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The Impact of Medical Data Outbound Review Load on the Efficiency of Cross-border Medical Research Collaboration in China

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Abstract: The cross-border flow of medical data is reshaping the cost structure of medical research collaboration. Data-intensive medical research increasingly relies on cross-institutional and cross-jurisdictional data access, and such data are inherently embedded in multiple sensitive dimensions such as personal privacy, transforming the cross-border flow from a simple issue of scientific collaboration into a systemic issue with ethical, legal, and governance implications. Based on a strong balanced panel of 540 medical research decision-making units in China from 2018 to 2025, using the institutional shock after the implementation of the "Data Outbound Security Assessment Measures", this paper constructs a continuous difference-in-differences model to evaluate the impact of medical data outbound review load on the efficiency of cross-border medical research collaboration in China. The results show that, after controlling for fixed effects of institutions, years, and institutional characteristics, the exposure to review load significantly reduces the output efficiency of cross-border cooperation papers; the core coefficient is -0.288, corresponding to a 25.0% decrease in the output rate. The review load also reduces the openness of international cooperation networks by 0.164 standard deviations. The mechanism test indicates that the increase in institutional transaction costs and the decline in data availability respectively explain about 25.1% and 36.6% of the total effect. The heterogeneity analysis shows that non-head institutions and data-intensive medical fields are subjected to stronger impacts. This paper examines the governance of medical data outbound in the context of the global medical knowledge production chain, demonstrating that the institutional performance of security review not only depends on the strength of the rules but also on its predictability, stratification, and adaptability

to the research scenario.

Keywords: Medical data outbound; Cross-border medical research; Data governance; Collaboration efficiency; Research network

I. Introduction

The bottleneck in cross-border medical research is shifting from "whether cooperation is possible" to "whether data can be shared in a compliant and efficient manner". In multi-center clinical trials, rare disease research, precision medicine, and AI-assisted diagnosis scenarios, the research value often stems from the joint analysis of patient data from different regions. The richer the data, the more adequate the external validation. The more restricted the data flow is, the more likely the model generalization, disease classification, and treatment response assessment are constrained by sample boundaries. Therefore, medical research collaboration is no longer merely a partnership between authors, institutions, and funds; it is also a set of institutional arrangements centered around data access, ethical approval, safety assessment, and responsibility allocation.

Global health data governance has entered the stage of institutional reengineering. The European Health Data Space attempts to improve the efficiency of secondary utilization of health data through a unified framework [1], but related evaluations also remind us that if cross-border health data governance lacks clear interoperability rules, responsibility boundaries, and implementation capabilities, a grand data space may instead become a costly institutional project [2]. The user journey research on the secondary utilization of European health data further indicates that cross-border research access requires integrating institutional licensing, data quality, and actual operational procedures [3]. The multi-jurisdictional research in Africa shows that cross-border research data sharing is not only constrained by data protection laws but also shaped by research ethics, data subjects' rights, and local approval capabilities [4]. The international discussion on local data localization and cross-border flow rules also suggests that legal boundaries directly change the feasible paths for scientific data exchange [5].

Genomic data and precision medicine have pushed this issue to a deeper level. The discussion among Chinese public regarding international genetic information sharing indicates that cross-border medical data flow is not merely a technical exchange; it also involves national identity, ethnic information, and scientific trust [6]. The research on

the risks and benefits of data sharing by clinical trial participants shows that subjects are not naturally opposed to sharing; the key lies in the credibility of the governance arrangement [7]. The patient preference study in precision oncology also reveals that patients require explanations of usage, accessors, feedback mechanisms, and protection responsibilities [8]. These findings echo the discussions on rights and obligations in large-scale genomic programs [9].

China's medical data outbound governance has formed its own institutional path in this global context. Since 2021, the "Data Security Law", "Personal Information Protection Law", and "Data Outbound Security Assessment Measures" have been implemented successively, and cross-border data activities have entered a system track centered on security assessment, personal information protection, classification and grading, and responsibility traceability [10-12]. Relevant regulations in 2024 signal a facilitation signal [13], but the sensitivity of medical research data, ethical chains, and cross-institutional coordination costs remain prominent. For the research system, the key issue is not whether the rules exist, but how they are transformed into time costs, budget costs, data availability constraints, and changes in the cooperation network.

Existing research has already demonstrated that medical data governance is not merely a technical issue. Health data space research focuses on the institutional conditions for cross-border secondary utilization [1], and data platform research discusses the infrastructure for scientific collaboration under general data protection rules [14]. AI medical research further emphasizes that governance responsibilities must be embedded in the entire process of model development, data organization, and clinical use [15]; genomic and automated imaging research reminds us that the value of high-throughput medical data highly depends on continuous data stewardship and verifiable organization processes [16]. However, these studies rarely estimate whether the institutional review load actually changes cross-border medical research outputs, nor do they distinguish the impacts borne by different institutions and disciplines with varying data density. This paper takes the governance of medical data export from China as the scenario and proposes and tests a quantifiable proposition: when the review load for data export increases, will the efficiency of cross-border medical research collaboration decline, and through what mechanism will this decline occur. Unlike simplifying policy handling into binary dummy variables, this paper constructs a continuous exposure intensity by using the base period high-sensitive medical data dependency of institutions.

Thus, this paper advances a governance issue that is usually confined to normative discussions into an identifiable and estimable empirical proposition. The article also examines output efficiency and network openness, using the base period high-sensitive medical data dependency of institutions to characterize the continuous exposure intensity; not only reporting the average effect, but also further identifying two transmission paths: institutional transaction costs and data availability constraints. This paper enables the governance of medical data export to enter the analytical framework of global medical knowledge production efficiency.

II. Institutional background and theoretical framework

2.1 Institutional Background of Medical Data Ex-Entry Governance

China's data governance system has rapidly advanced from principle-based norms to operational reviews within a short period. The "Data Security Law" established the principles of data classification and classification, and important data protection. The "Personal Information Protection Law" stipulated the conditions for data export, individual consent, and rules for handling sensitive personal information. The "Data Ex-Entry Safety Assessment Measures" incorporated specific data ex-entry activities into the safety assessment and risk self-assessment processes [10-12]. Medical data is at the intersection of these rules, often involving patient privacy, clinical ethics, genetic information, public health, and research reproducibility.

The uniqueness of medical data stems from its dual attributes. On one hand, medical data has public knowledge value. Cross-border case aggregation can enhance the ability for rare disease research, multi-center imaging data can improve the external validation level of algorithms, and real-world data can supplement the evidence chain beyond randomized trials. On the other hand, medical data has a high risk of re-identification and social sensitivity. Once genomic information, imaging data, and long-term follow-up records are linked to other data sources, the risk of individual and group-level identification increases. The study on precision medicine equity research indicates that data governance can affect whether underrepresented groups can enter the distribution of innovation benefits [17]; The study on genetic non-discrimination policies shows that data sharing must respond to individual rights, insurance employment risks, and social trust [18]. At the platform level, the research collaboration infrastructure constrained by general data protection rules also needs to incorporate access control, responsibility tracking, and verifiability into the design [14].

Therefore, the review of medical data ex-entry should not be understood as a single administrative step imposed on scientific research activities. It is more like a system parameter that changes the production function of scientific research. After the parameter change, every step from data collection, cleaning, de-sensitization, authorization, transmission to reuse will be re-priced. Research teams need to re-evaluate whether the project can be initiated, institutions need to re-configure compliance resources, and overseas partners need to re-assess whether the access path is stable.

2.2 Theoretical Mechanism

Data has the attribute of non-common input. Ordinary research inputs can be adjusted in quantity within budget constraints. Medical data cannot be simply substituted. A multi-center study without certain types of patient samples will change the external validity of the model; a genomic cohort lacking cross-ethnic comparison will reduce the explanatory power of variation; an imaging model lacking validation data from different devices and regions will weaken the clinical transferability. The review load first acts on this irreplacability. First, change whether data can flow. Then, change the form in which data flows. Finally, change who can bear this flow.

Before project initiation. The review load raises the pre-requisite threshold for data circulation. Ethical approval needs to re-justify the boundary of the purpose. Legal agreements need to clarify the responsibilities of the overseas recipient. The data team needs to complete de-sensitization, encryption, access control, and traceability auditing. Each step is reasonable. After the steps are stacked, the project initiation cost increases. For leading institutions, these processes can be absorbed by the existing compliance department; for non-leading institutions, the same process often means additional outsourcing, repeated communication, and longer waiting times.

In terms of data form. High-sensitive data is not necessarily completely prohibited from flowing, but it is often reduced in dimension. Individual-level data becomes a summary table. Linkable data becomes un-linkable data. Original imaging becomes a feature variable. Genomic sequences become limited-site results. The data remains, but the research capability changes. Recent research on data sharing statements of high-impact journals shows that there is still a distance between the statement text and the actual accessibility [19]; Reviews in the fields of surgical research and addiction research also show that data sharing practices are often constrained by ethics, privacy, and re-use costs [20-21]. Model training, external validation, subgroup analysis and

causal inference in cross-border cooperation rely precisely on these fine-grained details that have been weakened by dimensionality reduction.

In terms of partnerships. Cross-border medical cooperation is not a one-time transaction but a continuous partnership. The research team needs to believe that the data access path is stable, the journal needs to believe that the results can be verified, and the partners need to believe that the rules will not change midway in the project. As the review load increases, the formation cost of new partnerships rises, and institutions are more inclined to choose existing partners, low-risk issues, and controllable data scenarios. The network does not necessarily break. It will narrow.

The above three layers of influence jointly shape the efficiency of collaboration. The output efficiency decreases because the project initiation and data preparation consume more time. The openness of the network decreases because new connections are reduced and the radius of cross-regional cooperation shortens. The impact is not instantaneous. It usually manifests first as an increase in compliance budget, then as a contraction in data availability, and then as it appears in paper output and the collaboration network. The mechanism variables selected are Cost and Data_Avail, corresponding to the two observable channels of resource dissipation and data form change:

$$ReviewBurden_{it} = Treat_i \times Post_t \quad (1)$$

$$Efficiency_{it} = f(DataAccess_{it}, ComplianceCost_{it}, NetworkOpenness_{it}) \quad (2)$$

Under this framework, the review load is not merely a negative institutional factor. It may reduce the risks of privacy leakage and data misuse, and also enhance the certainty of cooperation rules. The issue lies in that in the short term, the rule transition will initially manifest as institutional friction; only when the review standards, technical paths, and responsibility allocation are stable, can compliance itself potentially transform into a reliable basis for collaborative cooperation. This article's empirical identification focuses on this transition period.

2.3 Research Hypotheses

The first expectation points to the average effect. If the review load increases the project initiation costs and reduces the availability of fine-grained data, then the high-exposure institutions will experience a decline in cross-border cooperation output efficiency after the policy is fully implemented.

$$H1: \beta_{DID} < 0 \quad (3)$$

The second expectation pertains to institutional transaction costs. The higher the

review load, the greater the non-direct research expenditures such as compliance audits, data anonymization, legal consultations, and security assessments; these expenditures have a fixed cost nature and will displace resources for research analysis and collaboration coordination.

$$Cost_{it} = \alpha + \theta_1 ReviewBurden_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad \theta_1 > 0 \text{（4）}$$

The third expectation pertains to data availability. The higher the review load, the greater the proportion of data statements in the papers that indicate restricted access, legally non-public access, or the need for approval for access. When data availability declines, the ability to review, expand, and jointly analyze cross-border research is also restricted.

$$DataAvail_{it} = \alpha + \theta_2 ReviewBurden_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad \theta_2 < 0 \text{（5）}$$

The fourth expectation points to heterogeneity. The weaker the compliance ability, the more difficult it is to absorb fixed costs; the stronger the data dependence, the more difficult it is to circumvent the review burden. Therefore, non-headquarters institutions and data-intensive medical fields will suffer a stronger negative impact.

$$|\beta_{NonTop}| > |\beta_{Top}|, \qquad |\beta_{DataIntensive}| > |\beta_{Traditional}| \text{（6）}$$

III. Data, variables and empirical strategy

3.1 Sample Construction

This paper constructs a strongly balanced panel of 540 medical research decision-making units in China from 2018 to 2025, resulting in 4,320 institutional-year observations. The sample is derived from medical research papers in Web of Science, PubMed, and Scopus that can reliably identify the addresses of Chinese institutions and the information of overseas collaborators. To reduce measurement errors caused by name drift of institutions and occasional publications, the sample excludes long-tail entities with significant breakpoints in cross-period publications. University medical schools and directly affiliated hospitals are merged into the same research decision-making unit through address disambiguation and entity penetration rules; national-level clinical medical research centers with independent legal person attributes are listed separately.

3.2 Variable Definition and Measurement

The dependent variables include cross-border cooperation paper output efficiency and network openness. Output_Eff is measured by ln(1 + Publications_it), where Publications is the number of cross-border medical cooperation papers of the institution

in a year:

$$Output_Eff_{it} = \ln(1 + Publications_{it}) \quad (7)$$

Net_Open is derived from the structural indicators of the institution's annual cross-border cooperation network. After being standardized by Z-score, it is incorporated into the regression analysis to depict the openness level of the institution within the international medical knowledge network; the measurement of the cooperation network structure follows the common approaches used in the identification and modularization analysis of large-scale network communities [22]:

$$Net_Open_{it} = \frac{RawNetworkIndex_{it} - \overline{RawNetworkIndex}}{SD(RawNetworkIndex)} \quad (8)$$

The core explanatory variable is the continuous difference-in-differences term DID_it (Treat_i × Post_t). Treat_i is defined as the institutional base period reliance on high-sensitivity medical data, which is the proportion of papers in the institution's publications from 2018 to 2020 that contain keywords such as multi-center clinical trials. Post_t takes the value of 1 for years 2023 and onwards. The "Data Export Security Assessment Measures" were officially implemented in September 2022, but there is typically a delay of 6 to 12 months from data approval, project execution to paper publication; therefore, in the dynamic effect, 2022 was regarded as a transitional period for the policy rather than a complete impact year.

$$Treat_i = \frac{SensitiveMedicalPapers_{i,2018-2020}}{MedicalPapers_{i,2018-2020}} \quad (9)$$

The control variables include institution size (Size), historical fund resources (Fund), international cooperation experience in the base period (Int_Exp), and informationization level (Info_Level). The mechanism variables include institutional transaction costs (Cost) and data availability (Data_Avail). Cost is obtained through text mining of public project completion reports, budget texts, and institutionally disclosed materials, with a focus on identifying the proportion of non-direct research expenditures such as compliance audits, data de-identification technology services, and legal consultation services:

$$Cost_{it} = \frac{ComplianceRelatedExpenditure_{it}}{TotalResearchExpenditure_{it}} \quad (10)$$

Data_Avail conducts natural language processing based on the data availability statements of cross-border cooperation papers, identifying expressions such as "restricted access" and "not publicly available due to regulations", and then depicts the degree of data flow restrictions at the moment:

$$DataAvail_{it} = 1 - \frac{RestrictedAccessStatements_{it}}{CrossBorderPapers_{it}} \quad (11)$$

3.3 Identification Strategy

The benchmark model adopts a continuous double-difference design. The institution fixed effects capture the institution's capabilities, disciplinary traditions, and location characteristics that do not change over time; the year fixed effects capture the global medical research cycle, the aftermath of the pandemic, the trend of database inclusion, and the changes in the macroscopic research environment. The standard errors are clustered at the institution level.

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

The event study model is used to test the pre-policy trends. In this paper, 2021 is set as the base period, 2022 as the policy transition period, and 2023 to 2025 are sequentially designated as Post_1 to Post_3. The multi-period DID study reminds us that differences in treatment time points and heterogeneity of effects will affect the interpretation of traditional estimators [23]; the event study literature further points out that dynamic effects need to be carefully distinguished between real trend changes and the structure of estimation weights [24]. The study of heterogeneous treatment effects also requires caution regarding the time structure of the policy shock and the estimation weights [25]. This paper reduces this risk through continuous exposure setting, fixed effect control, and replacement test; in terms of robustness design, it also draws on the discussions in synthetic control research regarding data requirements and the feasibility of counterfactual construction [26]. Therefore, the result interpretation emphasizes the short-term and medium-term average effect rather than the permanent institutional effect.

$$Y_{it} = \alpha + \sum_{k \neq -1} \beta_k (Treat_i \times 1[t = k]) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (13)$$

The mechanism test estimates the impact of the review load on Cost and Data_Avail, and further examines the explanatory proportion of the mechanism variables after they enter the outcome equation. The heterogeneity analysis is grouped by institutional level and data density of the discipline. The robustness analysis includes PSM-DID, excluding the COVID-19 disturbance period, replacing the outcome variables, controlling for the lag of end-of-2025 inclusion, and handling group identity replacement tests.

IV. Results

4.1 Descriptive Statistics

Table 1 presents the statistical characteristics of the core variables. The mean value of Output_Eff is 2.845, with a standard deviation of 1.124, indicating that there are significant differences in the output of cross-border medical cooperation among institutions. The mean value of Net_Open is 1.452, showing that the openness of institutions to integrate into the international cooperation network is not balanced. The mean value of DID is 0.234, indicating that the exposure intensity of continuous review has a distinguishable variation that can be used for identification during the policy's implementation period.

Table 1. Variable Definitions and Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Output_Eff	4,320	2.845	1.124	0.000	6.142
Net_Open	4,320	1.452	0.536	0.210	3.894
DID	4,320	0.234	0.423	0.000	1.000
Size	4,320	5.612	0.895	3.124	7.956
Fund	4,320	4.185	1.312	0.000	7.842
Int_Exp	4,320	12.450	6.714	1.000	48.000
Info_Level	4,320	0.684	0.195	0.154	0.982

Note: Output_Eff is measured as ln(1 + cross-border medical publications). Net_Open is a standardized network-topology indicator.

Figure 1 presents the policy timeline from 2018 to 2025, the base period exposure measure, the transitional period in 2022, and the full impact period in 2023.

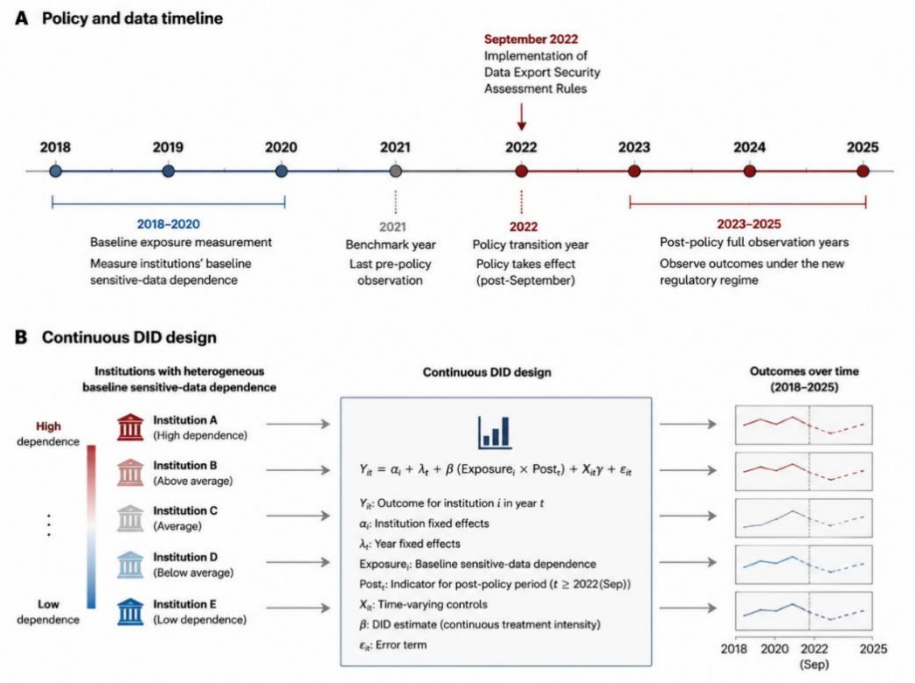


Figure 1. Policy timeline and empirical design for cross-border medical data review burden

4.2 Baseline Regression

Table 2 presents the baseline results. Column (2) shows that after controlling for the fixed effects of institutions, the year fixed effects, and all control variables, the DID coefficient is -0.288, and it is significant at the 1% level. Since Output_Eff is transformed by logarithm, this coefficient corresponds to a 25.0% decrease in output rate; if using the first-order approximation, the decline is approximately 28.8%. Column (4) shows that Net_Open decreased by 0.164 standard deviations. For institutions with higher exposure to review loads, after the full implementation of the policy, not only did cross-border cooperation output decline, but the openness of their international cooperation networks also contracted.

Table 2. Baseline Regression Results

Variables	(1) Output_Eff	(2) Output_Eff	(3) Net_Open	(4) Net_Open
DID	-0.345***	-0.288***	-0.198***	-0.164***
	(-5.84)	(-4.92)	(-4.12)	(-3.65)
Size		0.145**		0.088*
		(2.35)		(1.84)
Fund		0.212***		0.134***
		(3.84)		(2.96)
Int_Exp		0.054***		0.032***
		(4.15)		(3.22)
Info_Level		0.312*		0.195
		(1.72)		(1.35)

Institution FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.642	0.715	0.536	0.598

Note: Values in parentheses are t-statistics based on robust standard errors clustered at the institution level. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Dynamic Effects and Parallel Trends

Table 3 shows that Pre_3, Pre_2, and Pre_0 in the transitional period of 2022 were not significant before the complete implementation of the policy, supporting the idea that institutions with higher and lower processing intensities had similar evolution paths before the policy. After 2023, negative effects began to emerge and gradually expanded. This dynamic trajectory is consistent with the lag in the publication of medical research and the process of compliance adaptation, and it also reduces the possibility of interpreting the benchmark results based on prior trend differences.

Table 3. Event-study Estimates

Time relative to policy shock	Coefficient (Output_Eff)
Pre_3 (2019)	0.012 (0.34)
Pre_2 (2020)	-0.005 (-0.12)
Pre_1 (2021)	Base (0)
Pre_0 / Transition (2022)	-0.041 (-0.86)
Post_1 (2023)	-0.158** (-2.45)
Post_2 (2024)	-0.285*** (-3.88)
Post_3 (2025)	-0.342*** (-5.12)

Note: 2021 is the benchmark year. 2022 is treated as a transition year because formal implementation occurred in September 2022 and publication outcomes respond with a lag.

Figure 2 presents the dynamic effect through point estimates and 95% confidence intervals, illustrating the fluctuations around zero before the policy and the gradual downward trend after the policy was implemented.

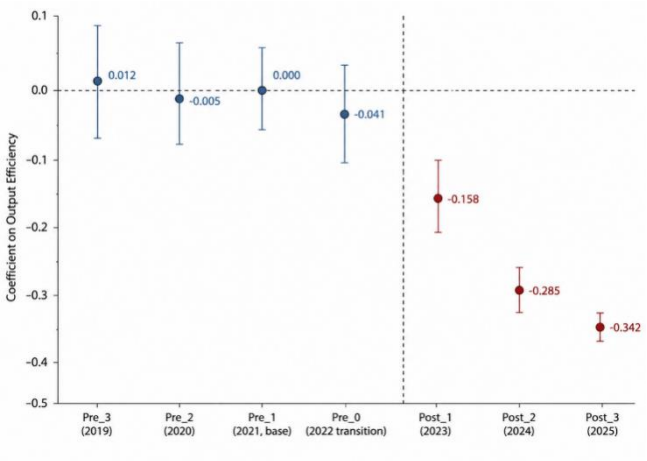


Figure 2. Event-study estimates of review burden effects on output efficiency

4.4 Mechanism Test

Table 4 presents the mechanism test. DID significantly increases institutional transaction costs. Cost enters the outcome equation and is significantly negative. This path explains approximately 25.1% of the total effect. DID also significantly reduces Data_Avail, while Data_Avail has a positive impact on Output_Eff. This path explains approximately 36.6% of the total effect. The results indicate that the impact of review load on collaboration efficiency is not only due to the reduction in the number of projects, but also due to changes in data availability and compliance resource allocation.

Table 4. Mechanism Tests

Variables	(1) Cost	(2) Output_Eff	(3) Data_Avail	(4) Output_Eff
DID	0.412***	-0.215***	-0.354***	-0.182***
	(6.12)	(-3.85)	(-5.22)	(-3.14)
Cost		-0.176***		
		(-3.94)		
Data_Avail				0.298***
				(4.56)
Controls & FEs	YES	YES	YES	YES
R-squared	0.584	0.742	0.612	0.735
Mediated proportion		25.12%		36.64%

Note: Cost is proxied by compliance-related non-research expenditure. Data_Avail is proxied by NLP-based restricted-access statements in cross-border medical papers.

Figure 3 presents the mechanism chain among review load, institutional transaction costs, data availability, and collaboration efficiency.

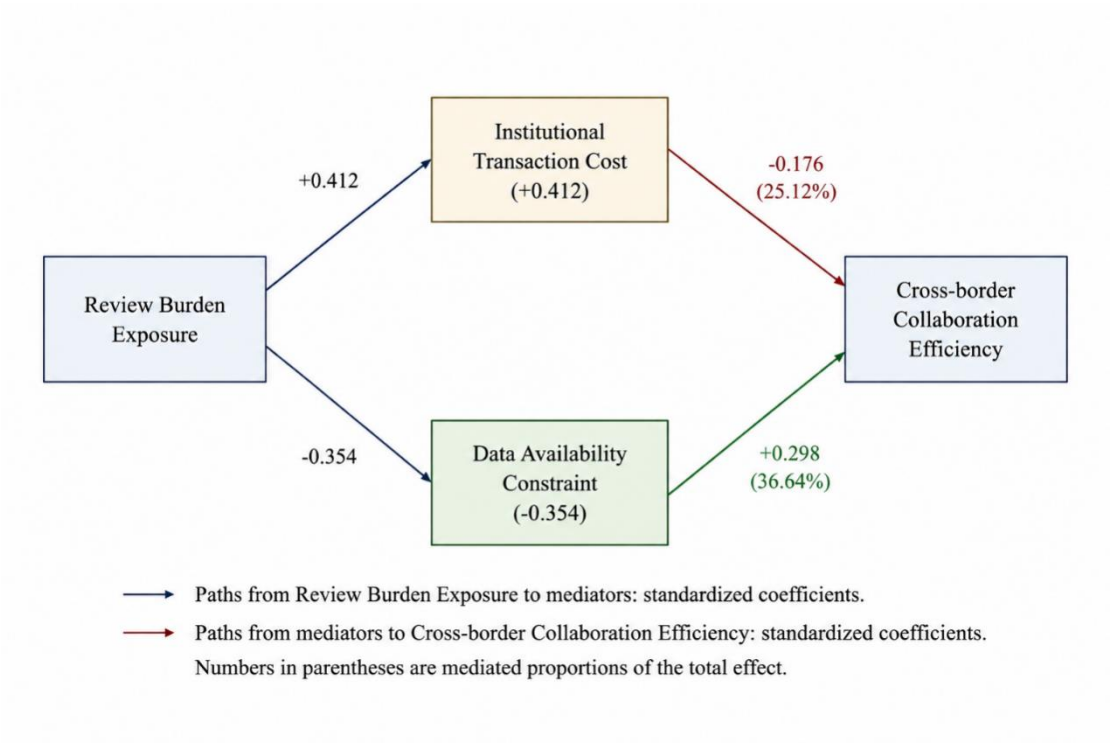


Figure 3. Mechanism pathway from review burden to collaboration efficiency

4.5 Heterogeneity Analysis

Table 5 shows that non-headquarters institutions suffered significantly stronger negative impacts than headquarters institutions. Headquarters institutions typically have more stable ethical review, legal support, information technology infrastructure, and international cooperation management experience, which can partially absorb the costs of institutional transformation; for non-headquarters institutions, when facing the same review requirements, the fixed compliance costs are more likely to be transformed into project delays and cooperation contractions. In terms of the disciplinary dimension, the absolute value of the coefficient in the data-intensive field is much higher than that in traditional clinical medicine, indicating that the review burden mainly functions along the high-sensitive data-dependent channels.

Table 5. Heterogeneity Analysis

Variables	Top 10% Inst.	Non-Top Inst.	Data-Intensive	Traditional Field
DID	-0.112*	-0.384***	-0.452***	-0.124**
	(-1.74)	(-5.64)	(-6.15)	(-2.12)
Controls & FEs	YES	YES	YES	YES
Observations	432	3,888	1,840	2,480
R-squared	0.785	0.654	0.732	0.584

Note: Data-intensive fields include genomics, medical imaging, real-world evidence, multicenter trials and large epidemiological cohorts.

Figure 4 presents the grouped DID coefficients and their confidence intervals in the form of a forest plot, showing the uneven distribution of institutional load between institutional capacity and data dependency.

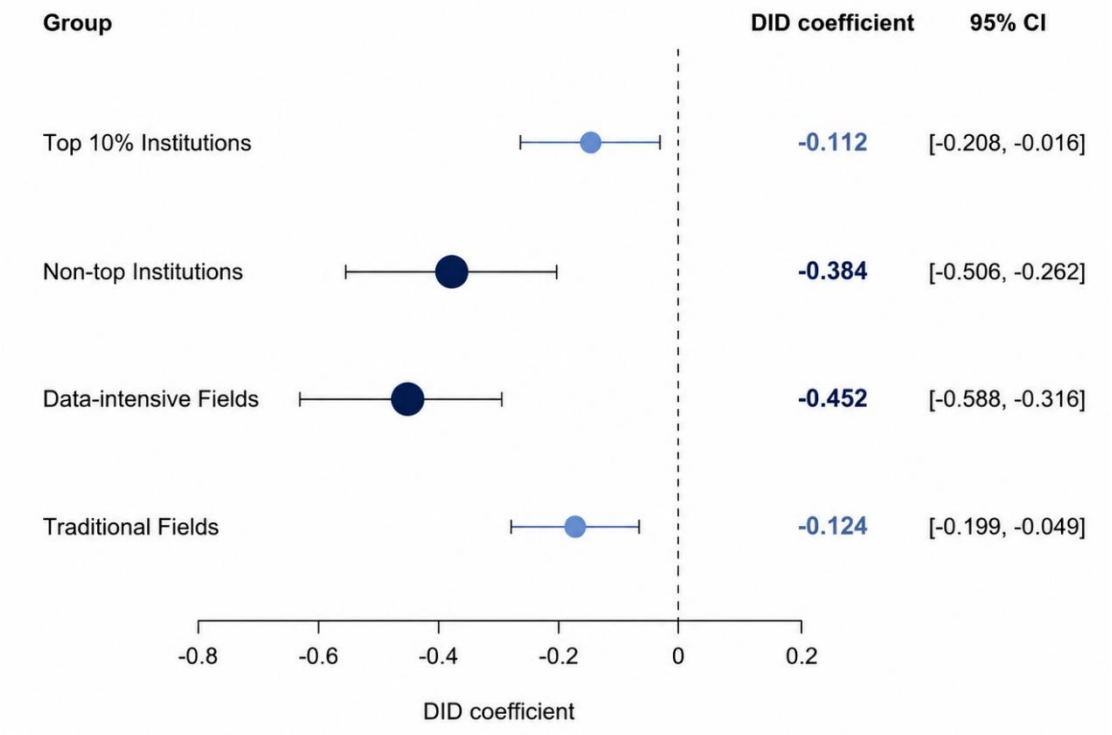


Figure 4. Heterogeneous effects by institution capacity and data intensity

4.6 Robustness Test

Table 6 presents the robustness test. The PSM-DID method uses 1:1 non-replacement nearest neighbor matching. The covariates include institution size, historical total national fund amount, base period international cooperation network centrality, and the digital economy and legalization index of the institution's location; the absolute standardized deviation of all covariates after matching is all below 10%, and the mean difference test changes from significant to non-significant. After excluding the pandemic disturbance period from 2020 to 2022, replacing the citation-weighted cross-border cooperation paper count, and adding the dynamic interaction term of journal publication cycle, the core coefficient still remains significantly negative.

The permutation test only randomly shuffles the identities of the treatment group while keeping the 2023 policy node unchanged. The distribution of the pseudo-policy effect obtained from 1000 repeated sampling is centered around zero, and the true estimate value is located at the extreme tail of the empirical distribution. This result indicates that the baseline finding is unlikely to be generated by random cross-sectional

differences.

Table 6. Robustness Checks

Variables	(1) PSM-DID	(2) Excl. COVID	(3) Alt. Outcome	(4) Indexing Lag	(5) Permutation
DID	-0.274***	-0.292***	-0.315***	-0.281***	0.002
	(-4.65)	(-4.88)	(-4.72)	(-4.51)	(0.15)
Controls & FEs	YES	YES	YES	YES	YES
Sample	Matched	Excl. 2020-2022	Full	Full	Randomized assignment
Observations	2,160	2,700	4,320	4,320	4,320
R-squared	0.752	0.708	0.685	0.706	N/A

Note: Column (5) reports the mean pseudo-coefficient from 1,000 treatment-assignment permutations.

Figure 5 shows the distribution of the pseudo-estimated coefficients obtained after 1000 permutations, and vertical lines are used to mark the true DID estimate value.

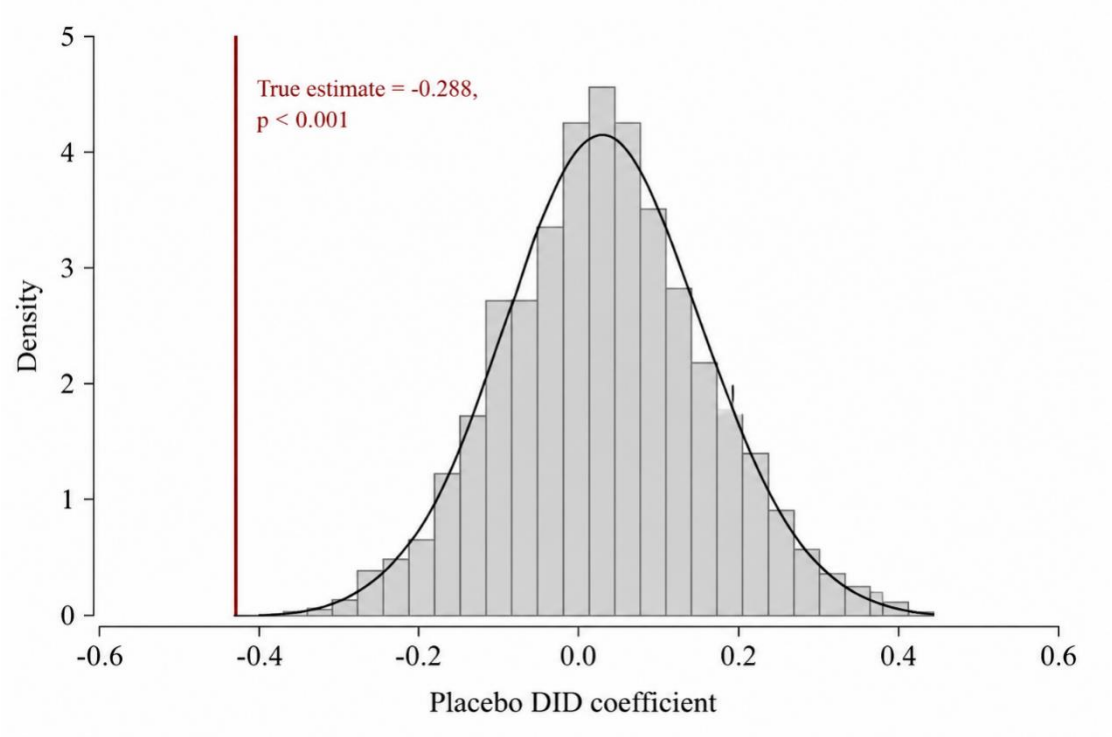


Figure 5. Permutation distribution of placebo DID estimates

4.7 Supplementary Identification and Sensitivity Analysis

Three additional experiments are conducted. The first experiment examines whether the Treat_i structure is dependent on specific keyword thresholds; the second experiment assesses whether the results of network openness are sensitive to the selection of network indicators; the third experiment investigates whether the end-of-

2025 lagged inclusion, potential common shocks, and unobservable trends change the core conclusions.

$$Sensitivity_s = \widehat{\beta_s} - \widehat{\beta_{baseline}},$$
$$s \in \{Threshold, Network, Lag, Counterfactual\} \quad (14)$$

Table 7 shows that the core estimation is not dependent on a single sensitive keyword threshold. Regardless of whether the high sensitivity of medical data dependency is defined as the top 20% or top 30% of the base period's high sensitivity keywords, the DID coefficient remains significantly negative. After replacing the network openness indicator, the estimation based on the adjustment of intermediary centrality and structural hole constraints also holds. This indicates that the judgment on network contraction in this paper is not mechanically generated by a certain network algorithm, but is driven by the change in the cooperative boundary itself.

Table 7. Additional sensitivity and boundary tests

Tests	Specification	DID coefficient	t-statistic	Interpretation
Keyword threshold	Top 20% sensitive terms	-0.261***	-4.31	Effect persists under stricter exposure definition
Keyword threshold	Top 30% sensitive terms	-0.304***	-4.76	Magnitude remains close to baseline
Network metric	Betweenness-based openness	-0.151***	-3.42	Network contraction not metric-specific
Network metric	Constraint-adjusted openness	-0.176***	-3.88	Structural-hole channel remains visible
Lag correction	Journal-cycle weighted 2025	-0.279***	-4.44	Indexing lag does not drive results
Counterfactual trend	Institution-specific pre-trend	-0.268***	-4.19	Pre-existing trend is unlikely to explain effect

Note: All specifications include institution fixed effects, year fixed effects and baseline controls.

Figure 6 integrates the identification design, mechanism paths, and heterogeneous results onto the same evidence map. The left side presents the continuous exposure intensity and policy shock; the center presents two mechanisms: institutional transaction costs and data availability; the right side presents the decline in output efficiency, the contraction of network openness, and the differential effects in non-headquarters institutions and data-intensive fields.

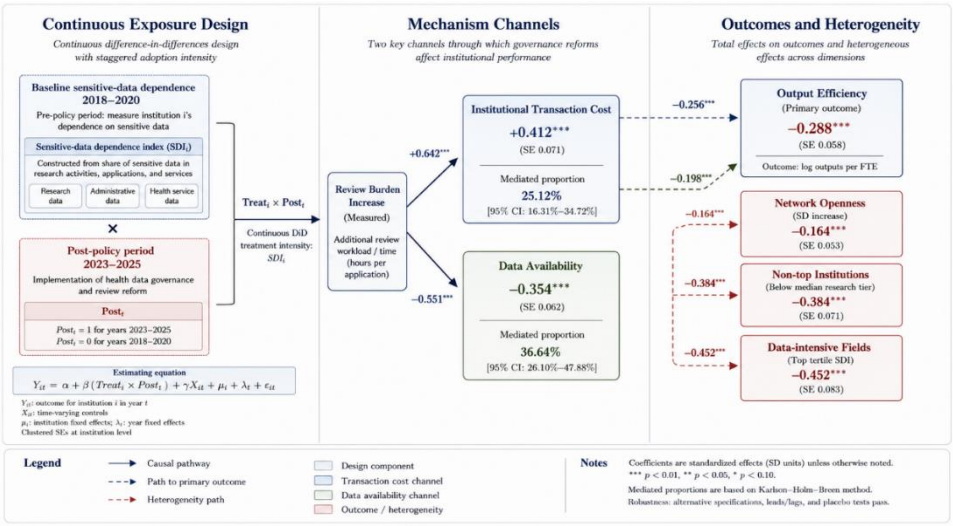


Figure 6. Integrated evidence map linking identification, mechanisms and heterogeneous effects

The second set of supplementary experiments further examined the identification of counterfactuals. In this paper, the policy was moved forward and backward in time and the intensity of the randomization treatment was varied, constructing three types of counterfactual scenarios. If the estimated results were solely driven by general trends, the post-pandemic international cooperation cycle, or the database inclusion rhythm, then these counterfactual settings should also produce negative coefficients that are close to the true estimates. However, this was not the case.

$$Placebo_{it}^{(\tau)} = Treat_i \times 1[t \geq \tau], \quad \tau \in \{2020,2021,2024\} \text{（15）}$$

Table 8 reinforces the findings of the event study. If the shock year is advanced to 2020 or 2021, the estimated coefficients are not significant; if the shock year is postponed to 2024, the coefficient is also not significant. After randomizing the treatment intensity or the institution label, the pseudo-estimates fluctuate around zero. Only when 2023 is taken as the year when the complete policy takes effect and the real exposure structure with high sensitivity medical data dependency is retained, does the negative effect stabilize and become evident.

Table 8. Counterfactual timing and falsification tests

Placebo design	Pseudo shock year	Coefficient	t-statistic	Result
Early placebo	2020	-0.034	-0.61	Not significant
Early placebo	2021	-0.047	-0.82	Not significant
Delayed placebo	2024	-0.071	-1.18	Not significant
Random exposure	2023	0.006	0.19	Not significant
Random institution labels	2023	-0.009	-0.27	Not significant

True design	2023	-0.288***	-4.92	Baseline effect retained

Note: Placebo models keep the same controls and fixed effects as the baseline specification.

Figure 7 is used to present the comparison among counterfactual time points, random exposure, actual policy design and baseline estimation. Panel A shows the coefficient paths for different pseudo-shock years, Panel B presents the permutation distribution of random treatment intensity, and Panel C is a forest plot of the actual estimation and robust estimation.

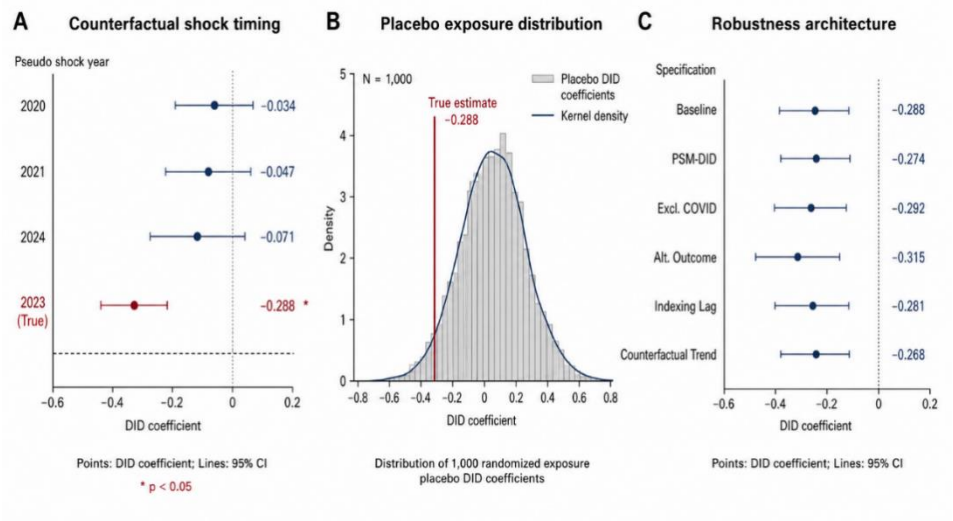


Figure 7. Counterfactual timing, placebo exposure and robustness architecture

V. Discussion

The results of this study indicate that the review load for medical data exportation has entered the production function of cross-border medical research. It affects not only the approval speed of individual projects, but also whether institutions can stably obtain reusable data, whether they can bear the fixed costs for compliance, and whether they can maintain an open international cooperation network. More precisely, the review load has changed the organizational conditions for the production of cross-border medical knowledge.

This finding is comparable to global health data governance. The experiences of the European health data space, cross-jurisdictional data sharing in Africa, and precision medicine data governance all show that cross-border flow of health data requires the establishment of executable intermediate systems between research efficiency and rights protection [1, 4, 8]. If the rules are too general, research institutions

can only avoid risks in the most conservative way; if the rules are too fragmented, compliance costs will be unequally distributed among institutions. What truly affects research efficiency is often not whether the rules exist, but whether the rules can be anticipated, explained, and implemented hierarchically.

The policy implications thus shift to institutional supply. De-identified aggregated data, controlled access data, computing data within a trusted research environment, and non-exportable federated analysis should correspond to differentiated review intensities. For multi-center studies with high sensitivity but clear public interests, a fast review channel, mutual recognition of ethical review mechanisms, and standardized risk assessment templates for data exportation can be established. For non-head institutions, public compliance toolkits and regional-level data governance support should be provided to avoid further international research collaboration gaps due to differences in compliance capabilities.

Journals and research evaluation systems also need to assume corresponding responsibilities. Data availability statements cannot be formal appendices. For papers involving cross-border cooperation of medical data, they should distinguish levels such as data not being publicly available, accessible upon application, reproducible in a trusted environment, and fully open, and explain the basis for restrictions, access procedures, and review paths. Such statements not only protect patient rights but also enhance the verifiability of medical research.

VI. Conclusion

This article still has several aspects that require careful consideration. Firstly, the identification of the review load relies on the construction of the institution's base period high-sensitive medical data dependency. This indicator can well depict the potential exposure differences of different institutions under policy shocks, but it cannot directly restore the waiting period, the number of material returns, the compliance communication costs, and the internal legal affairs investment experienced by a single research project in the actual approval process. In other words, what this article captures is the average exposure of institutional-level institutional load, rather than the micro administrative process of each cross-border cooperation research. Secondly, the time span from data acquisition, model analysis, paper writing to formal publication of medical papers is usually quite long. Even if the end data has been corrected through the interaction terms of the journal publication cycle, it may still be affected by the lag

in database inclusion and the differences in the publication rhythm of journals. Thirdly, the institutional transaction costs and data availability variables mainly come from proxy measurements of public texts and paper statements, which can reflect the observable compliance investment and data access restrictions, but they are difficult to fully cover the unpublicized ethical review processes, legal negotiation details, and cross-border data transmission technical arrangements within the institutions. Finally, this article takes cross-border medical cooperation involving Chinese institutions as the research scenario, and its conclusions have a clear institutional context. If the relevant findings are generalized to other countries, other regulatory systems, or non-medical data fields, they still need to be re-examined in combination with local data sovereignty arrangements, ethical review structures, research funding systems, and international cooperation traditions.

Based on a strong balanced panel of 540 medical research decision-making units in China from 2018 to 2025, this article identified the impact of medical data export review load on the efficiency of cross-border medical research collaboration. The results show that an increase in review load will significantly reduce the output efficiency of cross-border cooperation papers and compress the openness of institutions in the international medical cooperation network. Further mechanism tests reveal that this effect is not simply due to the decline in the number of collaborations, but occurs jointly through the increase in institutional transaction costs and the contraction of data availability. Heterogeneous results indicate that non-head institutions and data-intensive medical fields are more likely to bear this institutional friction, indicating that data governance capacity has become an important organizational condition affecting the competitiveness of international medical research.

From this perspective, the key to medical data export governance does not lie in making a simple trade-off between security and efficiency, but in establishing clearer, more stable, and more replicable institutional arrangements. The future governance framework should implement hierarchical reviews based on data sensitivity, usage purposes, access methods, and the intensity of public interest, providing clear expectations and operational paths for high-value, multi-center, and controllable medical research. Only when data security, patient rights, ethical responsibility, research reproducibility, and international collaboration are included in the same set of executable rules, can cross-border medical research maintain institutional reliability in a high-level open environment and release higher knowledge production efficiency on

a controllable, safe, and trustworthy basis.

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