

The innovation benefits and limits of institutionalized science-industry collaboration: Evidence from China's academician workstations

Shuai Wang

Hefei University of Technology

Yu Jin

Hefei University of Technology

Bojun Hou

2019800052@hfut.edu.cn

Hefei University of Technology

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Abstract

Governments increasingly institutionalize science-industry collaboration through formally recognized and publicly supported partnerships, yet whether their innovation benefits persist as such arrangements expand remains unclear. We examine this question using China's Academician Workstations, combining hand-collected workstation records with firm and patent data in a matched staggered difference-in-differences framework. We identify the effect by exploiting variation in the timing of workstation establishment across firms relative to matched control firms. Workstation establishment is associated with higher inventive output in the early period, accompanied by broader technological search, more collaborative patenting, and greater inventor participation. Comparable gains are not evident in the later expansion period, while citation intensity does not improve systematically. The marginal innovation benefit of new workstations also becomes less favorable as local workstation density increases. These findings suggest that institutionalized collaboration can scale more readily as an organizational form than the scientific engagement, technological matching, and knowledge-utilization conditions required to sustain its innovation benefits.

Keywords: Science-industry collaboration; Academician Workstations; Institutionalized collaboration; Knowledge utilization; Firm innovation

JEL classification O31 O32 O38 L52

1 Introduction

Governments support formal science-industry partnerships to make scientific expertise more accessible to firms. These arrangements institutionalize collaboration by giving it a recognized organizational form, often backed by public support. They can help participants mobilize resources and sustain exchanges that might otherwise depend heavily on individual relationships (Perkmann et al., 2013, 2021). Yet establishing a partnership and generating innovation are different achievements. An organizational arrangement can be replicated without reproducing scientists' sustained participation, the fit between their expertise and firms' technological needs, or firms' capacity to use external knowledge. Moreover, the recognition and resources attached to a partnership can make formal participation valuable apart from the research it enables. The same institutional support that facilitates collaboration may therefore change the incentives underlying it. Under what conditions does institutionalized science-industry collaboration generate innovation benefits, and what limits those benefits?

Research on academic engagement provides an important foundation for addressing this question. It identifies individual motivations, organizational support, and institutional conditions that shape engagement and its consequences (Almeida et al., 2011; Perkmann et al., 2013, 2021). Related research on academic technology transfer similarly shows that the motivations underlying academic entrepreneurship are heterogeneous and systematically associated with subsequent performance (Civera et al., 2020). More recent work shows that scientific outputs, commercializable results, and subsequent cooperation depend on different, partly interrelated conditions (Cantner et al., 2024; Giunta et al., 2026). Continued inventor involvement can be important for developing university inventions (Agrawal, 2006), while internal research investment and appropriately trained personnel shape firms' ability to use external science (Motohashi et al., 2025). These findings establish that productive collaboration requires more than a scientific connection. They also invite a question about the institutions through which such connections are organized. Evidence that particular collaborations benefit firms does not establish how broadly those benefits extend when a formally recognized arrangement is promoted among more participants. Addressing this issue requires connecting the incentives for establishing partnerships with the scientific inputs and knowledge utilization conditions that make them productive.

We develop an argument in which institutionalization both supports collaboration and shapes the incentives for participating in it. Formal arrangements can confer

legitimacy and facilitate resource access, while the considerations motivating their adoption may change as they diffuse (Meyer & Rowan, 1977; Tolbert & Zucker, 1983). Applied to science-industry collaboration, this suggests that the rewards attached to formal participation need not remain closely connected to joint research. When administrative recognition, eligibility for public support, or professional rewards depend more on establishing partnerships than on sustaining substantive engagement, public agencies, firms, and scientists may place greater weight on obtaining or maintaining formal affiliations (Kopczynska & Ferreira, 2021). A partnership may then remain attractive even when scientific involvement is limited or expertise is poorly matched to the firm's needs. This incentive problem differs from a capacity constraint, under which participants remain committed to collaboration but lack sufficient time, personnel, or capabilities. Both can limit innovation benefits without implying that a platform is inactive (Bromley & Powell, 2012). Conversely, wider participation may improve matching and help participants accumulate experience. Our argument therefore does not presume that institutionalization undermines collaboration. It identifies a tension between the incentives sustaining formal participation and the substantive conditions required for knowledge utilization.

China's Academician Workstations (AWs) provide a setting in which to examine these benefits and limits. Workstations connect host firms with eminent scientists and their teams through arrangements supported by public authorities and science and technology associations. They combine recognized scientific affiliations with an organizational platform for research, technical exchange, and resource mobilization. Their development has also involved changes in governance. National guidance issued in 2019 introduced limits on workstation appointments and requirements for scientists' participation, making the terms of continuing engagement an explicit policy concern (General Office of the CPC Central Committee and the State Council, 2019). Existing studies report positive innovation outcomes from workstations, emphasizing financing, talent attraction, and resource integration (Quan et al., 2021; Xu et al., 2021; Yin et al., 2023). These findings establish important benefits of the arrangement. We build on them by examining the scope of those benefits across development periods, innovation outcomes, and collaboration conditions, rather than treating the effect of workstation establishment as a single, time-invariant property.

We link hand-collected workstation records to business registration and patent data to construct a matched panel of listed and unlisted firms. Using variation in

establishment timing, we examine changes in patent output and citation intensity, comparing the period ending in 2016 with 2017-2022. Patent-output estimates are positive in the early period, close to zero in the later-period firm fixed effects specification. Citation intensity shows no consistent improvement and has a negative later-period estimate in the same specification. Positive early-period patent-output estimates are also observed among firms linked to academicians with fewer workstation affiliations and among larger or high-tech firms. Complementary evidence from a separate sample in the 2011-2013 China Enterprise Innovation Survey associates workstations with highly qualified research personnel. Together, these findings delineate the observed benefits and limits of institutionalized collaboration across periods, outcomes, and collaboration conditions, without directly identifying the mechanisms underlying the later-period results.

This study makes two contributions. First, we connect institutional explanations of formal participation with the substantive requirements of scientific knowledge utilization. By distinguishing recognized partnership status from the innovation value generated through collaboration, we show why institutionalized collaboration may scale more readily as an organizational form than the scientific engagement, technological matching, and knowledge-utilization conditions that make it productive (Bromley & Powell, 2012; Meyer & Rowan, 1977). Second, we provide a more conditional assessment of the innovation benefits of institutionalized science-industry collaboration by examining their variation across development periods, collaboration conditions, innovation-process outcomes, and local institutional diffusion. In doing so, we qualify existing positive assessments of AWs and distinguish the expansion of formal collaboration from the realization of innovation benefits.

Section 2 presents the institutional background, and Section 3 develops the theoretical framework. Section 4 describes the data and empirical strategy. Sections 5 and 6 report the main results and complementary evidence. Sections 7 and 8 provide the discussion and conclusion.

2 Institutional Background of China's Academician Workstations

2.1 Institutional evolution and policy milestones

AWs refer to China's government-supported "academician expert workstation" program, a distinctive institutional arrangement designed to organize science-industry collaboration by linking academicians and firms under local government endorsement and supervision. The program originated as a local experiment in the early 2000s. While

the first workstation was established in 2003, diffusion was slow at the beginning and only three workstations were created before 2007 (Yang et al., 2025). Our hand-collected registry provides coverage from 2007 onward, which enables us to track the program's scale-up and governance changes systematically. We therefore describe the early experimental years briefly and focus our institutional and descriptive analysis on 2007-2023 using our collected records (As shown in Figure 1).

In the early exploration period from 2003 to 2009, AWs developed largely through localized experimentation and were typically established to address specific needs for industrial upgrading. With limited standardization and a modest scale, workstation formation was more likely to be demand-driven, and attention dilution among academicians was less severe. This phase therefore provides a baseline setting in which substantive collaboration is relatively more plausible.

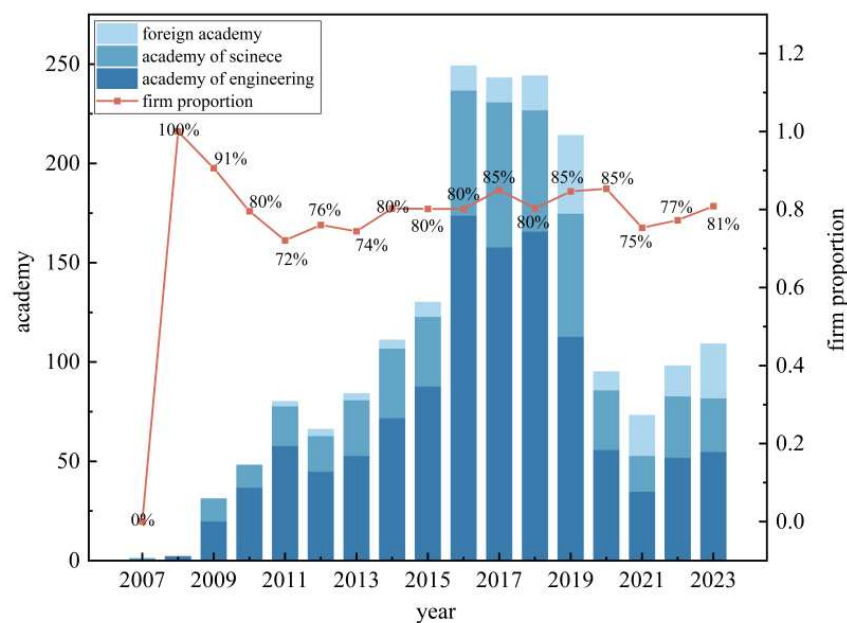
A key shift occurred during the institutionalization and expansion period from 2010 to 2016. In 2010, the China Association for Science and Technology (CAST) issued its first national guidance document on AW construction (CAST, 2010). Its main contribution was less about operational detail and more about creating policy legitimacy and coordination capacity. The document encouraged cooperation between CAST and local governments and positioned AWs as a long-term mechanism for connecting expert resources with enterprise needs. With this national endorsement, AWs became easier to scale as a policy instrument and, in many localities, were accompanied by stronger fiscal and administrative support. As a result, the program expanded rapidly and became embedded in broader innovation and talent policy frameworks.

Around 2016, the program entered a qualitatively different regime. In our hand-collected data, the number of newly established workstations begins to surge sharply from 2016 onward, indicating a transition into a high-saturation expansion phase. We therefore treat 2016 as the practical “shock” year in the analysis, because it marks the onset of accelerated proliferation and a corresponding rise in the risk that new workstation creation reflects weaker matching and more symbolic adoption. When expansion becomes rapid and less selective, institutionalization costs including attention dilution, compliance-oriented implementation, and resource misallocation become more likely to dominate, potentially weakening or even reversing innovation gains.

Policy responses followed soon after. In 2017, the CAST introduced an interim certification and management framework (CAST, 2017) that strengthened governance

by specifying eligibility and operational requirements and by introducing annual reporting and dynamic management, including rectification and possible decertification for non-compliance. In 2019, a higher-authority central document jointly issued by the General Office of the CPC Central Committee and the General Office of the State Council (State Council, 2019) imposed explicit limits on the number of workstations an academician can be affiliated with and required a minimum annual on-site time commitment for each workstation. These provisions directly addressed a structural constraint of the program, namely the scarcity of elite scientific attention and its tendency to be diluted when one academician is linked to multiple stations.

We interpret this staged evolution as a change not only in the scale of participation but also in the conditions under which collaboration was organized. As policy-backed adoption expanded, maintaining alignment between formal recognition, sustained scientific engagement, and firms' technological needs became increasingly important. This evolution provides the institutional rationale for treating the post-2016 expansion as a meaningful breakpoint in our empirical analysis. Rather than assuming a single, time-invariant effect, we examine whether AWs generate innovation benefits under conditions more conducive to substantive interaction and whether these benefits weaken or reverse as the risks of symbolic participation and resource misallocation become more salient.



Notes: The stacked bars show the annual number of newly established workstations, classified by the academy affiliation of their associated academicians. The line reports the percentage of newly established workstations hosted by firms. The figure is based on the records collected for this study

rather than a complete national census.

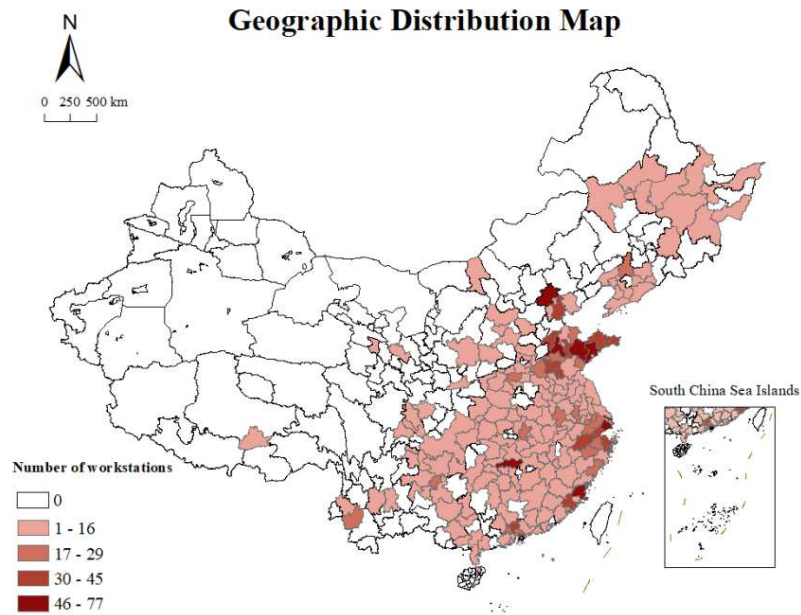
Fig. 1 Annual establishment of AWs by academician category

2.2 Distributional features of Academician workstations

We next describe the distributional features of AWs using our hand-collected registry for 2007-2023. These patterns characterize the structural conditions under which the arrangement operates and provide context for examining variation in innovation outcomes across development periods and collaboration settings. AWs are predominantly firm-oriented. Firms typically account for more than 70% of newly established workstations (Figure 1), indicating that the arrangement is directed primarily toward firm-level technological problem solving rather than the expansion of academic organizations.

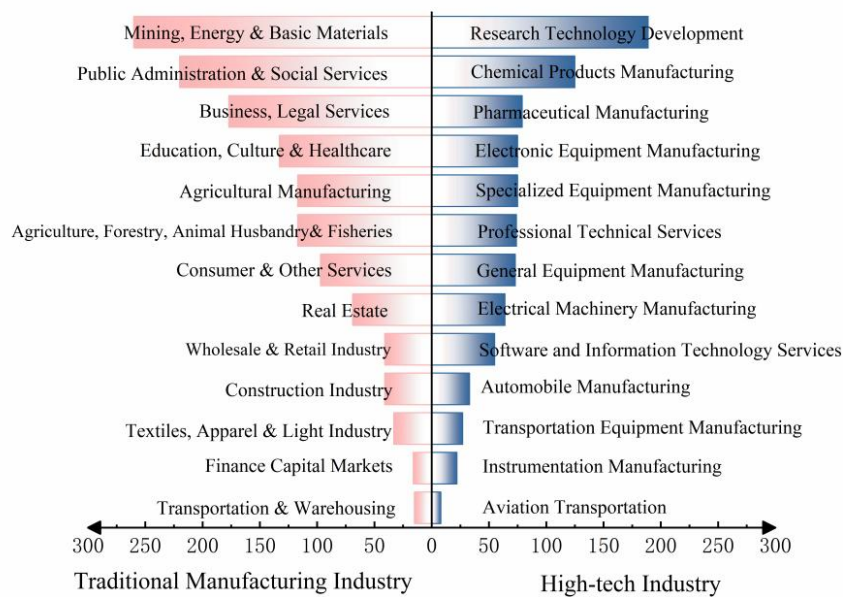
The scientific connections underlying these workstations are heterogeneous. Among newly established AWs, those associated with members of the Chinese Academy of Engineering (CAE) constitute the largest category, followed by those associated with members of the Chinese Academy of Sciences (CAS) and foreign academies (Figure 1). Multiple affiliations are also common. More than half of the academicians in our registry are associated with more than one workstation over the observation period. This pattern brings the allocation of scientific effort into focus. Multiple affiliations can broaden access to scientific expertise, but they may also create a trade-off between the breadth and depth of engagement when commitments overlap and the time and team resources available to support them do not expand accordingly.

The spatial distribution reveals pronounced regional concentration. Figure 2 maps cumulative recorded workstation establishments by city through 2023. Workstations are concentrated in eastern China, with cities such as Shanghai, Jinan, and Beijing featuring prominently, whereas many central cities host relatively few stations and western areas have a more limited presence. This uneven geography is consistent with regional differences in innovation ecosystems and the capacity to organize science-industry collaboration. The geography of establishment is complemented by a tendency toward local partnership formation. More than half of the firm hosts in our records collaborate with academicians based in the same city. Such proximity may reduce coordination costs and facilitate repeated interaction, while offering less scope for extending knowledge access beyond existing regional networks. The regional environment surrounding a workstation and the spatial relationship between its participants therefore represent distinct, although related, conditions of collaboration.



Notes: This figure shows the cumulative number of academician workstations established in each city in 2023. Darker colors indicate a higher number of workstations.

Fig. 2 Spatial distribution of AWs across cities



Notes: Following the OECD classification, R&D- and knowledge-intensive industries are defined as high-tech, while resource- and labor-intensive industries are categorized as traditional sectors. Longer bars indicate a higher number of workstations.

Fig. 3 Industry distribution of AWs

Sectoral participation further illustrates the range of technological needs served by AWs. Workstations are not confined to frontier high-technology industries. A

substantial share is established in traditional manufacturing and materials-related activities, consistent with an industrial upgrading role (as shown in Figure 3). Participation also varies by firm size, with large firms more likely to establish workstations than small and medium-sized enterprises. This pattern may reflect differences in the resources and absorptive capacity needed to organize sustained cooperation and integrate scientific knowledge into internal research activities. The sectoral and size distributions thus connect the program's broad coverage to differences in firms' technological needs and capacities for knowledge utilization.

Taken together, the program's evolution and distributional features highlight a central tension in institutionalized science-industry collaboration. Formal recognition can extend scientific partnerships across firms and regions, but it does not automatically secure the sustained engagement, technological fit, and capacity for knowledge utilization needed to generate innovation. As a common organizational form spreads across heterogeneous participants, the incentives to establish and maintain recognized affiliations may not remain aligned with the requirements of substantive collaboration. The question is therefore not simply whether workstations connect firms to scientists, but when institutional support helps turn those connections into productive collaboration and what limits the resulting innovation benefits. This question guides our examination of outcomes across development periods and collaboration conditions.

3 Theoretical Framework and Hypothesis Development

3.1 Institutionalized collaboration and knowledge utilization

The innovation value of institutionalized science-industry collaboration depends on how formal arrangements become connected to firms' research activities. Institutional theory provides a starting point for examining this connection. Recognized organizational structures can confer legitimacy and facilitate resource access without necessarily improving the technical activities they are intended to support (Meyer & Rowan, 1977). We therefore distinguish the value of formal partnership status from the innovation value generated through scientific knowledge utilization. In the AW setting, recognition can help participants organize and sustain cooperation, while also making an affiliation valuable apart from the joint research it enables. Institutionalization thus shapes both the conditions for collaboration and the incentives for participating in it.

Knowledge utilization involves identifying relevant scientific insights, adapting them to technological problems, and incorporating them into firms' research and development. It extends beyond obtaining access to expertise or receiving research

results. Academic engagement encompasses exchanges through which participants contribute knowledge and resources to collaborative work (Perkmann et al., 2013, 2021), and scientists' continued involvement can make knowledge available that is not fully conveyed through codified outputs (Agrawal, 2006). Firms must also possess the capacity to interpret and apply these inputs. Absorptive capacity research emphasizes the importance of prior knowledge and internal learning efforts (Cohen & Levinthal, 1990), while evidence on science-based innovation highlights the complementary roles of internal R&D and personnel capable of connecting scientific research with industrial applications (Bekkers & Bodas Freitas, 2008; Motohashi et al., 2025). External scientific connections therefore create opportunities for innovation, but their use requires effort within the firm.

These collaborative activities need not rest on identical objectives. Scientists' participation in technology-transfer activities may reflect heterogeneous motivations, and similar formal forms of engagement can consequently lead to different outcomes (Civera et al., 2020). Scientists often engage with industry to advance their research rather than primarily to commercialize existing knowledge (D'Este & Perkmann, 2011; D'Este & Patel, 2007). Moreover, scientific results, commercializable outcomes, and subsequent cooperation depend on different, partly interrelated conditions (Cantner et al., 2024). We accordingly view productive collaboration as requiring sufficient alignment between participants' objectives and the work needed to address the firm's technological problems, rather than uniform motivations. Formal recognition and organizational support matter insofar as they help sustain that alignment and enable participants to contribute complementary resources.

This framework also distinguishes the implementation of collaboration from its innovation consequences. A recognized partnership may remain weakly connected to substantive research, but collaborative activities may also occur without producing the intended innovation gains. These possibilities correspond to the distinction between gaps in implementation and gaps between activities and outcomes developed by Bromley and Powell (2012). Limited innovation benefits therefore do not, by themselves, establish an absence of cooperation. The central theoretical issue is how institutional support becomes connected to scientific engagement and firms' knowledge utilization, and whether this connection is sustained as the arrangement develops. The following sections derive the potential benefits and limits of institutionalized collaboration from this relationship.

3.2 Institutional support and innovation benefits

Institutional support can promote innovation by making problem-oriented collaboration easier to organize and sustain. In the AW arrangement, agreed research tasks and commitments of personnel and resources provide a basis for coordinating the contributions of firms and scientific teams. This organizational continuity creates opportunities to clarify technological problems, exchange feedback, and adapt research as projects develop. Research on university-industry partnerships identifies communication, trust, and the management of knowledge differences as important conditions for effective knowledge transfer (De Wit-de Vries et al., 2019). Applied to AWs, this suggests that formal arrangements can support innovation by enabling repeated interaction around shared research tasks (Xie et al., 2023).

A first channel is resource mobilization. Scientific collaboration requires firms to commit resources before technological returns are assured. Public support can reduce the financial burden of research and make projects feasible that would otherwise face financing constraints (Takalo & Tanayama, 2010). In the AW setting, such support can help firms sustain the experimentation, testing, and adaptation required to develop scientific insights into workable technologies. Combined with agreed project commitments, it can also concentrate complementary resources on problems that neither the firm nor the scientific team could readily address alone. The expected benefit arises from enabling this research activity, rather than from the receipt of support itself.

A second channel is human-capital development. Collaboration with academicians and their teams can help firms attract qualified researchers and provide opportunities for learning through joint work. These inputs strengthen the connection between external scientific expertise and internal technological development. Evidence from science-based innovation shows that research-trained personnel complement university collaboration by helping firms interpret and apply scientific knowledge (Motohashi et al., 2025). Within AWs, sustained engagement can similarly allow employees to learn how to formulate research questions, assess unfamiliar methods, and adapt scientific insights to the firm's technological context. Institutional support can therefore contribute to innovation by strengthening the capabilities through which external knowledge is used, alongside improving access to that knowledge.

These channels reinforce one another. Resources help sustain joint research, while skilled personnel and repeated interaction make its scientific content usable. As firms gain experience in collaboration, they can develop the collaborative know-how and

trust associated with learning and innovation benefits (Bellini et al., 2019). We accordingly expect substantive engagement within AWs to broaden technological search, support joint invention, and involve more researchers in problem solving, creating additional opportunities for inventive output.

In the relatively selective early development setting described in Section 2.1, we expect these enabling mechanisms to reinforce partnerships formed around identifiable technological needs. Where such needs guide collaboration, institutional support complements the scientific inputs and internal effort devoted to solving them. This alignment provides the basis for expecting positive innovation benefits during early AW program development.

Hypothesis 1. *During the early stage of program development, establishing an academician workstation increases firms' inventive output.*

3.3 Incentive misalignment and the limits of collaboration

The enabling mechanisms described above depend on institutional support remaining connected to substantive collaboration. Yet the legitimacy and resources conferred by formal arrangements can also make adoption attractive independently of their technical usefulness (Meyer & Rowan, 1977; Edler & Fagerberg, 2017). As an arrangement diffuses, the considerations motivating adoption may shift from internal organizational needs toward conformity with a recognized organizational form (Tolbert & Zucker, 1983). Applied to AWs, this suggests that wider policy-backed adoption may change not only the number of participants but also the criteria guiding partner selection and resource commitments.

One source of attenuation is incentive misalignment. When administrative evaluation places greater weight on workstation establishment and visible milestones than on continuing scientific engagement, program organizers have stronger incentives to expand recognized partnerships than to ensure their technological relevance. Firms may likewise give greater weight to the support and recognition attached to a workstation than to the suitability of its scientific partner. For scientists, the rewards associated with additional affiliations may encourage participation without proportionate commitments to joint research. The concern is therefore not that participants obtain benefits, but that these benefits can become weakly connected to the effort required for knowledge utilization. Evidence from Canadian university-industry programs illustrates how apparently successful implementation can coexist with a misalignment between collaboration incentives and broader innovation objectives

(Veletanlić & Sá, 2019).

These incentives can weaken innovation by changing how partnerships connect to firms' research activities. Muscio and Pozzali (2013) find that cognitive distance constrains the frequency of university-industry interaction without significantly reducing the likelihood of collaboration. Establishing a connection thus need not resolve the differences that impede its productive use. When recognition takes precedence over technological fit, partners may struggle to define relevant problems, interpret one another's knowledge, or integrate joint work into the firm's R&D. Maintaining such arrangements can absorb funding, personnel, and managerial effort that would otherwise support more relevant research. This possibility is consistent with means-ends decoupling, in which organizational activities persist while resources are diverted from the goals they are intended to serve (Bromley & Powell, 2012). Where these opportunity costs exceed the knowledge gains, innovation effects may become negative.

Expansion can also constrain scientific inputs even when participants remain committed to substantive cooperation. Knowledge transfer requires interaction through which scientific insights are interpreted, adapted, and applied to a different organizational context (De Wit-de Vries et al., 2019). Although research teams can extend an academician's reach, their time, expertise, and coordination capacity do not automatically expand with the number of partnerships. When additional commitments are not matched by corresponding resources, each firm may receive less sustained input. Reduced engagement can interrupt the feedback and experimentation needed to address technological problems and limit the opportunities for employees to learn through joint work. These capacity constraints differ from incentive misalignment, but both weaken the connection between formal affiliation and knowledge utilization.

The implication is not that expansion necessarily undermines collaboration. Wider participation can create opportunities for better matching and accumulated experience. However, these opportunities must be supported by adequate scientific inputs and incentives that remain tied to substantive work. In the transition from relatively selective development to broader policy-backed adoption described in Section 2.1, we expect pressures on technological matching, sustained engagement, and resource allocation to weaken the innovation benefits of workstation establishment. The prediction concerns a lower average effect in the later development period, rather than the absence of productive collaboration in every later partnership.

Hypothesis 2. *The effect of academician workstation establishment on firms' inventive output is weaker during the later expansion stage than during early development.*

3.4 Collaboration conditions and knowledge utilization

The preceding arguments allow for variation within, as well as between, development periods. On the scientific side, productive collaboration depends on the expertise and organizational resources that academicians and their teams bring to firms' technological problems. Research on academic engagement shows that scientists' interactions with industry are shaped by their institutional environments, not simply by academic standing (Ponomariov, 2008; Schuelke-Leech, 2013). In the AW setting, career circumstances, scientific orientation, and existing affiliations may influence the availability and relevance of research inputs. Multiple affiliations can extend access to scientific networks, but sustaining these connections requires sufficient time and team resources. These considerations make academician characteristics relevant to understanding collaboration without implying that any category of scientist necessarily generates greater innovation benefits.

Firms also differ in their capacity to incorporate scientific inputs into technological development. Prior knowledge and internal learning efforts support the recognition and application of external knowledge (Cohen & Levinthal, 1990; Escribano et al., 2009), while research on science-based innovation highlights the complementary roles of internal R&D and research-trained personnel (Motohashi et al., 2025). Firm size and technological orientation may capture differences in the resources, research routines, and technological needs underlying this process. The relevant complementarity is between the scientific inputs available and the capabilities used to interpret and develop them. Strong internal capabilities may facilitate knowledge utilization, but their value still depends on access to relevant scientific contributions.

Spatial conditions further shape the balance between knowledge access and coordination. Proximity can facilitate repeated interaction, whereas more distant partnerships may extend access to expertise unavailable locally. Partner selection therefore involves both geographical accessibility and the quality of scientific resources (Laursen et al., 2011). Local partnerships can also support the incorporation of knowledge originating elsewhere, so geographical closeness need not imply a narrow knowledge base (Messeni Petruzzelli & Murgia, 2020). Regional differences in research infrastructure and supporting resources may further condition these

relationships. Together, these considerations motivate heterogeneous analyses across academician characteristics, firm attributes, and spatial settings. They help assess the scope of period-specific innovation benefits rather than independently identify the mechanisms underlying them.

4 Data and Empirical Strategy

4.1 Data sources and sample construction

4.1.1 Workstation records

We construct a historical registry of AWs through manual collection of publicly available information. Starting from the official lists of academicians released by CAS and CAE in 2024, we conduct systematic online searches combining each academician's name with the Chinese term for academician workstation. For each identified station, we record the academician's name, academy affiliation, host organization, and establishment year. We also collect the academician's age and field of expertise when available, together with the host firm's industry and city location. These records identify when formal partnerships were established and provide information on their scientific and organizational characteristics.

After removing duplicates and invalid entries, the registry contains 3,353 workstation records covering establishments from 2003 to 2023. It is a historical record of publicly disclosed establishments rather than a census of all workstations or a count of those remaining in operation. The registry therefore supports an analysis of observed workstation establishments, but does not establish national representativeness or directly measure the intensity of ongoing scientific engagement. Nevertheless, the registry's substantial size and coverage across development periods, regions, and industries provide a broad empirical basis for systematically assessing the innovation consequences of workstation establishment across diverse collaboration settings.

To examine firm-level innovation, we retain workstations hosted by firms and exclude those established by universities, research institutes, and other non-firm organizations. After excluding observations with missing firm identifiers or essential firm-level information, the initial treatment pool comprises 2,016 workstation firms. These firms provide the basis for constructing the matched panel described in the following subsection.

4.1.2 Matched firm panel

To construct a comparison group for the workstation firms, we draw on a technology-based firm dataset from China's National Business Registration Database.

Potential controls are firms without workstations. We implement propensity score matching (PSM) within city-industry cells, using firm age, scale, and workforce size to select nearest neighbors at a ratio of four control firms to each treated firm. Matching within the same city and industry is intended to limit differences in local environments and sectoral conditions, while the firm-level variables account for observable differences in organizational characteristics. This procedure seeks to improve comparability on observed attributes rather than eliminate all sources of non-random adoption (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008).

We then link the matched firms to the China National Intellectual Property Administration Patent Database and Google Patents to construct an annual firm-level panel. The linked records provide information on patent applications and citations, with citation data obtained from Google Patents. They also identify partner firms in joint applications and participating inventors, supporting the supplementary analyses of collaborative patenting and inventor participation. These sources connect the establishment of formal scientific partnerships to observable inventive activity within host firms.

The patent-based analysis excludes firms with no patent records throughout the observation window. Its scope is therefore limited to firms with observed patenting activity during that period, rather than all firms eligible to establish workstations. The full-period baseline estimation uses 57,903 firm-year observations. This matched panel provides the basis for examining changes in innovation outcomes following workstation establishment under the empirical strategy described below.

4.2 Empirical strategy

We use the matched firm panel to examine changes in inventive output and citation intensity following AW establishment. Because firms establish workstations in different years, the empirical strategy combines matching with a staggered difference-in-differences (DID) framework. The regression specifications are summarized by

$$Y_{it} = \alpha + \beta DID_{it} + \delta Treat_i + X_i' \theta + \varphi_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Here, i indexes firms and t indexes years. Y_{it} denotes patent output or citation intensity, as defined in Section 4.3. DID_{it} equals one from the year of a firm's first workstation establishment onward and zero otherwise, capturing formal establishment rather than subsequent engagement intensity. $Treat_i$ equals one for treatment-group firms throughout the relevant estimation window and zero for matched controls. $\mathbf{X}_i$

contains the registration-based firm covariates, φ_i denotes the specification-specific fixed-effect component, and λ_t captures common year effects.

The baseline includes firm and year fixed effects. With firm effects represented by φ_i , the time-invariant indicator Treat_i and covariates X_i are absorbed and their coefficients are not separately estimated. Alternative specifications replace firm effects with industry and/or city effects, including industry-by-city effects, while retaining Treat_i and X_i . Year effects are included throughout. For the supplementary analyses, we adopt industry-by-city and year fixed effects, together with a treatment-group indicator and observed firm covariates, to align the estimation framework with the stratified matching design and adjust for residual observable differences within the matched sample. This provides a common framework for examining variation across subgroups and innovation outcomes, while the firm-fixed-effects specification remains the principal benchmark for accounting for unobserved, time-invariant firm heterogeneity. Sensitivity checks are compared with the corresponding industry-by-city specification in the baseline table.

The baseline analysis reports a full-period estimate and separate estimates for the early period ending in 2016 and the later period of 2017-2022. The later-period baseline restricts the treated group to firms first establishing an AW during 2017-2022. This division follows the development history discussed in Section 2.1. Early-period estimates provide evidence relevant to H1, while their comparison with later-period estimates informs H2. This comparison concerns separately estimated patterns rather than a formal test of the difference between the two effects.

A causal interpretation of the DID estimates requires parallel trends in untreated outcomes and no anticipation, neither of which is guaranteed by matching or fixed effects. Event-study analyses examine pre-establishment trends and post-establishment dynamics, separately from the calendar-period comparisons. We also use the group-time average treatment effect estimator of Callaway and Sant’Anna (2021) to accommodate heterogeneous effects across establishment cohorts and over time. Section 5 presents these estimates alongside placebo tests and sensitivity checks involving alternative sample restrictions and matching arrangements.

4.3 Variable measurement

4.3.1 Dependent variables

We measure inventive output using the annual number of patent applications filed

by each firm (Pat_num_{it}). Patent counts provide an observable indicator of inventive activity (Griliches, 1998). In the regressions, we use $(\ln(1 + Pat_num_{it}))$ to reduce skewness while retaining firm-year observations with zero applications. This transformed measure serves as the primary outcome for H1 and H2. Because patents differ in their technological value, however, an increase in patenting need not imply a corresponding improvement in technological impact (Trajtenberg, 1990).

To complement patent output, we use annualized citation intensity (Avg_pat_cited), defined as the firm's average citations received per patent per year, using citation records from Google Patents. Citation-based comparisons must account for differences in observation periods, as newer patents have had less time to accumulate citations and citation rates vary over a patent's life (Hall et al., 2001; Fisch et al., 2017). Annualization is intended to account for unequal exposure time, although it does not fully eliminate truncation or differences in citation-age profiles. We therefore interpret this indicator as a measure of observed citation intensity rather than a complete assessment of patent quality.

4.3.2 Independent variable

Our key independent variable is workstation establishment status, captured by DID_{it} . $DID_{it} = 1$ for firm i in the establishment year of AW and all subsequent years, and 0 otherwise. This definition reflects the institutional interpretation that the workstation creates a sustained collaboration interface rather than a one-time event.

4.3.3 Control variables

We include four firm characteristics drawn from China's National Business Registration Database to account for observable differences in organizational resources and technological orientation. Firm size is measured as the natural logarithm of total assets, while employment is measured as the natural logarithm of the number of employees. These variables capture asset scale and workforce size, respectively. Their inclusion is consistent with evidence that firm scale shapes the organization and allocation of R&D activities (Becker et al., 2022).

We also include a high-tech status indicator, equal to one for firms officially certified as national high-tech enterprises and zero otherwise, and firm age to account for differences in organizational maturity. These characteristics provide observable controls for resource and technological differences rather than direct measures of absorptive capacity, which also depends on internal R&D and research-specific human

capital (Motohashi et al., 2025). The registration-based covariates are time invariant in our dataset. As explained in Section 4.2, they enter specifications without firm fixed effects and are absorbed when firm fixed effects are included.

Table 1 reports descriptive statistics for the main variables. Firms with AWs exhibit a higher average patent count (22.036) than matched control firms (19.525). The treatment group also shows higher average citation intensity (0.171) than the control group (0.120), indicating meaningful baseline differences that motivate our matched design and within-firm identification strategy. Other covariates, including firm size, employment, firm age, and high-tech status, display similar mean values across the two groups, suggesting reasonable comparability in basic observable characteristics. Table 7 (see Appendix) presents the correlation matrix for the main variables. Correlations are generally modest, with the highest correlation between employment and firm size (0.635), and all others within conventional thresholds, indicating that multicollinearity is unlikely to materially affect the empirical estimates.

Table 1 Results of descriptive statistics

	Treatment Group				
	<i>Obs</i>	<i>Mean</i>	<i>S.D.</i>	<i>Min</i>	<i>Max</i>
<i>Pat_num</i>	11001	22.036	108.428	0.000	5798.000
<i>Avg_pat_cited</i>	11001	0.171	0.227	0.000	4.333
<i>Scale</i>	11001	9.191	1.713	3.932	15.427
<i>Staff</i>	11001	5.109	2.007	0.000	10.168
<i>Age</i>	11001	20.351	7.345	2.000	45.000
<i>Hightech</i>	11001	0.798	0.401	0.000	1.000
	Control Group				
	<i>Obs</i>	<i>Mean</i>	<i>S.D.</i>	<i>Min</i>	<i>Max</i>
<i>Pat_num</i>	47599	19.525	179.392	0.000	12723.000
<i>Avg_pat_cited</i>	47599	0.120	0.243	0.000	16.381
<i>Scale</i>	47599	9.054	1.695	2.398	16.683
<i>Staff</i>	47599	4.861	1.907	0.000	11.183
<i>Age</i>	47599	20.099	8.357	3.000	72.000
<i>Hightech</i>	47599	0.787	0.409	0.000	1.000

5 Results

5.1 Innovation benefits across development periods

Table 2 reports the estimated effects of AW establishment on inventive output and citation intensity over the full observation period and across the two development periods identified in Section 2.1. The period-specific estimates are central to our hypotheses. H1 predicts positive inventive-output benefits during early program development, whereas H2 predicts that these benefits become weaker during the later

expansion period.

5.1.1 Inventive output

Panel A reports the results for inventive output. Over the full observation period, the estimated coefficient on AW establishment is positive but statistically insignificant. The pooled estimate therefore provides little evidence of a uniform innovation benefit across the program's development. This average null result, however, may mask substantial heterogeneity across development regimes.

We therefore turn to stage-based analyses that reflect the program's evolution. For the early stage, which corresponds to the pre-surge regime (2007-2016 in our data), AW establishment is consistently associated with higher patenting. Across Columns (2)-(4), the coefficient on AW ranges from 0.126 to 0.139 and remains statistically significant under different fixed effects sets. Under the log specification, these estimates imply that establishing an AW increases a firm's patent output by roughly 12.6% to 13.9% during the early stage. Despite differences in the conditioning structure, these estimates consistently indicate higher patenting following workstation establishment during the early development period. This evidence supports H1.

By contrast, the later-period estimates provide no comparable evidence of a positive inventive-output benefit. When the treated sample is restricted to firms first establishing an AW during 2017-2022, the firm-fixed-effects estimate is 0.007 and statistically indistinguishable from zero (Column 5). Estimates under alternative fixed-effect structures are negative, although their magnitude and statistical precision vary across specifications. The contrast with the consistently positive early-period estimates is therefore consistent with the attenuation anticipated in H2.

As a complementary check on the later-period results, Table 8 in the Appendix expands the treated group to include firms whose workstations were established before 2017 but remained part of the program during the later period. The firm-fixed-effects estimate remains statistically insignificant (Column 1), while the estimates under the alternative industry and city fixed-effect specifications are negative and statistically significant (Columns 2-4). These models rely more heavily on cross-sectional comparisons than the within-firm DID baseline, so we interpret them as supplementary rather than as our preferred estimates. Nevertheless, they are directionally consistent with the broader conclusion that the later-stage regime is characterized by weakened or adverse innovation outcomes.

Table 2 Innovation effects of AW establishment across development periods

	All year: 2003-2022	Stage1: 2003-2016				Stage2: 2017-2022	
	Panel A. Inventive output						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>DID</i>	0.036 (0.031)	0.126** (0.056)	0.139** (0.061)	0.127** (0.058)	0.007 (0.045)	-0.091 (0.055)	-0.073 (0.051)
<i>Observations</i>	57903	23368	24087	23866	33868	34499	34352
<i>F</i>	1.293	5.103	151.054	96.879	0.025	345.165	257.165
<i>R</i> ²	0.556	0.595	0.255	0.407	0.638	0.286	0.418
	Panel B. Citation intensity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>DID</i>	-0.002 (0.004)	0.012* (0.006)	0.009 (0.007)	0.010 (0.007)	-0.014** (0.006)	-0.004 (0.006)	-0.007 (0.006)
<i>Observations</i>	57903	23368	24087	23866	33868	34499	34352
<i>F</i>	0.176	3.458	50.289	31.081	5.251	84.057	53.174
<i>R</i> ²	0.371	0.386	0.091	0.210	0.435	0.157	0.239
<i>Firm controls</i>	Absorbed	Absorbed	Yes	Yes	Absorbed	Yes	Yes
<i>Year-Fe</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm-Fe</i>	Yes	Yes			Yes		
<i>Industry-Fe</i>			Yes			Yes	
<i>City-Fe</i>			Yes			Yes	
<i>Industry#City-Fe</i>				Yes			Yes

Notes: Column (1) reports the full-sample regression. Columns (2)-(4) present the regression results for the first stage, and Columns (5)-(7) report the regression results for the second stage. In the stage-specific regressions, different sets of fixed effects are included across specifications. Because the firm-level controls are drawn from China's National Business Registration Database and are time-invariant, they are not included in specifications that absorb firm fixed effects. Robust standard errors in parentheses. Significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.1.2 Citation intensity

Panel B examines whether the innovation benefits extend to citation intensity. The full-period estimate is close to zero and statistically insignificant. During the early period, the firm-fixed-effects specification yields a small positive estimate, but this association is not robust across the alternative specifications. The later-period firm-fixed-effects estimate is negative and statistically significant, whereas the corresponding estimates under other fixed-effect structures are smaller and statistically insignificant.

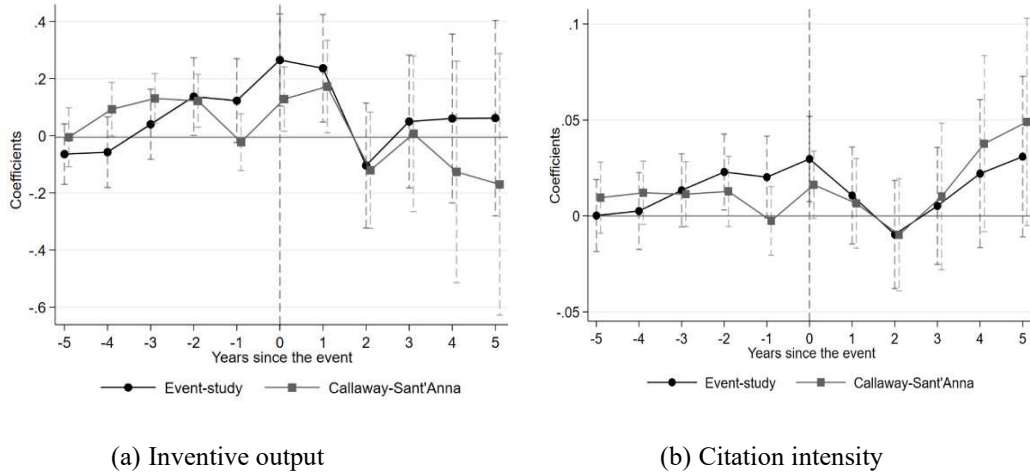
Taken together, the citation results provide no consistent evidence that AW establishment improves the citation performance of firms' patents. The early-period benefit is therefore more clearly reflected in the volume of inventive activity than in citation intensity. More broadly, the results suggest that the innovation benefits associated with institutionalized collaboration are neither uniform across development periods nor necessarily shared across different dimensions of inventive performance.

5.2 Dynamic patterns and robustness of the main findings

5.2.1 Dynamic effects

We further examine how innovation outcomes evolve around workstation establishment using two complementary approaches. The conventional event-study specification traces change relative to the establishment year, while the group-time average treatment effect estimator of Callaway and Sant’Anna (2021) accommodates staggered adoption and allows treatment effects to vary across establishment cohorts and over time. Reporting both estimates allows us to assess whether the observed dynamics are sensitive to treatment-effect heterogeneity under staggered adoption.

Figure 4 presents the dynamic estimates for the early period. For inventive output, the two approaches show a broadly similar pattern. Patent output increases around workstation establishment and remains higher shortly thereafter, but the effect subsequently attenuates and becomes statistically indistinguishable from zero. Citation intensity shows no systematic or persistent improvement following establishment. The dynamic evidence therefore suggests that the early innovation benefit is concentrated in a relatively short period after workstation formation and is more evident in inventive activity than in citation performance. For comparison, Figure 7 in the Appendix reports the corresponding dynamic estimates for the later period. It shows no comparable sustained positive pattern, reinforcing the period-specific contrast documented in Table 2.



Notes: The figure reports dynamic estimates of the effects of AW establishment during the early period using both the conventional event-study specification and the group-time average treatment effect estimator of Callaway and Sant’Anna. To retain observations in the tails while limiting the event window, event times of five or more years before establishment are grouped at ($t=-5$), and event times of five or more years after establishment are grouped at ($t=5$). Panel (a) reports inventive output, and Panel (b) reports citation intensity. Point estimates and 95% confidence intervals are reported.

Fig. 4 Dynamic effects of AW establishment in the early period

5.2.2 Robustness and sensitivity

We conduct a placebo exercise to assess whether the early-period estimate could arise from random treatment assignment or spurious timing. Within the matched control pool, firms are randomly assigned placebo treatment status and fictitious establishment years between 2007 and 2016. Repeating this procedure 500 times produces a distribution of placebo estimates centered close to zero, whereas the observed early-period estimate lies in the upper tail of the distribution (as shown in Figure 5). This result reduces the likelihood that the positive early-period association is generated solely by random assignment of treatment timing.

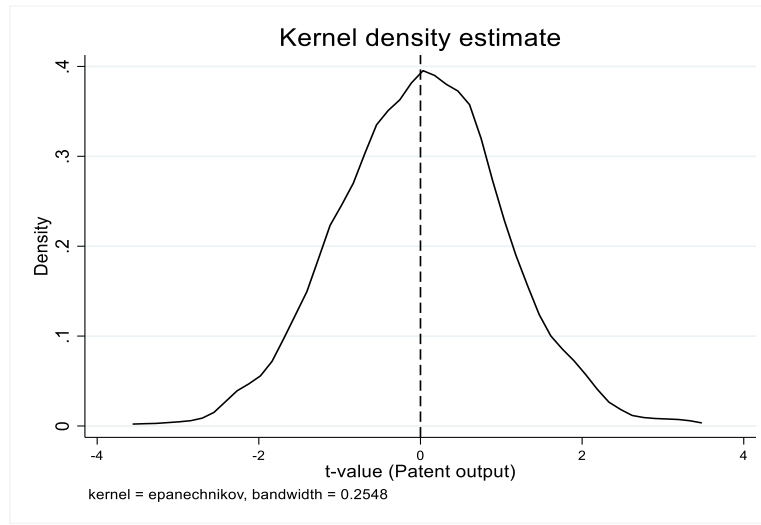


Fig. 5 Placebo test based on randomly assigned firms and adoption years

Table 3 examines the sensitivity of the period-specific findings under the industry-by-city specification in order to align the estimation framework with the stratified matching design. We first remove the top 1% of observations for the corresponding innovation outcome. We then exclude years associated with major macroeconomic disruptions, namely 2008-2009 for the early period and 2020-2022 for the later period. Finally, we reconstruct the matched control group using a 1:3 rather than 1:4 matching ratio. Across these exercises, the early-period estimates for inventive output remain positive and statistically significant, ranging from 0.121 to 0.135. The later-period estimates remain statistically insignificant and provide no comparable evidence of a positive effect. Citation intensity remains statistically insignificant in both periods.

Taken together with the placebo and dynamic analyses, they show that the positive early-period patenting pattern is not driven by a particular matching ratio, extreme observations, or the inclusion of major shock years, while the later period continues to

lack evidence of innovation gains comparable to those observed during early development.

Table 3 Robustness checks for the period-specific effects of AWs

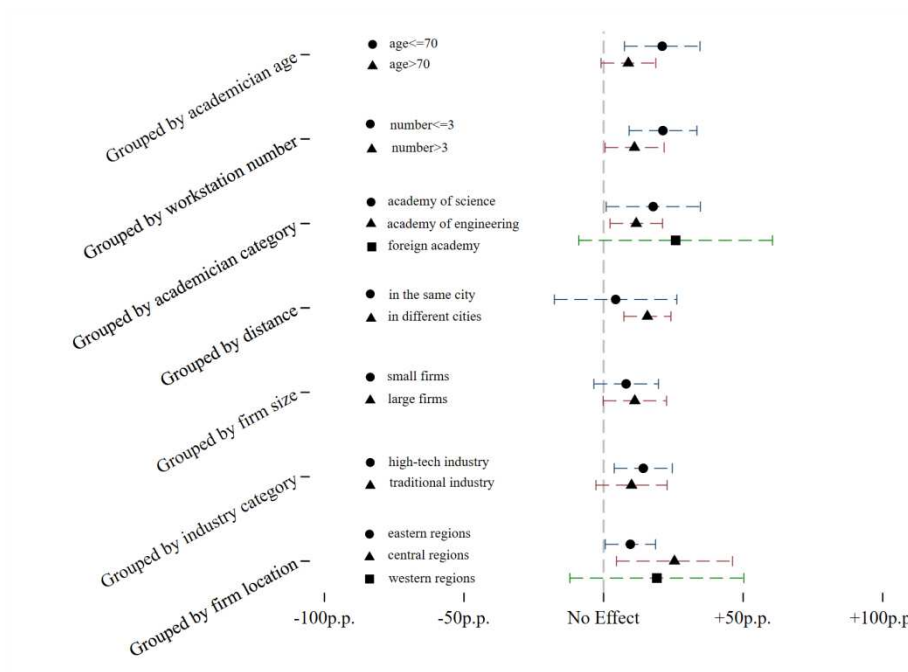
	Stage 1: 2003-2016			Stage 2: 2017-2022		
	Panel A. Inventive output					
	(1)	(2)	(3)	(4)	(5)	(6)
	1% tailed trimming	Excluding 2008-2009	Replacing control group	1% tailed trimming	Excluding 2020-2022	Replacing control group
<i>DID</i>	0.121** (0.057)	0.131** (0.059)	0.135** (0.059)	-0.048 (0.049)	-0.064 (0.061)	-0.056 (0.051)
<i>Observations</i>	23689	21793	19538	33950	15873	26816
<i>F</i>	123.421	101.838	84.015	296.931	170.699	210.502
<i>R</i> ²	0.389	0.416	0.432	0.379	0.404	0.443
	Panel B. Citation intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
	1% tailed trimming	Excluding 2008-2009	Replacing control group	1% tailed trimming	Excluding 2020-2022	Replacing control group
<i>DID</i>	0.008 (0.006)	0.008 (0.007)	0.008 (0.007)	-0.006 (0.005)	0.005 (0.009)	-0.006 (0.007)
<i>Observations</i>	23450	21793	19538	34127	16036	26816
<i>F</i>	46.694	30.225	25.385	85.050	32.273	40.516
<i>R</i> ²	0.219	0.217	0.224	0.267	0.246	0.251
<i>Firm controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year-Fe</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry#City- Fe</i>	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) and (4) present the results after excluding extreme observations, specifically the top 1% of patent applications and the top 1% of patent citations. Columns (2) and (5) report the results after excluding observations from special years. For the first stage, firm-year observations from 2008 and 2009 are excluded to account for the global financial crisis; for the second stage, observations from 2020 to 2022 are excluded to account for the COVID-19 period. Columns (3) and (6) present the results based on an alternative matching design, in which the control group is re-matched using a 1:3 propensity score matching ratio. Robust standard errors in parentheses. Significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

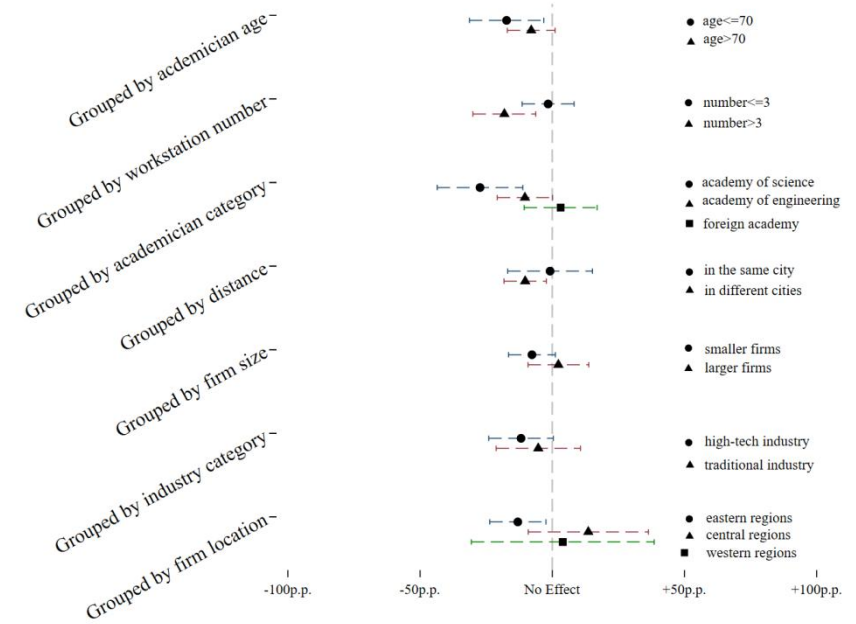
5.3 Innovation benefits across collaboration conditions

5.3.1 Scientific engagement conditions

Figure 6 examines whether the period-specific innovation effects of AWs vary with observable characteristics of the participating academicians. We focus on age, the breadth of workstation affiliations, and academy membership, which capture different aspects of the scientific side of collaboration.



(a) Early period



(b) Later period

Fig. 6 Heterogeneity in the effects of AWs on inventive output across development periods

We first distinguish academicians below and above age 70. We use age 70 as a practical cutoff because academicians commonly retire from regular institutional positions around this age, making it a reasonable proxy for differences in career stage and availability for sustained engagement. In the early period, workstations led by active academicians are associated with a significant increase in firms' patent output, whereas the coefficient for retired academicians is smaller and statistically insignificant. This pattern is consistent with the view that active academicians may have stronger capacity for sustained engagement and resource mobilization, which facilitates substantive problem-solving interaction. In the later stage, however, the estimate for workstations led by active academicians becomes negative and statistically significant, while the effect for the retired group remains statistically indistinguishable from zero, suggesting that the later-stage environment may erode innovation gains even for workstations anchored by more active scientific leaders.

We next examine whether the innovation effects vary with the number of workstations associated with each academician. Motivated by governance concerns over "one academician-multiple workstations," we classify workstations according to the number of workstations with which the leading academician is affiliated. Specifically, we distinguish academicians associated with three or fewer workstations from those associated with more than three. In the early stage, the positive effect on patent output is concentrated among academicians affiliated with no more than three workstations, whereas the estimate becomes weaker and statistically insignificant when the leading academician is linked to more than three workstations. This pattern is consistent with an attention constraint mechanism in which substantive scientific input becomes harder to sustain when an academician's time and effort are spread across too many stations. In the later stage, the subgroup with more than three affiliated workstations exhibits a significantly negative coefficient, suggesting that attention dilution becomes particularly consequential once the program enters a higher-saturation regime.

Finally, we distinguish workstations associated with CAE, CAS, and foreign academy members. Positive early-period effects are observed for workstations associated with domestic academicians, whereas the estimate for foreign members is statistically insignificant. One plausible explanation is that domestic academicians face lower communication and institutional frictions in repeated interaction with host firms, making substantive engagement easier to sustain. The particularly strong pattern for

CAE-associated workstations is also consistent with the engineering and application-oriented nature of CAE expertise, which may facilitate closer alignment with firms' practical technological problems. In the later period, however, these advantages weaken across categories, with the estimate for CAS-associated workstations becoming significantly negative.

Overall, the results show that the early innovation benefits of AWs are concentrated in scientific partnerships more conducive to sustained interaction and problem-oriented knowledge use, whereas these advantages become substantially less evident during the later expansion period. This pattern reinforces the broader conclusion that formal access to eminent scientists is not, by itself, sufficient to sustain the innovation benefits of institutionalized collaboration.

5.3.2 Firm knowledge-utilization conditions

We next turn to the firm side of the collaboration. Access to scientific expertise creates innovation opportunities, but realizing those opportunities requires internal resources and capabilities to interpret, integrate, and apply external knowledge (Cohen & Levinthal, 1990; Motohashi et al., 2025). We therefore examine whether the period-specific effects of AWs vary with firm scale and technological orientation, two observable characteristics related to the organizational conditions for knowledge utilization.

We first divide firms into large and small groups using the median firm scale. In the early period, the positive effect on inventive output is concentrated among larger firms, while the estimate for smaller firms is statistically insignificant. Larger firms typically possess broader research resources, more developed organizational routines, and greater capacity to coordinate external scientific inputs with internal R&D. The result is therefore consistent with complementarity between institutionalized access to science and firms' internal capacity to use it. In the later period, however, neither group exhibits a significant positive effect, suggesting that greater organizational resources alone are insufficient to preserve the early innovation benefits as the program expands.

A similar pattern emerges across firms with different technological orientations. During the early period, AW establishment is positively associated with inventive output among high-tech firms, whereas the corresponding estimate for traditional manufacturing firms is not statistically significant. This pattern is consistent with the greater research intensity and technological preparedness of high-tech firms, which can facilitate the integration of external scientific knowledge into ongoing innovation

activities. In the later period, the estimates for both groups weaken and become statistically insignificant.

Taken together, the firm-level results complement the scientific-partnership patterns reported above. Early innovation benefits are more evident where firms possess stronger organizational and technological conditions for utilizing scientific knowledge, but these advantages do not generate comparable gains in the later expansion period. Institutionalized access to science therefore appears most productive when external expertise is matched by internal capacity for knowledge utilization, while such capacity alone does not guarantee that the benefits of formal collaboration will persist across institutional settings.

5.3.3 Spatial and regional conditions

We finally examine whether the innovation benefits of AWs vary with the spatial configuration and regional environment of collaboration. Geographic proximity can facilitate repeated interaction and coordination, but firms may also benefit from reaching beyond local knowledge pools to access more specialized or differentiated scientific expertise (Laursen et al., 2011; Messeni Petruzzelli & Murgia, 2020). The spatial organization of a workstation may therefore shape both the knowledge it makes accessible and the costs of sustaining collaboration.

This trade-off is reflected in the same-city comparison. In the early period, the positive effect on inventive output is concentrated in cross-city collaborations, whereas same-city partnerships show no statistically significant effect. The pattern suggests that, when substantive interaction can be maintained, institutionalized collaboration may be particularly valuable in connecting firms to scientific knowledge beyond their immediate local environment. In the later period, however, the cross-city estimate becomes negative. Greater spatial separation may place higher demands on coordination and sustained engagement, making such partnerships more vulnerable when the conditions supporting substantive collaboration weaken.

Regional results reveal a related pattern. Early-period benefits are most evident in eastern China, with positive estimates also observed in the central region, whereas no robust effect is found in the west. These differences are consistent with variation in regional innovation infrastructure and firms' ability to mobilize complementary resources around scientific collaboration. Yet the eastern advantage does not persist into the later period, when the estimate becomes negative and those for the central and western regions are statistically imprecise. Overall, the spatial evidence reinforces that

the innovation value of institutionalized collaboration depends on whether access to external scientific knowledge is matched by conditions that support its effective coordination and utilization.

6 Complementary Evidence on Knowledge Utilization

6.1 Innovation-process outcomes

The baseline results show that the innovation benefits of AW establishment are concentrated in the early period. To examine whether these gains are accompanied by broader changes in firms' innovation activities, we consider three process-oriented outcomes: technological breadth, measured by the number of IPC subclasses represented in a firm's patent portfolio; collaborative patenting, measured by the number of partner firms appearing in joint patent applications; and inventor participation, measured by the number of distinct inventors involved in the firm's patenting activities. These measures capture different dimensions of how firms search for, combine, and mobilize knowledge, rather than simply the volume of resulting patents.

Table 4 reveals a consistent early-period pattern. AW establishment is positively associated with all three outcomes. Firms broaden the technological scope of their patent portfolios, engage with more external partners in joint invention, and involve more inventors in inventive activity. These results indicate that the early increase in patenting is accompanied by changes in the underlying innovation process. This pattern is consistent with the argument that institutionalized collaboration can support substantive knowledge utilization when scientific inputs are integrated into firms' technological search and internal inventive activity.

The later period shows a markedly weaker pattern. The estimate for technological breadth becomes negative, while the effects on collaborative patenting and inventor participation are statistically insignificant. Thus, the process-level changes observed during early development are not replicated in the later expansion period. These results complement the baseline findings by showing that the limits of institutionalized collaboration extend beyond aggregate patent output: as the early innovation benefit weakens, the associated broadening of technological search, collaborative invention, and inventor participation also becomes substantially less evident.

Table 4 Period-specific effects of AWs on innovation-process outcomes

Stage 1: 2003-2016			
	(1)	(2)	(3)
	<i>IPC_num</i>	<i>Collaborator_num</i>	<i>Inventor_num</i>
<i>DID</i>	0.056** (0.025)	0.047*** (0.016)	0.163*** (0.040)
<i>Observations</i>	23866	23866	23866
<i>F</i>	325.927	135.187	542.586
<i>R</i> ²	0.389	0.372	0.479
Stage 2: 2017-2022			
	(1)	(2)	(3)
	<i>IPC_num</i>	<i>Collaborator_num</i>	<i>Inventor_num</i>
<i>DID</i>	-0.047* (0.028)	0.008 (0.021)	-0.022 (0.041)
<i>Observations</i>	34352	34352	34352
<i>F</i>	568.853	327.210	1374.584
<i>R</i> ²	0.366	0.425	0.559
<i>Firm controls</i>	Yes	Yes	Yes
<i>Year-Fe</i>	Yes	Yes	Yes
<i>Industry#City-Fe</i>	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2 Institutional expansion and marginal innovation benefits

To complement the period-based analysis, we examine whether the innovation benefits of AW establishment vary with the local diffusion of the institutional arrangement. Local AW density is measured as the cumulative number of workstations established in a city by year ($t-1$), divided by the number of firms in that city in the same year. We interact this lagged density measure with AW establishment while controlling for their respective main effects. This specification captures whether the incremental innovation association of establishing an AW varies with the pre-existing prevalence of workstations in the local environment.

Table 5 reports the results under firm fixed effects and industry-by-city fixed effects. The interaction between AW establishment and local AW density is negative for both inventive output and citation intensity in both specifications. For inventive output, the interaction is negative but statistically insignificant under firm fixed effects and becomes significantly negative under industry-by-city fixed effects. Citation intensity exhibits the same pattern. The estimates therefore provide suggestive evidence that the innovation benefits associated with new workstation establishment become weaker as local AW prevalence increases.

Table 5 Local AW density and the marginal innovation benefits of workstation establishment

	(1)	(2)	(3)	(4)
	<i>Inventive output</i>		<i>Citation intensity</i>	
<i>DID * Local_AW_Density</i>	-0.250	-0.738***	-0.019	-0.085***
	(0.262)	(0.273)	(0.028)	(0.028)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Year-Fe</i>	Yes		Yes	
<i>Firm-Fe</i>	Yes		Yes	
<i>Industry#City-Fe</i>		Yes		Yes
<i>N</i>	58171	58696	58171	58696
<i>F</i>	0.969	160.676	0.452	62.114
<i>R²</i>	0.554	0.377	0.370	0.222

*Notes: Local AW density is measured as the cumulative number of academician workstations established in city c by year $(t-1)$, divided by the number of firms in that city in year $(t-1)$. All specifications include the main effect of local AW density. Standard errors are clustered at the city level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

This evidence reinforces the period-specific results from a continuous measure of institutional expansion. It is consistent with the argument that formal collaboration can diffuse more rapidly than the scientific engagement, technological matching, and knowledge-utilization conditions required to sustain its innovation benefits. The density analysis does not identify which of these constraints drives the attenuation, but it indicates that the limits of institutionalized collaboration become more salient as the organizational form spreads.

6.3 Early-period research inputs

To further examine the research inputs associated with the early innovation benefits, we draw on firm-level microdata from the China Enterprise Innovation Survey for 2011-2013. The survey provides information on innovation expenditure, government support, and the composition of R&D personnel that is unavailable in the patent and registration data. We identify 112 workstation firms in the survey and construct a matched control group using propensity score matching. Because the survey covers only the early period and a separate sample, the analysis is used to characterize research-input patterns associated with early workstation establishment rather than to explain the later-period attenuation.

Table 6 reveals two notable patterns. First, AW establishment is positively associated with government innovation subsidies, while neither total innovation expenditure nor private innovation spending changes significantly. The results therefore suggest that workstations facilitated access to public innovation resources without

producing a corresponding short-run expansion in overall R&D expenditure. Second, workstation establishment is not associated with a significant increase in total R&D employment, but is positively related to the number of researchers with senior professional titles and doctoral degrees. The early innovation gains thus coincide more clearly with an upgrading of R&D personnel composition than with an expansion of research headcount.

These patterns are consistent with the resource-mobilization and human-capital channels developed in Section 3.2. Institutional support appears to have complemented scientific collaboration by improving access to public resources and higher-level research personnel, providing conditions conducive to the utilization of external scientific knowledge. Given the restricted period and survey sample, however, these results should be interpreted as complementary evidence on the inputs accompanying early innovation benefits rather than as direct evidence of the mechanisms underlying the weaker later-period outcomes.

Table 6 Early-period research inputs associated with AW establishment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Patent output	R&D spend	Government R&D subsidy	Private R&D spend	R&D staff	R&D staff with senior title	R&D staff with Doctor degree
<i>DID</i>	0.296** (0.147)	0.061 (0.083)	0.813* (0.427)	0.060 (0.085)	0.175 (0.282)	0.315*** (0.116)	0.243** (0.102)
<i>Firm controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year-Fe</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry#City- Fe</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	1363	1537	1537	1537	1486	1486	1486
<i>F</i>	42.763	345.892	28.338	346.042	2.930	177.709	111.164
<i>R²</i>	0.303	0.747	0.248	0.746	0.128	0.566	0.476

*Notes: The analysis uses firm-level microdata from the China Enterprise Innovation Survey for 2011-2013. Workstation firms are matched to control firms using propensity score matching within the survey sample. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

7 Discussion

7.1 The benefits and limits of institutionalized science-industry collaboration

This study provides a more conditional account of the innovation value of institutionalized science-industry collaboration. Existing research generally emphasizes the benefits of academic engagement and science-industry collaboration for knowledge access, resource mobilization, and innovation (Perkmann et al., 2013, 2021). Research on AWs reaches a broadly similar conclusion. Prior studies report

positive effects on corporate innovation, highlighting knowledge management, financing, talent attraction, and resource integration as important explanations (Quan et al., 2021; Xu et al., 2021; Yin et al., 2023). Our early-period results are consistent with this literature. Workstation establishment is associated with greater inventive output, broader technological activity, more collaborative patenting, and greater inventor participation, while the innovation-survey evidence points to increased access to public innovation support and a more highly qualified R&D workforce.

The later-period evidence, however, places an important qualification on an unconditionally positive interpretation. The positive inventive-output association observed during early development is no longer evident under the firm-fixed-effects specification in the later period, citation intensity does not improve systematically, and the early process-level patterns are substantially weaker. The contribution is therefore not that institutionalized collaboration is either effective or ineffective, but that its innovation benefits have an identifiable scope. Formal recognition and policy support can create favorable conditions for collaboration, yet the existence of a recognized platform does not ensure that these conditions remain equally productive across periods and participants.

This distinction connects science-industry collaboration research to the institutional literature. Formal structures can provide legitimacy, resources, and organizational stability, while their adoption does not necessarily guarantee close coupling between formal arrangements and substantive activities (Meyer & Rowan, 1977; Bromley & Powell, 2012). Our findings do not establish that later workstations became merely ceremonial. Rather, they show why formal participation and innovation outcomes should be analytically separated. A workstation can remain an active organizational arrangement without generating innovation gains comparable to those observed earlier. Institutionalized collaboration should therefore be evaluated not only by whether partnerships are established and maintained, but also by whether the scientific and organizational conditions required for productive knowledge use remain in place.

7.2 From formal scientific access to knowledge utilization

The findings also clarify why access to eminent scientists should not be treated as equivalent to access to economically useful knowledge. Research on academic engagement emphasizes that productive science-industry interaction depends on repeated communication, alignment of expectations, and the ability to translate

knowledge across organizational boundaries (D'Este & Perkmann, 2011; De Wit-de Vries et al., 2019). Cantner et al. (2024) similarly show that different outcomes of science-industry collaboration depend on distinct and interrelated conditions. Our results extend this logic to an institutionalized setting by showing that formal scientific access generates more visible innovation benefits when both sides of the partnership are better positioned to sustain knowledge utilization.

On the scientific side, early-period benefits are concentrated among academicians whose observable characteristics are more compatible with sustained engagement, including younger academicians and those associated with fewer workstations. Domestic scientific connections, particularly those involving CAE academicians, also display stronger early-period patterns, consistent with lower interaction frictions and closer alignment between engineering-oriented expertise and firms' applied technological problems. These findings complement research showing that academic engagement varies with researchers' circumstances, disciplinary orientation, and institutional context (Ponomariov, 2008; Kehoe & Tzabbar, 2015; Scandura & Iammarino, 2022). They do not imply that age, affiliation counts, or academy membership directly measure scientific effort. Rather, they indicate that the value of formal access depends on how scientific expertise can be organized around the focal collaboration.

The corresponding firm-side evidence points to the same underlying relationship. Early benefits are more evident among larger and high-tech firms, while the innovation-survey results show an improvement in the composition rather than the overall size of R&D personnel. This is consistent with the absorptive-capacity argument that external knowledge becomes valuable through internal capabilities for recognizing, assimilating, and applying it (Cohen & Levinthal, 1990; Zahra & George, 2002). Recent evidence on science-based innovation likewise emphasizes the complementarity between external scientific knowledge, internal R&D, and research-trained personnel (Motohashi et al., 2025). The process-level results reinforce this interpretation. Broader technological search, greater collaborative invention, and increased inventor participation during the early period suggest that the benefits of AWs extended beyond access to an external expert and became embedded, at least to some extent, in firms' innovation activities.

Taken together, these results shift attention from scientific access to knowledge utilization. Institutionalized collaboration creates an interface through which external science can enter the firm, but the innovation value of that interface depends on

continuing scientific input, technological relevance, and firms' capacity to integrate external knowledge into internal R&D. This helps explain why a prestigious scientific affiliation may be valuable without being sufficient for innovation, and why the same formal arrangement can generate different outcomes across collaboration settings.

7.3 Scaling institutionalized collaboration

The period-specific results point to a fundamental distinction between scaling a formal organizational arrangement and scaling the conditions that make it productive. Institutionalization facilitates the diffusion of recognized partnerships, but scientific engagement, technological matching, and firms' capacity to use external knowledge remain relationship-specific. As organizational practices diffuse, the conditions and motivations surrounding their adoption may also change (Tolbert & Zucker, 1983). The ability to reproduce the formal structure of collaboration therefore need not imply an equal ability to reproduce its innovation-producing conditions.

Importantly, the absence of a positive average effect in the later period does not imply that later workstations are uniformly ineffective. Average estimates combine partnerships with different levels of scientific engagement, technological fit, and knowledge-utilization capacity. Workstations that maintain substantive interaction may continue to generate innovation benefits even when the average effect becomes weak or statistically indistinguishable from zero. The later-period results are therefore better understood as evidence that favorable collaboration conditions are less consistently translated into innovation across the population of workstations, rather than as evidence that productive collaboration has disappeared.

The local-density analysis strengthens this interpretation by moving beyond the discrete early-later comparison. As the pre-existing density of AWs increases, the estimated innovation benefit associated with establishing an additional workstation becomes less favorable. The interaction is negative across fixed-effect specifications, although its statistical precision varies, providing suggestive evidence that the marginal value of new formal collaborations declines as the organizational form becomes more prevalent. This pattern does not identify whether the underlying constraint arises from scientific-resource competition, weaker technological matching, changing participation incentives, or other features of the local innovation environment. It does, however, indicate that the limits observed in the later period are also associated with the extent of institutional diffusion rather than with calendar time alone.

This distinction has broader implications for the scalability of institutionalized

science-industry collaboration. Prior research shows that the productive use of scientific knowledge depends on continued scientist involvement during development (Agrawal, 2006), sufficient cognitive proximity to sustain interaction between scientific and industrial partners (Muscio & Pozzali, 2013), and internal R&D and research-trained human capital that enable firms to absorb external science (Motohashi et al., 2025). These conditions are inherently relationship- and firm-specific and need not expand proportionally with the number of formally recognized partnerships. Policy reach and innovation productivity are therefore distinct dimensions of performance. Scaling collaboration successfully requires not simply reproducing the organizational platform, but preserving the scientific engagement, technological fit, and knowledge-utilization capacity. Accordingly, the success of institutionalized science–industry collaboration should be assessed by the quality and productivity of the relationships it sustains, rather than by the reach of the organizational form alone.

8 Conclusion

This study examines the innovation benefits and limits of institutionalized science-industry collaboration using China’s AWs as an empirical setting. The evidence points to a distinctly period-specific pattern. Workstation establishment is associated with higher inventive output during the early period, accompanied by broader technological search, greater collaborative patenting, and increased inventor participation. Comparable gains are not evident during the later expansion period, while citation intensity shows no systematic improvement across periods. The local-density analysis further suggests that the innovation benefits associated with additional workstation establishment become less favorable as the organizational form becomes more prevalent.

These findings qualify an unconditional view of institutionalized collaboration. Formal recognition and policy support can facilitate access to scientific knowledge, mobilize complementary resources, and support firm innovation, but these benefits depend on the conditions under which collaboration is implemented and knowledge is utilized. Scientific engagement, technological fit, and firms’ capacity to absorb external knowledge remain central even when collaboration is formally organized and publicly supported. Institutionalization can therefore scale the organizational form of collaboration more readily than the conditions that make individual partnerships productive.

The results also have implications for policy design. Expanding the number of

recognized science-industry partnerships should not be treated as equivalent to expanding their innovation contribution. Evaluation systems should place greater weight on sustained scientific participation, technological relevance, knowledge integration, and observable capability development rather than on platform establishment alone. For firms, establishing a formal scientific partnership is most likely to generate value when external expertise is integrated into internal R&D activities rather than treated as a substitute for them.

Several limitations define the scope of these conclusions. The workstation registry is constructed from publicly available records and does not constitute a complete census. The period-specific estimates do not directly identify the mechanisms underlying the weaker later-period outcomes, and observable characteristics such as academician affiliations provide only indirect information on actual scientific input. The innovation survey offers complementary evidence only for the early period, while citation intensity captures one dimension of technological impact rather than innovation quality in its entirety. Future research with direct measures of collaboration intensity, partner matching, project-level resource allocation, and longer-term commercialization outcomes would allow the organizational processes underlying the benefits and limits of institutionalized science-industry collaboration to be identified more directly.

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Appendix

Table 7 Correlation matrix of the main variables

	<i>Ln pat</i>	<i>Ln avg pat</i>	<i>DID</i>	<i>Scale</i>	<i>Staff</i>	<i>Age</i>	<i>Hightech</i>
<i>Ln pat</i>	1.000						
<i>Ln avg pat</i>	0.309***	1.000					
<i>DID</i>	0.069***	0.016***	1.000				
<i>Scale</i>	0.355***	0.149***	-0.018***	1.000			
<i>Staff</i>	0.363***	0.162***	-0.025***	0.635***	1.000		
<i>Age</i>	0.074***	0.065***	-0.046***	0.275***	0.395***	1.000	
<i>Hightech</i>	0.164***	0.099***	-0.003***	0.223***	0.473***	0.117***	1.000

Table 8 Later-period effects with an expanded treatment group including pre-2017 workstation firms.

	Patent Quantity			
	(1)	(2)	(3)	(4)
<i>DID</i>	0.014 (0.044)	-0.211*** (0.059)	-0.147*** (0.057)	-0.122** (0.056)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Year-Fe</i>	Yes	Yes	Yes	Yes
<i>Firm-Fe</i>	Yes			
<i>Industry-Fe</i>		Yes	Yes	
<i>City-Fe</i>			Yes	
<i>Industry#City-Fe</i>				Yes
<i>Observations</i>	37062	37735	37729	37571
<i>F</i>	0.095	380.456	385.057	289.398
<i>R²</i>	0.649	0.263	0.292	0.426

Notes: Robust standard errors in parentheses. Significance levels at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

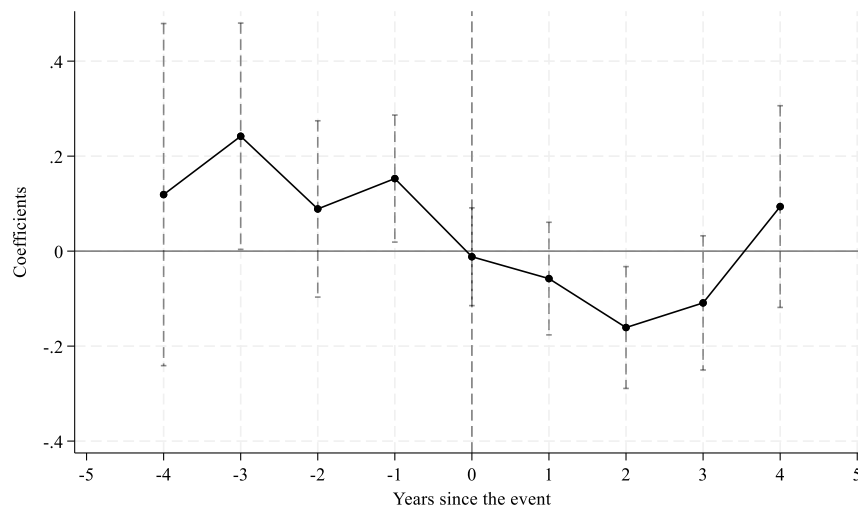


Fig. 7 Dynamic effects analysis in the second stage.