# A Study on the Impact of Academic Entrepreneurship on Basic Research

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#### **Abstract:**

The impact of academic entrepreneurship on basic research output has been widely debated, with disagreements arising from difficulties in collecting micro-level data and the limitations of traditional regression methods in addressing confounding factors beyond the "entrepreneurial identity" of academic entrepreneurs. To tackle these issues, we developed a large, multi-dimensional database of 13,762 science and engineering faculty members from 17 top universities in Shaanxi Province using computer-based data crawling techniques. By matching data on faculty research outputs and academic entrepreneurship activities, we applied propensity score matching (PSM) to examine the causal relationship between academic entrepreneurship and basic research output. Our findings indicate that academic entrepreneurship positively impacts the number of papers published annually, exploration of new knowledge, patent applications, and patent citations. These effects vary among faculty with different characteristics, suggesting a virtuous cycle between academic entrepreneurship and basic research. To foster scientific self-reliance, universities should encourage academic entrepreneurship, providing tailored support based on individual characteristics.

Keywords: university teachers, academic entrepreneurship, basic research, counterfactual estimate

### INTRODUCTION

Despite the academic community's recognition of the importance of both academic entrepreneurship and basic research, the impact of academic entrepreneurship on basic research remains highly debated. Scholars have examined this relationship from various theoretical perspectives, but consensus is lacking due to several factors: (1) the diverse forms of academic entrepreneurship, such as spin-offs, licensing, patenting, contract research, and consulting, each affecting scientific output differently; (2) inconsistent results across countries, institutions, and disciplines; (3) challenges in obtaining microdata, as many studies rely on subjective sources like surveys and expert interviews; and (4) methodological limitations in isolating external factors that influence the 'identity' of academic entrepreneurs, such as increased productivity and access to resources, making it difficult to determine whether academic entrepreneurship enhances or inhibits basic research output, or if it is simply a result of other influencing factors.

In 2023, China's universities employed 1,442,400 teaching and research staff, with research funds totaling 317.95 billion yuan. As a leading global research producer, examining the impact of academic entrepreneurship on basic research output is both theoretically and practically important, especially within China's unique university policies. Shaanxi, a major science and education hub, hosts over 110 universities, 1,800 research institutions, and more than 2 million professionals, including over 70 academicians. The region's rich scientific resources and strong innovation capabilities make it an ideal setting for investigating the relationship between academic entrepreneurship and basic research output. To address endogeneity issues in traditional OLS methods, this study uses the propensity score matching (PSM) technique to create a multivariate database on faculty research and entrepreneurial activities. The database, based on a large sample of science and engineering faculty from high-level universities in Shaanxi, aims to more accurately assess the impact of faculty involvement in academic spin-offs on their research output, filling a significant gap in the existing literature.

## LITERATURE REVIEW

The relationship between academic entrepreneurship and basic research output has garnered significant global attention, but no consensus has been reached. Some argue that academic entrepreneurship does not significantly affect research output, suggesting that academic entrepreneurship and open science can coexist independently, with a rise in one not necessarily diminishing the other. For many faculty members, publishing remains a primary output, even when engaging in academic entrepreneurship, as it helps secure peer recognition and university status [1,2]. Studies by Abramo (2012) on 382 academic entrepreneurs at an Italian university and by Prodan and Slavec

(2012) across three European universities support this view [3,4]. The debate currently centers around two competing perspectives: rival extrusion and synergistic symbiosis.

The perspective that academic entrepreneurship crowds out basic research argues that faculty entrepreneurial activities divert attention and resources away from their basic research output [5-7].

From the perspective of incentive salience, Nelson (2004) argues that academic entrepreneurship undermines the position of the Open Science Community by prioritizing confidentiality, leading faculty to withhold results from peers [8]. Murray and Stern (2007) suggest that patent protection issues could reduce the quality of basic research, potentially causing the 'tragedy of the anti-commons.' Stern (2007) further explains that academic entrepreneurship delays scholarly publication due to the proprietary nature of patents, which lowers citation rates for related papers [9]. These views suggest that faculty may prioritize material incentives over research incentives when both are present. From the perspective of role conflict, Prodan and Slavec (2012) identified a hybrid role identity in academic entrepreneurship. Faculty may focus on producing high-quality research as "academic researchers," but as "academic entrepreneurs," they prioritize commercialization. Guo Feng et al. (2019) and Xiong Wenming et al. (2021) noted the identity paradox and the need for role reconstruction to adopt an entrepreneurial identity. This identity conflict often limits publishing activities, as academic entrepreneurship prioritizes intellectual property over public dissemination, leading to self-interested behaviors like delayed or nonpublication of research and retention of critical knowledge [10-14]. From the perspective of time conflict, Buenstorf (2009) found that academic entrepreneurship negatively impacts both the quantity and quality of faculty publications, as entrepreneurial activities compete for time. Toole and Czarnitzki (2010) showed that academic entrepreneurship led to a 19% decrease in publications and a 20% drop in citations, with reduced NIH grants due to less time spent on academic research [15,16]. Related studies argue that successful entrepreneurship requires ongoing involvement from the inventor, which detracts from research activities [17,18].

The school of thought that views academic entrepreneurship as synergistic with basic research argues that academic entrepreneurship not only does not hinder faculty research productivity but actually enhances basic research [19-21].

From a resource dependence perspective, Van Looy et al. (2004) argue that academic entrepreneurship enhances research output without hindering scientific work, with synergies growing as resources increase [22]. Powers and McDougall (2005) suggest that industry reputation helps faculty secure collaborations [23], while Buenstorf (2009) notes that entrepreneurial activities provide financial returns and research support through partnerships [24]. Silva (2015) highlights that academic entrepreneurship enables access to critical resources [25]. These studies show that faculty involved in academic entrepreneurship can access resources that boost basic research [26]. From a knowledge reorganization perspective, Fabrizio and Di Minin (2008) argue that industry interactions inspire new research, foster collaborations, and provide funding, with patents not hindering publication [27]. Calderini et al. (2009) suggest that entrepreneurial activities accelerate knowledge construction by applying research [28]. Fini et al. (2022) found that spin-offs enhance research quality by promoting knowledge exploration [29]. Huan Li et al. (2022) confirmed that academic entrepreneurship improves collaboration and performance [30], helping faculty explore new topics and increase research impact [31,32]. From an incentive compatibility perspective, Thursby (2007) argues that academic entrepreneurship boosts research effort without conflicting with scholarly output, as licensing systems enhance total research effort [33,34]. A 2010 study found that patent licensing increased research volume without reducing basic research [35]. A 2011 study supported the view that commercialization enhances both basic and applied research [36], creating a "win-win" situation by boosting research quality and collaboration.

# RESEARCH DESIGN

# **Research Method**

To investigate the causal relationship between teachers' academic entrepreneurship and their basic research output, an ideal experimental design would involve randomly assigning teachers to intervention (engaged in academic entrepreneurship) and control (not engaged) groups. This would allow for a comparison of research output between the two groups, helping determine the causal effect. However, in social science research, observational data are common, making randomized experiments difficult. Additionally, confounding variables complicate

determining the "net effect" [37]. The Propensity Score Matching (PSM) method, developed by Rosenbaum and Rubin (1983), helps address selection bias and confounding variables. Initially used in biomedicine, PSM is now widely applied across various fields. It identifies control groups that closely match the treatment group, enabling counterfactual inference [38]. However, PSM requires large sample sizes for reliability. This study uses a large sample of faculty from high-level universities in Shaanxi to address endogeneity issues and minimize bias, ensuring accurate sample validity while balancing applicability and precision.

Specifically, this study first calculates the propensity score (Pscore) value by constructing a Logit model, which can be represented by the following formula:

$$P(Xi) = P(AEi = 1/Xi) = \frac{\exp(\beta Xi)}{1+\beta Xi}$$
 (1)

In Equation (1), AEi denotes the treatment variable and Xi denotes the covariate. The Pscore value represents the overall level of interfering factors, and the closer the Pscore values are, the more similar the characteristics of the two groups of research subjects become.

Second, the treatment and control groups are matched based on their calculated propensity scores (Pscore). To ensure robustness, this study uses three methods: k-nearest neighbor matching, kernel matching, and radius matching. Post-matching analyses assess the balance between academic entrepreneurial and non-entrepreneurial faculty across covariates, including evaluating basic matching information, post-matching standardized deviation, the PSM parallel hypothesis test, and the common support test. Finally, treatment effects are estimated using average causal effect (ATT) analysis, where ATT represents the difference in means between the two groups in the post-matched sample, as expressed by the following formula:

$$ATT = E(Y1i/AEi = 1) - E(Y0i/AEi = 0)$$
 (2)

In Equation (2), Y1i denotes the basic research output of teachers involved in academic entrepreneurship and Y0i represents the basic research output of non-academic entrepreneurial teachers. Following propensity score matching, the counterfactual result—the "basic research output of academic entrepreneurship teachers without academic entrepreneurship"—can be approximated by the basic research output of non-academic entrepreneurship teachers.

### Sample data

### Research sample

Due to the difficulty of collecting micro-level data, existing macro-level yearbook data is insufficient for this study. Therefore, the research focuses on science and technology faculty from 17 high-level universities in Shaanxi Province, including seven National 985 and 211 universities, and other top institutions. Universities with specific institutional attributes, like the Air Force University of Medical Sciences, are excluded, as are administrative staff, experimental technicians, expatriates, and retired faculty. By collecting and matching multisource data (CVs, grants, publications, patents, and academic entrepreneurship), this study creates a comprehensive database on university teachers' research and entrepreneurial activities.

The selection of university samples in this study is based on three key factors: (1) High-level universities in Shaanxi provide a sufficient number of academic entrepreneurship samples, as faculty innovations form the basis for such ventures; (2) Academic entrepreneurship is market-driven and influenced by regional factors, so focusing on universities within the same province reduces biases and external variability; (3) The research group is based at a leading university in Shaanxi, enabling effective communication with other institutions and collaborations with provincial and municipal science and technology departments for comprehensive data collection. Shaanxi's status as a science and education hub makes it an ideal choice for both data accessibility and representativeness.

### Data sources

This study compiled a dataset of 18,345 active teachers from 17 universities, focusing on science and technology faculties. Data were manually collected from teachers' personal homepages, including name, gender, birth year, faculty, title, highest degree and graduation year, email, talent title, and foreign mobility experience. For teachers without official websites, birth year data was supplemented using published paper details. Basic research outputs,

such as journal articles, grants, patents, and academic entrepreneurship information, were also gathered. Duplicate records were merged based on birth year, email, and work experience to ensure accuracy. Teachers with the same name within an institution were excluded. After removing records of teachers with degrees earned after 2021 and those without basic research achievements, 13,762 teachers remained for analysis.

The paper data for this sample were sourced from the Web of Science's Science Citation Index (SCI). Using search criteria of "teacher's name = author" and "university name = institution," we conducted multiple searches by varying name spellings and abbreviation conventions. This yielded comprehensive information on authors, corresponding authors, paper titles, publication dates, journal names, impact factors, citation frequencies, discipline categories, and research directions for journal papers published by teachers since 1981. In total, we collected 324,697 journal papers. Patent data were obtained from the State Intellectual Property Office's Patent Information Service Platform and the Innojoy Patent Search Engine, using the search criteria "university = applicant" and "teacher's name = inventor." We retrieved patent details such as patent name, category, status, application number, dates, classification, citations, and survival period, totaling 421,254 patent records. Funding data were sourced from the National Natural Science Foundation of China (NSFC) database on the MedPeer platform, using the search condition "teacher's name = project leader" for funding projects. This provided information on project names, approval numbers, types, funding amounts, and disciplines, resulting in 9,070 faculty funding records from the 17 sample universities.

Academic entrepreneurship data were collected from multiple sources, including the Shaanxi Provincial Department of Science and Technology's list of enterprises transforming scientific achievements (1,232 enterprises as of April 2024), faculty entrepreneur lists from Xi'an and Xianyang city Science and Technology Bureaus, university science and technology division websites, and the "Enterprise Check" database. Since academic entrepreneurship in China became formalized only in 2015, earlier instances were often not publicized. To compile a comprehensive list, the study used existing lists and additional methods: 1) matching enterprises to faculty through transformed scientific achievements and media profiles; 2) searching for entrepreneurial faculty across 17 universities; 3) collecting faculty research data from university websites; 4) using university incubator addresses to search the "Enterprise Search" database and match legal representatives with faculty; and 5) verifying records and removing irrelevant enterprises. Data on 1,363 entrepreneurial enterprises were compiled. The study focused on faculty who began academic entrepreneurial enterprises and 382 entrepreneurial faculty were identified, with 245 included in the final sample after exclusions.

#### Variable Settings

### Variable settings

Dependent variable. The dependent variable is faculty basic research output (Basic Research O), covering both pure and applied basic research outputs [39]. Pure basic research quantity (Pure BRN) is measured by the average annual number of papers (Paper Publish N), first-author papers (F Paper Publish N), and co-authors per paper (Paper Cooperative N). Quality (Pure BRQ) is assessed by citation frequency (Paper Cite N) and journal impact factor (Paper Impact Factor) [40-45]. Following Gong Lei et al. (2024), knowledge exploration is also considered as an indicator of pure basic research quality. Applied research quantity (Applied BRN) is measured by patent applications (Patent Apply N) and NSFC grants (NSFC N), while quality (Applied BRQ) is evaluated by patent citations (Patent Cite N), rights (Patent Right N), and NSFC funding (NSFC F) [46-47].

Independent variable. The independent variable in this study is faculty academic entrepreneurship (AE), represented by the dummy variable faculty academic entrepreneurship identity (AE ID) [48]. Academic entrepreneurship refers to market-oriented behaviors where faculty leverage research outcomes to create spin-off businesses. Faculty with prior or current entrepreneurial experience, including holding legal, shareholder, or management positions in an enterprise, are classified as academic entrepreneurs. These teachers are assigned an AE ID of 1, while those without such involvement are assigned an AE ID of 0. In the propensity-score matching analyses, academic entrepreneurs form the treatment group, while non-entrepreneurs are the control group.

Covariate variable. In the propensity-score matching method, improving counterfactual estimation accuracy requires considering both factors influencing the treatment variable and confounding factors affecting the outcome.

This study includes covariates at individual and organizational levels that impact faculty participation in academic entrepreneurship and basic research performance. Research shows that gender (female faculty often produce less due to domestic labor), age (an inverted U-shaped relationship exists between age and research output), title, work experience in enterprises, research achievements, and institutional resources (e.g., university rankings) influence both academic entrepreneurship and basic research output [49-50]. Therefore, this study includes individual-level variables like gender, academic age, and past productivity, as well as organizational-level variables like faculty size and university ranking as covariates [40,41,46].

### Research Hypotheses

This study, based on faculty mentors' academic entrepreneurship practices, posits that academic entrepreneurship among university faculty fosters a synergistic relationship with basic research output, leading to the core hypothesis H1. Drawing from the established indicator system for both pure and applied basic research output in terms of quantity and quality, the following ten sub-hypotheses are proposed across three dimensions: paper outcomes, patent outcomes, and research funding outcomes:

- H1: Academic entrepreneurship among university faculty positively promotes basic research output.
- H11: Academic entrepreneurship among university faculty positively promotes the number of papers published.
- H12: Academic entrepreneurship among university faculty positively promotes the number of first-author papers published.
- H13: Academic entrepreneurship among university faculty positively promotes the citation frequency of their papers.
- H14: Academic entrepreneurship among university faculty positively promotes the impact factor of the journals in which their papers are published.
- H15: Academic entrepreneurship among university faculty positively promotes the exploration of new knowledge.
- H16: Academic entrepreneurship among university faculty positively promotes the number of patent applications.
- H17: Academic entrepreneurship among university faculty positively promotes the number of National Natural Science Foundation of China (NSFC) grants.
- H18: Academic entrepreneurship among university faculty positively promotes the citation frequency of their patents.
- H19: Academic entrepreneurship among university faculty positively promotes the number of claims in their patents.
- H10: Academic entrepreneurship among university faculty positively promotes the funding amount of NSFC grants.

#### **EMPIRICAL ANALYSIS**

#### Descriptive statistical analysis

To ensure data matching quality and control for the sample, faculty members with no recorded basic research outputs and those who obtained their highest degree no earlier than 2021 were excluded. This resulted in a final sample of 13,762 faculty members for analysis. Descriptive statistics were then performed on the full sample, with the results presented in Table 1.

Academic age is calculated based on the year a faculty member obtained their highest degree. For NSFC funding, grant amounts are evenly distributed from approval to completion. Ongoing projects are allocated over four years, and if multiple grants are received in overlapping years, the amounts are summed. The average NSFC funding per project is then calculated. The final sample includes 13,762 faculty members, with 11,811 having patents, 11,710 with publications, 4,342 with research funding, and 245 engaged in academic entrepreneurship, as shown in Table 1.

Table 1. Descriptive statistics for full-sample variables

Variables	N	Mean	Sd	Min	Max
UniversityR	13,762	6.469	4.591	1	17
FacultyS	13,762	150.7	102.3	1	642
Genders	13,762	0.705	0.456	0	1
AcademicAge	13,762	14.53	7.913	4	43
AE	13,762	0.0178	0.132	0	1
Spin-off T	245	0.680	0.467	0	1
2020PostPaperN	11,710	3.536	4.638	0	86
2020PostFPaperN	11,710	0.0738	0.163	0	1
2020PostPaperCited	11,710	6.556	8.349	0	218
2020PostPaperImpact	11,710	1.000	0.518	0	5.570
NewKnow	11,710	0.730	0.444	0	1
2020PostPatentN	11,811	3.402	5.172	0	115.7
2020PostPatentCited	11,811	0.175	0.390	0	13
2020PostPatentRightN	11,811	1.940	1.471	0	17
2020PostFundN	4,342	0.119	0.162	0	0.670
2020PostFundAmount	4,342	14.02	34.18	0	821
2019PastPaperN	11,710	1.900	4.460	0	191
2019PastFPaperN	11,710	0.0962	0.209	0	4
2019PastPaperCited	11,710	20.26	23.02	0	656
2019PastPaperImpact	11,710	0.819	0.476	0	5.030
2019PastPatentN	11,811	2.262	4.449	0	134
2019PastPatentCited	11,811	1.343	1.613	0	28.50
2019PastPatentRightN	11,811	1.643	1.212	0	9
2019PastFundN	4,342	0.165	0.165	0	3
2019PastFundAmount	4,342	27.43	32.28	0	686

### **Pre-match Balancing Check**

In this study, the sample was divided into a treatment group of academic entrepreneurial teachers and a control group of non-academic entrepreneurial teachers based on their involvement in academic entrepreneurship. To assess whether significant differences exist between the groups in terms of individual characteristics, organizational resources, and basic research outputs before matching, a test was conducted. The results are presented in Table 2.

As shown in Table 2, faculty engaged in academic entrepreneurship have higher average annual publication counts, citation frequencies per paper, and journal impact factors compared to their non-entrepreneurial counterparts. They also engage more in new knowledge exploration. Additionally, academic entrepreneurs have higher averages in patent applications, NSFC grants, patent citation frequencies, and funding per NSFC grant. They tend to have more academic experience, belong to larger departments, and are affiliated with higher-ranked universities. In summary, academic entrepreneurs produce more basic research output, both in quantity and quality, with greater efficiency. The mean differences in several outcome variables between the two groups are statistically significant, justifying the application of the PSM method for the next phase of analysis.

Table 2. Analysis of variance for key variables

Variables		Control		Treated	MeanDiff	# Value
variables	N	Mean	N	Mean	MeanDill	p-Value
2020PostPaperN	11508	3.470	202	7.323	-3.854	0.000***
2020PostFPaperN	11508	0.0740	202	0.0540	0.0200	0.090*
2020PostPaperCited	11508	6.546	202	7.122	-0.576	0.331
2020PostPaperImpact	11508	0.998	202	1.086	-0.0880	0.017**
NewKnow	11508	0.728	202	0.876	-0.149	0.000***
2020PostPatentN	11582	3.329	229	7.125	-3.797	0.000***
2020PostPatentCited	4260	0.118	82	0.137	-0.0180	0.308
2020PostPatentRightN	11582	0.174	229	0.219	-0.0450	0.086*
2020PostFundN	11582	1.947	229	1.571	0.376	0.000***
2020PostFundAmount	4260	13.90	82	20.19	-6.292	0.099*
2019PastPaperN	13517	1.581	245	3.626	-2.046	0.000***
2019PastFPaperN	13517	0.0820	245	0.0650	0.0170	0.172
2019PastPaperCited	13517	17.22	245	18.34	-1.128	0.435
2019PastPaperImpact	13517	0.697	245	0.682	0.0150	0.654
2019PastPatentN	13517	1.909	245	3.756	-1.848	0.000***
2019PastPatentCited	13517	0.457	245	0.604	-0.147	0.023**
2019PastPatentRightN	13517	1.147	245	1.402	-0.256	0.011**
2019PastFundN	13517	1.410	245	1.267	0.144	0.077*
2019PastFundAmount	13517	8.577	245	12.92	-4.341	0.002***
AcademicAge	13517	14.48	245	17.22	-2.740	0.000***
Genders	13517	0.703	245	0.837	-0.134	0.000***
FacultyS	13517	150.5	245	161.4	-10.91	0.098*
UniversityR	13517	6.500	245	4.735	1.766	0.000***

Note: \*\*\* denotes p<0.01, \*\* denotes p<0.05, \* denotes p<0.1

# **Estimation of Propensity Index**

Table 3. Estimation of propensity index: Logit model

Variables	Coefficient	Odds ratio	Std. err.	Z	P> z			
2019PastPaperN	0.030***	1.031	0.009	3.28	0.001			
2019PastFPaperN	-0.552	0.576	0.436	-1.27	0.205			
2019PastPaperCited	0.0023	1.002	0.0031	0.73	0.463			
2019PastPaperImpact	-0.5770**	0.585	0.2580	-2.24	0.025			
2019PastPatentN	0.026***	1.027	0.0090	2.93	0.003			
2019PastPatentCited	-0.111*	0.895	0.0693	-1.61	0.100			
2019PastPatentRightN	0.077**	1.080	0.0368	2.10	0.036			
2019PastFundN	-0.137**	0.872	0.0664	-2.06	0.039			
2019PastFundAmount	0.002**	1.002	0.0023	0.74	0.460			
AcademicAge	0.033***	1.033	0.0081	4.07	0.000			
Genders	0.520***	1.682	0.178	2.92	0.003			
FacultyS	-0.000	1.0009	0.0007	-0.47	0.640			
UniversityR	-0.072***	0.931	0.0189	-3.79	0.000			
_cons	-4.991	0.007	0.494	-10.09	0.000			
Number of obs	13762							
R <sup>2</sup>	0.0735							
Log likelihood	-1139.4102							

Note: \*\*\* denotes p<0.01, \*\* denotes p<0.05, \* denotes p<0.1

This study uses Stata 17.0 software to estimate the propensity scores for faculty engagement in academic entrepreneurship. All potential variables influencing academic entrepreneurship are included in a Logit regression model, and the odds ratios for each covariate are calculated to analyze their effects. The results are presented in Table 3.

The results show that faculty with higher publication counts and patent applications are more likely to engage in academic entrepreneurship, while higher journal impact factors and NSFC grants decrease this likelihood. Patent citation frequency and NSFC funding positively correlate with entrepreneurial activity, while more patent claims have a negative effect. Older faculty and males are more likely to engage in entrepreneurship, as are those from higher-ranked universities. These findings emphasize the need to account for these variables when analyzing the impact of academic entrepreneurship on research output, and suggest that traditional OLS regression cannot adequately address selection bias in this study.

#### **Propensity Score Matching Estimation Results**

#### Matching validity tests

Table 4. Bias reduction before and after variable matching

Variables		Me	ean	%bias	%reduct	t-test	
variables		Control	Treated	7001as	70reduct	t	p> t
2019PastPaperN	Unmatched	4.398	1.856	32.30	35.60	8.050	0
2019PastPaperN	Matched	4.398	2.762	20.80	33.00	2.020	0.0440
2019PastFPaperN	Unmatched	0.0787	0.0965	-9.500	93.60	-1.200	0.232
2019PastrPaperN	Matched	0.0787	0.0799	-0.600	93.00	-0.0600	0.949
2019PastPaperCited	Unmatched	22.25	20.22	9.900		1.240	0.215
2019FastraperCited	Matched	22.25	20.80	7.100	28.40	0.780	0.434
2019PastPaperImpact	Unmatched	0.827	0.819	2		0.240	0.808
2019PastPaperImpact	Matched	0.827	0.790	8.800	-347.8	0.990	0.323
2019PastPatentN	Unmatched	3.700	1.819	34.40		6.760	0
2019PastPatentiN	Matched	3.700	3.096	11	67.90	0.940	0.345
2019PastFundN	Unmatched	0.698	0.516	15.90		2.420	0.0150
2019PastrundN	Matched	0.698	0.728	-2.600	83.70	-0.240	0.813
2019PastPatentCited	Unmatched	1.414	1.132	18.90		2.510	0.0120
2019FastFateIItCited	Matched	1.414	1.553	-9.400	50.40	-0.600	0.548
2019PastPatentRightN	Unmatched	1.210	1.361	-13.80		-1.680	0.0920
2019PastPatentRightN	Matched	1.210	1.104	9.700	30	1.120	0.262
2019PastFundAmount	Unmatched	15.03	9.641	18.50		3.240	0.00100
2019PastFundAmount	Matched	15.03	14.24	2.700	85.50	0.230	0.820
AcademicAge	Unmatched	17.09	14.47	32.40		4.670	0
AcademicAge	Matched	17.09	17.04	0.700	97.70	0.0700	0.944
Genders	Unmatched	0.827	0.703	29.40		3.820	0
Genuers	Matched	0.827	0.866	-9.400	67.90	-1.100	0.271
FacultyS	Unmatched	162.7	152.7	9.800		1.360	0.175
racunys	Matched	162.7	169.2	-6.300	35.90	-0.600	0.546
UniversityR	Unmatched	4.584	6.156	-35.60		-4.930	0
Olliveishyk	Matched	4.584	4.713	-2.900	91.80	-0.300	0.761

After estimating the propensity values using the Logit model, propensity score matching (PSM) is performed. To ensure the reliability of the matching effect, it is crucial to test whether the matched samples meet both the balance and common support assumptions. The results of the balance test are presented in Table 4 and Figure 1a, while the results of the common support test are displayed in Figure 1b and Figure 2.

As shown in Table 4, after propensity score matching, the standard deviations of all variables, except for the average number of papers published before 2019, are below 10%. The standard error for the journal impact factor increased, but the others decreased. T-test results show no significant differences between the treatment and control groups, indicating reduced differences and addressed sample heterogeneity. Figure 1a shows that the standard deviations for both groups are below 20%, confirming effective matching and meeting the balance assumption.

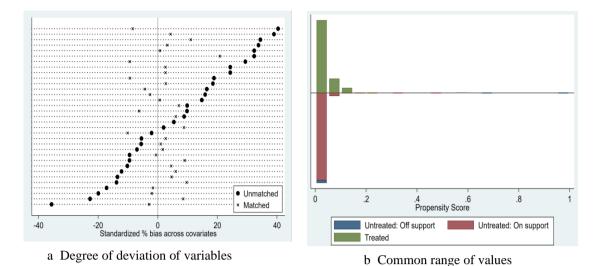
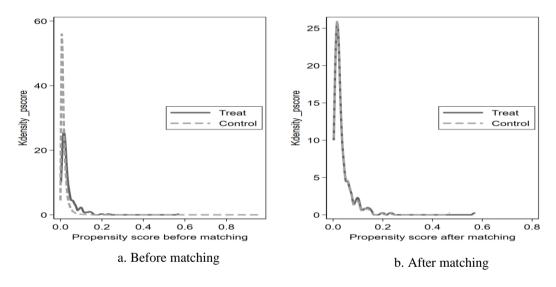


Figure 1. Degree of deviation of variables before and after propensity score matching and Common range of values for the propensity score



Figue 2. Kernel density function before and after propensity score matching

As shown in Figure 1b, most observations fall within the common range, with minimal systematic differences between the treatment and control groups post-matching. In Figure 2, the kernel density plots of the propensity scores before matching show significant deviations, but after matching, the curves for both groups align well. This suggests that the matching effect is satisfactory and meets the common support hypothesis.

### Propensity score matching estimation results

After passing the matching validity test, this study empirically analyzes the relationship between teachers' academic entrepreneurship and their basic research outputs. The study uses three matching methods—k-nearestneighbor matching, radius matching, and kernel matching—to estimate the average treatment effect (ATT) for the sample. The estimation results are presented in Table 5.

As shown in Table 5, matching reduces the difference in basic research output between the groups, indicating that without matching, the impact of academic entrepreneurship would be overestimated. PSM effectively controls for endogeneity and bias, with robust results across methods. Academic entrepreneurship significantly boosts faculty publication count, knowledge exploration, patent applications, and citations, enhancing both quantity and quality of research. It increased citation frequency and journal impact factor in pure basic research but decreased firstauthor papers, with no significant differences. Thus, hypotheses H12, H13, and H14 are not supported. However, it increased publication count and knowledge exploration, supporting H11 and H15. In applied research, academic

entrepreneurship increased NSFC grants and funding but reduced patent claims, with no significant differences, so H17, H19, and H10 are not supported. It did, however, increase patent applications and citations, supporting H16 and H18.

Table 5. Results of propensity value matching estimation

Variables		Methods	Control	Treated	ATT	S.E.	T-stat
	Unmatched		6.0381	2.9540	3.0841	0.2863	10.77***
2020D4D N		KNN matching	6.0381	3.6748	2.3633	0.6506	3.63***
2020PostPaperN	Matched	Radius matching	5.8176	3.6966	2.1209	0.6078	3.49***
		Nuclear matching	5.8675	3.2974	2.5701	0.6063	4.24***
	Unmatched		0.0449	0.0631	-0.0182	0.0099	-1.84*
2020D (ED. N		KNN matching	0.0449	0.0454	-0.0005	0.0098	-0.06
2020PostFPaperN	Matched	Radius matching	0.0453	0.0526	-0.0073	0.0090	-0.81
		Nuclear matching	0.0451	0.0571	0.0120	0.0088	-1.36
	Unmatched		5.8724	5.5735	0.2988	0.5188	0.58
2020D4DCi4-4		KNN matching	5.8724	5.7379	0.1345	0.4698	0.29
2020PostPaperCited	Matched	Radius matching	5.8363	5.7603	0.0760	0.4241	0.18
		Nuclear matching	5.8436	5.6039	0.2396	0.4177	0.57
	Unmatched		0.8955	0.8500	0.0455	0.0384	1.19
2020D (D. I.		KNN matching	0.8955	0.8610	0.0346	0.0425	0.81
2020PostPaperImpact	Matched	Radius matching	0.8942	0.8772	0.0170	0.0388	0.44
		Nuclear matching	0.8943	0.8555	0.0388	0.0383	1.01
	Unmatched		0.8762	0.7277	0.1486	0.0315	4.72***
N Z	Matched	KNN matching	0.8762	0.7792	0.0970	0.0283	3.43***
NewKnow		Radius matching	0.8756	0.7781	0.0976	0.0244	3.99***
		Nuclear matching	0.8756	0.7461	0.1295	0.0238	5.43***
	Unmatched		6.6600	2.8522	3.8079	0.3166	12.03***
2020D (D. (A)	Matched	KNN matching	6.6600	4.4093	2.2508	0.6019	3.74***
2020PostPatentN		Radius matching	6.4981	4.4200	2.0781	0.5619	3.70***
		Nuclear matching	6.5726	3.6060	2.9666	0.5630	5.27***
	Unmatched		0.0458	0.0373	0.0085	0.0069	1.24
2020D 4E IN		KNN matching	0.0458	0.0375	0.0084	0.0084	0.99
2020PostFundN	Matched	Radius matching	0.0462	0.0380	0.0082	0.0077	1.06
		Nuclear matching	0.0460	0.0375	0.0085	0.0077	1.11
	Unmatched		0.2048	0.1494	0.0554	0.0236	2.34**
2020D (D. (C') 1		KNN matching	0.2048	0.1827	0.0221	0.0309	2.02**
2020PostPatentCited	Matched	Radius matching	0.2062	0.1556	0.0506	0.0254	1.99**
		Nuclear matching	0.2054	0.1528	0.0526	0.0251	2.09**
	Unmatched		1.4684	1.6682	-0.1997	0.0981	-2.04**
2020D (D. (D. 1.27		KNN matching	1.4684	1.4995	-0.0311	0.0881	-0.35
2020PostPatentRightN	Matched	Radius matching	1.4783	1.5541	-0.0758	0.0766	-0.99
		Nuclear matching	1.4734	1.6178	-1.1444	0.0754	-1.91*
	Unmatched		6.7586	4.3811	2.3775	1.3068	1.82*
2020D 4E 14		KNN matching	6.7586	4.4893	2.2692	1.8104	1.25
2020PostFundAmount	Matched	Radius matching	6.8142	5.6203	1.1939	1.7496	0.68
		Nuclear matching	6.7863	4.9004	1.8858	1.7342	1.09

Note: \*\*\* denotes p<0.01, \*\* denotes p<0.05, \* denotes p<0.1

The failure of hypothesis H12 may be due to academic entrepreneurship shifting faculty from "researchers" to "entrepreneurial managers," focusing on resource integration and commercialization, leaving less time for indepth research. Increased collaboration may also dilute first authorship. The failure of hypothesis H13 could result from faculty shifting to applied research, which attracts fewer citations, and from reduced time for high-impact research. External factors like field popularity and collaborations also affect citation frequency. The failure of hypothesis H14 may arise from faculty prioritizing technology-focused publications in journals with lower impact

factors. Entrepreneurial activities may limit time for high-impact research, leading faculty to focus on quicker, impactful work rather than long-term, high-quality journal papers.

The failure of hypothesis H17 may result from academic entrepreneurship shifting faculty focus to short-term applied research and commercialization, reducing attention to foundational research needed for NSFC applications. Entrepreneurial funding from enterprises often prioritizes technology over basic research. The failure of hypothesis H19 may be due to faculty focusing on rapid commercialization, leading to narrower patent claims to protect key technologies and reduce enforcement costs. The failure of hypothesis H10 may be due to entrepreneurial faculty applying for smaller, more focused projects, limiting larger grants. NSFC funding favors theoretical depth, and faculty may prioritize industrialization over basic research.

# **Robustness Analysis**

Although this study included many matching variables, omitted variables or selection biases may still affect the results. To ensure robustness, sensitivity analyses were conducted using the Rosenbaum bounds method, based on the matching validity test and three matching methods. The Gamma value indicates the sensitivity to unobserved factors, with values closer to 1 showing higher sensitivity and values closer to 2 indicating lower sensitivity. A larger Gamma value suggests greater result robustness, as shown in Table 6.

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0.0207	0.0207	1.3266	1.3266	10.7738	12.6063
1.2	0.0282	0.0104	1.0405	1.7298	9.3845	14.1943
1.4	0.0345	0.0051	0.9203	1.8977	7.9725	14.805
1.6	0.0372	0.0023	0.9121	2.0158	6.4655	14.805
1.8	0.0445	0.0008	0.3096	2.2914	5.9373	16.176
2	0.0497	0.0001	0.1326	2.3999	4.2234	16.8653
2.2	0.0524	0.0000	0.0444	2.5084	2.5254	16.8653
2.4	0.0677	0.0000	0.3305	2.9806	1.6667	26.4909
2.6	0.0736	0.0000	-0.3305	2.9806	-1.5568	26.4909
2.8	0.0888	0.0000	-0.6551	3.1191	-2.6679	37.0867
3	0.0969	0.0000	-0.7982	3.4992	-4.9987	39.5568

Table 6. Rosenbaum boundary sensitivity analysis

As shown in Table 6, Gamma values between 1 and 2 are statistically significant at the P=0.05 confidence level, indicating that the model's average treatment effect (ATT) is valid without treatment bias. The Hodges-Lehmann (HL) estimate does not include 0 in the 95% confidence intervals, suggesting statistical significance. The ATT remains valid until the Gamma value exceeds 2.6, beyond which the HL estimate's confidence interval includes 0, indicating sensitivity to hidden bias. Overall, the ATT is robust, and significant hidden bias would be needed to alter the results.

# HETEROGENEITY ANALYSIS

# **Disciplinary Heterogeneity**

There are significant differences in academic entrepreneurship status and basic research output between faculty in science and engineering disciplines. Thus, it is important to further analyze the differential impact of academic entrepreneurship on the basic research output of science versus engineering faculty. Faculty are classified based on departmental divisions; for example, the Department of Basic Geology at Xi'an Shiyou University is classified as a "science" department (Science 1), as are the Department of Basic Teaching at Shaanxi University of Science and Technology and the School of Communication and Information Engineering at Xi'an University of Posts and Telecommunications. The results of this analysis are presented in Table 7.

Table 7. Impact of academic entrepreneurship of faculty with different disciplinary attributes on basic research outputs

Voriables	Variables		Science	faculty	Engineering faculty	
variables		Methods	ATT	T-stat	ATT	T-stat
		Unmatched	3.7702	4.45	2.9779	9.88***
2020PostPaperN		KNN matching	2.6728	1.40	2.4920	3.59***
2020PostPaperN	Matched	Radius matching	2.5938	1.44	2.1452	3.30***
		Nuclear matching	2.1862	1.26	2.4930	3.84***
		Unmatched	-0.0056	-0.18	-0.0196	-1.88*
2020PostFPaperN		KNN matching	0.0062	0.16	-0.0006	-0.06
2020F0StrFaperN	Matched	Radius matching	0.0216	0.57	-0.0094	-1.05
		Nuclear matching	0.0153	0.42	-0.1378	-1.55
		Unmatched	0.6489	0.38	0.2060	0.38
2020DoctDomanCited		KNN matching	-0.4982	-0.29	-0.0876	-0.16
2020PostPaperCited	Matched	Radius matching	0.2136	0.22	0.0517	0.11
		Nuclear matching	0.2939	0.31	0.1789	0.39
		Unmatched	0.1360	1.12	0.0319	0.79
2020D+DI		KNN matching	0.0950	0.75	-0.0056	-0.12
2020PostPaperImpact	Matched	Radius matching	-0.0130	-0.12	0.0106	0.26
		Nuclear matching	0.0397	0.36	0.0271	0.66
		Unmatched	0.2169	2.12**	0.1355	4.13***
N. W		KNN matching	0.1705	1.81*	0.1072	3.60***
NewKnow	Matched	Radius matching	0.1679	1.72*	0.0994	3.85***
		Nuclear matching	0.1431	1.70*	0.1203	4.77***
		Unmatched	2.5609	4.34***	3.8628	10.94***
2020D (D.) (M		KNN matching	1.5255	1.65*	2.0626	3.02***
2020PostPatentN	Matched	Radius matching	1.4934	1.64*	2.0177	3.24***
		Nuclear matching	1.5103	1.72*	2.9875	4.81***
		Unmatched	0.0201	0.94	0.0075	1.04
2020D (F 1N		KNN matching	-0.0153	-0.53	0.0062	0.70
2020PostFundN	Matched	Radius matching	-0.0060	-0.24	0.0077	0.95
		Nuclear matching	0.0070	0.27	0.0081	1.00
		Unmatched	0.1114	1.14	0.0490	2.16**
2020D (D) (G) 1		KNN matching	-0.0706	-0.48	0.0483	1.69*
2020PostPatentCited	Matched	Radius matching	-0.1323	-1.72*	0.0502	1.85*
		Nuclear matching	-0.0341	-0.47	0.0503	1.86*
		Unmatched	0.3449	1.09	-0.2878	-2.82***
2020D (D : (D' 1.2)		KNN matching	0.2639	1.01	-0.1013	-1.08
2020PostPatentRightN	Matched	Radius matching	0.0034	0.01	-0.1102	-1.36
		Nuclear matching	0.1075	0.45	-0.2028	-2.54**
		Unmatched	0.9443	0.26	2.6113	1.87
2020D - F - 1:		KNN matching	-1.1569	-0.39	0.5534	0.26
2020PostFundAmount	Matched	Radius matching	-2.1068	-0.89	1.4305	0.74
		Nuclear matching	-0.2133	-0.08	2.1522	1.12

Note: \*\*\* denotes p<0.01, \*\* denotes p<0.05, \* denotes p<0.1

Overall, the sensitivity of academic entrepreneurship's impact on the basic research output of engineering faculty is greater than that of science faculty. Specifically, academic entrepreneurship significantly enhances new knowledge exploration and the average number of patent applications per year for both groups. However, it notably positively affects the average number of papers published per year and the average number of patent citations specifically among engineering faculty. This discrepancy can be attributed to the fact that science disciplines prioritize theoretical basic research, while engineering disciplines are more focused on applied research, which facilitates practical transformations.

### **Talent Titles Heterogeneity**

The academic entrepreneurship status and the level of basic research output among faculty with different talent titles show significant differences. Therefore, it is important to further examine the impact of academic

entrepreneurship on the basic research output of faculty with talent titles compared to those without. The results are presented in Table 8, where (1) represents faculty with talent titles and (2) represents those without.

Table 8. Impact of different categories of faculty academic entrepreneurship on basic research outputs

Variables		Methods	(1)	(2)	(3)	(4)
	-	Unmatched	2.8678***	3,1037***	4.0086***	3.2966***
20200 (D. 31		KNN matching	0.7667	-2.5357*	2.3571***	1.9016***
2020PostPaperN	Matched	Radius matching	0.8992	-1.9441*	1.9287***	1.8959***
		Nuclear matching	1.3567	-1.9579*	2.4624***	2.3627***
	-	Unmatched		-0.0183	0.0433	-0.0247**
2020D4ED NI		KNN matching	-0.0093	-0.0146	0.0357	-0.0129
2020PostFPaperN	Matched	Radius matching	-0.0107	-0.0053	0.0862	-0.0112
		Nuclear matching	-0.0112	-0.0120	0.0894	-0.0168*
	-	Unmatched	-0.0689	-0.0539	-2.0855**	-5.4042*
2020D4DC'4-4		KNN matching	0.2267	-0.4020	-5.5818***	-0.1244
2020PostPaperCited	Matched	Radius matching	-0.1305	-0.1165	-7.5364***	0.1723
		Nuclear matching	0.1674	-0.1360	-5.9864***	0.2489
	-	Unmatched	-0.0032	-0.0005	-0.1029	0.0838
2020D (D. I)		KNN matching	-0.0197	-0.0358	0.0934	-0.0066
2020PostPaperImpact	Matched	Radius matching	-0.0014	-0.0119	0.0808	-0.0110
		Nuclear matching	0.0072	-0.0107	0.0846	0.0036
	Unmatched		-0.0232	0.1789***	0.0970*	0.0746
NV	Matched	KNN matching	0.0244	0.1543***	0.1667	0.1300***
NewKnow		Radius matching	0.0213	0.1462***	0.0790	0.1224***
		Nuclear matching	0.0084	0.1667***	0.0614	0.1421***
	-	Unmatched		2.9815***	2.6918***	2.2842
2020PostPatentN		KNN matching	3.6594*	1.7938***	2.535	2.6597***
2020PostPatentin	Matched	Radius matching	2.8245*	1.9669***	2.3420	2.1005***
		Nuclear matching	4.8426**	2.4530***	2.1193	3.0990***
	Unmatched		-0.0347*	0.0127	-0.0054	-0.0277
2020PostFundN		KNN matching	-0.0218	0.0037*	-0.0707	0.0120
2020Postrulian	Matched	Radius matching	-0.0136	0.0124	-0.0218	0.0079
		Nuclear matching	-0.0173	0.0128	-0.0163	0.0088
	-	Unmatched		0.0762***	0.0414	-0.0016
2020PostPatentCited		KNN matching	0.023	0.0533**	-0.1736	0.0653**
2020PostPatentCited	Matched	Radius matching	0.0203	0.0631**	-0.0632	0.0612**
		Nuclear matching	0.0230	0.0729***	-0.0710	0.0613**
	-	Unmatched	-0.0007	-0.2007*	-0.2034	-0.0955
2020DogtDotomtDial-tNI		KNN matching	0.3797*	-0.1830*	0.1946	-0.0410
2020PostPatentRightN	Matched	Radius matching	0.2115	-0.1220*	-0.1409	-0.0492
		Nuclear matching	0.2139	-0.1702**	-0.1976	-0.1237
	-	Unmatched	-6.2635	2.9657**	-0.1834	-3.2376
2020PostFundAmount		KNN matching	-3.9556	1.6445	-4.3071	1.1472
2020F08ti uliaAiliount	Matched	Radius matching	-2.2973	2.2797	-1.9789	1.0746
		Nuclear matching	-3.1393	2.6646	-2.4826	1.9473

Note: \*\*\* denotes p<0.01, \*\* denotes p<0.05, \* denotes p<0.1

As shown in Table 8, the impact of academic entrepreneurship on basic research output differs among educators with varying talent titles. Overall, the sensitivity of this impact is greater for teachers without talent titles than for those with them. Specifically, academic entrepreneurship positively and significantly affects the average annual

number of patent applications among teachers with talent titles. In contrast, for teachers without talent titles, it positively and significantly influences their average annual number of published papers, exploration of new knowledge, average annual patent applications, and patent citations, but has a negative and significant effect on the average number of patent claims. This disparity may be due to teachers with talent titles struggling with the dual role of educator and entrepreneur, which can limit their effectiveness.

#### **Overseas Study Experiences Heterogeneity**

The academic entrepreneurship status and basic research output levels of teachers with varying overseas study experiences show significant differences. Therefore, it is crucial to further analyze the impact of academic entrepreneurship on the basic research output of teachers with and without overseas study experiences. This study focuses exclusively on overseas study during the doctoral stage, specifically the attainment of a doctoral degree in a foreign country, excluding overseas study visits, postdoctoral experiences, and other forms of overseas work. The results are presented in Table 8, where (3) represents teachers with overseas study experience and (4) represents those without.

As shown in Table 8, the impact of academic entrepreneurship on research output differs between faculty with and without overseas study experience. The effect is stronger for those without overseas experience. While academic entrepreneurship boosts publications for both groups, it significantly increases citation frequency only for faculty with overseas study experience. For faculty without such experience, it also positively affects new knowledge exploration, patent filings, and patent citations. This difference may be due to the academic resources of faculty with foreign doctorates being less influential in academic entrepreneurship than those of locally trained faculty.

### CONCLUSIONS AND IMPLICATIONS

Academic entrepreneurship activities by university faculty can divert their time and energy from fundamental research, raising concerns about a potential decline in basic research output. This may influence policy support for academic entrepreneurship. This study aims to explore how academic entrepreneurship among university faculty in China affects their basic research output and assess whether there is a need to support or oppose such entrepreneurial activities.

Our findings show that academic entrepreneurship among university faculty is associated with higher average annual publication counts, increased exploration of new knowledge, and a greater number of patent applications and citations. This suggests a positive and significant effect on both the quantity and quality of basic research outputs. The impact of academic entrepreneurship on basic research is more pronounced among engineering faculty than science faculty. Additionally, faculty without talent titles are more sensitive to this impact than those with talent titles, and those without overseas study experience are more sensitive than their counterparts with such experience. This may be because faculty, regardless of academic entrepreneurship, prioritize their academic roles and research outputs. Moreover, academic entrepreneurship narrows the gap between the laboratory and the market, aligning faculty research with real-world needs and enhancing research quality, especially in applied sciences, engineering, and technology. Thus, both policy systems and organizational resources should support academic entrepreneurship among faculty. Targeted support strategies should be developed for faculty with different profiles. For example, policies should prioritize engineering over pure science fields and provide enhanced support for faculty without state-endorsed talent titles. Faculty without international exposure should also receive more substantial entrepreneurial empowerment compared to their globally networked counterparts.

The primary contribution of this study is to clarify the relationship between university teachers' academic entrepreneurship and their basic research outputs by constructing a micro-database that captures the multiple roles of a large sample of faculty, filling a gap in existing research. However, the study has two key limitations. First, due to difficulties in obtaining data on academic entrepreneurship, the study is limited to high-level universities in Shaanxi province, a representative region in China, which may limit the generalizability of the findings to other countries. Second, while the study explores the impact of academic entrepreneurship on basic research output, it does not fully address the underlying mechanisms. Future research is needed to further investigate the logical chain linking academic entrepreneurship to basic research output. These limitations suggest possible avenues for further exploration.

#### **REFRENCES**

- [1] Shibayama S. Conflict between entrepreneurship and open science, and the transition of scientific norms. Journal of Technology Transfer, 2012, 37(4):508-531.
- [2] Gulbrandsen M, Smeby JC. Industry funding and university professors'research performance. Research Policy,2005,34(6):932-950.
- [3] Abramo G, D'Angelo CA, Ferretti M, et al. An individual-level assessment of the relationship between spin-off activities and research performance in universities. R & D Management: Research and Development Management, 2012,42(3):225-242.
- [4] Prodan I, Slavec A. Academic entrepreneurship: what changes when scientists become academic entrepreneurs? // BURGER-HELMCHEN T(ed). Entrepreneurship-Born, Made and Educated. Rijeka: InTech,2012:159.
- [5] Barletta F, Yoguel G, Pereira M, et al. Exploring scientific productivity and transfer activities: Evidence from Argentinean ICT research groups. Research Policy, 2017, 46(8):1361-1369.
- [6] Jain S, George G, Maltarich M. Academics or entrepreneurs? Investigating role identity modification of university scientists involved in commercialization activity. Research Policy, 2009 (38): 922-935.
- [7] Adelowo CM, Surujlal J. Academic entrepreneurship and traditional academic performance at universities: evidence from a developing country. Polish Journal of Management Studies, 2020, 22(1):9-25.
- [8] Nelson RR. The market economy, and the scientific commons. Research Policy, 2004, 33(3):455-471.
- [9] Murray F, Stern S. Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. Journal of Economic Behavior&Organization, 2007, 63(4):648-687.
- [10] Prodan I, Slavec A. Academic entrepreneurship: what changes when scientists become academic entrepreneurs? // Burger-Helmchen T(ed). Entrepreneurship-Born, Made and Educated. Rijeka: InTech, 2012:159.
- [11] Guo F, Zou B, Li YX, Wu HY. Research on Academic Entrepreneurs' Identity Paradox Integration from the Perspective of Social Identity. R&D Management, 2019, 31(02):34-43. (in Chinese)
- [12] Xiong WM, Yu WX, Chen CM. Process of Academic Entrepreneur's Role Reconstruction-Multi-Case Study from the Perspective of Psychological Goal Dynamics. R&D Management, 2021, 33(05):25-39+182. (in Chinese)
- [13] Perkmann M, Tartari V, Mckelvey M, et al. Academic Engagement and Commercialization: A Review of the Literature on University-Industry Relations. 2013, 42(2):423-442.
- [14] Czarnitzki D, Grimpe C, Toole A A. Delay and secrecy: does industry sponsorship jeopardize disclosure of academic research? Industrial and Corporate Change, 2015, 24(1):251-279.
- [15] Buenstorf G. Is commercialization good or bad for science? Individual-level evidence from the max planck society. Research Policy, 2009, 38(2):281-292.
- [16] Toole A A, Czarnitzki D. Commercializing Science: Is There a University "Brain Drain" from Academic Entrepreneurship? Management Science, 2010, 56(9):1599-1614.
- [17] Lowe R A, Gonzalez-Brambila C. Faculty entrepreneurs and research productivity. Journal of Technology Transfer, 2007, 32(3):173-194.
- [18] Fabrizio KR, Di Minin A. Commercializing the laboratory: faculty patenting and the open science environment. Research Policy, 2008, 37 (5):914-931.
- [19] Breschi S, Lissoni F, Montobbio F. The scientific productivity of academic inventors: new evidence from Italian data. Economics of Innovation and New Technology, 2007,16 (2):71-99.
- [20] D'Este P, Patel P. University-industry linkages in the UK: What are the factors underlying the variety of interactions with industry? Research Policy, 2007, 36(9):1295-1313.
- [21] Bikard M, Vakili K, Teodoridis F. When Collaboration Bridges Institutions: The Impact of University-Industry Collaboration on Academic Productivity. Organization Science, 2019, 30(2):426-445.
- [22] Van Looy B, Ranga M, Callaert J, et al. Combining entrepreneurial and scientific performance in academia: towards a compounded and reciprocal Matthew-effect? Research Policy, 2004, 33(3):425-441.
- [23] Powers JB, McDougall PP. University start-up formation and technology licensing with firms that go public: a resource-based view of academic entrepreneurship. Journal of Business Venturing, 2005, 20(3): 291-311.

- [24] Buenstorf, G. Is commercialization good or bad for science? Individual-level evidence from the Max Planck Society. Research Policy, 2009, 38(2): 281-292.
- [25] Silva MD. Academic entrepreneurship and traditional academic duties: Synergy or rivalry? Studies in Higher Education, 2015, 41(12):2169-2183.
- [26] Meyer MS. Academic Inventiveness and Entrepreneurship: On the Importance of Start-up Companies in Commercializing Academic Patents. Journal of Technology Transfer, 2006, 31(4):501-510.
- [27] Fabrizio KR, Di Minin A. Commercializing the laboratory: faculty patenting and the open science environment. Research Policy, 2008, 37 (5):914-931.
- [28] Calderini M, Franzoni C, Vezzulli A. The unequal benefits of academic patenting for science and engineering research. IEEE Transactions on Engineering Management, 2009, 56(1):16-30.
- [29] Fini R, Perkmann M, Ross J M. Attention to Exploration: The Effect of Academic Entrepreneurship on the Production of Scientific Knowledge. Organization Science, 2022, 33(2):688-715.
- [30] Huan Li, Xi Yang, and Xinlan Cai. Academic spin-off activities and research performance: The mediating role of research collaboration." The Journal of Technology Transfer, 2022, 47 (4): 1037-1069.
- [31] Shichijo N, Sedita SR, Baba Y. How does the entrepreneurial orientation of scientists affect their scientific performance? Evidence from the quadrant model. Technology Analysis and Strategic Management, 2015, 27(9): 999-1013.
- [32] Van Looy B, Callaert J, Debackere K. Publication and patent behavior of academic researchers: Conflicting, reinforcing or merely co-existing? Research Policy, 2006, 35(4):596-608.
- [33] Thursby M, Thursby J, Gupta-Mukherjee S. Are There Real Effects of Licensing on Academic Research? A Life Cycle View. Journal of Economic Behavior & Organization, 2007, 63(4):577-598.
- [34] Thursby JG, Thursby MC. University licensing. Oxf Rev Econ Policy, 2007, 23(4):620-639.
- [35] Thursby JG, Thursby MC. University Licensing: Harnessing or Tarnishing Faculty Research? Innovation Policy and the Economy,2010,10(1):159-189.
- [36] Thursby JG, Thursby M C. Has the Bayh-Dole act compromised basic research? Research Policy, 2011, 40(8):1077-1083.
- [37] Hu AN. Propensity Score Matching and Causal Inference: A methodological review. Sociological Studies, 2012(1):221-242, 246. (in Chinese)
- [38] Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. Biometrika, 1983, 70(1):41-55.
- [39] Stokes D. Pasteur's Quadrant: Basic Science and Technological Innovation. Washington, D.C.: Brookings Institution Press, 1997.
- [40] Yang X, Li H. How Does Academic Entrepreneurship Affect Academics'Research Output? Data from Material Faculties at "Double First-Class" Construction Universities. China Higher Education Research, 2021, (03):37-43. (in Chinese)
- [41] Su Y. The Impact of Academic Entrepreneurship on Their Scientific Research Output: Evidence from Propensity-Score Matching. Fudan Education Forum, 2023, 21(04):114-121. (in Chinese)
- [42] Huan Li, Xi Yang, and Xinlan Cai. Academic spin-off activities and research performance: The mediating role of research collaboration. The Journal of Technology Transfer, 2022, 47(4):1037-1069.
- [43] Zhu JW, Liu NC. Research Performance of Chinese Universities from 1978 to 2009. Journal of Higher Education, 2010, 31(11):57-63. (in Chinese)
- [44] Chen KH, Zhang Y, Mu RP. The international comparison of the basic research capability in the science and technology field-Evidence from the field of energy storage. Studies in Science of Science, 2017, 35(01):34-44. (in Chinese)
- [45] Peng HT, Peng QH. Basic Research, Applied Research and Innovation Performance in Universities. Forum on Science and Technology in China, 2023, (11):46-55. (in Chinese)
- [46] Gong L, Chen Q, Chang XH, Shen TT. Research on the effect of academic entrepreneurship on faculty research output: The mediating role of knowledge exploration. Studies in Science of Science, 2024, 42(03):583-593. (in Chinese)
- [47] Arora A, Belenzon S, Sheer L. Knowledge Spillovers and Corporate Investment in Scientific Research. American Economic Review, 2021, 111(3):871-898.

- [48] Zhang XC, Yu ZY, Li SH. Spatio-temporal characteristics and knowledge spillover effects of basic research output in Chinese colleges and universities. Economic Geography, 2024, 44(03):118-126. (in Chinese)
- [49] Neves S, Brito C. Academic entrepreneurship intentions: a systematic literature review. Journal of Management Development, 2020, 39(5):645-704.
- [50] Abreu M, Grinevich V. The nature of academic entrepreneurship in the UK: Widening the focus on entrepreneurial activities. Research Policy, 2013, 42(2):408-422.