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Defining organized R&D: collective action for mission-oriented innovation

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This study establishes a theoretical framework linking organized R&D (ORD) and mission-oriented innovation (MOI) through a collective action lens. MOI performance is evaluated using three key indicators: academic publications, Science and Technology Awards (STA), and granted patents. ORD dimensions are operationalized through research teams, human resources, academic milieu, and public funding. Leveraging survey data and archival records from 23 Chinese universities, we employ baseline regressions and structural equation modeling (SEM) to elucidate ORD's influence pathways on MOI performance. Results indicate that research teams serve as significant mediators linking public funding, academic milieu, and human resources to MOI outcomes as well as the heterogeneous roles of ORD determinants in MOI performance. This study specifically highlights how the scale and allocation mechanisms of public funding more actively facilitate MOI performance outcomes through ORD. By integrating macro-micro connections between MOI and ORD, this research provides policymakers with targeted and actionable recommendations for enhancing MOI in higher education institutions.

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Introduction

Experiences from developed countries suggest that mission-oriented innovation (MOI) is crucial for promoting national innovation (Mazzucato, 2018; Deleidi and Mazzucato, 2021; Reale, 2021). MOI can prioritize long-term public interests and social development (Wanzenböck et al., 2020; Nylén et al., 2023), particularly in the context of addressing societal challenges, such as the outbreak of the novel Coronavirus and the subsequent innovation of vaccines. However, missions may represent contestation, complexity, and uncertainty (Reale, 2021; Brown, 2021; Alves et al., 2021), and lead to policy bias, top-down governance optimism, stakeholder monotony, picking winners and unintended effects (Kirchherr et al., 2023). Due to a lack of transparency, coordination uncertainties, insufficient detail, and failure to align with demand conditions, MOI is also supposed to be examined further at policy level (Brown, 2021; Alves et al., 2021; Henrekson et al., 2024).

The empirical background of MOI is further enriched in Chinese context (Xue et al., 2021). Top-down policy incentives and a centralized regulatory system enable the successful implementation of MOIs in alignment with national interests and societal demand. Nonetheless, disseminating misinformation would consequently result in erroneous decision-making in some MOI cases. For instance, the government's generous financial support, coupled with a paucity of regulatory oversight, has given rise to what has been termed "swindling subsidies" in the NEV and solar PV industries (Zhang et al., 2024).

In terms of collective innovation (de Graaf and van der Duin, 2013; Axelson et al., 2017), the presence of MOI within the university system fulfills an educational function and provides social benefits under non-competitive R&D projects. To promote MOI, the Chinese Ministry of Education officially issued "Strengthening Organized R&D in Universities" in 2022. This document delineates the hallmarks of organized R&D, encompassing the acceleration of MOI, the establishment of national laboratories, the development of key projects, and the utilization of research outcomes in pivotal industrial sectors. It is noteworthy that the nascent form of ORD emerged in Chinese universities in 2012 with the objective of fostering long-term development of science and technology (Ministry of Education, 2012). In the context of ORD, the term "organized" means that innovation resources are allocated in a highly organized and institutionalized manner, which can reduce the transaction costs of R&D activities. ORD is also regarded as a collective decision of many scientists, so it reduces the technical uncertainty in the transfer and commercialization of R&D results.

However, the existing literature does not discuss much about the determinants of ORD and its role in MOI. Especially, there is the lack of quantitative studies on the interplay between ORD and MOI. For policy makers, the detailed discussion of ORD is more essential to launch MOI policies more efficiently under the changing global landscape and the accelerating iterative process in technology.

The purpose of this paper is to conceptualize the compositional determinants of ORD and its links with MOI, especially bridging the methodological gap between quantitative measures of the links. We provide an integrated set of indicators and a quantitative methodology for assessing the performance of MOI influenced by ORD. The contribution of this study is threefold. Firstly, we define ORD in terms of diverse dimensions and indicators. Second, we develop a methodological system for quantitatively measuring the effect of MOI influenced by ORD. Thirdly, our study empowers policymakers to prioritize structured policy instruments in ORD at universities, thus enhancing MOI and challenging the current approach of treating universities as a packaged recipient of public funds and performer of research tasks. The study will provide policymakers with a deeper understanding of ORD within universities in China from the perspective of the "macro" and "micro" links between MOI and ORD.

Theoretical framework

Collective action in MOI. Collective action encompasses the establishment of collective goals, norms, and the alignment of diverse interests among actors (Storper, 1996; Koutsou and Partalidou, 2012; Sandler, 2015; Thomas et al., 2021). In the context of MOI, collective action is characterized by its collaborative nature and aims to address complex societal challenges that necessitate multi-stakeholder involvement. This form of collective innovation (de Graaf and van der Duin, 2013) is guided by a supervisory framework designed to generate and coordinate a range of R&D initiatives, thereby developing complementary solutions that effectively tackle collective problems.

The collective action in MOI also includes portfolios of experiments which generate multiple possible responses to a shared challenge and maximize learnings, synergies, and collaborations between likely and unlikely actors (Mazzucato, 2018; Boorman et al., 2023). A common agenda, shared measurement systems, mutually reinforcing activities, continuous communication, and backbone support organizations shape collective success (Kania and Kramer, 2013).

Additionally, collective action helps mitigate the limitations inherent in MOI mission design (Henrekson et al., 2024). Through collective action, stakeholders establish sustainable models of collaborative activity, adhering to consensus-building, fulfilling group obligations, and resolving disputes amicably through effective institutional arrangements (Olson, 1971; Feiock, 2013; Boorman et al., 2023).

Terminology of ORD

Definition. ORD refers to the collective action of clustering talents, funds, and innovation settings based on long-term research platform, R&D alliance, and leveraging results into society. Geiger (1990) provides the classifications of organized research. One is academic model outlined from disciplinary paradigms. Another is governmental contract programs. Either academic paradigm or governmental contract in organized R&D should serve for national interest; therefore, the two patterns both depend on the provision of sufficient and stable financial resources by the government for ORD.

Within ORD, the organizations can receive more public funding to pool talents and build multidisciplinary teams, and strengthen the interaction between actors. The most esteemed universities are at the vanguard of ORD, initially claiming the lion's share of available funding. This was done with the dual objective of enhancing their own research capabilities and institutional prestige (Sá and Oleksiyenko, 2011).

Unlike collaborative R&D, which is based on individual or team-level cooperation in specific research projects, ORD is a medium- and long-term mechanism that fulfills organizational or national innovation goals. Consequently, ORD is more macroscopic, long-term and stable compared to collaborative R&D projects. In addition, the objectives of research projects go beyond the achievement of research results; they also include the cultivation and development of the academic community (Sá and Oleksiyenko, 2011). For these reasons ORD represents an organizational approach and mode designed to achieve the goals of MOI.

Nevertheless, this does not imply that the ORD model is a monodisciplinary paradigm. Indeed, ORD is typically conducted in an interdisciplinary collaboration form in contexts where complex societal and scientific challenges intersect (Rylance, 2015; Menken and Keestra, 2016; Bromham et al., 2016; Szell et al. 2018). However, not all interdisciplinary collaboration is a model of ORD. Interdisciplinary integration can be achieved through free discussion between individuals, decentralized research behaviors and resource allocation to achieve longer-term, potential goals rather than direct quantitative research outcomes. ORD is a highly organized form of research paradigm, serving organizational or national innovation goals. The primary goal of interdisciplinary research is achieving specific research outcomes through the integration of diverse perspectives.

Policy incentives designed to mobilize and consolidate R&D resources are fundamental for establishing high-caliber ORD systems. Evidence from China demonstrates that public-sector actors serve as primary drivers of ORD frameworks. At the national level, the central government establishes National Laboratories and National Key Laboratories within universities. Concurrently, provincial and ministerial authorities institute corresponding laboratories at higher education institutions. Universities and public research organizations further integrate cross-disciplinary research resources through dedicated R&D platforms.

Determinants of ORD. Regarding the definition of organized R&D, it is evident that organized R&D is associated with both research team and pooling human resources, as well as academic milieu and public funding.

(1) Research team

ORD is embodied in collective action at a highly organized level, closely relating to research teams. Vicente-Saez et al. (2020) note that a research team is a relatively stable and cooperative research group of a certain size and organizational structure. Besides, the diverse expertise of team members has a demonstrably positive impact on information flow and clustering. More research teams in wider spatial networks are more likely to select projects with greater potential, given the opportunity cost of tying up resources in research teams (Mors and Waguespack, 2021).

However, the combination of highly skilled professionals and lax research practices would lead researchers to traditional norms and lax supervision (Harding, 1948). Research teams should be characterized by a considerable degree of organization, discipline, and businesslike procedure. Consequently, the effectiveness of management strategies and sufficiency of research teams is of paramount importance in ORD.

(2) Pooling of human resources

Human resources are the main and scarcest resource in R&D projects. Universities are essentially a collection of human resources (i.e., professors and researchers) (Colbert, 2004; Wright et al., 2001). Although resource-based theory derives from the early observations of firms (Penrose, 1995; Peteraf, 1993; Wernerfelt, 1984; Barney, 2001), the argument holds true for non-firm actors such as universities, which are also essential components of an innovation system (Li et al., 2021; Malerba, 2002). Human resources include the quality and accessibility of scientists, researchers, engineers, and technical personnel (DTTL, 2014). Dong et al. (2021) focused on how top scientists influence the growth of the basic research community, creating a virtuous cycle that attracts more productive researchers to the organization and increases research output.

MOIs are highly dependent on the concentration of human resources in interdisciplinary areas. A high proportion of human resources is an incentive for researchers to collaborate in research teams. There is a trend toward increased emergence of professionalization of various occupational groups (Akhilesh, 2014). Scientists and engineers within an ORD project can contribute to MOI. They have strong commitment and dedication to profession, with the characteristics of a strong sense of profession identity, high degree of freedom and autonomy and specialized training.

(3) Academic milieu

In today's more complex world, knowledge production is more dependent on the enabling environment (Bergek et al., 2015; Li et al., 2021; McAdam and Debackere, 2018). Organizational climate was the key factor that led to higher performance and motivated employees to have a positive outlook on their work (Amabile et al., 1996; Anderson et al., 1998; Hoe, 2011; Sarros et al. 2008). A favorable academic environment could reduce transaction costs and create positive spillovers. The excellence or otherwise of the innovation environment directly affects innovators' innovative behavior and innovation efficiency. Academic freedom (e.g., Shanker et al., 2017; Kim and Jang, 2021), academic integrity (e.g., Yang et al., 2021), and anti-authority constitute the academic milieu.

According to Shanker et al. (2017), innovative work behavior mediates the positive relationship between innovation milieu and organizational performance. Scholars must not be constrained by political, religious, or other doctrines in their pursuit of knowledge (AAC&U, 2006). Academic integrity is the moral code or ethical policy of academia. It includes avoiding cheating and plagiarism, maintaining academic standards, being honest, and conducting rigorous research and scholarly publishing (Yang et al., 2021). The academic milieu is also associated with anti-academic authority. Academic rank (e.g., Tien and Blackburn, 1996) or years of teaching (e.g., Bayer and Dutton, 1977; Evans, 1995) are used to explain academics' activities, faculty perceptions, and performance (Jung et al., 2015).

(4) Public funding

Public funding plays an important role in public R&D (Slaughter and Rhoades, 1996; Braun, 1993; Kleinman, 1994). Contracts and grants are the main sources of public funding to support basic research (David et al., 2000). The government, as the main source of public funding, is an important link in the innovation system in a non-hierarchical and non-linear way (Albuquerque et al., 2015; Etzkowitz and Leydesdorff, 1995; Jucevičius and Grumadaitė, 2014). The awarding of key projects and grants to research platforms strengthens the government's commitment to innovation (Marrocu et al., 2013).

Issues related to public funding include the flat funding rate, the post-evaluation method, and the personnel expenditure rate. Receiving flat public funding allows university researchers to safely invest their time in the research process instead of spending a lot of time writing application proposals to impress reviewers (Qian et al., 2010). Post-evaluation refers to monitoring and evaluating the outcomes of a project within 2–3 years to determine whether the project has the potential for continued funding.

Meanwhile, public funding for ORD projects leads to the most radical innovation and promotes research on high-risk and complex projects (Martín-Barrera et al., 2017). Public funding has also been shown to have the ability to influence the structure of innovation networks, thereby enhancing teamwork and facilitating team execution of MOI (Defazio et al., 2009). A study by Resce et al. (2022) argued that the role of public funding is much greater in scientific fields characterized by long-term projects, such as the life sciences and experimental physics, as well as in scientific fields characterized by large research infrastructures. Therefore, public funding for R&D teams, rather than for individuals, is pivotal to MOI performance by way of innovation network.

Linking framework of ORD with MOI in the collective action logic. MOIs are collaboratively developed by multiple

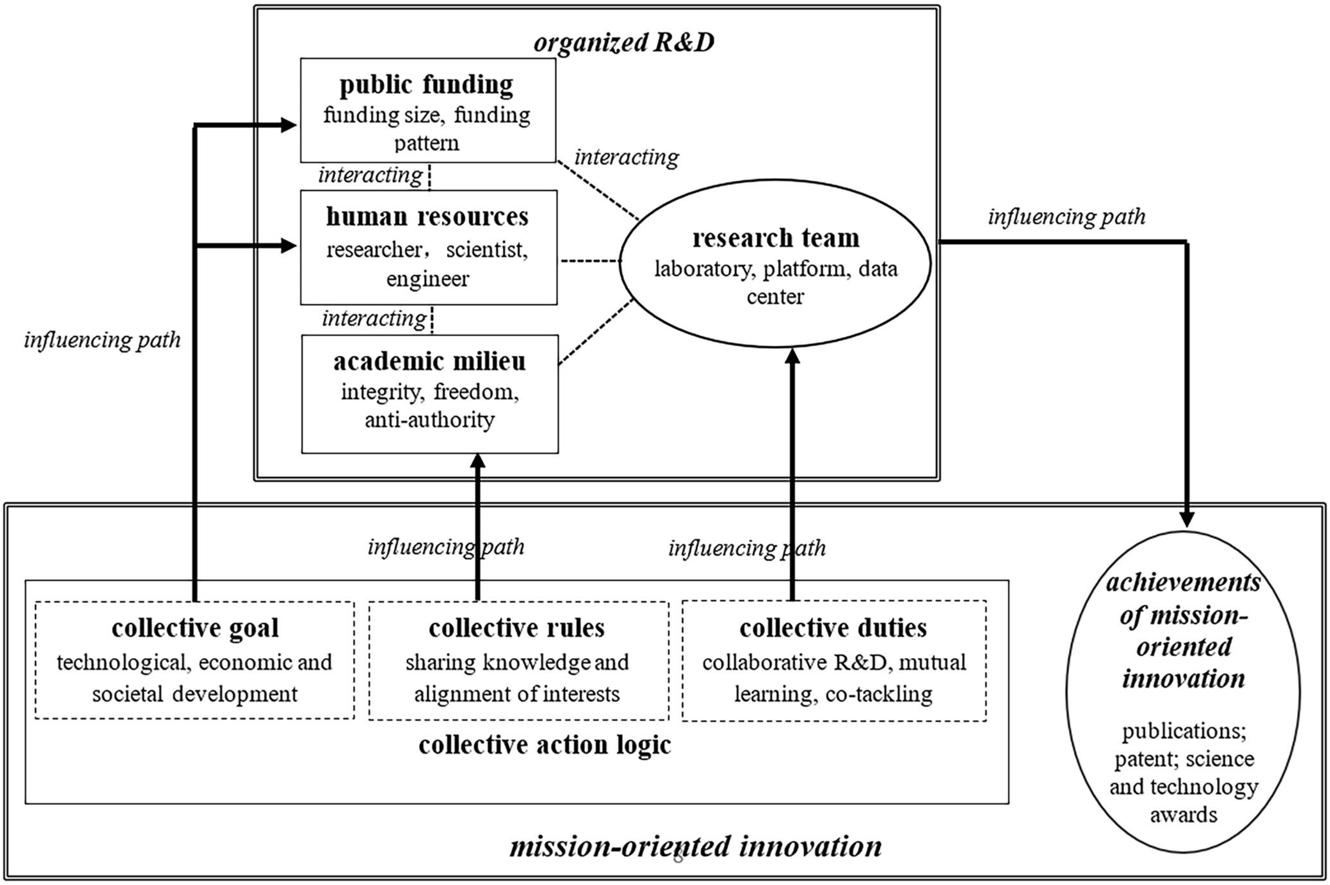

Fig. 1 Linking framework of organized R&D and mission-oriented innovation.

innovators within an innovation network (Rouyre et al., 2024), and efficient R&D outcomes are achieved when uncertainty in the innovation network is resolved through consistent practices (Axelson et al., 2017). Collective action is imperative for individuals within an ORD group to explicitly accept the collective goals, which determine the allocation of public funds and human resources.

Collective rules encompass the establishment of regulations for knowledge sharing and the harmonization of interests through collective commitments. These rules constitute a common code of conduct developed among individual researchers within the academic milieu. Consequently, the allocation of R&D resources, as well as the utilization and transformation of innovative outcomes (Salem et al., 2002), should adhere to the cooperative norms established by the team and in accordance with intellectual property agreements (Kristinsson et al., 2016).

Collective duty can be understood as the moral obligation of a group to impose various collective obligations on actors (Parker, 2011). Within ORD, these duties are grounded in the coordination of innovators and provide a common and coherent framework. Collective duty manifests in R&D teams through cooperative R&D efforts, mutual learning, and joint responses to established challenges.

Performance of MOI is evaluated based on indicators such as the number of high-level publications and high-quality researchers (Kerr, 2001; Chatterjee et al., 2018), as well as the widespread application of major scientific discoveries and technological achievements in economic and social systems (Wanzenböck et al. (2020). These outcomes are typically measured in terms of the number of publications, patents, and science and technology awards that have been successfully commercialized. Publications represent long-term knowledge spillovers with regard to economic and social development. Patents signify scientific and technological achievements with the potential to yield direct economic benefits. Science and technology awards denote significant advancements recognized by peer reviewers and utilized by governments and enterprises for shaping national competence. It can be reasonably argued that these three types of results effectively serve as proxies for the accomplishments of MOI. Here we propose the framework that connects ORD with MOI in terms of the collective action (see Fig. 1).

Methodology

MOIs in China's nationalized system. In terms of technology-oriented and societal challenge-oriented mission (Wanzenböck et al., 2020), mission-oriented basic research and mission-oriented applied research are the two dominant MOIs. In this paper, we will examine mission-oriented basic research. In China, mission-oriented basic research refers to the development of disciplines, scientific frontiers in line with major national needs and scientific research programs (Ministry of Science and Technology, 2006). Mission-oriented basic research embodies strategic, cutting-edge and forward-looking high-technology beneficial to economic and societal development.

The "973" Plan aims to expand human understanding of the world and solve scientific frontier problems, such as population and health, agriculture, energy, information, resources and environment, materials, manufacturing and engineering, as a national strategic demand. Since 1998, the strategic

Table 1 Dominant projects of mission-oriented innovation in China.

Administration	Name	Initial Time	Missions
MOST	"863" Plan	March 1986	• strategic high-tech industrial innovation and national economic development
MOST	"973" Plan	June 1997	• breakthroughs in major scientific issues, training of basic research teams, and promotion of sustainable economic and social development.
NSFC	Key Project	February 1986	• breakthroughs in important basic frontier scientific issues to promote national economic and social development
NSFC	Major Project	February 1986	• major scientific breakthroughs and strategic research team building for long-term national scientific and technological development

implementation of the "973" Plan has covered agriculture, energy, information, resources and environment, population and health, materials, and vast multidisciplinary fields. The "863" Plan and "973" Plan are all administered by Ministry of Science and Technology (MOST).

The National Science Foundation of China (NSFC) focuses on supporting basic research that adheres to the principles of free exploration and MOIs. The NSFC framework encompasses a multitude of research projects. Key projects and major projects of NSFC align with the features of MOIs. Key Projects of NSFC are designed to provide support for scientists engaged in in-depth, systematic, and innovative research in areas of scientific investigation or disciplinary growth points with a solid foundation. The aim is to facilitate the achievement of significant breakthroughs in key scientific domains. Major projects of NSFC address the country's most pressing strategic needs and advance the frontiers of scientific and technological knowledge. These projects promote interdisciplinary collaboration, nurture talent, and contribute to national economy and social development.

The "863" Plan was formally launched in March 1987. The plan is designed to address a range of strategic, cutting-edge and forward-looking high-technology issues with a view to ensuring the long-term development and national security of the country. The "863" Plan prioritizes the advancement of high-technology with independent intellectual property rights, the integration and application of high-technology, and the leadership of future industrial development.

The Chinese government has also established other significant research programs, for example, the National Key Laboratory Construction Plan and the Scientific and Technological Basic Work Special Knowledge Innovation Project. Please see Table 1.

Samples. The study was conducted on research universities in China. Research universities are those with strong basic scientific research capabilities and high level of talent training. According to the official classification of research universities, there were 36 research universities in China in 2012. This survey work was initially directed to the full sample of these 36 research universities. However, because we conducted statistical analyses after collecting the questionnaires, only 23 universities provided valid questionnaires. To maintain consistency in the measurement of longitudinal data over time, we employ the sample selection logic of these 23 universities and matches the data for the variables of interest. According to the data released by the 2020 China University Evaluation project, chaired by Wu Shulian, head of the China Academy of Management Sciences' China University Evaluation project. Twenty of the 23 universities in this study made it into the top 38 research universities in China in 2020 (by research score). Seven of the top 10 universities were among those selected for this study. Therefore, the sample selected for this study is highly representative.

The 23 universities are as follows: Beijing JiaoTong University, Beijing University of Posts & Telecommunication, Central South University, China Agricultural University, China University of Geosciences Beijing, Chongqing University, East China Normal University, Fudan University, Hunan University, Lanzhou University, Nanjing University. The data for the independent, dependent and control variables come from 23 universities: Nankai University, Northwest A&F University, Shanghai Jiao-Tong University, Sichuan University, Southeast University, Sun Yat Sen University, Tongji University, Tsinghua University, Beijing University of Science & Technology, Wuhan University, Xiamen University and Zhejiang University.

Variables and data source

Dependent variables and data source. In accordance with the typology of MOI proposed by Wanzenböck et al. (2020), we have chosen three dependent variables: journal papers (Calvert and Martin, 2001; Narin et al., 1976), science and technology awards (STA), and granted patents (Griliches, 1990; Archibugi and Pianta, 1996; Ernst, 2003; Zhao et al., 2013; Angori et al., 2024). In China, the production of papers and STA reflects long-term knowledge performance driven by economic and social development. Granted patents indicate technology-led innovation outcomes in economic development, approved by China Intellectual Property Office (CIPO). The data comes from the official Patent Search and Analysis website (https://pss-system.cponline.cnipa.gov.cn/conventionalSearch). The number of inventions is taken as the dependent variable. We used Python 3.11 to crawl the eligible patents and deposit them into a local MySQL database, where we then screened and analyzed the data.

Papers come from the Web of Science's Science Citation Index Expanded (SCIE) database. We select the papers by a funding symbol of NSFC's Key Project and Major Project, "973" Plan, and "863" Plan appears in the Acknowledgments at the end of each paper. Only articles with a first author from one of China's 23 universities are selected in our study. We limit the publication years of the papers to 9 years from 2012 to 2020.

STA indicate the attributes of public goods and knowledge spill-overs for major technological breakthrough, representing MOI performance. STA's data is derived from the three major national science and technology awards given annually by the Chinese government. These include the National Natural Science Award, the National Prize for Technological Inventions, and the National Prize for Scientific and Technological Progress.

Independent variables, control variables and data source. The independent variables are public funding, academic milieu, human resource and research team. The four variables are evaluated by the 14 indicators of 1-7 derived from the survey questionnaire commissioned by the Ministry of Education and conducted by the "S&T-Education Development Strategy Research Center" of Tsinghua University (Su et al., 2012). In 2011, the questionnaire was sent by email to researchers and faculties at 23 research universities in China. The respondents were supposed to provide their personal recognition of funding

Table 2 Variables and indicators.

	Variables	Indicators	Abbr.	Mean	Sd.	#N
dependent variables	MOI performance	sum of SCI-indexed papers	PAPER	299.5	219.0	207
		number of science and technology awards	STA	4.222	4.351	207
		number of granted patents (inventions)	PATENT	1173	982.4	207
control variables	funding quantity	expenditure on basic research ($1 million)	EB	238.8	251.9	207
	the number of human resources	personnel full-time equivalents	PB	544.8	413.6	207
independent variables	public funding	sufficiency of expenditure on basic research	SO	2.765	1.564	429
		flat funds outweigh competitive funds	FF	2.117	1.266	429
		sustainable tracking and post-evaluation	ST	2.140	1.178	429
		high ratio of personnel costs to expenditures	HE	2.168	1.318	429
	academic milieu	academic freedom	AF	3.096	1.803	429
		academic integrity	AI	2.963	1.609	428
		anti-academic monopoly	AM	2.383	1.450	428
	human resource	leading scientists	LS	2.793	1.509	429
		distinguished young researchers	DY	3.000	1.580	429
		high quality brain pool	BP	2.646	1.402	427
		talent development in basic research	TR	2.932	1.639	427
	research team	sufficiency of excellent research teams	ET	2.627	1.411	429
		level of team construction	TC	3.026	1.593	429
		teamwork spirit	TS	2.909	1.515	428

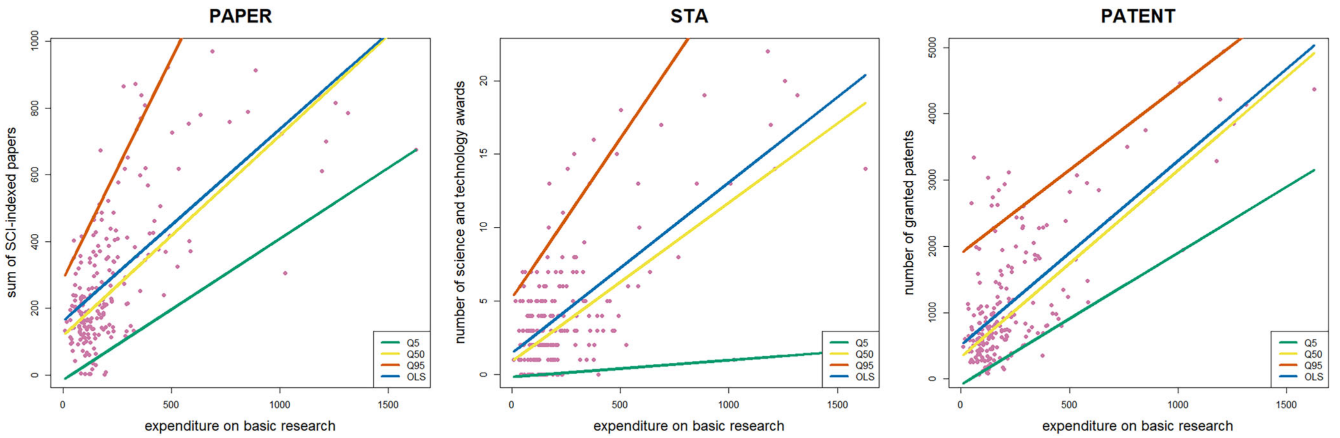

Fig. 2 The quantile regressions between the expenditure on basic research (EB) and PAPER, STA and PATENT, respectively. Note: Q5, Q50, and Q95 represent the 0.05, 0.50, and 0.95 quantile regression lines, respectively.

patterns, academic milieu, human resources regarding their universities. We collected usable questionnaires from these universities by random sampling in 2012. The respondents included full professors, associate professors, assistant professors and other researchers. The total sample size is 429, and some of these variables have some missing values.

The control variables are the amount of funding and the number of human resources. Public funding for university's MOI projects is used to indicate public funding quantity. The number of researchers involved in the university's MOI projects is taken as the number of human resources. The data were obtained from the Yearbook of Chinese Science and Technology (2009–2017), which records statistics from 2008 to 2016. It is noteworthy that no statistics related to these indicators have been published for universities since 2018. Furthermore, the dependent variable was lagged relative to the control variable by 4 years to align with the innovation law of lagging effects due to university research output. Table 2 reports variables, indicators and descriptive statistical results.

It is noteworthy that indicators pertaining to public funding and human resources are employed in both the independent variable and the control variable. However, the indicators associated with these two dimensions in the independent variable are structural indicators that are directly related to the ORD's management model. Conversely, quantitative indicators of these two dimensions are utilized in the control variable, aligning with the fundamental principle of R&D investment.

Model specification

Baseline regression. Figure 2 depicts the quantile regressions between the public funding (EB) and PAPER, STA and PATENT, respectively. The univariate quantile regression lines for the fifth, fiftieth and ninetieth quantiles, and OLS regression line are used, respectively. The sample points are derived from the data of funding and output of 23 universities over 9 years, with a 4-year lag between the two variables. The results indicate public funding is significantly positively correlated with MOI performance. The substantial variation in regression coefficients across different quantiles indicates the presence of heterogeneous effects. The impact of EB on STA exhibits the strongest heterogeneity, suggesting sensitivity among universities with either very low or very high funding, whereas the positive effect on PATENT is the most stable.

To ascertain the impact of various factors on PAPER, STA and PATENT, we employ a baseline regression model, as opposed to undertaking four dimensions of ORD. We use stepwise regression to create an interpretable model. The 14 indicators are taken directly from the questionnaire, with a total sample size of 423 after removing missing values. R&D expenditures (EB) and personnel full-time equivalents (PB) are used to construct control variables "input" and "personnel", respectively, which together affect the "output" measured by PAPER, STA and PATENT, respectively. The variables EB, PB (both from 2008 to 2016) and PAPER, STA and PATENT (both from 2012 to 2020) are all panel data, while 14 indicators are cross-sectional data collected in 2012. The dependent variable "output" lags "input" and "personnel" by four years, as it takes years for researchers to publish articles or apply for patents after receiving funding.

This lagging approach is consistent with the broader literature on innovation cycles (Yoav and Shchori-Bachrach, 1973; Schoen et al., 2005). Research output, especially in the academic and technological domains, typically requires a gestation period due to the time-intensive nature of experimentation, analysis, and dissemination. Furthermore, institutional and administrative processes, such as peer review for journal articles or the evaluation process for STA awards, inherently extend the timeline. From the perspective of the model, by introducing a lag of 4 years, the model ensures alignment with the causal logic underlying the relationship between inputs and outputs. This lag accounts for the time required to transition from funding and resource allocation to measurable innovation outputs, thereby enhancing the validity of the causal inferences drawn from the baseline regression and the subsequent structural equation models.

The indicators of "public funding", "academic milieu" and "research team" are assumed to be stable in each university over the past decade because the researchers do not readily perceive structural and environmental changes in the short term. Meanwhile, Chinese innovation policy since 2012 has been improved and the research environment has been steady.

To make the model more convincing, we changed the data for the three "human resource" indicators (LS, DY and BR) from cross-sectional to panel data. In 2012 and 2020, university i had full-time R&D equivalents as $Z_{i,2012}$ and $Z_{i,2020}$. We use the growth of full-time R&D personnel in a province or municipality to approximate the growth of full-time R&D personnel in a university. The annual growth rate of full-time R&D personnel in university i is calculated as

$$\gamma_i = \left(\frac{Z_{i,2020}}{Z_{i,2012}}\right)^{1/8} - 1.$$

The cross-sectional data for LS, DY, and BR have been adjusted as follows: the correction values are calculated using the formulas: $LS_{j,t} = LS_j \times \left(1+\gamma_i\right)^{t-2012}, DY_{j,t} = DY_j \times \left(1+\gamma_i\right)^{t-2012}, BR_{j,t} = BR_j \times \left(1+\gamma_i\right)^{t-2012}$ where it is assumed that the sample j (i.e., questionnaire) is completed by faculty members of the i-th university, and the value of t ranges from 2012 to 2020. LS_j represents the value of LS in the j-th sample. The notation $LS_{j,t}$ denotes the value of LS in the sample j of the year t after applying the correction. The meanings of $DY_{j,t}$ and $BR_{j,t}$ are similar. This correction is based on the premise that as a university increases its number of research and development personnel, its evaluation of human resources is enhanced accordingly.

Based on the above panel data, the equations are constructed as follows:

$$Y_{j,t} = \alpha_1 \cdot EB_{j,t-4} + \alpha_2 \cdot PB_{j,t-4} + \sum_{k=1}^{4} \beta_{1k} \cdot FB_{jk,t} + \sum_{k=1}^{3} \beta_{2k} \cdot AM_{jk,t} + \sum_{k=1}^{4} \beta_{3k} \cdot HR_{jk,t} + \sum_{k=1}^{3} \beta_{4k} \cdot RT_{jk,t} + \varepsilon_{j,t}, j = 1, \ldots, 423, t = 2012, \ldots, 2020$$

where $Y_{j,t}$ represents the value of the dependent variable (including PAPER, STA and PATENT respectively) in year t for the university in sample j, $EB_{j,t-4}$ and $PB_{j,t-4}$ represent the value of the control variable in year (t-4) for the university in sample j, $HR_{jk,t}$ represents the value of the k-th indicator that constitutes the variable "human resource" in sample j in year t. $HR_{j1,t}$ represents $LS_{j,t}$. For $FB_{jk,t}$, $AM_{jk,t}$, and $RT_{jk,t}$, similarly, even though they are time-series stable, we use the similar notations in the above equation, $\varepsilon_{j,t}$ is the independent and identically distributed control variable. In summary, the total number of observations for the above baseline linear regression model is 3807. The M-estimator is employed in robust test and in the modeling of the conditional median in quantile regression. These statistical methods enhance the reliability of regression analysis and facilitate a more nuanced understanding of the data and model behavior.

SEM model. We assessed the correlation between variables of ORD and MOI performance using a baseline regression approach. However, whether the four categories of ORD have significant impacts on MOI performance remains to be tested. Structural Equation Modeling (SEM) offers a comprehensive framework for exploring complex relationships among variables, accounting for mediation and moderation effects, and providing goodness-of-fit indices for rigorous model evaluation (Hair et al., 2021). The inclusion of latent variables (also known as constructs), which represent unobservable factors such as public funding and research team dynamics, increases the depth of analysis. The study emphasizes the visual representation of relationships using path models that incorporate both structural and measurement models. Empirical studies by Sohn et al. (2007), Guan and Ma (2009), and Choi and Lim (2017) highlight the effectiveness of SEM in evaluating research and government engagement.

Furthermore, our study emphasizes the logical sequence of key considerations in choosing partial least squares SEM (PLS-SEM) over covariance-based SEM (CB-SEM), highlighting its suitability for confirmatory research (Chin, 2010), especially with relatively smaller sample sizes (Chin et al., 2008) and complex models (Cassel et al., 1999). The reflective measurement model is justified by the nature of observed variables (also known as indicators) as reflections of the performance of latent variables rather than their causes (Bollen and Diamantopoulos, 2017). This thoughtful selection is considered overall research objectives, the complex interplay between observed and latent variables, and the need for a robust methodology to model multifaceted relationships influencing basic research findings. The choice of structural model is based on metrics such as adjusted R^2 and latent variable significance to assess model effectiveness. Other common selection criteria for a more general framework include the Akaike Information Criterion, cross-validation, etc. (Stoica and Selen, 2004). Cronbach's alpha (Cronbach, 1951), composite reliability rhoC (Jöreskog, 1979), and reliability rhoA (Dijkstra, 2010) are the primary measures of internal consistency reliability for reflective measurement models. The average variance

Table 3 Baseline regression results.

Variables	PAPER-ols	PAPER-step	STA-ols	STA-step	PATENT-ols	PATENT-step
EB	0.343***	0.342***	0.011***	0.011***	2.702***	2.698***
	(0.012)	(0.011)	(0.0003)	(0.0003)	(0.058)	(0.057)
PB	0.191***	0.191***	−0.001***	−0.001***	0.097***	0.010***
	(0.006)	(0.006)	(0.0002)	(0.0002)	(0.032)	(0.032)
SO	11.560***	11.388***	0.068*	0.059	43.404***	42.570***
	(1.737)	(1.729)	(0.041)	(0.040)	(8.678)	(8.468)
FF	4.287*	3.814*	−0.055		−5.167	
	(2.507)	(2.308)	(0.059)		(12.527)	
ST	−12.908***	−13.389***	−0.265***	−0.284***	−49.802***	−51.904***
	(2.549)	(2.488)	(0.060)	(0.057)	(12.739)	(12.037)
HE	−2.342		0.316***	0.298***	20.801*	19.767*
	(2.349)		(0.055)	(0.052)	(11.740)	(10.972)
AF	−8.024***	−7.480***	−0.144***	−0.144***	−34.560***	−32.563***
	(1.536)	(1.486)	(0.036)	(0.036)	(7.676)	(7.458)
AI	8.672***	9.238***	0.142***	0.142***	30.655***	30.591***
	(1.845)	(1.803)	(0.043)	(0.043)	(9.218)	(9.216)
AM	2.279		−0.169***	−0.174***	−83.276***	−83.321***
	(1.909)		(0.045)	(0.045)	(9.539)	(9.451)
LS	−12.751***	−12.960***	−0.229***	−0.228***	25.564***	24.393***
	(1.772)	(1.756)	(0.042)	(0.042)	(8.854)	(8.783)
DY	−9.149***	−9.065***	−0.206***	−0.205***	−21.155***	−20.686***
	(1.515)	(1.513)	(0.036)	(0.036)	(7.568)	(7.555)
BP	−9.329***	−8.919***	−0.068*	−0.072**	19.924***	21.782***
	(1.529)	(1.469)	(0.036)	(0.036)	(7.643)	(7.322)
TR	2.262		0.071*	0.073*	9.243	
	(1.730)		(0.041)	(0.041)	(8.644)	
ET	19.257***	19.978***	0.459***	0.460***	38.760***	41.911***
	(2.396)	(2.320)	(0.056)	(0.056)	(11.973)	(11.626)
TC	−5.147**	−5.234**	−0.112**	−0.109**	−28.565***	−27.731***
	(2.154)	(2.123)	(0.051)	(0.051)	(10.762)	(10.719)
TS	12.487***	13.253***	0.258***	0.258***	76.068***	76.978***
	(2.157)	(2.106)	(0.051)	(0.051)	(10.777)	(10.747)
Constant	146.912***	148.040***	2.388***	2.369***	298.681***	299.514***
	(8.418)	(8.394)	(0.198)	(0.197)	(42.066)	(41.774)
Observations	3807	3807	3807	3807	3807	3807
R^2	0.550	0.549	0.380	0.380	0.532	0.532
Adjusted R^2	0.548	0.548	0.377	0.377	0.530	0.530
F Statistic	289.450*** (df = 16; 3790)	355.866*** (df = 13; 3793)	145.045*** (df = 16; 3790)	154.661*** (df = 15; 3791)	269.533*** (df = 16; 3790)	307.992*** (df = 14; 3792)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

extracted (AVE) is used to assess the convergent validity of each measure.

Results discussion

Results of baseline regression. Table 3 indicates a positive correlation between SO, AI, ET, and TS with PAPER at a 1% significance. HE, AI, ET, and TS are positively correlated with STA, while SO, LS, BP, ET, and TS are positively correlated with PATENT. These findings suggest that high-quality R&D teams and team spirit significantly impact MOI performance. Academic integrity promotes PAPER and STA. Sufficient funding promotes PAPER. A higher ratio of personnel costs leads to increased STA output. R&D expenditures, leading scientists, and pooling high-quality talent all contribute to PATENT. The results presented in Table 4 demonstrate the robustness of the regression analyses.

Regression analyses reveal four typical effects of public funding on MOI performance: (1) Public funding volume (EB) significantly enhances three critical MOI performance indicators; (2) Non-competitive funding (FF) positively influences paper outputs but fails to affect patent production significantly; (3) Sustainable tracking and post-evaluation (ST) exhibit negative correlations with three MOI performance metrics; (4) Higher ratio of personnel costs to expenditures (HE) substantially boost patent outputs and STAs while significantly suppressing paper outputs.

Results of SEM. According to Table 5, most of the evaluation metrics meet the appropriate values “except academic milieu”. Table 6 shows that input and personnel are significantly positively correlated with output ($p < 0.01$) in PAPER PLS-SEM and PATENT PLS-SEM, indicating that increasing public funding and human resource can significantly increase PAPER output and PATENT output. The R^2 goodness of fit metrics of the three structural models are 0.504, 0.342, and 0.504, respectively. In three PLS-SEM models, “public funding”, “academic milieu”, and “human resource” all exhibit significant positive correlations with the mediator “research team”, suggesting that the latent variables have a substantial positive impact on the mediators. Prior to modeling, however, “public funding”, “academic milieu”, and “human resource” do not significantly affect the “output” in any of the three models.

Influential mechanism of ORD on MOI performance. As demonstrated in Figs. 3–5, the four dimensions of ORD have

Table 4 Robust regression and quantile regression results.

Variables	PAPER-robust	PAPER-quantile	STA-robust	STA-quantile	PATENT-robust	PATENT-quantile
EB	0.378***	0.375***	0.012***	0.012***	2.893***	2.944***
	(0.011)	(0.020)	(0.0002)	(0.0003)	(0.049)	(0.109)
PB	0.167***	0.160***	−0.001***	−0.001 ***	0.137***	0.088**
	(0.006)	(0.007)	(0.0001)	(0.0001)	(0.027)	(0.035)
SO	12.319***	15.075***	0.060*	0.081***	41.119***	46.169***
	(1.672)	(2.294)	(0.034)	(0.030)	(7.347)	(8.728)
FF	6.468***	5.579*	−0.060	−0.063	−19.880*	−24.983**
	(2.413)	(3.045)	(0.049)	(0.052)	(10.605)	(10.699)
ST	−13.260***	−14.057***	−0.277***	−0.296***	−85.222***	−99.027***
	(2.454)	(2.398)	(0.050)	(0.052)	(10.785)	(9.870)
HE	−5.826***	−8.207***	0.272***	0.231***	29.733***	24.034**
	(2.262)	(2.265)	(0.046)	(0.048)	(9.938)	(10.712)
AF	−7.233***	−4.507***	−0.131***	−0.150***	−35.401***	−35.438***
	(1.479)	(1.685)	(0.030)	(0.027)	(6.498)	(6.407)
AI	8.428***	9.012***	0.115***	0.127***	33.973***	28.884***
	(1.776)	(2.123)	(0.036)	(0.035)	(7.804)	(7.809)
AM	2.120	0.675	−0.136***	−0.140***	−62.201***	−37.605***
	(1.838)	(1.969)	(0.037)	(0.036)	(8.075)	(7.979)
LS	−12.159***	−9.803***	−0.179***	−0.142***	19.173**	28.129***
	(1.706)	(1.809)	(0.034)	(0.031)	(7.496)	(7.464)
DY	−8.754***	−8.520***	−0.139***	−0.136***	−21.458***	−18.702***
	(1.458)	(1.442)	(0.029)	(0.028)	(6.407)	(6.625)
BP	−8.525***	−6.447***	−0.048	−0.086***	16.220**	11.808*
	(1.472)	(1.548)	(0.030)	(0.026)	(6.470)	(6.470)
TR	3.389**	4.479**	0.088***	0.155***	4.601	−3.657
	(1.665)	(1.826)	(0.034)	(0.029)	(7.318)	(7.181)
ET	18.973***	15.831***	0.363***	0.341***	48.409***	29.734***
	(2.307)	(2.416)	(0.047)	(0.036)	(10.136)	(10.658)
TC	−3.942*	−5.103**	−0.054	−0.041	−28.798***	−32.723***
	(2.073)	(2.110)	(0.042)	(0.038)	(9.111)	(8.992)
TS	11.242***	11.316***	0.197***	0.222***	76.588***	85.330***
	(2.076)	(2.064)	(0.042)	(0.038)	(9.123)	(10.258)
Constant	133.158***	109.490***	2.081***	1.711***	207.738***	197.372***
	(8.104)	(8.422)	(0.163)	(0.178)	(35.612)	(32.992)
Observations	3807	3807	3807	3807	3807	3807

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 5 The evaluation metrics of reflective measurement model in PAPER, STA and PATENT PLS-SEM models.

Models	PAPER PLS-SEM				STA PLS-SEM				PATENT PLS-SEM			
Metrics	alpha	rhoC	rhoA	AVE	alpha	rhoC	rhoA	AVE	alpha	rhoC	rhoA	AVE
public funding	0.803	0.870	0.822	0.627	0.803	0.870	0.822	0.627	0.803	0.870	0.822	0.627
academic milieu	0.664	0.817	0.671	0.598	0.664	0.817	0.671	0.598	0.664	0.817	0.671	0.598
human resource	0.745	0.838	0.749	0.566	0.745	0.838	0.749	0.566	0.745	0.838	0.749	0.566
research team	0.725	0.846	0.723	0.648	0.725	0.846	0.723	0.648	0.725	0.846	0.723	0.648

significant positive impacts on the three models of MOI performance measured by PAPER, STA and PATENT, respectively. Among the determinants of ORD, research teams directly enhance MOI performance, while public funding, academic milieu, and human resources indirectly contribute through the mediating effect of research teams. This underscores that the strengthening of research teams represents a viable and crucial avenue for advancement. In addition to ensuring adequate funding and staffing of MOI, the pattern of public funding, the academic milieu and the pooling of human resources also facilitate the cultivation of research teams. The findings indicate that public funding, academic milieu and human resources follow a similar path in influencing MOI performance.

Regarding the heterogeneity among the three models, there are notable differences. For both PAPER and PATENT outputs, the effect of increasing the number of R&D personnel on MOI performance differs from that on STA output. Specifically, an increase in the number of R&D personnel is more effective in boosting PAPER and PATENT outputs but less effective in improving STA output. Furthermore, an increase in public funding proves to be more impactful in increasing PATENT output, which corresponds to applied research. Additionally, the mediating effect of research teams is more significant for STA output than for PAPER output.

The regression analysis establishes two critical findings regarding public funding impacts on MOI performance. Firstly, the volume of public funding (EB) significantly enhances all three MOI performance metrics. Secondly, the structural determinants of public funding demonstrate heterogeneous effects. Specifically, non-competitive funding (FF) fails to significantly promote STAs, and higher personnel expenditure ratios (HE) significantly inhibit paper outputs. Additionally, sustainable tracking and post-evaluation (ST) exhibit negative impacts on MOI performance. However, SEM reveals that when these factors are mediated through organizational proxies of research teams, both funding volume and allocation mechanisms generate significant positive effects across all three MOI performance metrics. This demonstrates that organized R&D, as an internalized resource allocation mechanism, exerts substantial positive influence on MOI performance.

These empirical results validate our theoretical proposition that public funding channeled toward research teams—rather than individuals—proves pivotal to MOI performance through innovation network effects.

Table 6 The regression results in PAPER, PATENT and STA PLS-SEM models.

Paths	PAPER	STA	PATENT
"public funding" to "research team"	0.124*** (0.012)	0.123*** (0.012)	0.123*** (0.012)
"academic milieu" to "research team"	0.407*** (0.017)	0.407*** (0.017)	0.406*** (0.017)
"human resource" to "research team"	0.379*** (0.014)	0.379*** (0.014)	0.380*** (0.014)
"research team" to "output"	0.035** (0.011)	0.055*** (0.014)	0.074*** (0.011)
"input" to "output"	0.367*** (0.014)	0.616*** (0.022)	0.683*** (0.015)
"personnel" to "output"	0.427*** (0.012)	-0.057*** (0.016)	0.042*** (0.012)
R^2 (goodness of fit)	0.504	0.342	0.504

The estimates of regression coefficients are based on original data, and the estimates of standard deviations are using bootstrapped data. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Cases of ORD influencing MOI performance. In addition to the quantitative assessment of the impact of ORD on the quantifiable performance indicators of MOI, cases have demonstrated the important positive impact of ORD on scientific development, economic growth and social well-being in MOI. For instance, the "Beijing-Tianjin-Hebei Groundwater Pollution Prevention and Control Key Technology Research and Engineering Demonstration" scientific research project, was awarded the first prize for technological invention of 2023, comprises 18 research units, including the China Academy of Environmental Sciences, Tsinghua University, Southern University of Science and Technology, and the Beijing Research Institute of Water Science and Technology. A total of 370 researchers from different disciplines participated in the project. The involvement of these researchers was not a random or improvised process of a simply interdisciplinary collaboration; rather, it was orchestrated through the formation of dedicated research teams within their respective units. These teams convened on a regular basis to deliberate on the progression of research, address the knowledge gaps between different disciplines, and ultimately converge on the application of groundwater pollution control technologies in the Beijing-Tianjin-Hebei region. The outcomes of this collaborative effort have enhanced the monitoring capabilities and regulatory capacity of the groundwater environment, and have contributed to the development of the nationwide water environment management and water pollution control capabilities, as well as to the advancement of the scientific and technological level of national water environment management and water pollution control. The project has also provided a robust technical foundation for ensuring public access to potable water. This case exemplifies the considerable potential of an ORD model in facilitating MOI performance.

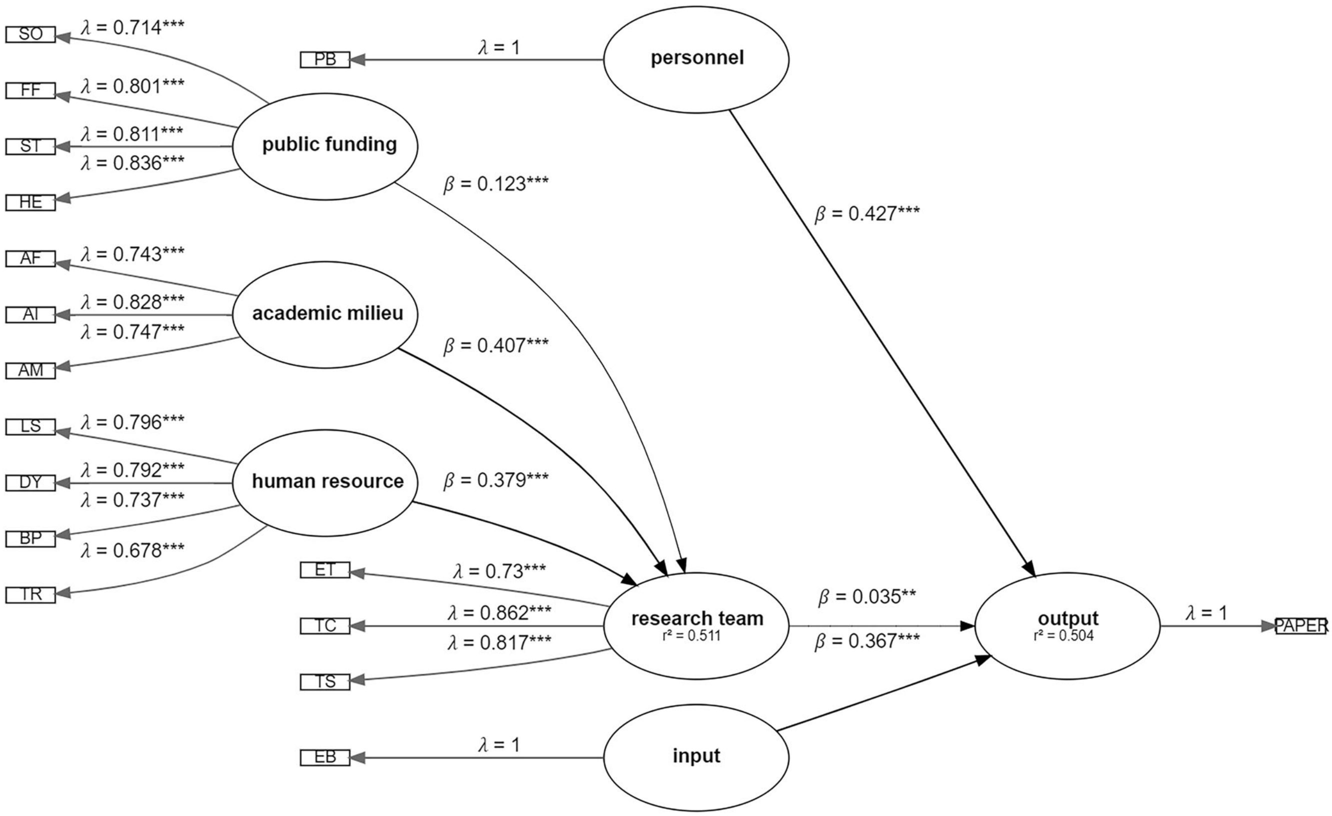

Fig. 3 The path diagram of PAPER PLS-SEM model. *Note: The nodes of indicators are displayed in gray.* *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

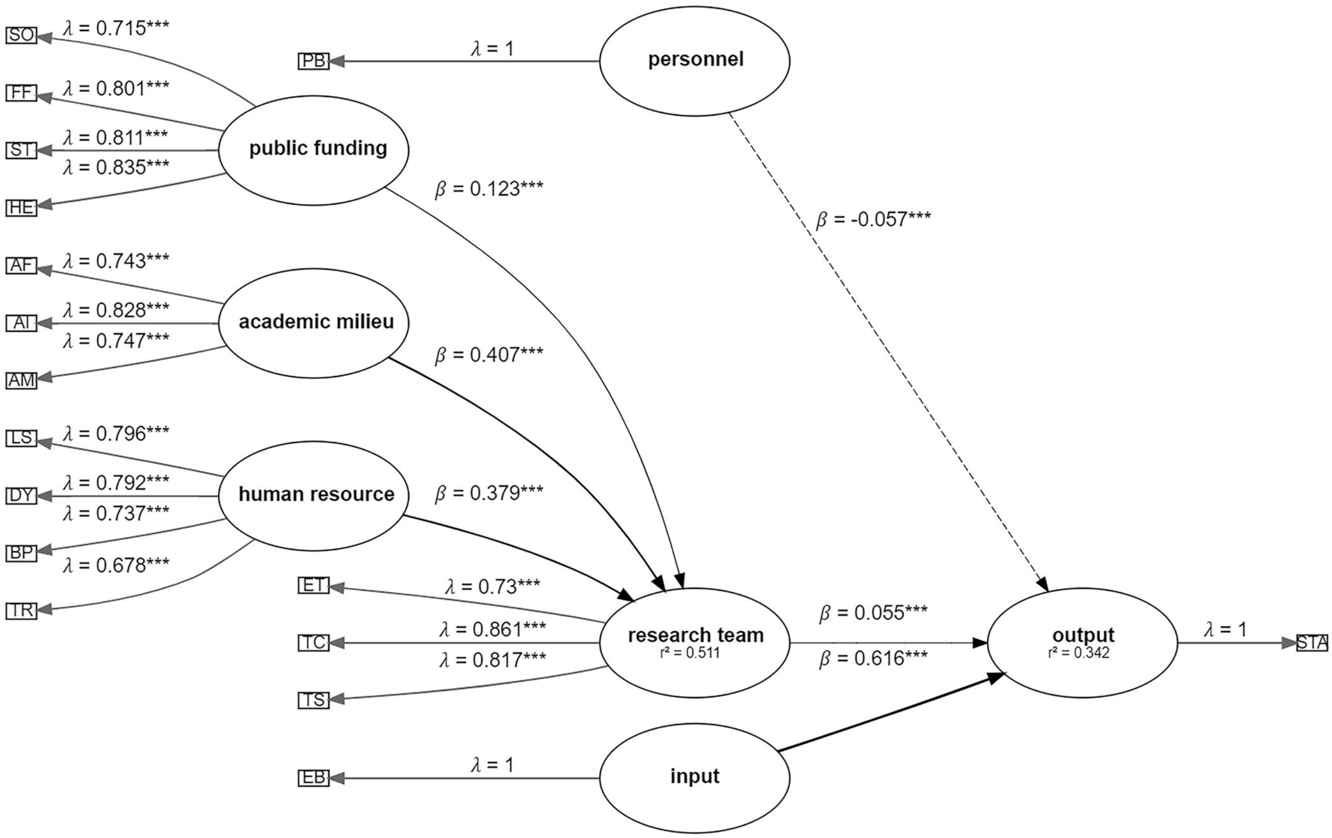

Fig. 4 The path diagram of STA PLS-SEM model. *Note: The nodes of indicators are displayed in gray.* **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

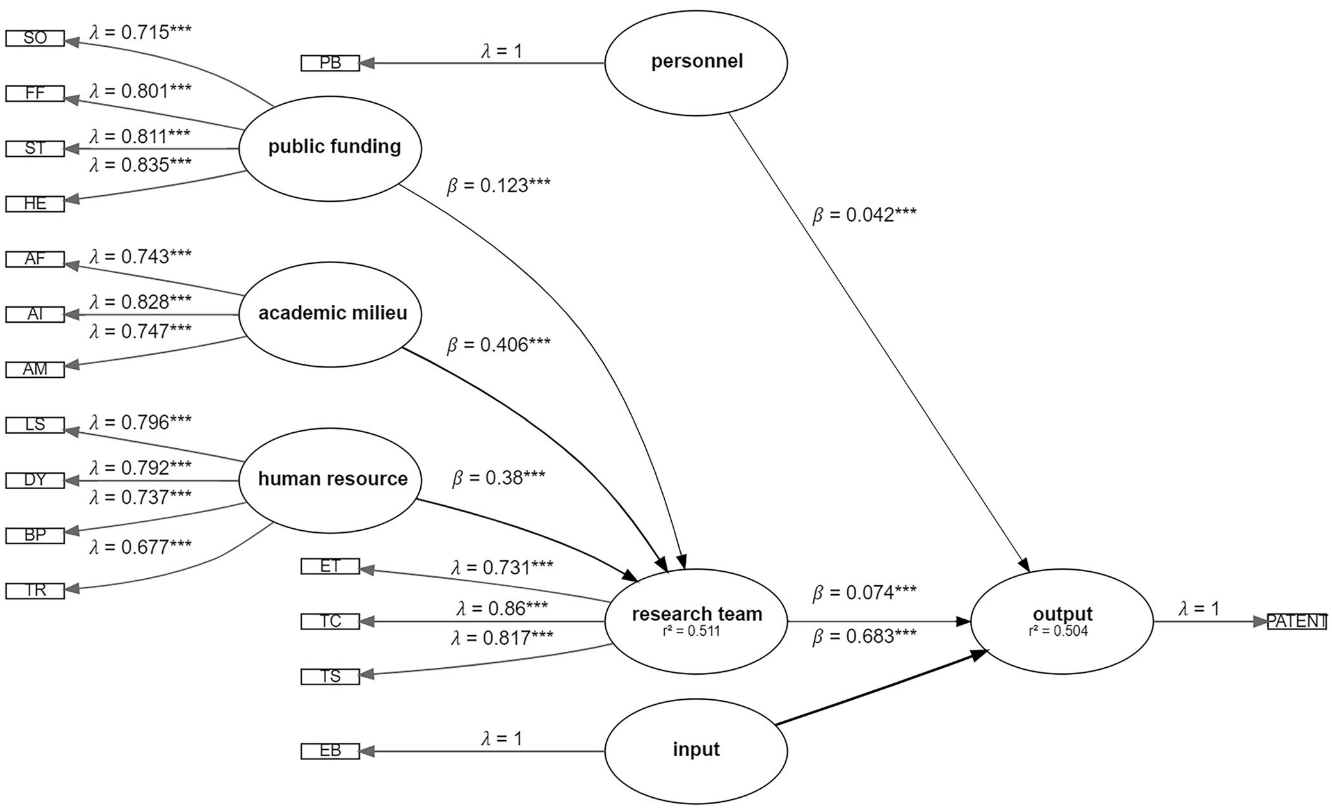

Fig. 5 The path diagram of PATENT PLS-SEM model. *Note: The nodes of indicators are displayed in gray.* **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Conclusion, policy implications and research limitations

Conclusion. The paper establishes the mechanism of association between mission-oriented innovation (MOI) and organized R&D (ORD) in the collective action framework and develops multi-dimensional measures of MOI performance and ORD. The paper utilizes baseline model and SEM model to test the path of ORD on MOI performance, bridging the gap between the theoretical mechanisms and quantitative research on MOI and ORD.

In this paper, we select the number of SCI-indexed papers which acknowledged funding from the National Natural Science Foundation of China (NSFC) and the Ministry of Science and Technology (MOST), as well as the number of Chinese national scientific awards as indicators of MOI performance to identify the social value of MOI. We select the number of patents as the indicator of economic value of MOI. We constructed the four determinants of ORD, namely R&D team, academic milieu, human resources and public funding. We adopted 14 indicators of influencing factors of the four determinants from 23 research universities in China. The results of the baseline regression model show that the 14 categories of sub-dimension indicators do not have a significant impact on MOI performance. The results of the SEM model show that if the R&D team, academic milieu, human resources, and public funding are analyzed as latent variables on the 14 indicators affecting MOI performance, the pathway of the ORD affecting MOI performance is clearly constructed.

The results indicate that the significant positive impact of ORD on MOI performance across three dimensions—PAPER, STA, and PATENT—mediated primarily by research teams. Among the determinants of ORD, public funding, academic milieu, and human resources indirectly enhance MOI performance by fostering high-quality research teams. However, the effect of funding volume on papers and patents is positively significant, while the effect on research awards is negatively significant. The findings of this paper help to understand the theoretical value of understanding the concepts and determinants of ORD through the lens of MOI under the collective action framework. Furthermore, there is a notable policy value in adopting a systematic and integrated perspective that considers sub-dimensional indicators to formulate policies that promote the performance of MOI through ORD.

Our investigation specifically provides enhanced analysis of public funding, a well-documented variable affecting MOI performance in existing literature. Our quantitative results align with the findings of previous studies (Defazio et al., 2009; Resce et al., 2022) by demonstrating that stable and adequate public funding volumes enhance MOI performance. However, our structural indicator analysis provides more innovative insights. It is vital to make smart changes to the way public funding is allocated to make MOI performance. Specifically, in contexts without ORD systems, MOI implementation requires three jobs: an increase in the proportion of competitive funding, a reduction in funding based on sustainable tracking and post-evaluation, and a moderate decrease in personnel expenditure ratios. When adopting ORD approaches, these factors become internalized within research teams to drive MOI performance. This evidence establishes that implementing MOIs through ORD—where public funding constructs high-caliber research teams in collective action framework—constitutes a critical policy mechanism.

Policy implications. The existing research literature on MOI policies (MOIP) argues that the design and implementation of MOIP is a governance model that highlights flexibility, multi-level coordination, policy mix and operational standards, as well as linkages to and acceptance by the public (Wittmann et al., 2021; Kirchherr et al., 2023). Our study, in turn, encourages policy makers to focus on the characteristics of MOIP in a collective action perspective when designing and implementing ORD-related policies. The results of this study solidify the conclusion that ORD is an effective means of advancing MOI, but rather than adopting a one-size-fits-all approach to ORD policies, it is important to design precisely policies in terms of MOI-specific domains.

Firstly, ORD policy should effectively incentivize universities to form a group of first-rate research teams, focusing on providing more resource support to researchers within the teams to strengthen cohesive spirit, clear responsibilities and rights between team members. Chinese universities have made significant progress in ORD, particularly through the establishment of national laboratories, the implementation of PI systems, the formation of R&D teams, the completion of MOI projects. However, it is prevalent for university teachers to establish the research team comprising their own students and lead by those teachers themselves, resulting in number of academic cliques. Despite the establishment of numerous research teams, there is a lack of interdisciplinary collaboration and knowledge flow. Furthermore, the allocation of research resources and the recognition of research results is not always sufficient to meet the needs of each researcher's career development and professional promotion. Consequently, university teachers are reluctant to collaborate on major projects, preferring to undertake them independently. Therefore, the policy should be designed in the presence of high-level research teams, effective management, and a strong interdisciplinary collaborative spirit are pivotal in fostering collective action in research.

Secondly, ORD-related policy should be precisely implemented on mission-specific MOI projects. The findings of the present study demonstrate that the significance of R&D teams on the number of STA is 1.57 times higher than the significance on the output of papers. This suggests that policy attention on ORD should be focused on building research teams for MOI projects with long-term social value, especially on the cultivation of leading scientists and distinguished young researchers, as well as the shaping of academic environments. In terms of enhancing the output of papers, the policy focus should be oriented towards the support of researchers, with an emphasis on individual contribution to MOI performance. For MOI projects with economic value, the policy focus should be placed on the leading scientists and distinguished young researchers, in addition to providing sufficient R&D funding and personnel support.

Thirdly, policy design should avoid possible systemic failures of MOI. This is crucial to prevent potential diffusion of responsibility and moral hazard among interest groups (Kuhlmann and Rip, 2018). Since the establishment of missions is typically based on a top-down approach to setting innovation goals, the role of ORD in MOI performance may be overestimated by over- or under-targeting in the implementation of ORD, even if the management model and resource inputs are sufficiently optimized. Targets that are either overly ambitious or insufficiently challenging if they are not aligned with existing innovation conditions. The collective action inherent in MOI projects focuses resources and authority on the specific task at hand, which may lead to the neglect of novel ideas and serendipitous results, as well as minor errors that occur during the innovation process, which could jeopardize the success of the entire innovation effort. Therefore, effective ORD policies should encompass goal setting, process management, conflict resolution regarding interests, and equitable benefit sharing in the collection action framework. The development of internal public funding models and human resource management models is essential for enhancing the academic environment within research teams.

Research limitations. The research limitations are as follows. Firstly, the 23 research universities selected for this study provide highly representative samples. However, there are over 1200 undergraduate institutions in China. The Teaching Quality Monitoring Report of Colleges and Universities Building First-Class Universities (2021 Edition) published by the Chinese Ministry of Education provides an overview of 41 first-class research universities in China. This shows that the 23 selected universities do not cover the basic situation of all universities and may be potentially biased.

Secondly, the data for the three determinants of organized R&D were obtained from the 2012 questionnaire, and the longitudinal data for the other variables were obtained from sources such as the China Science and Technology Yearbook and Web of Science. To better reflect the dynamic characteristics of individuals' perceptions of organized R&D, we converted the data for the three "human resource" indicators (LS, DY, and BR) from cross-sectional data to panel data and used annual growth rates. It may be a reasonable assumption that funding model policies, public funding policies, academic milieu and research teams in China have been considered stable since 2012 because organizational cultures and routines evolve over time. However, stable data does not reflect the true state of the indicators, even with a small change. Future research could collect more detailed data and more samples to make the findings more representative of real-world conditions.

Data availability

Data is provided within the supplementary information files.

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References

Akhilesh KB (2014) Human resource management in R&D. In: R&D management. Springer, New Delhi. https://doi.org/10.1007/978-81-322-1946-0_9

Albuquerque E, Suzigan W, Kruss G, Lee K (eds) (2015) Developing National Systems of Innovation: University-Industry Interactions in the Global South. Edward Elgar Publishing, Cheltenham. https://doi.org/10.4337/9781784711108

Alves AC, Vonortas NS, Zawislak PA (2021) Mission-oriented policy for innovation and the fuzzy boundary of market creation: the Brazilian shipbuilding case. Sci Public Policy 48:80–92. https://doi.org/10.1093/scipol/scaa059

Amabile TM, Conti R, Coon H, Lazenby J, Herron M (1996) Assessing the work environment for creativity. Acad Manag J 39:1154–1184. https://doi.org/10.5465/256995

Anderson NR, West MA (1998) Measuring climate for work group innovation: development and validation of the team climate inventory. J Organ Behav 19:235–258. https://doi.org/10.1002/(SICI)1099-1379(199805)19:3<235::AID-JOB837>3.0.CO;2-C

Angori G, Marzocchi C, Ramaciotti L, Rizzo U (2024) A patent-based analysis of the evolution of basic, mission-oriented, and applied research in European universities. J Technol Transf 49:609–641. https://doi.org/10.1007/s10961-023-10001-5

Archibugi D, Pianta M (1996) Measuring technological change through patents and innovation surveys. Technovation 16:451–519. https://doi.org/10.1016/0166-4972(96)00031-4

Association of American Colleges and Universities (AAC&U) (2006) Academic freedom and educational responsibility. In: Statement of Association of American Colleges and Universities. AAC&U, Washington. Available via ERIC. https://files.eric.ed.gov/fulltext/EJ744020.pdf. Accessed 28 Jun 2022

Axelson M, Netz J, Sandström C (2017) Collective action problems in public sector innovation: a business model perspective. Creat Innov Manag 26:370–378. https://doi.org/10.1111/caim.12250

Barney JB (2001) Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. J Manag 27:643–650. https://doi.org/10.1177/014920630102700602

Bayer AE, Dutton JE (1977) Career age and research-professional activities of academic scientists: tests of alternative nonlinear models and some implications for higher education faculty policies. J High Educ 48:259–282. https://doi.org/10.1080/00221546.1977.11780358

Bergek A, Hekkert M, Jacobsson S, Markard J, Sandén B, Truffer B (2015) Technological innovation systems in contexts: conceptualizing contextual structures and interaction dynamics. Environ Innov Soc Transit 16:51–64. https://doi.org/10.1016/j.eist.2015.07.003

Bollen KA, Diamantopoulos A (2017) In defense of causal-formative indicators: a minority report. Psychol Methods 22:581–596. https://doi.org/10.1037/met0000056

Boorman C, Jackson B, Burkett I (2023) SDG localization: mobilizing the potential of place leadership through collective impact and mission-oriented innovation methodologies. J Change Manag 23:53–71. https://doi.org/10.1080/14697017.2023.2167226

Braun D (1993) Who governs intermediary agencies? Principal-agent relations in research policy-making. J Public Policy 13:135–162. https://doi.org/10.1017/S0143814X00000994

Bromham L, Dinnage R, Hua X (2016) Interdisciplinary research has consistently lower funding success. Nature 534:684–687. https://doi.org/10.1038/nature18315

Brown R (2021) Mission-oriented or mission adrift? A critical examination of mission-oriented innovation policies. Eur Plan Stud 29:739–761. https://doi.org/10.1080/09654313.2020.1779189

Calvert J, Martin BR (2001) Changing conceptions of basic research. https://www.researchgate.net/publication/255593030_CHANGING_CONCEPTIONS_OF_BASIC_RESEARCH

Cassel C, Hackl P, Westlund AH (1999) Robustness of partial least-squares method for estimating latent variable quality structures. J Appl Stat 26:435–446. https://doi.org/10.1080/02664769922322

Chatterjee D, Dinar A, González-Rivera G (2018) An empirical knowledge production function of agricultural research and extension: the case of the University of California Cooperative Extension. Technol Forecast Soc Change 134:290–297. https://doi.org/10.1016/j.techfore.2018.06.037

Chin WW, Peterson RA, Brown SP (2008) Structural equation modeling in marketing: some practical reminders. J Mark Theory Pr 16:287–298. https://doi.org/10.2753/MTP1069-6679160402

Chin WW (2010) How to write up and report PLS analyses. In: Vinzi VE, Chin WW, Henseler J, et al. (eds) Handbook of partial least squares. Springer, Berlin, pp 655–690. https://doi.org/10.1007/978-3-540-32827-8_29

Choi YS, Lim U (2017) Contextual factors affecting the innovation performance of manufacturing SMEs in Korea: a structural equation modeling approach. Sustainability 9:1193. https://doi.org/10.3390/su9071193

Colbert BA (2004) The complex resource-based view: implications for theory and practice in strategic human resource management. Acad Manag Rev 29:341–358. https://doi.org/10.5465/amr.2004.13670987

Cronbach LJ (1951) Coefficient alpha and the internal structure of tests. Psychometrika 16:297–334. https://doi.org/10.1007/BF02310555

David PA, Hall BH, Toole AA (2000) Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Res Policy 29:497–529. https://doi.org/10.1016/S0048-7333(99)00087-6

Defazio D, Lockett A, Wright M (2009) Funding incentives, collaborative dynamics and scientific productivity: evidence from the EU framework program. Res Policy 38:293–305. https://doi.org/10.1016/j.respol.2008.11.008

Deleidi M, Mazzucato M (2021) Directed innovation policies and the supermultiplier: an empirical assessment of mission-oriented policies in the US economy. Res Policy 50:104151. https://doi.org/10.1016/j.respol.2020.104151

Dijkstra TK (2010) Latent variables and indices: Herman Wold's basic design and partial least squares. In: Vinzi VE, Chin WW, Henseler J, et al. (eds) Handbook of partial least squares. Springer, Berlin, pp 23–46. https://doi.org/10.1007/978-3-540-32827-8_2

Dong J, Liu J, Liu T (2021) The impact of top scientists on the community development of basic research directed by government funding: Evidence from program 973 in China. Scientometrics 126:8561–8579. https://doi.org/10.1007/s11192-021-04092-w

Ernst H (2003) Patent information for strategic technology management. World Pat Inf 25:233–242. https://doi.org/10.1016/S0172-2190(03)00077-2

Etzkowitz H, Leydesdorff L (1995) The triple helix—university-industry-government relations: a laboratory for knowledge based economic development. East Rev 14:14–19

Evans CH (1995) Faculty development in a changing academic environment. Acad Med 70:14–20. https://doi.org/10.1097/00001888-199501000-00007

Feiock RC (2013) The Institutional Collective Action Framework. Policy Stud J 41:397–425. https://doi.org/10.1111/psj.12023

Geiger RL (1990) Organized research units—their role in the development of university research. J High Educ 61:1–19. https://doi.org/10.1080/00221546.1990.11775088

de Graaf R, van der Duin P (2013) Collective innovation: a new approach for dealing with society induced challenges. A case study in the Dutch bakery sector. Proc Soc Behav Sci 75:139–145. https://doi.org/10.1016/j.sbspro.2013.04.016

Griliches Z (1990) Patent statistics as economic indicators: a survey. J Econ Lit 28:1661–1707

Guan J, Ma N (2009) Structural equation model with PLS path modeling for an integrated system of publicly funded basic research. Scientometrics 81:683–698. https://doi.org/10.1007/s11192-009-2058-7
Hair JF Jr, Hult GTM, Ringle CM, Sarstedt M, Danks NP, Ray S (2021) Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer, Berlin. https://doi.org/10.1007/978-3-030-80519-7
Harding TS (1948) The triumph of organized research. Am J Econ Socio 7:339–352. https://doi.org/10.1111/j.1536-7150.1948.tb00699.x
Henrekson M, Sandström C, Stenkula M (2024) Seven reasons why mission-oriented innovation policies seldom work in practice. Econ Aff 44:354–362. https://doi.org/10.1111/ecaf.12654
Hoe SL (2011) Measuring an organization's innovation climate: a case study from Singapore. Dev Learn Organ 25:13–15. https://doi.org/10.1108/14777281111173342
Jöreskog KG (1979) Basic ideas of factor and component analysis. In: Jöreskog KG, Sumorbom D, Magidson J (eds) Advances in factor analysis and structural equation models. Abt Books, Cambridge, pp 5–20
Jucevičius G, Grumadaitė K (2014) Smart development of innovation ecosystem. Proc Soc Behav Sci 156:125–129. https://doi.org/10.1016/j.sbspro.2014.11.133
Jung I, Kim JH, Ma Y, Seo C (2015) Mediating effect of academic self-efficacy on the relationship between academic stress and academic burnout in Chinese adolescents. Int J Hum Ecol 16:63–77. https://doi.org/10.6115/ijhe.2015.16.2.63
Kania J, Kramer M (2013) Embracing emergence: how collective impact addresses complexity. Stan Soc Innov Rev. https://doi.org/10.48558/ZJY9-4D87
Kerr C (2001) The uses of the university. Harvard University Press, Cambridge
Kim L, Jang DH (2021) Culturing atmosphere for spontaneous innovation: Academic action and triple-helix dynamics in South Korea. High Educ Policy 34:429–455. https://doi.org/10.1057/s41307-019-00143-3
Kirchherr J, Hartley K, Tukker A (2023) Missions and mission-oriented innovation policy for sustainability: a review and critical reflection. Environ Innov Soc Transit 47:100721. https://doi.org/10.1016/j.eist.2023.100721
Kleinman DL (1994) Layers of interests, layers of influence: Business and the genesis of the National Science Foundation. Sci Technol Hum Values 19:259–282. https://doi.org/10.1177/016224399401900301
Koutsou S, Partalidou M (2012) Pursuing knowledge and innovation through collective actions: the case of young farmers in Greece. J Agric Educ Ext 18:445–460. https://doi.org/10.1080/1389224X.2012.704857
Kristinsson K, Candi M, Sæmundsson RJ (2016) The relationship between founder team diversity and innovation performance: the moderating role of causation logic. Long Range Plan 49:464–476. https://doi.org/10.1016/j.lrp.2015.12.013
Kuhlmann S, Rip A (2018) Next-generation innovation policy and grand challenges. Sci Public Policy 45:448–454. https://doi.org/10.1093/scipol/scy011
Li D, Liang Z, Tell F, Xue L (2021) Sectoral systems of innovation in the era of the fourth industrial revolution: an introduction to the special section. Ind Corp Change 30:123–135. https://doi.org/10.1093/icc/dtaa064
Malerba F (2002) Sectoral systems of innovation and production. Res Policy 31:247–264. https://doi.org/10.1016/S0048-7333(01)00139-1
Marrocu E, Paci R, Usai S (2013) Proximity, networking and knowledge production in Europe: what lessons for innovation policy? Technol Forecast Soc Change 80:1484–1498. https://doi.org/10.1016/S0048-7333(01)00139-1
Martín-Barrera G, Zamora-Ramírez C, González-González JM (2017) Impact of flexibility in public R&D funding: how real options could avoid the crowding-out effect. Renew Sustain Energy Rev 76:813–823. https://doi.org/10.1016/j.rser.2017.03.086
Mazzucato M (2018) Mission-oriented innovation policies: challenges and opportunities. Ind Corp Change 27:803–815. https://doi.org/10.1093/icc/dty034
McAdam M, Debackere K (2018) Beyond 'triple helix' toward 'quadruple helix' models in regional innovation systems: Implications for theory and practice. RD Manag 48:3–6. https://doi.org/10.1111/radm.12309
Menken S, Keestra M (2016) An introduction to interdisciplinary research: Theory and practice. Amsterdam University Press, Amsterdam
Ministry of Education (2012) Outline of the National Program for Medium- and Long-Term Education Reform and Development (2010-2020). http://www.moe.gov.cn/srcsite/A01/s7048/201007/t20100729_171904.html. Accessed 28 Jun 2022
Ministry of Science and Technology (2006) Outline of the National Program for Medium- and Long-Term Scientific and Technological Development (2006–2020). http://www.gov.cn/zwgk/2006-02/14/content_191891.htm. Accessed 28 Jun 2022
Mors ML, Waguespack DM (2021) Fast success and slow failure: the process speed of dispersed research teams. Res Policy 50:104222. https://doi.org/10.1016/j.respol.2021.104222
Narin F, Pinski G, Gee HH (1976) Structure of the biomedical literature. J Am Soc Inf Sci 27:25–45. https://doi.org/10.1002/asi.4630270104
Nylén EJ, Johanson JE, Vakkuri J (2023) Mission-oriented innovation policy as a hybridisation process: the case of transforming a national fertilising system. Sci Public Policy 50:509–520. https://doi.org/10.1093/scipol/scad004
Olson M (1971) The logic of collective action: Public goods and the theory of groups. Harvard University Press, Cambridge
Parker JC (2011) Conscience and collective duties: do medical professionals have a collective duty to ensure that their profession provides non-discriminatory access to all medical services ?. J Med Philos 36:28–32
Penrose ET (1995) The theory of the growth of the firm. Oxford University Press, Oxford
Peteraf MA (1993) The cornerstones of competitive advantage: a resource-based view. Strateg Manag J 14:179–191. https://doi.org/10.1002/smj.4250140303
Qian X, Lee PW, Cao S (2010) China: forward to the green pesticides via a basic research program. J Agric Food Chem 58:2613–2623. https://doi.org/10.1021/jf904098w
Reale F (2021) Mission-oriented innovation policy and the challenge of urgency: lessons from Covid-19 and beyond. Technovation 107:102306. https://doi.org/10.1016/j.technovation.2021.102306
Resce G, Zinilli A, Cerulli G (2022) Machine learning prediction of academic collaboration networks. Sci Rep. 12:21993. https://doi.org/10.1038/s41598-022-26531-1
Rouyre A, Fernandez AS, Bruyaka O (2024) Big problems require large collective actions: managing multilateral coopetition in strategic innovation networks. Technovation 132:102968. https://doi.org/10.1016/j.technovation.2024.102968
Rylance R (2015) Grant giving: global funders to focus on interdisciplinarity. Nature 525:313–315. https://doi.org/10.1038/525313a
Sá CM, Oleksiyenko A (2011) Between the local and the global: organized research units and international collaborations in the health sciences. High Educ 62:367–382. https://doi.org/10.1007/s10734-010-9393-8
Salem DA, Foster-Fishman PG, Goodkind JR (2002) The adoption of innovation in collective action organizations. Am J Community Psychol 30:681–710. https://doi.org/10.1023/A:1016373215689
Sandler T (2015) Collective action: fifty years later. Public Choice 164:195–216. https://doi.org/10.1007/s11127-015-0252-0
Sarros JC, Cooper BK, Santora JC (2008) Building a climate for innovation through transformational leadership and organizational culture. J Leadersh Organ Stud 15:145–158. https://doi.org/10.1177/1548051808324100
Schoen J, Mason TW, Kline WA, Bunch RM (2005) The innovation cycle: a new model and case study for the invention to innovation process. Eng Manag J 17:3–10. https://doi.org/10.1080/10429247.2005.11415292
Shanker R, Bhanugopan R, Van der Heijden BI, Farrell M (2017) Organizational climate for innovation and organizational performance: the mediating effect of innovative work behavior. J Vocat Behav 100:67–77. https://doi.org/10.1016/j.jvb.2017.02.004
Slaughter S, Rhoades G (1996) The emergence of a competitiveness research and development policy coalition and the commercialization of academic science and technology. Sci Technol Hum Values 21:303–339. https://doi.org/10.1177/016224399602100303
Sohn SY, Joo YG, Han HK (2007) Structural equation model for the evaluation of national funding on R&D project of SMEs in consideration with MBNQA criteria. Eval Program Plann 30:10–20. https://doi.org/10.1016/j.evalprogplan.2006.10.002
Stoica P, Selen Y (2004) Model-order selection: a review of information criterion rules. IEEE Signal Process Mag 21:36–47. https://doi.org/10.1109/MSP.2004.1311138
Storper M (1996) Innovation as collective action: conventions, products and technologies. Ind Corp Change 5:761–790. https://doi.org/10.1093/icc/5.3.761
Su J, He J, Huang C (2012) Investing in the future: theoretical and empirical research on university basic research. China. Renmin University Press, Beijing
Szell M, Ma Y, Sinatra R (2018) A Nobel opportunity for interdisciplinarity. Nat Phys 14:1075–1078. https://doi.org/10.1038/s41567-018-0314-6
The US council on competitiveness and Deloitte Touche Tohmatsu Limited's (DTTL) (2014) 2013 Global Manufacturing Index Report. http://www2.deloitte.com/global/en.html. Accessed 15 Jun 2020
Thomas E, Faccin K, Asheim BT (2021) Universities as orchestrators of the development of regional innovation ecosystems in emerging economies. Growth Change 52:770–789. https://doi.org/10.1111/grow.12442
Tien FF, Blackburn RT (1996) Faculty rank system, research motivation, and faculty research productivity: measure refinement and theory testing. J High Educ 67:2–22. https://doi.org/10.1080/00221546.1996.11780246
Vicente-Saez R, Gustafsson R, Van den Brande L (2020) The dawn of an open exploration era: emergent principles and practices of open science and innovation of university research teams in a digital world. Technol Forecast Soc Change 156:120037. https://doi.org/10.1016/j.techfore.2020.120037
Wanzenböck I, Wesseling JH, Frenken K, Hekkert MP, Weber KM (2020) A framework for mission-oriented innovation policy: alternative pathways through the problem–solution space. Sci Public Policy 47:474–489. https://doi.org/10.1093/scipol/scaa027

Wernerfelt B (1984) A resource-based view of the firm. Strateg Manag J 5:171–180. https://doi.org/10.1002/smj.4250050207

Wittmann F, Hufnagl M, Lindner R, Roth F, Edler J (2021) Governing varieties of mission-oriented innovation policies: a new typology. Sci Public Policy 48:727–738. https://doi.org/10.1093/scipol/scab044

Wright PM, Dunford BB, Snell SA (2001) Human resource and the resource-based view of the firm. J Manag 27:701–721. https://doi.org/10.1177/014920630102700607

Xue L, Li D, Yu Z (2021) China's national and regional innovation system. In: Fu X, McKern B, Chen J (eds) Oxford handbook of China innovation. Oxford University Press, Oxford, pp 115–134

Yang T, Wang Y, Deng J, Huang C (2021) Attitude, social norms, and perceived behavioral control influence the academic integrity-related behavioral intentions of graduate students. Soc Behav Pers 49:1–12. https://doi.org/10.2224/sbp.9996

Yoav K, Shchori-Bachrach N (1973) The process of an innovation cycle. Am J Agric Econ 55:28–37. https://doi.org/10.2307/1238658

Zhang C, Wang C, Geng H, Liu N (2024) A tale of two cities: mission-oriented innovation policy in China's green industries. Ind Innov 31:352–376. https://doi.org/10.1080/13662716.2023.2271859

Zhao ZY, Lei XP (2013) Empirical analysis of the relationship between technology innovation and basic research. Curr Sci 104:714–720. http://www.jstor.org/stable/24092062

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Competing interests
The authors declare no competing interests.

Ethical approval
All procedures performed in this study involving human participants were in accordance with the ethical standards of the Helsinki Declaration. The present study utilized secondary data provided by the Major Strategic Research Project, which was conducted in 2011 by the Science and Technology Commission of the Ministry of Education of China. The project was entitled "Strengthening Basic Research in Universities and Enhancing Independent Innovation Capacity — Reform and Innovation of the Scientific Research System in Chinese Universities". The data presented in this study was printed in the book titled "Investing in the Nation's Future: Theoretical and Empirical Research on University Basic Research" (Su Jun, He Jinqiu, Huang Cui, Beijing: Renmin University of China Press, ISBN 9787300150475, 2012).

Informed consent
This study utilized secondary data provided by the Major Strategic Research Project conducted in 2011 by the Science and Technology Commission of the Ministry of Education of China. The original data collection by the Science and Technology Commission of the Ministry of Education of China included appropriate informed consent procedures for all participants. No additional informed consent was required for this secondary analysis.

Additional information
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