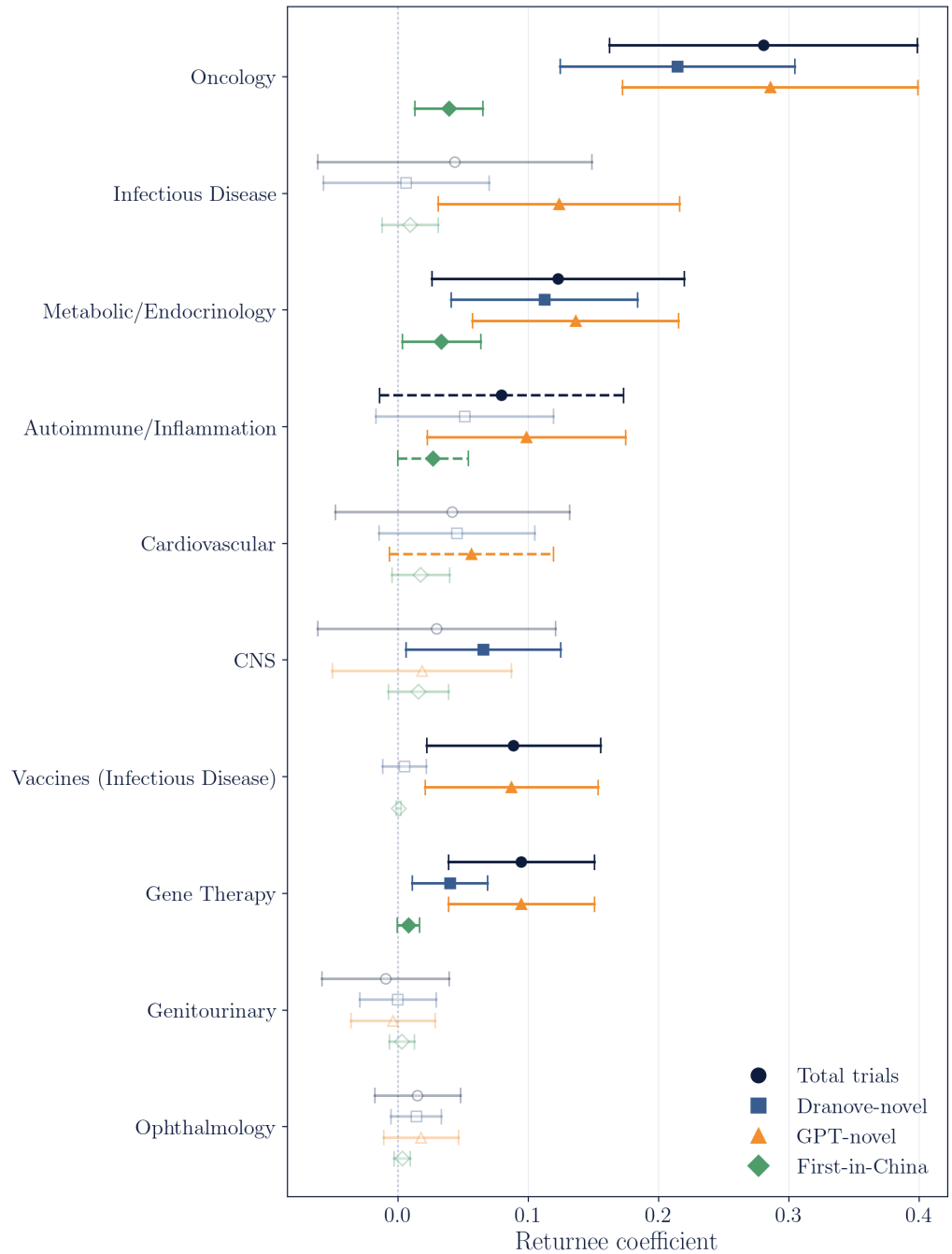
Figures

Figure 1: Employees and returnees at the sample firms, 2000–2025



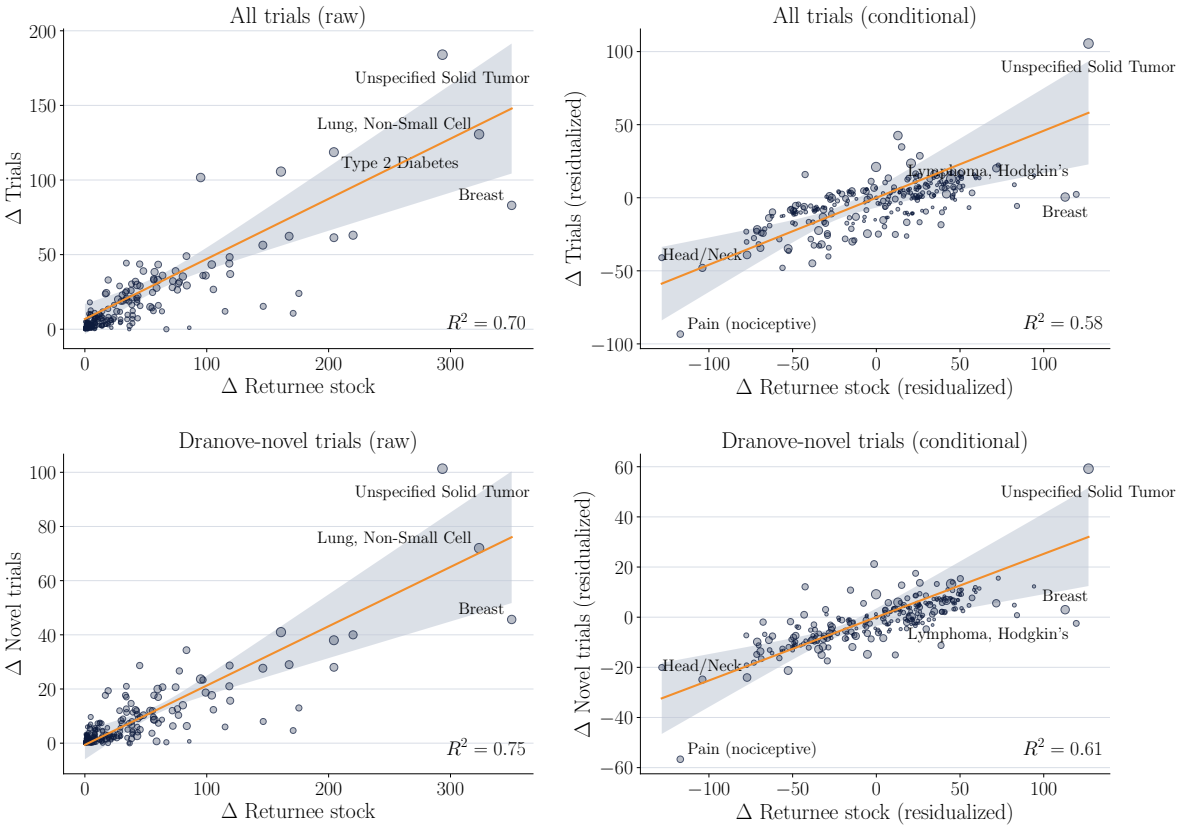
Notes: The figure plots total employment (left axis, thousands), returnee employment (left axis, thousands), and the returnee share of employees (bars, right axis, percent) at the 1,608 sample firms from 2000 to 2025. A person counts as employed in year t if a position at one of the firms spans t; a position with no end date is treated as ongoing. A person is a returnee if they hold both Chinese and foreign education, or if they are Chinese and held a foreign position before joining one of the firms, where Chinese means having Chinese education or an ethnically Chinese name as classified by a language model. China includes mainland China, Hong Kong, and Macau; Taiwan counts as foreign. In 2025 the firms employ 55,975 people, of whom 9,493 (17.0%) are returnees. The returnee share peaks in 2021, the year LinkedIn withdrew from China, after which Revelio's coverage of new hires thins.

Figure 2: The returnee premium across therapeutic areas



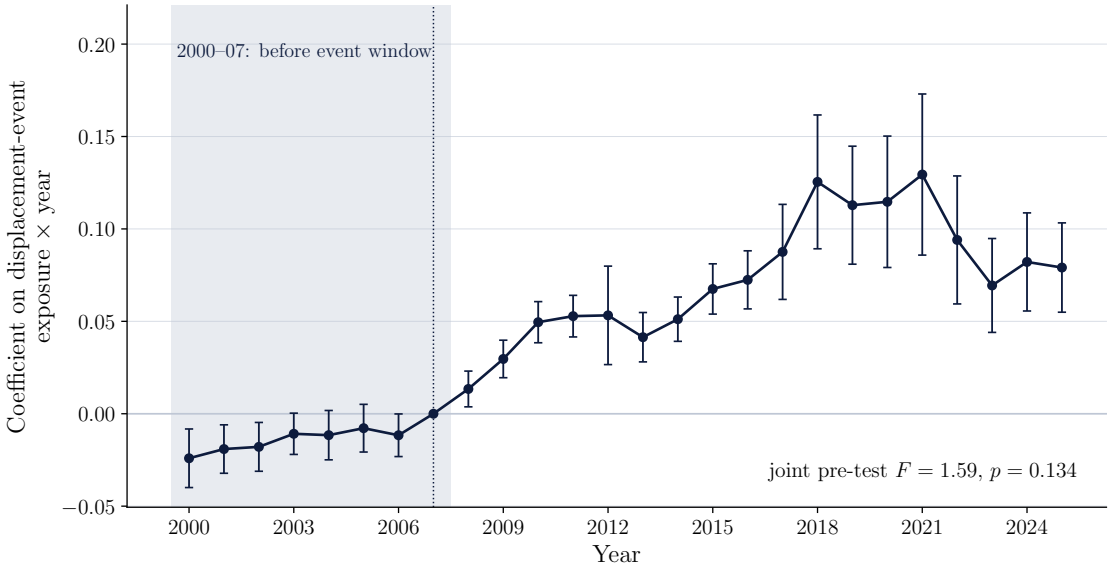
Notes: Each marker reports the coefficient on the returnee-managed indicator from a firm-level OLS regression estimated separately for the corresponding therapeutic area. All outcomes are trial counts transformed as $\log(1+y)$; controls and fixed effects follow Table 2. Horizontal bars show 95% confidence intervals. Navy circles represent total trials, blue squares Dranove-novel trials, orange triangles GPT-novel trials, and green diamonds first-in-China trials. Filled markers with solid intervals indicate $p < 0.05$; filled markers with dashed intervals indicate $0.05 \leq p < 0.10$; faded hollow markers indicate $p \geq 0.10$.

Figure 3: Returnee inflows and trial growth across diseases, 2010–2025



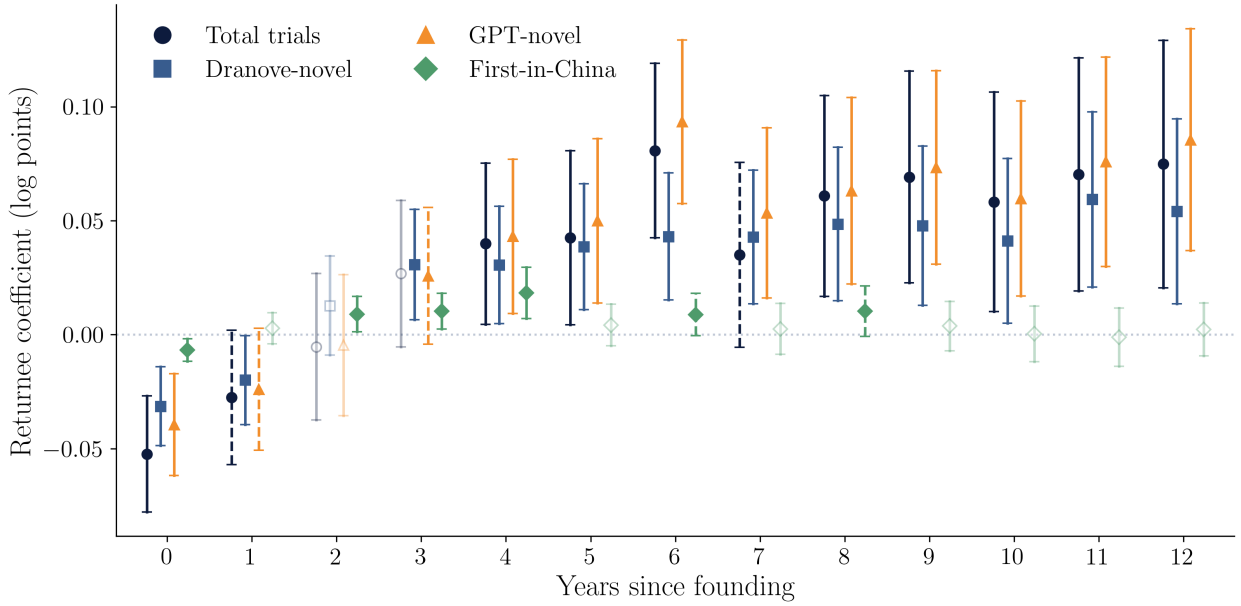
Notes: Each circle represents one of 260 diseases with trial activity. The horizontal axis measures the change in disease-level returnee stock between 2010 and 2025. The vertical axis measures the change in average annual trial counts from 2008–2010 to 2023–2025, for all trials (top row) and Dranove-novel trials (bottom row). The left panels show the raw relationship with a weighted linear fit. The right panels residualize both axes on changes in global non-Chinese trial activity over the same windows; baseline conditions, including average annual trials and global non-Chinese trials in 2008–2010 and the returnee stock in 2010; and therapeutic-area fixed effects. Circle sizes and regression weights are proportional to each disease's total trial count. All fits include 95% confidence bands based on robust standard errors. For total trials, the raw and conditional slopes are 0.403 (s.e. 0.076) and 0.458 (s.e. 0.120), respectively; for Dranove-novel trials, they are 0.219 (s.e. 0.043) and 0.253 (s.e. 0.067).

Figure 4: Exposure gradient in returnee inflows around the event window



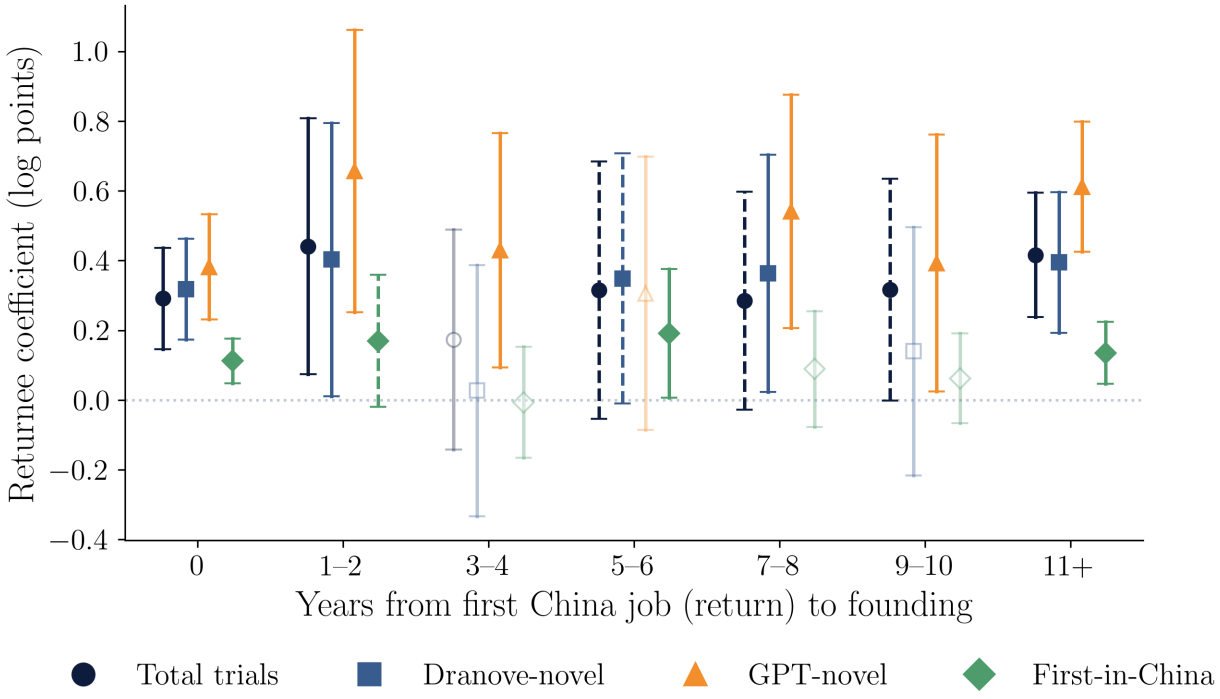
Notes: The figure reports the coefficients θ_y from the regression $\log(1 + \text{Inflow}_{dmt}) = \sum_{y \neq 2007} \theta_y \, s_{dm} \, \mathbf{1}[t = y] + \gamma' X_{dmt} + \mu_{dm} + \delta_{dt} + \lambda_{mt} + \varepsilon_{dmt}$, where s_{dm} is the disease–modality pair's standardized total exposure to displacement events and Inflow_{dmt} is the weighted number of newly returned professionals allocated to the disease-modality pair. X_{dmt} contains the controls in Table 3, and μ_{dm}, δ_{dt}, and λ_{mt} are disease–modality, disease–year, and modality–year fixed effects. The omitted year is 2007, so each coefficient measures the change in the exposure gradient relative to that year. The shaded region denotes 2000–2007, before the event window begins. Error bars indicate 95% confidence intervals based on standard errors clustered by disease–modality pair. A joint test that the coefficients for 2000–2006 equal zero yields $F = 1.59$ ($p = 0.134$).

Figure 5: Returnee coefficient on trial output, by years since founding



Notes: The figure shows how the returnee premium evolves with firm age, from founding through year twelve. Each plotted point is the returnee coefficient b_τ at firm age τ, measured as years since the verified founding year, taken from a single regression per outcome that interacts the returnee indicator with a full set of firm-age dummies and absorbs firm-age fixed effects. These age fixed effects absorb the common life-cycle profile, so b_τ measures the returnee versus non-returnee gap at age τ. The estimation panel is a group-by-calendar-year flow in which the outcome each year is the number of trials a firm starts that year. Each regression also includes calendar-year and HQ-province fixed effects and controls for employees and VC-backing, with standard errors clustered at the firm level. Whiskers are 95% confidence intervals. Solid lines indicate significance at the 5% level, dashed lines significance at the 10% level, and faded hollow markers estimates that are not statistically significant. The four outcomes are total trials, Dranove-novel, GPT-novel, and first-in-China.

Figure 6: Returnee coefficient on trial output, by years from return to founding



Notes: The figure shows how the returnee premium varies with the time between a manager's return to China and the firm's founding. Each plotted point is the returnee coefficient b_k for firms whose gap between the manager's return to China and the firm's verified founding year falls in bin k, measured relative to non-returnee firms. A manager's return is dated by the first China-based job in the career record, and returnee managers whose return year cannot be dated are dropped. The outcomes are firm-level trial counts entered as $\log(y+1)$, and each regression includes HQ-province and founding-year fixed effects together with controls for employees and VC-backing, with robust standard errors. Solid lines indicate significance at the 5% level, dashed lines significance at the 10% level, and faded hollow markers estimates that are not statistically significant. The four outcomes are total trials, Dranove-novel, GPT-novel, and first-in-China.

Tables

Table 1: Summary statistics

	Mean (1)	SD (2)	Median (3)	*N* (4)
Panel A: Firm level				
Treatments				
Returnee-managed (non-China edu)	0.636	0.481	1.00	1,608
Foreign-PhD top manager	0.328	0.470	0.00	1,608
Foreign industry experience (before joining)	0.507	0.500	1.00	1,608
Foreign academia, non-postdoc (before joining)	0.129	0.335	0.00	1,608
Outcomes				
Total trials	19.287	64.417	6.00	1,608
Novel trials (Dranove)	7.047	29.826	1.00	1,608
Novel trials (GPT)	12.754	51.285	3.00	1,608
First-in-China trials	0.559	2.306	0.00	1,608
Panel B: Disease×modality×year panel				
Treatments				
Returnee stock	1.264	5.777	0.02	44,278
Outcomes				
Total trials	0.971	5.463	0.00	44,278
Novel trials (Dranove)	0.406	2.594	0.00	44,278
Novel trials (GPT)	0.711	4.129	0.00	44,278
First-in-China trials	0.026	0.232	0.00	44,278

Notes: Panel A reports firm-level summary statistics, with one observation per sponsor firm. *Returnee-managed* and *Foreign-PhD top manager* equal one if at least one top manager holds a foreign degree or a foreign doctorate, respectively. For these classifications, China includes mainland China, Hong Kong, and Macau; Taiwan is classified as non-China. *Foreign industry experience* equals one if at least one top manager worked at a non-Chinese company before joining the firm. *Foreign academia, non-postdoc* similarly indicates prior employment at a non-Chinese academic institution, excluding postdoctoral positions. Panel B reports statistics for the disease–modality–year panel, covering 1,703 disease–modality pairs over 2000–2025 (44,278 observations). Each trial is counted once in every applicable disease–modality cell in its start year. *Returnee stock* is a weighted count of returnees in each cell, with weights updated dynamically using their employers' clinical-trial portfolios. Two alternative static weighting schemes are examined in the appendix. *Total trials* counts trials initiated by sample firms in each cell. *Novel trials (Dranove)* counts trials in the top half of the within-year distribution of the mechanism-of-action novelty index developed by Dranove et al. (2022). *Novel trials (GPT)* counts trials classified by a fine-tuned language model as testing a new molecular entity, a novel combination, or a new indication for an existing molecule. *First-in-China trials* counts trials for which no Chinese-firm trial in an earlier year tested the same mechanism of action at the same or a more advanced phase.

Table 2: Returnee management and firm-level clinical-trial activity

	(1) Total trials	(2) Dranove novel	(3) GPT novel	(4) First-in-China
Returnee-managed	0.268***	0.279***	0.408***	0.110***
	(0.061)	(0.061)	(0.064)	(0.027)
Employees (thousands)	0.399**	0.429**	0.481**	0.207**
	(0.184)	(0.173)	(0.201)	(0.105)
VC-backed	0.399***	0.359***	0.540***	0.0467
	(0.064)	(0.067)	(0.066)	(0.029)
Constant	2.084***	1.103***	1.584***	0.220***
	(0.026)	(0.027)	(0.028)	(0.012)
HQ-province FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Observations	1,596	1,596	1,596	1,596
R^2	0.199	0.165	0.228	0.139

Notes: Firm-level regressions of clinical-trial counts on the returnee-managed indicator; each outcome is log-transformed as $\log(y+1)$. *Returnee-managed* equals one if at least one of the firm's top managers was educated outside China. *Employees (thousands)* is employee headcount measured in thousands. All columns include the firm controls (employee headcount and the VC-backed indicator) and absorb headquarters-province and founding-year fixed effects. Regressors are centered over the sample, so the constant equals the sample mean of $\log(y+1)$. The estimation sample contains 1,596 of the 1,608 firms; 12 singleton observations are dropped by the province and founding-year fixed effects. Heteroskedasticity-robust standard errors in parentheses. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table 3: Returnee stock and clinical-trial activity at the disease–modality–year level

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
Panel A: OLS				
log(1+returnee stock)	0.587***	0.401***	0.479***	0.045***
	(0.027)	(0.023)	(0.023)	(0.006)
Observations	43,810	43,810	43,810	43,810
R^2	0.838	0.763	0.816	0.365
Panel B: IV (2SLS)				
log(1+returnee stock)	0.923***	0.762***	0.596***	0.059**
	(0.214)	(0.209)	(0.154)	(0.026)
Observations	43,810	43,810	43,810	43,810
Within R^2	0.314	0.173	0.270	0.012
First-stage coefficient		0.103***		
		(0.022)		
First-stage F-statistic		22.37		
Controls	Yes	Yes	Yes	Yes
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes

Notes: Panel A reports OLS estimates and Panel B reports IV (2SLS) estimates for the disease–modality–year panel. All outcomes and reported regressors are transformed as $\log(1 + x)$. Returnee stock uses the dynamic weights described in Section 2.2. The sample includes disease–modality pairs with a positive returnee stock or trial count in at least one year during 2000–2025. Both panels use the same sample, controls, and fixed effects. Controls include the number of global trials for each disease—modality pair in year t, the cumulative number of global trials for the same disease—modality pair through year $t - 1$, and employee stock, all transformed as $\log(1 + x)$. In Panel B, returnee stock is instrumented with standardized cumulative exposure to foreign-employer displacement events: 118 events at 89 pharmaceutical, biotechnology, and CRO employers during 2008–2023. Exposure combines the number of ethnically Chinese professionals whose overseas employment at each employer began by the end of 2007 with the employer's trial-portfolio weights, constructed using trials initiated by 2007. The first-stage coefficient is the coefficient on this standardized exposure in the regression of $\log(1 +$ returnee stock$)$ using the same controls and fixed effects as the 2SLS specification. The reported F-statistic is the Kleibergen–Paap rk Wald statistic. Standard errors clustered by disease–modality pair are reported in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 4: Returnee stock and trial activity, by the type of executing firm

	OLS		IV (2SLS)	
	Total Trials	Novel Dranove	Total Trials	Novel Dranove
	(1)	(2)	(3)	(4)
Panel A: Trials with at least one returnee-managed executing firm				
log(1+returnee stock)	0.554***	0.365***	0.808***	0.671***
	(0.025)	(0.022)	(0.195)	(0.188)
R^2	0.824	0.744	0.306	0.156
Panel B: Trials executed exclusively by locally managed firms				
log(1+returnee stock)	0.282***	0.157***	0.838***	0.533***
	(0.022)	(0.014)	(0.190)	(0.130)
R^2	0.675	0.574	-0.035	-0.096
First-stage coefficient		—	0.103***	
			(0.022)	
First-stage F-statistic		—	22.37	
Controls	Yes	Yes	Yes	Yes
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes
Observations	43,810	43,810	43,810	43,810

Notes: This table reports OLS estimates in columns 1–2 and IV (2SLS) estimates in columns 3–4 for the disease–modality–year panel, with each outcome count split by the type of executing firm. Panel A counts trials with at least one returnee-managed executing firm; Panel B counts trials executed exclusively by locally managed firms. The returnee-stock measure and sample follow Table 3. All regressions control for the number of global trials for each disease—modality pair in year t, the cumulative number of global trials for the same disease—modality pair through year $t-1$, and employee stock, and include disease–modality, disease–year, and modality–year fixed effects. Outcome counts, returnee stock, and the three controls are transformed as $\log(1+x)$. The IV specifications instrument returnee stock with the standardized cumulative exposure to foreign-employer displacement events used in Table 3. The first stage is common to both IV outcome columns and both panels; the reported F-statistic is the Kleibergen–Paap rk Wald statistic. Columns 1–2 report the full R^2; columns 3–4 report the within R^2 after absorbing the fixed effects. Standard errors, clustered by disease–modality pair, are reported in parentheses. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table 5: Trial activity and new drug projects

	(1) Total Trials	(2) Novel Dranove	(3) New Drugs
Returnee-managed	0.063***	0.039***	0.041***
	(0.016)	(0.011)	(0.013)
R^2	0.250	0.192	0.200
Within R^2	0.054	0.064	0.039
VC control	Yes	Yes	Yes
Employee control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes
HQ-province FE	Yes	Yes	Yes
Observations	32,241	32,241	32,241

Notes: This table reports OLS estimates of $\log(1 + y_{it}) = \alpha\,\text{ReturneeManaged}_i + \beta\,\text{VC}_{it} + \gamma\,\text{Emp}_{i,t-1} + \lambda_t + \phi_{f(i)} + \psi_{r(i)} + u_{it}$ on the firm–year panel that follows each sample firm from its founding year through 2025. The outcome y_{it} counts, for firm i in year t, all trial starts in column 1, Dranove-novel trial starts in column 2, and new drug projects in column 3. A new drug project is defined as a drug, identified through the Pharmaprojects–Trialtrove crosswalk, for which the firm initiates its first trial in year t. Each drug is counted once per firm, in the year of its first trial, with drugs tested in the same trial counted separately under this criterion. Subsequent trials of the same drug and trials without a linked drug (approximately 2–3% of trials) are excluded from the new-project count. VC_{it} indicates VC backing by year t, $\text{Emp}_{i,t-1}$ is Revelio employee headcount at the end of $t-1$ in thousands, and λ_t, $\phi_{f(i)}$, and $\psi_{r(i)}$ are year, founding-year, and headquarters-province fixed effects. The specification includes no firm fixed effects because the returnee-managed indicator is time-invariant. Standard errors clustered by firm in parentheses. One firm whose only VC round is undated is excluded. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 6: Disease selection: pre-entry characteristics of the diseases entered

	(1) log(1+heat) 3-yr avg	(2) Heat growth	(3) Late-phase share	(4) Phase advance
Panel A: Global trials				
Returnee-managed	-0.001	-0.013	-0.020***	-0.149***
	(0.028)	(0.028)	(0.006)	(0.052)
R^2	0.043	0.070	0.085	0.113
Within R^2	0.002	0.000	0.009	0.010
Observations	43,326	43,326	43,321	43,326
Panel B: Domestic trials				
Returnee-managed	-0.015	0.012	-0.001	-0.008
	(0.034)	(0.023)	(0.008)	(0.053)
R^2	0.335	0.124	0.180	0.187
Within R^2	0.002	0.000	0.001	0.001
Observations	43,326	43,326	42,394	43,326
Panel C: US trials				
Returnee-managed	0.119***	-0.008	-0.022***	-0.149***
	(0.041)	(0.027)	(0.008)	(0.057)
R^2	0.082	0.049	0.102	0.118
Within R^2	0.011	0.001	0.011	0.012
Observations	43,326	43,326	43,166	43,326
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
HQ-province FE	Yes	Yes	Yes	Yes

Notes: This table reports weighted OLS estimates of $Y_{d(p),t} = \alpha\,\text{ReturneeManaged}_i + \beta\,\text{VC}_{it} + \gamma\,\text{Emp}_{i,t-1} + \lambda_t + \phi_{f(i)} + \psi_{r(i)} + u_{pd}$, where p indexes a trial started by firm i in year t, $d(p)$ is one of the diseases the trial targets, and $Y_{d(p),t}$ is a pre-entry characteristic of that disease, measured with information from before t. For each firm–trial pair, there is one observation per targeted disease, weighted by $1/J$, where J is the trial's number of diseases. VC_{it} indicates VC backing by the trial's start year, $\text{Emp}_{i,t-1}$ is employee headcount at the end of $t-1$ (in thousands), and λ_t, $\phi_{f(i)}$, and $\psi_{r(i)}$ are trial-start-year, firm-founding-year, and headquarters-province fixed effects. All outcomes use information preceding t. *Heat* is the average annual number of trial starts over $[t-3, t-1]$, transformed as $\log(1+x)$. *Heat growth* is the change in $\log(1 + \text{annual trial starts})$ from $t-4$ to $t-1$. *Late-phase share* is the proportion of trial starts with recorded phases that are Phase II or higher over $[t-3, t-1]$; it is missing when no starts have recorded phases. *Phase advance* is the difference between $\log(1 + \text{Phase-III-type starts})$ over $[t-3, t-1]$ and $\log(1+\text{Phase-I-type starts})$ over $[t-5, t-3]$. Panel A constructs these measures from global trials with no sponsor or collaborator headquartered in mainland China, Hong Kong, or Macau, excluding all sample firms' trials. Panel B uses the other sample firms' trials, excluding the focal firm's own trials. Panel C restricts the Panel A sample to trials with at least one US-headquartered industry sponsor or collaborator; trial location does not determine inclusion. Standard errors, clustered by firm, are reported in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 7: Returnee firms and venture financing

	Raised VC		VC amount		First VC round in year t		Years from founding to first VC round
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Returnee-managed	0.013***	0.013***	0.048***	0.045***	0.004**	0.004**	-1.428***
	(0.004)	(0.004)	(0.009)	(0.009)	(0.002)	(0.002)	(0.352)
Pre-financing pipeline, log(1+total) over $t-3$ to $t-1$:							
Trials		0.006		0.022		-0.003	
		(0.005)		(0.015)		(0.002)	
Novel trials (Dranove)		0.005		0.046***		0.006**	
		(0.005)		(0.016)		(0.003)	
Phase II+ starts		0.004		0.019		-0.003	
		(0.009)		(0.030)		(0.005)	
Phase III+ starts		-0.023**		-0.090***		0.003	
		(0.010)		(0.032)		(0.005)	
R^2	0.142	0.143	0.104	0.106	0.075	0.075	0.755
Observations	32,241	32,241	31,686	31,686	27,968	27,968	521
Sample	All firm–years		All firm–years		Before first round		VC-backed firms
Employee control	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ-province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of the relationship between returnee management and venture financing. Columns 1–6 estimate $y_{it} = \alpha\,\text{ReturneeManaged}_i + \gamma\,\text{Emp}_{i,t-1} + \pi' P_{i,t-3:t-1} + \lambda_t + \phi_{f(i)} + \psi_{r(i)} + u_{it}$ using firm–year observations from founding through 2025. A VC round is a completed Seed, Early Stage, or Later Stage VC deal recorded in PitchBook. The dependent variable is an indicator for at least one VC round in year t in columns 1–2, $\log(1 + \text{amount raised})$ in columns 3–4, and an indicator for the first VC round in year t in columns 5–6. Amounts are measured in millions of US dollars and set to zero in years without a round. Columns 1–2 use all firm–years; columns 3–4 exclude firm–years with a round but no disclosed amount. Columns 5–6 retain observations through the first VC round, including the year of that round; firms that never raise VC remain in the sample through 2025. All six columns control for Revelio employee headcount at the end of $t-1$, in thousands, and include year, founding-year, and headquarters-province fixed effects, denoted by λ_t, $\phi_{f(i)}$, and $\psi_{r(i)}$, respectively. Columns 2, 4, and 6 additionally include $P_{i,t-3:t-1}$, comprising total trial starts, Dranove-novel trial starts, Phase II or later starts, and Phase-III+ starts (II/III, III, III/IV, or IV) over $[t-3, t-1]$, each transformed as $\log(1+x)$. Column 7 estimates $\text{YearsToVC}_i = \alpha\,\text{ReturneeManaged}_i + \phi_{f(i)} + \psi_{r(i)} + u_i$ using one observation per VC-backed firm. The outcome is the number of years from founding to the first VC round, with a sample mean of 4.8 years. This specification includes founding-year and headquarters-province fixed effects. One firm whose only VC round is undated is excluded from all specifications. Standard errors in parentheses are clustered by firm in columns 1–6 and heteroskedasticity-robust in column 7. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 8: Knowledge flow from the US frontier

	All trials		Dranove-novel	
	1–5	5–10	1–5	5–10
Returnee-managed × log(1+Frontier)	0.0025	0.0031*	0.0021**	0.0025**
	(0.0018)	(0.0019)	(0.0010)	(0.0010)
log(1+Frontier)	-0.0002	0.0045***	-0.0014	0.0007
	(0.0016)	(0.0016)	(0.0009)	(0.0008)
Constant	0.0275***	0.0144***	0.0130***	0.0070***
	(0.0029)	(0.0036)	(0.0015)	(0.0017)
Firm FE	Yes	Yes	Yes	Yes
Disease FE	Yes	Yes	Yes	Yes
Mean of dep. var.	0.0308	0.0308	0.0129	0.0129
Observations	390,744	390,744	390,744	390,744
R^2	0.141	0.142	0.105	0.105

Notes: This table tests whether a firm's trial activity in a disease tracks the US frontier in that disease more closely when the firm is returnee-managed. The unit of observation is a firm-by-disease cell over the full firm-by-disease grid, and the dependent variable is $\log(1 + y_{id})$, where y_{id} counts the firm's trials of the indicated type in disease d; the two column groups use all-trial and Dranove-novel counts. The key regressor is the interaction $\text{ReturneeManaged}_i \times \log(1 + \text{Frontier}_d)$, where Frontier_d is the number of US trials (trials with at least one clinical site in the United States) run by firms outside our sample in disease d, measured one to five years (first column of each group) or five to ten years (second column) after the top managers' return to China; the founding year is used when the return year cannot be dated. A positive interaction indicates that returnee-managed firms' disease-level activity tracks the US frontier more closely than locally managed firms'. All columns include firm and disease fixed effects, and standard errors are two-way clustered by firm and disease. $^{*}\, p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Table 9: Flows back: foreign-site trials and out-licensed drugs

	OLS		2SLS	
	World	US	World	US
	(1)	(2)	(3)	(4)
Panel A: Trials with a foreign site				
ln(1+returnee stock)	0.209***	0.131***	0.331***	0.202**
	(0.016)	(0.013)	(0.095)	(0.096)
R^2	0.649	0.605	0.099	0.063
Mean of dep. var.	0.0526	0.0344	0.0526	0.0344
Panel B: Drugs licensed out				
ln(1+returnee stock)	0.054***	0.032***	0.109***	0.078***
	(0.008)	(0.006)	(0.037)	(0.029)
R^2	0.647	0.617	0.019	0.007
Mean of dep. var.	0.0413	0.0303	0.0413	0.0303
Controls	Yes	Yes	Yes	Yes
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes
Kleibergen–Paap F			22.37	22.37
Observations	43,810	43,810	43,810	43,810

Notes: This table reports OLS and 2SLS estimates of equation (2) for foreign-site trials and drug out-licensing. All outcomes are transformed as $\log(1 + y_{dmt})$. In Panel A, y_{dmt} counts trials initiated by sample firms in disease d and modality m in year t with at least one foreign clinical site. In Panel B, it counts drugs linked to sample firms' trials in the corresponding disease–modality pair and licensed to foreign companies. "World" includes clinical sites or licensees outside mainland China, Hong Kong, and Macao; "US" restricts these to the United States. Columns 1–2 report OLS estimates, and columns 3–4 instrument $\log(1+\text{Stock}_{dmt})$ with standardized cumulative exposure to the foreign-employer displacement events described in Table 3. All regressions include the controls in Table 3 and disease–modality, disease–year, and modality–year fixed effects. Standard errors clustered by disease–modality pair are reported in parentheses. Columns 1–2 report the full R^2; columns 3–4 report the within R^2 after absorbing the fixed effects. Mean of dep. var. is the sample mean of $\log(1 + y_{dmt})$.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Aggregate magnitudes of the returnee contribution

	Total trials	Novel Dranove	Novel GPT	First-in-China
	(1)	(2)	(3)	(4)
Panel A: Firm-level back-of-the-envelope				
Implied premium ($e^{\beta}-1$)	+31%	+32%	+50%	+12%
Attributable to returnees	4,119	1,579	4,038	59
Share of total	17.2%	18.2%	25.7%	8.1%
Panel B: Cell-level back-of-the-envelope				
2SLS elasticity (β, Table 3)	0.923	0.762	0.596	0.059
Share of growth explained	84.9%	81.0%	71.5%	10.2%

Notes: Panel A reports the returnee contribution implied by the firm-level baseline estimates. The proportional premium is $e^{\beta}-1$, where β is the returnee coefficient from Table 2. The count attributable to the returnee channel is the returnee-managed trial count in Table A2 multiplied by $(1-e^{-\beta})$; it is the number of trials that would be lost if returnee-managed firms had instead behaved like otherwise similar local firms, holding the number and composition of firms fixed. Panel B converts the disease–modality–year 2SLS elasticities of Table 3 into trial counts through an observed-accumulation counterfactual. For $t > 2000$, each disease–modality combination's returnee stock is held at its year-2000 level, so predicted output scales by $\kappa_{ct} = ((1+\text{Stock}_{c,2000})/(1+\text{Stock}_{ct}))^{\beta}$, and counterfactual trials are $\tilde{T}_t = \sum_c n_{ct}^{\text{frac}}\,\kappa_{ct}$, where n_{ct}^{frac} counts unique trials, a trial spanning J combinations counting $1/J$ in each. The share of growth explained is the cumulative shortfall as a share of cumulative growth, $\sum_{t=2001}^{2025}(T_t-\tilde{T}_t)/\sum_{t=2001}^{2025}(T_t-T_{2000})$. The 2025 year is only partially covered in the data snapshot (479 unique trials against 2,977 in 2024) and enters both sums. Δx is the mean growth of $\log(1+\text{Stock})$ from 2000 to 2025 across combinations, weighted by each outcome's 2025 trial counts, and $\beta\Delta x$ is reported in log points ($100\times$ the log change). Unique trials grew from 2 in 2000 to 2,977 in 2024, Dranove-novel trials from 0 to 1,439, GPT-novel trials from 2 to 1,902, and first-in-China trials from 0 to 56.

Online Appendix

A Data Construction

A.1 Linkage across Datasets

This section documents how we link clinical trials from Citeline to firm and employee records from Revelio Labs and PitchBook. The linkage proceeds in four steps. We first identify the universe of Chinese corporate sponsors in Citeline. We then build a crosswalk between PitchBook and Revelio company records. Next, we match the Citeline sponsors to both databases, combining exact matching, fuzzy matching, large-language-model verification, and manual review. Finally, we group related corporate entities into firms and retain those with usable education records.

A.1.1 The Citeline Sponsor Universe

Each Citeline trial record identifies its sponsors and collaborators, their organization types,[18] and the headquarters country and city of their parent companies. We organize these fields into a sponsor-level dataset, assign a unique identifier to each distinct sponsor name, and link each sponsor to its associated trials through a trial–sponsor linkage table. We retain private-sector sponsors[19] whose parent companies are headquartered in mainland China, Hong Kong, or Macau. The resulting sample comprises 3,819 Chinese sponsor firms associated with 31,588 clinical trials and serves as the starting point for matching to Revelio and PitchBook.

18. Citeline classifies sponsors and collaborators into the following categories: Industry, Top 20 Pharma; Industry, all other pharma; Industry, generic; Industry, diagnostics or device; Industry, drug delivery; Industry, technology provider; Academic; Government; Cooperative Group; Not for Profit Funding Entity; Natural products, OTC, cosmetics; and Miscellaneous. Organizations without a recorded type are labeled Unassigned.

19. We classify a sponsor as private-sector if its Citeline type contains "Industry" or "Cooperative", or its name includes a corporate legal form such as Inc., Ltd., LLC, Co., or GmbH.

A.1.2 Linking PitchBook to Revelio

We begin by linking company records in PitchBook and Revelio. PitchBook identifies 1,937 companies headquartered in mainland China, Hong Kong, or Macau in the pharmaceutical and biotechnology industry. This classification also includes agricultural biotechnology, veterinary medicine, and other businesses outside human health. We therefore use a large language model to classify companies based on their business descriptions and retain 1,849 firms whose primary business involves pharmaceuticals and biotechnology for human use. We match these firms to Revelio company records using two complementary approaches.

The first approach matches company names. For each PitchBook company, we collect all recorded name variants, including legal names, former names, and "also known as" aliases, normalize them, and identify exact matches in Revelio. For firms without an exact match, we use string-distance metrics to generate candidate pairs and retain those above a conservative similarity threshold. A large language model then assesses these candidates, and we manually review its decisions. This approach matches 735 firms. The second approach uses company websites and LinkedIn profiles to identify additional matches when names differ. We normalize website domains and LinkedIn slugs in both databases and match exactly on either identifier, which links 1,358 company pairs; fuzzy candidates generated from the URL stems, assessed by a large language model and reviewed manually, add 182 pairs, covering 1,157 firms. The verified matches from both approaches form a crosswalk linking 1,277 of the 1,849 PitchBook firms (69.1%) to Revelio company identifiers.

A.1.3 Matching Citeline Sponsors to Revelio and PitchBook

We first normalize Citeline sponsor names and Revelio company names and identify exact matches. For unmatched sponsors, we compute fuzzy similarity scores against Revelio's full database of 31.8 million company records and retain candidate pairs with scores of at least 90. This yields approximately 86,000 candidate pairs for 2,700 sponsors. A large language model evaluates each sponsor's candidates jointly and classifies each pair as a match, a

non-match, or uncertain, following instructions designed to minimize false positives. We manually review these classifications. We then combine the exact matches, verified fuzzy matches, and indirect links through the PitchBook–Revelio crosswalk into a single sponsor-level file. A further manual review of this file, prioritizing sponsors with more trials, yields 262 corrections.

For sponsors that remain unmatched, we conduct a second round based on distinctive name components. We remove generic location, industry, and legal-form terms from each sponsor name, search the full Revelio database for names containing the remaining brand name, and score the resulting candidate pairs using partial-string similarity measures. A large language model reviews these candidates, and accepted matches are added to the sponsor-level file. We then consolidate the Citeline–Revelio and Citeline–PitchBook links into a final crosswalk that records each sponsor's matched identifiers in both databases and the source of each match.

The procedure matches 1,750 of the 3,819 Chinese sponsors (45.8%) to Revelio or PitchBook. Matched sponsors account for 79.5% of trials in the initial Citeline sample, indicating greater coverage of firms with more clinical activity.

A.1.4 Grouping Related Entities and the Final Sample

A firm may appear in Citeline under multiple sponsor records reflecting subsidiaries, name changes, or alternative spellings, and these records may correspond to different Revelio or PitchBook identifiers. Using name similarity and corporate relationships, we consolidate records belonging to the same firm into a single entity. Each entity combines the corresponding Citeline sponsor identifiers, Revelio company identifiers, and PitchBook records. We assign trials to these entities through the trial–sponsor linkage, counting each distinct trial once per firm.

Among the matched firms, 1,608 (91.9%) have at least one top manager or early employee for whom we can identify the country of an educational institution. These firms form our

regression sample and account for 23,957 unique clinical trials. We assign institution countries using a large language model and check these assignments against a manually curated list of institutions. Top managers are selected using Revelio seniority, as described in Section 2.2. For firms without matched top managers in Revelio, we use the managers listed in PitchBook.

A.2 Trial Novelty Calculation

We construct trial-level novelty measures following Barwick et al. (2026). First, we calculate a novelty score based on the extent to which a mechanism of action has not yet been explored, following Dranove et al. (2022). Second, we use a fine-tuned GPT model to classify a trial's objective into one of four categories: investigation of a new drug, a new combination of existing drugs, a new indication for an existing drug, or a bioequivalence test for a generic drug. Third, we classify a trial as first-in-China if no earlier trial by a Chinese firm tested the same mechanism of action at the same or a more advanced phase. This subsection provides the technical details underlying these measures.

A.2.1 Novelty Score

The first measure follows the approach proposed by Dranove et al. (2022), adapted to the structure of the Citeline database. Whereas Dranove et al. (2022) construct novelty using target-based actions from the Cortellis database, our data contain mechanisms of action (MOA), which are conceptually similar. An MOA describes the specific scientific strategy through which a molecule produces a pharmacological effect: each MOA pairs the biological entity targeted by the molecule (for example, p38 MAP kinase) with the mechanism used to modulate that entity (for example, inhibition). In total, there are 2,859 unique MOAs in the data. MOA information is available for 399,017 of the 463,412 trials in the database, covering approximately 86% of all trials, and the novelty score can be computed for 364,273 trials. These trials include not only those conducted in China and the United States but trials worldwide, ensuring that the novelty measure reflects the global frontier of drug development.

We compute translational novelty at the trial level by assessing the extent to which the MOA deployed in a given trial has previously been used. Consider a trial i that deploys a single MOA k. Let $D_{k(i)}$ represent the number of previous deployments of k in stages that are at least as advanced as that of trial i. For example, if i is a Phase II trial, $D_{k(i)}$ counts the earlier trials of k tested in Phases II or III before the initiation of trial i; Phase I deployments of k are not counted. This restriction follows Dranove et al. (2022): evidence generated at more advanced stages is more informative about translational potential than evidence generated earlier, and knowledge flows are asymmetric. The translational novelty score for trial i is

$$\text{Novelty}_i = \frac{1}{1 + D_{k(i)}} \in (0, 1].$$

The score equals one only if trial i deploys k for the first time ($D_{k(i)} = 0$). If $D_{k(i)} = 1$, the score is 0.5; if $D_{k(i)} = 2$, the score is 0.33; and so on, approaching zero as the number of prior deployments grows. Many trials deploy multiple MOAs. In such cases, we compute a trial-level score by averaging the MOA-specific values,

$$\text{Novelty}_i = \frac{1}{K_i} \sum_{k \in \text{MOAs}(i)} \frac{1}{1 + D_{k(i)}},$$

where K_i denotes the number of MOAs associated with trial i. Averaging yields a conservative measure of novelty for multi-target trials, balancing the contribution of highly novel targets and more established ones. Except for trials with no prior deployments, our inference does not exploit the specific value of the score and relies instead on the implied ordering.

Among the 23,957 trials of our sample firms, the novelty score can be computed for 19,638. Figure A2 plots its distribution, which is highly right-skewed: the mean score is 0.01, while the median is close to zero, reflecting that most trials rely on previously well-explored mechanisms. To classify novel trials, we compute the median novelty score within each start year, pooling trials across all countries, and designate a trial as novel if its score exceeds the median in its start year.

A.2.2 GPT-Classified Trial Objective

We also construct an innovation classifier using GPT to determine whether a clinical trial investigates (i) a new drug, (ii) a new combination of existing drugs, (iii) a new indication for an existing drug, or (iv) a bioequivalence test for a generic drug. This measure captures innovative content that is not directly observable from structured fields in Citeline. The classifier takes as input a rich set of trial-level information, including the trial title, phase, primary tested drug, mechanism of action, trial objective, primary endpoint, study design, treatment plan, and investigator notes. An illustrative example of the variables fed into the model is shown as follows.

```
TrialID: 322799

StartDate: 2015-07-06

TrialTitle: Intratumoral Phase Ib Clinical Trial Of IIb, IIIc, And IV M1a,
M1b Malignant Melanoma With Recombinant Human GM-CSF Herpes Simplex Virus
Injection (OrienX-010)

TrialPhase: Phase I (Ib)

PrimaryTestedDrug: OrienX-010

PrimaryTestedDrugMechanism: Immuno-oncology therapy

TrialObjective: To evaluate the safety and tolerability of continuous
administration of OrienX-010 intratumoral injection in patients with stage
IIIb, IIIc, and IV M1a/M1b malignant melanoma who failed standard therapy,
and to evaluate the biodistribution characteristics and biological effects
of continuous administration of OrienX-010 intratumoral injection in the
same patient population.
```

```
PrimaryEndpoint: Adverse events, immunogenicity, neutralizing antibody
response, safety and tolerability

StudyDesign: Single-arm, non-randomized, open-label study

TreatmentPlan: Recombinant human GM-CSF herpes simplex virus injection,
intratumoral administration, specification 2.0-8.0 × 10^7 PFU (1.0 ml) per
injection site, injection every two weeks for 16 consecutive weeks, maximum
dose not exceeding 10 ml (8 × 10^8 PFU), adjusted according to lesion size

TrialNotes: Registry ChinaDrugTrials; registration number CTR20150881;
sponsor Beijing Aoyuan Heli Biotechnology Co., Ltd.; recruitment completed;
first informed consent signed on 2015-07-06; trial end date 2017-05-24
```

However, large language models can hallucinate or infer information that is not explicitly present in the input, which is problematic when the classification must be strictly tied to verifiable trial attributes. To reduce hallucinations and ensure consistency, we use a supervised fine-tuned model based on GPT-4o-mini. The fine-tuning proceeds in three steps.

First, 200 clinical trials are randomly sampled from the full dataset, and each trial's treatment group, control group, and innovation category are labeled manually from the detailed textual descriptions. Two healthcare domain experts label all trials independently and reconcile discrepancies, ensuring reliability and high inter-annotator agreement. Second, we fine-tune GPT-4o-mini on the OpenAI platform using these 200 manually verified examples as the training set[20]. Fine-tuning forces the model to anchor its reasoning on the specific structure and terminology of the Citeline data rather than on external assumptions, which substantially reduces hallucination and improves reproducibility. Third, we deploy the fine-tuned classifier across the full set of clinical trials in our sample, generating for each trial: (i) a predicted innovation category, (ii) the treatment drug, and (iii) the control drug. The

20. Additional fine-tuning documentation: https://platform.openai.com/docs/guides/supervised-fine-tuning

prompt used for classification is as follows.

```
message_content = (
    "We provide the trial titles, targeted drug information, and summary below "
    "in the format of information name: information, separated by ';'. "
    "For each trial, follow a step-by-step process: "
    "Step 1: Answer the question: What drugs are used in the treatment versus "
    "control arms of the clinical trial described below? "
    "Extract treatment versus control arms of the clinical trial, If you do "
    "not find treatment drug or control drug, just say 'n/a'. "
    "If multiple drugs are in the treatment group, say 'drugAname+drugBname'. "
    "For drug with both code names and branded names, list both "
    "(branded names in brackets)"
    "Step 2: Answer the question: what type is each trial? Classify the "
    "treatment drugs into one of the four categories:"
    "'new drug', 'existing drug new indication', "
    "'existing drug new combination', 'generic drug'. "
    "'new drug' is a trial on a drug that is not yet on the market"
    "'existing drug new indication' is an investigatory trial to test whether "
    "an existing drug can treat a new disease"
    "'existing drug new combination' is a trial to test whether drugs "
    "can be combined"
    "'generic drug' is a trial to test bioequivalence of a drug "
    "to an existing drug"
    "Put all the information in two steps on one line, in the following format: "
    "'Treatment: [treatment drug]. Control: [control drug]. "
    "Classification: [treatment drug category]' "
    f"{text}"
)
```

Of the 23,957 trials of our sample firms, 23,869 are classified; the small remainder is counted as non-novel. We label a trial as GPT-novel when it falls into one of the first three categories, that is, a new drug, a new combination, or a new indication; 65.9% of the classified

sample trials are GPT-novel.

A.2.3 First-in-China Trials

The third measure applies the deployment logic of the novelty score to Chinese firms only. For each trial, we count the earlier deployments of its mechanism of action in trials by Chinese firms at the same or a more advanced phase, and classify the trial as first-in-China when this count is zero, that is, when no Chinese-firm trial had tested the mechanism at that stage before. Our sample firms run 727 first-in-China trials.

A.3 Returnee Stock Construction

The regressor of the disease–modality–year analysis is the returnee stock, which allocates each returnee employee of the sample firms to disease–modality cells in proportion to the clinical-trial portfolios of their employers. Of the 22,834 returnee employees, 8,778 have at least one employer matched to a Citeline sponsor and a datable return year. We build the stock in three ways from these people. The baseline construction, used throughout the paper, updates each person's weights year by year. Two alternative constructions, Method 1 with weights fixed at the return and Method 2 with lifetime in-tenure weights, underlie the robustness results in Tables A8 and A9.

The baseline stock is built in four steps.

1. *Date the return.* The return year is the start year of the first position based in mainland China, Hong Kong, or Macao that begins after the person's first foreign position. Returnees who never hold a China-based position in their Revelio history, typically employees of the sample firms' overseas branches, enter in the year they first join a sample firm.

2. *Build employer trial portfolios.* Each position's employer is linked to Citeline sponsors through the employer crosswalk described above. For a matched employer f, disease

d, modality m, and year y, $\text{Trials}_{fdm}(y)$ counts the dated trials that f started through year y, over 343 disease atoms and 8 drug-modality categories; a trial counts once in every disease–modality combination it involves.

3. *Compute dynamic weights.* Let N_{idmt} denote the cumulative number of trials in disease d and modality m associated with person i's employers through year t. It sums the portfolios of all matched employers joined by t, Chinese and foreign alike, with each employer's trials counted through year t if the person is currently employed there and through the end of the tenure if they have left,

$$N_{idmt} = \sum_{f \in F_i(t)} \text{Trials}_{fdm}\Big(\min(t,\, L_{if})\Big), \qquad w_{idmt} = \frac{N_{idmt}}{\sum_{d',m'} N_{id'm't}},$$

where $F_i(t)$ is the set of matched employers person i has joined by year t and L_{if} is the year the person left employer f, set to 2025 for ongoing positions. The weights sum to one across disease–modality cells for each person with an observed employer trial portfolio and are renormalized every year, so they evolve as employers initiate new trials and individuals change jobs.

4. *Aggregate.* The cell stock sums the weights of the returnees who are back in China,

$$\text{Stock}_{dmt} = \sum_{i:\, T_i \le t} w_{idmt},$$

where T_i is the year person i returned to China. The regressor in the cell-level regressions is $\log(1 + \text{Stock}_{dmt})$.

A small example illustrates the construction. Consider a returnee who works at foreign employer A from 2008 to 2014, returns to China in 2016 by joining domestic firm B, with both employers in the crosswalk. Suppose that through 2014 employer A started 30 trials in the cell breast cancer × conventional antibody and 10 trials in diabetes × small molecule, and that through 2017 firm B started 10 trials in breast cancer × cell therapy. In 2017 the

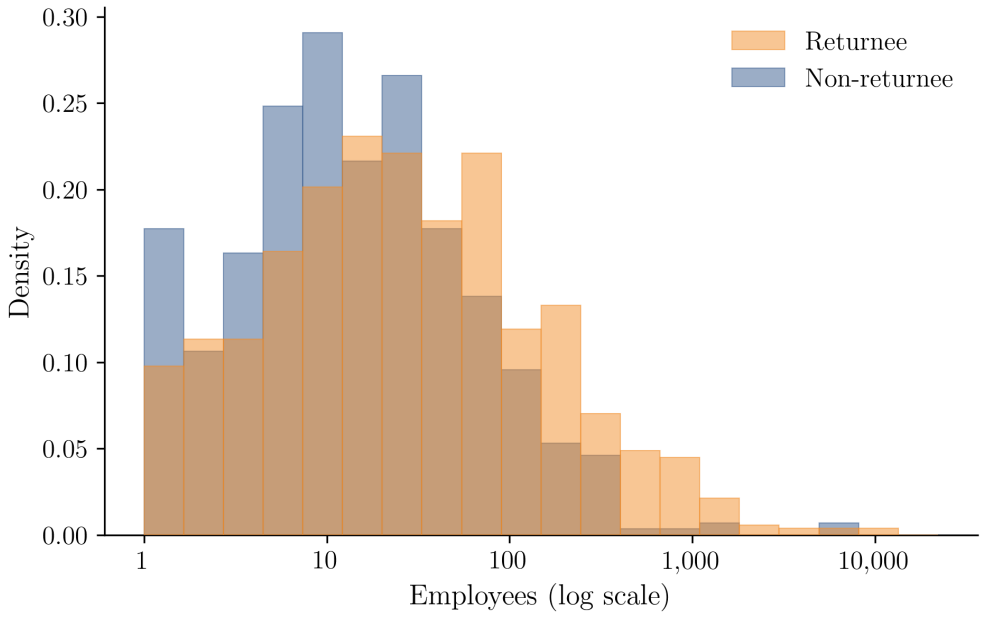
person's numerators are 30, 10, and 10, so the weight vector is $(0.6, 0.2, 0.2)$, and the person adds these amounts to the three cells' 2017 stock. If by 2020 firm B's count has grown to 40, the vector becomes $(0.375, 0.125, 0.5)$, so the allocation drifts toward the employer that is actively running trials.

Method 1 restricts the weights to pre-return employers and freezes them at the return. Only employers joined before the return date count, and each contributes its cumulative trials up to the year the person left it or returned, whichever came first. The weights are therefore fixed at return and predetermined with respect to anything that happens in China afterwards. An employer's trials from before the person joined do count, since the portfolio proxies the knowledge environment the person was exposed to rather than their personal output. Under this construction, 6,399 of the 8,778 returnees receive nonzero weights; the employers of the remaining 2,379 have no datable trials before the cutoff. In the example, only employer A counts, with its portfolio frozen in 2014, and the person adds $(0.75, 0.25)$ to the first two cells in every year from 2016 on.

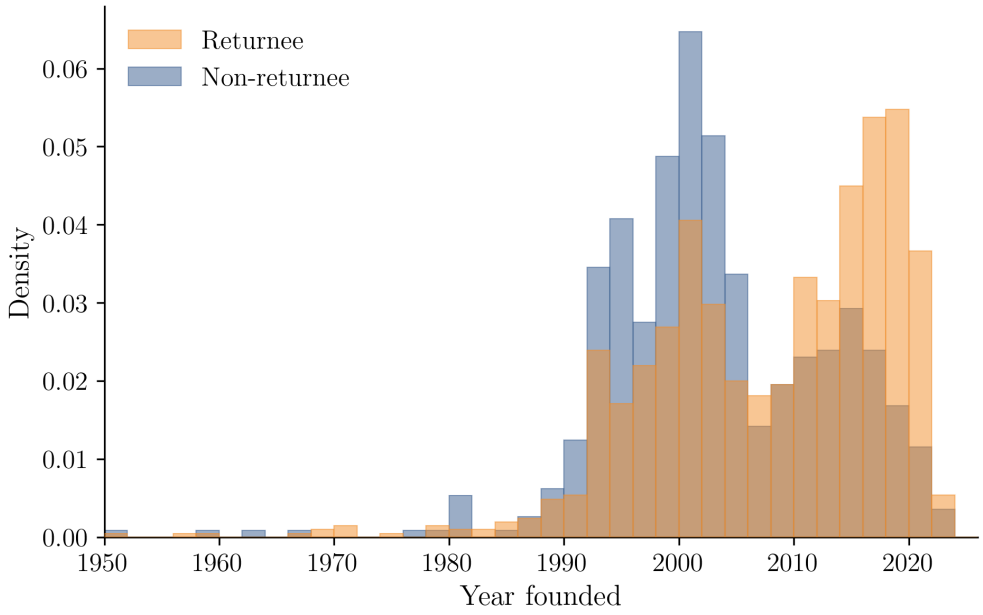
Method 2 keeps all matched employers but counts only the trials started during the person's own tenure, with each employment spell contributing the trials whose start year falls within it. The weights are computed once over the whole career and held static. In the example, if 10 of employer A's antibody trials and 5 of its small-molecule trials started during 2008–2014, and 5 of firm B's cell-therapy trials started after 2016, the lifetime weights are $(0.5, 0.25, 0.25)$ in every year from 2016 on. Under this construction, 7,834 of the 8,778 returnees receive nonzero weights.

B Appendix Figures

Figure A1: Distribution of firm characteristics by returnee status



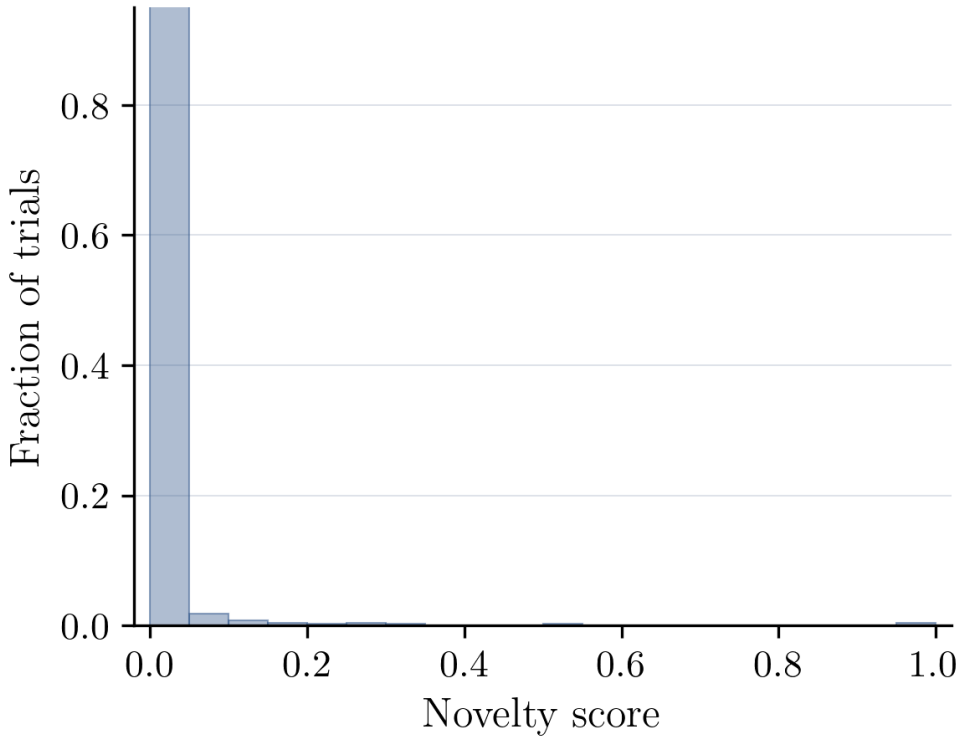
(a) Employee headcount (log scale)



(b) Year founded

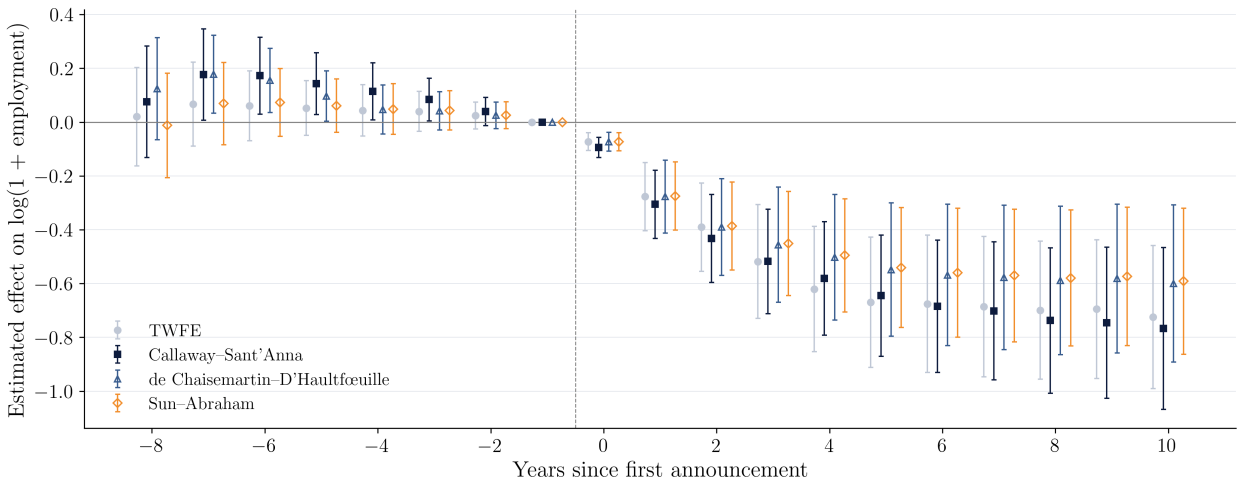
Notes: These figures compare the firm-level distributions of two key control variables across returnee-managed and locally managed firms. A firm is *returnee-managed* (orange) if at least one of its top managers holds a degree from a non-Chinese institution, and *locally managed* (blue) otherwise. Panel (a) plots the density of employee headcount on a log scale, and panel (b) plots the density of year founded.

Figure A2: Distribution of the trial novelty score



Notes: This figure plots the distribution of the mechanism-of-action novelty score described in Appendix A for the 19,638 trials of our 1,608 sample firms with a computable score. Prior deployments of a mechanism are counted against the full worldwide Citeline database, and each bar reports the fraction of trials with scores in the corresponding 0.05-wide bin. The mass near zero reflects trials deploying previously well-explored mechanisms; a score of one indicates a mechanism with no prior deployment. Data source: Citeline TrialTrove database.

Figure A3: Firm-level event study: displacement events and employment



Notes: This figure presents staggered difference-in-differences event-study estimates of the effect of workforce displacement events on employer-level employment. The sample is a balanced panel of 1,931 employers observed over 2000–2025. The treatment group comprises employers with at least one displacement event, as in the IV sample. The control group comprises never-treated employers that sponsored clinical trials and employed at least one Chinese national abroad before 2008. The outcome is $\log(1 + Emp_{it})$, where Emp_{it} denotes the number of distinct employees, regardless of nationality, holding a position at employer i in year t, as recorded in the Revelio Labs resume data. The two-way fixed-effects specification is

$$\log(1 + Emp_{it}) = \alpha_i + \lambda_{d(i),t} + \sum_{\substack{h=-9 \\ h\neq -1}}^{11} \beta_h \, \mathbf{1}\{t - g_i = h\} + \varepsilon_{it},$$

where α_i and $\lambda_{d(i),t}$ are employer and size-decile-by-year fixed effects, $d(i)$ is employer i's decile of 2007 headcount, and g_i is the year of its first displacement announcement. The year preceding the first announcement ($h = -1$) is the omitted reference period. The endpoint indicators pool event times $h \leq -9$ and $h \geq 11$; their coefficients are not plotted. The figure shows estimates for event times $h = -8, \ldots, 10$ from the TWFE specification and from three estimators robust to treatment-effect heterogeneity. The Callaway–Sant'Anna estimator uses not-yet-treated employers as controls and conditions on 2007 size rather than absorbing the decile-by-year effects. The Sun–Abraham estimator keeps the fixed effects above and uses never-treated employers as controls. In the de Chaisemartin–D'Haultfœuille estimator, which likewise compares treated with not-yet-treated employers, the size adjustment enters as decile-specific year effects. Vertical bars show 95% confidence intervals based on standard errors clustered at the employer level.

C Appendix Tables

Table A1: Summary statistics: additional regression variables

	Mean (1)	SD (2)	Median (3)	N (4)
Panel A: Firm level				
Employees	112.454	520.174	19.50	1,608
VC-backed	0.330	0.470	0.00	1,608
Founding year	2005.9	10.4	2005	1,608
Panel B: Disease×modality×year panel				
Alternative returnee stocks				
Returnee stock, Method 1	0.957	4.346	0.01	44,278
Returnee stock, Method 2	1.380	5.722	0.05	44,278
Controls				
Global trials	11.702	53.390	1.00	44,278
Global cumulative trials $(t-1)$	125.842	498.035	9.00	44,278
Employee stock	10.662	65.080	0.00	44,278

Notes: This table reports summary statistics for the regression variables not shown in Table 1. Panel A reports firm-level controls, with one observation per sponsor firm. *Employees* is the number of individuals matched to the firm in Revelio; for firms without matched Revelio employees, PitchBook's reported headcount is used. *VC-backed* equals one if the firm has completed at least one Seed, Early-Stage, or Later-Stage VC round in PitchBook. Panel B reports statistics on the sample of Table 1, Panel B: 1,703 disease–modality pairs over 2000–2025 (44,278 observations). *Returnee stock, Method 1* fixes each returnee's disease–modality weights at return, using the pre-return trial portfolios of their foreign employers. *Returnee stock, Method 2* uses all matched employers but counts only trials started during the individual's own tenure, with static lifetime weights. The main results use the dynamic-weight stock summarized in Table 1. *Global trials* counts trials initiated in the disease–modality pair in year t by firms headquartered outside China. *Global cumulative trials* accumulates these trials through year $t-1$. *Employee stock* allocates the sample firms' Revelio headcount in year t across pairs in proportion to each firm's cumulative trial portfolio through $t-1$. The regressions enter the stocks and controls as $\log(1+x)$.

Table A2: Returnee-managed firms' share of China's clinical trials and trial novelty

	Total trials	Novel Dranove	Novel GPT	First-in-China
	(1)	(2)	(3)	(4)
Total	23,957	8,674	15,731	727
Returnee-managed	17,519	6,487	12,053	566
Locally managed	6,438	2,187	3,678	161
Returnee share	73.1%	74.8%	76.6%	77.9%

Notes: Trial-level counts over the 23,957 unique trials linked to the 1,608 sample firms. A trial is counted as *returnee-managed* if at least one of its sample sponsors is a returnee-managed firm, and *locally managed* otherwise. Columns 2–4 restrict the counts to trials classified as novel under the Dranove measure, the GPT measure, and the first-in-China measure, respectively; a trial without a novelty score counts as not novel.

Table A3: Two-part model of disease-field entry and trial novelty

	Stage 1	Stage 2		
	Disease entry	Dranove novelty share	GPT novelty share	First-in-China novelty share
	(1)	(2)	(3)	(4)
Returnee-managed	0.274***	0.168***	0.240*	0.397***
	(0.082)	(0.065)	(0.125)	(0.110)
Employees (thousands)	0.251**	0.0889***	0.424***	0.135***
	(0.100)	(0.022)	(0.071)	(0.035)
VC-backed	0.264***	0.0526	0.275	0.0556
	(0.084)	(0.080)	(0.185)	(0.140)
Constant	-3.522***	-0.537***	0.785***	-4.023***
	(0.168)	(0.179)	(0.271)	(0.372)
HQ-province FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Disease FE	No	Yes	Yes	Yes
Mean of dep. var.	2.8%	35.7%	59.2%	3.5%
Implied Δ Pr (pp)	+0.85	+3.94	+5.64	+1.62
Observations	390,744	10,754	10,255	9,235

Notes: Two-part model on the firm-by-disease-field panel (1,608 firms × 243 disease fields, 390,744 cells). Column 1 is a binary logit for disease-field entry, estimated over all firm–disease cells. Columns 2–4 are grouped binomial logits for the share of a firm's trials in a field that are novel (successes out of total trials), estimated on the 10,980 entered cells under the three trial-level novelty measures. Entered cells in a headquarters-province, founding-year, or disease-field group with no (or only) novel trials are perfectly predicted by that fixed effect and dropped, so the estimation sample differs across columns. *Returnee-managed* equals one if at least one of the firm's top managers was educated outside China. All columns absorb headquarters-province and founding-year fixed effects; Stage 2 additionally absorbs disease-field fixed effects. Implied Δ Pr is the percentage-point change in the entry or novelty probability as the returnee indicator moves from zero to one, evaluated at the sample mean of the outcome. Standard errors clustered at the firm level in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table A4: The firm-level returnee premium by type of foreign human capital

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
Panel A: Foreign-PhD top managers				
Returnee-managed	0.148**	0.120*	0.253***	0.077***
	(0.067)	(0.066)	(0.069)	(0.029)
Foreign-PhD top manager	0.275***	0.366***	0.356***	0.076**
	(0.074)	(0.077)	(0.078)	(0.037)
R^2	0.207	0.179	0.240	0.142
Panel B: Foreign-experience channels				
Foreign industry experience	0.234***	0.246***	0.364***	0.088***
	(0.063)	(0.064)	(0.066)	(0.029)
Foreign academia experience	0.281***	0.355***	0.395***	0.103**
	(0.089)	(0.097)	(0.091)	(0.049)
R^2	0.206	0.177	0.242	0.143
Firm controls	Yes	Yes	Yes	Yes
HQ-province FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Observations	1,596	1,596	1,596	1,596

Notes: This table reports firm-level OLS estimates following Table 2, with firm controls (employee headcount and VC backing) and headquarters-province and founding-year fixed effects. Panel A enters the returnee-managed and foreign-PhD top-manager indicators jointly: the former compares returnee-managed firms without a foreign-PhD top manager with locally managed firms; the latter measures the additional premium associated with a foreign-PhD top manager among returnee-managed firms. Panel B enters two foreign-experience channels jointly: indicators for a top manager with a foreign industry position and for one with a non-China academic position outside postdoctoral training, counting only positions that began before the manager joined the firm. All outcomes are trial counts transformed as $\log(1+x)$. Heteroskedasticity-robust standard errors are reported in parentheses. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table A5: The disease–modality level returnee stock premium by type of foreign human capital

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
Panel A: Senior foreign experience				
log(1+senior returnee stock)	0.520***	0.738***	0.413***	0.061***
	(0.058)	(0.061)	(0.056)	(0.017)
log(1+junior returnee stock)	0.273***	-0.090*	0.232***	0.004
	(0.057)	(0.051)	(0.051)	(0.013)
Difference: senior − junior	0.247**	0.828***	0.181*	0.057*
	(0.110)	(0.108)	(0.103)	(0.029)
R^2	0.843	0.779	0.820	0.367
Panel B: Doctoral training				
log(1+PhD returnee stock)	0.422***	0.421***	0.365***	0.032*
	(0.065)	(0.061)	(0.056)	(0.018)
log(1+non-PhD returnee stock)	0.337***	0.154***	0.256***	0.028*
	(0.057)	(0.052)	(0.048)	(0.015)
Difference: PhD − non-PhD	0.086	0.267**	0.109	0.004
	(0.117)	(0.109)	(0.100)	(0.033)
R^2	0.842	0.772	0.819	0.366
Controls	Yes	Yes	Yes	Yes
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes
Observations	43,810	43,810	43,810	43,810

Notes: This table reports OLS estimates at the disease–modality–year level, using the controls, fixed effects, and sample of Table 3. Each panel jointly includes the two groups' $\log(1+\text{returnee stock})$ terms and reports both coefficients and their difference. Panel A defines senior returnees as those who attained Revelio seniority levels 5–7 abroad before returning; junior returnees comprise all other returnees. Panel B compares returnees with a recorded doctoral-level degree (PhD, MD, PharmD, or JD) with those without one. All outcomes are trial counts transformed as $\log(1+x)$. Standard errors in parentheses are clustered by disease–modality pair. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table A6: The firm-level returnee premium using the earliest five employees

	(1) Total trials	(2) Dranove novel	(3) GPT novel	(4) First-in-China
Returnee-managed	0.177***	0.210***	0.291***	0.0544**
	(0.060)	(0.060)	(0.063)	(0.026)
Employees (thousands)	0.406**	0.434**	0.490**	0.211**
	(0.185)	(0.174)	(0.202)	(0.105)
VC-backed	0.406***	0.364***	0.549***	0.0497*
	(0.064)	(0.066)	(0.066)	(0.029)
Constant	2.084***	1.103***	1.584***	0.220***
	(0.027)	(0.027)	(0.028)	(0.012)
HQ-province FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Observations	1,596	1,596	1,596	1,596
R^2	0.193	0.160	0.218	0.132

Notes: This table reports firm-level OLS regressions of clinical-trial activity using an alternative definition of returnee management based on the firm's earliest five employees. Among employees with identifiable education records, we select up to five with the earliest observed position start dates within the firm on or after its verified founding year. The returnee-managed indicator equals one if at least one of these employees was educated outside China. Firms with fewer than five eligible employees use all available employees; when no eligible Revelio employee is available, we use PitchBook-listed managers. Firms without identified managers' education are coded as non-returnee. Each trial-count outcome is transformed as $\log(1 + y)$. As in Table 2, all columns include employee headcount in thousands and the VC-backed indicator, and absorb headquarters-province and founding-year fixed effects. Regressors are centered over the estimation sample, so the constant equals the sample mean of $\log(1 + y)$. The estimation sample contains 1,596 firms. Heteroskedasticity-robust standard errors are reported in parentheses. $^{*}\, p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Table A7: Returnee share of the workforce and firm-level clinical-trial activity

	(1) Total trials	(2) Dranove novel	(3) GPT novel	(4) First-in-China	(5) Innov. ctrl Ph III
Returnee share (workforce)	0.154*	0.223**	0.461***	0.0407	0.0681*
	(0.091)	(0.097)	(0.099)	(0.039)	(0.040)
Employees (thousands)	0.410**	0.441**	0.494**	0.213**	0.237**
	(0.187)	(0.176)	(0.205)	(0.106)	(0.108)
VC-backed	0.436***	0.405***	0.592***	0.0590**	0.104***
	(0.065)	(0.068)	(0.067)	(0.030)	(0.032)
Constant	2.088***	1.107***	1.581***	0.222***	0.207***
	(0.027)	(0.027)	(0.028)	(0.012)	(0.013)
HQ-province FE	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,568	1,568	1,568	1,568	1,568
R^2	0.191	0.161	0.220	0.133	0.129

Notes: This table replaces the returnee-managed indicator in Table 2 with the returnee share of the firm's Revelio-matched workforce. The numerator counts distinct matched people with at least one non-China education record, and the denominator includes all distinct Revelio-matched people associated with the firm, including those without education records. People without a recorded non-China education are counted only in the denominator. The share is entered in levels on a 0–1 scale. All five trial-count outcomes are transformed as $\log(1+y)$ and estimated by OLS. All columns include employee headcount in thousands and the VC-backed indicator, and absorb headquarters-province and founding-year fixed effects. Regressors are centered over the estimation sample, so the constant equals the sample mean of $\log(1+y)$. The estimation sample contains 1,568 firms. Heteroskedasticity-robust standard errors are reported in parentheses. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table A8: Returnee stock and trial activity: alternative stock constructions

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
Panel A: Method-1 stock (weights fixed at return)				
log(1+returnee stock)	0.530***	0.387***	0.418***	0.036***
	(0.029)	(0.026)	(0.025)	(0.006)
log(1+global trials)	0.086***	0.041***	0.077***	0.003*
	(0.006)	(0.005)	(0.006)	(0.002)
log(1+global cum. trials, $t-1$)	0.008	-0.001	0.011*	-0.002
	(0.006)	(0.006)	(0.006)	(0.001)
log(1+employee stock)	0.120***	0.067***	0.094***	0.003
	(0.010)	(0.008)	(0.008)	(0.002)
R^2	0.834	0.762	0.811	0.366
Observations	42,718	42,718	42,718	42,718
Panel B: Method-2 stock (lifetime in-tenure weights)				
log(1+returnee stock)	0.634***	0.410***	0.524***	0.047***
	(0.026)	(0.023)	(0.023)	(0.005)
log(1+global trials)	0.050***	0.016***	0.049***	0.001
	(0.006)	(0.005)	(0.006)	(0.002)
log(1+global cum. trials, $t-1$)	-0.023***	-0.020***	-0.014**	-0.004***
	(0.006)	(0.006)	(0.006)	(0.001)
log(1+employee stock)	0.113***	0.073***	0.082***	0.001
	(0.009)	(0.007)	(0.008)	(0.002)
R^2	0.840	0.763	0.818	0.367
Observations	42,952	42,952	42,952	42,952
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of the baseline specification in Table 3 using the two alternative returnee-stock measures described in Section 2.2. Panel A fixes each returnee's disease–modality weights at the time of return, using the pre-return trial portfolios of their foreign employers. Panel B uses fixed lifetime weights based on trials initiated by matched domestic and foreign employers during the individual's employment spells over their entire career. For each measure, the sample includes disease–modality pairs with a positive returnee stock or trial count in at least one year during 2000–2025. All outcomes and reported regressors are transformed as $\log(1+x)$. All regressions include the controls in Table 3 and disease–modality, disease–year, and modality–year fixed effects. Standard errors clustered by disease–modality pair are reported in parentheses. $^{*}\,p<0.10$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

Table A9: Displacement-event IV with alternative stock constructions

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
Panel A: Method-1 stock (weights fixed at return)				
2SLS: log(1+returnee stock)	0.755***	0.622***	0.488***	0.048**
	(0.191)	(0.181)	(0.134)	(0.022)
First stage: displacement-event shock		0.127***		
		(0.023)		
Kleibergen–Paap first-stage F		29.56		
Observations		42,718		
Panel B: Method-2 stock (lifetime in-tenure weights)				
2SLS: log(1+returnee stock)	1.103***	0.907***	0.712***	0.070**
	(0.266)	(0.259)	(0.190)	(0.032)
First stage: displacement-event shock		0.087***		
		(0.019)		
Kleibergen–Paap first-stage F		21.76		
Observations		42,952		
Controls	Yes	Yes	Yes	Yes
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes

Notes: This table reports first-stage and 2SLS estimates using the alternative returnee-stock measures in Table A8: weights fixed at return in Panel A and fixed lifetime weights in Panel B. In each panel, log(1+returnee stock) is instrumented with cumulative exposure to the foreign-employer displacement events described in Table 3, standardized within the panel's initial sample. Trial outcomes and the three controls are also entered as $\log(1 + x)$. The first-stage row reports the coefficient on the instrument, and the reported F-statistic is the Kleibergen–Paap rk Wald statistic. Each panel retains disease–modality pairs with a positive stock under the corresponding measure or a positive total trial count in at least one year during 2000–2025. Both stages include the controls in Table 3 and disease–modality, disease–year, and modality–year fixed effects. Standard errors clustered by disease–modality pair are reported in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table A10: Returnee management and firm-level clinical-trial activity: PPML estimates

	(1) Total trials	(2) Dranove novel	(3) GPT novel	(4) First-in-China
Returnee-managed	0.359**	0.416**	0.392**	0.617***
	(0.161)	(0.204)	(0.194)	(0.237)
Employees (thousands)	0.332***	0.338***	0.372***	0.317***
	(0.105)	(0.125)	(0.135)	(0.111)
VC-backed	0.133	0.120	0.214	0.037
	(0.165)	(0.214)	(0.196)	(0.198)
Constant	2.905***	1.888***	2.409***	-0.704***
	(0.145)	(0.212)	(0.225)	(0.214)
HQ-province FE	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.337	0.310	0.337	0.215
Observations	1,596	1,594	1,596	1,474

Notes: This table reports Poisson pseudo-maximum likelihood (PPML) estimates of the specification in Table 2. The conditional mean is $\mathbb{E}[y_i \mid \cdot] = \exp\big(\beta\,\text{ReturneeManaged}_i + \gamma' X_i + \delta_{p(i)} + \theta_{f(i)}\big)$, where y_i is the untransformed trial count, X_i includes employee headcount in thousands and the VC-backed indicator, and $\delta_{p(i)}$ and $\theta_{f(i)}$ denote headquarters-province and founding-year fixed effects. For the returnee-managed indicator, $100(e^{\beta} - 1)$ gives the percentage difference in expected trial counts relative to locally managed firms, conditional on the controls and fixed effects. All columns draw on the same initial sample as Table 2. Heteroskedasticity-robust standard errors are reported in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table A11: Returnee stock and trial activity: PPML estimates

	(1) Total Trials	(2) Novel Dranove	(3) Novel GPT	(4) First-in-China
log(1+returnee stock)	0.166***	0.055	0.139***	0.274
	(0.050)	(0.082)	(0.048)	(0.334)
log(1+global trials)	0.385***	0.320***	0.337***	0.495**
	(0.032)	(0.050)	(0.032)	(0.236)
log(1+global cum. trials, $t-1$)	0.143*	0.104	0.072	0.071
	(0.073)	(0.154)	(0.073)	(0.401)
log(1+employee stock)	-0.000	0.038	-0.027	-0.219**
	(0.022)	(0.031)	(0.021)	(0.091)
Disease×modality FE	Yes	Yes	Yes	Yes
Disease×year FE	Yes	Yes	Yes	Yes
Modality×year FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.813	0.734	0.773	0.315
Observations	12,856	7,520	12,104	1,483

Notes: This table reports Poisson pseudo-maximum likelihood (PPML) estimates of the baseline specification in Table 3. The conditional mean is $\mathbb{E}[n_{dmt} \mid \cdot] = \exp\big(\beta \log(1 + \text{Stock}_{dmt}) + \gamma' X_{dmt} + \mu_{dm} + \delta_{dt} + \lambda_{mt}\big)$, where n_{dmt} is the untransformed trial count. The returnee-stock measure and controls follow Table 3, with all four regressors entered as $\log(1 + x)$. The terms μ_{dm}, δ_{dt}, and λ_{mt} denote disease–modality, disease–year, and modality–year fixed effects, respectively. The initial sample includes pairs with a positive returnee stock or total trial count in at least one year during 2000–2025, comprising 1,703 pairs and 44,278 pair-year observations. Estimation samples differ across outcomes because PPML excludes singleton and separated observations, including observations in fixed-effect groups with exclusively zero outcomes. Standard errors clustered by disease–modality pair are reported in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.