From Free Rider to Innovator: The Rise of China's Drug Development

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Abstract

In 2010, China accounted for less than 8% of global clinical trials; by 2020, it had surpassed the U.S. in annual registered clinical trial volume. To study this transformation, we compile a comprehensive, synchronized database spanning the pharmaceutical drug development supply chain: global data on scientific publications, clinical trials, and drug development milestones, combined with data on drug sales and government policies in China over the same period. We provide evidence that China's National Reimbursement Drug List (NRDL) reform dramatically expanded the effective market size for innovative drugs and contributed to the country's rise in biomedical innovation. We document a sharp increase in both the quantity (86%) and novelty of Chinese drug trials post-reform relative to U.S. trials, with similar patterns relative to Europe. This growth is concentrated in reform-exposed disease categories, first- or best-in-class drugs, and domestic firms. A quantification exercise reveals that the NRDL reform accounts for 59% of the growth in oncology trial activity, comparable to the combined contribution of upstream knowledge accumulation and talent flows (21%) and venture capital investment (19%), while other government policies play a minor role. Finally, dynamic gains from induced innovation exceed the reform's static gains in consumer access to innovative drugs by threefold, underscoring the importance of accounting for the reform's long-run effects on innovation incentives beyond near-term improvements in drug affordability.

Keywords: Clinical Trials, Pharmaceutical Innovation, NRDL, China

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1 Introduction

Since World War II, the global landscape of the pharmaceutical industry has been defined by a clear hierarchy. The U.S. serves as the undisputed leader in upstream R&D, generating the vast majority of novel drug concepts and first-in-class therapies, with Europe and Japan serving as a strong second pillar. The rest of the world, by contrast, plays a peripheral role, functioning primarily as consumers of existing medicines or producers of generic copies rather than creators of novel technologies.

This hierarchy aligns with the conventional wisdom among economists: smaller or low-income nations optimally rely on the diffusion of innovation from wealthy nations rather than investing in indigenous creation (Olson and Zeckhauser, 1966; Kyle, 2007; Dubois et al., 2015; Lakdawalla, 2018; Garthwaite, 2025). The logic is straightforward. Pharmaceutical R&D entails high uncertainty and enormous fixed costs, with only 6% of projects ultimately receiving drug approval and a median pivotal (Phase III) trial costing $19 million (Moore et al., 2018; Aryal et al., 2024). For most countries where market size is limited, budgets are constrained, and the technological frontier is distant, catching up to the global innovation frontier seems out of reach.

This paper challenges this conventional wisdom and asks two questions. First, can a country move from a downstream consumer to an upstream innovator in drug development? Second, what forces or policy designs contribute to the emergence of a local innovation ecosystem?

To answer the first research question, we start from the Citeline TrialTrove database, a comprehensive census of global clinical trial activities and drug development projects. We document a striking structural shift in the global supply of pharmaceutical innovation: over the past decade, China has grown from a marginal player, accounting for less than 8% of global clinical trials in 2010, to an active innovator, surpassing the U.S. and Europe in total annual registered clinical trials by 2020.

To formally evaluate China's catch-up in innovation, we employ an event-study framework that benchmarks China's trajectory against the U.S., the global frontier in biomedical research. We use Europe as an alternative counterfactual to ensure robustness. All analyses are conducted at the disease-country-year level and include disease-by-country fixed effects to absorb time-invariant heterogeneity in country- and disease-specific demand and comparative advantage, along with year (and disease-year) fixed effects to account for global temporal shocks. The event study confirms a

sharp structural break in China's clinical trial activity beginning in 2016, preceded by a flat pre-trend. By 2024, China's annual trial volume had expanded by 172% relative to the U.S.

Does this surge reflect genuinely novel development, or merely low-value "me-too" activity? Three findings point toward genuine innovation. First, the growth is concentrated in high-novelty trials: by 2024, China's high-novelty trial activity had risen by 52 to 127 percent relative to the U.S. across three complementary measures: (1) trials classified as novel by Dranove et al. (2022)'s novelty score, (2) trials involving new molecules rather than generics, and (3) trials that use patented drugs, rather than placebos or off-patent medicines, as control arms. Second, the expansion extends beyond trial initiation to downstream markers of commercially consequential innovation: out-licensing transactions with multinational corporations (MNCs) doubled, and first-in-world regulatory approvals for drugs developed in China rose by 36 percent. Third, the rise is driven primarily by indigenous Chinese firms rather than by foreign firms relocating existing pipelines: domestic firms account for 88 percent of the post-2015 increase in trials, while the pipelines of firms headquartered outside China remain comparatively flat. Taken together, these results indicate not merely an increase in China-based clinical activity, but a shift toward more novel, domestically generated, and internationally relevant pharmaceutical development.

To answer the second research question and causally examine the underlying drivers of this transformation, we integrate the trial registries with complementary data sources at the country-disease-year level. Three sources are global in scope: (a) scholarly publications and author affiliations from OpenAlex; (b) venture capital investment from PitchBook; and (c) disease prevalence rates from the Global Burden of Disease database. Three others capture the Chinese market and policy environment: (d) annual drug sales from SinoHealth; (e) central policy documents issued by the State Council; and (f) trial application backlogs from the National Medical Products Administration. To our knowledge, this assembled dataset provides the most comprehensive view of the pharmaceutical innovation supply chain in the existing literature.

We find that China's transformation was not an incidental byproduct of aggregate economic growth but the consequence of a specific policy shock: the 2016 National Reimbursement Drug List (NRDL) reform. By combining centralized price negotiations with a large-scale expansion of insurance coverage, the reform fundamentally altered the effective market size facing innovative pharmaceutical firms: the quantity expansion dominated the price contraction, more than doubling the revenues

of covered drugs. To trace this market-size shock through to innovation, we exploit variation in the reform's treatment intensity across disease categories. Therapeutic areas with greater NRDL exposure experienced disproportionately larger increases in clinical trial activity relative to the U.S. To address potential endogenous targeting of government support, we instrument NRDL exposure using shift-share instruments: the interaction between aggregate annual NRDL spending and each disease category's pre-determined attributes.

Two placebo tests further rule out alternative explanations. First, disease categories never covered by the NRDL show no systematic increase in trial activity after 2015. Second, NRDL exposure is unrelated to trial activity for the same diseases in Europe: if our estimates merely reflected global, disease-specific innovation trends that happened to correlate with NRDL exposure, trial activity in exposed categories should have risen in Europe as well. Together, these results support a demand-pull mechanism whereby an expanded effective market size stimulates pharmaceutical innovation.

Beyond the NRDL, we conduct a comprehensive analysis of alternative drivers operating through demand- and supply-side channels. On the demand side, we examine China's accession to the ICH (International Council for Harmonization of Technical Requirements for Pharmaceuticals for Human Use), which aligned China's regulatory framework with international standards and may have lowered barriers to global markets for drugs developed in China. On the supply side, we evaluate upstream knowledge accumulation and international talent flows, specifically the return migration of scientists from the U.S. to China, which provides essential inputs for pharmaceutical innovation. We also consider venture capital investment, along with sector-specific regulatory reforms and industrial policies — most notably the 2015 clinical trial application reform, which reduced approval backlogs, and Made in China 2025, which increased public investment in biomedicine. A quantification exercise reveals that the NRDL reform accounts for 59% of the observed surge in oncology trials, while upstream knowledge creation and talent inflows contribute 21% and venture capital investment explains 19%. Other policies and regulatory changes play a comparatively modest role, confirming that the NRDL was a crucial catalyst of China's pharmaceutical innovation boom.

Finally, we compare two welfare effects of the NRDL: the static gains from improved patient access to existing drugs, and the dynamic gains from newly induced innovation. A conservative back-of-the-envelope calculation implies that the reform induces at least 82 additional successful oncology drugs, measured as the discounted expected number of future approvals. Valuing these

drugs using realized outcomes for comparable recent oncology launches yields annual social-surplus gains of approximately ¥90.3 billion domestically — roughly four times the static gains from improved access estimated in Barwick et al. (2025).[1] While necessarily illustrative, this comparison suggests that a healthcare reform's welfare effects arise not only from improving access to existing therapies but also from redirecting firms toward the development of novel treatments. Moreover, as these induced therapies reach patients worldwide — through out-licensing to multinational firms, global trials, and first-in-world launches — the reform's benefits could extend well beyond China's borders.

Related Literature Our analysis contributes to several strands of literature. First, it relates to the literature on market size and innovation. A large body of work based on the U.S. context has established that expected revenue is a key determinant of pharmaceutical R&D, providing empirical support for Schmookler (1966)'s hypothesis. Acemoglu and Linn (2004) demonstrates that exogenous market expansions driven by demographic changes stimulate drug innovation, with subsequent contributions by Yin (2008); Blume-Kohout and Sood (2013); Dubois et al. (2015); Ji and Rogers (2024), and most recently, Vogel et al. (2024)'s study of Medicare price negotiation under the Inflation Reduction Act.

We provide the first evidence from an emerging economy context. Several features make NRDL a distinctive setting for studying how demand-side policy shapes innovation. First, unlike the broad insurance expansions commonly studied in the literature, such as Medicare Part D, NRDL inclusion is narrowly targeted at innovative drugs and explicitly favors those with high clinical effectiveness. Second, the reform was implemented in an economy that had historically been a consumer rather than a producer of frontier pharmaceutical innovation, offering a rare opportunity to study whether demand-pull incentives can catalyze indigenous R&D in a market with limited pre-existing capacity.

Our results indicate that by expanding effective market size while containing drug prices via government monopsony power, the NRDL offers compelling evidence that a well-designed insurance policy can help reconcile the tension between affordability and innovation incentives, corroborating Conti et al. (2021)'s proposal on future U.S. policy design.

Consistent with studies on firms' strategic responses to market-based incentives (e.g., Finkelstein

[1] Barwick et al. (2025) examines negotiation and healthcare insurance policy design using China's NRDL reform as a case study.

(2004), Budish et al. (2015), Hermosilla (2021), Agha et al. (2022), Cunningham et al. (2025), Dix and Lensman (2025), Bignon (2026), and Liu et al. (2026)), we find that firms reorient clinical trial efforts toward therapeutic areas with higher expected profitability. However, while the existing literature tends to find that demand-side shocks often pull incremental innovation (Dranove et al., 2022; Geng and Shi, 2024), the trials induced by the NRDL reform are characterized by high scientific novelty. This likely reflects the NRDL's inclusion criteria, which explicitly reward novelty/originality and prioritize unmet clinical needs.

Second, our paper contributes to the literature on industrial policy and innovation. Much of the existing research focuses on direct supply-side interventions such as government subsidies and tax credits (Branstetter and Sakakibara, 2002; Bronzini and Piselli, 2016; Howell, 2017; Dechezleprêtre et al., 2023; Melnik and Smyth, 2024). In the pharmaceutical sector specifically, Ward and Dranove (1995), Azoulay et al. (2019), and Gross and Sampat (2025) show that public funding (such as U.S. Committee on Medical Research contracts and NIH grants) can increase private-sector patenting and R&D investment, though Wallsten (2000) cautions that such grants may crowd out firm-financed research. A notable exception is Finkelstein (2004), which finds that government vaccine recommendations (a demand-side intervention) have dynamic effects that stimulate R&D. We extend this literature in two directions: by providing evidence from an emerging economy context, and by comprehensively analyzing both demand- and supply-side drivers within a unified framework rather than examining each channel in isolation.

Third, our study contributes to a growing literature documenting China's rapid technological ascent, while speaking directly to the debates about the quality of this progress.[2] Chen et al. (2021) cautions that reported R&D growth may partly reflect expense relabeling in response to tax incentives; Wei et al. (2023) finds negative average returns and a proliferation of low-quality patents from China's flagship innovation policy (InnoCom); and Li and Branstetter (2024) argues that the policy-induced increase in the R&D-sales ratio does not translate into patenting or productivity gains. On the other hand, Lerner et al. (2026) documents a dramatic rise in high-potential entrepreneurship and venture capital in China that contributes to innovation. We contribute to this debate by providing the most comprehensive evidence to date on China's biopharmaceutical innovation. Leveraging granular

[2]For recent debates in the public media, see "Why China Biotech Is Getting Its Own DeepSeek Moment," *Bloomberg Opinion*, June 10, 2025, and "China's Edge over U.S. Biotech Was Never Scientific," *The Washington Post*, September 22, 2025.

novelty indices and quantifying the sources of growth, we show that the surge in clinical development reflects a genuine reorientation toward the global quality frontier rather than a mere scaling-up of low-value activity.

The remainder of the paper is organized as follows. Section 2 details the institutional background of the Chinese healthcare system and describes the data. Section 3 analyzes both the quantity and quality of clinical trials in China relative to the U.S., as well as downstream business development and drug licensing activities. Section 4 investigates the underlying mechanisms. Section 5 quantifies the long-run vs. short-run welfare implications. Section 6 concludes.

2 Institutional Background and Data

2.1 Drug Development Process

The regulatory process governing drug development and market authorization in China and the U.S. is similar. In both jurisdictions, a drug sponsor must demonstrate that a product is safe and effective through a series of randomized clinical trials, typically benchmarking the investigational drug against a placebo or the prevailing standard of care.

The drug development lifecycle begins with the identification of a lead compound. To protect the underlying intellectual property, sponsors generally file patent applications during preclinical development, before human testing begins.[3] Clinical trials require regulatory clearance: sponsors must obtain approval of an Investigational New Drug (IND) application, which compiles comprehensive preclinical evidence on the compound's toxicity and pharmacological profile.

Clinical evaluation proceeds through three main stages before sponsors may apply for market approval. Phase I trials assess basic safety, dosage ranges, and potential side effects, typically enrolling a small group of healthy volunteers. Phase II and III trials evaluate efficacy, continue to monitor safety, and benchmark the drug against existing therapies. Phase III studies, often involving hundreds of subjects in a blinded and randomized setting, serve as the "pivotal" trials required for regulatory

[3]Contrary to the perception that drugs are not protected in China, China's patent regime is broadly similar to that of the U.S.: novel pharmaceutical compounds have been eligible for product-patent protection since the 1992 amendment to China's Patent Law. While enforcement is imperfect, drugs developed in China command substantial commercial value. In the first half of 2025 alone, U.S. drugmakers signed 14 licensing deals with Chinese biotech firms worth up to $18.3 billion, transactions that would be considerably less likely if rivals could freely copy the underlying drug candidates. (See Reuters, "U.S. Pharma Bets Big on China to Snap Up Potential Blockbuster Drugs," June 16, 2025.)

approval. Approval in a country (or region) typically requires evidence that these pivotal results extend to the local population and medical practice, a requirement that motivates sponsors to enroll local patients or conduct local trials. After approval, sponsors and public organizations may conduct Phase IV studies, which are usually observational and focus on longer-term safety and real-world effectiveness.

Clinical trials represent the most capital-intensive part of the R&D pipeline, with per-study costs rising sharply across phases and varying widely across therapeutic areas (Sertkaya et al., 2016). Focusing on Phase III trials, Moore et al. (2018) estimate a median cost of $19 million (with an interquartile range of $12.2–33.1 million) across novel therapeutics approved by the U.S. FDA. In addition, trials involve high risks of failure (Aryal et al., 2024). In our data, a new drug discovery is associated with an average of 123 clinical trials, while only about 6 percent of Investigational New Drug (IND) projects ultimately result in a successful drug.

2.2 The Chinese Healthcare System

The Chinese healthcare system (CHS) provides nearly universal coverage to over 95% of the population, making it the world's largest public health insurance program (Yu, 2015). Established in 1999, it has since evolved into two main schemes: the urban employee basic medical insurance (UEBMI), which covers formal-sector employees and retirees, and the urban and rural resident basic medical insurance (URRBMI), which covers the remaining population, including children and the elderly.

The CHS is the dominant purchaser in the domestic drug market, spending over ¥573 billion ($82 billion) on pharmaceuticals in 2022 (National Health Commission of the PRC, 2023).[4] In contrast, the private commercial insurance market remains underdeveloped, accounting for less than 7% of total health expenditures. Consequently, inclusion in the National Reimbursement Drug List (NRDL) is the primary gateway to the Chinese pharmaceutical market. Historically, the NRDL prioritized low-cost generics and off-patent molecules due to budget considerations, effectively excluding innovative, high-priced therapies and forcing patients to bear the full cost out-of-pocket when purchasing in the private market.[5]

[4]We apply a 35% coinsurance rate to the reported total expenditure on pharmaceutical sales of ¥881 billion.

[5]Ministry of Human Resources and Social Security, "National Reimbursement Drug List (2017 Edition)," 2017.

The NRDL Reform In response to growing public demand for broader access to innovative drugs, the National Healthcare Security Administration (NHSA) launched a landmark reform in 2016, integrating innovative therapies into the national insurance catalog through centralized price negotiations. This ongoing reform represents a fundamental shift from a rigid, budget-capped formulary to a value-based reimbursement model.

The negotiation process follows an annual cycle. Each spring, NHSA defines an eligible list of drugs, targeting innovative drugs (usually new molecules obtaining market approval within the last five years) that address significant unmet clinical needs.[6] Firms with eligible drugs and NHSA exchange information on costs and medical effectiveness during the pre-negotiation stage, which can last for months. On the day of negotiation, government representatives negotiate with delegates from each drug company simultaneously and independently. Successful negotiations result in inclusion in the NRDL, typically involving average price reductions of 50–60%. If the negotiation fails, the drug remains on the private market. The reform has successfully included 634 chemical drugs or biologics in the NRDL by 2025 (Table 1).

The National Reimbursement Drug List (NRDL) reform has three features central to our analyses. First, since 2019, the eligibility criteria have explicitly favored truly innovative drugs. During the pilot years (2016–2018), negotiations mainly brought patented drugs already sold on the private market onto the list to improve affordability. Since 2019, however, more than 80% of negotiated drugs qualified as "new molecular entities approved (by the National Medical Products Administration, or NMPA) within the past five years," according to the government document.[7] Final selections likewise favor new, popular, and effective drugs that are first or best in class: at the time of NRDL inclusion, the median drug is five years past FDA approval and one year past NMPA approval.

Second, the policy represents a sophisticated exercise of government monopsony power. Rather than relying on a laissez-faire approach or direct R&D subsidies, the Chinese government employs "price-for-volume" negotiations: firms accept deep, centralized price cuts in exchange for a massive expansion in effective market size through nearly universal insurance coverage and low coinsurance

[6]National Healthcare Security Administration, "2024 National Reimbursement Drug List Adjustment: Eligibility Criteria," 2024.

[7]National Healthcare Security Administration, "Public Announcement of the Eligible List of Drugs Submitted for Formal Review in the 2021 National Reimbursement Drug List (NRDL)," 2021. Other pathways to NRDL include traditional Chinese medicines, orphan drugs, and eligible children's drugs.

rates. This institutional design confronts a classic trade-off between static efficiency (patient access through lower prices) and dynamic efficiency (innovation incentives through firm profits). Whether the reform encourages or deters innovation—that is, whether it raises or lowers the net present value of innovative drug projects—depends on whether the quantity expansion outweighs the price compression. In Section 4.1, we directly evaluate this and exploit the staggered entry of therapeutic categories into the negotiation rounds to identify the impact of this policy shock on the direction and quality of R&D.

Third, the scale of the commitment is massive. The reform represents one of the largest public expansions of insurance coverage for innovative drugs globally: spending on negotiated drugs exceeded ¥100 billion in 2024 alone, which is over 40% of total innovative drug sales in China that year (¥233 billion) and more than the entire innovative drug sales in 2017 (¥66 billion, authors' calculation using SinoHealth data).

While the reform's effect on innovation is ex ante ambiguous, ex post, both the government and industry appear to credit it with supporting innovation. An NHSA official cited the 2024 spending as evidence of "real, tangible financial support for innovation".[8] Industry sentiment brackets the reform. Before it, Betta, a leading Chinese pharmaceutical firm, warned that lack of coverage — "No matter how good a new drug is, it has no opportunity to be included in NRDL" — was "detrimental to public welfare, industrial development, and incentives for innovation."[9] After its drug conbercept (Lumitin®) entered the NRDL in 2017, Chengdu Kanghong Pharmaceutical hailed the inclusion of innovative drugs as "of great significance — whether in improving people's well-being, promoting industrial innovation, or supporting pharmaceutical companies' own development."[10]

Other Policies and Ecosystem Changes Two other policy changes are relevant for our study. In 2015, China reformed its clinical trial application (CTA) process and streamlined regulatory procedures, clearing a substantial backlog of pending investigational new drug (IND) applications and accelerating review timelines (Jia et al., 2024). It therefore likely boosted clinical trial activity, especially around 2015. In June 2017, China joined the International Council for Harmonization of

[8] National Healthcare Security Administration, press release, July 1, 2025.

[9] "Medical Insurance Catalog Unchanged for Seven Years; Some Innovative Drugs Fail to Recoup R&D Costs Five Years After Launch," *China Economic Net*, March 30, 2016.

[10] "Domestic Innovative Drugs Enter Medical Insurance Negotiation for the First Time; Pharmaceutical Innovation Ushers in a New Era," *National Business Daily*, August 16, 2017.

Technical Requirements for Pharmaceuticals for Human Use (ICH), aligning its regulatory framework with international standards and potentially broadening access to foreign markets. Unlike the NRDL, these policies applied uniformly across drug categories and did not favor innovative drugs at particular times, a distinction we exploit in our analyses below.

Beyond regulatory reforms, two features of the broader innovation ecosystem are central to the mechanisms we examine. First, knowledge creation and the inflow of overseas-trained scientists and executives into Chinese biopharma firms expand firms' capacity to absorb and produce frontier science. Second, venture capital investment channels financing to R&D-intensive projects that established revenue streams cannot support. We examine both talent flows and venture funding as potential mechanisms in Section 4.

2.3 Data

Our empirical analyses integrate six primary data sources with several auxiliary datasets to track the lifecycle of pharmaceutical innovation and to measure a broad set of demand- and supply-side factors that could drive innovation activity. To our knowledge, this is the first empirical paper that conducts a comprehensive evaluation of both demand- and supply-side policies and regulatory changes in the context of pharmaceutical innovation.

Citeline TrialTrove Database We utilize the Citeline TrialTrove database (2010–2024) to construct a comprehensive census of clinical trials initiated globally. TrialTrove aggregates data from official national registries (e.g., ClinicalTrials.gov in the U.S. and the ChiCTR in China) alongside public disclosures. For each trial, we observe the tested drug, sponsor, therapeutic area, disease/indication, trial start date, completion status, trial phase, objective, methodology, duration, and trial population. Table 2 reports the number of trials across nine therapeutic areas and phases in China and the U.S.

Citeline Pharmaprojects Database To capture the commercial realization of R&D, we link trials to the Citeline Pharmaprojects database, which tracks key development milestones including patenting, out-licensing, and regulatory approvals (Cunningham et al., 2021). These events serve as proxies for downstream development and commercial success, as licensing deals, particularly those

acquired by multinational firms, reflect market recognition of the underlying innovation.

SinoHealth Drug Sales Data We obtain granular pharmaceutical sales data from SinoHealth (2017–2024), a leading health-data provider in China (Xia, 2024). SinoHealth provides coverage of both hospital channels and retail pharmacy channels, through which nearly all innovative drugs in China are dispensed. The data are at the SKU (stock keeping unit)-year level and report quantities dispensed and monetary sales. Furthermore, we restrict the analysis to chemical drugs and biologics and exclude Traditional Chinese Medicine (TCM), which is subject to different approval standards and typically does not undergo clinical trials.

OpenAlex Publications To measure upstream knowledge creation, we utilize OpenAlex, an open, large-scale scholarly database that systematically tracks global scientific publications and the related metadata. It provides comprehensive information about authors, citations, institutions, journals, and concepts (i.e., keywords). We focus on biomedical publications with valid PubMed IDs, where the first and last authors are affiliated with either Chinese or U.S. institutions.

PitchBook We use data from PitchBook, a comprehensive commercial database that tracks venture capital (VC), private equity, and startup activity worldwide. PitchBook provides detailed information on financing events, including deal dates, investment amounts, investor identities, and firm characteristics. We use these data to construct measures of VC funding at the firm level and aggregate them to the disease-country-year level based on firms' clinical trial portfolios.

IND Application and Approval Dates To quantify the effect of the 2015 CTA reform and measure the backlog days between IND application and approval, we collect the application and approval dates for all IND applications from China's NMPA Center for Drug Evaluation. We further assign each IND to a disease in order to calculate backlog days for each disease category. The data construction process is documented in Appendix A.2.

Auxiliary Dataset: Disease Prevalence Data We collect disease prevalence data from the Global Burden of Disease (GBD) database.[11] This dataset provides standardized disease-level preva-

[11] Available from https://vizhub.healthdata.org/gbd-results/.

lence measures across countries and years.

Auxiliary Dataset: Policy Documents We have scraped all biopharma-related policies in China from the State Council Policy Document Library and identified relevant policy documents targeting the biopharmaceutical sector. We use GPT to classify these documents into four categories: (a) policies that promote advanced manufacturing; (b) innovation policies that reduce reliance on foreign technologies; (c) capital market reform; and (d) fiscal subsidies. See Appendix A.3 for details.

Data Contributions A significant contribution of our data work is linking these disparate sources systematically at the disease category-country-year level. Appendix B.1 details the procedures undertaken to link drug names in the SinoHealth sales data with the disease categories in the Citeline databases, including GPT-based semantic mapping and manual verification. Appendix B.2 explains the graph embedding approach we use to link keywords in OpenAlex scientific publications with disease categories in Citeline. By representing both keywords and disease categories as points in a high-dimensional vector space, we systematically identify the OpenAlex keywords most closely related to each Citeline disease category.

To track China's movement toward the global technological frontier, we construct three novelty measures on clinical trials. Appendix C provides details on how these measures are constructed.

3 Empirical Results

3.1 Descriptive Evidence of the Time Trend of Trials and Drugs

We begin our empirical analyses by documenting the aggregate trends in clinical trial initiations in China, the U.S., and Europe. Beyond simple counts, we investigate whether this growth represents a move toward the global technological frontier.

R&D Volume and Novelty Figure 1 illustrates the time trends in the number of clinical trials launched in China, the U.S., and Europe from 2010 to 2024. Panel (a) shows that while trial activity in the U.S. and Europe remained relatively stable, China underwent a dramatic structural shift. Starting from a baseline of 800 annual trials in 2010, China's volume surged after 2015, ultimately

surpassing the U.S. and Europe in 2020. By 2024, China was initiating more than 5,000 clinical trials annually.

A volume-based comparison may be confounded by low-value R&D. To address this, Panels (b) to (d) utilize three complementary measures to evaluate trial novelty. First, following Dranove et al. (2022), we construct a novelty index that measures how frequently a drug's mechanism of action (i.e., its molecular target) has been explored in prior research. Trials scoring above the global median of this index are classified as "high-novelty" projects.[12]

Second, we utilize a fine-tuned GPT-4o-mini model to perform a functional classification of trial objectives based on textual registry data. This classification distinguishes between (i) new molecular entities (NMEs), (ii) novel drug combinations, (iii) new indications for existing molecules, and (iv) bioequivalence tests for generic drugs.[13]

Third, Phase III trials are typically conducted with both a treatment group and a control group, where the control consists of a placebo, a generic drug, or an innovative drug. We focus on trials that use an *innovative* drug as the control, which are positioned against the existing clinical frontier and therefore reflect a higher degree of novelty relative to trials compared against a placebo or generics.

The results in Panel (b) of Figure 1 demonstrate that China's expansion is not limited to incremental projects. The volume of high-novelty trials rose from around 500 in 2015 to over 2,400 by 2021. Furthermore, Panel (c) confirms that the surge is primarily driven by trials investigating novel mechanisms, new combinations, or new indications, while generic bioequivalence testing accounts for a small and diminishing share of the total growth. Panel (d) shows a notable increase in Phase III trials that use an innovative drug as the control arm, indicating that a growing number of late-stage trials in China are explicitly benchmarked against the existing clinical development frontier.

Post Trial Outcomes Whether this increased investment in trial activity translates into progress at later stages of the drug development lifecycle is an open question. Given that the majority of

[12]To be more specific, Dranove et al. (2022) compute novelty of a trial i with mechanism $m(i)$ at stage $j(i)$ as:

$$Novelty_i = \frac{1}{1 + \text{Number of prior trials at stage } j(i) \text{ using mechanism } m(i)}.$$

This measure distinguishes drugs with mechanisms rarely explored before from those relying on well-established pathways. We calculate the novelty median within each year, pooling observations across all countries to benchmark novelty against the global clinical development frontier rather than country-specific baselines.

[13]We manually labeled a training set of trials and used the model to classify the remaining trials. Fine-tuning reduces hallucination risk and enables consistent large-scale categorization of trial novelty.

observed trials were initiated within the last decade and the average pharmaceutical development cycle spans 8–12 years, many long-run product-market outcomes remain unobserved. To partially bridge this gap, we examine intermediate milestones along the commercialization pathway using multiple data sources. In particular, we analyze license-out transactions and new drug approvals (NDAs) that are recorded in the Citeline Pharmaprojects database, which capture market-based valuation and final regulatory validation of clinical success, respectively. We further examine new firm entry into clinical development, measured as the number of firms conducting their first clinical trials.

Figure 2 compares these downstream milestones for China and the U.S. Panel (a) shows a gradual rise in license-out events for Chinese-originated drugs starting several years after 2016, a pattern consistent with the expected lag between early-stage trials and subsequent commercialization activity. Panel (b) reveals a similar acceleration in global first approvals of drugs originated by Chinese firms, which rose from fewer than 5 drugs before 2016 to over 40 by 2024.[14] Panel (c) displays a sharp increase in the number of new drugs approved by the Chinese administration, rising from fewer than 20 before 2016 to around 100 by 2024. Panel (d) shows a rapid increase in the number of firms conducting clinical trials for the first time in China after 2016, with annual counts rising from fewer than 100 before 2016 to over 300 by 2024.[15]

3.2 Structural Break Test

The descriptive evidence suggests a notable inflection point in China's clinical trial activity relative to the U.S. (and Europe) during the mid-2010s. To identify the timing of this shift, we employ a structural break test following the framework established by Quandt (1960) and Andrews (1993). Specifically, we implement a supremum Wald (Sup-W) test, which identifies an unknown break date by maximizing the Wald statistic across a series of Chow tests for all possible partitions of the sample period.

The test results yield evidence of a regime shift in China's trial output around 2016–2017.[16] Since

[14] For each drug, we only count the first approval anywhere in the world.

[15] These findings are corroborated by an industry report: over the past five years, China approved 192 new drugs, overtaking the EU4+UK (187) and trailing only the U.S. (267), with many of its approvals first-in-world and first-in-class (IQVIA Institute for Human Data Science, 2024).

[16] The p-value of the chi-square test is 0.046 for 2016 and 0.0003 for 2017. P-values for earlier candidate break years are significantly higher.

a break identified in 2016 reflects a divergence in the data-generating process beginning that year, we designate 2015, the final year of the pre-break regime, as the reference period. This data-driven identification procedure provides the empirical basis for the treatment period used in the event-study and difference-in-differences specifications presented in the following sections.

3.3 DID and Event Study

Having identified 2015 as the final pre-break year, we now formally quantify the magnitude of this shift, exploiting the granular nature of our micro-data and estimating regressions at the disease-country-year level. This approach is motivated by three considerations. First, drug development is frequently catalyzed by global scientific breakthroughs that are disease-specific, such as the emergence of checkpoint inhibitors in oncology. Our framework accounts for these time-varying, disease-specific global shocks that might otherwise confound the estimates. Second, this framework allows us to better investigate heterogeneity across disease types, firm origins, and trial phases. Finally, the therapeutic area serves as the economic unit of decision-making, as pharmaceutical firms typically allocate R&D budgets and manage pipelines along specific disease classifications.

We use the U.S. as our primary comparison group for two reasons. First, it serves as a proxy for the time-varying global innovation frontier. Since scientific knowledge is a global public good, the supply of new drug targets is simultaneously available to all countries; using the U.S. as a control allows us to isolate China-specific changes in innovation activity from global technological shifts. Second, the U.S. represents a stable, mature pharmaceutical market whose clinical trial trends parallel those in Europe, supporting its suitability as a benchmark. In robustness checks, we also use Europe and the U.S. + Europe combined as alternative comparison groups.

We estimate the following event-study specification at the disease-country-year level, using 2015 as the omitted reference year:

$$Y_{d,c,t} = \sum_{\tau \neq 2015} \beta_\tau \mathbf{1}(\text{China})_c \times \mathbf{1}(t = \tau) + \phi_{d,c} + \xi_t + \epsilon_{d,c,t}, \tag{1}$$

where the dependent variable is the log number of trials (or drug projects) for disease d in country c and year t. We include disease-by-country fixed effects ($\phi_{d,c}$), which absorb time-invariant differences across country–disease pairs, including country-specific comparative advantages in particular

therapeutic areas. Year fixed effects (ξ_t) absorb global changes in drug development common across countries. The coefficients β_τ trace the evolution of China's clinical output relative to the control, with 2015 normalized to zero (due to the structural break identified in Section 3.2). The pre-2015 coefficients allow us to assess whether China and the comparison countries followed similar trends. Under the parallel-trends assumption, the post-2015 coefficients can be interpreted as the differential growth in China's clinical output relative to the comparison countries. We also estimate a DID version to obtain the average post-treatment effect.

R&D Volume and Novelty Figure 3 plots the event-study coefficients. The estimated coefficients before 2016 are small in magnitude and statistically indistinguishable from zero, suggesting that China and the U.S. followed comparable growth trajectories in clinical trial activity during the pre-treatment period, as shown in Panel (a). Beginning in 2017, we observe a clear divergence. By 2024, the relative increase reaches approximately 100 log points, representing a 172% expansion in China's trial volume relative to the U.S. Table 3 reports the baseline difference-in-differences estimates (we examine robustness in Section 3.4 below). Across all specifications, the coefficients are positive and statistically significant at the 1% level, indicating a substantial acceleration in China's clinical trial output relative to the U.S. The estimate in Column (1) implies that the total number of trials in China increased by approximately 86.1% ($e^{0.62} - 1$) post 2015.

Beyond volume, we find evidence of a corresponding surge in the quality and novelty of these trials. We examine three novelty measures. High-novelty trials, defined as those with above-global-median novelty scores according to Dranove et al. (2022) (Panel b of Figure 3) and those investigating non-generic compounds (Panel c of Figure 3), increased by 127% and 103%, respectively.[17] Panel (d) of Figure 3 shows a significant increase in Phase III trials that use an innovative drug as the control arm, though the magnitude at 42 log points (a 52% increase) is slightly smaller. This partly reflects the smaller share of Phase III trials in overall clinical activity and the stringent bar imposed by the control-arm criterion. Together, these results indicate that China's post-2015 growth reflects a broad-based strengthening of clinical development capabilities across therapeutic areas, rather than a concentrated shift toward low-value, imitative projects.

[17] In the measure developed by Dranove et al. (2022), a novelty score of one indicates a first-in-class drug, defined as the first drug to explore a given mechanism of action or biological target. The corresponding event-study results using first-in-class trials are reported in Appendix Figure A4.

Post-trial Outcomes Appendix Figure A5 examines the transmission of China's surge in clinical trial activity to downstream outcomes in drug development and industry entry, including license-out transactions, new drug approvals, and the entry of new firms. Across Panels (a) through (d), the estimated coefficients exhibit a clear post-2015 upward trajectory. By 2024, out-licensing transactions to multinational corporations (MNCs) had doubled, China's NMPA drug approvals had tripled, first-in-world regulatory approvals for China-developed drugs (in any country) had risen by 36%, and firm entry had increased by 27%, all relative to 2015 and benchmarked against the control group (the U.S.). In addition, license-out activity and approvals of Chinese-originated drugs exhibit a marked upturn beginning around 2021. This timing is consistent with the multi-stage nature of pharmaceutical development, whereby downstream milestones such as licensing deals and regulatory approvals respond with a lag to earlier increases in clinical trial activity. Relative to the trial-level results, the estimated coefficients are more dispersed, reflecting the sparsity of licensing, approval, and entry events at the disease-year level. Nevertheless, the broadly rising post-2015 patterns across all four panels indicate that China's expansion in clinical activity is translating into tangible downstream outcomes, spanning commercialization, regulatory success, and new firm participation in the pharmaceutical innovation ecosystem. We examine the long-run welfare benefits of induced drug innovation in Section 5.

3.4 Heterogeneity and Robustness

In this subsection, we conduct robustness checks using alternative specifications and sample choices and investigate heterogeneity across trial stages and sponsor type (private or public entities).

Domestically-led R&D Could the rapid acceleration in clinical activity be driven by multinational (MNC) incumbents operating within China instead of by domestic Chinese firms?[18]

Appendix Figure A6 compares trial initiations by the nationality of sponsoring firms. Panel (a) focuses on trials conducted in China and shows that the post-2015 expansion is driven primarily by domestic firms, which account for 88% of the increase in trials initiated by private organizations.

[18]Many multinational pharmaceutical companies operate in China through local subsidiaries: for example, Roche through Roche China, and Novartis through affiliated entities such as Sandoz. We adopt a strict ownership-based definition of domestic firms: firms whose ultimate controlling parent is headquartered outside China are classified by the parent's home country. Roche China and Sandoz are thus classified as Swiss rather than domestic firms. Multinationals occasionally operate through joint ventures, but these account for a negligible fraction of trials in our sample.

Non-Chinese firms, in contrast, account for only a small fraction of trials in China, and their activity remained relatively stable over the sample period. Panel (b) turns to trials conducted in the U.S. Although Chinese sponsors were nearly absent in 2010, their U.S. trial initiations rose steadily after 2015, suggesting a nascent "internationalization" of Chinese pharmaceutical firms.[19]

Figure 4 conducts an event study and decomposes trial activity in China by firm origin, by estimating specification (1) with clinical trials split into three groups: $c \in \{\text{China}^{\text{in}}, \text{China}^{\text{out}}, \text{US}\}$, where China^{in} denotes trials conducted in China by firms headquartered in China:

$$Y_{dct} = \sum_{\tau \neq 2015} \left[\beta_\tau^1 \mathbf{1}(China^{\text{in}})_c + \beta_\tau^2 \mathbf{1}(China^{\text{out}})_c\right] \times \mathbf{1}(t = \tau) + \phi_{dc} + \xi_t + \epsilon_{dct}. \tag{2}$$

The post-2015 trajectories diverge sharply: while the relative growth for firms headquartered in China climbs to approximately 120 log points by 2024 (a 232% increase), the estimates for firms headquartered outside China (including subsidiaries of foreign firms) remain relatively flat. This asymmetry, along with a flat pre-trend, suggests that the post-2015 acceleration primarily reflects indigenous capacity building driven by domestic firms, rather than a result of global firms reallocating their R&D pipelines to China.

Heterogeneity Across Trial Stages and Sponsor Types Figure 5 shows that the post-2015 expansion in clinical trials differed systematically across development stages in both timing and magnitude. Phase I trials increased immediately after 2015, while the increases in Phase II and Phase III trials emerged after several years. The magnitude of the response follows the same ordering: Phase I trials recorded the largest increase, at $e^{0.667} - 1 = 95\%$, followed by Phase II trials at $e^{0.332} - 1 = 39\%$ and Phase III trials at $e^{0.165} - 1 = 18\%$ (Appendix Table A2). These patterns are consistent with the high failure rates and attrition inherent in drug development, as only a fraction of newly initiated early-stage projects progress to later phases. The delayed increase in advanced-phase trials is also consistent with the time required for new projects to move through the development

[19]The relatively modest increase in U.S.-based trials initiated by Chinese firms does not imply a lack of innovativeness. Conducting clinical trials in the U.S. is costly, and Chinese firms face additional institutional and regulatory frictions when operating overseas. As a result, they commonly enter the U.S. market through out-licensing arrangements or collaborations with MNCs rather than by directly sponsoring trials. The post-2021 dip in U.S. trials is not specific to Chinese sponsors (non-Chinese firms exhibit a similar pattern) and is possibly driven by rising trial costs.

pipeline.[20]

Across sponsor types, we find that private sponsors drove the largest increases in Phase I and Phase III trials, stages most critical for establishing safety, efficacy, and securing regulatory approval (Appendix Table A2). In contrast, public sponsors (hospitals, universities, etc.) exhibited the strongest growth in Phase IV trials that focus on post-approval observational studies and real-world evidence generation, which are less commercially driven. These patterns are consistent with the division of labor: private firms prioritize high-stakes, market-entry R&D in early and pivotal phases, while public institutions focus on post-market surveillance and broader clinical evidence generation following a drug's commercial launch.

Alternative Specifications We evaluate the sensitivity of our baseline estimates to alternative specifications and sample definitions. Appendix Table A3 assesses robustness to different sets of fixed effects and functional form choices. Column (1) replicates the baseline specification from Column (1) of Table 3. In Column (2), we augment the baseline model with disease-by-year fixed effects, which control for time-varying, disease-specific shocks at the global level. Columns (3) to (5) address observations with zero trials and functional form choices. Column (3) follows Chen and Roth (2024) and defines the dependent variable as log(number of trials) when at least one trial is observed in a country-disease-year cell and as -1 otherwise.[21] To ensure that our results are not driven by the log transformation of the dependent variable, Columns (4) and (5) report estimates using the raw trial counts as the outcome, employing both OLS and Poisson Pseudo-Maximum Likelihood (PPML) estimators. Across all specifications, the post-2015 uptick remains robust to fixed-effect choices and functional form assumptions.

Appendix Table A4 explores alternative DID designs. Globalization of R&D can lead to multi-center trials. To avoid spillovers across the treated and control groups, Column (2) excludes trials conducted in both the U.S. and China, thereby ensuring that the estimated effect is not driven by an increasing number of global trials that include a Chinese site. Furthermore, Columns (3) and (4) verify that our results are not sensitive to the choice of the U.S. as the control group by using Europe

[20] As shown in Section 4.3, the 2015 Clinical Trial Application reform cleared a significant backlog of pending applications, also contributing to the increase in trial volume around 2016.

[21] This approach assumes that the effect of moving from zero to one trial is equivalent to 100 log points. Results are robust to alternative cutoffs of 0 and -0.1 and slightly larger with a cutoff of -3, as expected.

(and U.S. + Europe) as alternative control groups. The consistency of the coefficients across these samples suggests that our findings reflect a distinct shift in the treatment group (China) rather than idiosyncratic trends in the control group (U.S.).

Collectively, these results provide some of the first empirical evidence of a developing economy transitioning into a global frontier in pharmaceutical innovation. In the next section, we turn to the institutional and policy drivers behind this growth, assessing the extent to which this transition was catalyzed by deliberate regulatory reforms versus broader economic growth and demographic shifts.

4 Mechanisms

In this section, we investigate the institutional and economic drivers behind China's rapid ascent in pharmaceutical R&D, considering both demand-side and supply-side factors discussed in the literature (Finkelstein, 2004; Acemoglu et al., 2006; Kremer and Snyder, 2018; Bloom et al., 2019). On the demand side, we examine the NRDL reform, which began in 2016 (the year of the structural trend break identified in Section 3.2), as well as China's accession to the ICH in June 2017. On the supply side, we examine three factors: knowledge creation and human capital; venture capital (VC) investment, which finances pharmaceutical innovation particularly for early-stage biotechnology firms; and the 2015 clinical trial application (CTA) reform. Finally, we explore industrial policies, most notably "Made in China 2025" (MIC2025), a national strategic plan to upgrade China's manufacturing sectors, including biomedicine. These industrial policies may affect both the demand for and supply of pharmaceutical innovation. We conclude with a quantification exercise that estimates the relative contribution of each driver.

4.1 The NRDL Reform

Effect on Market Size To evaluate the effect of NRDL on market size for innovative drugs, we first estimate the direct effect of NRDL inclusion on drug sales using the doubly robust estimator from Callaway and Sant'Anna (2021). Figure 6 decomposes the impact on prices, quantities, and total revenue by comparing the included drugs (treated group) with the eligible but not included drugs (control group) before and after the inclusion. Following successful negotiation, retail prices drop by an average of 50% (and 66% for oncology drugs). However, this price compression is more

than offset by a massive market expansion: quantities sold increase by 350% on average, with cancer drugs seeing a nearly ten-fold (900%) increase in volume.

The net effect on producer revenue (and profit) is overwhelmingly positive. Panels (e) and (f) show a 100% average increase in revenue post-inclusion, with oncology drugs experiencing a 500% surge. Given that marginal production costs for drugs are typically low relative to prices, these revenue gains translate into a significant increase in producer profit. Appendix Figure A7 documents a sharp expansion of the innovative drug market between 2016 and 2024. The number of NRDL-covered innovative drugs increased from zero in 2015 to 530 in 2024, public insurance spending surpassed ¥100 billion in 2024, and hospital market sales quadrupled over the period. These results provide compelling evidence that the NRDL reform fundamentally altered the profitability of covered innovative drugs.

Effect on Clinical Trials To formally test whether the NRDL-induced market expansion catalyzed the surge in clinical activity, we construct disease-specific measures of policy exposure. By merging the Citeline TrialTrove dataset with granular drug-level sales data from SinoHealth (2017–2024), we exploit variation in the intensity of reimbursement coverage across 332 distinct disease categories. This allows us to quantify the "market size" effect on innovation, a central theme in the economics of R&D.

Figure 7 visualizes the relationship in the raw data by plotting the change in clinical trial activity against the expansion of NRDL coverage, measured by the number of drugs included in the NRDL, across disease categories between 2016 and 2024. Disease categories with the largest expansions in NRDL coverage — such as non-small cell lung cancer — also experienced some of the sharpest increases in trial volume. The upward-sloping fitted line highlights a strong positive cross-sectional association between reimbursement expansion and subsequent R&D activity. Such raw-data patterns provide suggestive evidence that clinical trial activity expands more strongly in disease areas experiencing larger increases in effective market size.

To put the analyses in a formal regression framework, we construct four complementary measures of disease-level NRDL exposure that proxy for the magnitude of market expansion: (a) the log number of covered drugs; (b) the log revenue of covered drugs; (c) the share of covered drugs in the disease category's drug count; and (d) the share of covered drugs in the category's revenue. The first two

capture the scale of coverage, while the latter two capture its intensity relative to the overall market for each disease. We estimate the relationship between clinical trial activity and NRDL exposure using the following specification:

$$\log(\text{Trials})_{d,c,t} = \beta\, \text{NRDL Exposure}_{d,c,t} + \phi_{d,c} + \xi_t + \epsilon_{d,c,t}, \tag{3}$$

where $\text{Trials}_{d,c,t}$ is the number of trials in disease category d in country c at time t, and coefficient β identifies the semi-elasticity of trial activity with respect to NRDL-driven market expansion. All specifications control for disease prevalence and the number of drugs at the disease category-country-year level, with the U.S. serving as the control group. We use this same specification throughout Section 4 for all mechanism analyses, replacing only the key regressor with the measure corresponding to each mechanism.

Table 4 shows that greater NRDL exposure is associated with significantly larger increases in clinical trial activity across all four measures, indicating that both the extensive and intensive margins of reimbursement expansion stimulate pharmaceutical R&D.

IV Estimates Because NRDL exposure is not randomly assigned, the OLS estimates may be biased upward if coverage targets fast-growing or policy-prioritized diseases, or downward if the reform targets diseases with weak prior commercial incentives or if exposure is measured with error. We employ two shift-share-style instruments, each interacting aggregate annual NRDL spending (driven by national budget decisions rather than disease-specific conditions) with a predetermined disease-level characteristic that determines how much of the aggregate expansion accrues to each disease.

The first instrument interacts aggregate annual NRDL spending (in Appendix Figure A7) with predetermined disease-level demand elasticity, estimated separately for each disease category using price and quantity variation. This IV exploits the fact that reductions in out-of-pocket prices generate larger market-size increases in categories with more *elastic* demand. Elasticity thus predicts how strongly utilization and revenue respond when NRDL coverage expands, making it a good proxy for the reform's market-expansion effect. At the same time, conditional on disease-by-country and year fixed effects and controls for drug availability and disease prevalence, predetermined elasticity should affect post-2016 trial activity only through the reform-induced market expansion.

The second instrument interacts aggregate spending with the number of U.S.-approved innovative drugs in each disease between 2010 and 2015. This IV is correlated with NRDL exposure, as the NRDL can only cover drugs that already exist, and over two-thirds of the innovative drugs included in the NRDL by 2025 are foreign-developed. Diseases with a larger pre-reform stock of globally available therapies thus offered more candidates for inclusion, translating aggregate spending into larger coverage expansions in those categories. The exclusion restriction is plausible because the stock is fixed before the reform and reflects U.S. scientific and commercial conditions rather than Chinese firms' post-2016 research choices. Persistent cross-disease differences in scientific opportunity are absorbed by disease-by-country fixed effects.[22] The main residual concern — that a large pre-period drug stock proxies for expanding scientific opportunities that would have drawn Chinese R&D even absent the reform — is mitigated by the flat pre-trends in Figure 3 and by the fact that identification comes from the *timing* of aggregate NRDL spending, not from cross-disease differences alone.

As shown in Panel B of Table 4, the IV estimates are positive and statistically significant across all four NRDL exposure measures, with strong first stages: the Kleibergen–Paap F-statistics range from 14 to 83, and both instruments enter with the expected positive signs. The magnitudes are economically meaningful: the coefficient in Columns (1) and (2) of Panel B implies that a 100% increase in NRDL-covered drug count and revenue is associated with a 17.5% and 21.3% increase in trials, respectively, comparable to the cross-disease market-size estimates of 25% in Dubois et al. (2015).[23] The estimate in Column (4) implies that moving the revenue share of covered drugs from zero to its sample mean (0.091) increases trial activity by about 7%.

Two robustness exercises corroborate these results. First, because trial planning takes time and firms may respond to reimbursement expansion with a delay, Appendix Table A5 replaces contemporaneous exposure with its average over years $t-2$ to t. The estimates (0.64–0.87 across the four measures) remain statistically significant and close to the IV estimates, indicating that the results are not an artifact of the timing convention. Second, Appendix Table A6 reports specifications using each instrument separately and jointly. The elasticity-based instrument alone delivers estimates

[22] Time-varying global shocks are captured by disease-year fixed effects in some specifications.

[23] We use $\log(1+x)$ transformations in Columns (1) and (2) because some disease categories were never exposed to the NRDL reform. The implied average elasticity is $\epsilon = \beta \times [\bar{X}/(1+\bar{X})] \times [(1+\bar{Y})/\bar{Y}]$, where β is the coefficient estimate and $\bar{\cdot}$ denotes the sample mean. $\bar{X}$ equals 0.33 and 0.51 in Columns (1) and (2), respectively, and $\bar{Y}$ is 10.6 trials per disease category-country-year.

qualitatively similar to the joint-IV baseline, confirming that the results are not driven by the U.S. drug-stock instrument. The second IV produces weaker first stages for intensive exposure measures (as expected), which motivates our preference for the joint specification. Together, these results support the conclusion that NRDL-induced market expansion increased clinical trial activity.

A common concern with demand-side policies is that they often pull incremental innovation (Dranove et al., 2022; Geng and Shi, 2024). The NRDL appears to be a notable exception. As shown in Appendix Table A7, the trials it induces are characterized by high scientific novelty, likely because the NRDL's inclusion criteria explicitly reward originality and prioritize unmet clinical needs. By tying market access to therapeutic advances, the NRDL does not merely enlarge the pie for existing drug categories; it reshapes the direction of innovation itself.

Placebo Test To distinguish the NRDL effect from broader national or global innovation trends, we conduct two placebo tests. First, as shown in Panel (a) of Figure 8, applying the baseline event-study specification (Equation (1)) to disease categories that never experienced NRDL expansion reveals no systematic post-2015 increase in Chinese trial activity.[24] Second, as shown in Panel (b) of Figure 8, applying the baseline event-study specification (Equation (1)) to European trials, we find no increase in European clinical trials in NRDL-exposed disease categories. Consistent with this, Appendix Table A8 finds no positive association between European trial activity and any of the four NRDL exposure measures. Together, these results suggest that our estimates are unlikely to be driven by general trends in Chinese pharmaceutical development or global disease-specific innovation opportunities.

These findings highlight that the government can use the insurance policy and the "price-for-volume" mechanism to expand effective market size and strengthen innovation incentives, consistent with the broader demand-pull logic in Kremer and Snyder (2018). The reform also shapes the direction of innovation by expanding demand in therapeutic areas with large patient populations and unmet medical needs. This dynamic effect is a central welfare consequence of the reform: beyond improving patient access to existing drugs, the NRDL changes the future pipeline of therapies. Section 5 quantifies these long-run benefits.

[24] We also exclude oncology and infectious diseases to ensure a clean control group because the former is subject to high expectations of future coverage, and the latter was confounded by the COVID-19 pandemic.

4.2 Other Demand-side Factors

ICH Harmonization China joined the ICH in June 2017, aligning its drug regulatory framework with international technical standards. By harmonizing requirements across jurisdictions, this alignment lowers barriers to cross-border drug development and approval, potentially expanding the effective international market size for drugs developed in China.

To test whether ICH accession encouraged China-based trials targeting foreign (for example, U.S.) markets, we interact U.S. disease prevalence with a post-ICH indicator (country-specific disease prevalence is added as a control).[25] If ICH is important, we should expect a disproportionate rise in trials for diseases with higher U.S. or global prevalence. However, as shown in Column (2) of Table 5, the estimated effect is economically small and statistically insignificant. Meanwhile, the NRDL coefficient remains unchanged, suggesting that easier access to the U.S. market does not attenuate the domestic demand-side channel. This result is perhaps unsurprising because the FDA strongly prefers direct evidence from trials conducted in the U.S. or in populations relevant to the U.S. context, particularly for pivotal Phase III studies.[26] Using prevalence per existing drug to control for prevailing therapies or global prevalence to capture global demand delivers very similar results (Columns (1)-(2) of Appendix Table A9).

4.3 Supply-side Factors

Knowledge Creation and Talent Flow A competing hypothesis is that China's clinical surge was driven by a supply-side expansion in innovation inputs — specifically, the accumulation of scientific knowledge and the return of high-skilled talent from abroad. Existing literature shows that the stock of public science provides the "fertile soil" for private-sector R&D (Azoulay et al., 2019). Furthermore, high-skilled scientist mobility has been shown to enhance invention, with immigration, diaspora networks, and return migration facilitating the cross-border diffusion of ideas (Kerr, 2008).

To test this mechanism, we leverage the OpenAlex database to construct disease-country-year measures of knowledge production and talent flows. We proxy for knowledge accumulation using

[25] We focus on U.S. disease prevalence, as it is the largest pharmaceutical market in the world. Column (1) of Appendix Table A9 uses the global prevalence rate as a robustness check.

[26] Although the FDA permits the use of foreign clinical data and multi-regional clinical trials (MRCTs), pivotal trials supporting New Drug Applications must establish safety and efficacy in populations relevant to the U.S. context (e.g., 21 CFR 314.106). In practice, this makes it difficult to rely primarily on Chinese-based trials for U.S. approval.

total PubMed-indexed publications and measure talent inflows using "returnees": scientists with at least three publications affiliated with U.S. institutions who subsequently published under a Chinese affiliation.

Figure 9 presents the temporal trends for China and the U.S. While China's scientific output has grown substantially, Panel (a) shows a steady, secular increase in publication volume since 2010, with no detectable structural break around 2016. Similarly, Panel (b) shows that the inflow of U.S.-trained talent has followed a smooth, long-term upward trajectory. These patterns suggest that while China's scientific capacity has been increasing, these supply-side factors lack the discontinuity needed to explain the post-2015 acceleration in trial activity.

We formally evaluate the contribution of these factors in Table 5 by estimating the effects of knowledge accumulation and talent inflow alongside NRDL exposure. Column (3) shows that paper volume is positively associated with trial activity, with an additional 1,000 papers corresponding to 18% more trials in a disease category, while Column (4) finds a significant positive relationship between returnee talent and trial growth, consistent with international expertise supporting domestic innovation. To address concerns that contemporaneous knowledge and talent measures may be noisy or mechanically correlated with clinical activity in the same year, Columns (3)–(4) of Appendix Table A9 replace them with three-year moving averages measured from year $t-2$ through year t. The estimates remain similar to the baseline results.

Importantly, the coefficient on NRDL exposure remains stable (and large, positive, and statistically significant) across all specifications. These findings suggest that absent the demand-side shock to expected returns, the accumulated supply of knowledge and talent would likely have translated into a more gradual increase in clinical activity rather than the dramatic shift documented in this paper.

Venture Capital Investment Venture capital plays an important role in financing pharmaceutical innovation, particularly in biotechnology, where young firms rely heavily on external private capital to fund R&D and clinical trials (e.g., Gompers and Lerner, 2001). Figure 10 plots both the number of VC investment deals and the total amount invested in U.S. and Chinese pharmaceutical and biotechnology firms over time separately. Although VC investment in China has grown substantially, it remains well below the level observed in the United States. Moreover, VC activity in both countries

appears to follow broader global monetary and financing cycles and exhibits no clear structural break around 2016, with a peak in 2021 and a sharp decline afterward. In China, total VC investment in pharmaceutical and biotechnology sectors increased from ¥2 billion in 2016 to a peak of ¥16 billion in 2021, before declining to ¥3 billion in 2024. We map firm-level investments to diseases according to each firm's clinical trial portfolio.[27] Column (5) of Table 5 shows that, after controlling for NRDL exposure, an additional $100 million in VC investment per disease is associated with an 8.1% (or roughly 1 trial) increase in clinical trial activity. Dropping government-backed venture capital or excluding firms receiving foreign revenue from licensing events deliver similar results (Columns (5)-(6) of Appendix Table A9).

Trial Application Reform We next consider several government policies that may have complemented the rise in drug innovation. The first is the 2015 clinical trial application (CTA) reform, which streamlined regulatory procedures by clearing the backlog of pending IND (investigational new drug) applications required before initiating clinical trials (Jia et al., 2024).

We collect application and approval dates for all IND submissions from the Center for Drug Evaluation of China's NMPA to calculate backlog duration. Figure 11 shows that the backlog accumulated before 2014 was resolved rapidly, and approval times flattened after 2019. This timing suggests that the reform's contribution was real but transitory: the clearance of pending applications likely contributed to the uptick in trial volume around 2016,[28] but a one-time removal of administrative bottlenecks cannot generate the persistent upward trajectory observed thereafter. Moreover, the reform did not specifically target innovative drugs, so it cannot explain the heterogeneous increases across therapeutic categories, firm nationality, and trial novelty.

The regression evidence points to the same conclusion. Column (6) of Table 5, which controls for both NRDL exposure and application backlog, shows that a 100-day reduction in backlog is associated with a 4.0% increase in clinical trials within a disease category, implying an 8% increase for the observed 200-day reduction from 2016 to 2024, a modest effect relative to the overall post-2015 expansion. Results are unaffected by controlling for the fraction of applications with long approval

[27] For example, if a firm conducts 10 of its 25 trials in a given disease, we assign 40% of investment in that firm to that disease.

[28] Other factors underlying the trial increase in 2016–2017 include the resumption of paused projects and the acceleration of projects already in development.

times to reflect regulatory uncertainty (Column (7) of Appendix Table A9). Taken together, these results indicate that the CTA reform, by shortening approval times, complemented the rise in trial activity around the reform years but is unlikely to have been its primary driver.

4.4 Industrial Policies

Made in China 2025 Made in China 2025 (MIC2025) is a national strategic plan released by China's State Council in May 2015, aimed at shifting China's growth model from large-scale, low-cost manufacturing toward technology-intensive production with higher value added. Biomedicine and pharmaceuticals are designated as one of its strategic industries.[29] As part of the policy implementation, MIC2025 designates a set of pilot cities and city clusters as key sites for experimentation and policy rollout, providing them with targeted support including fiscal subsidies, preferential financing, and coordinated regulatory arrangements.[30]

To assess whether the surge in R&D is driven by targeted support under MIC2025, Figure 12 excludes all trials sponsored by firms headquartered in MIC2025 pilot cities. Both the trajectory and the magnitude of the increase are comparable to the baseline event study using all trials (Figure 3(a)), indicating that the rise in clinical activity is not confined to cities receiving direct MIC2025 support. Consistent with this, the NRDL coefficient in Column (8) of Table 5, which excludes trials from firms headquartered in MIC2025 pilot cities, is comparable to the baseline estimate in Column (1) of Table 5, suggesting that both pilot and non-pilot cities exhibit comparable growth in R&D activity in disease categories with high NRDL exposure.

Other Policy Reforms Finally, we examine whether other government policies have contributed to the rise in clinical trial activity. We scrape all policy documents from the State Council Policy Document Library and use GPT-based classification to identify those relevant to biopharma innovation, grouping them into four categories: (a) advanced manufacturing policies, which aim to strengthen domestic production capacity; (b) innovation independence policies, which seek to reduce reliance on

[29] State Council of the People's Republic of China, "Notice on Issuing 'Made in China 2025'," 2015.

[30] These cities include: Ningbo, Quanzhou, Shenyang, Changchun, Wuhan, Wuzhong, Qingdao, Chengdu, Ganzhou, Guangzhou, Hefei, Huzhou, and city clusters: Sunanshi (Nanjing, Wuxi, Changzhou, Suzhou, Zhenjiang), Pearl River West Bank (Zhuhai, Foshan, Shunde, Zhongshan, Jiangmen, Yangjiang, Zhaoqing), Chang-Zhu-Tan-Heng (Changsha, Zhuzhou, Xiangtan, Hengyang), Zheng-Luo-Xin (Zhengzhou, Luoyang, Xinxiang). See "MIIT: Significant Progress in the Drive to Revitalize Manufacturing," *People's Daily Online*, October 27, 2017.

foreign technology; (c) capital market reform policies, which improve firms' access to financing; and (d) tax or subsidy policies, which provide direct fiscal incentives for R&D.

Column (7) of Table 5 quantifies the relationship between these policies and clinical trial activity. Although the count of biopharma-related policies is positively correlated with trial growth, the coefficient is modest economically, while the coefficient on NRDL exposure remains large and stable after controlling for these policies. This suggests that while broader state-led initiatives may have contributed at the margin, they do not account for the sharp post-2015 increase in clinical trials.

4.5 Relative Importance of Mechanisms

The preceding analyses identify several empirically important drivers of China's clinical expansion. Because supply-side and demand-side changes occurred simultaneously, we adopt a unified framework to quantify their relative importance. We proceed in two steps. First, we estimate semi-elasticities of clinical trial activity with respect to each mechanism using the most saturated specification, reported in Column (9) of Table 5, which regresses trial activity on NRDL exposure, knowledge accumulation, talent flows, VC investment, and other policy variables, controlling for disease-by-country and year fixed effects, as well as disease-country-year specific prevalence rates.

Second, we combine these coefficient estimates with observed changes for each mechanism from 2016 to 2024 to translate the semi-elasticities into implied changes in trial counts.[31] We aggregate the contribution of mechanism M across the constituent disease categories from the full set of 332:

$$\Delta Y_d(M) = \beta_M \times \sum_{t=2016}^{2023} \sum_{j \in d} (M_{j,t+1} - M_{j,t}) \times \text{TrialNumber}_{j,t}, \tag{4}$$

where β_M denotes the coefficient on each mechanism as estimated in Column (9) of Table 5, and "TrialNumber"$_{j,t}$ denotes the number of trials in disease j and year t in China. This approach quantifies the contributions of demand-pull and supply-push mechanisms, providing a ranking of the drivers behind China's surge in pharmaceutical innovation.

Figure 13 presents the results. To illustrate the economic magnitudes, we focus on Oncology, the largest therapeutic area in our sample. Out of the 1,004 additional oncology trials initiated in China in 2024 relative to the 2016 baseline, NRDL accounts for approximately 59%. Knowledge

[31] We exclude changes between 2015 and 2016, as this period predates the NRDL reform.

accumulation and talent flows together explain 21%, VC investment explains 19%, trial application reform explains 9.5%, while other policies account for a negligible share (less than 1%); the remaining variation is attributed to unobserved factors.[32] Across all therapeutic areas, the NRDL consistently emerges as the most influential driver, explaining at least 25% of the aggregate increase in clinical trial activity. These results reinforce a central finding of this paper: while secular growth in scientific knowledge, international talent flows, and venture capital financing provided a critical foundation for China's innovative capacity, the demand-side shock from the NRDL reform was the principal catalyst of the post-2015 acceleration, with other policies playing a comparatively modest role.

5 Welfare Implications

In this section, we provide a back-of-the-envelope calculation to benchmark the NRDL's long-run welfare gains from induced drug development against its short-run gains from expanded market access.

To fix ideas, consider a simple model in which each patented drug is produced by a monopolist setting price p_j^m. Patient demand is $q_j(p_j^m, \gamma_j)$, where γ_j denotes the coinsurance rate. If the drug is excluded from the national reimbursement list, $\gamma_j = 1$, and consumers bear the full cost out of pocket. The NRDL reform lowers the effective price faced by patients through two channels: the introduction of insurance coverage (with an average coinsurance rate of $\gamma_j^{\text{NRDL}} \approx 0.35$) and negotiated price reductions ($p_j^{\text{NRDL}} < p_j^m$). Together, these reduce out-of-pocket prices from p_j^m to $\gamma_j^{\text{NRDL}} p_j^{\text{NRDL}}$ and raise demand to $q_j(p_j^{\text{NRDL}}, \gamma_j^{\text{NRDL}})$. The resulting short-run welfare gain reflects increased utilization of existing innovative drugs, generating static surplus gains by mitigating monopoly markups. We also include changes in firm profit and government expenditure when calculating short-term welfare effects.

The long-run welfare gain operates through innovation incentives. Before the reform, a pharmaceutical company invests in drug development if expected profit (the clinical success rate η_j multiplied by the long-run monopolist profit conditional on success) exceeds R&D cost c_j: $\eta_j \Pi_j(p_j^m; \gamma) > c_j$. Post-reform, the NRDL expands demand, raising expected profits to $\Pi_j(p_j^{\text{NRDL}}, \gamma_j^{\text{NRDL}})$. This profit increase contributes to a rise in clinical trial activity, spurs drug development, and yields more drugs

[32] The contributions from different mechanisms may sum to above 100% because they are regression-based rather than components of an accounting identity. See also Autor et al. (2003).

in the future. The long-run consumer surplus gains are computed as:

$$\sum_{k \in \text{Future drug projects}} \eta_k \mathbb{1}[\eta_k \Pi_k(p_k^{\text{NRDL}}; \gamma_k^{\text{NRDL}}) > c_k] CS_k(p_k^{\text{NRDL}}, \gamma_k^{\text{NRDL}})$$

where CS_k denotes consumer surplus from drug project k and η_k denotes the clinical trial success rate. Long-run changes in firm profit and government expenditure are calculated analogously.

The static and dynamic gains differ in nature, not just in timing. Static gains arise from expanded access to existing drugs: lower prices reduce the Harberger deadweight loss created by pharmaceutical firms' market power. Dynamic gains, in contrast, arise from drugs that would not otherwise exist, and therefore comprise the entire consumer surplus (reflected by the full area under the demand curve) generated by each new drug, net of production costs. Ceteris paribus, the welfare gain per new drug should be much greater than the gain per existing drug brought into NRDL coverage.

For the calculation of short-term welfare gains, we borrow estimates of consumer surplus, firm profit, and government expenditure for all 57 cancer drugs included in the NRDL during 2016–2022 from Barwick et al. (2025). For these cancer drugs alone, the reform generates ¥35.6 billion ($5.1 billion) per year in consumer surplus, ¥22.9 billion in firm profits, and ¥22.5 billion in social surplus after netting out government spending.

The calculation of long-term welfare gains requires us to first quantify the discounted cumulative increase in oncology trials attributable to the NRDL and convert it into an expected number of new drugs, and second calculate the welfare benefits of these new drugs. We begin with the observed increase in oncology trials relative to the pre-2016 level: as reported in Appendix Table A1, the cumulative increase from 2016 to 2024 totals 7,084 trials.[33] To project beyond 2024, we conservatively assume that annual trial counts remain at the 2024 level, i.e., 1,004 trials above the pre-2016 baseline, and discount future years using a discount factor of 0.9. The cumulative discounted increase from 2016 onward is then $7{,}084 + 1{,}004 \times \frac{1}{1-0.9} = 17{,}124$ trials.[34] Applying the quantification results in Section 4.5, which attribute 59% of the increase in oncology trials to the NRDL reform, this corresponds to 10,103 NRDL-induced trials. Finally, given an average success rate of $\bar{\eta} = 1/123$ (123

[33] This is the cumulative sum of the year-over-2016 differences in trial counts (i.e., the difference between 2017 and 2016, between 2018 and 2016, and so on).

[34] This estimate represents a lower bound for several reasons. First, our 2024 trial count excludes ongoing trials that have not yet concluded. Second, we hold future trial counts flat despite a significant upward trend. Third, we apply a low discount factor, which further reduces the present discounted value of future trials.

trials per successful new drug in the oncology sector during our sample period), these trials translate into approximately 82 new oncology drugs.

The social value of these future drugs is uncertain ex ante. We proxy for it using the realized welfare gains from recent new drug launches in comparable oncology categories (based on demand and marginal cost estimates in Barwick et al. (2025)). Figure 14 presents the results. The dynamic consumer surplus gain is estimated at ¥92.8 billion per year (interquartile range: ¥[16.5, 136.7] billion), and the dynamic social surplus gain is ¥90.3 billion per year (interquartile range: ¥[16.6, 147.8] billion). Even under conservative assumptions, the dynamic gains are roughly four times the static efficiency gains, underscoring that the NRDL reform's most consequential welfare impact may operate through its effect on innovation incentives.

International Spillover Drug development is a global public good: once a molecule is developed and approved, it can potentially benefit patients everywhere. Successful products can reach foreign patients through two channels documented in Section 3.3: Chinese developers increasingly pursue foreign regulatory approval directly, as reflected in the rise of Chinese-sponsored trials in the U.S., or out-license ex-China development and commercialization rights to MNCs, as reflected in the surge of license-out transactions.[35]

To gauge the potential magnitude of these international spillovers, we compare per-drug revenues in China and the U.S. In China, an innovative oncology drug generated average annual sales of ¥0.78 billion (approximately $0.11 billion) in 2022; the corresponding U.S. figure is roughly $0.47 billion, about four times the Chinese benchmark.[36] This comparison implies that if NRDL-induced drugs were to reach the U.S. and other international markets, the resulting spillover gains could amount to several times China's domestic benefit.

[35]For example, toripalimab, developed by Shanghai Junshi Biosciences to treat nasopharyngeal carcinoma (a nose and throat cancer) and sold in the U.S. under the brand name Loqtorzi, illustrates the second channel: approved in China in 2018 and included in the NRDL in 2020, the drug was licensed to Coherus for U.S. and Canadian development and commercialization, and received FDA approval in 2023. Similarly, BeiGene's zanubrutinib (brand name Brukinsa) and tislelizumab (brand name TEVIMBRA) were first approved by the U.S. FDA in 2019 and 2024, respectively.

[36]See IQVIA report.

6 Conclusion

This paper documents an ongoing shift in the global landscape of pharmaceutical innovation. Using granular data on clinical trials and an event study framework, we provide the first empirical evidence of China's transition from a follower in generic manufacturing to a contributor at the global frontier of clinical R&D. By 2024, China's clinical trial activity had surged by over 170% relative to 2015 and benchmarked against the U.S., driven primarily by domestic firms and increasingly concentrated in high-novelty compounds, with early evidence of licensing and approval success.

Our analyses demonstrate that this transition was not a passive consequence of aggregate economic growth; we identify the 2016 National Reimbursement Drug List (NRDL) reform as its primary catalyst. A growth-accounting quantification reveals that this demand-pull effect explains a substantially larger share of the R&D surge than supply-side factors such as knowledge accumulation or talent inflows. Our welfare exercise further indicates that the long-run gains from induced innovation are at least four times the short-run gains from expanded access. Beyond these direct gains, NRDL delivers a subtler benefit: by pulling trials in China, it generates clinical evidence for populations historically underrepresented in U.S. and European trials, evidence that is more valuable because trial participants resemble the patients ultimately treated (Alsan et al., 2024).

These findings offer a new perspective on the policy studied here. While the pharmaceutical literature often frames the trade-off between static efficiency (patient access) and dynamic efficiency (innovation) as close to a zero-sum game, the Chinese experience suggests that a sufficiently large and well-designed market expansion can mitigate this tension, as the same reform that drove down out-of-pocket costs for hundreds of millions of patients simultaneously pulled frontier R&D into the domestic market. An important direction for future research is to examine optimal design for innovation policies that account for both static and dynamic gains.

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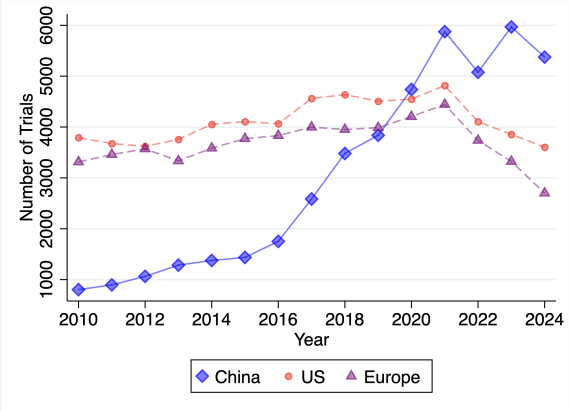
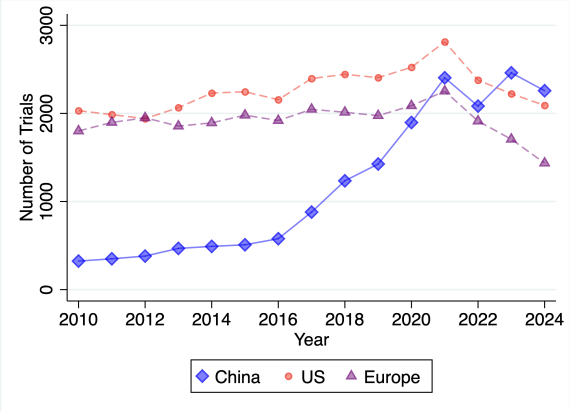
Figures

Figure 1: Time Trend - Trial Quantity and Novelty

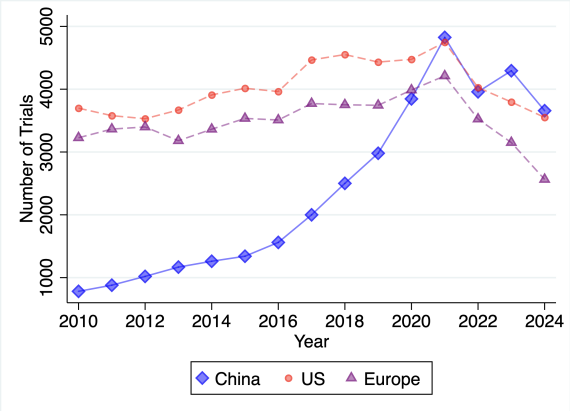
(a) All Trials
China vs U.S. vs Europe



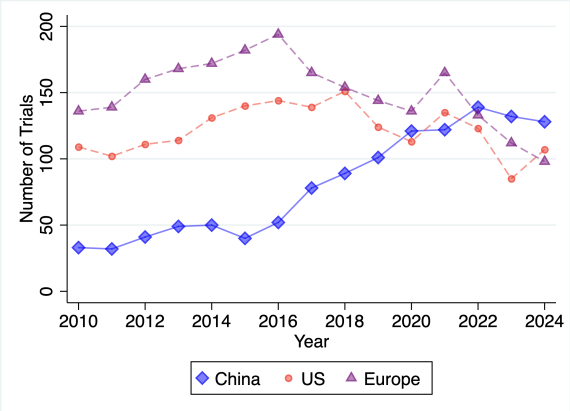
(b) Novelty Score > Median
China vs U.S. vs Europe



(c) Non-Generic Trials
China vs U.S. vs Europe



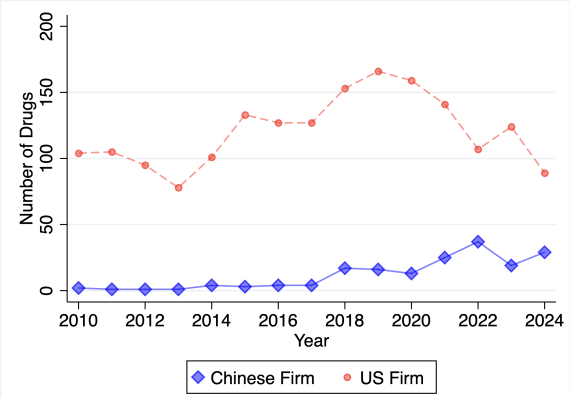
(d) Phase III Trials w. Innovative Control Arm
China vs U.S. vs Europe



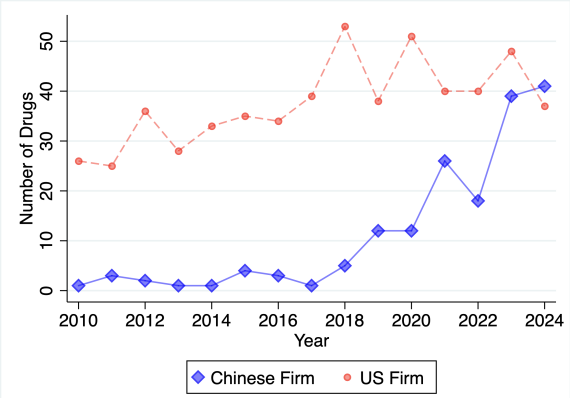
Notes. These figures plot the annual number of clinical trials launched in each year in China, the United States, and Europe. The vertical axis measures trial counts, and the horizontal axis indicates calendar years (2010–2024). Panel (a) compares all trials conducted in the three regions. Panel (b) restricts the sample to trials with above-global-median novelty scores, calculated following Dranove et al. (2022). Panel (c) restricts to trials investigating non-generic drugs, and Panel (d) limits the sample to Phase III trials that use a patented drug as the control arm. Data source: Citeline TrialTrove database.

Figure 2: Time Trend - Number of Drugs and New Firms

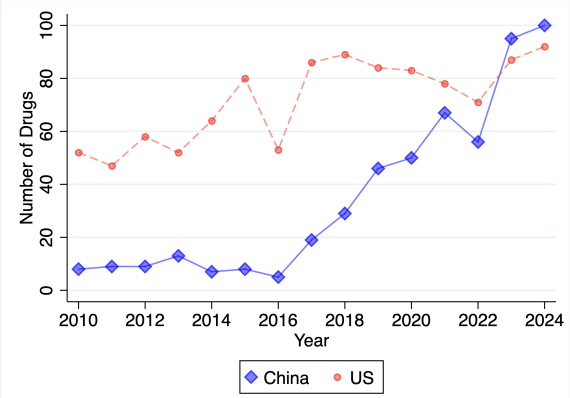
(a) Number of Licensed-Out Drugs
Chinese Firms vs U.S. Firms



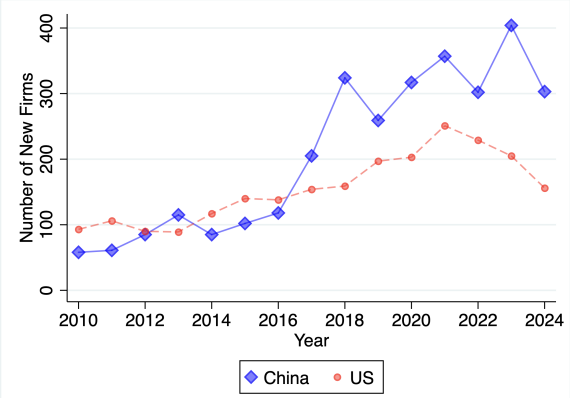
(b) First-in-world Regulatory Approval of Drugs
by Firms Headquartered in China vs U.S.



(c) Number of Drug Approvals
by Chinese vs U.S. Administration



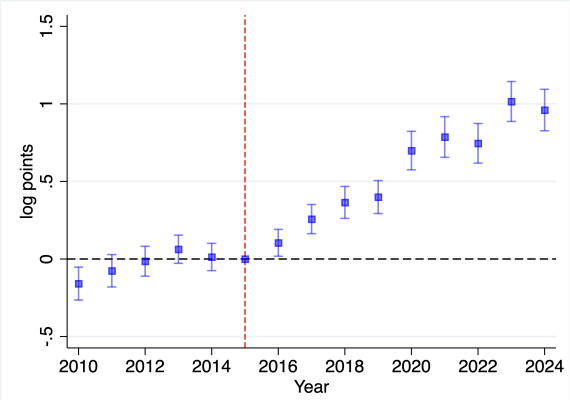
(d) Number of New Firms
China vs U.S.



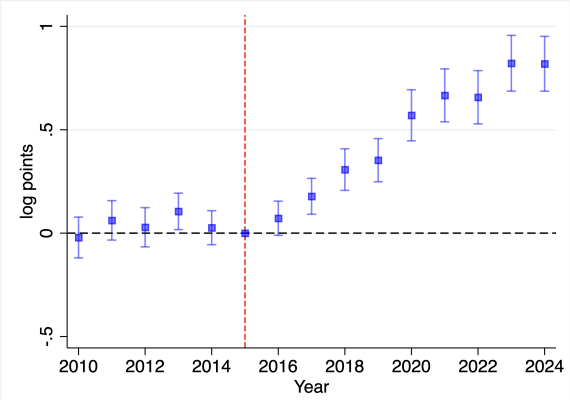
Notes. Panel (a) compares drugs licensed out to multinational corporations by firms headquartered in China and the U.S. Panel (b) compares first-in-world regulatory approvals for drugs developed by Chinese- vs. U.S.-headquartered firms. Panel (c) compares newly approved drugs by the Chinese and U.S. regulatory authorities. Panel (d) compares the number of firms conducting clinical trials for the first time in each country. Data source: Citeline Pharmaprojects database.

Figure 3: Event Study - Trial Quantity and Novelty

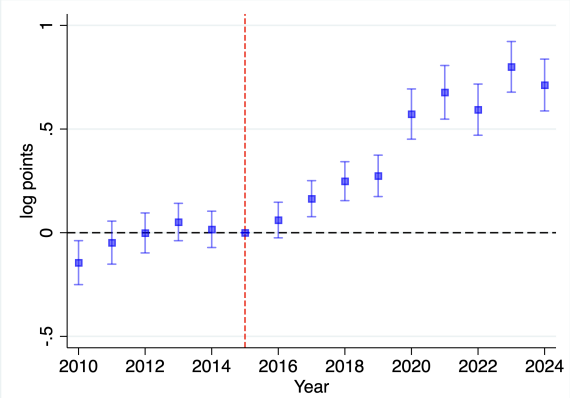
(a) All Trials
China vs U.S.



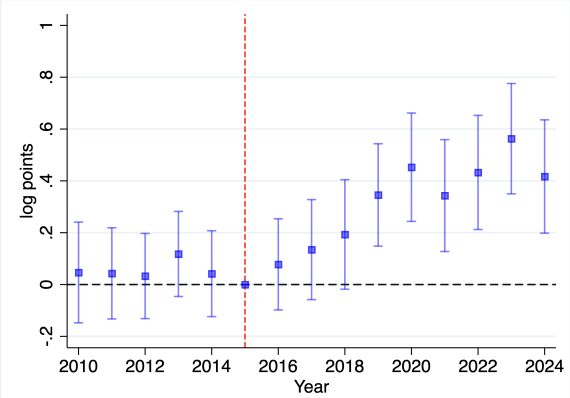
(b) Novelty Score > Median
China vs U.S.



(c) Non-Generic Trials
China vs U.S.

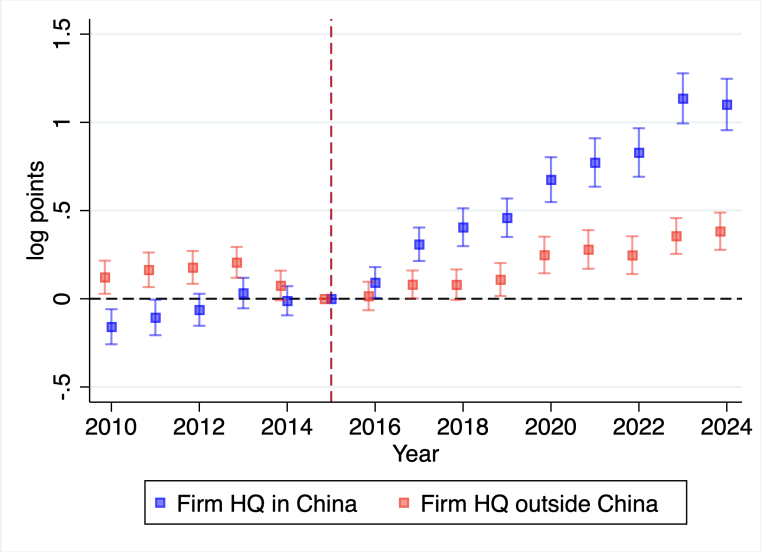


(d) Phase III Trials w. an Innovative Control Arm
China vs U.S.



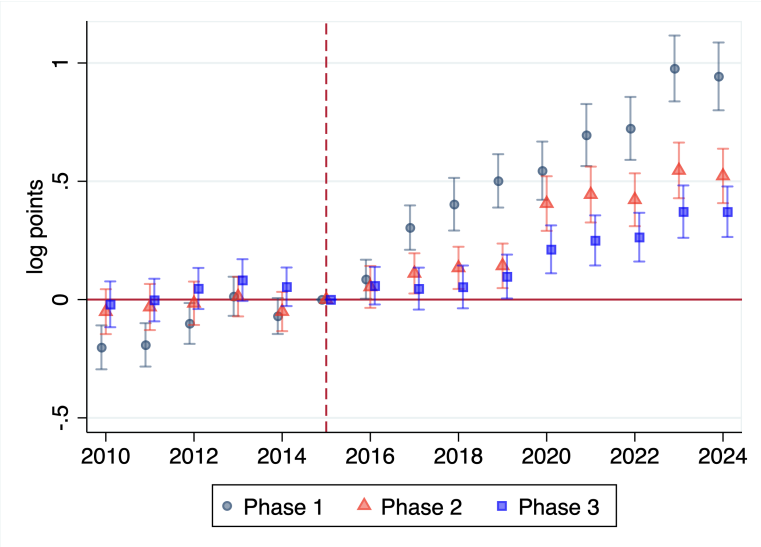
Notes. This figure presents an event-study analysis of clinical trial activity at the disease-country level, with 2015 as the base year and the U.S. as the control group. The vertical axis plots the estimated coefficients (in 100 log points) on the interactions between the China indicator and event-year dummies from the difference-in-differences specification, along with 95% confidence intervals. The horizontal axis indicates calendar year (2010–2024). Panel (a) includes all trials conducted in China and the U.S., Panel (b) restricts to trials with above-global-median novelty scores, and Panel (c) restricts to trials investigating non-generic compounds. These three panels use $\log(\text{trials}+1)$ as the dependent variable, where trials is the number of trials launched in that year. Panel (d) focuses on Phase III trials that use a patented drug as the control arm. Because the large number of zero trials in this subsample attenuates estimates (relative to the raw data shown in Figure 1(d)), we follow Chen and Roth (2024) and define the dependent variable as log(trials) when at least one trial is observed in a country-disease-year cell and as -1 otherwise. Results are robust to alternative cutoffs. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Figure 4: Event Study - Trials by Chinese Firms vs Non-Chinese Firms



Notes. This figure presents an event-study analysis of clinical trial activity in China, separately for Chinese and non-Chinese firms, with 2015 as the base year and U.S. trials as the control group. The blue line plots the coefficients on the interactions between ChineseFirmInChina and event-year indicators, while the red line plots the coefficients on the interactions between NonChineseFirmInChina and event-year indicators. The vertical bars represent 95% confidence intervals. The dependent variable is $\log(\text{trials}+1)$. The specification includes disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

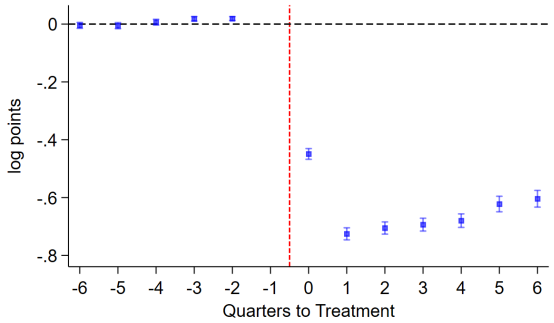
Figure 5: Event Study - Trials by Different Phases



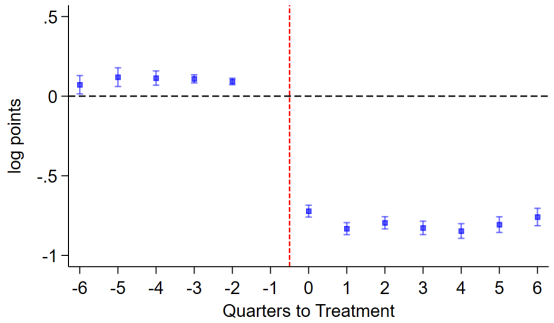
Notes. This figure presents an event-study analysis of clinical trial activity in China, separately for Phase I to Phase III, with 2015 as the base year and U.S. trials as the control group. The vertical bars represent 95% confidence intervals. The dependent variable is $\log(\text{trials}+1)$. The specification includes disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Figure 6: Effects of the NRDL Reform on Price and Quantity

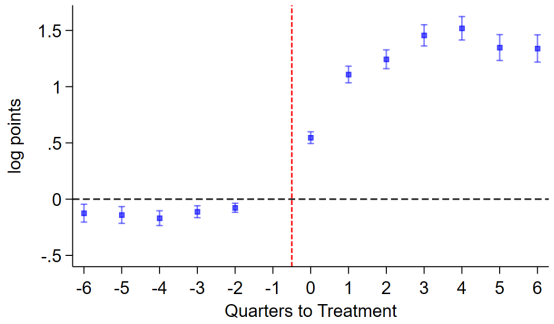
(a) Log Retail Price: All Drugs



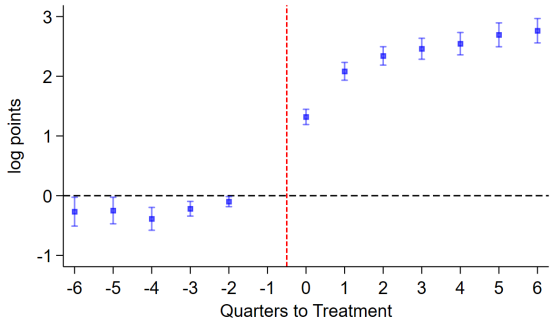
(b) Log Retail Price: Cancer Drugs



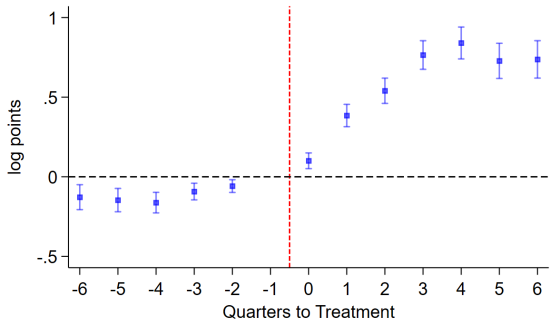
(c) Log Quantity: All Drugs



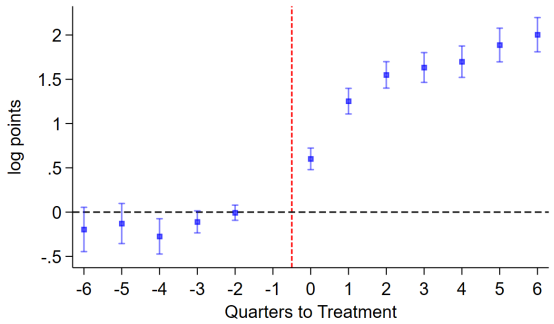
(d) Log Quantity: Cancer Drugs



(e) Log Revenue: All Drugs

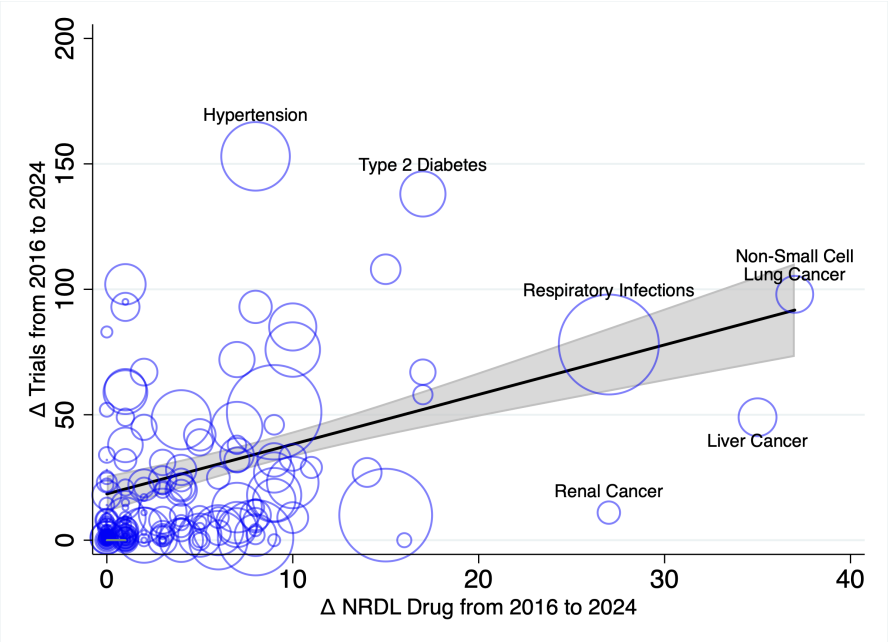


(f) Log Revenue: Cancer Drugs



Notes. This figure reports the Callaway and Sant'Anna (2021) estimated effects of the NRDL Reform on log(retail prices) in Panels (a) and (b), log(quantities) in Panels (c) and (d), and log(revenue) in Panels (e) and (f) using data from 2017 to 2023. The treated group is the innovative drugs included in NRDL, and the control group is the eligible yet not included drugs. The horizontal axis denotes quarters relative to the NRDL inclusion. The vertical axis reports estimated treatment effects in 100 log points and 95% confidence intervals using the CSDID method from Callaway and Sant'Anna (2021). Data source: SinoHealth.

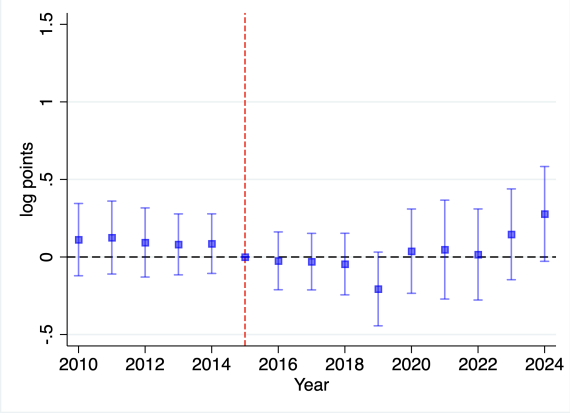
Figure 7: Mechanism - Effect of NRDL across Disease Categories



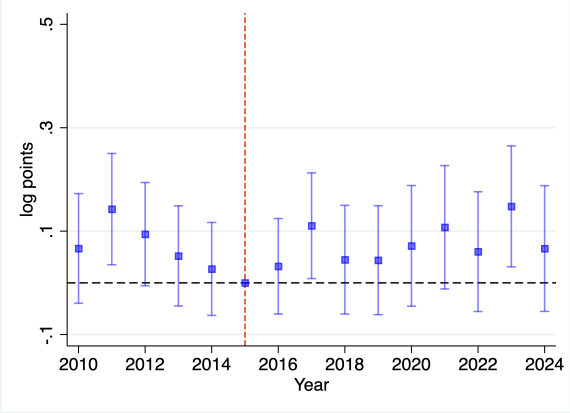
Notes. This figure plots the change in clinical trial activity against the change in the number of NRDL-included drugs between 2016 and 2024 for each disease category. Circle size is proportional to the total number of drugs in the category. Data source: Citeline TrialTrove Database.

Figure 8: Placebo Tests

(a) Categories without NRDL Exposure (Placebo)



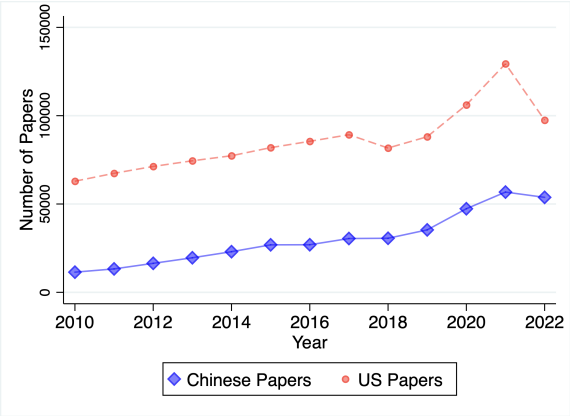
(b) Trials in NRDL-exposed categories in Europe



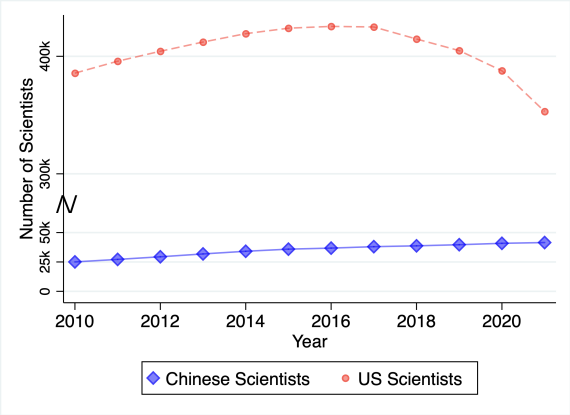
Notes. This figure is a placebo test of Equation (3). Panel (a) restricts to disease categories that did not experience NRDL expansion during our sample period. Oncology and infectious disease are excluded due to high expectations of future coverage (oncology) and COVID (infectious disease). Panel (b) replaces Chinese trials with European trials, and we find no increase in European clinical trials in NRDL-exposed diseases. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Figure 9: Mechanism - Time Trend of Scientific Publications and Talent Inflows

(a) Number of Publications



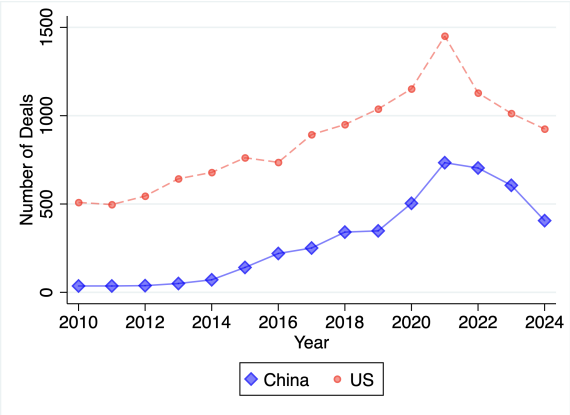
(b) Number of Scientists w. U.S. Experience



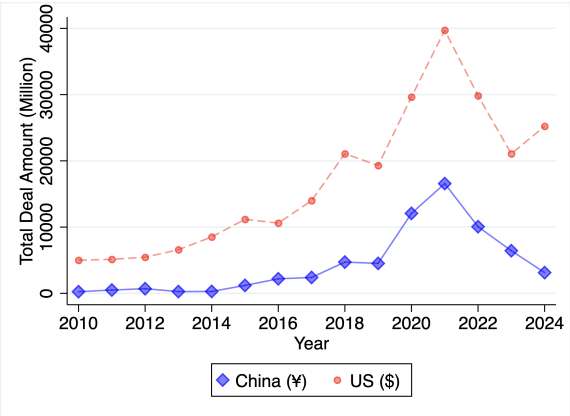
Notes. This figure plots trends in knowledge production and international talent flows for China and the U.S. Panel (a) reports the annual number of publications (restricted to papers with PubMed IDs). Panel (b) reports the number of scientists with U.S. experience, defined as those with at least three publications under a U.S. affiliation. For China, this measure captures "returnees": scientists with at least three U.S.-affiliated publications who subsequently publish under a Chinese affiliation. Data source: OpenAlex publication database.

Figure 10: Mechanism - VC Investment

(a) Number of Deals

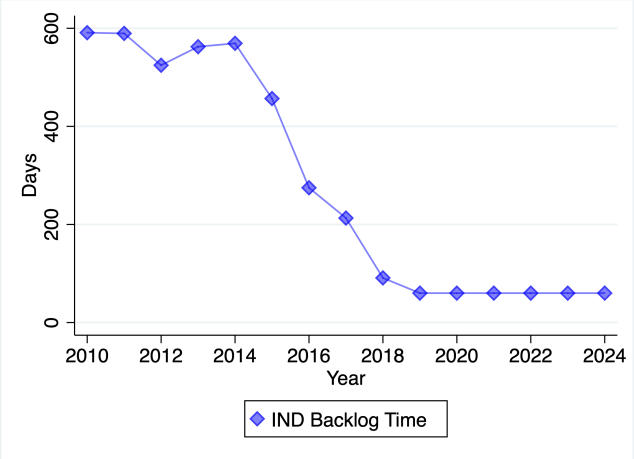


(b) Total Deal Amount



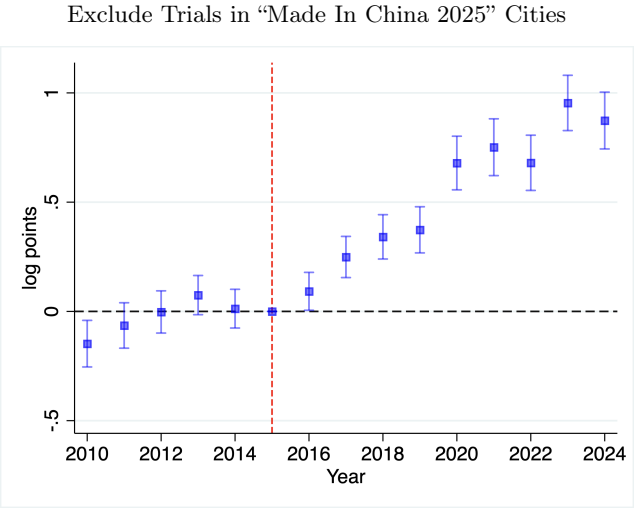
Notes. This figure plots trends in venture capital (VC) investment deals and total VC investment amounts for China and the U.S. Panel (a) reports the number of VC deals, and Panel (b) aggregates the VC investment amount to the country-year level. For Panel (b), the VC amount is measured in Chinese yuan for China and in U.S. dollars for the U.S.; the exchange rate is approximately 1 USD $\approx$ 7 CNY. Data source: PitchBook database.

Figure 11: Mechanism - Application Backlog Time in Days



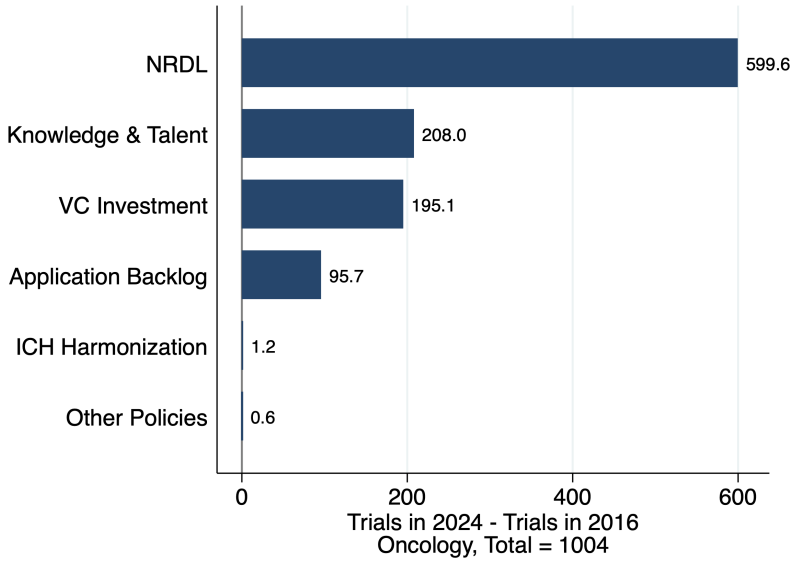
Notes. This figure plots the mean application backlog in days (i.e. approval date - application date) by year. The vertical axis reports the average regulatory backlog, while the horizontal axis indicates calendar year. Data source: National Medical Products Administration (NMPA).

Figure 12: Mechanism - "Made in China 2025"



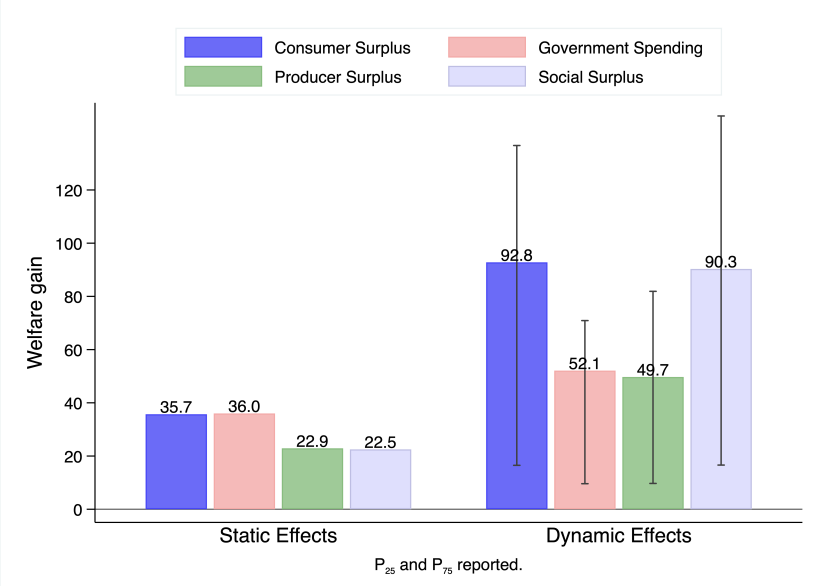
Notes. This figure presents an event-study analysis of clinical trial activity at the disease-country-year level, with 2015 as the base year. It replicates the baseline specification from Figure 3(a), but restricts the sample to trials sponsored by firms headquartered outside the "Made in China 2025" cities or city clusters, with U.S. trials as the control group. The specification includes disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove Database and the State Council Policy Document Library.

Figure 13: Quantification of Different Mechanisms (Oncology Trials)



Notes. This figure quantifies the contribution of each mechanism to the observed increase in clinical trials in the oncology therapeutic area. The contribution of each mechanism is computed by multiplying the observed change in the mechanism by its corresponding coefficient from Table 5, scaling by the total trial counts within each disease category, and aggregating to the oncology therapeutic area. The procedure follows Equation 4. Data sources: Citeline TrialTrove, SinoHealth, OpenAlex, PitchBook, and the State Council Policy Document Library.

Figure 14: Welfare Decomposition: Static vs. Dynamic Gains (Billions of ¥)



Notes. This figure compares the static (short-run) and dynamic (long-run) welfare gains from the NRDL reform, decomposed into consumer surplus, government spending, producer surplus, and social surplus. Static gains reflect expanded patient access to existing drugs. Dynamic gains capture long-run welfare effects through induced pharmaceutical innovation and future drug development. The vertical bars report the interquartile range of dynamic gains. All values are reported in billions of ¥.

Tables

Table 1: Number of New Drugs included in NRDL 2016-2025

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	All
# Drugs Added via NRDL Negotiation	3	31	17	52	89	54	93	113	78	104	634

Notes. This table reports the total number of chemical drugs/biologics included in NRDL since 2016. Traditional Chinese medicines are excluded. Data source: National Health Security Administration (NHSA) website.

Table 2: Descriptive Statistics - Number of Trials by Disease and Country (2010-2024)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	China				US			
	Phase I	Phase II	Phase III	Phase IV	Phase I	Phase II	Phase III	Phase IV
Autoimmune/Inflammation	2061	1154	731	920	1529	2730	1758	1060
Central Nervous System (CNS)	2327	508	441	2029	2091	3004	2030	2746
Cardiovascular	2726	343	534	1572	797	1053	854	1005
Genitourinary	416	102	96	428	136	188	184	288
Infectious Disease	2198	853	618	1306	1735	1853	1145	1256
Metabolic/Endocrinology	2291	462	572	1294	1296	1589	1154	905
Oncology	4293	7711	2528	1463	6579	10241	1892	348
Ophthalmology	85	92	90	142	130	499	311	204
Vaccines (Infectious Disease)	33	13	53	42	36	48	34	12

Notes. This table reports the total number of clinical trials by therapeutic area and trial phase (Phase I–IV), aggregated across 2010–2024 for China and the U.S. Data source: Citeline TrialTrove Database.

Table 3: Difference in Differences Regression - Trial Quantity and Novelty

	(1)	(2)	(3)	(4)
	(Log) Number of All Trials	(Log) Novelty Score > Median Trials	(Log) Non-Generic Trials	(Log) Phase III Trials w. Innovative Control
China × (Year ≥ 2016)	0.621***	0.460***	0.477***	0.282***
	(0.045)	(0.044)	(0.043)	(0.057)
Constant	1.251***	0.923***	1.233***	-0.608***
	(0.012)	(0.012)	(0.012)	(0.015)
Disease × Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.864	0.829	0.862	0.512
Observations	9030	9030	9030	3990

Notes. This table reports difference-in-differences estimates of Equation (1). The key independent variable is an indicator for post-2015 years interacted with an indicator for China, with the U.S. as the control group. The dependent variable is log(all trials + 1) for Column (1), log(trials with novelty score above median + 1) for Column (2), and log(trials investigating non-generic compounds + 1) for Column (3). Column (4) restricts to Phase III trials that use a patented drug as the control arm. Because the large number of zero-valued observations in this subsample attenuates estimates (relative to the raw data shown in Figure 1(d)), we follow Chen and Roth (2024) and define the dependent variable as log(trials) when at least one trial is observed in a country-disease-year cell and as −1 otherwise. All specifications include disease-by-country fixed effects and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Table 4: Mechanism Test - NRDL Intensity and Trial Counts

	(1)	(2)	(3)	(4)
D.V.	(Log) Number of Trials			
	Panel A: OLS			
Log(Number of NRDL-Included Drugs)	0.163***			
	(0.038)			
Log(Revenue of NRDL-Included Drugs)		0.142***		
		(0.033)		
Ratio of NRDL-Included Drugs			0.466***	
			(0.164)	
Revenue Ratio of NRDL-Included Drugs				0.524***
				(0.143)
Constant	1.141***	1.123***	1.119***	1.105***
	(0.137)	(0.135)	(0.136)	(0.135)
Mean of Independent Variable	0.428	0.396	0.052	0.091
	Panel B: IV			
Log(Number of NRDL-Included Drugs)	0.646***			
	(0.221)			
Log(Revenue of NRDL-Included Drugs)		0.577***		
		(0.211)		
Ratio of NRDL-Included Drugs			0.812***	
			(0.291)	
Revenue Ratio of NRDL-Included Drugs				0.798***
				(0.250)
	First Stage			
Elasticity × NRDL Expansion	44.4865***	28.8780**	60.4136***	68.5741***
	(6.5604)	(13.1497)	(5.1067)	(5.3294)
US Innovative Drugs × NRDL Expansion	0.8020***	0.8985***	0.0063	0.0838*
	(0.1614)	(0.1891)	(0.0174)	(0.0484)
KP F-stat	37.70	14.20	70.05	83.08
Disease × Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. This table estimates the effect of NRDL exposure on clinical trial activity using disease-country-year level observations. NRDL exposure is measured in four ways: (1) log number of NRDL-included drugs, (2) log revenue of NRDL-included drugs, (3) share of NRDL-included drugs among all drugs in the disease area, and (4) revenue ratio of NRDL-included drugs relative to total disease-level drug revenues. The dependent variable is log(number of trials + 1). Panel A reports the OLS estimation results, and Panel B reports the IV estimation results. The first instrument is *Elasticity* × *NRDL Expansion*. *Elasticity* is estimated separately for each disease from a regression of $\log(1 + \text{revenue})$ on an indicator for post-NRDL inclusion, where post-NRDL inclusion is defined relative to the earliest year in which a drug for that disease is included in the NRDL. *NRDL Expansion* is measured by total insurance expenditure on innovative drugs, which is zero before the 2016 NRDL reform. The second instrument is *2010-2015 U.S. Innovative Drugs* × *NRDL Expansion*. *2010-2015 U.S. Innovative Drugs* is defined as the number of innovative drugs approved in the U.S. during 2010–2015 for each disease. All specifications include disease-by-country and year fixed effects and control for the number of drugs and prevalence rate in a given disease-country-year. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove database and SinoHealth.

Table 5: Summary of Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mechanisms	NRDL	ICH Harmonization	Papers	Talents	VC Investment	Application Backlog	Other Policies	MadeInChina 2025	All
D.V.	(Log) Number of Trials								
Revenue Ratio of NRDL-Included Drugs	0.798***	0.800***	0.785***	0.783***	0.807***	0.663***	0.706***	0.613***	0.651***
	(0.250)	(0.253)	(0.249)	(0.250)	(0.245)	(0.248)	(0.246)	(0.236)	(0.243)
US Prevalence (Per Hundred) × Post-ICH		0.010						0.005	0.005
		(0.007)						(0.007)	(0.007)
Number of Papers (Thousands)			0.179**					0.221*	0.219*
			(0.082)					(0.115)	(0.116)
Number of Scientists w. US Experience (Thousands)				0.023***				-0.028	-0.026
				(0.008)				(0.025)	(0.025)
Deal Amount (Billion USD)					0.811***			0.688**	0.700**
					(0.300)			(0.270)	(0.272)
Application Backlog Days (Hundreds)						-0.039***		-0.029***	-0.031***
						(0.007)		(0.007)	(0.007)
Number of Policies							0.005***	0.003**	0.003**
							(0.001)	(0.001)	(0.001)
Disease × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP F-stat	83.083	82.283	82.976	82.879	83.105	83.642	86.624	84.701	84.701
Observations	9030	9030	9030	9030	9030	9030	9030	9030	9030

Notes. This table examines the contribution of various demand- and supply-side mechanisms to clinical trial activity, using disease-country-year-level observations. Column (1) replicates Column (4) of Panel B of Table 4. Column (2) adds ICH harmonization, measured as the interaction between U.S. disease prevalence and a post-ICH indicator. Column (3) examines the effect of scientific publications, and Column (4) examines the effect of returnees (scientists with U.S. experience). Column (5) examines venture capital investment and uses the annual investment amount as the independent variable. Column (6) examines the trial application reform, where the key independent variable is the average backlog in days (approval date minus application date) by disease category. Column (7) examines other policies and uses the annual number of industrial policies as the key regressor. Column (8) tests robustness to the Made in China 2025 initiative by excluding all trials sponsored by firms headquartered in cities or city clusters designated under the program. Column (9) includes all mechanisms jointly. The dependent variable is $\log(\text{trials}+1)$. NRDL exposure in all columns are instrumented by *Elasticity* × *NRDL Expansion* and *2010-2015 U.S. Innovative Drugs* × *NRDL Expansion* as in Table 4. All specifications include disease-by-country and year fixed effects and control for the number of drugs and prevalence rate in a given disease-country-year. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove, SinoHealth, OpenAlex, PitchBook, and the State Council Policy Document Library.

Online Appendix

A Auxiliary Data Cleaning and Variable Construction

A.1 Papers and Scientists

OpenAlex provides comprehensive, high-quality metadata on scientific publications, including publication year, author names, affiliations, citations, journal identifiers, and concept tags that summarize a paper's scientific content (Priem et al., 2022). To study knowledge production relevant to biopharma innovation, we focus on papers whose first or last authors are affiliated with institutions in China or the United States and restrict the sample to publications with valid PubMed IDs to ensure biomedical relevance. In total, there are 33,809,530 OpenAlex publications with PubMed IDs. Among these, 9,734,217 are affiliated with the U.S., and 2,321,944 are affiliated with China.

After each paper is linked to one or more Citeline disease categories,[37] we construct disease-year level measures of knowledge quantity and international talent flows. These measures aggregate paper-level or author-level information to the disease-country-year unit of analysis used in the main text.

Knowledge quantity (number of papers). Knowledge quantity is defined as the total number of PubMed-indexed papers in a given disease-country-year. If a paper maps to multiple diseases, we assign fractional counts based on the number of disease assignments. The distribution of paper counts varies substantially across diseases, with a median of 31 papers and a mean of 199 papers at the disease-country-year level.

Talent flows (weighted number of scientists with U.S. experience). Talent flows capture the presence of researchers with international training or collaboration. A scientist is classified as having U.S. experience if they have published at least three papers with a U.S. affiliation on or before year t. We then compute, for each disease-year, the weighted sum of such scientists, where each scientist's weight equals the share of their total publications associated with that disease category. For example, if 50% of a scientist's publications map to Disease A and 20% to Disease B, they contribute weights of 0.5 and 0.2, respectively. There are 7,552,293 unique scientists in OpenAlex, and among them, 2,539,289 have prior experience in the United States.

[37] Details on the linkage can be found in Appendix B.2.

Together, these measures allow us to quantify how scientific knowledge and international talent evolve across diseases and over time, and to examine whether these upstream factors help explain the rise of clinical trial activity documented in the main analysis.

A.2 Application Backlog Time

The clinical trial application reform in 2015, studied in Jia et al. (2024), streamlined regulatory procedures by clearing the backlog of pending IND (investigational new drug) applications, which are required before initiating clinical trials for new drugs under investigation. To calculate application backlog days across diseases and over time, we collect the application and approval dates for almost all IND applications from the Center for Drug Evaluation of China's NMPA. The detailed data collection and cleaning process is as follows.

First, we collect data on all IND applications from the Center for Drug Evaluation (CDE) of China's National Medical Products Administration (NMPA). The NMPA publicly discloses all drug applications on its website,[38] including information such as the *Application ID*, *Drug Name*, *Drug Type*, *Application Type*, *Registration Category*, *Company Name*, and *Submission Date*. In addition, the NMPA provides the approval date for each application on a separate webpage,[39] which we merge to construct the full application and approval timeline.

Second, we restrict the sample to applications whose fourth character is the letter "L," indicating clinical trial applications, and whose "Application Type" is 1 or 2, which correspond to innovative drugs and are therefore relevant for our focus on IND applications. Moreover, in July 2018, the NMPA introduced the implied approval (silent approval) system, under which applications pending for more than 60 days are automatically approved. This policy change is reflected in the data: after its introduction, most applications no longer received mailed approval documents, indicating that the silent approval mechanism was effectively in operation. However, because some applications were still rejected, we additionally scraped the database of silent approvals and matched entries from this database to the main dataset using the application acceptance number.

Finally, we link these IND drugs to their corresponding therapeutic areas and disease categories. We first use large language models to classify diseases based on drug names, company information,

[38] https://www.cde.org.cn/main/xxgk/listpage/9f9c74c73e0f8f56a8bfbc646055026d

[39] https://www.nmpa.gov.cn/zwfw/zwfwpjfbzs/pjfbzsyp/index.html

and drug types. We then search the drug names in the Citeline Pharmaprojects database, which provides drug name histories, corresponding diseases, and textual descriptions. We feed this additional information back to a large language model to perform reclassification. This procedure yields 15,079 IND applications with classified diseases and calculated application backlog days.

```
# GPT prompt
def classify_direct(drug_name, drug_type, company):
    prompt = f"""
        You are a senior pharmaceutical and clinical indication expert.
        Please determine the therapeutic area and disease category based on
        the drug name I provide, and return the confidence level of this judgment.
        First choose ONE therapeutic_area.
        Then choose ONE disease_category ONLY from that area.

def classify_with_evidence(drug_name, drug_type, company, candidates):
    evidence = "\n\n".join(f"[{i+1}] {c['summary']}" for i, c in enumerate(candidates))
    prompt = f"""
        You are a senior pharmaceutical and clinical indication expert.
        Please determine the therapeutic area and disease category based on
        the drug name and evidence I provide, and return the confidence level
        of this judgment.
        First choose ONE therapeutic_area.
        Then choose ONE disease_category ONLY from that area.
```

A.3 Policy Documents and Classification

We also scraped all biopharma-related policies in China from the State Council Policy Document Library. There are 273 policy documents relevant to biopharma innovation. We use GPT to classify these documents into four categories: (a) advanced manufacturing policies that promote the scale-up and modernization of industry production capacity; (b) innovation independence policies that aim to strengthen domestic R&D capabilities and reduce reliance on foreign technologies; (c) capital market reform policies that lower financing barriers and improve firms' access to external funding; and (d) tax and subsidy policies that provide fiscal incentives to support innovation. The detailed steps are as follows:

To construct this dataset, we first scraped all policy documents available in the State Council Policy Document Library, obtaining 18,488 entries. We then implemented a two-stage classification procedure using GPT-4o. In the first stage, we used a broad screening prompt to filter out all policies potentially related to the four categories of innovation policy described above. This step substantially reduced the number of documents requiring manual or fine-grained review. In the

second stage, we applied a more detailed prompt to each remaining document, asking the model to assign (i) a relevance score capturing how closely the policy pertains to biopharma innovation and (ii) a brief explanatory note summarizing the policy's purpose and mechanism. The first stage returned 3,474 policy documents relevant to innovation. These documents were further scored in the second stage. Among them, 273 have a relevance score greater than 0.5. These outputs were used both to validate relevance and to facilitate the final four-way policy categorization described above.

The two prompts used in this procedure are provided below:

```
# GPT prompt
SYSTEM_PROMPT = (
    "You are a careful Chinese policy classification expert."
    "You will receive UP TO 10 Chinese policy documents at once."
    "For EACH document, you must extract:"
    "1) the policy date (政策日期) from the text "
    "(any explicit date of issuance/publishing/promulgation; "
    "return as the original string; if none, return \"\")."
    "2) whether it clearly relates to these 4 themes (0/1):"
    "   - high_end_mfg: 高端制造业/高端装备/战略性新兴产业/高端生物医药制造 等。"
    "   - innovation_independence: "
    "     自主创新/科技自立自强/提升原始创新能力/创新平台与人才基地建设 等。"
    "   - capital_market_reforms: 支持通过资本市场/多层次资本市场/股权基金/债券/上市/并购/"
    "     融资工具来促进上述产业或创新的政策。"
    "   - tax_subsidy: 对医药/药物研发/临床试验/"
    "     创新平台等提供的减税、税收优惠、财政补贴、进口免税、费用减免、贷款贴息等。"
    "Return STRICT JSON ONLY, as a list of objects, in the SAME ORDER as input."
)
```

```
# GPT prompt
SYSTEM_PROMPT = (
    "You are a senior policy evaluation expert "
    "working inside a pharmaceutical company in China."
    "You will be shown Chinese policy documents."
    "Your task is to judge **specifically from the perspective "
    "of a drug/biopharmaceutical R&D enterprise** whether this policy creates "
    "incentives to invest more in drug R&D."
    "When you evaluate, consider the following channels:"
    "1) The policy directly reduces R&D cost "
    "(税收优惠、财政补贴、进口免税、费用加计扣除、贷款贴息等)."
    "2) The policy increases the expected revenue/profit from new drugs "
    "(医保支付、带量采购配套激励、市场准入加速、知识产权保护等)."
    "3) The policy expands or improves the domestic human capital / innovation"
    "ecosystem for biopharma (人才计划、平台建设、国家重点实验室、创新载体、医工结合)."
    "4) The policy explicitly includes '高端生物医药制造', '生物医药', '医药产业' "
    "within broader high-end manufacturing / strategic emerging industries "
    "and provides concrete support measures."
    "Important:"
    "- Some policies talk about 'high-end manufacturing', "
    "'strategic emerging industries', or 'innovation-driven development'. "
    "You must judge whether biopharma / drug R&D is "
```

```
    "**actually covered or very likely covered** by that scope."
    "- If the policy is very general, very macro, or only about administration"
    "without concrete support instruments, the incentive should be low."
    "- Output a score between 0 and 1 (inclusive). "
    "0 = no meaningful incentive for drug R&D. 1 = very strong and direct incentive. "
    "Values in between (e.g. 0.3, 0.5, 0.8) represent your strength of belief."
    "Return STRICT JSON ONLY, in a list of objects, in the same order as input."
)
```

B Linkage across Datasets

B.1 Linking Citeline Data to SinoHealth and GBD Data

Citeline provides detailed disease information for each clinical trial and drug project, covering nine therapeutic areas and 332 granular disease categories. Therapeutic areas include Oncology, Autoimmune or Inflammation, Central Nervous System (CNS), Metabolic Endocrinology, Cardiovascular, Infectious Disease, Genitourinary, Ophthalmology, and Vaccines. Examples of disease categories are Non-Small Cell Lung Cancer, Type 2 Diabetes, and Rheumatoid Arthritis. In contrast, the SinoHealth sales data report molecule names (and ATC classification) and sales volumes, but do not contain disease classifications. There are 1,377 unique molecules. To merge the two datasets, we perform a multi-step mapping procedure that combines structured ATC information with LLM-assisted classification and expert review.

First, we construct candidate disease information for each drug. For every drug in the SinoHealth dataset, we extract (i) the drug name, including all synonyms, and (ii) its ATC (Anatomical Therapeutic Chemical) classification. We also assemble the complete list of 332 disease categories from Citeline, which will serve as the candidate set to which each SinoHealth drug can be assigned. Second, we use GPT-4o to generate disease assignments based on drug profiles. We provide GPT-4o with the drug name, its ATC code, and the full set of disease categories. The model is instructed to determine the most likely disease indications for each drug and to output at most five disease categories in ranked order of relevance. This step leverages GPT's ability to interpret pharmaceutical naming conventions, ATC structure, and therapeutic context. Third, we implement manual clinical validation by domain experts.

One drug might be linked to several diseases. For instance, a typical drug is mapped to three disease categories, reflecting the common presence of multiple approved or off-label indications. We

divide the drug sales equally across the linked diseases.

Together, this pipeline enables us to reliably map sales data to disease categories at a level of granularity comparable to Citeline, allowing us to measure disease-specific market expansion and relate it to clinical trial activity. We apply the same pipeline to link Citeline data with disease prevalence measures from the Global Burden of Disease database.

The prompt used for GPT-4o is as follows:

```
# GPT prompt
message_content = (
    "We provide information about drugs and diseases. "
    "For each drug, we include details in Chinese, such as the drug name "
    "and its ATC classification. "
    "Please primarily rely on the most granular information available, "
    "such as the fields 'shiyingzheng_fenlei' and 'atc4_fenlei', "
    "when making your judgment. "
    "For diseases, we provide a list of disease names (i.e., category) "
    "and their category in a format starting with a numeric disease id. "
    "Please determine which disease(s) this drug is likely used to treat, "
    "based on the drug's information and your knowledge. "
    "Select AT MOST 5 relevant diseases from the disease list, "
    "ranked in descending order of relevance. "
    "Please ONLY output from the disease list in its original format. "
    "Do NOT include any other information. "
    "Return in the format starting with: 'Answer:' followed by the diseases "
    "separated by periods. "
    "Example output: "
    "Answer: 1-(therapeutic area: ...); (disease category: ...). "
    "2-(therapeutic area: ...); (disease category: ...)."
    " "
    f"{text}"
)

# Send message_content to the GPT model and retrieve output
completion = call_gpt_api(
    client=client,
    model=MODEL,
    messages=[
        {"role": "system", "content": "You are a healthcare economist"},
        {"role": "user", "content": message_content},
    ],
    temperature=0.5
)

gpt_output = completion.choices[0].message.content.strip()
```

B.2 Linking Citeline Data to OpenAlex Data

Linking OpenAlex publications to Citeline disease categories is challenging for two main reasons. First, the scale of the data makes direct paper-level classification infeasible. Our sample contains

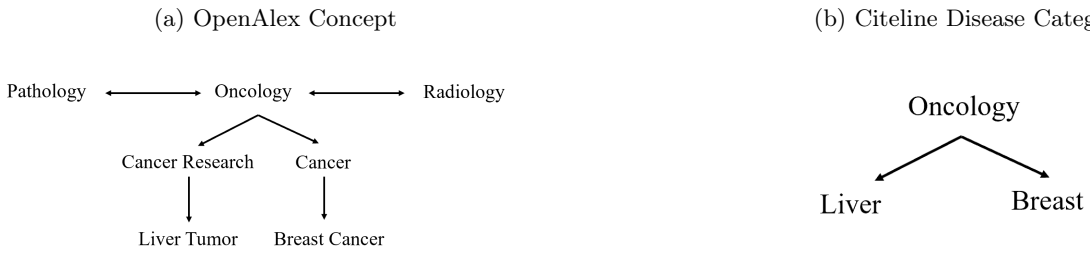
33,809,530 publications, and mapping each paper's abstract directly to diseases using large language models would impose a computational burden. We therefore rely on OpenAlex concepts as an intermediate layer.

Second, the two databases use entirely different classification systems. OpenAlex concepts are algorithm-generated scientific keywords (e.g., "protein folding," "mental health," "immunotherapy"), whereas Citeline assigns each clinical trial or drug project to a structured hierarchy of nine major therapeutic areas and 332 granular disease categories. Moreover, the relationship between OpenAlex concepts and Citeline disease categories is inherently many-to-many. Each paper is associated with multiple concepts, concepts exist at different levels of abstraction, and a given concept may be relevant to multiple disease categories, while each disease typically corresponds to many distinct concepts. Finally, many concepts are semantically ambiguous or not directly tied to a specific disease, so surface-level keyword matching fails to capture their relevance.

To bridge these systems systematically and avoid ad hoc manual matching, we construct a unified semantic space, using graph embedding, in which both OpenAlex concepts and Citeline disease categories can be jointly represented and compared.

First, we build graphs separately in OpenAlex and Citeline. In OpenAlex, we extract all concepts associated with biomedical papers. Separately, we build an analogous graph for Citeline diseases, where nodes represent therapeutic areas or disease categories and edges represent their structured parent–child hierarchy (e.g., "oncology → non-small cell lung cancer"). An example can be found in Figure A1.

Figure A1: Example Graph - OpenAlex Concepts and Citeline Disease Categories

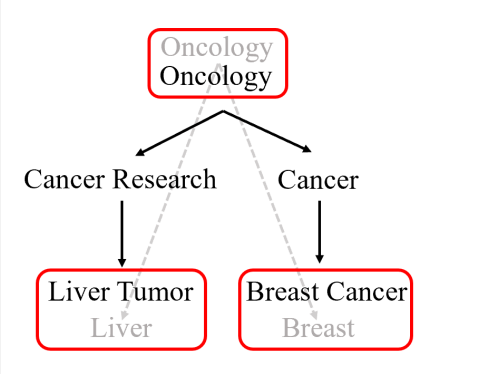


Notes. OpenAlex provides two types of relationships among concepts. The first is ancestor–descendant relationships (directed edges), which capture hierarchical scientific topics (e.g., "oncology → breast cancer"). The second is related relationships (undirected edges), which link concepts that frequently appear together in the scientific literature, such as oncology and radiology. We construct a graph in which each concept is represented as a node, and each hierarchical or related relationship forms a connection between nodes.

Second, we embed concepts and diseases into a vector space using *node2vec* (Grover and Leskovec,

2016). We convert each graph into a high-dimensional vector representation using the node2vec algorithm, which embeds nodes so that concepts frequently appearing together or closely connected in the graph lie near each other. Disease categories in Citeline are similarly embedded based on their hierarchical structure. This produces two embedding spaces: one for OpenAlex concepts and one for Citeline diseases. Embeddings learned from different graphs of databases (i.e., OpenAlex and Citeline) are not directly comparable because their coordinates are identified only up to an arbitrary rotation. We therefore align the two embedding spaces using a set of anchor pairs to provide common reference points across graphs. This alignment preserves within-graph structure while making cross-graph similarity measures interpretable. One example is shown in Figure A2.

Figure A2: Example - Alignment of Two Embedding Spaces



Note: In this example, *Liver Tumor* and *Breast Cancer* are OpenAlex concepts under the broader concept *Oncology*, while *Liver* and *Breast* are Citeline disease categories under the therapeutic area *Oncology*. We treat (*Liver Tumor*, *Liver*) and (*Breast Cancer*, *Breast*) as anchor pairs. These anchors provide shared reference points that allow us to rotate the two embedding spaces into a common coordinate system. After alignment, nodes that are close to these anchors in their respective graphs—illustrated by the local structure around *Oncology* and its neighbors—become comparable across databases, so that cross-graph similarity between a Citeline disease category and an OpenAlex scientific concept has a consistent interpretation.

Lastly, we link OpenAlex concepts and Citeline diseases using the anchor pairs we constructed. For each Citeline disease category, we search OpenAlex concepts for lexical matches, synonyms, or closely related terms, yielding 15,958 initial linkages across the 332 categories. Each linkage is then evaluated through two layers of validation: manual review by research assistants and a GPT-4o assessment of semantic similarity. After filtering, 12 disease categories had no suitable matches, and 23 had only one; for these 35 cases, research assistants identified additional synonyms or clinically equivalent concepts. Following these adjustments, all disease categories received valid OpenAlex

concept matches.

After this process, we retrieve the embeddings of all concepts associated with each publication, align them using the anchor pairs, and compute similarity scores. Specifically, for each publication, we first obtain its concept embeddings and align them via the anchor pairs. We then compute a weighted average of these concept embeddings using the associated confidence scores. The resulting publication-level vector is compared with all disease vectors using cosine similarity, and the five diseases with the highest similarity scores are selected. About 60% of publications have at least one disease whose cosine similarity with the publication-level vector is greater than or equal to 0.5.

```
prompt = f"""
    You are a medical terminology audit expert. Please evaluate the relationship
    between a disease category and a medical concept, using the following criteria:

    - If the concept is a broader or more general area (a hypernym) of the
    category → Output: 0.2, Reason: concept is broader
    - If the concept is a narrower or more specific instance (a hyponym) of the
    category → Output: 0.8, Reason: concept is more specific
    - If the concept is at the same level (e.g., treatment method, diagnostic
    tool, body location) → Output: 0.5, Reason: same-level concept

    Output strictly in the following format:
    Match Score: [0.8 / 0.5 / 0.2]
    Reason: [in Chinese, 10-20 characters]

    therapeutic_area: {area}
    disease_category: {cat}
    concept: {concept}
"""
```

C Trial Novelty Calculation

We construct measures of trial novelty in several ways. First, we calculate a novelty score based on the extent to which a target has not yet been explored, following Dranove et al. (2022). Second, we use GPT 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, for phase III trials, we further classify the control group as an innovative drug, a generic drug, or a placebo. This appendix provides the technical details underlying the construction of these measures.

C.1 Novelty Score

The first novelty measure follows the approach proposed by Dranove et al. (2022), adapted to the structure of the Citeline database. Whereas Dranove et al. (2022) constructs novelty using "target-based actions" (TBA) from the Cortellis database, our data contain mechanisms of action (MOA), which are conceptually similar. MOAs describe the specific scientific strategy through which a molecule produces a pharmacological effect. Each MOA corresponds to a pair consisting of the biological entity targeted by the molecule (e.g., p38 MAP kinase) and the mechanism used to modulate that entity (e.g., inhibition). In total, there are 4,053 unique MOAs in the data. MOA information is available for 379,993 out of 463,412 trials in the database, covering approximately 82% of all trials. These trials include not only those conducted in China and the United States but also trials conducted in other countries, ensuring that the novelty measure reflects the global frontier of drug development. For the 107,256 trials conducted in China and the United States between 2010 and 2024 (our main analysis sample), the required information is available for 103,959 trials.

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, $D_{k(i)}$ would represent the count of other trials associated with k that have been tested in Phases II or III before the initiation of trial i, that is, Phase I deployments of k are not counted. This restriction follows Dranove et al. (2022): evidence generated at more advanced stages (e.g., Phase III) is more informative about translational potential than evidence generated earlier, and knowledge flows are asymmetric (Phase III $\rightarrow$ Phase I, but not vice versa).

The translational novelty score for trial i is computed as:

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

Thus, 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. That is, the score decreases as the number of k's previous trials increases, approaching zero in the limit. Many trials deploy multiple MOAs. In such cases, we compute a trial-level novelty score by taking the average of the MOA-specific novelty

values for that trial:

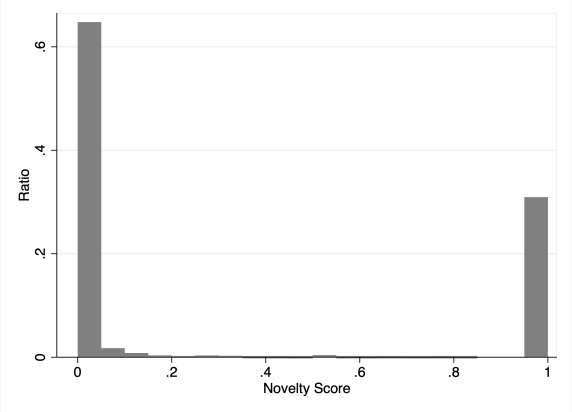
$$\text{Novelty}_i = \frac{1}{K_i} \sum_{k \in \text{MOAs}(i)} \frac{1}{1 + D_{k(i)}},$$

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.

It is important to note that, except for trials with no prior deployments, our inference will not exploit information contained in the specific value of scores and instead relies on the implied ordering.

Figure A3 plots the distribution of the novelty scores, which is highly right-skewed: the mean novelty score is 0.32, while the median is close to zero, reflecting that most trials rely on previously well-explored mechanisms. This distribution closely matches the pattern documented in Dranove et al. (2022), despite relying on MOAs from Citeline rather than TBAs from Cortellis. To classify novel trials, we first compute the median novelty score for each year, pooling trials across all countries. We then designate a trial as "novel" if its novelty score exceeds the median in its corresponding year.

Figure A3: Distribution of Novelty Score (Dranove et al. (2022))



Notes. Data source: Citeline TrialTrove Database.

C.2 GPT-classified Novelty Objective and Control Group

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 allows us to capture 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 develop a supervised fine-tuned model based on GPT-4o-mini. The fine-tuning process proceeds in three steps.

First, we randomly sample 200 clinical trials from the full dataset and manually label each trial's treatment group, control group, and innovation category using the detailed textual descriptions described above. Two healthcare domain experts independently label all trials 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.[40] Fine-tuning forces the model to anchor its reasoning on the specific structure and terminology of Citeline data rather than relying on external assumptions, which substantially reduces hallucination and improves the reproducibility of trial-level classifications. 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. This produces a scalable measure of whether a trial contains at least some innovative content.

The prompt used for classification is provided below. In total, the model successfully classified all 107,256 trials, of which 35% were labeled as new-drug trials, 23% as new-combination trials, 32% as new-indication trials, and 10% as generic bioequivalence trials.

```
# GPT prompt
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}"
)

# Send message_content to the GPT model and retrieve output
completion = call_gpt_api(
    client=client,
    model=MODEL,
    messages=[
    {"role": "system", "content": "You are a healthcare economist"},
    {"role": "user", "content": message_content},
    ],
```

[40] Additional fine-tuning documentation: https://platform.openai.com/docs/guides/supervised-fine-tuning

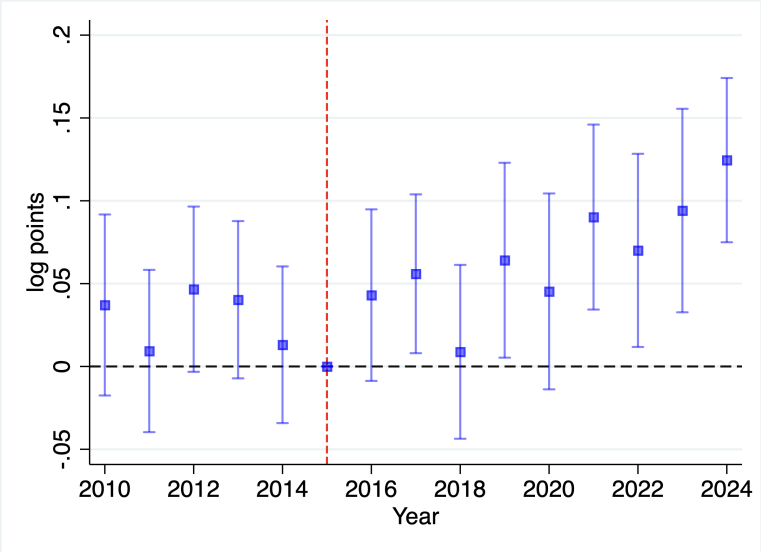
```
    temperature=0.5
)
```

Moreover, Phase III trials are typically designed with both a treatment arm and a control arm. The control arm may involve an innovative drug, a generic drug, or a placebo. Trials that use a patented drug as the control are benchmarked against the existing clinical frontier and therefore represent a higher degree of novelty than those using generics or placebos. We classify the control arm into these three categories—patented drug, generic drug, or placebo—based on the treatment drug name, the control drug name, and the trial start date. The prompt used for this classification is provided below. Among Phase III trials in our sample, 17.77% use an innovative drug as the control, 12.04% use a generic drug, and 70.19% use a placebo.

```
# GPT prompt
message_content = (
    f"You will be given one clinical trial record with (i) start date and "
    f"(ii) control group drug(s).\n\n"
    f"Your task is to determine whether the CONTROL group should be "
    f"considered a 'generic drug', an 'innovative drug', or a 'placebo' "
    f"AT THE TIME of the start date.\n\n"
    f"Use your background pharmaceutical knowledge to judge whether the "
    f"control group uses an "
    f"originator/brand/innovator product, a generic version, or a placebo, and consider "
    f"whether the timing (start date) "
    f"matters for generic entry.\n\n"
    f"Definitions (for the control group at the start date):\n"
    f"- generic drug: a non-originator generic version of an existing drug.\n"
    f"- innovative drug: an originator/brand/innovator product (including "
    f"biologics and patented products).\n"
    f"- placebo: a placebo control without an active comparator drug.\n\n"
    f"IMPORTANT RULES:\n"
    f"- Base your judgment on the situation at the start date, not today.\n"
    f"- If multiple control drugs exist, classify based on the main comparator.\n"
    f"- Always choose one of: generic drug, innovative drug, placebo. Do not output 'unknown'.\n"
    f"- Do NOT output anything except the final answer line.\n\n"
    f"Output format (ONE LINE ONLY):\n"
    f"id: {row['id']}; control_type: <generic drug OR innovative drug OR placebo>\n\n"
    f"Input:\n"
    f"startdate: {row.get('StartDate', 'n/a')}\n"
    f"control_group: {row.get('control', 'n/a')}\n"
)
completion = call_gpt_api(
    client=client,
    model=MODEL,
    messages=[
        {"role": "system", "content": "You are a healthcare economist"},
        {"role": "user", "content": message_content},
    ],
    temperature=0.5
)
```

D Online Figures

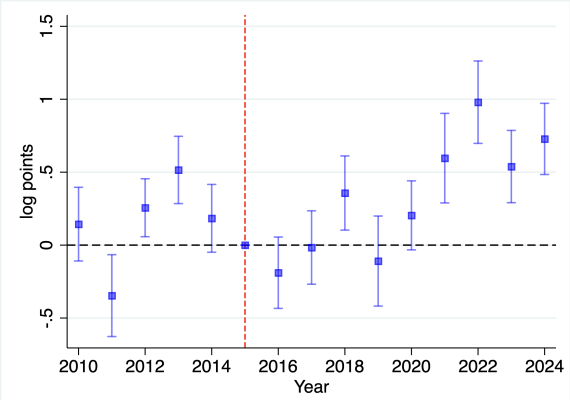
Figure A4: Event Study - First-in-Class Trials



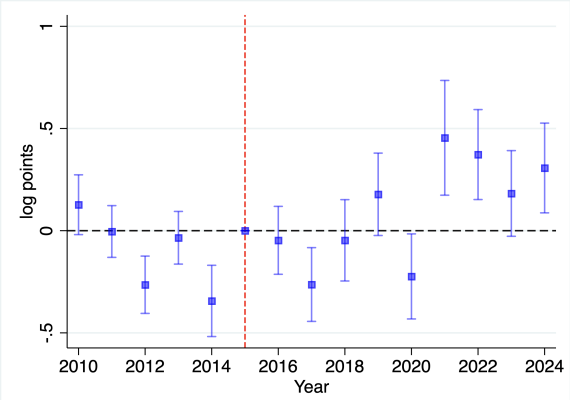
Notes. This figure presents an event-study analysis of first-in-class trials at the disease-country level, with 2015 as the base year and the U.S. as the control group. The vertical axis plots the estimated coefficients (in 100 log points) on the interactions between the China indicator and event-year dummies from the difference-in-differences specification, along with 95% confidence intervals. The horizontal axis indicates calendar year (2010–2024). The dependent variable is the number of first-in-class trials, defined as trials that explore a mechanism of action or biological target for the first time. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Figure A5: Event Study - Drug Pipelines and New Firms

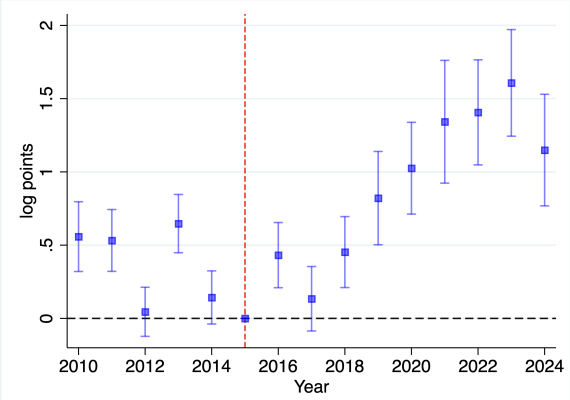
(a) Number of Licensed-Out Drugs
Chinese Firms vs U.S. Firms



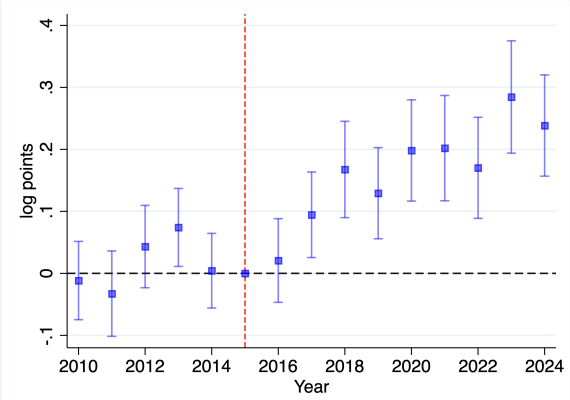
(b) First-in-world Regulatory Approval of Drugs
by Firms Headquartered in China vs U.S.



(c) Number of Drug Approvals
by Chinese vs U.S. Administration



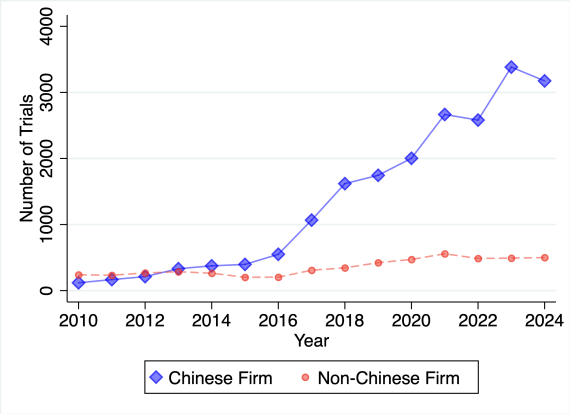
(d) Number of New Firms
China vs U.S.



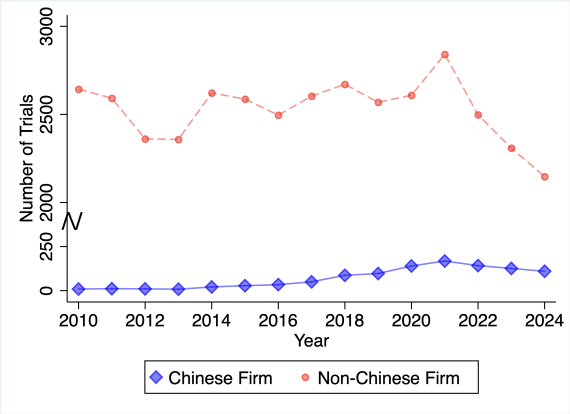
Notes. This figure presents event-study analyses of post-trial outcomes and firm entry at the disease-country-year level, with 2015 as the base year and the U.S. as the control group. Panel (a) examines out-licensing transactions to multinational corporations for drugs developed by Chinese- vs U.S.-headquartered firms. Panel (b) examines first-in-world regulatory approvals (i.e., the first approval in any country) for drugs developed by firms in each country. Panel (c) compares newly approved drugs by the Chinese and U.S. regulatory authorities. Panel (d) compares the number of new entrants (firms conducting clinical trials for the first time) in each country. The dependent variable is $\log(y+1)$, where y is the corresponding count outcome. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease $\times$ country level. Data source: Citeline Pharmaprojects Database.

Figure A6: Time Trend - Number of Trials by Chinese Firms and Non-Chinese Firms

(a) Trials in China
Chinese Firms vs Non-Chinese Firms

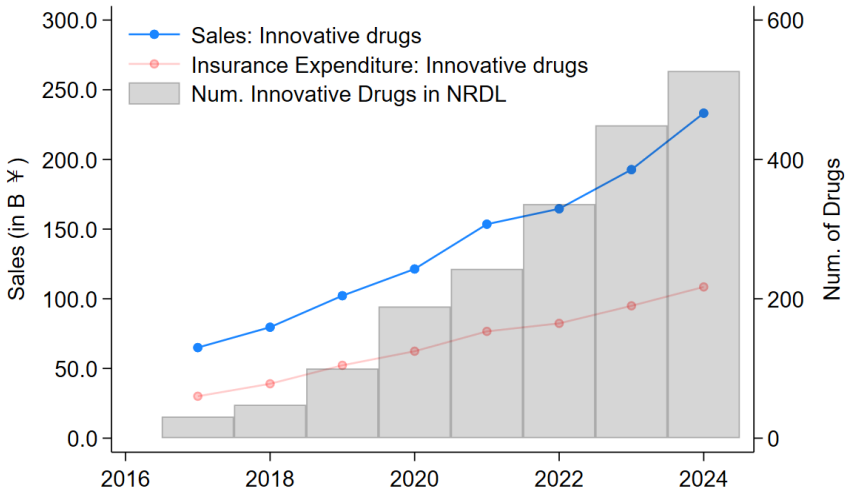


(b) Trials in the U.S.
Chinese Firms vs Non-Chinese Firms



Notes. This figure plots the annual number of clinical trials conducted in China and the U.S., distinguishing between Chinese and Non-Chinese firms. Trials sponsored by public entities are excluded. Panel (a) reports trials conducted in China, while Panel (b) reports trials conducted in the U.S. Data source: Citeline TrialTrove database.

Figure A7: Overview of NRDL and the Chinese Pharmaceutical Market



Notes. This figure reports annual sales of innovative (patented drugs) in China, public expenditure on innovative drugs through the NRDL, and the number of innovative drugs covered by the NRDL from 2017 to 2024. Traditional Chinese Medicines (TCM) are excluded. Data source: SinoHealth.

E Online Tables

Table A1: Number of Oncology Trials and Difference Relative to 2016

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024	All
Panel A: China										
Number of Trials	759	919	1171	1442	1779	2262	1878	1942	1763	
- Difference from 2016		160	412	683	1020	1503	1119	1183	1004	7084
Panel B: U.S.										
Number of Trials	1267	1464	1386	1343	1309	1448	1266	1199	1163	
- Difference from 2016		197	119	76	42	181	-1	-68	-104	442

Notes. This table reports the annual number of oncology trials conducted in China and the United States from 2016 to 2024. For each country, we also report the difference relative to the 2016 baseline year, calculated as the number of trials in a given year minus the number of trials in 2016. Data source: Citeline TrialTrove Database.

Table A2: Heterogeneity - Different Sponsor Types

	(1)	(2)	(3)	(4)
	(Log) Trials by			
	Any Sponsors	Private Sponsors	Public Sponsors	Hybrid Sponsors
All Trials				
China × (Year ≥ 2016)	0.621***	0.575***	0.393***	0.327***
	(0.045)	(0.048)	(0.035)	(0.031)
Phase-I Trials				
China × (Year ≥ 2016)	0.667***	0.630***	0.153***	0.185***
	(0.050)	(0.050)	(0.023)	(0.024)
Phase-II Trials				
China × (Year ≥ 2016)	0.332***	0.186***	0.245***	0.163***
	(0.038)	(0.033)	(0.030)	(0.022)
Phase-III Trials				
China × (Year ≥ 2016)	0.165***	0.128***	0.073***	0.044***
	(0.031)	(0.029)	(0.016)	(0.011)
Phase-IV Trials				
China × (Year ≥ 2016)	0.295***	0.054***	0.261***	0.117***
	(0.028)	(0.017)	(0.026)	(0.015)
Disease × Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	9030	9030	9030	9030

Notes. This table examines heterogeneity across trial phases and sponsor types. The key independent variable is an indicator for post-2015 years interacted with an indicator for China, with the U.S. as the control group. The dependent variable is log(number of trials + 1), where trial counts are computed by sponsor types and trial phase within each disease-country-year cell. Public sponsors are trial sponsors that are public organizations, such as hospitals, universities, or government agencies, while private sponsors are trial sponsors that are firms. Trials with hybrid sponsors are trials sponsored jointly by public organizations and firms. All specifications include disease-by-country fixed effects and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Table A3: Robustness - Different FEs and Functional Forms

	(1)	(2)	(3)	(4)	(5)
	(Log) Number of Trials			Number of Trials	
Model	OLS	OLS	OLS	OLS	PPML
China × (Year ≥ 2016)	0.621***	0.643***	0.757***	10.808***	1.303***
	(0.045)	(0.046)	(0.055)	(1.349)	(0.079)
Constant	1.251***	1.354***	0.719***	7.642***	2.940***
	(0.012)	(0.014)	(0.015)	(0.370)	(0.030)
Percentage Change	86.1%	90.2%	113.2%	102.0%	268.1%
Disease × Country FE	Yes	Yes	Yes	Yes	Yes
Disease × Year FE	No	Yes	No	No	No
Year FE	Yes	No	Yes	Yes	Yes
Observations	9030	9030	9030	9030	9030

Notes. This table reports robustness checks for the baseline difference-in-differences specification from Column (1) of Table 3. The key independent variable is an indicator for post-2015 years interacted with an indicator for China, with the U.S. as the control group. Column (1) replicates the baseline specification with log(number of trials + 1) as the dependent variable. Column (2) adds disease × year fixed effects. Columns (3) to (5) address zero-valued observations and functional form choices. Column (3) follows Chen and Roth (2024) and defines the dependent variable as log(number of trials) when at least one trial is observed in a country-disease-year cell and as −1 otherwise. Columns (4) and (5) use trial counts instead of log(trials+1) as the dependent variable, estimated via OLS and Poisson pseudo-maximum likelihood (PPML), respectively. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Table A4: Robustness - Different Treatment or Control Groups

	(1)	(2)	(3)	(4)
	(Log) Number of Trials			
China × (Year ≥ 2016)	0.621***	0.619***	0.643***	0.630***
	(0.045)	(0.046)	(0.044)	(0.045)
Constant	1.251***	1.224***	1.184***	1.432***
	(0.012)	(0.013)	(0.012)	(0.012)
Disease × Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Exclude Trials Conducted in US & China	No	Yes	No	No
Control Group	US	US	Europe	Europe+US
Adjusted R-squared	0.864	0.862	0.867	0.882
Observations	9030	9030	9030	9030

Notes. This table reports robustness checks using alternative samples and control groups. The key independent variable is an indicator for post-2015 years interacted with an indicator for China. Column (1) replicates the baseline specification from Column (1) of Table 3. Column (2) excludes trials conducted in both the U.S. and China. Column (3) uses trials conducted in Europe as the control group, and Column (4) uses trials conducted in either Europe or the U.S. as the control group. The dependent variable is log(number of trials + 1). All specifications include disease-by-country fixed effects and year fixed effects. Robust standard errors are clustered at the disease × country level. Data source: Citeline TrialTrove Database.

Table A5: Robustness - NRDL Intensity from $Year_{t-2}$ to $Year_t$ and Trial Counts

	(1)	(2)	(3)	(4)
D.V.	(Log) Number of Trials			
Log(Number of NRDL-Included Drugs)	0.707***			
	(0.247)			
Log(Revenue of NRDL-Included Drugs)		0.639***		
		(0.238)		
Ratio of NRDL-Included Drugs			0.873***	
			(0.323)	
Revenue Ratio of NRDL-Included Drugs				0.807***
				(0.257)
Disease × Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
KP F-stat	33.58	12.80	60.40	88.16
Adjusted R-squared	0.060	0.054	0.115	0.119
Observations	9030	9030	9030	9030

Notes. This table reports IV estimates of the effect of NRDL exposure on clinical trial activity using disease-country-year level observations. The dependent variable is log(number of trials + 1). NRDL exposure is measured in four ways: (1) the log number of NRDL-included drugs, (2) the log revenue of NRDL-included drugs, (3) the share of NRDL-included drugs among all drugs in the disease area, and (4) the revenue ratio of NRDL-included drugs relative to total disease-level drug revenues. Unlike the baseline specification, each NRDL exposure measure is constructed as the average exposure from year $t-2$ to year t. The instruments are *Elasticity* × *NRDL Expansion* and *2010-2015 U.S. Innovative Drugs* × *NRDL Expansion*. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove database and SinoHealth.

Table A6: Robustness - Separate and Joint IV Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(Log) Number of Trials											
Log(Number of NRDL-Included Drugs)	1.032***	0.559**	0.646***									
	(0.343)	(0.232)	(0.221)									
Log(Revenue of NRDL-Included Drugs)				1.534**	0.501**	0.577***						
				(0.734)	(0.200)	(0.211)						
Ratio of NRDL-Included Drugs							0.801***	23.912	0.812***			
							(0.290)	(30.287)	(0.291)			
Revenue Ratio of NRDL-Included Drugs										0.703***	4.617*	0.798***
										(0.239)	(2.737)	(0.250)
	First Stage											
KP Wald F-stat	44.74	24.68	37.70	5.65	22.64	14.20	140.12	0.63	70.05	163.05	3.16	83.08
Elasticity× NRDL Expansion	46.8790***		44.4865***	31.5583**		28.8780**	60.4324***		60.4136***	68.8242***		68.5741***
	(7.0087)		(6.5604)	(13.2764)		(13.1497)	(5.1052)		(5.1067)	(5.3899)		(5.3294)
US Innovative Drug× NRDL Expansion		0.8113***	0.8020***		0.9045***	0.8985***		0.0190	0.0063		0.0982*	0.0838*
		(0.1633)	(0.1614)		(0.1901)	(0.1891)		(0.0238)	(0.0174)		(0.0552)	(0.0484)
Disease × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.102	0.081	0.082	-1.601	0.083	0.082	0.118	-9.234	0.118	0.122	-0.399	0.122
Observations	9030	9030	9030	9030	9030	9030	9030	9030	9030	9030	9030	9030

Notes. This table reports robustness checks for the IV estimates of the effect of NRDL exposure on clinical trial activity using disease-country-year level observations. The dependent variable is log(number of trials + 1). NRDL exposure is measured in four ways: (1) the log number of NRDL-included drugs, (2) the log revenue of NRDL-included drugs, (3) the share of NRDL-included drugs among all drugs in the disease area, and (4) the revenue ratio of NRDL-included drugs relative to total disease-level drug revenues. For each NRDL exposure measure, we report three IV specifications: only *Elasticity* × *NRDL Expansion* as the instrument, only *2010-2015 U.S. Innovative Drugs* × *NRDL Expansion* as the instrument, and both instruments jointly. Columns (3), (6), (9), and (12) correspond to the main IV specifications reported in the main text. *Elasticity* is estimated separately for each disease from a regression of log(1 + revenue) on an indicator for post-NRDL inclusion, where post-NRDL inclusion is defined relative to the earliest year in which a drug for that disease is included in the NRDL. *NRDL Expansion* is measured by total insurance expenditure on innovative drugs and equals zero before the 2016 NRDL reform. *2010-2015 U.S. Innovative Drugs* is defined as the number of innovative drugs approved in the United States during 2010–2015 for each disease. The first-stage coefficients are reported in the lower panel, and the KP Wald F-statistic reports the Kleibergen–Paap rk Wald F-statistic for weak identification. All specifications include disease-by-country and year fixed effects and control for the number of drugs and the prevalence rate in a given disease-country-year. Robust standard errors are clustered at the disease-by-country level and reported in parentheses. Data sources: Citeline TrialTrove and SinoHealth. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7: Robustness - NRDL Intensity and Novel Trial Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(Log) Novelty Score > Median Trials				(Log) Non-Generic Trials			
Log(Number of NRDL-Included Drugs)	0.359**				0.467**			
	(0.149)				(0.215)			
Log(Revenue of NRDL-Included Drugs)		0.316**				0.390*		
		(0.159)				(0.205)		
Ratio of NRDL-Included Drugs			0.496**				0.852***	
			(0.251)				(0.306)	
Revenue Ratio of NRDL-Included Drugs				0.480**				0.791***
				(0.220)				(0.259)
Disease × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP F-stat	37.70	14.20	70.05	83.08	37.70	14.20	70.05	83.08
Adjusted R-squared	0.038	0.040	0.047	0.051	0.040	0.044	0.062	0.068
Observations	9030	9030	9030	9030	9030	9030	9030	9030

Notes. This table reports IV estimates of the effect of NRDL exposure on novel clinical trial activity using disease-country-year-level observations. In Columns (1)–(4), the dependent variable is log(number of trials with a novelty score above the global median + 1). In Columns (5)–(8), the dependent variable is log(number of trials investigating non-generic compounds + 1). NRDL exposure is measured in four ways: the log number of NRDL-included drugs in Columns (1) and (5), the log revenue of NRDL-included drugs in Columns (2) and (6), the share of NRDL-included drugs among all drugs in the disease area in Columns (3) and (7), and the revenue ratio of NRDL-included drugs relative to total disease-level drug revenues in Columns (4) and (8). The instruments are *Elasticity* × *NRDL Expansion* and *2010-2015 U.S. Innovative Drugs* × *NRDL Expansion*. All specifications include disease-by-country and year fixed effects and control for the number of drugs and prevalence rate in a given disease-country-year. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove Database and SinoHealth.

Table A8: Robustness - NRDL Intensity and Trials Conducted in Europe (Placebo)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D.V.	(Log) Number of Trials in EU							
	All Trials				Trials before 2022			
Log(Number of NRDL-Included Drugs)	-0.098***				-0.058			
	(0.027)				(0.039)			
Log(Revenue of NRDL-Included Drugs)		-0.079***				-0.046		
		(0.025)				(0.031)		
Ratio of NRDL-Included Drugs			-0.016				-0.094	
			(0.108)				(0.120)	
Revenue Ratio of NRDL-Included Drugs				-0.074				-0.110
				(0.093)				(0.117)
Disease × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.858	0.858	0.858	0.858	0.872	0.872	0.872	0.872
Observations	9030	9030	9030	9030	7224	7224	7224	7224

Notes. This table reports a placebo test of Equation (3) using clinical trials in Europe. The dependent variable is log(number of trials + 1). Columns (1)-(4) use all European trials, while Columns (5)-(8) restrict to trials conducted before 2022 (as trial volume in Europe declined post 2021). NRDL exposure is measured in four ways: (1) the log number of NRDL-included drugs, (2) the log revenue of NRDL-included drugs, (3) the share of NRDL-included drugs among all drugs in the disease area, and (4) the revenue ratio of NRDL-included drugs relative to total disease-level drug revenues. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. Data sources: Citeline TrialTrove database and SinoHealth.

Table A9: Robustness - Alternative Mechanism Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robustness	ICH Harmonization		Knowledge in [t-2,t]		VC Investment		Application Backlog
	Global	Drug-Adjusted	Papers	Scientists	No GVC	No License-out	
D.V.	(Log) Number of Trials						
Revenue Ratio of NRDL-Included Drugs	0.792***	0.798***	0.786***	0.785***	0.807***	0.786***	0.785***
	(0.252)	(0.251)	(0.249)	(0.250)	(0.248)	(0.254)	(0.246)
Global Prevalence (Per Hundred) × Post-ICH	0.001						
	(0.001)						
Drug-Adjusted Prevalence (Per Hundred) × Post-ICH		-0.004					
		(0.011)					
Average Number of Papers from $t-2$ to t			0.162**				
			(0.076)				
Average Number of Scientists from $t-2$ to t				0.022***			
				(0.008)			
Deal Amount (Billion USD)					0.744**		
					(0.309)		
Share of Backlog $\geq$ 180 Days							-0.047
							(0.042)
Disease × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP F-stat	82.42	82.60	82.97	82.89	83.12	83.08	82.73
Adjusted R-squared	0.125	0.122	0.129	0.123	0.124	0.124	0.121
Observations	9030	9030	9030	9030	9030	9030	9030

Notes. This table examines the robustness of the mechanism analysis to alternative measures of ICH exposure, knowledge stock, and VC investment, as well as the potential roles of licensing-related cash flows and application backlogs, using disease-country-year level observations. The dependent variable is log(number of trials + 1). All columns include NRDL exposure, measured as the revenue share of NRDL-included drugs relative to total disease-level drug revenues. Columns (1) and (2) examine alternative measures of ICH exposure: Column (1) uses global disease prevalence interacted with a post-ICH indicator, while Column (2) uses drug-adjusted prevalence, defined as the U.S. disease prevalence divided by one plus the cumulative number of previously launched drugs for the disease, interacted with the post-ICH indicator. Columns (3) and (4) use three-year moving averages from year $t-2$ through year t of scientific publications and scientists, respectively. Column (5) measures VC investment after excluding investments from government-backed investors. Column (6) addresses the concern that licensing deals may provide firms with additional cash flows that could support clinical development by excluding trials conducted by sponsors with a license-out deal in year t, $t-1$, or $t-2$. Column (7) measures the application backlog as the share of applications with backlog durations exceeding 180 days. All columns report IV estimation results. The instruments are *Elasticity* × *NRDL Expansion* and *2010–2016 U.S. Innovative Drugs* × *NRDL Expansion*. All specifications include disease-by-country and year fixed effects. Robust standard errors are clustered at the disease × country level. The KP F-statistic reports the Kleibergen-Paap rk Wald F-statistic. Data sources: Citeline TrialTrove and Pharmaprojects, SinoHealth, OpenAlex, PitchBook, and the State Council Policy Document Library.