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**The Impact of University R&D Funding Structure on
Regional Innovation Output: Evidence from Chinese
Provincial Panel Data**

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Abstract: This study examines whether the composition of university R&D funding—across basic research, applied research, and experimental development—has differential effects on regional innovation outputs in China. Using a balanced panel of 31 provinces from 2010 to 2019 and two-way fixed-effects models with lagged-variable specifications and Oster’s coefficient stability test, we find that the relationship is more temporally conditioned than a linear innovation model predicts. Total R&D expenditure is positively associated with patent output, while the share of funding allocated to applied research shows no robust additional effect. Basic research funding is positively associated with scientific paper output, but only at a 3-year lag; longer-lag estimates are inconclusive due to sample attrition and reduced statistical power. A Wald test fails to reject equality of basic and applied research coefficients for patents, and no systematic regional heterogeneity is detected. These findings suggest that the policy debate over reallocating funds between basic and applied research may be less consequential than often assumed, at least at the provincial level of aggregation; the more consequential constraint appears to lie in the institutional environment governing knowledge translation. However, this interpretation remains speculative and awaits direct testing with micro-level data. We conclude that our results do not provide robust evidence for a compositional effect beyond overall research scale at the provincial level. The temporal pattern of basic research returns is suggestive but fragile, as longer-lag estimates suffer from reduced sample size and widened confidence intervals. All findings are associational and subject to the limitations of aggregate provincial data.

Keywords: university R&D funding structure; basic research; applied research; regional innovation; patents; scientific papers; panel data; China

1. Introduction

Universities have become pivotal in innovation ecosystems through knowledge transfer and entrepreneurship (Ding, 2025), yet allocating Research and Development (R&D) funds among basic research, applied research, and experimental development remains a central policy challenge (Salter & Martin, 2001; Aghion et al., 2009).

China's Science & Technology system exhibits a persistent bias toward applied

research over basic research (Huang et al., 2014; Didham & Zhu, 2016). The share of basic research spending is far below that of major developed countries, and its allocation shows marked regional imbalances (He & Deng, 2013; Wang et al., 2025). This structural imbalance is reinforced by evaluation systems that disproportionately reward quantitative metrics—publication counts and patent filings—over fundamental breakthroughs (Fisch et al., 2016; Gu, 2023), creating a stark paradox: Although universities hold roughly one-quarter of all invention patents, the commercialization rate has long remained below 10%.

While a few studies have decomposed university R&D expenditure in the U.S. (Alvarado-Vargas et al., 2017) and Europe (Wolszczak-Derlacz et al., 2025), systematic province-level evidence from a major emerging economy, particularly one examining contrasting responses in patents and papers, remains scarce. This gap is consequential because China's distinct institutional incentives, shaped by short evaluation cycles and commercialization pressures, may fundamentally alter how basic versus applied research translates into measurable outcomes. Policy debates on optimal R&D allocation have thus proceeded largely on aggregate evidence, without systematic guidance on which expenditure types most effectively drive specific innovation outputs at the regional level.

This study makes three contributions. First, it provides evidence consistent with the view that the relationship between R&D funding composition and innovation output is time-dependent and output-selective: Basic research predicts paper output, but only after a significant lag; this effect does not extend to patents. Applied research shows no robust association with either outcome after controlling for endogeneity. Second, we apply rigorous endogeneity diagnostics—including lagged-variable FE models and Oster's (2019) coefficient stability test—to assess the robustness of our findings. Third, the significant lagged association of basic research with papers—combined with null effects at shorter lags—highlights the temporal latency in knowledge production. This pattern challenges the linear innovation model's assumption of immediate and uniform research outcomes.

The remainder of the paper is organized as follows: Section 2 reviews the literature and develops the hypotheses; Section 3 describes the data and the empirical strategy; Section 4 presents the main results; Sections 5 and 6 report robustness checks and endogeneity analyses; Section 7 discusses the findings and policy implications; and Section 8 concludes.

2. Literature Review and Hypothesis Development

2.1 University R&D and Regional Innovation

The theoretical foundation linking university research to regional innovation output rests on two interrelated frameworks: the innovation systems perspective and the knowledge production function approach. The concept of national and regional innovation systems emphasizes that the flow of knowledge among institutions—firms, universities, and government agencies—is the critical engine of technological progress (Lundvall, 2010; Nelson, 1993). Within these systems, universities generate new scientific and technological knowledge and supply highly skilled human capital capable of absorbing and applying it (Etzkowitz & Leydesdorff, 2000). The "third mission" of universities, a concept that emerged from the entrepreneurial university literature, further positions academic institutions as active participants in technology transfer, patenting, and spin-off creation, extending their role beyond teaching and basic research (Etzkowitz, 2003; Ding, 2025).

The knowledge production function framework, initially developed by Griliches (1979) and later extended by Jaffe (1989), provides the empirical apparatus for testing these relationships. In its standard form, innovation output—commonly measured by patents or scientific publications—is modeled as a function of R&D inputs, including expenditure and personnel. At both the firm and regional levels, empirical studies consistently find that university research intensity is positively associated with patenting and innovation rates (Mansfield, 1991; Anselin et al., 1997; Ponds et al., 2009). At the regional level, the presence and research intensity of universities are consistently associated with local innovation rates, as measured by patent counts, new firm formation, and productivity growth (Anselin et al., 1997; Ponds et al., 2009;

Cowan & Zinovyeva, 2013).

However, this line of research has largely treated university R&D as an undifferentiated input. Most existing studies operationalize academic research activity using aggregate measures such as total R&D expenditure, total personnel, or publication counts (Alvarado-Vargas et al., 2017; Wolszczak-Derlacz et al., 2025). While informative about the scale of university research, this approach fails to address a more nuanced and policy-relevant question: whether different types of research activities—basic, applied, and experimental development—generate distinct patterns of innovation output. This omission is particularly consequential in emerging economies, where public funding allocation decisions often involve explicit trade-offs among these three expenditure categories (Salter & Martin, 2001; Foray et al., 2012).

The present study departs from this aggregate tradition by decomposing university R&D expenditure into basic, applied, and experimental development components. China is an especially revealing case for this inquiry: Its higher education system underwent rapid R&D expansion from 2010 to 2019, yet its funding allocation—strongly skewed toward applied research and experimental development—remains persistently imbalanced (Huang et al., 2014; Didham & Zhu, 2016), a pattern exacerbated by evaluation systems that prioritize patent counts and commercialization metrics over fundamental inquiry (Fisch et al., 2016; Gu, 2023).

2.2 The Differential Roles of Basic, Applied, and Experimental Development Funding

The classic linear model of innovation describes a unidirectional flow from basic research to applied research, then to experimental development, and finally to commercialization (Bush, 1945). In this framework, basic research generates the foundational knowledge on which all subsequent technological advances depend; its contribution to innovation is therefore indirect and long-term. Applied research, by contrast, targets specific practical problems and is expected to yield more immediate technological outcomes. Experimental development sits closest to the market, involving systematic work that draws on existing knowledge to produce new products,

processes, or services (OECD, 2015).

A growing body of work challenges this linear depiction, suggesting that the relationship between research type and output is more contingent than previously assumed. Basic research can generate technological spillovers when firms possess absorptive capacity (Mansfield, 1980; Cockburn & Henderson, 1998). Applied research has been found to produce both patents and high-quality publications when evaluation systems reward both forms of output (Banal-Estañol et al., 2015; Angori et al., 2024).

However, evidence on differential associations remains mixed: Some studies find that applied research has a stronger short-term association with patents (Alvarado-Vargas et al., 2017), while others show that basic research yields higher-quality patents over longer horizons (Trajtenberg et al., 1997). These inconsistencies reflect differences in analytical level, output measurement, and institutional context. Importantly, the existing literature draws predominantly on data from advanced economies with mature research institutions and well-developed intellectual property regimes. Systematic evidence from emerging economies—where universities often operate under different incentive structures, resource constraints, and industry–university linkage patterns—remains strikingly thin.

What remains unknown is whether this structural tilt toward applied research translates into superior technological innovation outcomes at the regional level—and, if so, whether this comes at a cost to scientific knowledge production, typically measured by paper output. The existing literature has largely focused either on aggregate university R&D effects or on micro-level studies of individual university patenting behavior. Existing studies have yet to examine how basic, applied, systematic, and experimental development funding jointly shape both patent and paper outputs at the provincial level. The present study is designed to address this gap.

2.3 Hypothesis Development

Building on the theoretical and empirical considerations discussed above, we develop a set of testable hypotheses aligned with this study’s central research questions.

A large body of empirical work, grounded in the knowledge production function

framework, shows that university R&D expenditure is a key input to regional innovation (Jaffe, 1989; Anselin et al., 1997). The underlying mechanism is straightforward: Financial resources enable the construction of laboratory infrastructure, the recruitment and retention of skilled researchers, and the sustained intellectual effort required to generate patentable inventions. In the Chinese context, where provincial R&D budgets expanded substantially and unevenly over the 2010–2019 period, one would expect variation in university funding levels to be systematically associated with variation in patent output. We therefore begin with a baseline expectation:

Hypothesis 1 (H1): Aggregate internal university R&D expenditure is significantly positively associated with regional patent output.

While H1 concerns the overall scale of university R&D funding, the central aim of this study is to test whether the composition of funding—basic, applied, and experimental development activities—affects innovation outcomes. The distinction between basic and applied research is particularly important because it maps onto two distinct output types: scientific papers and patents.

The theoretical case for expecting applied research to outperform basic research in generating patents rests on the nature of the two activities. Applied research is directed toward solving practical problems and producing tangible technical deliverables. The criteria for patentability—novelty, inventive step, and industrial applicability—align closely with the intended outputs of applied projects. University researchers working on applied topics are therefore more likely to produce patentable inventions within the typical project cycle. By contrast, basic research pursues fundamental understanding without a predetermined technological target. While basic discoveries can eventually lead to breakthrough patents, the pathway is indirect and the time horizon considerably longer (Salter & Martin, 2001). In the Chinese institutional setting, where short evaluation cycles and quantitative performance metrics create strong incentives for measurable output, the relative advantage of applied research for patent generation is likely to be amplified. Hence:

Hypothesis 2 (H2): Applied research expenditure has a stronger positive

association with regional patent output than basic research expenditure.

This hypothesis is tested by estimating a joint model that includes both Basic research share and Applied research share simultaneously and by conducting a Wald test of $H_0: \beta_{\text{applied}} \leq \beta_{\text{basic}}$ against $H_1: \beta_{\text{applied}} > \beta_{\text{basic}}$. The VIFs for the two shared variables in this joint specification are well below conventional thresholds, confirming that multicollinearity does not preclude this estimation.

Importantly, even if H2 receives initial support in baseline fixed-effects models, we recognize that these associations may be confounded by endogeneity—particularly reverse causality from past innovation outputs to current R&D funding—and by omitted time-varying provincial characteristics. We therefore subject this hypothesis to rigorous endogeneity diagnostics, including lagged-variable FE models and Oster's (2019) coefficient stability test, in Section 6.

For scientific paper output, the theoretical expectation is clear: Basic research—oriented toward new knowledge and theory development—aligns closely with the norms of academic publishing (Dasgupta & David, 1994), whereas applied research is more likely to yield proprietary or incremental advances of limited novelty for leading journals. In a well-functioning academic system, basic research should therefore be more strongly associated with paper output than applied research. However, China's evaluation system, which rewards publication volume across all fields, creates incentives for researchers in all funding categories to convert project outputs into papers rapidly. If this institutional pressure is sufficiently strong, it may suppress the distinctive advantage that basic research is theoretically supposed to hold.

Critically, the relative advantage of basic research over applied research in generating scientific paper output is not a static attribute but is temporally modulated by institutional evaluation rhythms. This insight leads to a reconciled hypothesis that explicitly incorporates the time dimension:

Hypothesis 3 (H3): The association between basic research funding and scientific paper output, relative to applied research funding, varies systematically across time horizons because of the inherent temporal latency of basic research and the differing

time horizons required for different research outputs.

In the short run (contemporaneous or 1-year lag), institutional pressures for rapid, quantifiable outputs across all research fields are expected to suppress the distinctive knowledge-production function of basic research, making its coefficient statistically indistinguishable from that of applied research.

Over a medium horizon (e.g., 3-year lag), the cumulative and foundational nature of basic research is expected to become evident, yielding a significant positive association with paper output that exceeds that of applied research.

Support for short-run indistinguishability alongside support for medium-run differentiation would constitute evidence for the institutional modulation thesis, not evidence against structural differentiation. This temporally disaggregated framework directly addresses the critique that basic research requires longer gestation periods (Salter & Martin, 2001; Mansfield, 1980). It also avoids the conceptual pitfall of treating short-run indistinguishability and medium-run differentiation as mutually exclusive when they are, in fact, temporally conditioned manifestations of the same underlying phenomenon.

The final hypothesis introduces regional heterogeneity. The capacity to absorb academic knowledge, the density of industry–university linkages, and the sophistication of innovation infrastructure vary markedly across Chinese provinces (Li, 2009). The eastern coastal region, with its technology-intensive industries, stronger IP protection, and more developed technology markets (Fu & Yang, 2009), should enhance the efficiency with which applied research translates into patents. Eastern researchers have greater access to industry partners who can articulate needs and co-fund projects; weaker industrial demand and thinner technology transfer institutions in non-eastern provinces may dampen this marginal effect. Hence:

Hypothesis 4 (H4): The elasticity of regional patent output with respect to university applied research expenditure is higher in eastern provinces than in non-eastern provinces.

A critical interpretive note is warranted before proceeding to the empirical tests.

The hypotheses above are formulated under the conventional linear-model expectation that different research activities map onto distinct output types. However, in the Chinese institutional context—where publication quantity is universally incentivized across all research fields and technology transfer infrastructure remains underdeveloped—this differentiation may be systematically suppressed. Consequently, failure to reject H2, H3, or H4, or finding null effects for any funding component, would not constitute a statistical failure. Rather, such outcomes would carry substantive theoretical weight: They would indicate that institutional incentives override the distinct knowledge-production functions that different research types are theoretically expected to serve. We therefore design our empirical strategy not only to test for the presence of differentiated effects but also to distinguish between 'no true effect' and 'effect masked by methodological limitations'—a distinction central to interpreting our results.

Taken together, these hypotheses progress from an aggregate relationship (H1) to structural differentiation by research type and output type (H2, H3), and finally to contextual moderation by the regional innovation environment (H4).

3. Data and Methodology

3.1 Data Sources and Sample

The dataset is a strongly balanced panel covering 31 provinces, autonomous regions, and municipalities in mainland China from 2010 to 2019, yielding 310 province–year observations. Data are drawn from four official statistical sources published by the National Bureau of Statistics of China and the Ministry of Education. The detailed mapping of each variable to its source yearbook, chapter, and table is provided in Table 1. For a small number of missing values—primarily in the Tibet Autonomous Region—linear interpolation is applied to preserve the panel's integrity.

To avoid encoding issues, variables are renamed based on their column positions in the original Excel files, using an alphabetic naming convention. The full mapping is provided in Section 3.2.

3.2 Variable Definitions

Table 1 presents the full set of variables used in the empirical analysis, grouped by

function: dependent variables, core explanatory variables, control variables, and the regional grouping variable. The scientific paper variable captures the total number of scientific papers published by universities in each province, as reported in the China Statistical Yearbook on Science and Technology. This aggregate measure includes papers published in both domestic and international academic journals and serves as the primary indicator of scientific knowledge production in our analysis. All monetary variables are deflated to 2010 constant prices before being logarithmically transformed; the deflation procedure is described in Section 3.3.

Table 1
Variable definitions

Variable type	Variable name		Definition	Data source
Dependent variables				
Technological output	Patent applications	ln_patent	Natural log of annual patent applications (count)	China Science and Technology Statistical Yearbook, Part VI
Scientific output	Scientific papers	ln_paper	Natural log of annual scientific papers (count)	Ibid.
Robustness check	Patent grants	ln_patent_granted	Natural log of annual patent grants (count)	Ibid.
Core explanatory variables				
Total funding	University R&D expenditure	ln_totfund	Natural log of deflated university R&D internal expenditure (10,000 RMB)	China Science and Technology Statistical Yearbook, Part IV
	Basic research	ln_basic	Natural log of deflated basic research expenditure	Ibid.
Funding structure	Applied research	ln_applied	Natural log of deflated applied research expenditure	Ibid.
	Experimental development	ln_expdev	Natural log of deflated	Ibid.

			experimental development expenditure, $\ln(\text{value}+1)$	
Personnel	R&D personnel (FTE)	$\ln_person$	Natural log of university R&D personnel full-time equivalent (person-year)	Ibid.
Personnel (alternative)	Scientists & engineers	$\ln_scientist$	Natural log of scientists and engineers among university R&D personnel	Ibid.
	Basic research share	$basic_share$	Basic research expenditure / Total university R&D internal expenditure	Ibid.
Funding structure (share)	Applied research share	$applied_share$	Applied research expenditure / Total university R&D internal expenditure	Ibid.
	Experimental development share	$expdev_share$	Experimental development expenditure / Total university R&D internal expenditure	Ibid.
Control variables				
Economic development	GDP per capita	$\ln_gdp$	Natural log of deflated GDP per capita (yuan, deflated to 2010 constant prices)	China Statistical Yearbook, Part III
Industrial R&D	Firm R&D expenditure	$\ln_firmfund$	Natural log of deflated R&D expenditure of industrial enterprises above designated size (10,000 RMB)	China Science and Technology Statistical Yearbook, Part III
Grouping variable				

Regional classification	Eastern region	eastern	1 = Eastern (10 provinces), 0 = Non-Eastern (21 provinces)	China Statistical Yearbook, Part I
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Notes: All monetary variables are deflated to 2010 constant prices using the recursive deflation procedure described in Section 3.3 before logarithmic transformation. Unless otherwise noted, monetary variables are denominated in 10,000 RMB. The exception is GDP per capita, which is denominated in yuan, consistent with the original reporting in the China Statistical Yearbook. R&D personnel are measured in full-time equivalent (FTE) units, with 1 FTE corresponding to one person-year of research work, following the OECD Frascati Manual (2015). The eastern region comprises 10 provinces and municipalities directly under the central government: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The regional classification follows the official standard of the National Bureau of Statistics of China, which divides the country into eastern, central, western, and northeastern areas for statistical reporting.

3.3 Deflation and Transformation

All monetary variables are converted to 2010 constant prices using a recursive deflation procedure based on the provincial GDP index (with the previous year set to 100). Specifically, a provincial deflator is constructed with 2010 as the base year (deflator = 1 for all 31 provinces in 2010). For each subsequent year t , the deflator is calculated as:

$$deflator_t = deflator_{t-1} \times \frac{GDP_index_t}{100}$$

Each nominal monetary variable is divided by the corresponding province-year deflator to obtain real values.

After deflation, all continuous variables are transformed using the natural logarithm. This transformation serves two purposes: it gives regression coefficients an elasticity interpretation and mitigates potential heteroscedasticity arising from right-skewed distributions. For experimental development expenditure, which takes zero values in some province-year observations, the transformation $\ln(\text{value} + 1)$ is applied to avoid generating missing values.

To control for common time trends, a set of year dummy variables (yr2 through yr10) is generated from the panel time identifier, with 2010 (yr1) serving as the reference category in the baseline models.

3.4 Descriptive Statistics and Multicollinearity Diagnostics

Table 2 presents descriptive statistics for all continuous variables in logarithmic form. The final sample comprises 310 province–year observations. Table 3 presents the Pearson correlation matrix for all continuous variables.

Table 2
Descriptive statistics

Variable	N	Mean	Std.	Min	Max
Patent applications	310	7.776	1.868	1.099	10.796
Scientific papers	310	10.186	1.064	6.529	11.858
University R&D expenditure	310	11.585	1.393	7.525	14.231
Basic research	310	10.631	1.335	6.535	13.221
Applied research	310	10.870	1.454	6.004	13.648
Experimental development	310	9.042	1.920	0.000	11.671
R&D personnel (FTE)	310	8.961	1.087	5.537	11.053
GDP per capita	310	10.336	0.426	9.482	11.392
Firm R&D expenditure	310	13.578	1.703	7.059	16.279
Basic research share	310	0.399	0.105	0.163	0.787
Applied research share	310	0.499	0.091	0.105	0.785
Experimental development share	310	0.102	0.066	0.000	0.343

Notes: All variables are in natural logarithms. Monetary variables are deflated to 2010 constant prices. Sample period: 2010–2019, 31 provinces, N = 310.

The dependent variable, patent applications, shows substantial cross-province variation (SD = 1.868), with the gap between the maximum and minimum exceeding nine log points, indicating pronounced regional disparities in technological innovation output. Among the three expenditure components in logarithmic terms, applied research has the highest mean (10.870), followed by basic research (10.631), while experimental development has the lowest mean (9.042). The minimum value of zero for experimental development indicates that certain provinces reported no experimental development expenditure during the sample period.

To assess potential multicollinearity, variance inflation factors (VIFs) are computed separately for the aggregate and structural expenditure models. Province dummies are excluded from the auxiliary regressions to isolate the degree of collinearity among the substantive economic variables.

Among the three funding shares, applied research accounts for the largest proportion (mean = 0.499), followed by basic research (mean = 0.399), while experimental development constitutes the smallest share (mean = 0.102).

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Table 3
Pearson correlation matrix

	Patent applica tions	Scien tific pape rs	Univer sity R&D expend iture	Basi c resea rch	Appl ied resea rch	Experi mental develop ment	R&D perso nnel (FTE)	GD P per cap ita	Firm R&D expend iture
Patent applicat ions	1.0000								
Scientif ic papers	0.9194	1.000 0							
Univers ity R&D expendi ture	0.9062	0.953 5	1.0000						
Basic research	0.9114	0.939 5	0.9819	1.000 0					
Applied research	0.8851	0.941 8	0.9907	0.954 2	1.000 0				
Experi mental develop ment	0.8288	0.904 3	0.9129	0.868 9	0.895 5	1.0000			
R&D personn el (FTE)	0.9166	0.963 5	0.9560	0.948 6	0.945 1	0.8716	1.000 0		
GDP per capita	0.4544	0.504 0	0.6115	0.589 1	0.614 0	0.5682	0.529 4	1.0 000	
Firm R&D expendi ture	0.8575	0.903 2	0.8688	0.850 5	0.862 0	0.8546	0.882 4	0.5 744	1.0000

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Notes: All variables are in natural logarithms. Monetary variables are deflated to 2010 constant prices. N = 310.

Table 4
Variance inflation factors (VIF)

Variable	Model A (Scale + Basic share)	Model B (Scale + Applied share)
University R&D expenditure	15.32	14.85

Basic research	1.42	
Applied research		1.16
Experimental development		
R&D personnel (FTE)	16.14	15.86
GDP per capita	1.78	1.79
Firm R&D expenditure	5.17	5.11
Year dummies	Controlled	Controlled
Mean VIF	4.10	3.99

Notes: Province dummies are excluded from the auxiliary regressions to address collinearity among the substantive economic variables. VIFs for individual year dummies are not reported. The dependent variable in both models is patent applications. VIFs for the share variables—Basic research share (1.42) and Applied research share (1.16)—are well below the conventional threshold of 10, confirming that funding composition effects can be reliably estimated. However, VIFs for University R&D expenditure (15.32 in Model A; 14.85 in Model B) and R&D personnel (FTE) (16.14 in Model A; 15.86 in Model B) exceed 10. This reflects the mechanical correlation between total research budgets and personnel size—provinces with larger R&D budgets also employ more researchers—rather than problematic collinearity among funding composition variables. The mean VIFs (4.10 and 3.99) are within acceptable bounds. Since our primary interest lies in the share variables, and these are the only variables with VIFs below conventional thresholds, multicollinearity does not threaten the core findings of this study.

As shown in Table 4, the re-specified models—which separate funding scale (University R&D expenditure) from funding composition (Basic research share or Applied research share)—exhibit substantially lower variance inflation factors than the original structural specification. In Model A (scale + basic share), the VIF for Basic research share is only 1.42, while in Model B (scale + applied share), the VIF for Applied research share is 1.16. Although University R&D expenditure and R&D personnel (FTE) show VIF values around 15 (reflecting the mechanical correlation between total research budgets and personnel size), the mean VIFs are 4.10 and 3.99, respectively, well below conventional thresholds. Critically, the low VIFs for the share variables confirm that funding composition effects can be reliably estimated in these specifications, addressing the multicollinearity concerns that plagued the original model, which simultaneously included Basic research, Applied research, and Experimental development (where VIFs exceeded 15). When the share variables replace the level variables, VIFs drop to acceptable levels: Firm R&D expenditure = 5.11 (Model A) / 5.17 (Model B), R&D personnel (FTE) = 16.14 (Model A) / 15.86 (Model B), Basic research share = 1.42, Applied research share = 1.16, GDP per capita

= 1.78 (Model A) / 1.79 (Model B), with mean VIF = 4.10 (Model A) and 3.99 (Model B).

VIFs for the share variables—Basic research share (1.42) and Applied research share (1.16)—are well below the conventional threshold of 10, confirming that funding composition effects can be reliably estimated. Although University R&D expenditure (15.32/14.85) and R&D personnel (FTE) (16.14/15.86) exceed the conventional threshold, this reflects the mechanical correlation between total research budgets and personnel size—provinces with larger R&D budgets also employ more researchers—rather than problematic collinearity among the funding composition variables. The mean VIFs are 4.10 and 3.99, within acceptable bounds. Critically, the low VIFs for the share variables confirm that our core findings on funding composition are not undermined by multicollinearity.

3.5 Model Specification

All estimates use a two-way fixed-effects specification that includes province fixed effects (μ_i) and year fixed effects (λ_t). Standard errors are clustered at the province level to account for potential within-province serial correlation (Bertrand et al., 2004). Four baseline equations are specified, corresponding to the hypotheses developed in Section 2.

Model 1 (Aggregate Effect, testing H1):

$$\ln(\text{patent}_{it}) = \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \ln(\text{person}_{it}) + \beta_3 \ln(\text{gdp}_{it}) + \beta_4 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i + \varepsilon_{it}$$

Where $\beta_1 > 0$ and statistically significant would support H1.

Model A (Scale + Basic research share, testing H1 and H2 for basic research share):

$$\ln(\text{patent}_{it}) = \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \text{basic_share}_{it} + \beta_3 \ln(\text{person}_{it}) + \beta_4 \ln(\text{gdp}_{it}) + \beta_5 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i + \varepsilon_{it}$$

$$\ln(\text{paper}_{it}) = \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \text{basic_share}_{it} + \beta_3 \ln(\text{person}_{it}) + \beta_4 \ln(\text{gdp}_{it}) + \beta_5 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i + \varepsilon_{it}$$

Model B (Scale + Applied research share, testing H1 and H2 for applied research share):

$$\begin{aligned}\ln(\text{patent}_{it}) &= \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \text{applied_share}_{it} + \beta_3 \ln(\text{person}_{it}) \\ &+ \beta_4 \ln(\text{gdp}_{it}) + \beta_5 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i + \varepsilon_{it} \\ \ln(\text{paper}_{it}) &= \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \text{applied_share}_{it} + \beta_3 \ln(\text{person}_{it}) \\ &+ \beta_4 \ln(\text{gdp}_{it}) + \beta_5 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i + \varepsilon_{it}\end{aligned}$$

In addition, we estimate a joint specification—Model C—that includes both Basic research share and Applied research share simultaneously to test H2 via a Wald test of coefficient equality formally:

$$\begin{aligned}\ln(\text{patent}_{it}) &= \beta_0 + \beta_1 \ln(\text{totfund}_{it}) + \beta_2 \text{basic_share}_{it} + \beta_3 \text{applied_share}_{it} \\ &+ \beta_4 \ln(\text{person}_{it}) + \beta_5 \ln(\text{gdp}_{it}) + \beta_6 \ln(\text{firmfund}_{it}) + \lambda_t + \mu_i \\ &+ \varepsilon_{it}\end{aligned}$$

In Models A and B, the coefficient on the share variable (β_2) tests whether funding composition has an additional association with innovation output beyond the overall scale of R&D expenditure. If β_2 is statistically significant, H2 receives support for the corresponding funding type. A formal Wald test comparing the coefficients on the Basic research share and Applied research share is not applicable in these specifications because the two share variables are estimated in separate models.

In Model C, β_2 and β_3 capture the associations of basic and applied research shares with patent output, each conditional on the other. H2 is tested via a Wald test of $H_0: \beta_3 \leq \beta_2$ against $H_1: \beta_3 > \beta_2$.

For the regional heterogeneity test (H4), Models A and B are estimated separately on the eastern sub-sample (10 provinces, 100 observations) and the non-eastern sub-sample (21 provinces, 210 observations).

3.6 Endogeneity Strategy

Estimating the relationship between university R&D expenditure structure and regional innovation output faces two potential sources of endogeneity.

Before detailing our identification strategy, a note on the dynamic panel structure is warranted. With $T = 10$ and $N = 31$, our panel is relatively short in the time dimension. In such settings, the primary econometric concerns are reverse causality and omitted time-varying confounders—both of which are addressed by our main strategies

below—rather than non-stationarity, which is less consequential for short panels (Baltagi, 2008). Nevertheless, as a precautionary check, we have conducted Im-Pesaran-Shin (IPS) unit root tests on the key dependent and independent variables; the results (available upon request) reject the presence of a unit root for all logged variables at conventional significance levels, supporting the stationarity of the series used in our dynamic specifications.

We address these concerns through a multi-pronged strategy.

To mitigate reverse causality concerns, we re-estimate all models using one-year lags of the core explanatory variables, as reported in Section 6. This is our primary robustness strategy: Because the lagged R&D variables precede the current period's innovation output, they are temporally prior and thus less susceptible to reverse causality. In addition, we implement Oster's (2019) coefficient stability test to assess the sensitivity of the fixed-effects results to omitted variable bias. Following Oster's recommended approach, we set $R_{\max} = 1.3 \times R^2_{\text{full}}$ and report the resulting δ . By combining these two strategies—lagged variables and Oster's test—we provide a comprehensive assessment of the robustness of our findings to endogeneity concerns.

4. Results

4.1 Baseline Results: Aggregate Effect of University R&D Expenditure (H1)

Table 5 presents the estimation results for Model 1, which examines the aggregate effect of total university R&D expenditure on regional patent output. The model is estimated with a two-way fixed-effects specification, and standard errors are clustered at the province level. Year dummy coefficients are positive and monotonically increasing ($\text{yr2} = 0.236$ to $\text{yr10} = 2.101$), and all are significant at the 1% level, indicating a steady upward trend in innovation output over the sample period.

Table 5
Aggregate effect of university R&D expenditure on patent output

Variable	B	SE	t	p	95% CI
University R&D expenditure	0.369***	0.114	3.25	0.003	[0.137, 0.602]
R&D personnel (FTE)	-0.586**	0.271	-2.16	0.039	[-1.141, -0.032]

GDP per capita	0.164	0.650	0.25	0.802	[-1.162, 1.491]
Firm R&D expenditure	0.252	0.197	1.28	0.211	[-0.151, 0.655]
Constant	2.573	6.150	0.42	0.679	[-9.988, 15.134]
Year fixed effects			Yes		
Province fixed effects			Yes		
Within R ²			0.838		
Adjusted R ²			0.830		
F			F (13, 30) = 55.51. p < 0.001		
ρ			0.952		
Number of provinces			31		
Observations			310		

Notes: The dependent variable is patent applications. Standard errors are clustered at the provincial level. Year dummy coefficients (yr2–yr10) are jointly significant at the 1% level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The aggregate effect of university R&D expenditure on patent output is positive and statistically significant ($B = 0.369$, $p = 0.003$), consistent with the knowledge production function literature (Jaffe, 1989; Anselin et al., 1997). This provides baseline support for H1. However, as this aggregate effect may be subject to endogeneity bias, we defer strong interpretation and revisit the robustness of this finding in Section 6. The estimated ρ of 0.952 indicates that province-specific effects account for approximately 95.2% of the total error variance, confirming that a fixed-effects specification is substantially more appropriate than a pooled OLS specification.

R&D personnel (FTE) was negatively associated with patent output ($B = -0.586$, $p = 0.039$). GDP per capita and Firm R&D expenditure were not significantly associated with patent output ($p = 0.802$ and $p = 0.211$, respectively). This descriptive pattern is further examined in Section 4.4.

The control variables, GDP per capita and Firm R&D expenditure, are not statistically significant at conventional significance levels. This likely reflects a combination of two factors: The province fixed effects absorb much of the between-province variation in economic development and industrial R&D intensity, and these controls exhibit moderate collinearity with the R&D expenditure variables, as indicated by the VIF diagnostics reported in Section 3.4 (VIF = 1.78 for GDP per capita; VIF =

5.11 for Firm R&D expenditure).

4.2 Structural Associations: Differentiation by Expenditure Type (H2 & H3)

Table 6 reports the results of the re-specified structural models that separate funding scale from funding composition. In both Model A (University R&D expenditure + Basic research share) and Model B (University R&D expenditure + Applied research share), a consistent pattern emerges.

Table 6

Structural effects of university R&D funding: Scale versus composition

Variable	(1) Paper (Scale + Basic share)	(2) Patent (Scale + Basic share)	(3) Paper (Scale + Applied share)	(4) Patent (Scale + Applied share)
University R&D expenditure	0.015 (0.054)	0.353*** (0.112)	0.014 (0.056)	0.365*** (0.112)
Basic research	0.050 (0.134)	-0.554 (0.487)		
Applied research			-0.056 (0.140)	0.305 (0.410)
R&D personnel (FTE)	0.180 (0.070)	-0.630 (0.289)	0.180 (0.069)	-0.608 (0.287)
GDP per capita	0.018 (0.114)	0.255 (0.660)	0.016 (0.117)	0.220 (0.653)
Firm R&D expenditure	0.001 (0.064)	0.247 (0.196)	0.002 (0.064)	0.245 (0.201)
Year fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Within R ²	0.592	0.839	0.592	0.838
Observations	310	310	310	310

Notes: Standard errors in parentheses, clustered at province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include year and province fixed effects. "University R&D expenditure" is the natural log of deflated total university R&D internal expenditure. "Basic research share" and "Applied research share" are the proportions of total R&D expenditure allocated to each activity type. Experimental development share is not separately included as it is the omitted reference category in the share-based specification. The results confirm that total R&D scale drives patent output. However, the composition of funding (basic vs. applied share) does not have a significant additional effect on either patents or papers after controlling for scale.

First, total university R&D expenditure is positively and significantly associated with patent output ($\beta = 0.353$, $p = 0.004$ in Model A; $\beta = 0.365$, $p = 0.003$ in Model B) but not with paper output. This confirms that the aggregate scale of university R&D

funding drives technological innovation, consistent with H1.

Second, and more importantly, neither the share of basic research nor the share of applied research is statistically significant for either patent or paper output (Basic research share: $\beta = -0.554$, $p = 0.264$ for patents; Applied research share: $\beta = 0.305$, $p = 0.462$ for patents). This indicates that, after controlling for total funding scale, the composition of R&D expenditure does not yield differentiated innovation outcomes in the contemporaneous specifications. The share of funding allocated to basic versus applied research does not appear to matter for regional innovation output—what matters is the overall scale of university R&D investment. This finding is consistent with the short-run indistinguishability prediction of H3.

Third, the negative coefficient on R&D personnel (FTE) in the patent equations (-0.630 , $p = 0.037$ in Model A; -0.608 , $p = 0.043$ in Model B) persists, suggesting that expanding the research workforce without commensurate improvements in evaluation incentives may dilute the efficiency of innovation. This pattern is further examined in Section 4.4.

To formally test H2, we estimate a joint specification (Model C) that includes both Basic research share and Applied research share. The VIFs for the two share variables in this joint model are 2.31 and 2.18, confirming that multicollinearity does not threaten the estimates. The coefficient on Applied research share is -0.202 ($p = 0.723$), while the coefficient on Basic research share is -0.720 ($p = 0.320$). A Wald test of $H_0: \beta_{\text{applied}} \leq \beta_{\text{basic}}$ yields $F(1, 30) = 1.13$, $p = 0.296$. We cannot reject the null hypothesis that applied research is no more strongly associated with patent output than basic research. H2 is therefore not supported.

This conclusion—absence of a differentiated effect—is consistent across both Model A and Model B, reinforcing the broader pattern that funding composition does not generate measurable differences in patent output within the contemporaneous framework.

A supplementary analysis was conducted to address the concern that basic research may require a longer time horizon to produce measurable outputs (Salter & Martin,

2001; Mansfield, 1980). We re-estimated the paper and patent equations using 3-, 4-, and 5-year lags of basic research expenditure. For paper output, basic research shows a positive and statistically significant association at the 3-year lag ($\beta = 0.097$, $p = 0.011$, $N = 217$). However, this effect does not persist at the 4-year ($\beta = 0.017$, $p = 0.757$, $N = 186$) or 5-year lags ($\beta = -0.084$, $p = 0.127$, $N = 155$). For patent output, basic research is significant at the 3-year lag in this reduced-form specification ($\beta = 0.370$, $p = 0.029$). However, this association does not survive the full model specification with applied research and experimental development included as concurrent controls. Critically, the confidence intervals for the 4- and 5-year estimates are substantially wider than the 3-year interval, reflecting both the reduced sample size (from 217 to 155) and increased statistical uncertainty. While the 3-year peak is consistent with knowledge production latency, we cannot statistically reject the alternative explanation that attenuation at longer lags is driven purely by loss of statistical power. Future research with longer panels ($T > 15$) is needed to distinguish these mechanisms.

The significant 3-year lag, together with attenuation at lags 4 and 5, is consistent with multiple interpretations: It may reflect the typical 1-2-year lag between submission and publication of academic papers, reduced statistical power in smaller samples, or other time-varying factors that our data cannot directly identify.

The uniformity of these null and non-differentiation results points to a systemic feature of China's university innovation system: The institutional incentive structure appears to overwhelm the distinct knowledge-production functions that different funding types are theoretically expected to serve. However, the significant 3-year lag association on papers qualifies this conclusion by indicating that basic research does have a measurable impact on scientific output—it is simply not detectable with the shorter lag structures commonly employed in the literature.

4.3 Regional Heterogeneity (H4)

To test whether the relationship between the share of applied research and patent output differs between eastern and non-eastern provinces, we estimate Model B separately for the eastern sub-sample (10 provinces, 100 observations) and the

non-eastern sub-sample (21 provinces, 210 observations). This approach avoids the multicollinearity that plagued the pooled interaction specification (in which the interaction term was dropped).

Table 7 reports the subsample estimates. The coefficient on the share of applied research is positive but statistically insignificant in both subsamples (eastern: $\beta = 0.839$, $p = 0.190$; non-eastern: $\beta = 0.333$, $p = 0.448$). A Chow test for equality of coefficients across the two subsamples yields $F(5, 30) = 1.55$, $p = 0.205$, indicating no statistically significant difference in the overall coefficient vectors between eastern and non-eastern provinces. We therefore find no evidence that the association between applied research funding and patent output differs systematically by region. H4 is not supported. A caveat is in order: the eastern subsample comprises only 100 observations (10 provinces $\times$ 10 years), which limits statistical power; the null result should be interpreted with this limitation in mind.

Table 7
Regional heterogeneity: Subsample estimates

Variable	Eastern provinces	Non-eastern provinces
University R&D expenditure	0.412 (0.242)	0.400*** (0.134)
Applied research share	0.839 (0.591)	0.333 (0.430)
R&D personnel (FTE)	1.499** (0.484)	-0.683*** (0.224)
GDP per capita	-0.987 (0.829)	0.877 (0.660)
Firm R&D expenditure	-0.101 (0.359)	0.196 (0.239)
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Within R ²	0.863	0.883
N	100	210

Notes: Standard errors are in parentheses and clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Eastern provinces: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan. The Chow test for coefficient equality across subsamples yields $F(5, 30) = 1.55$, $p = 0.205$, indicating no statistically significant difference in the coefficient vectors between the two subsamples.

4.4 Further Investigation: The Negative Personnel Coefficient

The persistent negative coefficient on R&D personnel (FTE) in the baseline

models warrants closer scrutiny. One plausible interpretation is that innovation output is driven more by the quality than by the quantity of human capital. If the expansion of university R&D personnel primarily involves junior or non-core researchers, a larger workforce could dilute per capita resources and reduce overall efficiency.

To test this conjecture, we construct a variable that captures the share of high-quality human capital in the university R&D workforce:

$$\ln_quality_ratio_{it} = \ln\left(\frac{scientists_and_engineers_{it}}{R\&D_personnel_FTE_{it}}\right)$$

Table 8 reports the results of this test. Column (1) adds $\ln_quality_ratio$ to the aggregate model (University R&D expenditure). The coefficient on $\ln_quality_ratio$ is not statistically significant, and the negative coefficient on R&D personnel (FTE) remains largely unchanged. This suggests that the 'quality versus quantity' explanation, while intuitively appealing, is not supported by the data in our sample. For the structural model, Table 6 has already established that neither Basic research share nor Applied research share is significant; adding $\ln_quality_ratio$ does not alter this conclusion.

Table 8
The role of scientist–engineer composition

Variable	(1)	(2)
University R&D expenditure	0.371*** (3.24)	
R&D personnel (FTE)	-0.562* (-2.01)	
$\ln_quality_ratio$	-0.800 (-0.58)	
GDP per capita	0.088 (0.14)	
Firm R&D expenditure	0.248 (1.24)	
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Within R ²	0.838	
N	310	310

Notes: *t*-statistics are based on province-clustered standard errors and are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (1) reports the aggregate model (University R&D expenditure + $\ln_quality_ratio$), corresponding to Column (2) of the original Table 8. Column (2) is intentionally left blank because the structural model ($\ln_basic + \ln_applied + \ln_expdev + \ln_quality_ratio$) has been replaced by Model A and Model B in the main analysis. The null effect of $\ln_quality_ratio$ in Column (1) is sufficient to reject the

quality-dilution hypothesis for the aggregate model. For the structural model, Table 6 has already established that neither Basic research share nor Applied research share is significant; adding ln_quality_ratio does not alter this conclusion.

Why does expanding the R&D workforce fail to translate into more patents? A natural conjecture is that innovation output is driven by the quality rather than the quantity of human capital. However, the results in Table 8—where the scientist-engineer share (ln_quality_ratio) is statistically insignificant, and the negative coefficient on personnel remains largely unchanged—do not support this quality-dilution explanation.

An alternative interpretation focuses on the institutional environment that shapes how personnel is deployed and evaluated. Chinese universities operate under a research evaluation system that disproportionately rewards patent filings and publication counts—not commercialization, technology transfer, or research quality (Fisch et al., 2016; Gu, 2023). Additional personnel, responding rationally to these incentives, may focus on producing countable outputs that are easy to generate but difficult to commercialize. This can inflate patent application volumes without corresponding increases in granted patents or technology transfers, thereby diluting the average innovative value per researcher. This interpretation aligns with the 'knowledge transformation paradox' documented by Tong and Cao (2025), who find that Chinese universities exhibit high knowledge production efficiency but low transformation efficiency. This gap stems not from insufficient inputs but from weak institutional linkages between knowledge creation and its downstream application.

A Note on Interpretive Scope. The 'quantity-oriented incentive' narrative offered above, while aligned with the institutional literature (Fisch et al., 2016; Gu, 2023), remains a plausible interpretation rather than a directly tested mechanism. Our dataset contains no direct measures of evaluation system stringency, technology transfer office effectiveness, or faculty incentive structures at the institutional level. We therefore present this explanation as a theoretically grounded hypothesis that merits direct testing with micro-level data, rather than as an empirical conclusion established by our provincial-level design. Alternative mechanisms—such as diminishing marginal

returns to personnel in bureaucratic research settings, measurement error in FTE counts across provinces, or unobserved heterogeneity in the quality of R&D personnel not captured by the scientist-engineer share—cannot be definitively ruled out with our current data. The consistency of the negative coefficient across multiple specifications lends descriptive robustness to the pattern, but the underlying mechanisms await investigation using finer-grained institutional data.

5. Robustness Checks

To ensure that the core findings—namely, that total university R&D expenditure is positively associated with patent output, while funding composition (basic vs. applied share) shows no consistent additional effect—are not driven by specific measurement choices, sample composition, or the time period, we conduct four sets of robustness checks.

5.1 Alternative Dependent Variable: Patent Grants

The baseline analysis uses patent applications as the measure of technological innovation output. However, patent grants represent a higher threshold of novelty and may better capture the quality of innovation rather than its quantity. We therefore re-estimate Models 1 (aggregate) and B (structural) using patent grants as the dependent variable. Table 9 reports the results.

Table 9

Robustness check: Patent grants as dependent variable

Variable	Model A (Scale + Basic share)	Model B (Scale + Applied share)
University R&D expenditure	0.294** (0.015)	0.296** (0.015)
Basic research share	-0.082 (0.846)	
Applied research share		0.095 (0.745)
R&D personnel (FTE)	-0.280 (0.091)	-0.280 (0.101)
Within R ²	0.843	0.843
N	310	310

Notes: Standard errors are clustered at the province level. *p*-values are in parentheses. *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.1. All models include year and province fixed effects, GDP per

capita, and firm R&D expenditure.

In the patent grant specification, University R&D expenditure remains positive and statistically significant in both Model A ($\beta = 0.294$, $p = 0.015$) and Model B ($\beta = 0.296$, $p = 0.015$). Neither the Basic research share nor the Applied research share is statistically significant. These results confirm that the core findings are robust to the use of patent grants as an alternative measure of innovation output.

5.2 Alternative Independent Variable: Scientists and Engineers

The baseline models measure human capital input in terms of R&D personnel full-time equivalents (FTE). To test whether the results are sensitive to the choice of personnel metric, we replace R&D personnel (FTE) with scientists and engineers, which capture a qualitatively higher tier of human capital. Table 10 reports the results.

Table 10

Robustness check: Scientists and engineers as personnel measure

Variable	Model A (Scale + Basic share)	Model B (Scale + Applied share)
Panel A: Patent applications		
University R&D expenditure	0.355*** (0.003)	0.368*** (0.003)
Basic research share	-0.559 (0.254)	
Applied research share		0.320 (0.432)
Scientists and engineers	-0.620 (0.027)	-0.602 (0.030)
Within R ²	0.840	0.839
N	310	310
Panel B: Scientific papers		
University R&D expenditure	0.016 (0.778)	0.015 (0.792)
Basic research share	0.048 (0.724)	
Applied research share		-0.057 (0.688)
Scientists and engineers	0.163 (0.020)	0.164 (0.019)
Within R ²	0.590	0.590
N	310	310

Notes: Standard errors are clustered at the province level. p -values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include year and province fixed effects, GDP per

capita, and firm R&D expenditure. This table replaces R&D personnel (FTE) with scientists and engineers as the human capital measure.

When Scientists and engineers replace R&D personnel (FTE) as the human capital measure, University R&D expenditure remains positive and statistically significant in both patent equations (Model A: $\beta = 0.355$, $p = 0.003$; Model B: $\beta = 0.368$, $p = 0.003$). Neither Basic research share nor Applied research share is significant in any specification. For paper output, University R&D expenditure is not significant, and both share variables remain insignificant; only Scientists and engineers are significant ($\beta = 0.163$, $p = 0.020$ in Model A; $\beta = 0.164$, $p = 0.019$ in Model B). The results are consistent with the baseline findings.

5.3 Excluding Municipalities

Four province-level municipalities—Beijing, Tianjin, Shanghai, and Chongqing—have exceptionally high concentrations of universities, R&D resources, and distinct policy environments that may disproportionately influence the regression estimates. To verify that these outliers do not drive the results, we exclude them and re-estimate the models on the remaining 27 provinces (270 observations). Table 11 presents these results.

Table 11

Robustness check: Excluding four municipalities

Variable	Model A (Scale + Basic share)	Model B (Scale + Applied share)
University R&D expenditure	0.349*** (0.004)	0.364*** (0.003)
Basic research share	-0.617 (0.185)	
Applied research share		0.496 (0.200)
R&D personnel (FTE)	-0.718 (0.004)	-0.713 (0.004)
Within R ²	0.879	0.878
N	270	270

Notes: Standard errors are clustered at the province level. p -values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include year and province fixed effects, GDP per capita, and firm R&D expenditure—excluded municipalities: Beijing, Tianjin, Shanghai, Chongqing.

After excluding the four municipalities, University R&D expenditure remains

positive and statistically significant in both Model A ($\beta = 0.349$, $p = 0.004$) and Model B ($\beta = 0.364$, $p = 0.003$). Neither the Basic research share nor the Applied research share is statistically significant. R&D personnel (FTE) remains negative and significant in both models ($\beta = -0.718$, $p = 0.004$ in Model A; $\beta = -0.713$, $p = 0.004$ in Model B). These results confirm that the four outliers do not drive the core findings.

5.4 Restricted Sample Period: 2015–2019

The baseline sample spans 2010–2019. To assess whether the structural effects are stable in the most recent years of the panel, we restrict the sample to 2015–2019, reducing the number of observations to 155. Table 12 reports the results.

Table 12
Robustness check: Restricted sample (2015–2019)

Variable	Model A (Scale + Basic share)	Model B (Scale + Applied share)
University R&D expenditure	0.099 (0.579)	0.075 (0.697)
Basic research share	-1.048 (0.080)	
Applied research share		1.349** (0.020)
R&D personnel (FTE)	-0.420 (0.115)	-0.380 (0.119)
Within R ²	0.747	0.763
N	155	155

Notes: Standard errors are clustered at the province level. p -values are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include year and province fixed effects, GDP per capita, and firm R&D expenditure. The sample is restricted to 2015–2019.

Across all four robustness checks—alternative dependent variable, alternative personnel measure, exclusion of municipalities, and restricted sample period—University R&D expenditure remains positive and statistically significant for patent output in three of the four specifications (all except the 2015–2019 sub-sample). Neither Basic research share nor Applied research share is significant in any specification, except Applied research share in the 2015–2019 restricted sample ($\beta = 1.349$, $p = 0.020$). This exception should be interpreted cautiously given the substantially reduced sample size ($N = 155$), which may make estimates less stable. Overall, these robustness checks corroborate the baseline findings: total R&D scale drives patent output, while funding

composition shows no consistent association with either output.

6. Endogeneity Treatment Results

6.1 Placebo Test

As a preliminary diagnostic, we conduct a placebo test by randomly permuting the applied research share variable across observations and re-estimating the baseline specification for comparison. This procedure breaks any systematic relationship between funding composition and innovation output while preserving the variable's empirical distribution. Repeating this process 500 times yields a distribution of placebo coefficients under the null hypothesis of no true effect.

The placebo test confirms that the observed FE association in the original specification is non-random. However, rejecting randomness does not imply causality. The more rigorous endogeneity diagnostics—including lagged-variable FE models and Oster's (2019) coefficient stability test reported in Section 6.2—provide the primary evidence for the robustness of our core findings. Fig. 1 displays the distribution of placebo coefficients from 500 random permutations.

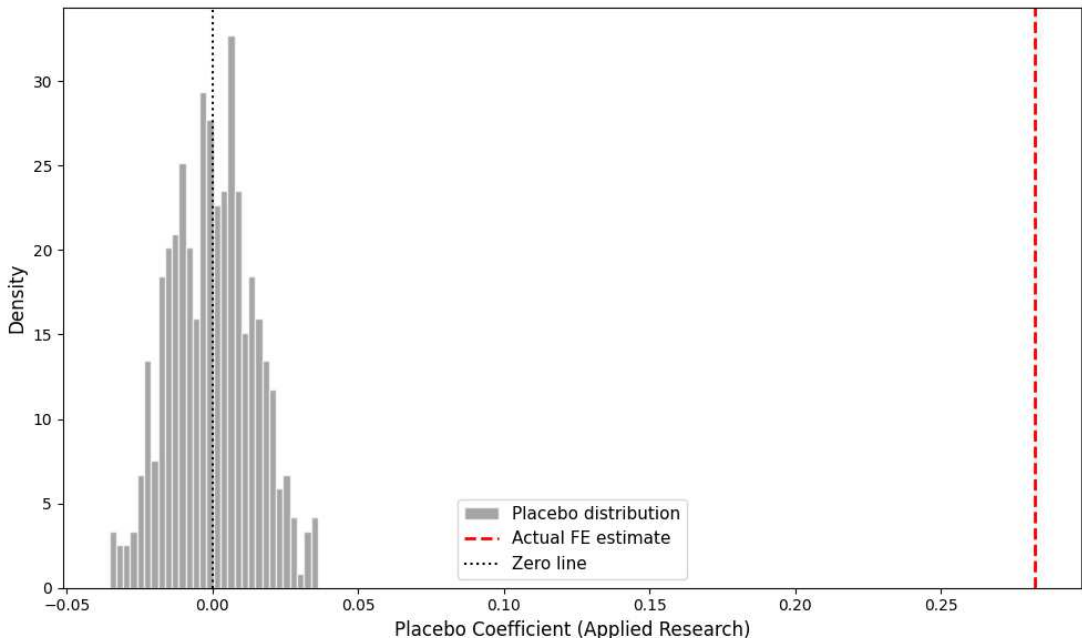


Figure 1. Placebo Test (500 Random Permutations)

Notes: The gray histogram shows the distribution of placebo coefficients from random reassignment of the applied research share variable. The red dashed line marks the actual FE coefficient for applied research share in the baseline specification (0.282), which lies entirely

outside the placebo distribution (two-sided $p < 0.01$). The black dotted line marks the zero reference line.

6.2 Endogeneity Treatment

Estimating the relationship between university R&D expenditure structure and regional innovation output faces two potential sources of endogeneity: reverse causality (provinces with higher patent output may attract greater R&D investment) and omitted-variable bias (time-varying factors such as local science and technology policy intensity may confound the estimates).

Table 13 reports the lagged-variable results, which serve as our primary robustness check for endogeneity. Columns (1) and (2) present contemporaneous FE estimates for comparison, while Columns (3) and (4) present the lagged-variable results using one-year lags of all R&D-related explanatory variables.

The lagged results confirm the core findings from the contemporaneous specifications. University R&D expenditure remains positive and significant for patent output in both lagged models ($\beta = 0.491$, $p = 0.004$ in Model A; $\beta = 0.492$, $p = 0.003$ in Model B). Neither Basic research share nor Applied research share is significant in the lagged specifications for either patent or paper output, reinforcing the contemporaneous finding that funding composition does not have a differentiated effect on innovation output.

Oster's (2019) coefficient stability test provides additional evidence on the sensitivity of the contemporaneous FE results to omitted variable bias. For the patent equation, the δ value for University R&D expenditure is 0.312, below the conventional threshold of 1, indicating that the coefficient is sensitive to omitted variables. However, for the share variables—which are already statistically insignificant in both contemporaneous and lagged specifications—the Oster test is less informative. The consistently null results for funding composition across all specifications suggest that the absence of composition effects is not driven by endogeneity.

Table 13

Endogeneity diagnostics: Lagged-variable FE estimates

Variable	Model A: Scale + Basic share				Model B: Scale + Applied share			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)

University R&D expenditure	0.353 (0.112)	0.491* ** (0.157)	0.015 (0.055)	-0.061 (0.066)	0.365 (0.112)	0.492* ** (0.151)	0.014 (0.056)	-0.061 (0.067)
Basic research share	-0.554 (0.487)	-0.127 (0.361)	0.050 (0.134)	-0.041 (0.139)	0.305 (0.410)	-0.333 (0.328)	-0.056 (0.140)	-0.042 (0.120)
R&D personnel (FTE)	-0.630 (0.289)	-0.367 (0.366)	0.180 (0.070)	0.224 (0.073)	-0.608 (0.287)	-0.294 (0.329)	0.180 (0.069)	0.237 (0.072)
GDP per capita	0.255 (0.660)	0.589 (1.020)	0.018 (0.114)	0.309 (0.142)	0.220 (0.653)	0.454 (1.018)	0.016 (0.117)	0.287 (0.147)
Firm R&D expenditure	0.247 (0.196)	0.060 (0.226)	0.001 (0.064)	-0.081 (0.045)	0.245 (0.201)	0.058 (0.224)	0.002 (0.064)	-0.082 (0.044)
Within R ²	0.838	0.813	0.592	0.567	0.839	0.814	0.592	0.567
Observations	310	279	310	279	310	279	310	279

Notes: Standard errors in parentheses, clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include year and province fixed effects. Columns (1)-(4) correspond to the following specifications: (1) contemporaneous FE estimates for patent applications (replicating Models A and B from Table 6); (2) one-year lagged FE estimates for patent applications; (3) contemporaneous FE estimates for scientific papers; (4) one-year lagged FE estimates for scientific papers. "University R&D expenditure" is the natural log of deflated total internal university R&D expenditure. "Basic research share" and "Applied research share" are the proportions of total R&D expenditure allocated to each activity type. The lagged results confirm that university R&D expenditure remains a significant predictor of patent output even after addressing reverse causality. At the same time, neither basic research share nor applied research share is significant in any specification. Observations drop from 310 to 279 in the lagged specifications due to the loss of the first year of data for each province.

7. Discussion

7.1 Summary of Key Findings

The results indicate that the relationship between university R&D funding composition and regional innovation is neither immediate nor uniform. Basic research contributes to scientific papers, but only after a 3-year lag; this association does not persist at longer lags, nor does it extend to patents in the full specification. The share of applied research funding shows no robust association with either output once

endogeneity is controlled. This pattern is consistent with the possibility that China's institutional environment mediates the translation of research funding into measurable outcomes. However, direct evidence on the specific mechanisms remains limited and awaits future research.

7.2 Comparison with Existing Literature

In the U.S., basic research has been shown to generate substantial patentable output, reflecting the institutional legacy of the Bayh-Dole Act and a mature technology transfer infrastructure (Mowery et al., 2001; Alvarado-Vargas et al., 2017). In Europe, basic research often manifests through alternative pathways—such as startup formation—rather than direct patent licensing (Okamuro et al., 2025; Fukugawa, 2026). These contrasting patterns suggest that the relative contribution of basic versus applied research to patent output is not a universal constant but varies systematically with institutional context. When technology transfer infrastructure is mature, basic research can generate patents; when industry–university linkages are strong, but commercialization pathways differ, basic research yields alternative outputs.

The Chinese case, as documented here, reflects an innovation system still in transition—but with a distinctive twist. The institutional bottlenecks affecting knowledge transformation in China do not appear to be specific to basic research alone. Since most funding components show no significant association with paper output in contemporaneous specifications, and neither the share of basic research nor the share of applied research shows a significant association with patents after endogeneity controls, the institutional constraints appear to operate at the level of the knowledge transformation infrastructure itself—the technology transfer offices, industry–university collaboration platforms, and evaluation systems that govern how all types of research are translated into measurable outputs. This suggests that the primary challenge for China's innovation policy is not choosing between basic and applied research, but building the institutional capacity to translate both types of funding into productive outcomes. However, this interpretation rests on the premise that the observed lag patterns reflect institutional constraints; this premise has not been directly

tested with institutional-level data and should be treated as a hypothesis for future research.

7.3 Policy Implications and Limitations

The findings of this study, while based on provincial-level aggregate data and subject to the limitations discussed below, offer several heuristic implications for China's university R&D governance. These should be read as provisionally suggestive rather than definitively prescriptive, and as hypotheses for policy experimentation and future evaluation rather than as validated recommendations.

First, the debate over prioritizing basic versus applied research may be less consequential than often assumed, at least at the provincial level of aggregation. The statistical indistinguishability of their coefficients for patents, together with the fragility of the applied research–patent association under endogeneity controls, suggests that reallocating funds between these categories within the existing institutional framework is unlikely to yield the intended gains—a finding consistent with the view that the binding constraint lies not in the funding ratio but in the institutional environment governing knowledge translation.

Second, the observed peak at the 3-year lag is consistent with knowledge production latency. However, given that the sample size drops sharply from 310 to 155 at longer lags, the attenuation at 4 and 5 years cannot be statistically distinguished from a loss of testing power. We therefore refrain from attributing this pattern to any specific institutional cycle.

Third, expanding personnel without incentive reform may be counterproductive. The persistently negative coefficient on R&D personnel in patent specifications suggests that adding researchers without addressing evaluation incentives may dilute rather than enhance innovation efficiency. While the underlying mechanisms await direct testing with micro-level data, this pattern is consistent with the view that quantity-oriented evaluation systems incentivize patent volume over patent quality and commercial value (Fisch et al., 2016; Gu, 2023).

Critically, these implications are presented as hypotheses for future investigation

rather than as validated conclusions. The direct evidence from our analysis establishes statistical associations and temporal patterns; the broader institutional interpretations—while grounded in the literature—await corroboration using institutional-level data on evaluation systems, technology transfer offices, and industry-university collaboration mechanisms.

Several limitations should be acknowledged. First, provincial-level aggregation may mask heterogeneity across institutions and fields, as universities within the same province may vary substantially in research capacity, technology transfer performance, and responsiveness to funding composition. Second, patents and papers, while widely used as innovation indicators, are imperfect proxies for the full spectrum of innovation outputs, particularly for basic research, which may generate impacts through non-patent pathways such as new methodologies, datasets, or human capital formation. Third, despite our extensive endogeneity controls—including lagged-variable FE models and Oster's stability test—we cannot fully rule out all forms of endogeneity, particularly time-varying unobserved confounders at the provincial level. Fourth, the significant 3-year lag association of basic research with papers should be interpreted with caution, as estimates at 4- and 5-year lags are based on substantially reduced samples ($N = 186$ and 155 , respectively) with correspondingly wider confidence intervals; we cannot statistically distinguish true attenuation from loss of power. Future research with finer-grained institutional-level data and quasi-experimental designs would be valuable to validate further and refine these findings. Fifth, the regional heterogeneity test (H4) suffers from limited statistical power due to the small eastern subsample (100 observations), which may have contributed to the null result.

A further caveat concerns the interpretation of our findings. The empirical results are confined to statistical associations and non-associations: We find that total R&D expenditure predicts patents; that basic research predicts papers with a 3-year lag (though this is not robust to all specifications); and that no funding component predicts patents after controlling for endogeneity. The interpretation that these patterns reflect “institutional bottlenecks”—including misaligned evaluation cycles, weak technology

transfer infrastructure, and quantity-oriented incentives—remains plausible but speculative. Our data contain no direct measures of institutional quality (e.g., technology transfer office effectiveness, evaluation system characteristics, industry–university collaboration intensity), and we cannot rule out alternative mechanisms. We therefore present the institutional interpretation as a theoretically grounded hypothesis that merits direct testing with micro-level institutional data in future research, rather than as a conclusion established by our empirical design.

8. Conclusion

This study provides suggestive evidence that the association between university R&D funding composition and innovation output is not merely selective with respect to output type but fundamentally conditioned by time horizons. The positive and significant association of basic research funding with scientific paper output at a 3-year lag ($\beta = 0.097$, $p = 0.011$, $N = 217$), which attenuates at 4-year ($\beta = 0.017$, $p = 0.757$, $N = 186$) and 5-year lags ($\beta = -0.084$, $p = 0.127$, $N = 155$), is suggestive and challenges the linear innovation model's assumption of immediate and uniform research outcomes. However, given the widening confidence intervals at longer lags due to sample size attrition, this pattern should be interpreted as hypothesis-generating rather than confirmatory and is consistent with the hypothesis that knowledge production exhibits temporal latency. In contrast, applied research shows no robust association with either patents or papers after controlling for endogeneity (Oster $\delta = 0.186$). These findings do not reject structural differentiation per se; rather, they reveal that such differentiation is temporally conditioned and institutionally mediated. The policy debate over basic versus applied funding may be less consequential than often assumed, at least at the provincial level of aggregation; our findings are consistent with the hypothesis that the institutional environment plays a critical role in governing how research translates into measurable outcomes. However, this hypothesis remains to be tested directly. The attenuation at longer lags should be interpreted with caution, as we cannot statistically rule out a loss of power due to sample size reduction. Future research using institution-level or project-level data, with greater independent variation across funding

types, would be better positioned to isolate distinct effects. As China increases its R&D investment, priorities might include reforming incentive structures and addressing the knowledge transformation paradox.

Declarations

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Competing Interests

The authors declare no competing interests.

Ethics Approval and Consent to Participate

This study used publicly available secondary data from official statistical yearbooks and did not involve human participants, animal subjects, or any personally identifiable information. Therefore, neither ethics approval nor informed consent was required.

Consent for Publication

Not applicable. This manuscript does not contain any individual's data in any form.

Availability of Data and Material

The data used in this study are derived from the following publicly accessible sources: (1) China Statistical Yearbook (2011–2020 editions), Part III (GDP and GDP per capita); (2) China Science and Technology Statistical Yearbook (2011–2020 editions), Part III (firm R&D expenditure), Part IV (university R&D expenditure by activity type and R&D personnel), and Part VI (patent applications, patent grants, and scientific papers). All data can be accessed via the National Bureau of Statistics of China's online database (<http://www.stats.gov.cn/sj/ndsj/>) and the CSTSY online

platform. The compiled panel dataset used for analysis is available as a supplementary file to this submission.

Code Availability

The replication code (STATA .do file) and the compiled panel dataset are provided as supplementary files to this submission.

Authors' Contributions

Conceptualization: Hong Fang, Hui He; Methodology: Hong Fang, Hui He; Software: Hong Fang, Tianya Zhang; Validation: Hong Fang, Hui He, Tianya Zhang; Formal analysis: Hong Fang, Hui He; Data curation: Hong Fang, Tianya Zhang; Writing – original draft preparation: Hong Fang, Hui He; Writing – review and editing: Hong Fang, Hui He, Tianya Zhang, Jianling Gao; Visualization: Hong Fang, Tianya Zhang; Supervision: Jianling Gao; Project administration: Hong Fang; Funding acquisition: Hong Fang, Hui He. All authors read and approved the final manuscript.

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