Expected Insurance Coverage and Pharmaceutical Innovation: Evidence from China's National Drug Price Negotiation Policy*

Chenyuan Liu† Yi Lu‡ Ronghe Sun§ Wanyu Yang¶

October 2026

Abstract

How can developing countries promote pharmaceutical innovation when price negotiations threaten firms' incentives? China's National Drug Price Negotiation policy offers a natural experiment, combining large price cuts with expanded insurance coverage for innovative drugs. Using a difference-in-differences design that compares drug trials with vaccine trials, we find the policy raises trial numbers by 0.385–0.650 per disease per year. Mechanism analysis indicates that higher expected returns from market expansion primarily drive this response, complemented by relaxed financial constraints. The policy encourages more novel innovations and higher-quality trials, with stronger innovation responses among domestic firms, while stimulating entry by small R&D firms.

JEL Codes: I18, O31.

*We thank Shengmao Cao, Andrew Ching, Hui Ding, Ce Matthew Shi, Xuan Zhang, and seminar participants at Singapore Management University, Shanghai Jiaotong University, Chinese University of Hong Kong - Shenzhen, Lingnan University, Fudan University, and the Chinese University of Hong Kong Workshop on Industrial Economics for helpful discussions and feedback.

†Email: liuchy3@sem.tsinghua.edu.cn. School of Economics and Management, Tsinghua University, Beijing, 100084, China. Liu gratefully acknowledges financial support from the National Natural Science Foundation of China (project numbers 72203120 and 72342032) and from the Tsinghua University Initiative Scientific Research Program (No. 2026THZWYY02).

‡Email: luyi@pbcsf.tsinghua.edu.cn. PBC School of Finance, and School of Economics and Management, Tsinghua University, Beijing, 100084, China.

§Email: srh23@mails.tsinghua.edu.cn. School of Economics and Management, Tsinghua University, Beijing, 100084, China.

¶Email: wanyu.yang@dufe.edu.cn. Center for Industrial and Business Organization and Institute for Advanced Economic Research, Dongbei University of Finance and Economics, 116025, China

1 Introduction

Pharmaceutical innovation is essential to improving population health, yet high drug prices have become a major and growing concern for healthcare systems worldwide, straining public insurance budgets and limiting patient access to effective treatments. High prices largely reflect the economics of pharmaceutical R&D: drug development entails substantial fixed costs, high failure rates, and long development timelines, whereas successful drugs have negligible marginal production costs. Temporary market exclusivity and premium pricing during patent protection are therefore widely viewed as a key mechanism for firms to recoup R&D investments and finance future innovation (Garthwaite, 2025).

This linkage between prices and innovation makes drug price regulation inherently contentious. Policies that limit or negotiate drug prices can improve affordability and access for current patients, but may reduce firms' expected returns and weaken incentives for future R&D. These concerns have long shaped U.S. healthcare policy, including Medicare Part D's historical prohibition of direct government price negotiation. They have re-emerged with the Inflation Reduction Act, which authorizes Medicare to negotiate prices for selected high-expenditure Part D drugs beginning in 2026. Whether cost containment can be achieved without discouraging pharmaceutical innovation remains a central and unresolved question in health economics.

China's National Drug Price Negotiation (NDPN) policy provides a compelling institutional context to study this question. Since 2016, the Chinese government has conducted centralized price negotiations targeting exclusive drugs on the market. The policy functions through two primary mechanisms: first, the government bargains prices with firms for exclusive drugs; second, upon a successful outcome, the drug is included in the National Reimbursement Drug List (NRDL) at the negotiated price and becomes eligible for generous coverage under the basic public health insurance program. By combining large price reductions with expanded market access and increased demand, the policy reshapes firms' expected returns in a theoretically ambiguous manner, making it an ideal natural experiment for evaluating how drug price negotiation affects pharmaceutical innovation.

This paper first examines the impact of the negotiation policy on the sales of successfully negotiated drugs. Using sales data from more than 500 representative public hospitals across 20 cities between 2013 and 2021, we employ a staggered difference-in-differences (DID) design to quantify the policy's effects on retail prices, out-of-pocket prices, sales volumes, and revenues. We find that the policy substantially reduces drug prices. At the same time, the availability of public health insurance coverage results in an even greater reduction in patients' out-of-

pocket costs. We also find that the policy significantly broadens market access, resulting in a volume expansion that more than offsets price reductions, thereby driving a net increase in total drug revenues. A back-of-the-envelope calculation suggests that, under the negotiation policy, the expected revenue of launching a new drug exceeds the industry estimates of the mean development costs, suggesting that the policy provides a strong incentive for pharmaceutical R&D.

Next, we evaluate the policy's impact on pharmaceutical innovation. We measure firms' innovation activities using comprehensive clinical trial data from the Center for Drug Evaluation (CDE) under the National Medical Products Administration (NMPA) for the period from 2013 to 2023. We focus exclusively on clinical trials for new products that have not been marketed anywhere globally. These trials are more likely to represent true innovation in new drugs than research efforts to bring existing products to China's markets. We employ a difference-in-differences design to compare innovation activities in chemical drugs and therapeutic biologics—both eligible for price negotiation and insurance coverage—against preventive vaccines, which are not covered by China's public health insurance system by law and therefore unaffected by the policy. Vaccines serve as a natural control group because they share similar technological foundations and regulatory oversight with the treatment group, ensuring they are exposed to the same industry-wide shocks. We construct a disease-by-group-by-year panel, where a group is one of the following two categories: chemical drugs and therapeutic biologics, or preventive vaccines. We then examine changes in the incidence and number of clinical trials following the introduction of the negotiation policy in 2016.

We find that the negotiation policy increases both the incidence and the number of clinical trials. Specifically, the number of clinical trials increases by 0.385–0.650 per disease per year after the policy, a significant rise compared to the pre-policy mean of 0.187. This effect is concentrated in more innovative drugs, while trials involving incremental changes to existing molecules show negligible responses.[1] The main findings are robust to several checks. Moreover, we find no evidence that firms strategically reallocate clinical trials away from early-stage discovery to later-stage development or post-marketing studies.

Furthermore, we investigate the mechanisms driving the innovation response: increased expected returns from market expansion among all firms and relaxed financial constraints from improved cash flow among successfully negotiated firms. We estimate the overall policy effect by comparing pharmaceutical firms with vaccine firms and isolate the financial-constraint channel by comparing successfully negotiated firms with firms that participated but failed. This decom-

[1] We measure drug novelty using the registration category in China.

position indicates that the expected return mechanism is the primary driver of the innovation response, accounting for 56.57% of the overall effect.

Finally, we explore the policy's impacts on the quality of clinical trials and industry dynamics. Beyond increasing trial quantity, the policy encourages higher-quality clinical trials with greater information content and research intensity. Decomposing the increase in clinical trials into intensive and extensive margins, we find that the policy effect is primarily driven by the extensive margin: existing pharmaceutical firms pursue more research fields, and firm entry into the pharmaceutical R&D market increases net of exit. Subsample analysis on foreign and domestic firms shows that the impact is markedly more pronounced among domestic firms for which China constitutes the primary market.

This paper contributes to the existing literature in several important ways. First, we contribute to the literature on the determinants of pharmaceutical innovation. Prior studies emphasize the roles of market size (Acemoglu and Linn, 2004; Blume-Kohout and Sood, 2013; Dubois et al., 2015; Agha, Kim and Li, 2022), intellectual property protection (Kyle and McGahan, 2012; Budish, Roin and Williams, 2015; Gaessler and Wagner, 2022; Budish et al., 2025; Dix and Lensman, 2025), and regulatory practices (Jia et al., 2025) in shaping innovation incentives in both developed and developing countries. In the context of China, prior studies find that insurance coverage increases pharmaceutical innovation (Zhang and Nie, 2021), while price controls reduce it (Geng and Shi, 2024). We contribute to the literature by examining the synergistic impact of price negotiation and expanded insurance coverage and highlighting the role of demand-side policies in shaping firms' R&D decisions.

Second, we contribute to the literature on the economics of pharmaceutical price regulation. Prior studies primarily examine competitive bidding and centralized procurement for generics (Cao, Yi and Yu, 2024; Jiang et al., 2025; Zhang et al., 2025; Liu, Lu and Yang, 2026) and medical equipment (Ding, Duggan and Starc, 2025). In this literature, Ji and Rogers (2024) document substantial long-run innovation losses following large, sustained Medicare price cuts in the medical device market, highlighting the potential dynamic costs of aggressive price regulation. Similarly, using a forward-looking framework, Vogel et al. (2024) assess the expected revenue exposure and innovation implications of Medicare drug price negotiation under the Inflation Reduction Act and find modest but highly heterogeneous effects.

We offer new insights into the regulation of prices for innovative drugs by studying a policy that combines price negotiation with expanded insurance coverage. The papers most closely related to ours are Barwick, Swanson and Xia (2025) and Barwick, Xia and Xia (2026). The

former analyzes the same policy but focuses on bargaining design and static consumer welfare. The latter documents China's emergence as a major pharmaceutical innovator and identifies the expansion of the NRDL as a central driver of this transformation, using cross-country comparisons. We extend their analysis by shifting attention to firms' long-run innovation responses. In contrast to the pessimistic predictions in prior work, we provide direct empirical evidence that price negotiation—when paired with market expansion—can mitigate innovation losses and meaningfully shape pharmaceutical R&D incentives.

The rest of the article is organized as follows. Section 2 describes the institutional background of China's NDPN policy and its effects on drug revenues. Section 3 presents the data, sample construction, and empirical strategy. Section 4 reports the baseline results and robustness checks. Section 5 investigates the mechanisms. Section 6 analyzes the policy's impacts on innovation quality and industry dynamics, and Section 7 concludes.

2 Institutional Background

2.1 Pharmaceutical Industry in China

China hosts one of the largest pharmaceutical markets in the world, yet domestic pharmaceutical firms historically invested little in innovative R&D and contributed minimally to global drug innovation (Friedman, 2010). As of the 2010s, China's pharmaceutical sector comprised more than 5,000 domestic manufacturers, yet large- and medium-sized pharmaceutical firms spent less than 2% of sales on R&D by 2010, compared with a global average of around 8% and more than 15% in developed economies (Qiu et al., 2014; Li, 2016; Kanavos, Mills and Zhang, 2019). As a result, the pharmaceutical industry in China was dominated by generic production and incremental modifications, with relatively few innovative drugs developed domestically.

This lack of innovation is largely attributable to the demand-side constraints embedded in China's public health insurance system. Prioritizing cost containment, broad population coverage, and fiscal sustainability, the insurance system historically reimbursed essential drugs with affordable generic substitutes, while excluding many high-priced innovative drugs. The exclusion of such drugs from the NRDL resulted in high out-of-pocket payments for patients (Barwick, Swanson and Xia, 2025)[2], which in turn suppressed effective demand and shrank the potential market for innovative drugs. Consequently, firms' expected returns to R&D investment

[2]Before the negotiation policy was implemented, the NRDL had stagnated since the 2009 update, leaving the drugs launched between 2009 and 2016 uncovered by public health insurance and fully paid out of pocket by patients (Ministry of Human Resources and Social Security, 2017).

were diminished, weakening their incentives to invest in new drug development. Empirical studies support this mechanism: expansions in insurance coverage have been shown to increase pharmaceutical innovation in affected disease areas (Finkelstein, 2004; Blume-Kohout and Sood, 2013; Zhang and Nie, 2021; Agha, Kim and Li, 2022).

2.2 China's NDPN Policy

China began to launch NDPN in 2015. In February of that year, the State Council proposed a transparent, multi-shareholder negotiation mechanism specially targeting patented drugs and drugs with exclusive manufacturers. Following rigorous expert assessment, patented drugs characterized by high prices, significant disease burden, and significant clinical benefits for rare and serious conditions such as hepatitis B, lung cancer, and multiple myeloma were selected as candidates for the pilot price negotiation. In May 2016, the government completed its first pilot round, successfully negotiating price reductions for three out of five candidate drugs and publicly announcing the corresponding negotiated prices and procurement periods. Under this framework, public hospitals were required to procure these drugs at the negotiated prices, though no specific volume guarantees were required.

During 2017-2019, the negotiation process became institutionalized through annual cycles. Candidates were selected and voted on by clinical and pharmaceutical experts, while health insurance and pharmacoeconomic specialists assessed and determined the reference prices deemed appropriate for inclusion in the NRDL. If a pharmaceutical firm agreed to participate in the negotiation, the government bargained with the firm based on the assessed price. Upon successful negotiation, the drug was added to the NRDL at the negotiated price, either by the end of the same year or in the following year. Notably, the 2018 round focused exclusively on anticancer drugs.

A landmark shift occurred in 2020 when the process transitioned to a firm-initiated application system. Under this new paradigm, the National Healthcare Security Administration (NHSA) issues annual application guidelines specifying eligibility criteria for drugs seeking inclusion in the NRDL. In addition to being supplied by a single firm in China, eligible drugs must also satisfy at least one of several conditions, such as being a new molecular entity launched within the past five years or having undergone a major change in approved indications within the past five years; notably, drugs launched within the past five years account for the majority of negotiated drugs. After firms submit applications within the designated period, NHSA conducts a preliminary formal review and publicly discloses the submitted materials. Eligible

drugs are then identified through expert evaluation, followed by price negotiations between the government and pharmaceutical firms according to procedures similar to those used in previous rounds.

Figure 1 illustrates the 2016-2022 trends for exclusive drugs launched within the past five years (thus eligible for negotiation), drugs selected by the government or passing the formal review after firm applications, and drugs successfully negotiated and listed. The number of eligible exclusive drugs increased steadily and substantially, rising from 125 in 2016 to 312 in 2022. At the same time, the number of participating drugs rose sharply after 2020 and remained above 100 thereafter, reflecting firms' increased participation under the firm-initiated application system. The number of successfully negotiated drugs increased steadily, from only a few in 2016 to 79 in 2022, highlighting the expanding scope and growing importance of China's NDPN policy.

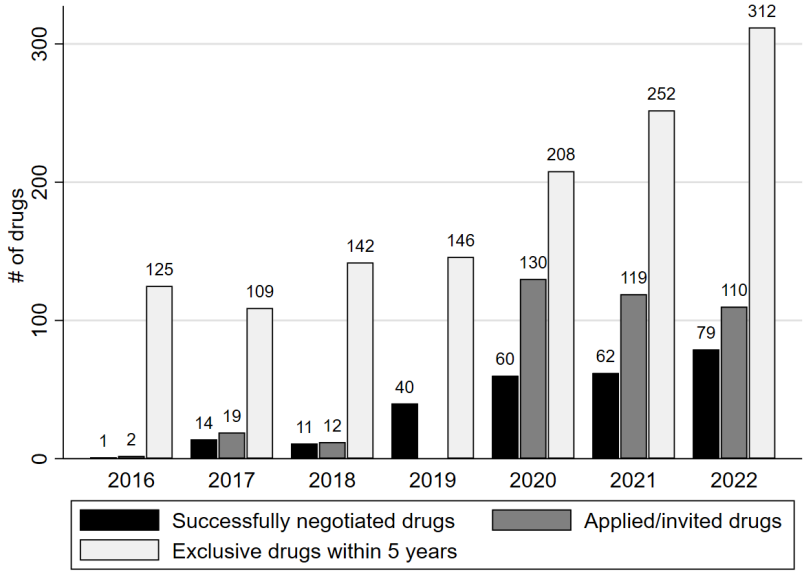


Figure 1: Trends in Drug Eligibility, Participation, and Success in China's National Drug Price Negotiation

Notes: This figure shows the evolution of drugs related to China's National Drug Price Negotiation from 2016 to 2022, including exclusive drugs launched within the past five years, drugs selected by the government or passing the formal review following firm applications, and drugs that were successfully negotiated and added to the National Reimbursement Drug List.

To explore how drugs were selected into the NDPN policy and to understand the policy's goals, we classify all marketed exclusive drugs into four groups: successfully negotiated drugs, drugs that participated in the negotiation but ultimately failed, drugs eligible for negotiation

but that did not participate, and other ineligible exclusive drugs.[3] Table 1 summarizes the characteristics of these four groups. First, in terms of the competition landscape, we find that relative to ineligible drugs, the eligible drugs face more competing drugs before launch, though among eligible drugs, firms participating in the negotiation do not face more competition than those that opt out of the negotiation. Second, consistent with its stated goal, the policy targeted, attracted, and selected more exclusive drugs treating rare and serious diseases. Third, we also find foreign products are more likely to successfully negotiate, although domestic firms are more likely to participate.

Table 1: Characteristics of Exclusive Drugs by Negotiation Status

	(1) Successfully Negotiated	(2) Participated but Unsuccessful	(3) Eligible but Not Participated	(4) Ineligible Exclusive
Imported Drug (%)	57.91	30.77	54.72	44.82
Competing Drugs at Last Negotiation	20.53	17.04	.	.
Sole Drug at Last Negotiation (%)	9.09	2.05	.	.
Competing Drugs Before Launch	17.67	13.14	18.47	7.08
Sole Drug Before Launch (%)	12.79	21.03	10.24	30.79
Drug for Rare Disease (%)	8.42	7.69	3.23	1.52
Drug for Infectious Disease (%)	17.85	26.15	23.72	21.34
Drug for Crowded Disease (%)	78.79	82.56	79.25	79.73
Drug for Under-Served Disease (%)	6.40	3.59	5.39	4.12
Observations	297	195	371	656

Notes: This table classifies all exclusive drugs approved for marketing in China as of June 2022 into four groups and reports their corresponding characteristics: (1) successfully negotiated drugs; (2) drugs that participated but ultimately failed the negotiation; (3) drugs marketed within five years that were eligible for negotiation but never participated; and (4) ineligible exclusive drugs. Rows labeled "(%)" report the percentage of drugs in each group with the indicated characteristic. Competing Drugs is the number of other marketed drugs indicated for the same diseases, measured either at the drug's most recent negotiation or immediately before its market launch. Sole Drug is an indicator for whether the drug was the only marketed treatment for its target diseases at the corresponding date. Diseases are defined at the ICD-10 three-character category level. Rare diseases are identified according to China's First List of Rare Diseases. Therapeutically crowded and under-served disease areas are defined as diseases in the top and bottom quartiles, respectively, of the distribution of the number of marketed drugs available for treatment.

[3]From 2016–2019, the negotiation was initiated by the government, and we define "participated but unsuccessful" firms as those that participated in the negotiation but failed, and "eligible but not participated" refers to firms that either declined the invitation to negotiation or were not invited for negotiation (we could not distinguish the two due to lack of data). Since 2020, "participated but unsuccessful" firms are those that were eligible and applied for the negotiation but failed the negotiation, and "eligible but not participated" are those that were eligible but did not apply for the negotiation.

2.3 Stylized Facts: Changes in Revenues after Successful Negotiation

The policy's impact on firms' R&D activities depends crucially on how it alters firms' expectations of future revenues. We therefore begin by documenting the policy impacts of successful drug negotiation on revenues. Since Kremer (2002) documents that marginal production costs are negligible relative to high R&D costs in drug development, revenue changes are a good proxy for profit changes—the unobserved variable of ultimate interest.[4] Our results complement those of Barwick, Swanson and Xia (2025), while employing different control groups.

Data To evaluate the effect of successful negotiation on revenues, we use a dataset on drug sales obtained from a consulting firm. The dataset records quarterly sales revenues and quantities, measured in the stock-keeping unit, for drug products produced by pharmaceutical firms across 20 cities from 2013 to 2021.[5] The dataset is collected from more than 500 representative public hospitals, so the ratio of sales revenue to quantity of a product represents the retail price before insurance reimbursement. We aggregate the raw sales data to the city-by-quarter level and restrict the analysis sample to exclusive drugs supplied by a single firm; therefore, each drug corresponds to one molecule.

We supplement the sales data with additional drug information obtained from government websites. Information on successfully negotiated drugs and the exact implementation dates of negotiated prices are collected from the official websites of the Ministry of Human Resources and Social Security (MOHRSS) and the NHSA. Drugs eligible for negotiation are identified based on whether their molecules are supplied by a single firm (i.e., exclusive drugs) using drug registration records published by the National Medical Products Administration (NMPA). In addition, we obtain provincial coinsurance rates for the NRDL from the Provincial Healthcare and Security Administration.

Empirical Strategy We estimate the impact of successful price negotiation on revenues using a staggered DID design. The treatment group consists of drugs that were successfully negotiated and added to the insurance coverage. We construct two never-treated groups. In the baseline analysis, we use drugs launched in China within the past five years that are therefore eligible for negotiation but never successfully negotiated. We also construct an alternative group with drugs

[4]The argument is particularly true for small molecule drugs. For biologics, the marginal production cost may not be negligible, thus the revenue change represents the upper bound for profit change.

[5]The included cities are Beijing, Changchun, Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Hangzhou, Harbin, Jinan, Nanjing, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Tianjin, Wuhan, Xi'an, and Zhengzhou.

that participated in the negotiation but eventually failed and remained uninsured. Results are similar across both groups[6].

There are two potential concerns regarding the empirical design above. First, successfully negotiated drugs may generate spillover effects on other drugs treating similar conditions, because insurance coverage could shift demand away from unsuccessfully negotiated or non-negotiated substitutes. To address this concern, we follow Dubois and Lasio (2018) to use the Anatomical Therapeutic Chemical (ATC) classification to identify close substitutes and remove from the control group any drug sharing the same ATC-4 code as a treated drug.

Second, treatment and control drugs may not be comparable before the policy implementation. We compare baseline characteristics at each drug's first appearance in our sample. We find that the treated and never-treated drugs are similar in domestic manufacturing status, first-launch year, and quarterly revenues, suggesting ex-ante balance on observables (see Appendix Table B1).

We use the staggered DID method to estimate the effects of the negotiation policy on drug prices, quantities, and revenues. To mitigate the bias of two-way fixed-effects estimators in staggered-adoption settings, we follow Cengiz et al. (2019) and Deshpande and Li (2019) to reconstruct the sample as follows. First, we split the full sample into six subsets: one for each of the five rounds of successfully negotiated drugs, and one for never-treated drugs. Second, for each negotiation round, we construct a subsample in which the treatment group consists of drugs successfully negotiated in that round and the control group consists of drugs not negotiated in that round but negotiated in later rounds and drugs that are never successfully negotiated. Third, for each subsample, we define the event quarters based on the implementation date of the negotiated price for the treatment drugs and restrict the observation window to periods before the control group becomes treated. Finally, we stack all subsamples to form the final analysis sample, which contains 215 drugs. We further restrict our main sample to three years before and two years after the negotiation, comprising a total of 11,819 drug-by-subsample-by-quarter observations.

We then estimate the following staggered DID specification:

$$\ln(y_{isq}) = \sum_{k \neq -1} \beta_k \; treat_{is} \times \mathbf{1}\{q - \tau_s = k\} + \delta_{is} + \mu_{sq} + \varepsilon_{isq}, \tag{1}$$

where the dependent variable, $\ln(y_{isq})$, represents the natural logarithm of the price, quantity, or revenue of drug i in subsample s and calendar quarter q. $treat_{is}$ indicates whether drug i in

[6] Appendix Tables B2 and B3 present the results.

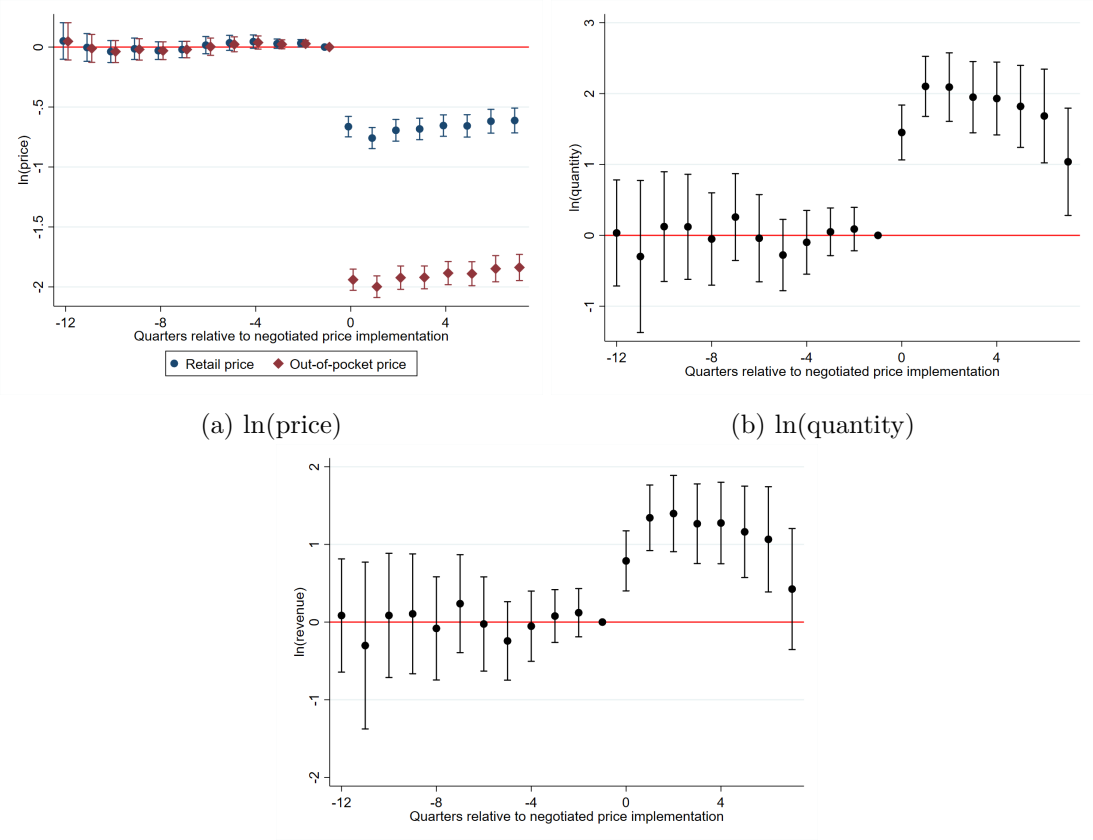
subsample s is in the treatment group. $\mathbf{1}\{q - \tau_s = k\}$ is an indicator that equals one if quarter q is k quarters after the event quarter τ_s in which the negotiated price and insurance coverage take effect for subsample s. The coefficient β_k captures the dynamic treatment effect relative to the implementation quarter ($k = -1$ is omitted). δ_{is} and μ_{sq} denote drug-by-subsample and subsample-by-quarter fixed effects, respectively. Standard errors are clustered at the drug level.

Results Figure 2 shows the result. Panel (a) jointly presents the estimated effects on retail prices and patients' out-of-pocket prices. We find that successful negotiation results in a substantial 50.2% reduction in retail price, suggesting that the negotiation is quite aggressive.[7] Combined with city-specific coinsurance rates for covered drugs, this retail price cut translates into an 85.5% decline in patients' out-of-pocket payments, highlighting the substantial financial relief brought to patients through insurance coverage. Panel (b) shows that the policy also increases the quantity by 476.6%, suggesting that the price reduction, along with the insurance coverage, greatly expands the market size. Panel (c) shows that the combined effect on revenues is positive: revenues of successfully negotiated drugs increase by 187.2%, indicating a strong and persistent positive response.

To put the estimated revenue change into context, we conduct a back-of-the-envelope calculation of the expected return from developing a new drug under the negotiation policy. We combine the estimates of the annual revenue of a new drug before and after successful negotiation with the probability and timing of successful negotiation to calculate the expected revenue generated by an exclusive new drug over its effective patent life. We then compare this figure with the industry estimates of the mean R&D cost of new drugs. Appendix A specifies the details of the calculation.

We estimate that the present value of expected cumulative revenue from a newly launched drug in China is approximately USD 551.07 million under the NDPN policy, compared with USD 359.85 million in the policy's absence. By comparison, the estimated capitalized R&D cost of a new drug in China ranges from approximately USD 519.70 million to USD 779.55 million. Thus, the NDPN policy moves expected revenue from below the lower bound of the estimated cost range to just within that range. Although the resulting revenue may remain insufficient to cover the costs of more expensive projects, the policy substantially improves the economic viability of new drug development and may enable firms with relatively low development costs to recover their R&D investment. However, the policy may also increase investment risk because

[7] Percentage changes are calculated as $(e^{\hat{\beta}} - 1) \times 100\%$. Appendix Table B2 reports the regression estimates, while Appendix Table B3 presents robustness check results using participating drugs during the negotiation.



(a) ln(price)

(b) ln(quantity)

(c) ln(revenue)

Figure 2: Effects of Successful Negotiation on Price, Quantity, and Revenue

Notes: These figures plot the estimated effects of successful NRDL negotiation on log retail price, out-of-pocket price, sales quantity, and sales revenue, along with their 95% confidence intervals. The analysis uses drug sales data and a staggered DID design with reconstructed subsamples. Observations are at the drug–by-subsample–by-quarter level, and successfully negotiated drugs are compared with eligible drugs that did not successfully enter the NRDL through negotiation during the corresponding subsample period. Drug-by-subsample and subsample-by-quarter fixed effects are included in the regressions. Standard errors are clustered at the drug level.

firms incur substantial and largely sunk R&D expenditures before learning whether a drug will be successfully developed, whether the negotiation will succeed, what price reduction will be required, and whether the subsequent sales volume expansion will be sufficient to offset that reduction. That motivates our analysis in the next section to quantify the policy impacts on innovation.

3 Data and Empirical Strategy

In this section, we examine how the policy subsequently changes pharmaceutical firms' innovation activities.

3.1 Research Design: Disease-Level Analysis

We measure innovation using clinical trial activity from 2013 to 2023. In principle, all new exclusive drugs, including chemical drugs and therapeutic biologics, are eligible for negotiation. Thus, we use clinical trials for new drugs as the treatment group. We choose clinical trials for preventive vaccines as the control group for two primary reasons. First, new exclusive chemical drugs and therapeutic biologics are generally eligible for negotiation, whereas preventive vaccines are excluded from the national health insurance program and financed through separate public health funds.[8] Second, vaccines are an R&D-intensive sector that shares similar technologies and regulatory environments with new drugs in China and globally, allowing us to difference out structural changes in the industry (Laroia and Singh, 2025; Tan et al., 2025).[9] A similar strategy has also been used in the literature. For example, Kong and Zhao (2023) use antivirals and antibacterial vaccines as controls for antibiotic innovation to difference out common demand shocks.

We construct a disease-by-group-by-year-level sample for analysis, where "group" refers to one of the two categories: drugs/therapeutic biologics (treatment group) or vaccines (control group). The dependent variable is whether a clinical trial is conducted, or the number of clinical trials conducted, in each year for each disease-by-group. If no clinical trial is conducted for a given disease-by-group in a particular year, the value is recorded as 0. We use the ICD-10

[8] Article 8 of the Interim Measures for the Administration of Drugs under Basic Medical Insurance stipulates that preventive vaccines shall not be included in the NRDL.

[9] In China, drug and vaccine development are overseen by the same regulatory authorities, follow comparable standards for classifying innovative products, and have similar clinical development processes. Moreover, a few policy shocks on clinical trials in China are applied to both drugs and vaccines, including a 2015 reform to shorten administrative waiting times in the clinical trial application (CTA) process, China's accession to the International Council for Harmonisation (ICH) in 2017, and the introduction of a patent term extension (PTE) system under the fourth amendment to China's Patent Law in 2021.

three-character category level to define disease, ensuring consistent and comparable disease classification.[10] In total, our dataset includes 3,481 diseases. According to the WHO, a preventive vaccine functions solely to prevent infectious diseases. Thus, we restrict the vaccine sample to infectious diseases.[11] Summary statistics for the treatment and control groups are reported in Appendix Table B4. Appendix Figure B1 illustrates the raw pattern of the average number of clinical trials per disease for each group. We find that before 2016, both groups followed a similar trend. However, after 2016, drug trials increased markedly.

We estimate the following model using two-way fixed effects:

$$y_{it} = \beta \; treat_i \times post_t + \zeta_i + \eta_t + \varepsilon_{it}, \tag{2}$$

where the subscript i denotes a disease-by-group combination, and t denotes a year. The dependent variable y_{it} is either an indicator of any clinical trial, the total number of trials, or the corresponding measures for trials of different trial types. $treat_i$ indicates the treatment group, and $post_t$ equals one for years after 2016. The coefficient β measures the average change in clinical trial activity for drugs relative to vaccines after the implementation of the negotiation policy. ζ_i and η_t denote disease-by-group and year fixed effects, respectively. Standard errors are clustered at the disease-by-group level.

We also estimate the following event study specification to examine the pre-trend and dynamics of the innovation response:

$$y_{it} = \sum_{k \neq -1} \beta_k \; treat_i \times \mathbf{1}\{t - \tau = k\} + \zeta_i + \eta_t + \varepsilon_{it}, \tag{3}$$

where τ denotes the year in which the negotiation policy began (i.e., 2016). The coefficient β_k captures the dynamic effect relative to the implementation year ($k = -1$ is omitted).

3.2 Data and Sample

Clinical Trials Data We use clinical trial data to gauge firms' R&D activities. This measure has been used in similar contexts, including in China (Geng and Shi, 2024; Gu, 2024; Jia et al.,

[10] The ICD-10 adopts a hierarchical structure consisting of four levels: (1) chapters, which group diseases into 21 broad categories identified by letters (A–Z); (2) blocks, which organize related diagnostic conditions within each chapter; (3) three-character categories, the level used in our analysis, each represented by one letter followed by two digits (e.g., C50); and (4) four-character subcategories, which add a decimal digit to provide more detailed diagnostic information (e.g., C50.1). We do not use the ATC system to classify drugs or vaccines because many trials lack ATC codes.

[11] The definition of infectious diseases follows WHO's Global Health Estimates, covering 207 ICD-10 categories. See `https://www.who.int/data/global-health-estimates`.

2025). The initiation of a new clinical trial represents the final and most expensive stage of a drug candidate's development (Finkelstein, 2004), and new clinical trials directly reflect firms' investment decisions under current market conditions (Yin, 2008). In contrast, other measures are less suitable for our context. R&D expenditure measures innovative inputs rather than outputs (Griliches, 1990), and increases in spending do not necessarily translate into meaningful or high-quality innovation. Patent data also provide a noisy proxy for innovation: firms typically apply for patents well before clinical trials begin (Acemoglu and Linn, 2004), and patenting behavior often reflects strategic motives rather than genuine scientific progress (Budish, Roin and Williams, 2015). Likewise, using new drug approvals as an innovation measure is impractical in our sample period: given the decade-long development process from initial discovery to market approval (DiMasi, Hansen and Grabowski, 2003), any approval observed today mirrors R&D decisions made many years earlier and thus cannot capture firms' immediate responses to policy changes.

The clinical trial data are obtained from the Center for Drug Evaluation (CDE) under the NMPA. This data source has been widely used in recent studies examining pharmaceutical innovation in China (Geng and Shi, 2024; Gu, 2024; Jia et al., 2025). Since 2013, all clinical trials conducted in China, including bioequivalence studies and Phase I-IV clinical trials, have been required to be registered and disclosed on a public platform. We obtain detailed information on active ingredient, dosage form, companies, registration category, indication, trial phase, date of first patient enrollment, and the first Institutional Review Board (IRB) approval date. We use the date of first patient enrollment as the clinical trial timestamp and conduct robustness checks using the first approval date of the IRB committee.

We implement the following data cleaning steps. First, we restrict our sample to clinical trials conducted since 2013, because earlier data are incomplete. Second, each clinical trial is assigned a registration category reflecting its marketing status in both domestic and international markets. We use this information to drop clinical trials for generic drugs (i.e., bioequivalence studies) and for products already marketed abroad but requiring local trials upon entry into China. Thus, our sample comprises clinical trials of new drugs and vaccines that have not been marketed in any country at the time of trial application. Third, we drop COVID-19-related clinical trials. COVID-19 spurred research activity, but this shock was unforeseen and may interact with other policies.

We further classify the clinical trials into two types based on novelty, using the registration category in China. The first is Type I clinical trials, which are for new drugs with novel chemical entities and well-defined structures, as well as new vaccines that embody substantial

innovation, such as those featuring new antigen forms, new adjuvants or adjuvant systems, or new multivalent formulations incorporating new antigens. The second is Type II clinical trials, which are for new drugs or vaccines that are improved and refined versions of known active ingredients, such as modifications to their chemical structure, dosage form, formulation process, route of administration, or therapeutic indication. This classification is similar to the U.S. Food and Drug Administration (FDA)'s new drug application classification, with Type I clinical trials being more novel and including trials for first-in-class drugs and vaccines.[12]

For each clinical trial, we map its indication listed in the application form to the National Clinical Version 2.0 of the Disease Coding System in China to determine the corresponding treated disease. This system is fully aligned with the ICD-10 framework while incorporating adjustments and refinements tailored to China's clinical practice.

Firm Characteristics Firm characteristics are obtained from Qichacha and the Orbis database. Qichacha is a leading Chinese business information platform that compiles all official registration records from the State Administration for Market Regulation and other government agencies. As of 2025, the platform covers more than 500 million enterprises, providing comprehensive data on company profiles, shareholder structure, historical operations, credit information, financial status, and change logs. Orbis, maintained by Bureau van Dijk, provides standardized firm-level data from official registries and financial disclosures. From these two sources, we extract key firm characteristics, including the year of establishment, year of deregistration (if applicable), firm size category, ownership type, and country or region of registration.

4 Results

This section presents the main empirical results. We estimate the effect of the NDPN on clinical trial activity and conduct a series of robustness checks.

4.1 Baseline Results

Table 2 presents the baseline DID estimates. Overall, the negotiation policy leads to an increase of 0.534 in the average number of drug clinical trials relative to vaccines, significant at the 1% level. We also find the results are mainly driven by Type I, i.e., more radical, innovations: after the negotiation policy, drugs exhibit a 2.1 percentage point increase in the likelihood of

[12]Note that Type I drugs are not necessarily first-in-class drugs, since according to the FDA, first-in-class drugs have mechanisms of action that differ from those of existing therapies, while Type I drugs with new molecular structures do not necessarily have new mechanisms of action.

conducting Type I clinical trials and an average increase of 0.540 Type I trials (both of which are significant). In contrast, the policy has no significant effect on Type II clinical trials for drugs.

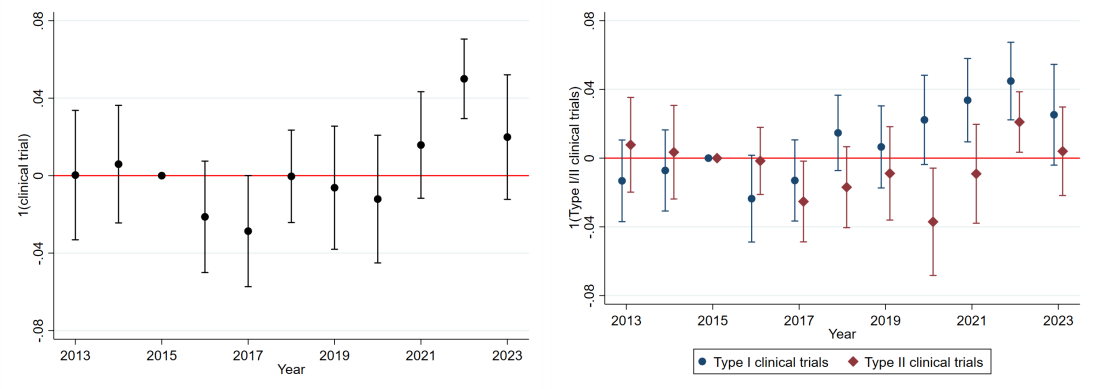
Table 2: Effects of the Negotiation Policy on Clinical Trials

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
treat × post	0.000	0.021**	-0.013	0.534***	0.540***	-0.006
	(0.010)	(0.009)	(0.008)	(0.109)	(0.084)	(0.039)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Pre-Policy Mean	0.050	0.033	0.029	0.187	0.119	0.068
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.661	0.643	0.560	0.671	0.616	0.633
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table reports the baseline DID estimates of the price negotiation policy's effects on clinical trial activity. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)–(3) present the estimated effects on the incidence of any new trial, while columns (4)–(6) present the effects on the number of new trials. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 presents the event study estimates of the policy impacts on the incidence of conducting any clinical trials (panel (a)) and separately for more novel Type I and less novel Type II trials (panel (b)). Both panels exhibit parallel pre-2016 trends, and the policy effect is shown to be more pronounced for Type I drugs, with a statistically significant increase of 3.37% in 2021. The lagged effects observed in the event study estimates reflect firms' expansion into new disease areas beyond those already addressed by their existing drugs. Entering a completely new disease area generally requires firms to begin with target identification and validation, proceed through candidate discovery and preclinical development, and only then initiate human trials. Paul et al. (2010) estimate that progression from the target-to-hit stage to the initiation of Phase I clinical trials takes approximately 5.5 years. Consistent with this development timeline, our event study estimates show that the policy's effect on firms' entry into new disease areas emerges only after a substantial lag.

Figure 4 presents the event study estimates of the negotiation policy's effects on the number of clinical trials for all types (panel (a)) and separately for Type I and Type II clinical trials (panel (b)). Trial counts began to rise steadily in 2017 and stabilized at nearly one clinical trial per disease per year after 2021. This effect is solely driven by Type I trials, consistent with the observation that Type I new drugs often have higher clinical values and enjoy longer



(a) All New Clinical Trials (b) Type I and Type II Clinical Trials

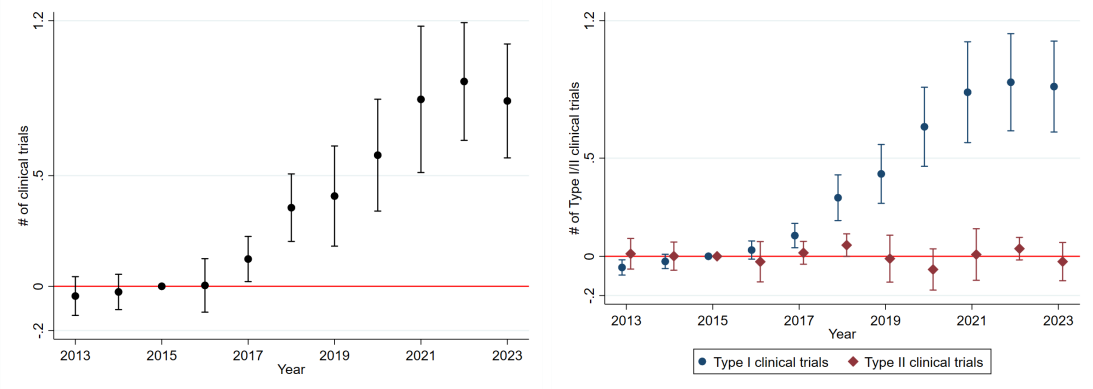
Figure 3: Event Study for the Incidence of Clinical Trials

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the incidence of new clinical trials (Panel a) and on the incidence of new Type I and Type II trials separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.

patent protection (i.e., are more likely to receive patent extension approval), which may amplify revenue gains from successful negotiation. Overall, these patterns indicate that the negotiation policy primarily stimulates more innovative drug development.

Further, we examine whether the negotiation policy altered the composition of pharmaceutical clinical trials across development phases. When a trial simultaneously spans multiple phases (e.g., a combined Phase I/II study), we count it toward each phase total. Panel (a) of Figure 5 presents stacked bar charts showing the annual shares of Phase I-IV trials. The distribution of trials across phases remains broadly stable over time. The share of Phase I trials shows no discernible change following the policy, while the share of Phase II trials increases slightly and the shares of Phase III and Phase IV trials decline modestly. Panel (b) of Figure 5 presents event study estimates separately for Phase I-IV trials, comparing drug- and vaccine-related clinical trials. Notably, Phase I shows an immediate increase, while Phases II and III show one- to two-year lagged increases. Because transforming a new molecular discovery into clinical trials typically takes many years, the immediate Phase I response suggests that firms had accumulated trial-ready candidates that were withheld from launch before the policy due to insufficient expected market size. The policy's expansion of market access enabled an immediate release of these pent-up candidates into Phase I trials.

These results speak directly to the concern that the negotiation policy's repeated revisions since its inception might have prompted firms to concentrate their R&D on safer investments—for example, drugs that are near approval or recently approved—whose value is less sensitive to



(a) All Clinical Trials (b) Type I and Type II Clinical Trials

Figure 4: Event Study for the Number of Clinical Trials

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of new clinical trials (Panel a) and on the number of new Type I and Type II trials separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.

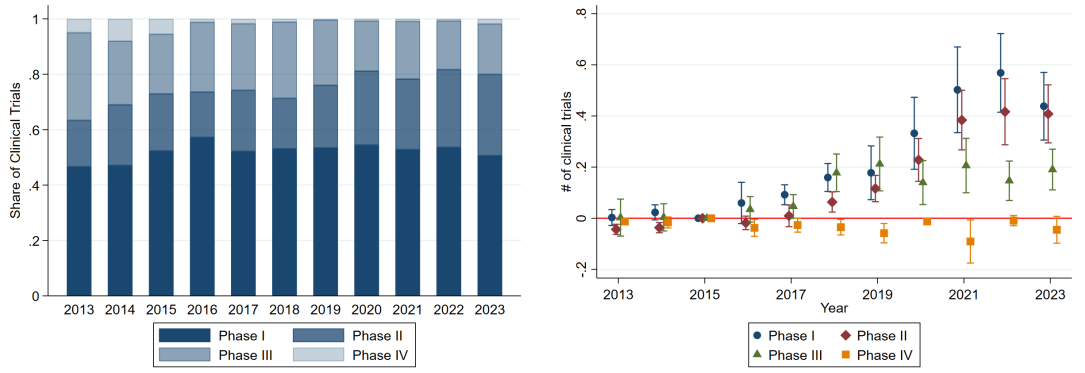
long-run pricing uncertainty. Contrary to this concern, we find no evidence of a strategic reallocation away from early-stage trials toward later-stage development or post-marketing studies; if anything, the opposite pattern holds.

4.2 Robustness Checks

We conduct a series of robustness checks. All results consistently confirm the robustness of our baseline findings. Across various specifications, we find that the policy increases the number of clinical trials by 0.385 to 0.675.

4.2.1 Vaccines as Control Group

A potential concern for identification is whether vaccine-preventable diseases provide an appropriate control group for drug-treatable diseases. As an initial diagnostic, we find that the disease burdens are similar for infectious diseases (eligible for vaccine prevention and drug treatment) and noninfectious diseases (only eligible for drug treatment) in China. Nevertheless, vaccines may differ from drugs in their demand patterns, market structure, and innovation incentives. These differences may induce distinct innovation dynamics and therefore violate the parallel-trends assumption. To mitigate this concern, we conduct four sets of robustness checks. Across all specifications, the results remain highly similar to the baseline estimates.



(a) Phase Distribution of Drug Clinical Trials (b) Phase-Specific Event Study Estimates

Figure 5: Phase Composition and Phase-Specific Effects of the NDPN Policy

Notes: This figure presents the annual phase composition of drug clinical trials in Panel (a) and the phase-specific event study coefficients of the negotiation policy's effects on the number of new clinical trials in Panel (b), together with their 95% confidence intervals. The unit of analysis in Panel (b) is a disease-by-group-by-phase-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions and standard errors are clustered at the disease-by-group-by-phase level in Panel (b).

Excluding Diseases Preventable by Long-Lasting and National Immunization Program (NIP) Vaccines We exclude diseases for which vaccines have fundamentally different demand and market structures, including diseases preventable by long-lasting vaccines and those covered by China's NIP.[13] In total, these exclusions involve 18 ICD-10 categories and we drop the corresponding observations for both drug and vaccine clinical trials. Panel A of Table 3 shows that the estimated effects are similar to the baseline results.[14]

Therapeutic Biologics versus Vaccines We divide the treatment group into chemical drugs and therapeutic biologics. Therapeutic biologics are more similar to preventive vaccines with respect to R&D processes, manufacturing complexity, and clinical evaluation standards, making the comparison tighter and ensuring that the comparison is not affected by other policy changes regarding the pharmaceutical market.[15] Appendix Table B5 shows that the results are consistent with the baseline estimates: the policy impacts on therapeutic biologics are positive and significant, measured by both the probability of initiating Type I clinical trials and the

[13]Vaccines conferring long-lasting protection generate limited recurrent demand. Following Vashishtha and Kumar (2024), we exclude diseases for which vaccine protection exceeds twenty years. NIP vaccines are centrally procured by the government and provided free under the national immunization schedule, so their demand reflects public-health objectives and positive externalities rather than patients' ability to pay. Consequently, the economic incentives and aggregate shocks affecting R&D for these vaccines may differ from those affecting drugs.

[14]Appendix Figure B2 presents the event study results.

[15]For example, during this period, China gradually implemented bioequivalence evaluation, beginning with chemical generic drugs and subsequently extending to therapeutic biologics and vaccines. In addition, China implemented central procurement for selected generic drugs, which targeted only chemical products, leaving therapeutic biologic drugs and vaccines unaffected during the sample period.

number of trials. Moreover, the estimated policy effect is noticeably larger for therapeutic biologics than for chemical drugs.[16]

Controlling for Pre-policy Trends A potential concern regarding the use of vaccine diseases as the control group is that drug and vaccine diseases may differ systematically in their pre-policy disease burden, market structure, and innovation activity. To account for potential differential pre-trends across disease-by-group observations, we interact a set of pre-policy disease and disease-by-group characteristics with year fixed effects. Specifically, these characteristics include the average number of patients in China and worldwide[17], the average number of competing drugs or vaccines, and the average number of completed clinical trials. Panel B of Table 3 shows estimates similar to the baseline results, suggesting that our findings are robust to controlling for potential differential pre-trends across disease groups.[18]

Potential Confounding from the COVID-19 Pandemic The COVID-19 pandemic may affect our estimates if firms reallocated R&D resources toward COVID-19 drug or vaccine development, potentially reducing innovation in other therapeutic areas.[19] To address this concern, we exclude all clinical trials conducted by firms that engaged in COVID-19 drug or vaccine R&D, so the remaining firms were less likely to have diverted their R&D resources toward COVID-19-related projects. As reported in Panel C of Table 3, the estimated effects remain similar to the baseline results. These results suggest that our findings are unlikely to be materially affected by the reallocation of R&D resources induced by the COVID-19 pandemic.[20]

Potential Within-Firm Spillovers between Drug and Vaccine R&D Although only 4.33% of firms in our sample conduct clinical trials for both drugs and vaccines, potential spillovers between their drug and vaccine R&D activities could affect our comparison between treatment and control groups. To address potential within-firm spillovers, we conduct a robustness check excluding all clinical trials conducted by firms that undertook clinical trials for both

[16] Appendix Figure B3 presents separate event study estimates for therapeutic biologics and chemical drugs, using vaccines as the control group.

[17] We obtain pre-2016 patient counts from the Global Burden of Disease (GBD) Results Tool maintained by the Institute for Health Metrics and Evaluation (IHME). The GBD synthesizes information from administrative records, household surveys, hospital data, and other sources to generate comparable estimates of disease prevalence across locations and over time. We map GBD cause categories to the ICD-10 codes used in our clinical trial data. The GBD does not report prevalence estimates for some ICD-10 disease categories and we exclude them from these analyses; these regressions therefore contain fewer observations than the baseline specification.

[18] Appendix Figure B4 presents the event study results.

[19] As a first step, we examine the raw data pattern in clinical trial activity for drugs and vaccines when COVID-19-related trials are retained. The resulting patterns are qualitatively similar to those in our main analytical sample.

[20] Appendix Figure B5 presents the event study results.

drugs and vaccines. As reported in Panel D of Table 3, the results remain robust.[21]

Table 3: Robustness Results: Effects of the Negotiation Policy on Clinical Trials, Addressing Concerns about the Vaccine Control Group

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
Panel A: Excluding Diseases Preventable by Long-Lasting and NIP Vaccines						
treat × post	0.005	0.017*	-0.008	0.542***	0.532***	0.010
	(0.010)	(0.010)	(0.008)	(0.111)	(0.086)	(0.040)
Observations	40,172	40,172	40,172	40,172	40,172	40,172
Adj. R^2	0.662	0.643	0.564	0.671	0.616	0.635
Panel B: Including Control Variables						
treat × post	0.010	0.028***	-0.005	0.413***	0.430***	-0.018
	(0.011)	(0.009)	(0.009)	(0.156)	(0.150)	(0.027)
Observations	24,871	24,871	24,871	24,871	24,871	24,871
Adj. R^2	0.656	0.645	0.535	0.884	0.868	0.714
Panel C: Excluding Firms Conducting COVID-19 Trials						
treat × post	0.003	0.023***	-0.013*	0.434***	0.503***	-0.069**
	(0.010)	(0.009)	(0.008)	(0.093)	(0.078)	(0.034)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.633	0.626	0.446	0.610	0.605	0.448
Panel D: Excluding Firms Conducting Clinical Trials for Both Drugs and Vaccines						
treat × post	0.017**	0.027***	0.002	0.650***	0.566***	0.084***
	(0.007)	(0.006)	(0.006)	(0.098)	(0.081)	(0.021)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.658	0.646	0.551	0.671	0.616	0.635

Notes: This table reports robustness checks examining the validity of using vaccine diseases as the control group in the DID analysis. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)–(3) present the estimated effects on the incidence of any new trial, while columns (4)–(6) present the effects on the number of new trials. Disease-by-group and year fixed effects are controlled in all regressions. Standard errors are clustered at the disease-by-group level. Panel A excludes diseases preventable by long-lasting vaccines and vaccines included in China's National Immunization Program (NIP). Panel B controls for pre-policy disease-specific and disease-by-group-specific characteristics—the average number of patients in China and worldwide, the average number of competing drugs or vaccines, and the average number of completed clinical trials—interacted with year fixed effects. Panel C excludes clinical trials conducted by firms engaged in COVID-19 drug or vaccine R&D. Panel D excludes clinical trials conducted by firms engaged in both drug and vaccine R&D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2 Addressing Potential Confounding Effects of Other Policies

During our sample period, several reforms besides the NDPN were introduced in China, including the 2015 clinical trial application (CTA) reform, the Marketing Authorization Holder (MAH) reform introduced in 2015 through a regional pilot and expanded nationwide in 2019, China's accession to the International Council for Harmonisation of Technical Requirements for

[21] Appendix Figure B6 presents the event study results.

Pharmaceuticals for Human Use (ICH) in 2017, and the patent term extension (PTE) system introduced by the 2020 amendment to China's Patent Law. These reforms affect both drug and vaccine development, and thus our baseline design would difference out their impacts if they affect drug and vaccine development similarly. However, there might be a remaining concern that these reform effects may affect each group differently. In this section, we examine whether our baseline results are robust to controlling for exposure to these reforms directly.

CTA Reform In August 2015, China introduced a reform for both drugs and vaccines to address the backlog of clinical trial applications and accelerate the approval process. Jia et al. (2025) show that faster approval of clinical trial applications encourages additional applications. Following Jia et al. (2025), we use clinical trial application data to calculate the reduction in average approval days for each disease-by-drug or disease-by-vaccine category between the pre-2015 and post-2015 periods to measure the policy intensity. We then control for the interaction between this decline in days and a post-2015 indicator in Equation (2). Panel A of Table 4 reports the estimation results after accounting for the 2015 CTA reform. The estimated effects of the NDPN policy on pharmaceutical innovation remain positive and statistically significant, and the coefficient magnitudes are comparable to those in the baseline specification. These results suggest that our findings are not driven by the acceleration of clinical trial application approvals.

MAH Reform China introduced the MAH system in some pilot regions for drug products in 2015 and then extended it nationwide to both drugs and vaccines in 2019. By separating marketing authorization from manufacturing, the reform allowed firms to outsource production rather than maintain in-house facilities, lowering entry barriers and potentially increasing clinical trial activity (Gu, 2024). To rule out potential confounding effects of the MAH reform, we calculate, for each disease-by-drug or disease-by-vaccine category, the share of clinical trials exposed to the MAH reform, using either November 2015 (pilot announcement date) or May 2016 (pilot implementation date) as the reform start date. We then add both of these corresponding MAH exposure measures to Equation (2) to account for both the policy's announcement and implementation effects. Panel B of Table 4 shows that the estimated effects remain quantitatively similar to the baseline estimates.

China's Accession to the ICH In June 2017, China joined the ICH, aligning its clinical trial standards more closely with international regulatory requirements and encouraging multi-

national pharmaceutical firms to conduct more clinical trials for drugs and vaccines in China. Following Barwick, Xia and Xia (2026), we augment Equation (2) by interacting a post-2017 indicator with the average pre-2017 disease prevalence in the United States, the European Union, Japan, and South Korea, which represent China's major international pharmaceutical markets and regulatory partners. This specification allows disease categories with greater international market potential to follow different post-2017 trends associated with China's integration into the global clinical development system.[22] Panel C of Table 4 reports the estimation results, showing that our findings remain robust after accounting for the potential confounding effects of China's accession to the ICH.

PTE Reform On June 1, 2021, the fourth amendment to China's Patent Law took effect, introducing a patent term extension (PTE) system to compensate for time lost during the regulatory review and approval of new drugs and vaccines. Upon the patentee's request, patent terms may be extended for Type I innovative drugs and vaccines and certain Type II products involving structural modifications, improvements in bacterial or viral strains, or indication expansions. To account for the potential effect of the PTE reform on pharmaceutical innovation, we augment Equation (2) with an interaction between a post-2021 indicator and each disease-by-group combination's expected exposure to PTE.[23] Panel D of Table 4 shows that the estimated effects remain quantitatively similar to the baseline estimates.

Finally, we jointly account for all four of these concurrent policy changes in the same specification. Panel E of Table 4 reports the estimation results. The estimated effects remain positive and statistically significant, with coefficient magnitudes comparable to those in the baseline specification.[24] These findings suggest that our results are robust to accounting for the simultaneous influence of the 2015 CTA reform, China's accession to the ICH, the MAH reform, and the PTE reform, and are therefore unlikely to be driven by these concurrent policy changes.

[22] Pre-2017 prevalence in these markets is also obtained from the GBD Results Tool. This specification likewise contains fewer observations than the baseline regression because GBD estimates are unavailable for some ICD-10 disease categories in our sample.

[23] We construct this exposure measure by multiplying the disease-by-group-specific shares of pre-2020 clinical trials that satisfy the PTE eligibility criteria, the group-specific probabilities of receiving PTE, and the group-specific extension lengths conditional on receiving the extension reported by Yao, Zhang and Zhou (2026). For drug disease groups, the measure sums the expected exposure associated with chemical drugs and therapeutic biological products. For vaccine disease groups, the measure is based on preventive biological products and we assume that preventive and therapeutic biological products have the same probability of receiving PTE and the same conditional extension length.

[24] Appendix Figure B7 presents the event study results.

Table 4: Robustness Results: Effects of the Negotiation Policy on Clinical Trials, Accounting for Confounding Policies

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
Panel A: Controlling for the CTA Reform						
treat × post	0.002	0.022**	-0.012	0.573***	0.571***	0.003
	(0.009)	(0.009)	(0.007)	(0.119)	(0.099)	(0.035)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.681	0.660	0.573	0.685	0.628	0.649
Panel B: Controlling for the MAH Reform						
treat × post	-0.006	0.015*	-0.014*	0.550***	0.569***	-0.018
	(0.010)	(0.009)	(0.008)	(0.110)	(0.089)	(0.038)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.679	0.661	0.561	0.674	0.622	0.636
Panel C: Controlling for China's Accession to the ICH						
treat × post	0.004	0.027***	-0.011	0.521***	0.534***	-0.013
	(0.011)	(0.010)	(0.009)	(0.125)	(0.100)	(0.042)
Observations	24,871	24,871	24,871	24,871	24,871	24,871
Adj. R^2	0.655	0.643	0.528	0.663	0.612	0.592
Panel D: Controlling for the PTE Reform						
treat × post	-0.005	0.016*	-0.016*	0.397***	0.414***	-0.017
	(0.010)	(0.009)	(0.008)	(0.095)	(0.070)	(0.039)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.672	0.658	0.566	0.688	0.637	0.636
Panel E: Controlling for All Four Policies						
treat × post	-0.012	0.011	-0.016**	0.385***	0.422***	-0.037
	(0.009)	(0.009)	(0.008)	(0.112)	(0.095)	(0.036)
Observations	24,871	24,871	24,871	24,871	24,871	24,871
Adj. R^2	0.702	0.691	0.548	0.694	0.645	0.610

Notes: This table reports DID estimates of the price negotiation policy's effects on pharmaceutical innovation after accounting for other concurrent policy changes. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)–(3) present the estimated effects on the incidence of any new trial, while columns (4)–(6) present the effects on the number of new trials. Disease-by-group and year fixed effects are controlled in all regressions. Standard errors are clustered at the disease-by-group level. Panel A controls for the 2015 Clinical Trial Application (CTA) reform by including an interaction between the disease-by-group-specific reduction in average application approval time before and after the reform and a post-2015 indicator. Panel B controls for the Marketing Authorization Holder (MAH) reform by including the shares of clinical trials exposed to the reform, constructed using both the announcement and implementation dates of the pilot program. Panel C controls for China's accession to the International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) by including interactions between average pre-2017 disease prevalence in the United States, the European Union, Japan, and South Korea and a post-2017 indicator. Panel D controls for the patent term extension (PTE) reform by including an interaction between a post-2021 indicator and each disease-by-group combination's expected exposure to PTE. Panel E simultaneously includes the controls for all four policy changes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.3 Additional Robustness Checks

Extending the Sample Period To address the concern about the short pre-treatment period, we extend the sample period back to 2010. The CDE platform made trial registration and public disclosure mandatory only in 2013; earlier trials appear in the data only if firms voluntarily register their trials. This data availability issue may mechanically cause a pre-trend, which makes inferring the latent pre-trend from the 2010 data challenging. Despite that, we conduct a robustness check by extrapolating the trend in 2010-2015 and following Dobkin et al. (2018) to difference it out from the outcome variable in the post-reform period. The corresponding results are reported in Appendix Table B6 and Appendix Figure B8. The estimated effects remain quantitatively similar to the baseline results.

Poisson Regression Model We quantify the effect of the negotiation policy on the proportional change in clinical trials using a Poisson regression model. Specifically, we estimate the following DID specification:

$$y_{it} = exp(\beta\ treat_i \times post_t + \zeta_i + \eta_t) + \xi_{it}, \tag{4}$$

where all variables are as defined in Equation (2). The coefficient β represents the proportional change in the outcome variable. Its magnitude can be interpreted as a percentage change, calculated as $(e^{\beta} - 1) \times 100\%$. We find that the number of overall new clinical trials for all drugs increases by 50.23% (see Appendix Table B7). In 2022, the number of Type I trials increased by 194.34% relative to the baseline period (2015) (see Appendix Figure B9). In contrast, the number of new Type II trials does not change significantly. Overall, our findings remain robust when the model is estimated using a Poisson specification.

Alternative Definitions of Clinical Trial Timing We adopt an alternative definition of clinical trial timing that sets trial start dates equal to the IRB approval dates. In China, clinical trials must obtain approval from the IRB before investigators are allowed to begin participant recruitment. As a result, some trials in the data have received IRB approval but have not yet completed participant enrollment, which increases the number of trials captured under this alternative definition (8,741 trials, compared with 7,445 trials in the baseline specification). Appendix Table B8 and Appendix Figure B10 confirm that our findings are robust to this alternative timing definition.

Alternative Measures of R&D Activity We use alternative measures of R&D activity based on project-level counts, measuring innovation as the number of new or active clinical projects at the active ingredient-by-dosage form-by-firm level. A new clinical project is defined as one that starts a clinical trial in a given year. In addition, a clinical project is classified as active in a given year if the firm continues to develop the same drug or vaccine, even if no clinical trial happens to be carried out in that specific year. The corresponding results are reported in Appendix Table B9 and Appendix Figures B11 and B12. The results remain robust, and the observed increase in innovation is primarily driven by Type I projects.

5 Mechanisms

5.1 Increased Expected Returns versus Relaxed Financial Constraints

Having shown that the NDPN substantially increased pharmaceutical innovation, we next examine two complementary mechanisms underlying this response. First, the prospect of NRDL inclusion may increase expected returns through market expansion, affecting all potentially eligible firms when the policy is introduced. For example, the founder of Akeso Biopharma stated that national health insurance policies gave the company greater confidence to invest in high-risk and capital-intensive original drug discovery (Ding, 2026). Second, successful negotiation may also expand cash flow and relax financial constraints for firms that secure inclusion. For example, Keymend Biosciences, having invested more than RMB 2 billion since its establishment, expected successful negotiations to provide the sustained cash flow needed to advance its pipeline of over 50 products (China Central Television News, 2025).

Distinguishing these two channels matters because they highlight different policy priorities. The expected-return channel emphasizes credible and predictable coverage and broad patient access, whereas the financial-constraint channel emphasizes timely payment, adequate post-negotiation cash flow, and complementary R&D financing. Their relative importance therefore determines which features of the negotiation policy matter most for sustaining innovation.

As an initial piece of suggestive evidence for the increased expected returns channel, we find that the policy effects are larger among diseases with larger patient populations in China during the pre-policy period. The results suggest that firms respond more strongly where domestic health needs, potential demand, and hence the expected insured market are larger, consistent with the expected market return channel. We also provide suggestive evidence for the relaxed financial constraints channel using each firm's average assets in 2014 and 2015,

calculated from corporate income tax filings in China. We employ a firm-level staggered DID specification that compares successfully negotiated firms with firms that were invited or selected to negotiate but failed to reach an agreement, before and after their respective negotiation rounds. We additionally estimate the interaction between the staggered treatment indicator and firms' average pre-policy assets. We find a significantly negative interaction coefficient, indicating a larger policy effect on trial counts for firms with lower pre-policy assets, consistent with the policy easing financing constraints.[25]

We further quantify the relative size of the two channels by shifting the unit of analysis from the disease-by-year level used in the baseline analysis to the firm-by-year level. This shift is necessary because both expected returns and financial resources affect innovation through firms' R&D decisions. In particular, successful negotiation and the resulting revenue increase occur at the firm-by-drug level, making it difficult to isolate the associated firm-specific response in the disease-level analysis. Therefore, we first estimate the policy's overall effects using all firms. And then we estimate the financial constraint channel using successfully negotiated firms. Finally, we derive the expected return channel by subtracting the financial constraint channel from the overall effect, and compare the two channels' relative contributions.

To estimate the policy's overall effects on all pharmaceutical firms, we use a firm-level two-way fixed effects model with pharmaceutical firms as the treatment group and vaccine firms as the control group:

$$y_{ft} = \alpha \; treat_f \times post_t + \theta_f + \lambda_t + \nu_{ft}, \tag{5}$$

where the subscript f indexes firms, and t indexes years. The dependent variable y_{ft} is either an indicator of any clinical trial, the total number of trials, or the corresponding measures separately for Type I and Type II trials. $treat_f$ indicates whether firm f is in the treatment group. $post_t$ equals one for years after 2016. The coefficient α captures the overall policy effect for all pharmaceutical firms. θ_f and λ_t denote firm and year fixed effects, respectively. Standard errors are clustered at the firm level.

The firm-level sample used for the above estimations includes pharmaceutical and vaccine firms that conducted clinical trials in our baseline sample and participated in the negotiation during 2016-2023. For each firm, we collect information on its establishment and deregistration year (if applicable) and calculate the number of clinical trials conducted during this period. We impute zeros for years without trials. Following the baseline classification, firms that conducted only vaccine clinical trials during 2013-2023 serve as the control group, as they were not affected

[25] These results are available upon request.

by the negotiation policy. All other firms engaged in drug R&D constitute the treatment group. Appendix Table B10 reports summary statistics at the firm level. In general, vaccine firms are more likely to be domestic but similar in size.

We then estimate the financial constraint channel, namely the effects of successful negotiation, using a staggered DID approach. After reconstructing the corresponding sample as described in Section 2.3, we compare successfully negotiated firms with those that participated in the corresponding or a later round but had not succeeded yet. The estimation equation is specified as:

$$y_{fmt} = \gamma \; treat_{fm} \times post_{mt} + \theta_{fm} + \lambda_{mt} + \nu_{fmt}, \tag{6}$$

where f indexes firms, m indexes subsamples, and t indexes years. $treat_{fm}$ equals one if firm f in subsample m successfully negotiated during the sample period, and $post_{mt}$ equals one for the negotiation year and all subsequent years in subsample m and zero otherwise. The coefficient γ captures the effect of successful negotiation. Firm-by-subsample fixed effects θ_{fm} and subsample-by-year fixed effects λ_{mt} are included, and standard errors are clustered at the firm level.

5.2 Results

Table 5 reports the DID estimates of the negotiation policy's overall effects for all pharmaceutical firms, obtained from Equation (5).[26] Relative to vaccine firms, pharmaceutical firms conducted, on average, 0.123 additional clinical trials per year after the implementation of the NDPN policy. Consistent with the baseline disease-level results, decomposing the effect by trial type, we find a significant increase in both the incidence and the number of Type I clinical trials following the implementation of the policy. In contrast, both the incidence and the number of Type II clinical trials decline significantly after the policy.

Table 6 reports the staggered DID estimates of the financial constraint channel, obtained from Equation (6).[27] Relative to pharmaceutical firms that participated in the negotiation but were unsuccessful, successfully negotiated firms conducted, on average, 1.590 additional clinical trials after their drugs were included in the NRDL. However, we find no significant rise in the likelihood of starting any new trial. A plausible interpretation is that the substantial revenue gains from successful negotiation provide the corresponding firms with greater financial resources to accelerate their existing R&D pipeline, while the lag from discovery to clinical

[26] Appendix Figure B13 presents the event study results.
[27] Appendix Figure B14 reports the event study results.

Table 5: Overall Effects of the Negotiation Policy on Clinical Trials for All Firms

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
treat × post	-0.054	0.065**	-0.120***	0.123	0.342***	-0.219**
	(0.036)	(0.030)	(0.036)	(0.113)	(0.064)	(0.088)
Observations	18,303	18,303	18,303	18,303	18,303	18,303
Pre-Policy Mean	0.117	0.080	0.046	0.222	0.142	0.080
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.262	0.286	0.286	0.562	0.544	0.427
Within R^2	0.000	0.000	0.002	0.000	0.001	0.001

Notes: This table reports the firm-level DID estimates of the price negotiation policy's effects on clinical trial activity, using the full sample of pharmaceutical firms (treatment group) and vaccine firms (control group). The unit of analysis is a firm-by-year observation. Columns (1)-(3) present the estimated effects on the incidence of any new trial, while columns (4)-(6) present the effects on the number of new trials. Standard errors are clustered at the firm level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

trials prevents an extensive margin from responding in the short run. Decomposing by trial type, successfully negotiated firms experience significant gains in the number of new Type I trials. For Type II trials, both the incidence and count increase significantly, although the increase in count is small.

Based on the preceding estimates, we quantify the expected returns channel as

$$\widehat{\delta}^{ER} = \widehat{\alpha} - \widehat{\gamma} \times Share^{SN}, \tag{7}$$

where $\widehat{\delta}^{ER}$ represents the estimated expected return channel, $\widehat{\alpha}$ denotes the estimated overall effect from Equation (5), $\widehat{\gamma}$ denotes the estimated financial constraint channel from Equation (6), and $Share^{SN}$ denotes the proportion of pharmaceutical firm-by-year observations in which the firm has already successfully negotiated and entered the NRDL in the year. $Share^{SN}$ equals 3.36%. Substituting this value into the decomposition equation yields an estimated expected return channel of 0.070 additional clinical trials per pharmaceutical firm-by-year. Thus, the expected return channel accounts for approximately 56.57% of the policy's overall effect, while the financial constraint channel accounts for the remaining 43.43%, suggesting that the NDPN policy stimulates innovation primarily by increasing the prospective returns to pharmaceutical R&D through expanded market access, while the additional financial resources generated by successful negotiation provide a complementary stimulus to firms' clinical development activities.

Table 6: Effects of Successful Negotiation on Clinical Trials per Firm

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
treat × post	0.018	0.025	0.066*	1.590***	1.246**	0.344***
	(0.037)	(0.033)	(0.033)	(0.567)	(0.518)	(0.119)
Observations	12,501	12,501	12,501	12,501	12,501	12,501
Pre-Policy Mean	0.324	0.243	0.155	1.020	0.639	0.381
Firm-by-subsample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Subsample-by-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.436	0.458	0.344	0.622	0.590	0.533
Within R^2	0.000	0.000	0.002	0.019	0.015	0.008

Notes: This table reports staggered DID estimates of the price negotiation policy's effects on the conduct of new clinical trials for firms involved in negotiation, using reconstructed subsamples of pharmaceutical firms that succeeded in each round of negotiations (treatment group) and that participated in the corresponding or a later round but had not succeeded yet (control group). The unit of analysis is a firm-by-subsample-by-year observation. Columns (1)-(3) present the estimated effects on the incidence of any new trial, while columns (4)-(6) present the effects on the number of new trials. Standard errors are clustered at the firm level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Further Analysis

In this section, we conduct a set of further analyses. We first examine whether the negotiation policy affects not only the quantity but also the quality of clinical trials. We then turn to industry dynamics, which are crucial for understanding the policy's broader economic consequences (Lenox, Rockart and Lewin, 2007). Beyond influencing firms' incentives to undertake innovation activities, the policy may also alter the competitive environment (Acemoglu and Linn, 2004) and affect firm entry and exit (Parker, 2025). Moreover, its impacts are likely to vary across different types of firms, for example, by firm size (Acemoglu and Linn, 2004) and firm origin. These structural adjustments shape not only the aggregate level of innovation but also the long-run configuration of the pharmaceutical industry.

6.1 Quality of Clinical Trials

Prior studies highlight the importance of trial characteristics in determining the informativeness and quality of clinical evidence. Given that clinical evidence can shape subsequent drug demand (McKibbin, 2023), we examine whether and how the negotiation policy affects the quality of clinical trials. Following the literature, we measure trial quality along four dimensions. First, we classify Phase III trials using active comparators rather than placebos as high-quality because active-comparator trials, particularly head-to-head comparisons, provide

more informative evidence on relative efficacy and are therefore especially valuable for government decision-making (Oostrom, 2024; Barwick, Xia and Xia, 2026). Second, we classify trials as high-quality if their targeted enrollment, number of eligibility criteria, or number of endpoints exceeds the corresponding sample median. These measures capture trial scale, design complexity, and research intensity, as landmark trials tend to involve larger participant pools, more complex eligibility criteria, and more endpoints (Ching et al., 2016).

Table 7 reports the estimated policy effects on the number of high- versus low-quality trials using the baseline specification. In Panels A, C, and D, the estimated effects on high-quality trials are larger than those on low-quality trials, with differences primarily driven by Type I trials. In Panel B, the effects on above-median targeted-enrollment trials are somewhat smaller for the full sample but remain larger for Type I trials. Appendix Figure B15 presents the event study results. Overall, the negotiation policy not only increased trial volume but also encouraged higher-quality clinical evidence with greater information content and research intensity, particularly for innovative (Type I) trials.

6.2 Margins: Intensive versus Extensive

Our baseline results indicate that the negotiation policy increases the number of new pharmaceutical clinical trials per disease per year. We decompose the increase into the intensive and extensive margins. On the intensive margin, we find that both pharmaceutical and vaccine firms conduct a similar number of clinical trials each year within each disease in which they already operate (see Appendix Figure B16). In contrast, on the extensive margin, we find that there are more pharmaceutical firms conducting clinical trials per disease, as presented in Table 8.[28] To be specific, after the negotiation policy, more firms conduct Type I clinical trials for drugs relative to vaccines per disease, whereas no significant effect is observed for Type II trials. Overall, these results indicate that the policy impact is primarily driven by the extensive margin, with the number of active firms rising and the market becoming more competitive.

We find that the extensive margin changes come from both incumbent firms entering more research fields and more firms entering the market. We define a disease-by-group combination as a research field in which a firm engages in R&D activity. First, at the firm level, we compare firms that develop only drugs and those that develop only vaccines and estimate the effects of the policy on the accumulated number of research fields in which each pharmaceutical firm has conducted clinical trials since its establishment. Table 9 shows the DID regression results.

[28] Appendix Figure B17 shows the event study estimates.

Table 7: Effects of the Negotiation Policy on the Quality of Clinical Trials

	High Quality			Low Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Type I	Type II	All	Type I	Type II
Panel A: Phase III Trials: Active Comparator vs. Placebo						
treat × post	0.085***	0.086***	-0.001	0.057***	0.036***	0.022***
	(0.024)	(0.017)	(0.012)	(0.011)	(0.006)	(0.007)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.641	0.542	0.500	0.525	0.395	0.412
Panel B: Number of Targeted Participants						
treat × post	0.238***	0.275***	-0.036	0.296***	0.266***	0.030***
	(0.076)	(0.054)	(0.034)	(0.038)	(0.033)	(0.007)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.649	0.565	0.598	0.661	0.644	0.447
Panel C: Number of Inclusion Criteria						
treat × post	0.427***	0.374***	0.053***	0.107**	0.166***	-0.059**
	(0.068)	(0.056)	(0.017)	(0.048)	(0.031)	(0.028)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.647	0.588	0.587	0.664	0.616	0.518
Panel D: Number of End Points						
treat × post	0.337***	0.341***	-0.004	0.197***	0.199***	-0.002
	(0.077)	(0.057)	(0.031)	(0.034)	(0.028)	(0.011)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Adj. R^2	0.611	0.564	0.536	0.719	0.656	0.500

Notes: This table reports DID estimates of the price negotiation policy's effects on the quality of clinical trials. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)-(3) present the estimated effects on the number of high-quality clinical trials, while columns (4)-(6) present the effects on the number of low-quality clinical trials. Disease-by-group and year fixed effects are controlled in all regressions. Standard errors are clustered at the disease-by-group level. Panel A employs Phase III trial observations and measures trial quality based on whether Phase III trials use active comparators rather than placebos. Its smaller estimated coefficient relative to the baseline reflects the exclusion of earlier-phase and Phase IV trials. Panels B-D measure trial quality based on whether trials exceed the median in targeted participants, inclusion criteria, and endpoints, respectively. Standard errors are clustered at the disease-by-group level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Policy Effects on the Number of Firms Conducting Clinical Trials Per Disease

	(1) All	(2) Type I	(3) Type II
treat × post	0.367***	0.388***	-0.013
	(0.082)	(0.063)	(0.034)
Observations	40,568	40,568	40,568
Pre-Policy Mean	0.140	0.087	0.054
Disease-by-group Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.663	0.618	0.631
Within R^2	0.000	0.000	0.000

Notes: The table shows the disease-by-group-by-year level DID results, where group distinguishes drugs (treatment group) from vaccines (control group). The dependent variable is the number of firms conducting clinical trials in each disease, group, and year. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Following the negotiation policy, pharmaceutical firms enter 0.744 additional research fields on average relative to vaccine firms, concentrating on Type I trials.[29]

Second, consistent with Parker (2025), we find substantial firm entry and exit. Figure 6 presents the number of firms conducting Phase I clinical trials for the first time in each year. Before 2016, the number of first-time entrants into clinical trials of drugs or vaccines remained relatively stable. After 2016, however, the number of new pharmaceutical firm entries increased markedly, especially among micro and small firms, while the number of new vaccine firms stayed stable.[30] Appendix Figure B19 plots the annual numbers of exiting pharmaceutical and vaccine firms, defined as firms conducting no additional clinical trials for at least three consecutive years after their last observed trial (with a five-year inactivity window as an alternative definition). As shown in the figure, the policy also increased firm exit. However, exiting firms remained fewer than entering firms, resulting in a net increase in the number of firms engaged in pharmaceutical clinical development.

6.3 Heterogeneity by Firm Origin

To examine how the negotiation policy affects firms' R&D behavior, we conduct separate analyses for domestic and foreign pharmaceutical firms. Although we exclude diffuse drugs from the sample, clinical trials conducted by foreign firms may still primarily reflect efforts

[29] Appendix Figure B18 reports the event study estimates.

[30] Firm size is classified according to the *Standards for the Classification of Large, Medium, Small, and Micro Enterprises* issued by the National Bureau of Statistics of China in 2017. We map the Orbis categories to the same four size groups to ensure consistency with the domestic classification.

Table 9: Policy Effects on the Number of Research Fields in Which Each Firm Conducts Clinical Trials

	(1) All	(2) Type I	(3) Type II
treat × post	0.744***	0.858***	-0.096
	(0.135)	(0.094)	(0.091)
Observations	18,303	18,303	18,303
Pre-Policy Mean	0.467	0.283	0.189
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.607	0.581	0.573
Within R^2	0.001	0.001	0.000

Notes: This table reports DID estimates of the price negotiation policy's effects on the number of research fields in which a firm is actively engaged in clinical trials, using the full sample of pharmaceutical firms (the treatment group) and vaccine firms (the control group). The unit of analysis is a firm-by-year observation. Standard errors are clustered at the firm level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

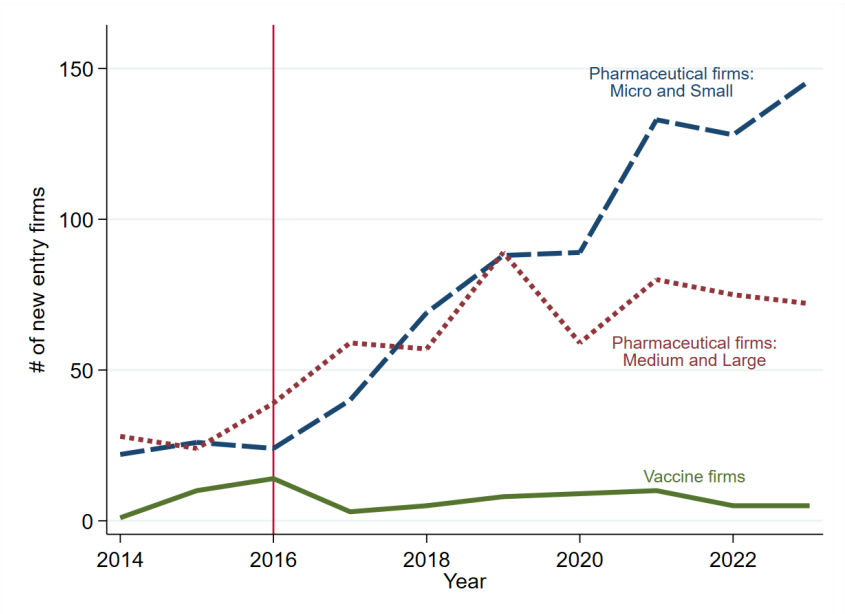


Figure 6: Number of New Firm Entries

Notes: This figure shows the time-series pattern of the number of firms that start conducting Phase I clinical trials for drugs or vaccines.

to enter the Chinese market rather than genuinely new innovations developed exclusively for China. These trials are typically components of global development programs conducted across multiple regions, where China is rarely the primary or initial target; consequently, their presence in our data may represent a localized expansion of existing global R&D rather than a direct response to China-specific policy incentives. In contrast, innovation by domestic firms is more likely to be directly driven by the negotiation policy, given that China constitutes their primary market. Accordingly, we separately examine clinical trials conducted by domestic and foreign firms at the disease level, classifying firms as domestic or foreign based on their country of location and whether the drug under development is domestically developed or imported.

Table 10 reports the DID regression results of the policy's effects on the number of Type I and Type II drug clinical trials conducted by domestic and foreign firms, relative to vaccine trials per disease, using the baseline specification.[31] Consistent with Geng and Shi (2024), we find that following the implementation of the negotiation policy, Type I drug innovation activities increase for both domestic and foreign firms, with domestic firms exhibiting a markedly larger rise. For Type II clinical trials, the policy has a statistically significant negative effect on innovation by domestic firms but significantly promotes innovation by foreign firms. These heterogeneous effects may be explained by differences in R&D capabilities and strategic responses across firm types and innovation categories. Domestic firms, which have historically focused on building original innovation capacity, may therefore react more strongly to the negotiation policy by increasing Type I clinical trial activities. In contrast, Type II innovation, often involving incremental modifications of existing drugs, entails relatively lower R&D risk and technological uncertainty. Foreign firms, which possess extensive global pipelines and accumulated experience in incremental development, may be better positioned to rapidly adapt existing products or indications to the Chinese market in response to improved reimbursement prospects. As a result, the policy significantly stimulates Type II clinical trials among foreign firms, while domestic firms exhibit no comparable response.

7 Conclusion

This study provides novel empirical evidence on the effects of China's NDPN policy on pharmaceutical innovation in a developing-country context. Using drug sales data, we show that the negotiation policy significantly reduces drug prices while expanding market size and increasing drug revenues, thereby improving firms' expected returns from innovation. Leveraging detailed

[31] Appendix Figure B20 reports the event study estimates.

Table 10: Effects of the Negotiation Policy on the Number of Clinical Trials by Firm Origin

	Type I		Type II	
	(1)	(2)	(3)	(4)
	Domestic	Foreign	Domestic	Foreign
treat × post	0.494***	0.055***	-0.076**	0.072***
	(0.077)	(0.009)	(0.036)	(0.012)
Observations	40,568	40,568	40,568	40,568
Pre-Policy Mean	0.102	0.012	0.038	0.029
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.621	0.412	0.441	0.586
Within R^2	0.000	0.000	0.000	0.000

Notes: This table reports DID estimates of the price negotiation policy's effects on the number of new clinical trials by different firm origins. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)-(2) present the estimated effects on the number of new Type I clinical trials, while columns (3)-(4) present the effects on the number of new Type II clinical trials. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

clinical trial data, we document that the policy substantially stimulates pharmaceutical R&D relative to vaccine development, with particularly pronounced effects on more innovative Type I trials and early-stage trials.

We further investigate the mechanisms through which the negotiation policy affects pharmaceutical innovation. Decomposition results suggest that both the expected return and financial constraint channels promote innovation, but the former plays a quantitatively larger role, accounting for approximately 56.57% of the policy's overall effect.

We also show that the NDPN improves clinical trial quality and reshapes industry dynamics. The increase in innovation operates primarily through the extensive margin: new firms enter clinical development, and incumbent pharmaceutical firms expand into additional research fields. Small and micro firms account for an important share of this entry. Moreover, the increase in clinical trial activity is more pronounced among domestic firms, suggesting that the increase in clinical trials captures frontier innovation rather than mere market-entry strategy.

Finally, we compare the expected revenue from a new drug with its R&D costs. We find that the NDPN policy moves the expected revenue from below the lower bound of the estimated cost range to just within that range. Therefore, the policy incentivizes firms with relatively low development costs to initiate or continue their R&D investment. However, without detailed drug-level cost information, we cannot verify whether all induced R&D investments are justified.

In the context of a developing country, China's NDPN policy combines price reductions with expanded insurance coverage, thereby increasing consumer surplus and fostering incentives for

innovation. Our findings provide empirical evidence for other countries considering the adoption of similar drug price negotiation policies. One limitation of this study is that we do not conduct a full welfare evaluation: the policy's cost is the resulting increase in government expenditure. Future research is needed to evaluate the program's overall welfare effects.

8 Bibliography

Acemoglu, Daron, and Joshua Linn. 2004. "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry*." *The Quarterly Journal of Economics*, 119(3): 1049–1090.

Agha, Leila, Soomi Kim, and Danielle Li. 2022. "Insurance Design and Pharmaceutical Innovation." *American Economic Review: Insights*, 4(2): 191–208.

Barwick, Panle Jia, Ashley T Swanson, and Tianli Xia. 2025. "A Double Dose of Reform: Insurance and Centralized Negotiation in Drug Markets." National Bureau of Economic Research Working Paper 33832.

Barwick, Panle Jia, Hongyuan Xia, and Tianli Xia. 2026. "From Free Rider to Innovator: The Rise of China's Drug Development." National Bureau of Economic Research Working Paper 34977.

Blume-Kohout, Margaret E., and Neeraj Sood. 2013. "Market size and innovation: Effects of Medicare Part D on pharmaceutical research and development." *Journal of Public Economics*, 97: 327–336.

Budish, Eric, Benjamin N. Roin, and Heidi Williams. 2015. "Do Firms Underinvest in Long-Term Research? Evidence from Cancer Clinical Trials." *American Economic Review*, 105(7): 2044–85.

Budish, Eric, Maya M Durvasula, Benjamin N Roin, and Heidi L Williams. 2025. "Missing Markets for Innovation: Evidence from New Uses of Existing Drugs." National Bureau of Economic Research Working Paper 34222.

Cao, Shengmao, Lisa Xuejie Yi, and Chuan Yu. 2024. "Competitive Bidding in Drug Procurement: Evidence from China." *American Economic Journal: Economic Policy*, 16(3): 481–513.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs*." *The Quarterly Journal of Economics*, 134(3): 1405–1454.

China Central Television News. 2025. "Innovative drugs are advancing at "medical insurance speed", reaching patients faster and at lower cost." *https://news.bjd.com.cn/2025/12/07/11448830.shtml*.

Ching, Andrew T., Robert Clark, Ignatius Horstmann, and Hyunwoo Lim. 2016. "The Effects of Publicity on Demand: The Case of Anti-Cholesterol Drugs." *Marketing Science*, 35(1): 158–181.

Damodaran, Aswath. 2026. "Costs of Capital by Industry Sector." *Stern School of Business, New York University*, China dataset. Updated January 9, 2026. Accessed September 7, 2026.

Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy*, 11(4): 213–48.

DiMasi, Joseph A., Henry G. Grabowski, and Ronald W. Hansen. 2016. "Innovation in the pharmaceutical industry: New estimates of RD costs." *Journal of Health Economics*, 47: 20–33.

DiMasi, Joseph A, Ronald W Hansen, and Henry G Grabowski. 2003. "The price of innovation: new estimates of drug development costs." *Journal of Health Economics*, 22(2): 151–185.

Ding, Hui, Mark Duggan, and Amanda Starc. 2025. "Getting the Price Right? The Impact of Competitive Bidding in the Medicare Program." *The Review of Economics and Statistics*, 107(1): 204–220.

Ding, Yixin. 2026. "From the Laboratory to the Production Line: China's Homegrown Innovative Drugs Benefit Tens of Millions of Patients." *http://health.people.com.cn/n1/2026/0804/c14739-40773710.html*.

Dix, Rebekah, and Todd A. Lensman. 2025. "Combining Complements: Theory and Evidence from Cancer Treatment Innovation." Working Paper.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J. Notowidigdo. 2018. "The Economic Consequences of Hospital Admissions." *American Economic Review*, 108(2): 308–52.

Dubois, Pierre, and Laura Lasio. 2018. "Identifying Industry Margins with Price Constraints: Structural Estimation on Pharmaceuticals." *American Economic Review*, 108(12): 3685–3724.

Dubois, Pierre, Olivier de Mouzon, Fiona Scott-Morton, and Paul Seabright. 2015. "Market size and pharmaceutical innovation." *The RAND Journal of Economics*, 46(4): 844–871.

Finkelstein, Amy. 2004. "Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry." *The Quarterly Journal of Economics*, 119(2): 527–564.

Friedman, Yali. 2010. "Location of pharmaceutical innovation: 2000-2009." *Nature Reviews Drug Discovery*, 9(11): 835–836.

Gaessler, Fabian, and Stefan Wagner. 2022. "Patents, Data Exclusivity, and the Development of New Drugs." *The Review of Economics and Statistics*, 104(3): 571–586.

Garthwaite, Craig. 2025. "Economic Markets and Pharmaceutical Innovation." *Journal of Economic Perspectives*, 39(2): 3–26.

Geng, Hao, and Ce Matthew Shi. 2024. "Health policy, price regulation, and innovation: Evidence from China's vaccine industry." *Journal of Development Economics*, 167: 103229.

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

Gu, Shi. 2024. "Production Outsourcing and Innovation: Evidence from China's Pharmaceutical Industry." SSRN Working Paper.

Huang, Yanzhong. 2026. "A Biopharmaceutical Superpower: China's Rise, Its Limits, and What Comes Next." *Center for International Relations and Sustainable Development*, Accessed July 23, 2026.

Jiang, Tianyuan, Xuan Tian, Nina Yin, and Xuan Zhang. 2025. "Unlocking the Hidden Pharmaceutical Financing: Resilient RD Investment and Malleable Selling Expenses." SSRN.

Jia, Ruixue, Xiao Ma, Jianan Yang, and Yiran Zhang. 2025. "Improving Regulation for Innovation: Evidence from China's Pharmaceutical Industry." National Bureau of Economic Research Working Paper 31976.

Ji, Yunan, and Parker Rogers. 2024. "The Long-Run Impacts of Regulated Price Cuts: Evidence from Medicare."

Kanavos, Panos, Mackenzie Mills, and Anwen Zhang. 2019. "Pharmaceutical policy in China." London School of Economics and Political Science, LSE Library LSE Research Online Documents on Economics 108473.

Kong, Edward, and Olivia Zhao. 2023. "Market Incentives and the Drug Development Pipeline: Evidence from Antibiotics." Social Science Research Network SSRN Working Paper. November 28, 2023.

Kremer, Michael. 2002. "Pharmaceuticals and the Developing World." *Journal of Economic Perspectives*, 16(4): 67–90.

Kyle, Margaret K., and Anita M. McGahan. 2012. "Investments in Pharmaceuticals Before and After TRIPS." *The Review of Economics and Statistics*, 94(4): 1157–1172.

Laroia, Dharika, and Swati Singh. 2025. "Chapter 18 - Regulatory pathways for the development of drugs and vaccines." In *Drug Discovery and One Health Approach in Combating Infectious Diseases. Drug Discovery Update*, , ed. Kanti Bhooshan Pandey, David J. Newman and Chukwuebuka Egbuna, 347–361. Elsevier.

Lenox, Michael J., Scott F. Rockart, and Arie Y. Lewin. 2007. "Interdependency, Competition, and Industry Dynamics." *Management Science*, 53(4): 599–615.

Li, Songtao. 2016. "From 2% to 8%: How Far Are Pharmaceutical Companies from "China Innovatio"?" *http://www.ce.cn/cysc/sp/info/201603/01/t20160301*$_9$190997*.shtml*.

Liu, Chenyuan, Yi Lu, and Wanyu Yang. 2026. "Excessive Pharmaceutical Marketing Expenditure: Policy Remedies from China." *The Review of Economics and Statistics*, 1–30.

McKibbin, Rebecca. 2023. "The effect of RCTs on drug demand: Evidence from off-label cancer drugs." *Journal of Health Economics*, 90: 102779.

Ministry of Human Resources and Social Security. 2017. "Filling gaps, expanding coverage, selecting the best, and improving quality: Interpretation of work related to the 2017 edition of the National Reimbursement Drug List." *https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201705/t20170531*$_2$71735*.html*.

Moore, Thomas J., Hanzhe Zhang, Gerard Anderson, and G. Caleb Alexander. 2018. "Estimated Costs of Pivotal Trials for Novel Therapeutic Agents Approved by the US Food and Drug Administration, 2015-2016." *JAMA Internal Medicine*, 178(11): 1451–1457.

Oostrom, Tamar. 2024. "Funding of Clinical Trials and Reported Drug Efficacy." *Journal of Political Economy*, 132(10): 3298–3333.

Parker, Simon C. 2025. "Public Policy Impacts on Entrepreneurial Entry and Exit: A Real Options Framework." *Academy of Management Perspectives*, 39(2): 330–353.

Paul, Steven M., Daniel S. Mytelka, Christopher T. Dunwiddie, Charles C. Persinger, Bernard H. Munos, Stacy R. Lindborg, and Aaron L. Schacht. 2010.

"How to Improve R&D Productivity: The Pharmaceutical Industry's Grand Challenge." *Nature Reviews Drug Discovery*, 9(3): 203–214.

Qiu, Lan, Zi-Ya Chen, Deng-Yu Lu, Hao Hu, and Yi-Tao Wang. 2014. "Public funding and private investment for R&D: a survey in China's pharmaceutical industry." *Health Research Policy and Systems*, 12(1): 27.

Sertkaya, Aylin, Hui-Hsing Wong, Amber Jessup, and Trinidad Beleche. 2016. "Key cost drivers of pharmaceutical clinical trials in the United States." *Clinical Trials*, 13(2): 117–126. PMID: 26908540.

Tan, Ruirong, Hua Hua, Siyuan Zhou, Zhimin Yang, Changming Yang, Guo Huang, Jin Zeng, and Junning Zhao. 2025. "Current Landscape of Innovative Drug Development and Regulatory Support in China." *Signal Transduction and Targeted Therapy*, 10(1): 220.

Vashishtha, Vipin M, and Puneet Kumar. 2024. "The durability of vaccine-induced protection: an overview." *Expert review of vaccines*, 23(1): 389—408.

Vogel, Matthew, Pragya Kakani, Amitabh Chandra, and Rena M. Conti. 2024. "Medicare price negotiation and pharmaceutical innovation following the Inflation Reduction Act." *Nature Biotechnology*, 42(3): 406–412.

Wouters, Olivier J., Martin McKee, and Jeroen Luyten. 2020. "Estimated Research and Development Investment Needed to Bring a New Medicine to Market, 2009-2018." *JAMA*, 323(9): 844–853.

Yao, Xuefang, Yan Zhang, and Jin Zhou. 2026. "Patent Term Extension for Innovative Drugs in China: A Cohort Study from 2021 to 2024." *Therapeutic Innovation & Regulatory Science*, 60(2): 544–550.

Yin, Wesley. 2008. "Market incentives and pharmaceutical innovation." *Journal of Health Economics*, 27(4): 1060–1077.

Zhang, Xuan, and Huihua Nie. 2021. "Public health insurance and pharmaceutical innovation: Evidence from China." *Journal of Development Economics*, 148: 102578.

Zhang, Xuan, Nina Yin, Jiayu Zhang, Qingyuan Xue, and Bin Jiang. 2025. "Centralized Drug Procurement for Affordable and Sustainable Healthcare: Evidence from China." SSRN.

(For Online Publication Only)

Appendix A. Estimation of Expected Revenue and Costs of New Drugs Under the Negotiation Policy

Estimating Expected Revenue We employ a staggered DID design using annual sales data for exclusive drugs approved within five years to estimate the following equation:

$$Revenue_{ist} = \beta_0 + \beta_1 treat_{is} \times post_{st} + \lambda_{is} + \mu_{st} + \epsilon_{ist}, \tag{A1}$$

where the subscripts i, s, and t index drugs, subsamples, and years, respectively. β_0 estimates the average revenue before successful negotiation, and β_1 estimates the increased revenue after successful negotiation. We first express all revenue figures in constant 2018 RMB and then discount future revenue streams to the year of marketing approval using an annual real cost of capital of 10.5% adopted by DiMasi, Grabowski and Hansen (2016) and Wouters, McKee and Luyten (2020).[1] This allows the present value of expected revenues to be comparable to capitalized R&D costs.[2] Let $\hat{\beta}_0$ and $\hat{\beta}_1$ denote the estimates of β_0 and β_1 in Equation (A1).

We then plug $\hat{\beta}_0$ and $\hat{\beta}_1$ into the following equation to calculate the expected revenue of launching a new drug under the negotiation policy:

$$\begin{aligned} \mathbb{E}[Rev] &= \hat{\beta}_0 \times \tau \times (1-p) + p \times \sum_{r=1}^{5} SuccessRatio_r \left[\hat{\beta}_0 \times r + (\hat{\beta}_0 + \hat{\beta}_1) \times (\tau - r)\right] \\ &= \hat{\beta}_0 \times \tau + \hat{\beta}_1 \sum_{r=1}^{5} NegoRatio_r \times (\tau - r). \end{aligned} \tag{A2}$$

where τ denotes the expected post-approval patent life of a new drug. We set τ at 11.579 years, calculated as the weighted average of the median post-approval patent lives (Yao, Zhang and Zhou, 2026). p denotes the probability that an eligible drug is successfully included in the NRDL through negotiation within five years of marketing approval. $SuccessRatio_r$ denotes the conditional probability that, among the drugs successfully negotiated within this five-year window, the negotiation occurs r years after approval. Accordingly, $NegoRatio_r = p \times SuccessRatio_r$ is the share of eligible drugs successfully negotiated in the NRDL r years after approval. Because our sales data cover only a subset of public hospitals in 20 cities, we extrapolate the estimated revenue to the national level based on the share of hospital beds accounted for by

[1] This discount rate is comparable to the industry-level cost of capital reported by Damodaran (2026).

[2] Capitalized cost includes both out-of-pocket R&D expenditures and the opportunity cost of capital during the development process, with all expenditures expressed at their value at the time of marketing approval.

these hospitals. Data on the total number of hospital beds nationwide are obtained from the *2021 Statistical Bulletin on the Development of China's Health Sector*, published by the National Health Commission of China.

We estimate that the present value of expected cumulative revenue from a newly launched drug in China is approximately USD 551.07 million under the NDPN policy, compared with USD 359.85 million ($= \hat{\beta}_0 \times \tau$) in the policy's absence. These estimates imply that the NDPN policy increases the present value of expected cumulative revenue by approximately 53.1%, strengthening the financial incentives for new drug development.

Estimating Expected Cost Wouters, McKee and Luyten (2020) report that the mean capitalized cost of developing a new drug in the United States is USD 1,559.1 million. Huang (2026) argues that both drug discovery and clinical development are substantially less costly in China: discovery expenditures are estimated to be one-third to one-half of global levels, while clinical development costs are approximately 20-50% of those in the United States. As a result, the overall cost of developing a new drug in China ranges from USD 519.70 million ($= 1{,}559.1 \times \frac{1}{3}$) to USD 779.55 million ($= 1{,}559.1 \times 0.5$).[3]

[3]Given that clinical trial costs are primarily driven by trial-specific characteristics, we assume that average costs remain broadly stable as trial activity expands (Sertkaya et al., 2016; Moore et al., 2018), supporting our use of the benchmark R&D cost estimate.

Appendix B. Supplementary Figures and Tables

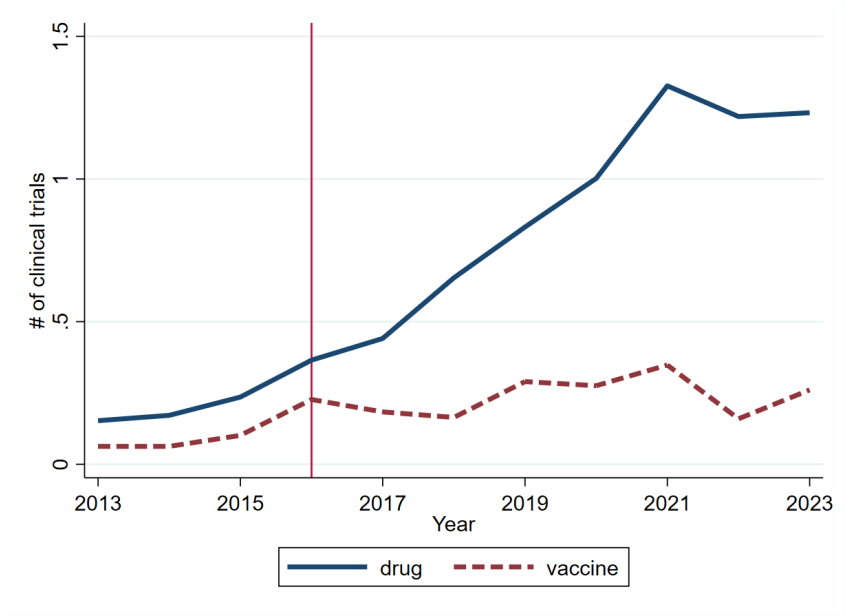
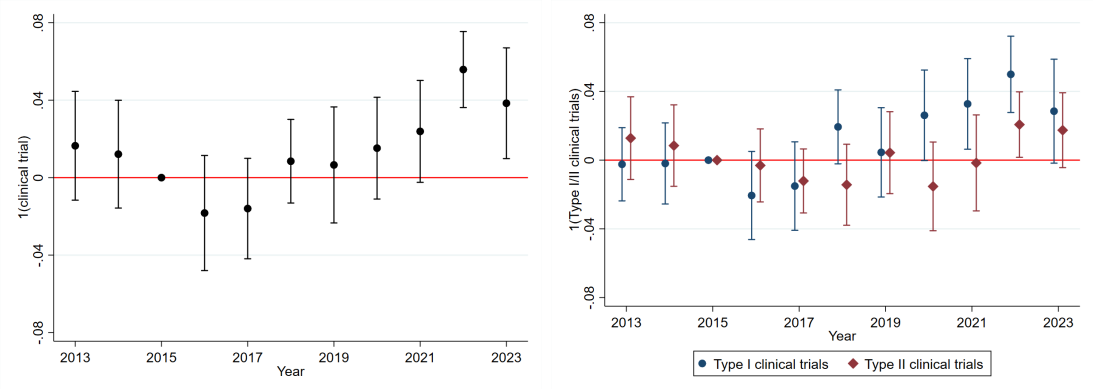
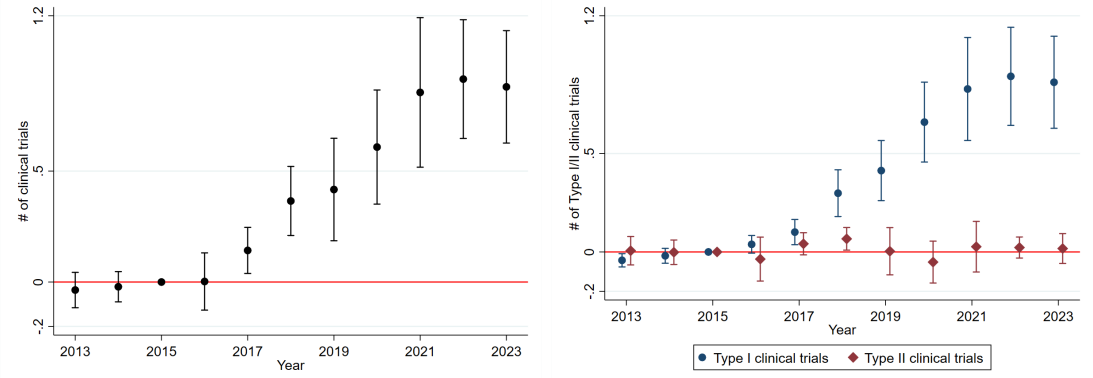


Figure B1: Raw Pattern of the Average Number of Clinical Trials per Disease

Notes: This figure shows the time-series pattern of the average number of drug or vaccine clinical trials, measured at the disease level.



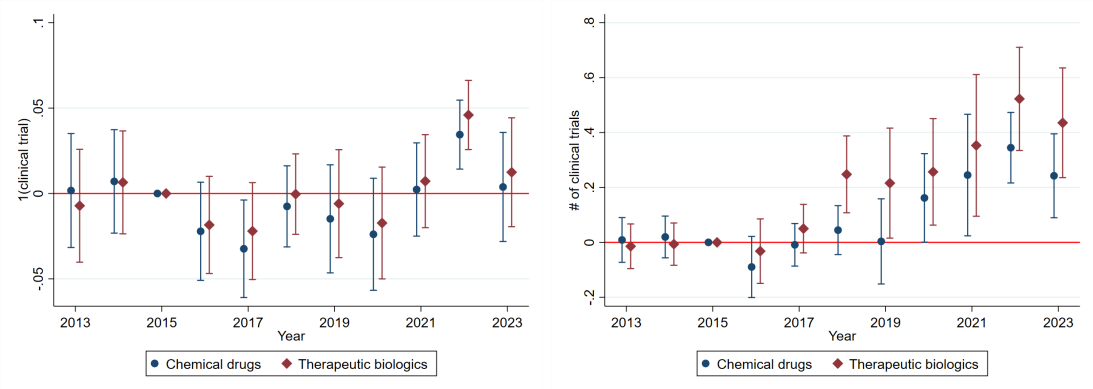
(a) Incidence of Clinical Trials



(b) Number of Clinical Trials

Figure B2: Robustness Event Study: Excluding Long-Term Immunization Diseases and Diseases Covered by the NIP

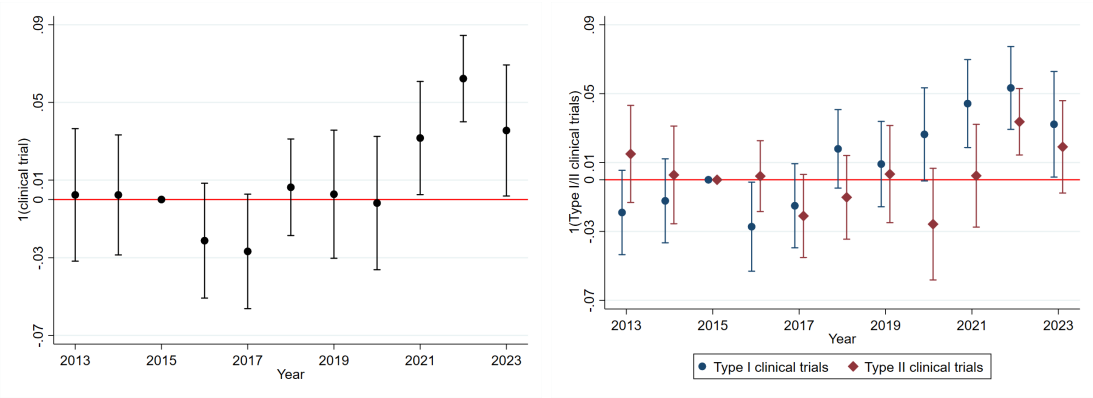
Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, excluding diseases preventable through long-term immunization and those covered by China's NIP, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



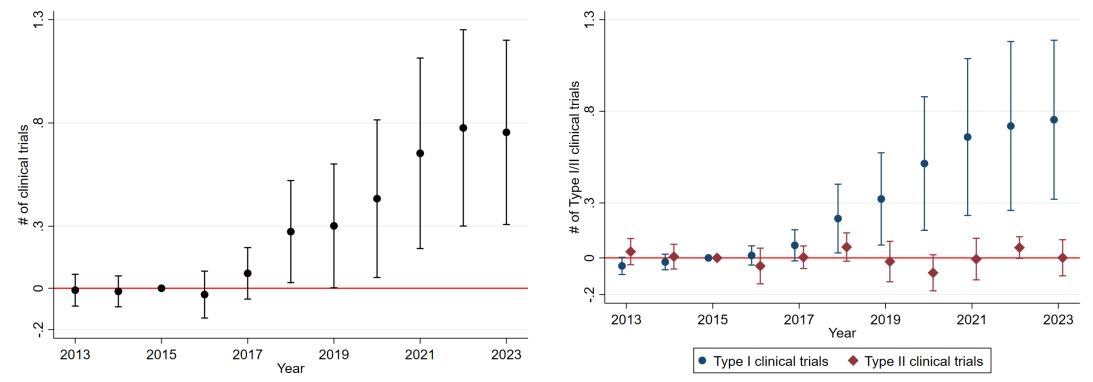
(a) Incidence of Conducting Clinical Trials (b) Number of Clinical Trials

Figure B3: Event Study: Chemical Drugs and Therapeutic Biologics

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the incidence of new clinical trials (Panel a) and on the number of trials (Panel b), splitting the treatment group into chemical drugs and therapeutic biologics, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes chemical drugs or therapeutic biologics (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



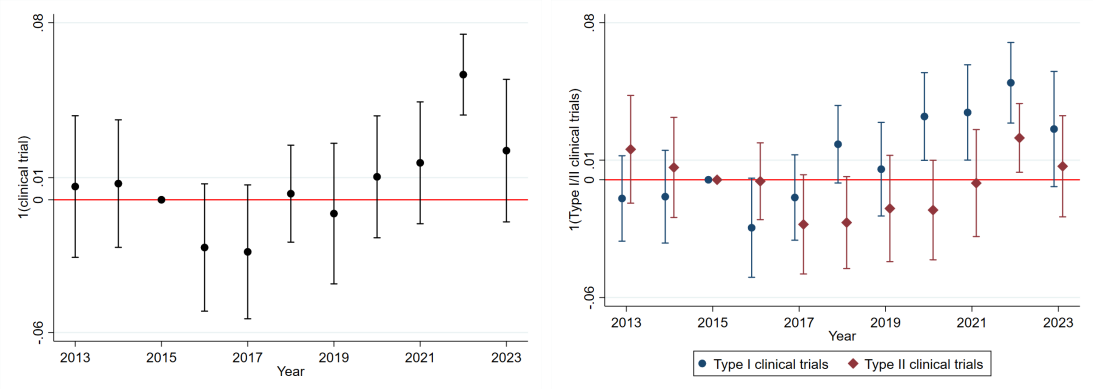
(a) Incidence of Clinical Trials



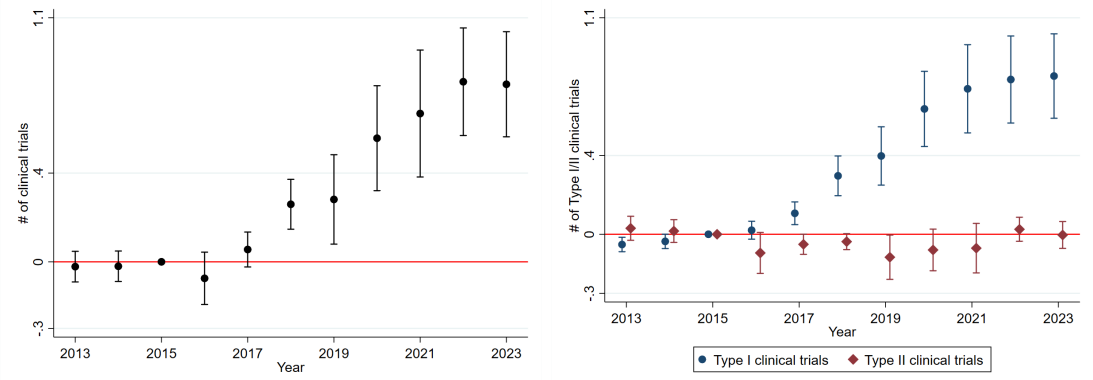
(b) Number of Clinical Trials

Figure B4: Robustness Event Study: Controlling for Differential Pre-Trends

Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, adding interactions between three pre-policy control variables—the average number of patients in China and worldwide, the average number of competing drugs or vaccines, and the average number of completed clinical trials—and year fixed effects to account for potential differential pre-trends across disease groups, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



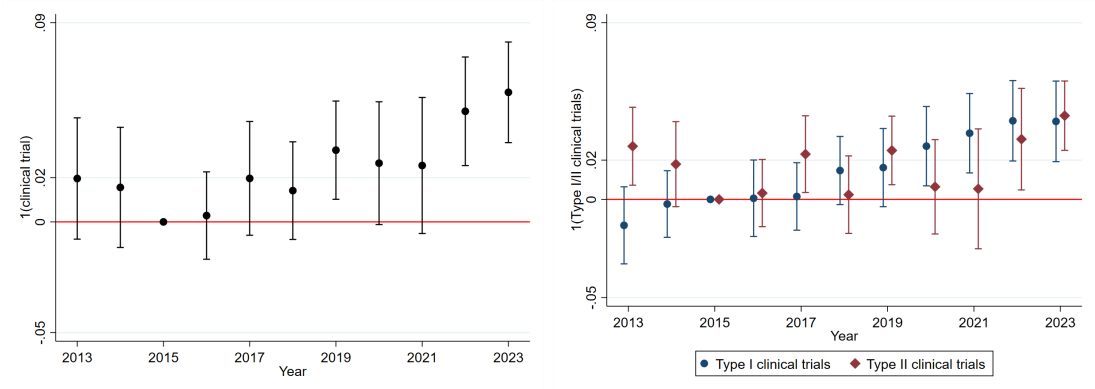
(a) Incidence of Clinical Trials



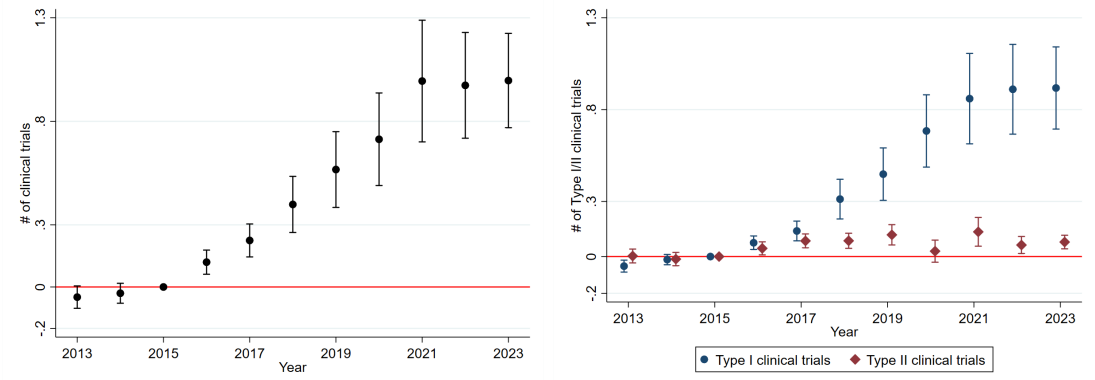
(b) Number of Clinical Trials

Figure B5: Robustness Event Study: Excluding Clinical Trials Conducted by Firms that Engaged in COVID-19 R&D

Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, excluding all clinical trials conducted by firms that engaged in COVID-19 drug or vaccine R&D, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



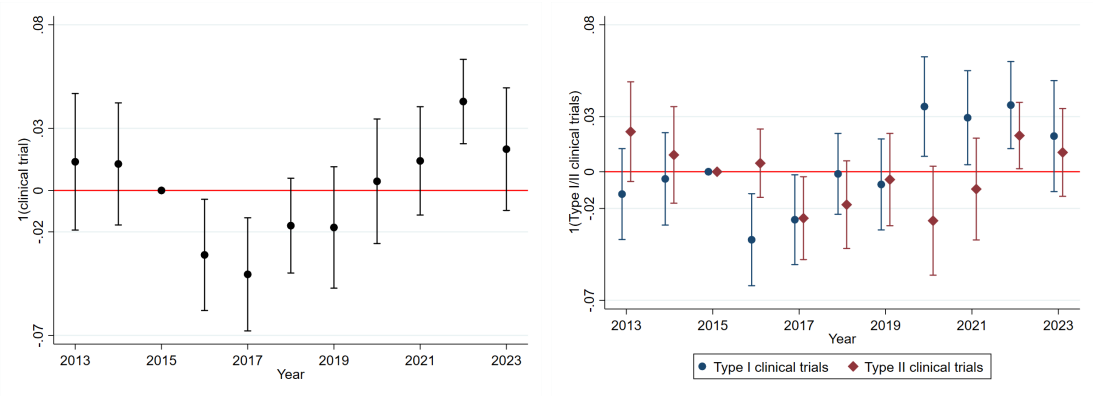
(a) Incidence of Clinical Trials



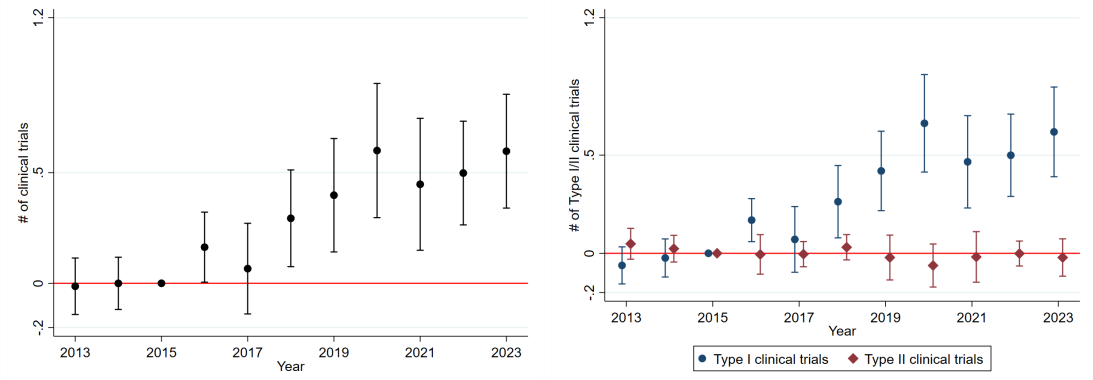
(b) Number of Clinical Trials

Figure B6: Robustness Event Study: Excluding Clinical Trials Conducted by Firms that Engaged in Both Drug and Vaccine R&D

Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, excluding all clinical trials conducted by firms that engaged in both drug or vaccine R&D, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



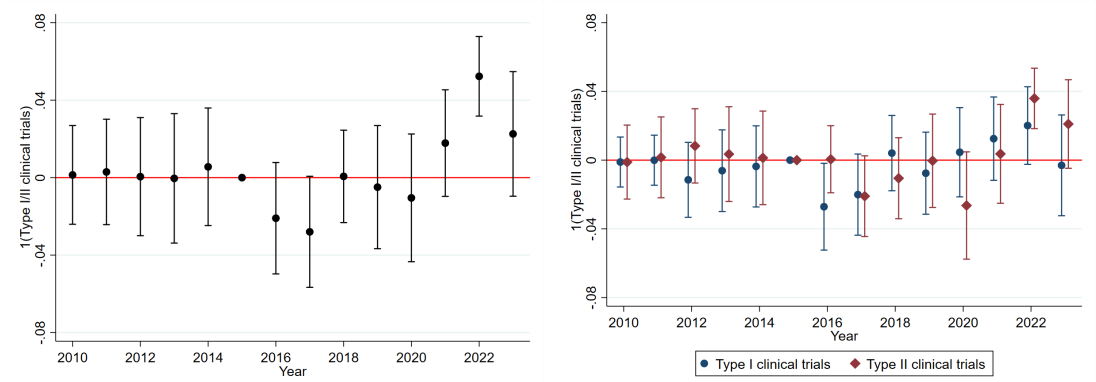
(a) Incidence of Clinical Trials



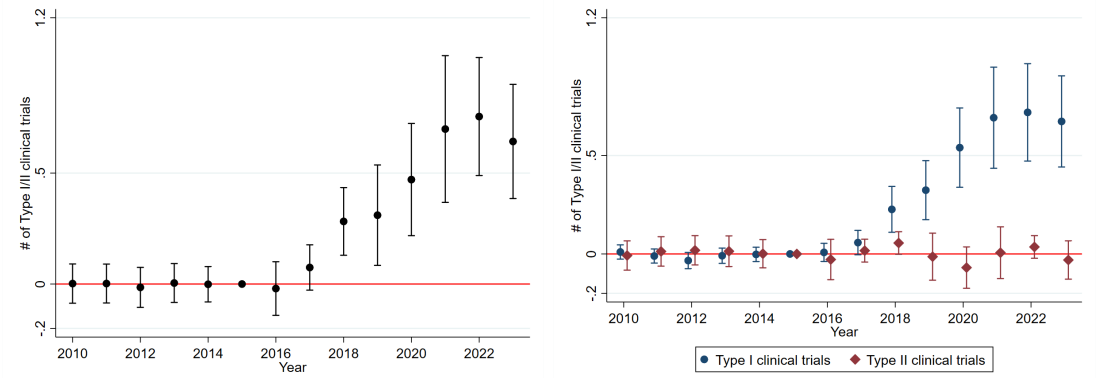
(b) Number of Clinical Trials

Figure B7: Robustness Event Study: Accounting for All Four Confounding Policies

Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, controlling for all four confounding policiesthe 2015 clinical trial application (CTA) reform, the Marketing Authorization Holder (MAH) reform, China's accession to the International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) in 2017, and the patent term extension (PTE) reform, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



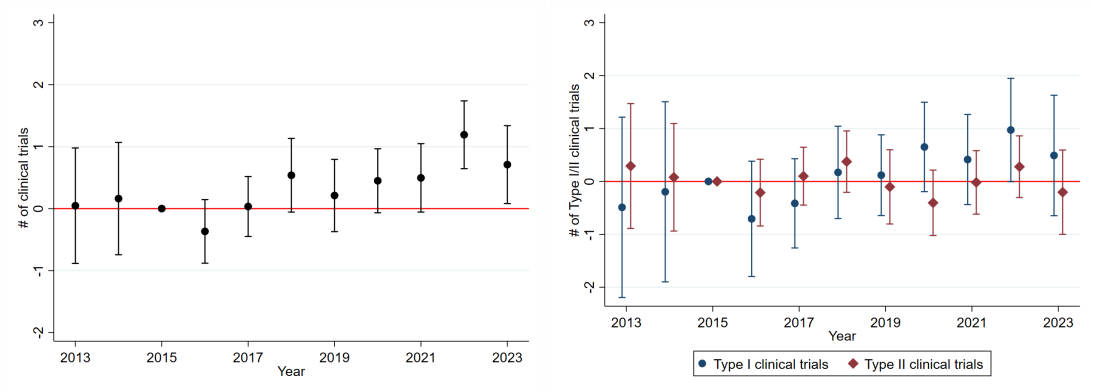
(a) Incidence of Clinical Trials



(b) Number of Clinical Trials

Figure B8: Robustness Event Study: Extending the Sample Period and Extrapolating the Pre-policy Trend

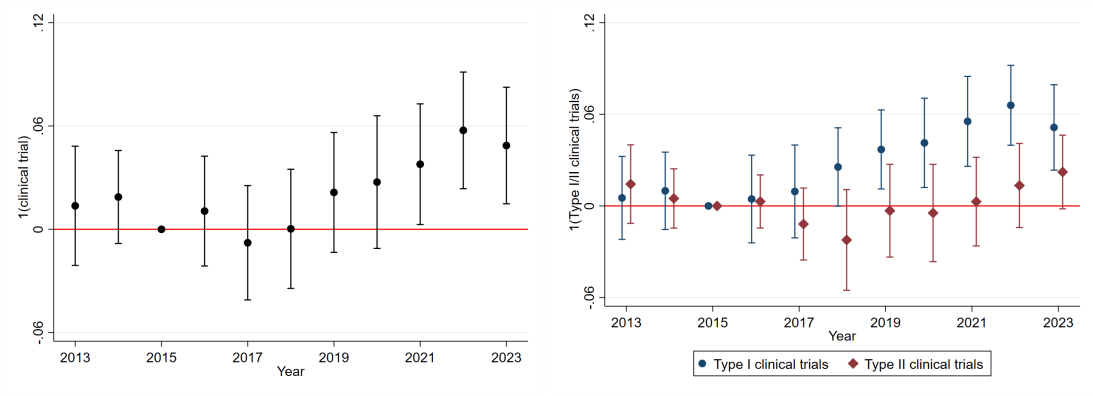
Notes: This figure plots the robustness estimates of the event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number (Panel b) of new clinical trials, using the extended sample period beginning in 2010 and extrapolating the trend in 2010-2015 and difference it out in the post-reform period following Dobkin et al. (2018), together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



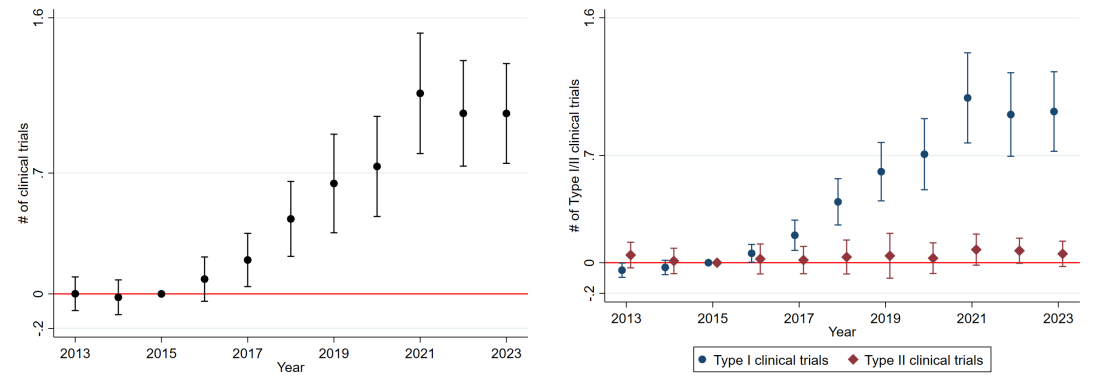
(a) All Clinical Trials (b) Type I and Type II Clinical Trials

Figure B9: Robustness Event Study: Poisson Regression Model

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of new clinical trials (Panel a) and on the numbers of new Type I and Type II trials separately (Panel b), using a Poisson regression model, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



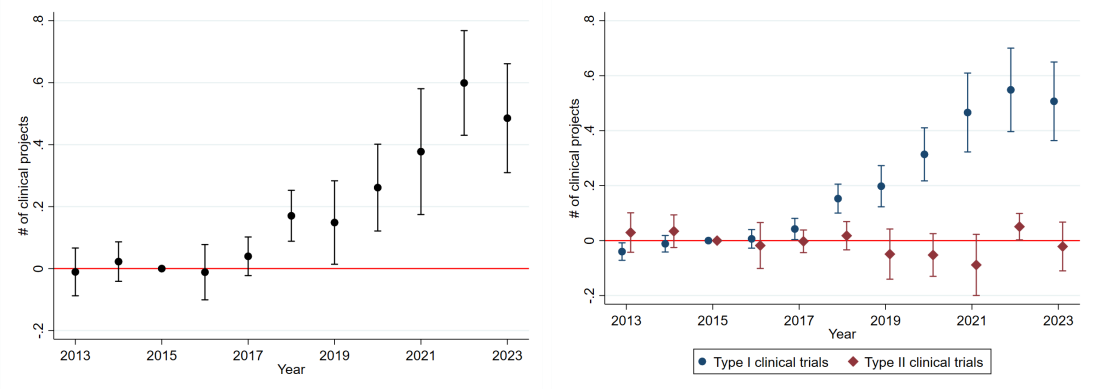
(a) Incidence of Clinical Trials



(b) Number of Clinical Trials

Figure B10: Robustness Event Study: Alternative Definition of Clinical Trial Start Date

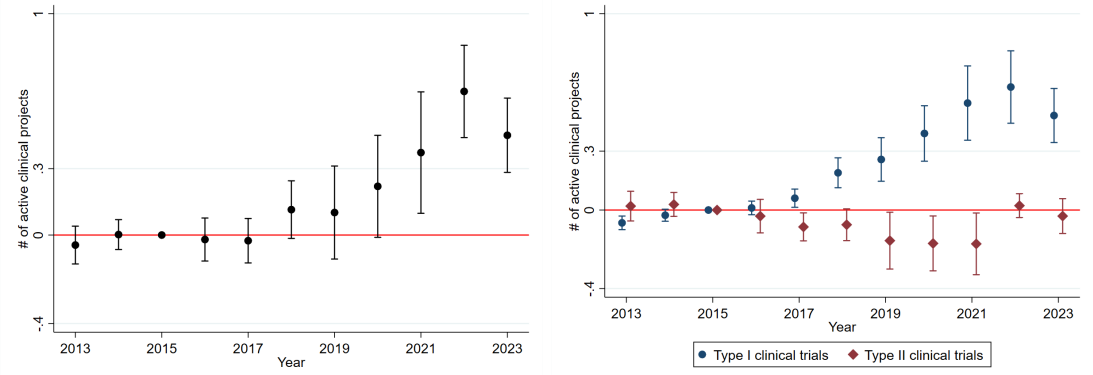
Notes: This figure plots the robustness estimates of event study coefficients of the negotiation policy's effects on the incidence (Panel a) and number of new clinical trials (Panel b) separately, using an alternative definition of clinical trial start date —IRB approval dates, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



(a) All Clinical Trials (b) Type I and Type II Clinical Trials

Figure B11: Robustness Event Study: Effects of the Negotiation Policy on the Number of New Clinical Projects

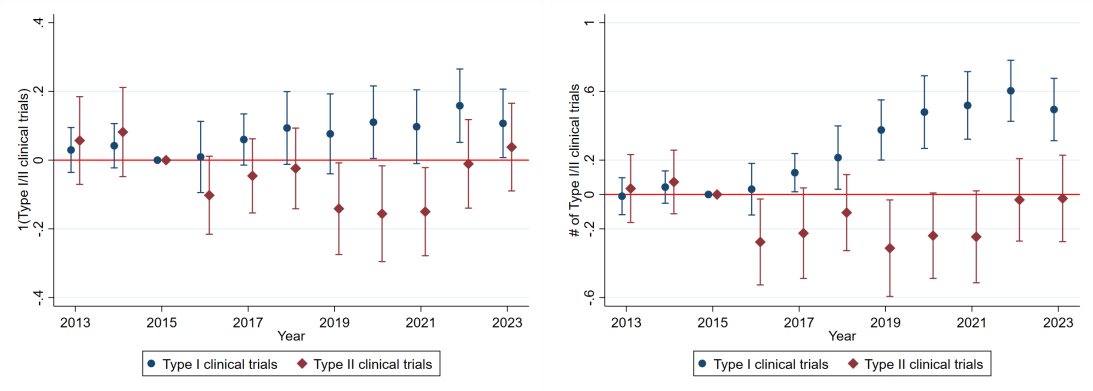
Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of new clinical projects (Panel a) and on the numbers of new Type I and Type II projects separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



(a) All Clinical Trials (b) Type I and Type II Clinical Trials

Figure B12: Robustness Event Study: Effects of the Negotiation Policy on the Number of Active Clinical Projects

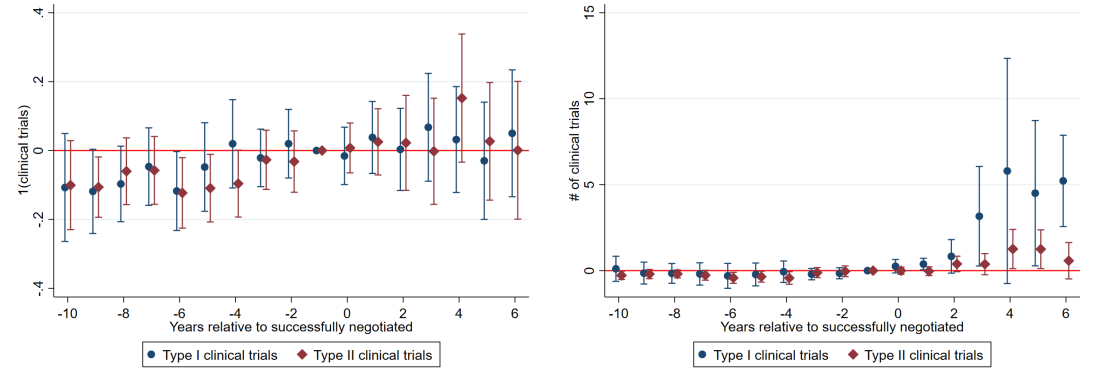
Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of active clinical projects (Panel a) and on the numbers of active Type I and Type II projects separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.



(a) Incidence of Clinical Trials (b) Number of Clinical Trials

Figure B13: Event Study for the Overall Effects of the Negotiation Policy on Clinical Trials for All Firms

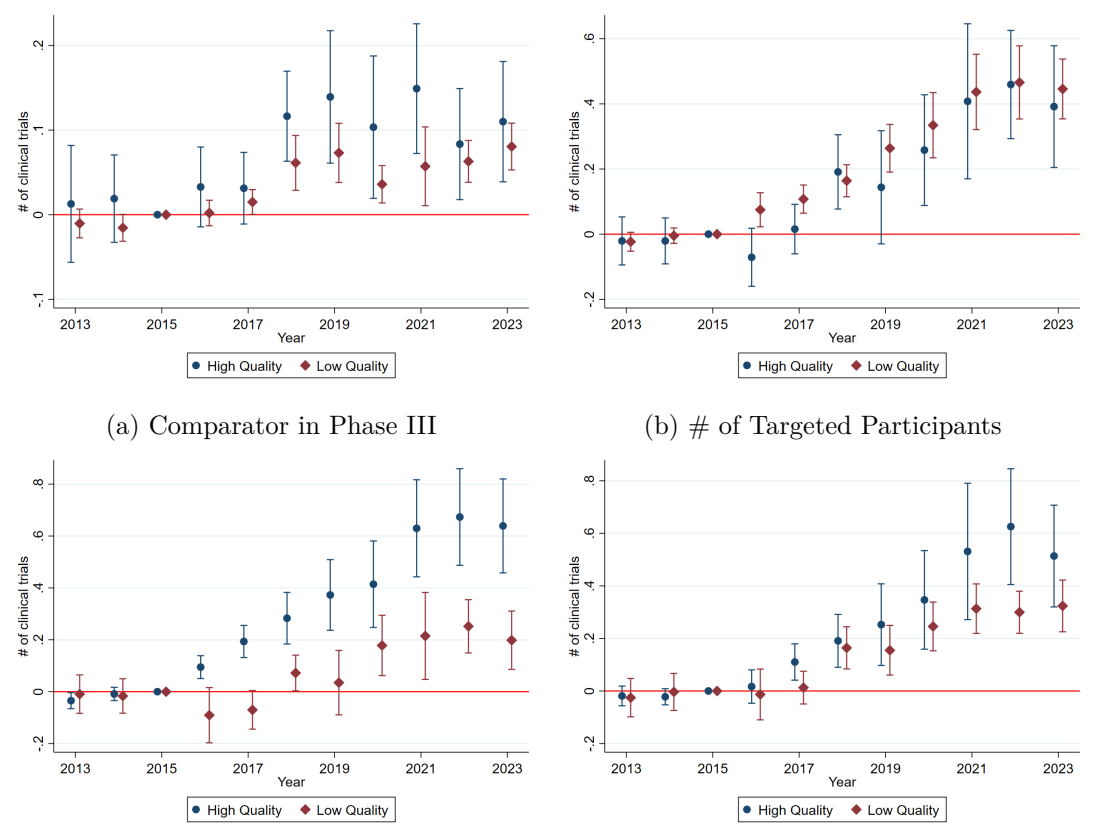
Notes: This figure plots the estimated event study coefficients of the overall effects of the negotiation policy on a firm's initiation of any new Type I and Type II clinical trial separately (Panel a) and on a firm's numbers of new Type I and Type II trials separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a firm-by-year observation. The treatment group includes pharmaceutical firms and the control group includes vaccine firms. Firm and year fixed effects are included in the regressions. Standard errors are clustered at the firm level.



(a) Incidence of Clinical Trials (b) Number of Clinical Trials

Figure B14: Event Study for the Relaxed Financial Constraint Effects of Successful Negotiation on Clinical Trials per Firm

Notes: This figure plots the estimated event study coefficients of the relaxed financial constraint effects of the successful negotiation on the corresponding firm's initiation of any new Type I and Type II clinical trial separately (Panel a) and on the corresponding firm's number of new Type I and Type II trials separately (Panel b), together with their 95% confidence intervals. The unit of analysis is a firm-by-subsample-by-year observation. The treatment group includes pharmaceutical firms that succeeded in each round of negotiations and the control group includes pharmaceutical firms that participated in the corresponding or a later round but had not succeeded yet. Firm-by-subsample and subsample-by-year fixed effects are included in the regressions. Standard errors are clustered at the firm level.



(a) Comparator in Phase III

(b) # of Targeted Participants

(c) # of Inclusion Criteria

(d) # of Endpoints

Figure B15: Event Study for Quality of Clinical Trials

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of high- and low-quality clinical trials, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.

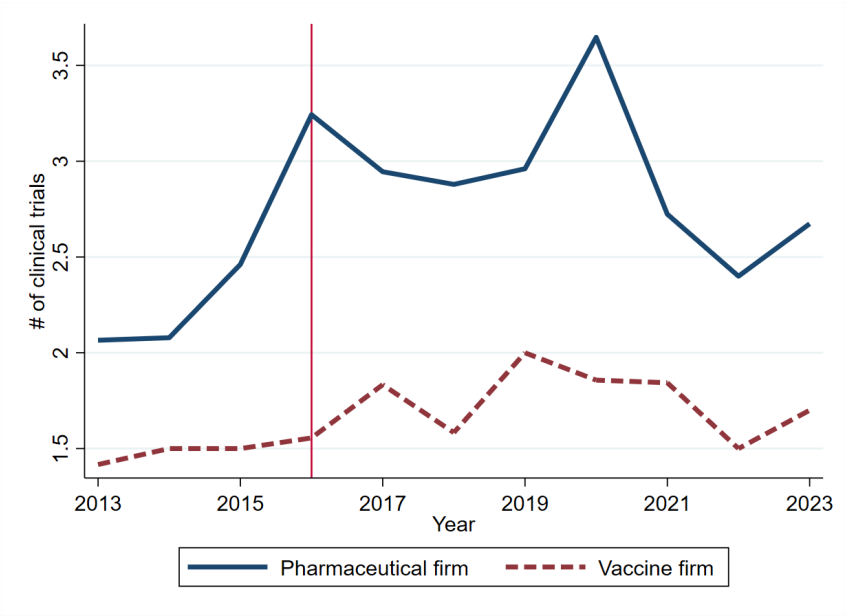
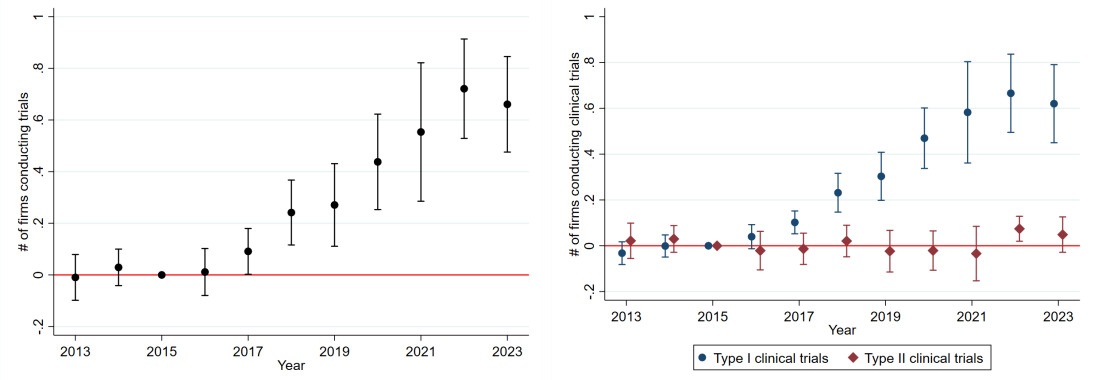


Figure B16: Raw Pattern of the Average Number of Clinical Trials per Research Field per Firm

Notes: This figure shows the time-series pattern of the average number of clinical trials a firm conducts within each research field it already operates in.



(a) All Clinical Trials

(b) Type I and Type II Clinical Trials

Figure B17: Event Study for Number of Firms Conducting Clinical Trials per Disease

Notes: This figure presents the estimated event study coefficients of the negotiation policy's effects on the number of firms conducting clinical trials per disease, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.

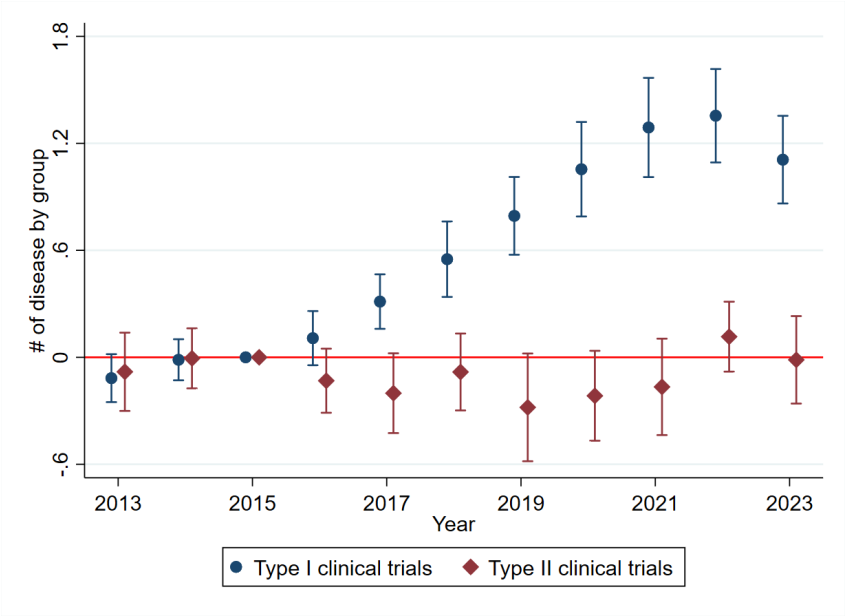
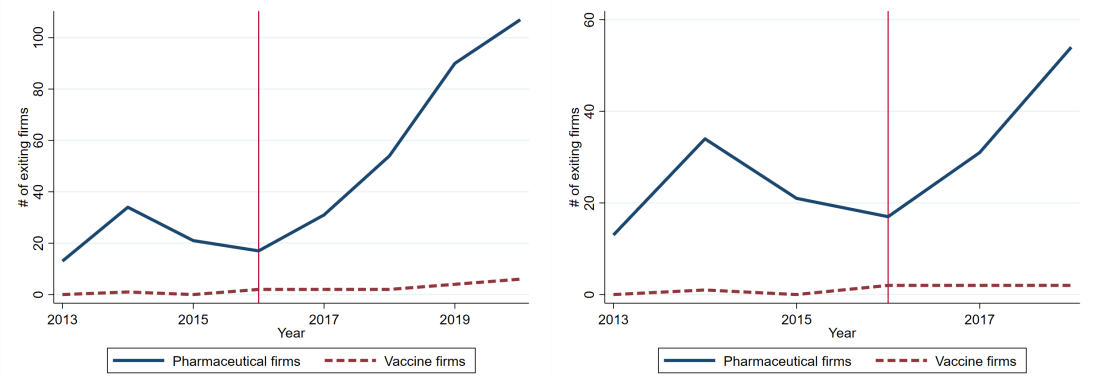


Figure B18: Event Study for Number of Research Fields per Firm

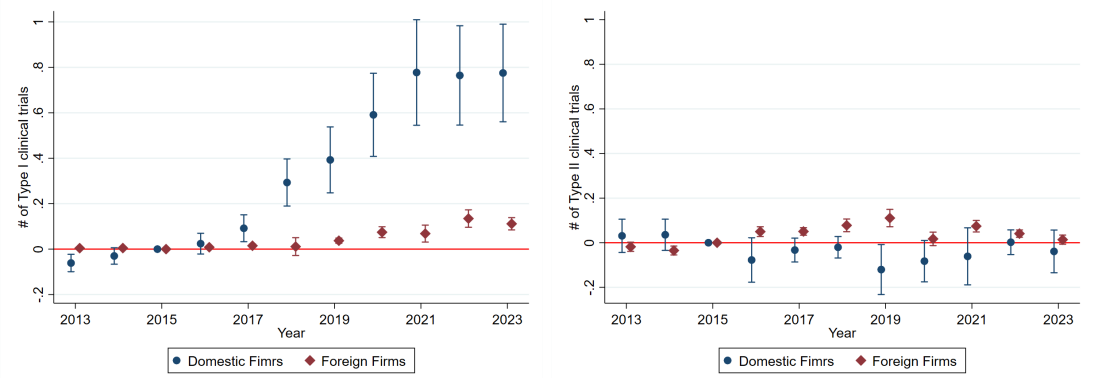
Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the number of research fields per firm, together with their 95% confidence intervals. The unit of analysis is a firm-by-year observation. The treatment group includes pharmaceutical firms and the control group includes vaccine firms. Firm and year fixed effects are included in the regressions. Standard errors are clustered at the firm level.



(a) Three-Year Inactivity Definition (b) Five-Year Inactivity Definition

Figure B19: Number of Firm Exits

Notes: This figure shows the time-series patterns of the number of pharmaceutical and vaccine firms exiting clinical development under two alternative definitions of firm exit. Panel a defines a firm as having exited if it conducts no additional clinical trials for at least three consecutive years after its last observed trial, while Panel b applies a five-year inactivity window.



(a) Type I Clinical Trials

(b) Type II Clinical Trials

Figure B20: Event Study for Number of Clinical Trials by Firm Origin

Notes: This figure plots the estimated event study coefficients of the negotiation policy's effects on the numbers of Type I (Panel a) and Type II (Panel b) clinical trials conducted by domestic and foreign firms separately per disease, together with their 95% confidence intervals. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Disease-by-group and year fixed effects are included in the regressions. Standard errors are clustered at the disease-by-group level.

Table B1: Comparison between Successfully Negotiated and Control Drugs

	Treatment group	Control group		Robustness check	
	(1)	(2)	(3)	(4)	(5)
	Negotiated drugs	Exclusive drugs	Difference	Participating drugs	Difference
ln(revenue)	10.751	10.467	0.285	11.549	-0.798*
	(2.019)	(2.358)	(0.30)	(2.404)	(0.44)
First launch year	2017.257	2014.609	2.648***	2016.892	0.365
	(2.144)	(3.285)	(0.38)	(3.332)	(0.59)
1(Domestic drug)	0.352	0.382	-0.029	0.351	0.001
	(0.480)	(0.488)	(0.07)	(0.484)	(0.09)
N	105	110	215	37	142

Notes: This table reports the summary statistics of key characteristics for the treatment group (successfully negotiated drugs) and two control groups (exclusive drugs and participating drugs), as well as the mean differences between each control group and the treatment group in the first observed quarter of the sample. Reported values are sample means, with standard deviations in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Effects of Successful Negotiation on Price, Quantity, and Revenue

	(1)	(2)	(3)	(4)
	ln(retail price)	ln(OOP price)	ln(quantity)	ln(revenue)
treat × post	-0.697***	-1.934***	1.752***	1.055***
	(0.049)	(0.052)	(0.264)	(0.264)
Observations	11,819	11,819	11,819	11,819
Pre-Policy Mean	5.230	5.229	8.189	13.419
Drug-by-subsample Fixed Effects	Yes	Yes	Yes	Yes
Subsample-by-quarter Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.992	0.992	0.895	0.831
Within R^2	0.148	0.564	0.050	0.020

Notes: This table reports staggered DID estimates of successful price negotiation on drugs' quarterly retail price, out-of-pocket price, quantity, and revenue. The analysis uses drug sales data and observations are at the drug–by-subsample–by-quarter level. Successfully negotiated drugs are compared with eligible drugs that did not successfully enter the NRDL through negotiation during the corresponding subsample period. Standard errors are clustered at the drug level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Robustness Results for the Effects of Successful Negotiation on Price, Quantity, and Revenue with an Alternative Control Group

	(1) ln(retail price)	(2) ln(OOP price)	(3) ln(quantity)	(4) ln(revenue)
treat × post	-0.770***	-2.006***	1.870***	1.100***
	(0.053)	(0.053)	(0.258)	(0.257)
Observations	6,859	6,859	6,859	6,859
Pre-Policy Mean	5.252	5.252	7.879	13.131
Drug-by-subsample Fixed Effects	Yes	Yes	Yes	Yes
Subsample-by-quarter Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.997	0.997	0.919	0.848
Within R^2	0.417	0.808	0.074	0.027

Notes: This table reports staggered DID estimates of the effect of successful price negotiation on drugs' quarterly retail price, out-of-pocket price, quantity, and revenue. The analysis uses drug sales data and observations are at the drug–by-subsample–by-quarter level. Successfully negotiated drugs are compared with drugs that participated in the corresponding or a later round but had not successfully entered the NRDL through negotiation during the corresponding subsample period. Standard errors are clustered at the drug level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Disease-Level Summary Statistics

	Drug		Vaccine	
	(1) 2013-2015	(2) 2016-2023	(3) 2013-2015	(4) 2016-2023
1(clinical trial)	0.050	0.081	0.040	0.071
	(0.217)	(0.272)	(0.197)	(0.257)
1(Type I clinical trial)	0.033	0.069	0.014	0.030
	(0.180)	(0.254)	(0.120)	(0.170)
1(Type II clinical trial)	0.029	0.043	0.029	0.056
	(0.168)	(0.202)	(0.168)	(0.229)
# of clinical trials	0.187	0.884	0.076	0.239
	(1.311)	(7.143)	(0.443)	(1.189)
# of Type I clinical trials	0.119	0.707	0.019	0.066
	(0.927)	(6.033)	(0.169)	(0.524)
# of Type II clinical trials	0.068	0.177	0.056	0.172
	(0.551)	(1.426)	(0.387)	(0.901)
# of Phase I clinical trials	0.072	0.427	0.014	0.086
	(0.569)	(3.445)	(0.120)	(0.509)
# of Phase II clinical trials	0.060	0.311	0.005	0.028
	(0.526)	(2.886)	(0.069)	(0.196)
# of Phase III clinical trials	0.049	0.232	0.050	0.091
	(0.473)	(2.097)	(0.330)	(0.551)
# of Phase IV clinical trials	0.009	0.009	0.006	0.036
	(0.143)	(0.131)	(0.098)	(0.310)
N	10,443	27,848	621	1,656

Notes: This table shows the summary statistics of characteristics for drugs and vaccines separately. Reported values are sample means, with standard deviations in parentheses.

Table B5: Robustness Results: Chemical Drugs and Therapeutic Biologics versus Vaccines

	1(clinical trial)		# of clinical trials	
	(1)	(2)	(3)	(4)
	Chemical Drugs	Biologics	Chemical Drugs	Biologics
treat × post	-0.010	0.000	0.108*	0.263***
	(0.010)	(0.010)	(0.064)	(0.086)
Observations	40,568	40,568	40,568	40,568
Pre-Policy Mean	0.044	0.014	0.149	0.038
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.658	0.593	0.680	0.620
Within R^2	0.000	0.000	0.000	0.000

Notes: This table reports the baseline DID estimates of the negotiation policy's effects on the conduct of new clinical trials, comparing chemical drugs or therapeutic biologics (treatment group) with vaccines (control group) separately. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)–(2) present the estimated effects on the incidence of any new trial, while columns (3)–(4) present the effects on the number of new trials. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Robustness Results: Extending the Sample Period and Extrapolating the Pre-policy Trend

	1(clinical trial)			# of clinical trials		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any	Type I	Type II	All	Type I	Type II
treat × post	0.002	0.002	-0.002	0.403***	0.413***	-0.010
	(0.011)	(0.007)	(0.010)	(0.117)	(0.088)	(0.046)
Observations	51,632	51,632	51,632	51,632	51,632	51,632
Pre-Policy Mean	0.037	0.034	0.016	0.181	0.135	0.046
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.591	0.563	0.493	0.534	0.490	0.507
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table reports the robustness DID estimates of the negotiation policy's effects on the conduct of new clinical trials, using the extended sample period beginning in 2010 and extrapolating the trend in 2010-2015 and difference it out in the post-reform period following Dobkin et al. (2018). The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)-(3) present the estimated effects on the incidence of any new trial, while columns (4)-(6) present the effects on the number of new trials. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: Robustness Results: Poisson Regression Model

	(1) All	(2) Type I	(3) Type II
treat × post	0.407**	0.546	-0.151
	(0.193)	(0.469)	(0.154)
Observations	5,841	4,708	3,982
Pre-Policy Mean	1.292	1.011	0.687
Disease-by-group Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Pseudo R^2	0.838	0.837	0.564

Notes: This table reports the Poisson regression estimates of the price negotiation policy's effects on the number of new clinical trials. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: Robustness Results: Alternative Definition of Clinical Trial Start Date

	1(clinical trial)			# of clinical trials		
	(1) Any	(2) Type I	(3) Type II	(4) All	(5) Type I	(6) Type II
treat × post	0.014	0.031***	-0.006	0.675***	0.648***	0.026
	(0.011)	(0.009)	(0.009)	(0.125)	(0.099)	(0.038)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Pre-Policy Mean	0.050	0.035	0.029	0.207	0.144	0.063
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.663	0.656	0.563	0.668	0.633	0.603
Within R^2	0.000	0.001	0.000	0.000	0.000	0.000

Notes: This table reports robustness DID estimates of the price negotiation policy's effects on the conduct of new clinical trials, using an alternative definition of the trial start date—IRB approval dates. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Columns (1)-(3) present the estimated effects on the incidence of any new trial, while columns (4)-(6) present the effects on the number of new trials. Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B9: Robustness Results: Effects of the Negotiation Policy on the Number of Clinical Projects

	# of new clinical projects			# of active clinical projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Type I	Type II	All	Type I	Type II
treat × post	0.255***	0.296***	-0.042	0.247***	0.351***	-0.103**
	(0.062)	(0.047)	(0.027)	(0.092)	(0.061)	(0.052)
Observations	40,568	40,568	40,568	40,568	40,568	40,568
Pre-Policy Mean	0.111	0.070	0.041	0.131	0.082	0.049
Disease-by-group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.641	0.594	0.664	0.666	0.622	0.711
Within R^2	0.000	0.000	0.000	0.000	0.000	0.001

Notes: This table reports robustness DID estimates of the price negotiation policy's effects on the number of new clinical projects and the number of active clinical projects, respectively. The unit of analysis is a disease-by-group-by-year observation, where group distinguishes drugs (treatment group) from vaccines (control group). Standard errors are clustered at the disease-by-group level. Pre-policy means of the outcome variables for the treatment group are presented in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B10: Firm-Level Summary Statistics

	Pharmaceutical firm		Vaccine firm	
	(1)	(2)	(3)	(4)
	2013-2015	2016-2023	2013-2015	2016-2023
1(domestic firm)	0.834	0.785	0.963	0.960
	(0.372)	(0.411)	(0.189)	(0.195)
1(MAH)	0.662	0.654	0.798	0.771
	(0.473)	(0.476)	(0.403)	(0.421)
1(clinical trial)	0.117	0.282	0.147	0.352
	(0.321)	(0.450)	(0.355)	(0.478)
1(Type I clinical trial)	0.080	0.234	0.037	0.141
	(0.271)	(0.423)	(0.189)	(0.348)
1(Type II clinical trial)	0.046	0.079	0.123	0.253
	(0.210)	(0.270)	(0.329)	(0.435)
# of clinical trials	0.222	0.700	0.221	0.625
	(0.885)	(2.426)	(0.599)	(1.102)
# of Type I clinical trials	0.142	0.545	0.049	0.191
	(0.675)	(2.096)	(0.268)	(0.513)
# of Type II clinical trials	0.080	0.155	0.172	0.433
	(0.472)	(0.770)	(0.504)	(0.930)
1(Micro firm)	0.136	0.158	0.135	0.130
	(0.343)	(0.365)	(0.343)	(0.337)
1(Small firm)	0.341	0.368	0.301	0.312
	(0.474)	(0.482)	(0.460)	(0.464)
1(Medium firm)	0.290	0.268	0.288	0.312
	(0.454)	(0.443)	(0.454)	(0.464)
1(Large firm)	0.233	0.205	0.276	0.245
	(0.423)	(0.404)	(0.448)	(0.431)
N	3,517	14,102	163	554

Notes: This table shows the summary statistics of characteristics for treatment and control groups of firms separately. Reported values are sample means, with standard deviations in parentheses.