

Impact of National Medical Insurance Purchases for Innovative Drugs on Pharmaceutical Firm R&D Investment—A Policy Study Based on Medical Insurance Access Negotiation in China

Fenghong Yang

China Pharmaceutical University

Fanyue Meng

China Pharmaceutical University

Rui Wang

China Pharmaceutical University

Lu Zhang

China Pharmaceutical University

Jinxi Ding

China Pharmaceutical University

Jiaming Li

2448015398@qq.com

China Pharmaceutical University

Research Article

Keywords: Chinese medical insurance access negotiation, pharmaceutical firm, R&D investment, DID model, innovation incentive

Posted Date: September 25th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10791693/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: No competing interests reported.

1 **Impact of National Medical Insurance Purchases for**
2 **Innovative Drugs on Pharmaceutical Firm R&D**
3 **Investment—A Policy Study Based on Medical Insurance**
4 **Access Negotiation in China**

5 **Fenghong Yang^{1†}, Fanyue Meng^{1†}, Rui Wang¹, Lu Zhang¹, Jinxi Ding^{1,2*},**
6 **Jiaming Li^{1,2*}**

8 ¹School of International Pharmaceutical Business, China Pharmaceutical University,
9 Nanjing, China

10 ²Pharmaceutical Market Access Policy Research Center, China Pharmaceutical
11 University, Nanjing, China

13 ***Correspondence:**

14 Jinxi Ding
15 13605152326@163.com

17 Jiaming Li
18 2448015398@qq.com

20 †These authors contributed equally and share the first authorship.

22 **keywords:** Chinese medical insurance access negotiation, pharmaceutical firm, R&D
23 investment, DID model, innovation incentive

24 **Abstract**

25 **Objective:** This study evaluates the net impact of China's medical insurance
26 negotiation policy on pharmaceutical R&D investment, analyzing how it balances drug
27 price control and innovation incentives. The findings provide policy references for
28 optimizing China's negotiation mechanism and guiding the design of innovative drug
29 payment policies in other middle-income countries.

30 **Methods:** This study was based on panel data from 335 Chinese pharmaceutical
31 manufacturing firms from 2010 to 2024, with core variables such as R&D investment
32 collected from the China Stock Market & Accounting Research (CSMAR) database and

corporate annual reports. It employed a multi-period difference-in-differences (DID) model to evaluate the dynamic effects of policy implementation. To verify the robustness of the conclusions, the study further performed the stepwise inclusion of control variables, re-estimation using alternative multi-period DID specifications, and placebo tests with 500 random samples.

Results: Baseline regression results showed that the core explanatory variable was statistically significant at the 1% statistical level. After adding control variables, the coefficient remained stable within the range of 4.07 to 4.10, indicating that medical insurance access increased firms' R&D intensity. Parallel trend tests confirmed that no significant heterogeneity existed between the treatment and control groups before policy implementation. The policy effect persisted both in the year of medical insurance access and in subsequent periods. All robustness checks supported the baseline findings, and the placebo tests ruled out interference from unobservable random factors. Analysis of the control variables revealed that firm size was positively correlated with R&D investment, whereas the asset-liability ratio and profitability showed no statistically significant influence.

Discussion: Chinese medical insurance access negotiation policy operates through strategic purchasing, whereby the government secures lower drug prices in exchange for expanding market access for pharmaceutical firms, ultimately realizing the volume-for-price scale effect. This creates a win-win outcome: patients benefit from reduced financial burden, and pharmaceutical firms offset price reductions through higher sales volume, which provides a positive incentive for increased R&D investment and further promotes industry innovation and sustainable development. The policy achieves a dynamic balance between cost containment and innovation incentives, providing a replicable middle path for global health system reform.

59 **1 Introduction**

60 Pharmaceutical innovation is a key driver of the high-quality development of the
61 national healthcare system. In most countries with public health insurance systems, the
62 insurance payer is typically the largest purchaser in the pharmaceutical market. For
63 example, across OECD countries, public insurance schemes finance a substantial share
64 of pharmaceutical expenditure, accounting for more than half on average and exceeding
65 three-quarters in several countries, highlighting their central purchasing power in the
66 drug market. The payer's decisions can directly influence drug pricing, market scale,
67 and corporate revenue structures, which in turn shape the R&D investments and
68 innovation strategies of pharmaceutical firm[1]. Therefore, whether innovative drugs
69 are included in the insurance reimbursement is not only a matter of patient access but
70 also a critical institutional factor that determines the innovation incentives of
71 pharmaceutical firms.

72 Since the establishment of the National Healthcare Security Administration in
73 2018, China has gradually established a regularized mechanism for medical insurance
74 access negotiations. It selects innovative drugs with high clinical value and urgent
75 patient demand through expert review, pharmacoeconomic evaluation, and medical
76 insurance fund budget impact analysis. Relying on its strategic purchasing position, it
77 engages in price negotiations with pharmaceutical firms to achieve the policy objective
78 of trading lower prices for higher volumes.

79 By 2025, eight rounds of medical insurance access negotiations have been
80 completed, resulting in the inclusion of 949 drugs. Among these, 199 are innovative
81 drugs targeting major diseases, including oncology, rare diseases, and chronic
82 conditions. Driven by negotiations, the prices of innovative drugs have declined
83 substantially, with an average price reduction of around 60%. The affordability of
84 negotiated drugs has significantly improved. Combined with cost-sharing mechanisms,
85 patients' medication burden has been notably alleviated, enabling more patients to
86 benefit from health improvements brought by scientific and technological progress.

87 However, the R&D of innovative drugs is characterized by high investment, high
88 risk, and lengthy development cycles. The substantial price reductions under medical
89 insurance access negotiations have raised a critical question: while expanding market
90 share, can pharmaceutical firms still secure sustainable profits to support R&D? This
91 issue directly determines whether the policy can provide long-term incentives for
92 innovation and remains an essential challenge to be clarified in current policy
93 evaluations. This is particularly pertinent in China, as a typical middle-income country,
94 where the tension between insurance fund sustainability and innovation incentives is
95 more pronounced. Existing international research lacks robust empirical evidence on
96 whether medical insurance purchases in China effectively promote corporate R&D.

97 Therefore, this study seeks to systematically assess the net effect of medical
98 insurance access negotiations on pharmaceutical firms' R&D investment in China,
99 providing not only empirical evidence for optimizing domestic medical insurance
100 access negotiation policies, but also policy references for other middle-income
101 countries facing similar trade-offs.

102 The structure of the study is as follows: Part 2 outlines the theoretical mechanisms
103 and research status; Part 3 introduces the research methodology and data; Part 4
104 presents the empirical results and robustness tests; Part 5 summarizes the research
105 findings and discusses policy implications.

106 **2 Theory and Hypothesis**

107 The impact of national medical insurance purchases on firm R&D investment is
108 multi-pathway and complex. Existing studies have primarily identified three main
109 perspectives: the incentive effect, the inhibitory effect, and the non-significant effect.

110 **2.1 Incentive Effect**

111 Medical insurance purchases primarily promote firm R&D through two major
112 pathways. On the demand side, broad insurance coverage lowers patient out-of-pocket
113 costs, releasing latent medication demand and thereby rapidly expanding the market
114 size for specific drugs[2, 3]. This raises firms' expectations of future sales of new drugs,

strengthens their confidence and motivation to invest in high-risk R&D projects, and may accelerate clinical trials and market approval processes[2]. On the supply side, medical insurance access provides pharmaceutical firms with two critical forms of support. First, it serves as a governmental quality endorsement of a drug's innovative value, sending a clear signal of policy support. This creates stable, long-term market expectations, enabling firms to engage in R&D planning with greater confidence. Second, the stable cash flow generated from insurance reimbursement directly improves a firm's financial position. This allows firms to reallocate more resources originally earmarked for marketing toward R&D activities[4].

Numerous related studies support this view. Blume-Kohout et al.[1], using the implementation of the US Medicare Part D as a natural experiment, found that this policy substantially increased the number of new drug clinical trials targeting the elderly population by improving medication accessibility for seniors. Their study also showed that the elasticity of corporate R&D investment to sales was close to 1, demonstrating that revenue growth can be directly translated into R&D funding. Duggan and Scott Morton's research[5] further pointed out that price negotiations achieved overall corporate revenue growth through considerably increased sales volume, providing cash flow support for R&D. In the Chinese context, Yin[6] also noted that medical insurance access inclusion is equivalent to an official endorsement, which can reduce corporate marketing costs and uncertainty, thereby channeling more funds towards R&D.

2.2 Inhibitory Effect

The inhibitory effect of medical insurance purchasing primarily stems from its price-regulating nature. By setting payment standards or reference prices, the insurance payer compresses the profit margin of innovative drugs[7]. This not only reduces the excess returns from a single product but may also generate spillover effects through the reference pricing mechanism[8], affecting the price level across entire therapeutic areas.

Faced with squeezed expected returns, firms may reassess the risks and rewards

of R&D projects. Their rational choice often leans towards allocating resources to me-too or incremental improvement projects with shorter development cycles, higher success probabilities, and easier passage of insurance price reviews[9]. This creates a crowding-out effect on high-risk, high-investment first-in-class innovation. Furthermore, intense competition for inclusion may also lead to industry resources concentrating on leading firms, causing an averaging of the innovation structure.

Currently, some scholars also focus on the inhibitory effect of medical insurance management. Peltzman's early research[10] pointed out that stringent medical insurance price controls and approval delays can reduce corporate technological innovation efficiency. Analysis by Schulthess et al.[11] indicated that if medical insurance pricing (e.g., Medicare Part B) is forcibly linked to international minimum prices, firms may reduce R&D investment in high-risk areas such as oncology and rare diseases due to insufficient profit margins. Frank & Zeckhauser's research[12] also explored how medical insurance pricing mechanisms may distort firms' R&D resource allocation, leading firms to favor specific types of innovation that cater to payer preferences, rather than pursuing truly breakthrough therapies.

2.3 Non-significant Effect (Irrelevance Theory)

Scholars holding this perspective argued that in complex real-world environments, the independent impact of medical insurance policy on corporate R&D investment may be offset or obscured by other more dominant factors. Pharmaceutical firms' R&D decision-making is a long-term strategic behavior jointly influenced by multiple factors, including the patent system strength, the global technological competition landscape, capital market conditions, and other regulatory policies (e.g., drug review and approval speed). Under certain periods or specific conditions, the decisive role of these factors on R&D investment may far exceed changes in medical insurance payment policies. As a result, it becomes difficult to observe a statistically significant and stable correlation between the two from macro-level data.

For example, Acemoglu et al.[13] employed long-term data from the US (1965-

1999) to conduct research and found that the expansion of insurance coverage did not have a statistically significant impact on the pharmaceutical industry's R&D investment. They speculated that its effect might have been offset by factors like stronger patent protection and globalized competition during the same period. Similarly, Fan C's empirical analysis[2], based on differences in health insurance mandates across US states, also found that the overall impact of insurance expansion on drug innovation was statistically insignificant. These studies suggest that when analyzing the effect of medical insurance on innovation, a broader, dynamic multi-factor system needs to be considered.

However, China's medical insurance access negotiation policy exhibits more complex characteristics compared to most other countries in terms of its pathways affecting firm R&D:

Firstly, China's medical insurance acts as the largest single payer in the market. The position gives its purchasing decisions powerful market influence. Simultaneously, in order to control expenditure within the insurance fund and address societal concerns about drug affordability, the insurance payer needs to conduct proactive price negotiations. This dual role places the medical insurance negotiation in a dilemma. It aims to expand market access and encourage innovation through trading lower prices for higher volumes, while the substantial price cuts inevitably squeeze corporate profit margins.

Secondly, while the over 1.4 billion insured population offers enormous market potential, it also implies that including new drugs in the insurance catalog may trigger substantial expenditure pressure on the fund. Consequently, the insurance payer is exceptionally price-sensitive in negotiations, and its stance on price reductions tends to be more resolute. Furthermore, as a middle-income country, China's medical insurance fund adheres to the principle of covering basic needs. When evaluating high-priced innovative drugs, the payer must carefully balance the drug's social value against fund sustainability. The consideration often results in larger negotiation-driven price

reductions. This economic and institutional foundation, rooted in the national context, makes theories from developed countries, such as “demand-induced innovation” or “price-suppressed innovation,” difficult to directly explain China’s practice.

In summary, studying the impact of China’s medical insurance access negotiation policy on firm R&D must recognize its high degree of complexity. The empirical research in this study precisely aims to clarify the true net effect of China’s medical insurance negotiations on corporate innovation behavior within this unique and complex policy environment.

3. Methodology

Based on a review of the existing literature, this study employed data from the CSMAR database (<https://data.csmar.com/>) on the R&D investment of Chinese pharmaceutical firms to precisely investigate the impact of medical insurance access negotiation on R&D investment. Missing values were supplemented using annual reports published on the official websites of listed companies.

Using a 14-year panel dataset covering the full sample of Chinese pharmaceutical manufacturers, this study adopted a quasi-natural experiment design to comprehensively analyze the long-term effects of medical insurance access negotiation on corporate R&D investment.

3.1 Research Sample

The research sample comprises 335 pharmaceutical manufacturing enterprises operating in China, covering the period from 2010 to 2024. The sample was constructed through the following steps:

First, all A-share listed pharmaceutical firms in China were identified, resulting in 322 enterprises listed before 2018.

Second, 50 A-share listed firms that participated in medical insurance access negotiations and successfully had their products approved since 2018 were selected.

Additionally, 12 China-based firms listed only on the Hong Kong stock market repeatedly participated in and successfully completed negotiations, and were therefore

added to the research sample.

Ultimately, the research sample consisted of 62 firms in the policy treatment group and 273 firms in the policy control group.

3.2 Empirical strategy

Given that the Chinese medical insurance access negotiation policy was implemented in multiple rounds over time, different firms were subject to the policy's effects at varying points in time. Therefore, this study employed a Multi-period Difference-in-Differences (Multi-period DID) model to evaluate the impact of medical insurance access negotiation on corporate innovation and R&D[14-17].

Considering the persistence and adjustment costs of R&D investment in pharmaceutical firms, the impact of policies on R&D decisions may involve a certain time lag. To more accurately capture the policy effects and mitigate potential endogeneity issues, this study, following relevant literature, applied a one-period lag to the core explanatory variables and control variables. The baseline regression model is specified as follows:

$$Y_{it} = \beta_0 + \beta_1(treat_i \times post_{it}) \times \gamma X_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

In the model, Y_{it} denotes the R&D investment level of pharmaceutical firm i in year t , measured by the firm's annual revenue.

$treat_i$ is a dummy variable for the treatment group, equal to 1 if pharmaceutical firm i is ever affected by the policy in that year, meaning the firm has at least one product included in the national negotiations. Otherwise, it takes the value of 0.

$post_{it}$ is a dummy variable for the treatment period, equal to 1 if pharmaceutical firm i is exposed to the policy in year t , meaning that the firm has entered medical insurance access negotiation by year t . Otherwise, it takes the value of 0.

X_{it} represents a vector of control variables. α_i captures firm fixed effects. δ_t captures year fixed effects, and ϵ_{it} is the random error term.

$DID=treat_i \times post_{it}$ is the core explanatory variable in the model. When $DID=1$, it indicates that pharmaceutical firm i has entered medical insurance access

negotiation in year t . The coefficient β_1 is the primary parameter of interest, as it measures the net impact of the negotiation policy on pharmaceutical firms' R&D investment.

In terms of variable selection, with reference to prior literature[18-23], this study selected seven variables. Specifically, the dependent variable, used to measure the level of corporate R&D investment, is defined as the firm's total R&D expenditure. This includes all direct expenses related to R&D activities, such as salaries of R&D personnel, material costs, depreciation, and amortization.

The explanatory variable is DID. To verify the robustness of the model, this study involved two DID-based variables: DID_fixed and DID_period. Among them, DID_fixed treats 2018 as a uniform policy implementation point. For firms in the treatment group, this variable takes a value of 0 before 2018, indicating no policy impact, and 1 from 2018 onward, indicating policy impact. DID_period takes the specific year in which each firm entered the medical insurance access negotiation as its individual policy impact point. For a treatment group firm, this variable is 0 before its entry year and becomes 1 from that year onward.

Regarding control variables, based on established practices in the literature, LN_size, LEV, ROA, and TAT were included as standard controls. Among them, LN_size serves as a proxy for firm size, measured by the natural logarithm of total assets. LEV represents the asset-liability ratio, reflecting the firm's financial leverage and long-term solvency. ROA (Return on Assets) measures the efficiency with which a firm utilizes its total assets to generate profit. TAT (Total Asset Turnover) indicates the efficiency of a firm in employing its total assets for operations. The definitions of all the variables are summarized in Table 1.

Table 1 Variable Selection.

Category	Variable	Full Name	Meaning and Calculation Method	Unit
Dependent Variable	RD_exp	R&D Expenditure	The total expenditure on research and development activities. Measured as the R&D spending reported in the financial statements.	Billion CNY
		Time-fixed		
Independent Variables	DID_fixed	Difference-in-Differences	The interaction term for the single, universally implemented policy shock in 2018.	Unitless
	DID_period	Multi-period	The interaction term for the staggered policy shock	

Control Variables		Difference-in-Differences	where treatment timing varies by firm. The interaction term for the staggered policy shock where treatment timing varies by firm.		
	LN_size	Natural Logarithm of Total Assets	The natural logarithm of total assets, used to control for firm size. Calculated as $\ln(\text{Total Assets})$.		Unitless
	LEV	Leverage Ratio	The ratio of total liabilities to total assets, measuring financial leverage. Calculated as $\text{Total Liabilities} / \text{Total Assets}$.		Unitless
	ROA	Return on Assets	The ratio of net income to total assets, indicating profitability. Calculated as $\text{Net Income} / \text{Total Assets}$.		Unitless
	TAT	Total Asset Turnover	The ratio of operating revenue to total assets, measuring asset utilization efficiency. Calculated as $\text{Operating Revenue} / \text{Total Assets}$.		Unitless

3.3 Data

The data utilized in this study were sourced from the CSMAR database and subsequently processed. Missing values were supplemented using annual reports published by listed companies on their official websites. The raw dataset consisted of 2911 observations covering 335 pharmaceutical firms from 2010 to 2024. Data cleaning was performed as follows. First, we applied linear interpolation to impute missing values[24, 25], and then we conducted winsorization at the 1% and 99% percentiles to mitigate the influence of outliers[26, 27], resulting in the final dataset for analysis.

Descriptive statistics of the experimental data variables are shown in Table 2. The results show that the mean value of corporate R&D expenditure (RD_exp) is 1.699, with a relatively large standard deviation (3.344), indicating variation in R&D investment levels across different firms. The standard deviations of firm size (LN_size) and total asset turnover (TAT) are relatively small, suggesting that the sample firms are relatively concentrated in terms of size and asset operation efficiency. Furthermore, the average leverage ratio (LEV) of the sample firms is 30.3%, reflecting a moderate overall debt level. The average return on assets (ROA) is 8.2%, indicating a certain degree of profitability.

Table 2 Descriptive Statistics.

Var	N	Min	Max	Mean	SD
RD_exp	2911	0.000	21.850	1.699	3.344
LN_size	2911	0.970	6.380	3.579	1.089
LEV	2911	0.037	0.840	0.303	0.178
ROA	2911	0.002	0.374	0.082	0.066
TAT	2911	0.327	0.989	0.805	0.136

3.4. Parallel trend test

The parallel trend assumption is a fundamental prerequisite for applying the Difference-in-Differences (DID) method in policy effect evaluation[28-30]. It requires that, prior to the policy shock, the treatment and control groups follow a consistent development trend. This ensures that any observed differences between the two groups after policy implementation can be reasonably attributed to the policy intervention itself, rather than to pre-existing inherent heterogeneity.

To validate this assumption, this study used a DID model that incorporates year-fixed effects to conduct the parallel trend test[31]. Considering that within-group correlation may lead to the underestimation of true variance by ordinary standard errors, the study further employed robust standard errors for regression estimation[32]. These were calculated using the Variance-Covariance Matrix Estimation Method, with standard errors clustered at the firm level. The parallel trend test result is plotted in Figure 1.

Figure 1 presents the estimated coefficients and their corresponding 95% confidence intervals for each year within the policy event window. The results show that in the pre-policy periods (from pre_9 to pre_1), the estimated coefficients for the treatment and control groups fluctuate around zero, and all confidence intervals include zero. This indicates no statistically significant systematic difference between the two groups before the policy shock, thus satisfying the parallel trend assumption.

In the policy implementation period (current) and subsequent periods (from las_1 to las_5), the estimated coefficients are significantly positive and remain statistically significant. This pattern clearly demonstrates the dynamic effect of the policy

intervention.

The parallel trend test confirms that the fundamental assumption of the DID model is met in this study, providing essential methodological assurance for the reliability and validity of the subsequent policy effect evaluation.

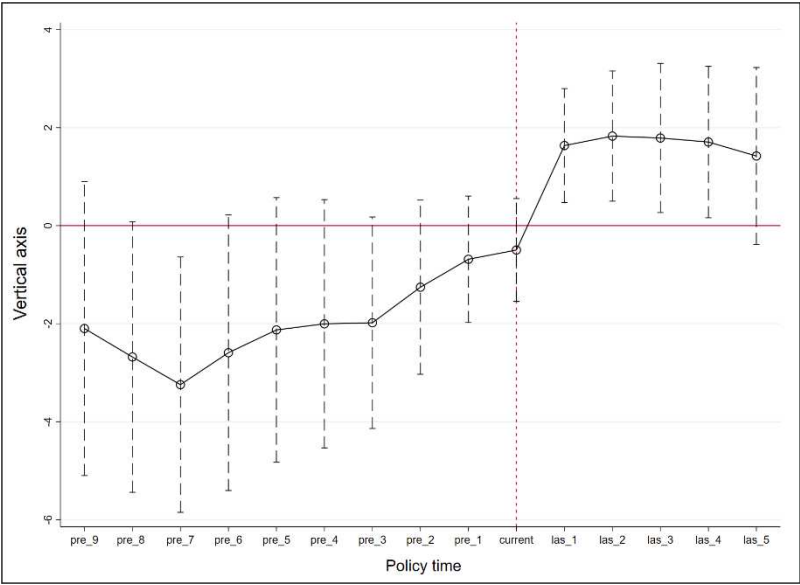


Figure 1 Parallel trend test.

4 Empirical results

4.1 Baseline Regression

To identify the net effect of the policy on corporate R&D investment, this study constructed a two-way fixed effects model within the DID framework for baseline regression analysis. Considering potential heteroscedasticity and serial correlation in the panel data, robust standard errors clustered at the firm level were employed during regression to mitigate estimation bias.

To verify the robustness of the baseline results, the study also adopted a stepwise introduction of control variables in the regression design, with specific results shown in Table 3. Across all model specifications (Reg1 to Reg5), the estimated coefficient of the core explanatory variable, DID_fixed, is consistently positive and statistically significant at the 1% level. In the baseline model without any control (Reg1), the coefficient of DiD_fixed is 5.122. As control variables such as LN_size, LEV, ROA, and TAT are gradually added, the coefficient stabilizes within the range of 4.07-4.10,

showing no significant fluctuation and demonstrating good stability.

This result indicates that the policy implementation generated a statistically significant and positive promoting effect on corporate R&D investment, and this effect remains highly robust.

Regarding the control variables, the coefficient for LN_size is statistically significant and positive in all models. This indicates a positive correlation between firm size and R&D investment level, suggesting that larger firms typically possess more resources to support R&D activities and exhibit relatively higher R&D investment intensity. However, the coefficients for LEV, ROA, and TAT are not statistically significant. This implies that, after controlling for other factors, the firm's leverage, profitability, and asset operation efficiency do not exhibit a statistically significant impact on its R&D investment.

Furthermore, with the gradual introduction of control variables, the adjusted R² of the model increases from 0.269 to 0.368. This improvement indicates an enhanced explanatory power of the model regarding the variation in R&D expenditure, further validating the rationality of the regression setup.

In conclusion, the baseline regression results provide robust empirical support for the study's core hypothesis: the policy shock increased the R&D investment intensity of firms in the treatment group.

Table 3 Baseline Regression.

Var	Reg1	Reg2	Reg3	Reg4	Reg5
	RD_exp				
DID_fixed	5.122***	4.072***	4.078***	4.101***	4.080***
LN_size		1.475***	1.488***	1.508***	1.529***
LEV			-0.716	-0.775	-1.076
ROA				1.628	1.711
TAT					-1.132
cons	0.995***	-4.142***	-3.972***	-4.163***	-3.237***
N	2911				
R-sq	0.269	0.365	0.366	0.367	0.368

[1] ***, **, and * represent statistical significance at the 1, 5, and 10% levels, respectively. [2] Robust standard errors are reported in parentheses.

4.2 Robustness Test

To verify the reliability of the above conclusions, this study further conducted the following robustness tests.

Firstly, the study conducted robustness tests by changing the core estimation method. Since the timing of firms' entry into medical insurance access negotiation varies, the traditional two-way fixed effects estimation may produce bias, while the multi-period DID model can more accurately identify treatment effects[30]. Therefore, following previous scholarly research[33, 34] and considering the temporal heterogeneity of policy implementation in the baseline regression (i.e., different firms are affected at various times), the study re-estimated the baseline results using a more appropriate multi-period DID model, thereby further validating the reliability of the conclusions.

The estimated results presented in Table 4 reveal that the coefficient for the core explanatory variable, DID_period, remains consistently positive at the 1% statistical level, with its coefficient value stable around 3.50. It closely aligns with the coefficient range of the baseline regression (4.07-4.10). This result indicates that after fully accounting for the temporal heterogeneity of policy implementation, the positive promoting effect of the policy on corporate R&D expenditure remains highly robust. This also confirms that the baseline regression conclusion is not influenced by model specification bias, and the core research findings are methodologically sound.

Table 4 Multi-period DID Test.

Var	Reg1	Reg2	Reg3	Reg4	Reg5
	RD_exp				
DID_period	4.54***	3.503***	3.506***	3.519***	4.080***
LN_size		1.655***	1.667***	1.684***	1.706***
LEV			-0.633	-0.678	-1.013
ROA				1.248	1.342
TAT					-1.259
cons	1.37***	-4.478***	-4.328***	-4.477***	-3.447***
N	2911				

R-sq	0.196	0.320	0.321	0.322	0.323
------	-------	-------	-------	-------	-------

[1] ***, **, and * represent statistical significance at the 1, 5, and 10% levels, respectively. [2] Robust standard errors are reported in parentheses.

Secondly, to rule out interference from unobservable random factors or potential omitted variables in the baseline results, this study conducted a placebo test. By randomly assigning the treatment status within the full sample and repeating this process multiple times, a synthetic distribution of the coefficients for a placebo policy variable can be created. This allows for an assessment of whether the baseline estimate significantly differs from randomly generated effects[35].

Following previous studies[32, 36], this study conducted 500 random sampling simulations of the dependent variable. In each simulation, policy treatment statuses (i.e., placebo treatment group and control group) were randomly assigned across the full sample, and the baseline regression process was repeated to generate an estimated coefficient distribution for the placebo policy variable.

The test results, shown in Figure 2, indicate that the estimated coefficients from the 500 simulations are densely clustered near zero, approximating a normal distribution centered at zero (mean $\mu \approx -0.003$). In contrast, the estimated coefficient for the true core explanatory variable from the baseline regression (approximately 4.08) significantly deviates from this distribution's center, lying in the right tail and far exceeding the 95% confidence interval, constituting a statistically low-probability event.

Figures 3 and 4 further illustrate that the p-values generated by the random simulations are mostly concentrated at insignificant levels, and the t-values follow a standard normal distribution centered around zero.

In summary, the placebo test results confirm that the significant policy effects observed in the baseline regression are not driven by unobservable random factors or potential omitted variables, but represent the genuine effect of policy intervention. This finding also strengthens the internal validity and reliability of the study's core conclusions.

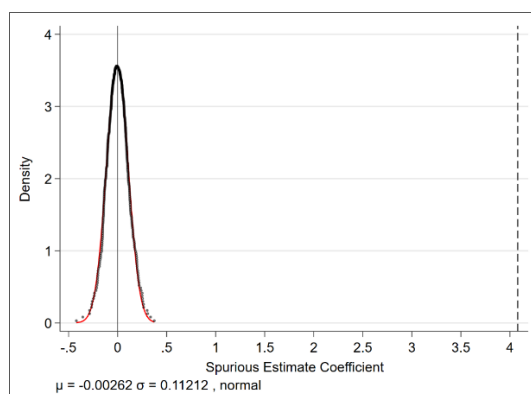


Figure 2 Regression Coefficient Test.

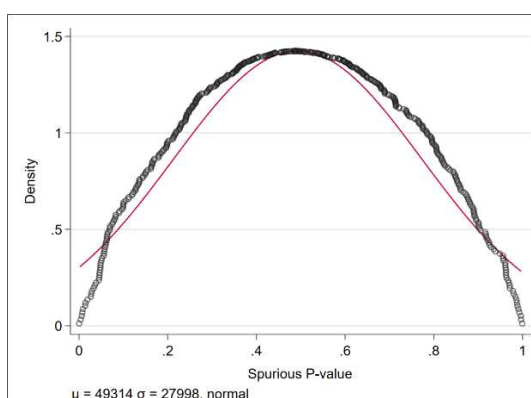


Figure 3 P-value Test.

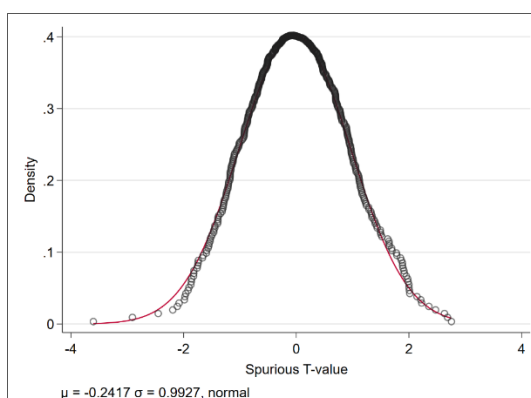


Figure 4 T-value Test.

5 Conclusion and Discussion

This empirical study demonstrates that the Chinese medical insurance access negotiation policy has significantly stimulated R&D investment of pharmaceutical firms. The baseline regression results show that the core explanatory variable is positive and statistically significant at the 1% level, indicating that firms with products successfully included in the national reimbursement drug list experienced a greater

increase in R&D investment compared to the control group firms. This conclusion remains valid after a series of robustness tests, including multi-period DID model estimation and placebo tests. It confirms the reliability of the study's conclusion that the policy shock from the negotiations does not suppress, but rather effectively incentivizes, corporate innovation investment.

This finding reveals that, within the current Chinese pharmaceutical market environment, the national medical insurance system engages in strategic purchasing by negotiating lower drug prices in exchange for expanded and more stable market access. Through this volume-for-price mechanism, the resulting scale effects can effectively offset the profit pressure induced by price reductions and ultimately transform into financial resources for corporate R&D investment. It shows that, while controlling drug prices and alleviating patient burdens, the medical insurance access negotiation policy has not compromised the momentum for industrial innovation. This suggests a preliminary achievement of policy balance between cost containment and innovation incentive, providing strong empirical support for continuing to uphold and optimize the current negotiation mechanism.

This Chinese experience holds important implications for other countries worldwide, especially middle-income countries grappling with the challenge of balancing rising healthcare costs and innovation incentives. It demonstrates that a single payer with a large population base can build a market environment that ensures patient accessibility while continuously motivating local pharmaceutical industry innovation through strategic purchasing and rigorous price negotiations. It offers a feasible middle path reference for global healthcare system reform.

However, this study also has certain limitations. Due to constraints in length and data availability, this research primarily verifies the net effect of medical insurance access negotiation on corporate R&D investment but does not delve into the specific transmission pathways of this impact. In other words, it fails to clearly identify and test the intermediary variables, such as corporate cash flow, market expectations, and R&D

pipeline adjustment strategies, and their underlying mechanisms.

Therefore, future research should focus on constructing and testing mediating effect models to deeply reveal the specific operation of the “price-volume-profit-R&D” chain. Additionally, it should further investigate the heterogeneous effects of the policy on firms of different sizes, ownership structures, and different types of innovation (e.g., original innovation and incremental innovation), thereby providing more detailed scientific references for formulating more targeted industrial incentive policies.

Declarations

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' contributions

Conceptualization, F.Y., J.L, and F.M.; methodology, F.Y.; validation, F.M, and J.L.; formal analysis, F.M.; resources, F.Y.; data curation, F.Y; writing—original draft preparation, F.Y and F.M; writing—review and editing, F.Y., F.M, J.L, R.W, L.Z and J.D.; supervision, J.L. and J.D.; project administration, J.L. and J.D. All authors have read and agreed to the published version of the manuscript.

Funding

No funding was received for the research, authorship, and/or publication of this article.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Acknowledgements

Special thanks go to the anonymous reviewers and the editorial team for their insightful

comments, which have significantly improved the quality and clarity of this paper. All remaining errors and omissions are solely our own responsibility.

References

- [1]. Blume-Kohout ME, Sood N. Market Size and Innovation: Effects of Medicare Part D on Pharmaceutical Research and Development. *Journal of Public Economics* 2013;97:327-36.
- [2]. Fan C, Song X, Li C. The Relationship between Health Insurance and Pharmaceutical Innovation: An Empirical Study Based on Meta-Analysis. *Healthcare (Basel, Switzerland)* 2023;11:18.
- [3]. Li C, Zhu J, Shan L, Zhou Y, Liu G, Zhu H, et al. Impact of Medical Insurance Access Negotiation on the Utilization of Innovative Anticancer Drugs in China: An Interrupted Time Series Analysis. *BMC Health Services Research* 2024; 24.
- [4]. Kiriyama N. Trade and Innovation: Pharmaceuticals. *OECD Trade Policy Papers* 2011;10:147-64.
- [5]. Duggan M, Morton FS. The Effect of Medicare Part D on Pharmaceutical Prices and Utilization. *The American Economic Review* 2010;100:590-607.
- [6]. Yin W. Market Incentives and Pharmaceutical Innovation. *Journal of Health Economics* 2008;27:1060-77.
- [7]. Mi, Tang, Peipei, Song, Jiangjiang, He. Progress on Drug Pricing Negotiations in China. *Bioscience Trends* 2019;13:464-8.
- [8]. Vernon JA. Examining the Link between Price Regulation and Pharmaceutical R&D Investment. *Health Economics* 2005;14:1-16.
- [9]. Grossmann, Volker. Do Cost-Sharing and Entry Deregulation Curb Pharmaceutical Innovation? *Journal of Health Economics* 2013;32:881-94.
- [10]. Mulligan CB. Peltzman Revisited: Quantifying 21st Century Opportunity Costs of Fda Regulation. *NBER Working Papers*;2021.
- [11]. Schulthess D, Bowen HP, Popovian R, Gassull D, Zhang A, Hammang J. The Relative Contributions of Nih and Private Sector Funding to the Approval of New Biopharmaceuticals (September, 10.1007/S43441-022-00451-8, 2022). *Therapeutic innovation & regulatory science* (2023).
- [12]. Frank RG, Zeckhauser RJ. High-Priced Drugs in Medicare Part D: Diagnosis and Potential Prescription. *Social Science Electronic Publishing*.
- [13]. Acemoglu D, Cutler D, Finkelstein A, Linn J. Did Medicare Induce Pharmaceutical Innovation? *American Economic Review* 2006;96:103-7.
- [14]. Sant'Anna PHC, Zhao JB. Doubly Robust Difference-in-Differences Estimators. *SSRN Electronic Journal* (2018).
- [15]. Abadie A. Semiparametric Difference-in-Differences Estimators. *Review of Economic Studies* 2010;72:1-19.
- [16]. Ban K, Kédagni D. Robust Difference-in-Differences Models.;2022.
- [17]. Egami N, Yamauchi S. Using Multiple Pretreatment Periods to Improve Difference-in-Differences and Staggered Adoption Designs. *Political Analysis*

2022; 31:195 - 212.

[18]. Li J, Zhang X, Wang R, Cao K, Wan L, Ren X, et al. Impact of National Centralized Drug Procurement Policy on Chemical Pharmaceutical Enterprises' R&D Investment: A Difference-in-Differences Analysis in China. *Frontiers in Public Health* (2024) 12:1402581.

[19]. Eberhart AC, Maxwell WF, Siddique AR. An Examination of Long - Term Abnormal Stock Returns and Operating Performance Following R&D Increases. *The journal of finance* 2004; 59:623-50.

[20]. Shen Y, Ruan Q. Accounting Conservatism, R&D Manipulation, and Corporate Innovation: Evidence from China. *Sustainability* 2022;14:9048.

[21]. Performance—An B. Exploring the Relationship between R&D Investment and Business Performance—an Empirical Analysis of Chinese Ict Smes. *FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES* 2023:75.

[22]. Wang Z. Science and Technology Finance Policy and Corporate Investment Efficiency -- a Quasi-Natural Experiment Based on Pilot Policies for Integrating Technology with Financer. *Highlights in Business, Economics and Management* 2024;36:580-97.

[23]. Liang S. Managerial Ability and R&D Investment: An Empirical Analysis Based on Dea-Tobit Model. *E3S Web of Conferences* 2021; 235:01069.

[24]. Jin Z. Principle, Methodology and Application for Data Cleaning Techniques. *BCP Business & Management* 2022;26:724-32.

[25]. Weerasinghe S. A Missing Values Imputation Method for Time Series Data: An Efficient Method to Investigate the Health Effects of Sulphur Dioxide Levels. *John Wiley & Sons, Ltd* 2009;(2).

[26]. Hamadani A, Ganai N, Raja TG, Alam S, Andrabi SM, Hussain I, et al. Outlier Removal in Sheep Farm Datasets Using Winsorization. *Bhartiya Krishi Anusandhan Patrika* (2022).

[27]. Dixon WJ, Yuen KK. Trimming and Winsorization: A Review. *Statistische Hefte* 1974;15:157-70.

[28]. Athey S, Imbens G. Design-Based Analysis in Difference-in-Differences Settings with Staggered Adoption. *Susan Athey* ;2018.

[29]. Angrist JD, Pischke J-S. Mostly Harmless Econometrics: An Empiricist's Companion. *europaen review of agricultural economics* ;2008.

[30]. Callaway B, Sant'Anna PHC. Difference-in-Differences with Multiple Time Periods. *CJRN: Criminology Research Methodology (Topic)* ;2018.

[31]. Abraham S, Sun L. Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. *Papers*;2018.

[32]. Marianne B, Esther D, Sendhil M. How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics* 2003;1: 249-75.

[33]. Deyou M, Wenfeng C, Yuqi L. Impacts of High-Speed Railway on the Spatial Pattern of the Regional Accessibility in China. *Areal Research and Development* ;2011.

- [34]. Niu S, Luo X, Yang T, Lin G, Li C. Does the Low-Carbon City Pilot Policy Improve the Urban Land Green Use Efficiency?—Investigation Based on Multi-Period Difference-in-Differences Model. *International Journal of Environmental Research and Public Health* 2023; 20:2704.
- [35]. Bertrand M, Mullainathan DS. How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics* 2004;119:249-75.
- [36]. Liangwen L, Jiahua L. Synergetic Effect of China's Carbon Market Policies on Pollution Reduction and Carbon Reduction. *Resources Science* 2024;46:53-68.