

University Intermediation and Regional Agglomeration in Academic Entrepreneurship: Evidence from panel data in Japan

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Abstract

Universities, embedded within regional innovation systems, promote entrepreneurship through intermediary functions, including resource provision, consulting, and networking. Drawing on perspectives from entrepreneurial ecosystems and innovation intermediation, this study examines how the effectiveness of these university functions varies according to regional innovation contexts and institutional types. The analysis integrates comprehensive panel data from 1,027 universities (2019–2023) with detailed patent and basic research funding databases. Fixed-effects negative binomial regression models with lagged independent variables are employed to control for unobserved time-invariant heterogeneity and to mitigate simultaneity bias. The results show that basic research capacity is consistently and positively associated with startup formation, highlighting its foundational role in academic entrepreneurship. However, the effects of other support functions are highly context-dependent: human resource and knowledge service linkages promote startup activity only when universities are embedded within innovation agglomerations. Investor linkages show no significant overall effect but become positively associated with startup formation in peripheral regions where access to capital is limited. These findings underscore the need for differentiated, ecosystem-sensitive intermediation strategies and highlight the importance of aligning university support mechanisms with the structure and maturity of surrounding innovation environments.

Keywords: Entrepreneurial Ecosystems, Japan, Innovation Intermediaries, Regional Innovation Systems, University Spin-offs

JEL classification: L26, O31, O32, R12, I23, G24

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1. Introduction

The entrepreneurial process requires a diverse set of skills, including the ability to identify new opportunities, translate information into markets, technologies, and products, secure financial resources, take risks, design incentive systems, and provide leadership within a firm (Leibenstein, 1968). Many of these skills are inherently non-transferable or difficult to market, often compelling entrepreneurs to establish their own firms rather than offering their abilities in the marketplace (Leibenstein, 1968, pp. 74–75). Consequently, successful entrepreneurs tend to be "jacks of all trades," even if they do not necessarily master every skill (Lazear, 2005).

While some entrepreneurial skills—particularly those related to general human capital, such as intelligence and analytical reasoning—can be cultivated through formal education, acquiring more specialized skills requires experience in entrepreneurship (Jovanovic, 1982). This challenge is especially pronounced for academic entrepreneurs, who often struggle more than traditional entrepreneurs due to their adherence to the behavioral norms of scientific realism. Unlike conventional entrepreneurs, who are accustomed to uncertainty, risk-taking, and market-driven decision-making, academic entrepreneurs are trained in systematic validation and precision. While these traits are essential for research credibility, they may create barriers to navigating the ambiguous and dynamic environment of entrepreneurship. One way to mitigate these challenges is to leverage external managerial talent. Many university startups, in fact, are led by individuals from industry with managerial expertise. This highlights the critical role that universities play as connectors—linking academic researchers with external sources of entrepreneurial resources to improve commercialization outcomes.

This view aligns with the concept of innovation intermediaries (Feser, 2023; Zhang & Liu, 2024), which take on varied forms across sectors and perform diverse functions (Fukugawa, 2024). In agriculture, such intermediaries include extension stations (Brenya & Zhu, 2023; Fukugawa, 2019), cooperatives (Yang et al., 2014; Fukugawa et al., 2018), international consultants (e.g., FAO), and self-help groups (Deininger & Liu, 2012; Ofuoku & Agbamu, 2013). In manufacturing, examples include R&D consortia (Odagiri et al., 1997), research and technology organizations (Intarakumnerd & Goto, 2018; Fukugawa, 2025), science parks (Fukugawa, 2006a; Fukugawa & Chang, 2025), trade associations (Intarakumnerd & Charoenporn, 2013), and voluntary groups (Fukugawa, 2006b; Fukugawa, 2018a).

Innovation intermediaries address failures in innovation systems by reducing transaction costs, fostering collaborative networks, and helping firms—especially startups—overcome barriers to accessing knowledge and resources. The literature identifies three core functions of these intermediaries: consulting (providing expert

guidance), brokering (connecting firms to complementary actors), and resource provision (facilitating access to financial, technological, and human capital) (Fukugawa, 2024; Intarakumnerd & Charoenporn, 2013).

Universities may perform similar intermediary functions, but their effectiveness varies depending on the structure and maturity of the surrounding innovation ecosystem. In densely networked regions, entrepreneurial support services—including venture capital, patent attorneys, accelerators, and executive talent—are more readily available. Conversely, in less agglomerated areas, universities may need to compensate for missing market functions through direct support or more intensive intermediation. Recent data underscore the regional variation in university startup formation. Between 2015 and 2023, universities in Tokyo accounted for approximately 31% of all university-based startups in the country, while other regions produced far fewer. Although this partly reflects differences in the scale of the university sector, it also points to disparities in innovation infrastructure, talent concentration, and commercialization support.

Rather than framing these patterns as simple regional inequalities, this study uses them to motivate a broader research question: How do university intermediary functions perform across different types of innovation environments? Specifically, it asks whether the effectiveness of brokering depends on the density of technological activity and the availability of specialized services. The main aim of this study is to examine how universities can best design strategic alliances with external organizations, given their embeddedness within broader entrepreneurial ecosystems such as innovation agglomerations. This perspective builds on existing work on entrepreneurial ecosystems and innovation intermediaries, proposing that university-led entrepreneurship is shaped not only by internal institutional capacities but also by the external innovation context. In strong ecosystems, universities may act primarily as connectors, linking academic outputs to fertile landscapes of talent and services. In thinner ecosystems, they may serve as substitutes for missing infrastructure, assuming a more active brokerage and support role.

The remainder of this paper is structured as follows. Section 2 reviews the literature on entrepreneurial ecosystems and university intermediation. Section 3 develops hypotheses regarding the relationship between university support functions and startup formation under varying ecosystem conditions. Section 4 describes the dataset, variables, and modeling strategy. Section 5 presents the results, followed by the discussion in Section 6. Section 7 concludes by outlining the study's limitations and implications for research and policy.

2. Literature Review

2.1. Entrepreneurial Ecosystems and Their Key Components

Entrepreneurial ecosystems have garnered increasing academic attention globally since the 2010s (Spigel et al., 2020). The concept draws on a biological metaphor, recognizing that a combination of elements—such as scientists, inventors, entrepreneurs, regulators, and intermediaries-and functions-such as knowledge creation, intermediation, and diffusion-collectively enable innovative startups to emerge, grow, and evolve into selfsustaining industrial agglomerations (Isenberg, 2016; Nishizawa & Gibson, 2018). This framework encompasses both static and dynamic perspectives on entrepreneurship and innovation (Klerkx et al., 2012). The static view emphasizes the roles of system components and their interactions as drivers of entrepreneurial outcomes. In contrast, the dynamic view highlights system innovation, wherein the structure and nature of the ecosystem are transformed through exogenous shocks or the gradual accumulation of endogenous changes. Many studies have implicitly or explicitly adopted the static perspective, focusing on identifying key components that enhance the efficiency of entrepreneurial ecosystems. A notable characteristic of this approach is the clear delineation of system boundaries, which facilitates the identification of relevant elements for cross-sectional comparison and the assessment of system performance.

Entrepreneurial ecosystems comprise multiple interconnected elements that influence the creation and growth of startups. These ecosystems function differently across geographical levels, with national, regional, and city-specific factors playing distinct roles. At the national level, the foundation of an entrepreneurial ecosystem is shaped by technology adoption, financial access, human capital, and business culture, as well as formal institutions such as intellectual property rights, economic policies, and regulatory frameworks that support venture capital (Szerb et al., 2013). This framework provides a structured approach to assessing how different countries and regions foster entrepreneurship. Combined with the penalty-for-bottleneck approach, this framework has been applied to evaluate entrepreneurial ecosystems in 22 urban regions across Europe (Szerb et al., 2022). The results emphasize the role of regional policies, innovation networks, governance quality, and infrastructure in shaping entrepreneurial activity at the subnational level.

Beyond regional analyses, research has examined entrepreneurial ecosystems at finer geographical levels, particularly in developing cities (Isenberg & Onyemah, 2016; Audretsch et al., 2021). Key factors such as startup communities, informal networks, mentorship, and cultural norms shape city-based entrepreneurship. Intermediaries—including incubators, accelerators, and business service providers—play a crucial role in fostering new ventures. At an even finer scale, technology incubators influence ecosystem dynamics by supporting startups, whose success depends on essential elements like talent, technology, capital, and infrastructure (Yuan et al., 2022). A meta-

analysis highlights that different factors drive entrepreneurship at various ecosystem levels: human resources (mentorship and leadership) are most influential at the city level, formal institutions and government support are important at the state level, and intermediaries are essential at the national level (Queissner et al., 2022).

Despite these variations, core pillars consistently underpin entrepreneurial success: financial capital (venture funding and subsidies), technology (R&D and patents), human resources (mentorship and leadership), infrastructure (physical and economic conditions), intermediaries (incubators, accelerators, technology transfer offices), and institutions (laws and culture). Strengthening these pillars helps policymakers and stakeholders address bottlenecks, ensuring resources, networks, and institutional support align to foster innovation and business growth.

2.2. Universities as a Unit of Entrepreneurial Ecosystem Analysis

Universities provide a refined perspective on academic entrepreneurship through three lenses: knowledge stock generators, spatial units of entrepreneurial activity, and sources of entrepreneurial resources. The knowledge spillover theory of entrepreneurship emphasizes the commercialization of science through entrepreneurship as a crucial mechanism for knowledge-based economic growth (Acs et al., 2013). Research universities generate numerous undeveloped inventions due to their embryonic nature and the complexities of licensing agreements, leaving a significant portion of the knowledge stock underutilized. This creates entrepreneurial opportunities for sciencebased startups. Universities thus play a key role in fostering localized knowledge spillovers, enhancing both competition and collaboration within regional entrepreneurial ecosystems and contributing to economic growth through innovationdriven enterprises.

Universities also function as geographical units for entrepreneurial activity, often embedded within innovation districts, science parks (Fukugawa & Chang, 2025), and technology clusters. These spaces co-locate startups, research institutions, and industry partners, reinforcing university-driven entrepreneurship. Empirical evidence indicates that university spin-offs tend to cluster at micro-geographical levels, including university campuses, incubators (Fukugawa, 2018a), university hospitals, and science parks, strengthening their role in spatial innovation dynamics (Fukugawa, 2022a). Beyond spatial and institutional functions, universities also operate as pedagogical units, where entrepreneurship education can shape long-term ecosystem dynamics. Heinonen and Hytti (2010) emphasize that teaching plays a foundational role in the development of entrepreneurial universities, suggesting that curriculum design and pedagogical practices are the central mechanisms through which universities foster entrepreneurial mindsets and capabilities.

2.3. University Startup Ecosystem and Its Key Components

Universities are central to startup ecosystems, providing critical entrepreneurial resources for venture creation and growth. These resources include human capital, such as faculty inventors, student entrepreneurs, and researchers (Gubitta et al., 2016; Shane, 2004), as well as financial capital in the form of grants, subsidies, and endowments (Karnani, 2013; Zerbinati et al., 2012). Technological assets, such as patents and intellectual property (Czarnitzki et al., 2014), and physical infrastructure, including research laboratories and incubators (Prokop et al., 2019; Siegel et al., 2008; Sansone et al., 2019), further support entrepreneurial activities.

Beyond tangible resources, universities act as innovation intermediaries, facilitating knowledge transfer and commercialization. Key intermediaries include technology transfer offices (Siegel et al., 2008; Sansone et al., 2019), incubators (Siegel et al., 2008), science parks (Sansone et al., 2019; Prokop et al., 2019), and accelerators, all of which support startup development. Institutional frameworks—such as intellectual property ownership, regulatory policies, and incentive structures—further shape entrepreneurial outcomes (Markman et al., 2004; Fini et al., 2011; Damsgaard & Thursby, 2013).

Universities influence spin-off trajectories beyond traditional business environments, with scientific knowledge serving as a foundation for radical innovation and broad commercial applications (Gubitta et al., 2016; Maine & Thomas, 2017). These innovations frequently disrupt existing technologies and create new markets (Acemoglu et al., 2022). Established firms, wary of the replacement effect (Arrow, 1962a), often hesitate to commercialize such innovations, making academic entrepreneurship a viable alternative to patent licensing. Scientific excellence enhances university startups' credibility, increasing their chances of securing VC (Roche et al., 2020; Fukugawa, 2022b, 2023). Czarnitzki et al. (2014) further highlight the role of academic inventions and star scientists in driving employment growth in German university spin-offs. These findings suggest that scientific excellence positively influences university startup creation.

Building on these insights, this study proposes a theoretical framework (Figure 1) in which universities function as entrepreneurial ecosystems embedded within broader regional innovation environments. At the core of this framework is the process of startup formation, driven by internal university resources—including basic research, intellectual property, institutional support staff, physical infrastructure, and financial assistance. These resources provide the foundation for entrepreneurial activity by transforming academic knowledge into commercially viable outputs.

Universities also act as innovation intermediaries by offering consulting services and facilitating external linkages to key ecosystem actors such as investors, human resource agents, and knowledge-intensive business service (KIBS) providers. These linkages are not directly part of the core entrepreneurial functions but serve as conduits through which universities connect startups to the broader innovation system. As emphasized by Hess et al. (2025), the effectiveness of ecosystem elements is contingent upon their interplay with local environmental conditions. Their findings suggest that entrepreneurial success does not depend on the uniform presence of all ecosystem pillars but may instead result from context-sensitive complementarity or substitutability among elements. This insight parallels this study's framework, which highlights that the utility of university linkages depends significantly on the surrounding agglomeration of innovation infrastructure.

The framework emphasizes that the effectiveness of these external linkages depends heavily on regional agglomeration—specifically, the availability of specialized services and innovation-related infrastructure. In dense innovation environments, the "soil" into which these university-mediated linkages extend is fertile, enabling startups to access talent, services, and partnerships more efficiently. Thus, universities are not only generators of internal capacity but also bridges to external opportunity, with the quality of regional ecosystems shaping how effectively they support entrepreneurship.

Figure 1. Theoretical Framework

3. Hypotheses

This section formulates hypotheses based on the theoretical perspectives outlined in the introduction and literature review, particularly the role of university intermediaries in mitigating barriers to entrepreneurship. Universities that actively supply key entrepreneurial inputs—such as basic research, patents, funding, physical infrastructure, and support personnel—are expected to foster higher startup formation rates.

H1: The availability of entrepreneurial resources provided by universities positively influences the likelihood of startup creation.

Academic entrepreneurs often face challenges due to limited practical business knowledge and market insights, making consulting services a vital support mechanism. These services offer strategic guidance on business development, intellectual property management, and commercialization pathways, helping to reduce uncertainty and facilitate more informed entrepreneurial decision-making.

H2: University consulting services positively influence startup creation.

Brokerage functions help establish linkages that might not naturally emerge within fragmented innovation systems (Intarakumnerd & Charoenporn, 2013; Fukugawa, 2018a, 2019). Given that academic entrepreneurs often face challenges in accessing critical market networks, brokerage services play a crucial role in connecting them with external stakeholders, such as venture capitalists, industry partners, and government agencies. By facilitating these connections, universities enhance the likelihood of successful startup formation.

H3: University brokerage functions facilitate startup formation.

Agglomerations enhance knowledge spillovers by fostering intra- and inter-industry interactions, as described by Marshall–Arrow–Romer (MAR) and Jacobs externalities (Arrow, 1962b; Jacobs, 1969; Marshall, 1890; Romer, 1986; Glaeser et al., 1992). While the relative influence of specialization versus diversity may vary across contexts (Beaudry & Breschi, 2003; de Groot et al., 2016; Neffke et al., 2011), there is broad consensus that agglomeration drives innovation and productivity by facilitating knowledge sharing, reducing search costs, and strengthening collaborative ties.

In innovation-dense regions, agglomeration not only fosters knowledge exchange but also enables the accumulation of critical entrepreneurial resources. High concentrations of talent, specialized knowledge, and potential investors create a fertile environment for university startups. Tokyo exemplifies this dynamic: university spin-off creation is highly concentrated in the region (Fukugawa, 2022a), where universities operate within a densely connected entrepreneurial ecosystem and benefit from superior access to venture capital, research funding, and skilled labor. This pattern mirrors Lerner's (1999) seminal finding on the SBIR program, which demonstrated that its positive effects were limited to firms located in zip codes with substantial VC activity—underscoring the decisive role of capital accessibility in shaping entrepreneurial success.

Within such ecosystems, the intermediary functions of universities—linking startups to knowledge providers, human capital, and commercialization partners—become more effective. Agglomeration amplifies the value of external linkages by increasing their relevance, responsiveness, and potential for follow-through. Accordingly, the benefits of university-facilitated external networks are likely to be magnified in regions characterized by innovation agglomeration.

H4: The positive effects of university external linkages on startup creation are strengthened in regions with high innovation agglomeration.

4. Method

4-1. Data

This study analyzes panel data from 1,027 universities covering the period from 2019 to 2023. The dataset was obtained from a comprehensive annual survey conducted by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). In 2020, the survey was distributed to all 86 national universities, 102 public universities, and 810 private universities. All national and public universities responded, while private universities had a 97% response rate, resulting in an overall response rate of 98%. This makes the MEXT survey the most comprehensive dataset on university technology transfer in Japan. The survey collects data on the intermediary functions of universities, including consulting, resource provision, and brokerage, which form the basis for the empirical analysis in this study.

4-2. Variables

The dependent variable represents the number of university spin-offs (USO) established in year *t* at university *i*. The survey defines USOs based on at least one of the following four criteria: firms established to commercialize patents invented by faculty, postdoctoral researchers, graduate students, or undergraduate students; firms established to commercialize university research outcomes other than patents; firms founded by faculty, postdoctoral researchers, graduate students, or undergraduate students; and firms officially recognized by universities as USOs.

Human resources are represented by the number of researchers, serving as a proxy for university size and reflecting research capacity and potential for knowledge creation. Larger universities generally have more faculty engaged in research activities, which enhances the likelihood of academic entrepreneurship through knowledge spillovers and commercialization efforts.

Scientific research intensity and quality are measured by the number of accepted KAKENHI projects, Japan's largest national basic research grant program, while controlling for the number of researchers. Fundamental research serves as a foundation for high-tech startups, and KAKENHI funding reflects a university's capacity for upstream knowledge production. Prior research highlights the role of KAKENHI in enhancing research quality. Wang et al. (2018) found that competitive funding, primarily KAKENHI, increases the novelty of research outputs, while Onishi and Owan (2020) demonstrated that KAKENHI recipients experience a 20–26% increase in forward citations. Data on KAKENHI projects were obtained from the National Institute of Informatics (NII) KAKENHI database.

Patent applications serve as an indicator of technological output, measuring applied

research and innovation. The volume of patent applications reflects a university's ability to generate intellectual property, which is crucial for startup creation. A higher number of patent applications suggests stronger research commercialization potential, as universities with extensive patent activity are more likely to facilitate technology transfer and entrepreneurial ventures.

The logarithm of funds allocated to university startups is used as a measure of financial resources. Robustness checks using a binary dummy variable indicating the presence of a gap fund—designed to support proof of concept, R&D, and prototyping—yield consistent results.

The number of FTE staff dedicated to entrepreneurship support serves as a measure of a university's institutional commitment to fostering startup activity. Universities implement various policies that shape entrepreneurial outcomes, and the presence of specialized support personnel reflects their capacity to assist academic entrepreneurs. Additionally, the number of support measures implemented indicates the extent of institutional efforts to promote entrepreneurship and facilitate research commercialization. FTE staff are calculated as the sum of regular employees plus half of non-regular employees involved in entrepreneurship support.

A binary indicator for the presence of an incubator represents physical infrastructure for academic entrepreneurship, encompassing resources such as research labs, offices, and reception areas.

Intermediary functions encompass both consulting and brokerage roles that universities play in supporting startup creation. Consulting functions include mentorship programs led by experienced entrepreneurs and assistance in refining business models. Brokerage functions capture six types of external linkages that facilitate access to financial, human, and knowledge resources. Specifically, investor linkages refer to connections with venture capitalists, accelerators, and other financial institutions; human resource linkages involve connections with agencies that support general and managerial talent acquisition; and knowledge linkages pertain to licensed business service providers, such as accountants, lawyers, and patent attorneys. It should be noted that information on the total number of external partners is not available; therefore, the variables capture the diversity of linkage types rather than the number of individual relationships. This typology-based measure reflects the breadth of university intermediation within the entrepreneurial ecosystem.

The Cronbach's alpha value of 0.869 demonstrates strong internal consistency among variables representing intermediary functions, suggesting that consulting, networking,

and resource provision constitute a cohesive construct. This high reliability indicates these functions are interrelated rather than independent. Due to their strong correlation, including all variables simultaneously in regression models could introduce redundancy. Therefore, these variables are introduced into regression analyses alternatively.

To represent innovation agglomerations, this study utilizes comprehensive patent data compiled by the Institute of Intellectual Property Patent Database (IIPPD), which includes information on all patents registered with the Japan Patent Office. The year of application is used to indicate the timing of innovation activity. Due to a significant decline in data availability after 2021—attributable to delays in dataset compilation—the analysis is restricted to the period from 2017 to 2021. It is assumed that regional innovation agglomeration influences university startup formation with a two-year lag.

Innovation agglomerations are measured by the number of patent applications filed in each region. To prevent double counting from joint applications, the location is determined using the address of the first applicant. Importantly, the dataset used in this study is confined to private-sector applicants, thereby focusing exclusively on innovation activities carried out by profit-oriented organizations. This ensures that the indicator reflects proprietary technological development that aligns closely with corporate R&D strategies and long-term regional investment in innovation.

Five types of technology-specific innovation agglomeration are identified: biotechnology, chemicals, electronics, precision instruments, and mechanical engineering. The classification of patents into technological fields follows the concordance table developed by the World Intellectual Property Organization (WIPO, 2013), which links international patent classifications (IPC) to broader technology domains. These technological categories are introduced with the expectation that the relationship between startup formation and innovation agglomeration exhibits sectoral patterns, as different technologies may follow distinct trajectories of regional concentration and entrepreneurial responsiveness. For additional methodological details, see Fukugawa (2016).

Table 1 presents the categories, definitions, and descriptive statistics of the variables.

Table 1 Descriptive Statistics

4-3. Model

The dependent variable represents count data characterized by a high number of zeros, indicating significant zero inflation. Descriptive statistics in Table 1 confirm the presence of overdispersion, thereby justifying the use of a negative binomial model

rather than a standard Poisson approach. Additionally, results from Hausman's specification test indicate that a fixed-effects model is preferable, highlighting the importance of controlling for unobserved heterogeneity in the estimation process.

Although a large number of observations consist of zero startup formations, the structure of the model suggests that the excess zeros are adequately handled within the negative binomial framework rather than requiring a separate zero-inflation component. If zeroinflation were a major issue, the zero-inflated negative binomial model would have yielded a substantially lower Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), but there is no clear evidence of this improvement. Additionally, the log-likelihood of the negative binomial regression model demonstrates a much better fit relative to the zero-inflated negative binomial estimation. This suggests that the negative binomial specification sufficiently captures the data's distribution without requiring a zero-inflation correction.

To complement the baseline specification, ancillary estimations are conducted by stratifying the sample along key time-invariant institutional characteristics—namely, location (e.g., Tokyo vs. non-Tokyo), academic discipline (e.g., presence of medical schools), and ownership type (e.g., national universities). These factors, while constant over time, may systematically moderate the relationship between university characteristics and startup formation. Incorporating such subsample estimations does not serve solely as a robustness check but also reveals the conditional nature of the main effects. In cases where the direction or significance of key predictors differs markedly across subsamples, these results highlight the contextual vulnerability—rather than universal robustness—of the baseline findings. This approach allows researchers to uncover heterogeneous mechanisms underlying university entrepreneurship and ensures that policy implications derived from the models remain sensitive to institutional and regional variation.

Although multilevel modeling could be considered to account for potential clustering of universities within broader regional innovation systems, the substantive variation in startup formation is primarily captured by university-specific fixed effects. Given that regional-level random variance is negligible in ancillary estimations, multilevel modeling is unlikely to yield additional insights beyond the current fixed-effects framework and subsample analyses.

4-4. Robustness Test

To assess the robustness of the fixed-effects estimations, a correlated random effects (CRE) negative binomial model is employed. This approach addresses potential concerns regarding the treatment of unobserved heterogeneity by incorporating

university-specific means of key independent variables—such as research output, entrepreneurship support staffing, and external linkage activities—into a random-effects specification (Mundlak, 1978). By doing so, the CRE model enables simultaneous estimation of within-university (over time) and between-university (structural) effects without assuming strict exogeneity of regressors.

The CRE estimations focus on three dimensions of external linkage activities—investor linkages, human resource agent linkages, and KIBS provider linkages—each evaluated separately. Consistency between the fixed-effects and CRE results would reinforce the robustness of the main findings regarding the conditional importance of external linkages for startup formation.

5. Results

Table 2 presents the main estimation results and Table 3 summarizes the results of the main estimation and estimation by subsample.

Table 2 Estimated Fixed-effects Negative Binomial Models with Lagged Independent Variables

Table 3 Summary

5-1. Main Results

For H1, which posits that "the provision of entrepreneurial resources by universities positively influences the likelihood of startup creation," the results offer partial support. Among the components of university resources, scientific research output, measured by the number of KAKENHI-funded basic research projects, shows a consistently significant positive association with startup formation across all model specifications. This finding reinforces the central importance of sustained investment in basic research for promoting academic entrepreneurship across regional contexts.

The number of full-time employees dedicated to entrepreneurship support also exhibits a positive effect in most models. This suggests that institutional support staff can facilitate startup activity.

Other resource-related variables—including the presence of incubators and the total amount of startup funding—do not show statistically significant effects, indicating that these factors may be less influential in driving startup creation, at least in isolation. Thus, the evidence provides partial support for H1, with basic research emerging as the most robust contributor among university-provided entrepreneurial resources.

While the magnitude of marginal effects suggests that substantial changes in university resources would be required to generate large increases in startup formation, the primary insights of the analysis lie in the direction and statistical significance of relationships rather than in the literal size of marginal changes. The results robustly identify which types of university resources are more closely linked to entrepreneurial outcomes, offering clear priorities for institutional strategies and policy interventions. Emphasizing these directional findings ensures that policy recommendations remain both analytically grounded and practically actionable.

The results do not support H2, as mentorship does not exhibit a significant positive effect on startup formation in any model specification. This suggests that university-led consulting services, as currently implemented, may have limited direct influence on the likelihood of startup creation.

The results do not support H3, as none of the university brokerage linkages show a significant association with startup formation. This suggests that simply having external connections is not sufficient to stimulate academic entrepreneurship. Several interpretations are possible. First, the effectiveness of brokerage may depend on complementary conditions, such as the absorptive capacity of startups or the maturity of regional innovation ecosystems. Second, brokerage functions may influence later stages of startup development (e.g., growth or survival) rather than initial formation. Third, the lack of significance could reflect limited depth or functionality in these linkages—universities may formally report connections without those relationships being operationally meaningful for startup success. These findings indicate that brokerage alone does not automatically translate into entrepreneurial outcomes, and that quality, context, and integration of these linkages matter more than their existence.

The results provide partial and context-dependent support for H4, which posits that the effectiveness of university intermediary functions is moderated by regional innovation agglomeration. While the base model highlights a robust augmentation mechanism—particularly in human resource and knowledge service linkages—stratified analyses by location, institutional type, and ownership reveal considerable heterogeneity, suggesting that agglomeration-based complementarities are not uniformly realized across all university contexts.

In the base model, interactions between university linkages to human resource agents and all five categories of innovation agglomeration are consistently positive and statistically significant at the 1% level, supporting the idea that access to specialized talent becomes increasingly effective for startup formation when embedded in dense technological clusters. These results reinforce the view that human capital intermediation is most productive in environments where search costs are low and knowledge flows are frequent.

University linkages to knowledge service providers—including patent attorneys, IP consultants, and other KIBS actors—also exhibit significant positive interaction effects across most agglomeration types in the base model, with significance levels at 1% or 5%. These results suggest that such services are critical enablers of academic entrepreneurship in innovation-intensive regions, likely because they facilitate the codification, protection, and strategic positioning of early-stage knowledge assets. However, these positive effects do not persist in any of the subsample estimations, indicating that the contribution of knowledge service linkages is highly dependent on institutional and locational ecosystems and may not generalize across university types.

By contrast, linkages to investors—which are not significant in the base model—exhibit positive interaction effects in the non-Tokyo subsample, particularly in the biotechnology, electronics, precision instruments, and mechanical fields. This suggests that financial intermediation becomes relevant only when universities operate in lesscentralized regions, where access to capital may be more constrained and university brokerage can meaningfully reduce information frictions. Interestingly, in the private university subsample, all investor-related interactions are significantly negative, implying that financial brokerage mechanisms may be structurally less effective or even counterproductive in these institutions due to limited scale, credibility, or network positioning.

The stratified results for human resource linkages show that the significant complementarities observed in the base model do not hold in the non-Tokyo or national university samples, and are only partially retained among medical and private universities. This highlights the bounded applicability of HR intermediation effects, which appear to be strongest in metropolitan and comprehensive research universities where talent density and relational infrastructure are well developed.

Finally, although innovation agglomeration is generally assumed to be beneficial, the results show that in several subsample models—particularly among private universities—these interactions either lose significance or become negative. This implies that agglomeration alone does not automatically produce favorable entrepreneurial outcomes. Without strong university engagement as a relational broker, dense innovation environments may foster competition over limited resources or reinforce exclusivity, thus inhibiting inclusive startup formation.

In sum, the findings support the augmentation hypothesis only under certain

institutional conditions. University intermediation through HR and knowledge linkages is most effective when reinforced by innovation agglomeration, but this effect is conditional on the university's structural position, location, and organizational type. Financial intermediation, in contrast, appears selectively important in peripheral regions, further underscoring the importance of context-specific intermediation strategies.

5-2. Robustness Test Results

Table 4 presents the results of the CRE models. Robustness checks using correlated random effects negative binomial models reveal that short-term within-university changes in external linkage activities do not exhibit statistically significant effects on startup formation. By contrast, persistent between-university differences—captured by the university-level means of external linkage variables—show significant positive associations with startup outcomes. In particular, the mean level of investor linkages is positively associated with startup formation (coefficient = 0.402, p = 0.033), as is the mean level of human resource agent linkages (coefficient = 0.765, p = 0.039). Evidence for KIBS provider linkages is weaker but suggestive, with the mean coefficient estimated at 0.751 and marginal significance (p = 0.070). These findings reinforce the interpretation that external linkage activities contribute structurally over time, through accumulated differences across universities, rather than exerting immediate year-to-year impacts.

Table 4 Estimated CRE models

6. Discussion

This study examined how university intermediary functions—namely, resource provision (H1), consulting (H2), and external networking or brokerage (H3)—are associated with startup formation, and how these relationships are moderated by regional innovation agglomeration (H4). The findings reveal that the effectiveness of these functions is highly context-dependent, varying significantly across institutional types and regional innovation environments.

H1 posits that university-provided entrepreneurial resources positively influence startup formation. Among the internal resources assessed, basic research capacity—proxied by KAKENHI-funded projects—exhibits a consistently strong positive effect across all model specifications, underscoring the foundational role of sustained public investment in upstream scientific research. In contrast, technology outputs (patents) and entrepreneurship support staffing are more effective in less agglomerated regions, suggesting that in the absence of dense ecosystems, universities must compensate by reinforcing their internal capabilities. These context-sensitive effects caution against one-size-fits-all policies: while high-capacity internal resources are essential in

peripheral regions, their marginal benefit declines in richer ecosystems unless they are complemented by external connectivity.

H2 evaluated whether consulting and mentorship services provided by universities influence startup formation. Across all specifications, these services show no significant effects. This may indicate that mentorship plays a more critical role in later stages of venture development (e.g., survival or growth), or that the quality and relevance of consulting are mismatched with the needs of early-stage startups, especially in nascent ecosystems. Thus, the absence of a measurable impact does not necessarily negate the value of consulting, but highlights the need for ecosystem-specific tailoring and integration with broader entrepreneurial support systems.

H3 examined the brokerage role of universities through external linkages to investors, KIBS providers, and HR agents. The base model shows no direct effect of these linkages on startup formation, suggesting that mere presence or formal establishment of partnerships is insufficient. However, when interacted with regional agglomeration, HR and KIBS linkages exhibit strong positive effects, particularly in dense innovation ecosystems. These findings support the view that relational infrastructures—such as trust, proximity, and shared norms—enhance the utility of external connections by lowering search and transaction costs. In this sense, brokerage becomes effective only when activated within supportive ecosystems.

H4 investigated whether regional innovation agglomeration enhances the effectiveness of university intermediation. The results provide partial and context-dependent support for the augmentation hypothesis. In the base models, agglomeration reinforces the role of HR and KIBS linkages, consistent with theories of knowledge spillovers and relational infrastructure. However, this complementarity breaks down in the non-Tokyo, national, and most medical university subsamples, suggesting that the benefits of agglomeration are not universally transferable but depend on a university's degree of institutional embedding within its local ecosystem.

In contrast, linkages to investors—insignificant in the base model—become positively significant in non-Tokyo universities, especially in sectors such as biotechnology and mechanical engineering. This pattern suggests that universities in peripheral regions play a compensatory role by brokering access to early-stage capital in less developed financial ecosystems. Conversely, investor linkages exhibit a significant negative interaction in private universities, potentially reflecting limited institutional scale, lower external credibility, or weaker integration with regional startup networks. National universities show no significant agglomeration—intermediation effects for any linkage type, possibly due to organizational rigidity or a weaker institutional mandate

for entrepreneurial engagement.

In the medical school subsample, one model specification reveals a significant complementary effect between biotechnology agglomeration and HR agent linkages. This indicates that in life science-oriented contexts, talent-based intermediation may help activate entrepreneurial potential. However, this effect is not robust across all models, implying that the observed synergy may be contingent on specific institutional or ecosystem conditions. The inconsistency highlights possible structural barriers—such as regulatory complexity or limited translational infrastructure—that constrain the full realization of biotech-based entrepreneurship within medical schools.

Additionally, the results do not reveal a consistent sectoral pattern in the effects of agglomeration across biotechnology, chemicals, electronics, precision instruments, and mechanical domains. This suggests that the amplification of university intermediation by agglomeration is not driven by sector-specific technological properties, but rather by broader contextual factors such as institutional credibility, relational density, and the availability of support services.

Overall, the findings affirm that agglomeration functions as an amplifier—rather than a substitute—for university intermediation. Startup outcomes depend not just on being embedded in an innovation-rich environment, but also on the university's strategic alignment with ecosystem conditions, its capacity to mobilize relevant resources, and the functionality of its external linkages. When these conditions are met, universities can effectively translate agglomeration advantages into startup creation. Where they are absent, even dense innovation regions may fail to generate inclusive or sustained entrepreneurial activity.

7. Conclusion

This study finds that among university intermediary functions, basic research capacity as measured by KAKENHI-funded projects—is the most consistent and robust driver of startup formation. In contrast, other forms of university support, including patents, entrepreneurship support staffing, consulting, and external linkages, exhibit conditional effectiveness that depends on regional and institutional contexts. Specifically, linkages to human resource agents and KIBS providers are positively associated with startup formation only in regions characterized by dense innovation agglomeration. While investor linkages show no overall effect, they appear to play a compensatory role in non-Tokyo regions, where access to private capital is more constrained. These results underscore the importance of ecosystem alignment, suggesting that external linkages are not inherently effective but derive their value from the surrounding innovation environment. By integrating university-level panel data with regional patent-based indicators of innovation agglomeration, this study contributes new empirical evidence to the literature on academic entrepreneurship. It advances the understanding of universities as boundary-spanning institutions whose entrepreneurial impact arises from the interaction between internal strategic capacity and external structural conditions. Rather than advocating a uniform model of university intermediation, the findings support a contextualized perspective—one that emphasizes adaptive strategies responsive to differences in geography, sector, and institutional structure. In sum, this study reinforces the view that universities are key actors in entrepreneurship, but their effectiveness depends on how well internal capacities are matched to the external opportunities and constraints presented by their regional innovation environments. Policies aimed at supporting academic entrepreneurship must therefore reflect this dual dependence—on both internal capabilities and the external innovation environment—to foster inclusive, resilient, and regionally balanced innovation.

Several limitations should be noted. First, the five-year panel used in this study does not capture long-term institutional change or ecosystem evolution, both of which may shape the trajectory of university entrepreneurship over time. This limitation is particularly relevant given the robustness test results, which indicate that structural differences in external linkages—rather than short-term fluctuations—are key drivers of startup formation. Second, while the fixed-effects estimation accounts for unobserved heterogeneity, it does not allow for strong causal inference, and internal organizational transformations within universities are not directly observed. Although the robustness tests suggest that persistent external linkages structurally contribute to startup formation, these findings cannot fully rule out the possibility of reverse causality or omitted timevarying factors. Third, the study relies on regionally bounded indicators, even though many ecosystem actors, such as investors and KIBS providers, operate across multilevel and inter-regional networks. While the robustness checks highlight the importance of persistent university-level external linkages, they do not fully resolve potential measurement mismatches arising from the complex geographic reach of innovation networks.

Building on these limitations, future research should pursue three directions. First, extending the observation period beyond five years would allow for a deeper understanding of how universities evolve structurally and adapt within changing innovation ecosystems. Second, the use of causal inference methods could provide stronger evidence regarding the effects of university strategies and external linkages on startup outcomes. Third, incorporating data that captures multi-level and cross-regional interactions, such as co-patenting, investment flows, or collaboration networks, would

enable a more accurate representation of the distributed nature of contemporary innovation ecosystems.

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Table 1 Descriptive Statistics

Category	Variable	Definition	Obs	Mean	Std. dev.	Min	Max
Dependent variable	STARTUP	Number of university-affiliated startups.	3,904	0.353	1.803	0	45
Human	RESEARCHER	Number of full-time equivalent academic researchers.	3,898	293.540	606.472	0	7331
Science	KAKENHI	Number of competitive grants awarded for basic research projects.	3,904	94.003	298.874	0	5309
Technology	РАТАРР	Number of patent applications filed by the university.	3,904	12.804	56.990	0	869
Institution	FTESTAFF	Number of full-time equivalent staff dedicated to entrepreneurship support activities.	3,904	0.407	1.628	0	38
Infrastructure	INCUBATOR	Binary indicator for whether the university operates a startup incubator.	3,904	0.123	0.329	0	1
Finance	USOFUNDS	Natural logarithm of total funds secured for university spin-offs.	3,904	0.403	2.358	0	18.083
Consulting	CONSULT	Binary indicator for mentorship programs supporting business model refinement.	3,904	0.116	0.419	0	2
Brokerage	EXT_INV	External linkages to investors.	3,904	0.144	0.510	0	3
Brokerage	EXT_HR	External linkages to human resource agencies supporting startup talent acquisition.	3,904	0.049	0.235	0	2
Brokerage	EXT_KIBS	External linkages to providers offering specialized licensed business services.	3,904	0.030	0.171	0	1
Innovation agglomeration	BIO	Regional private-sector biotechnology patent application counts.	3,904	830.0	1338.3	1	3783

Category	Variable	Definition	Obs	Mean	Std. dev.	Min	Max
Innovation	CHEM	Regional private-sector chemicals patent	3,904	2816.1	4919.2	2	13625
agglomeration		application counts.	3,904	2010.1	4919.2	2	13023
Innovation	ELE	Regional private-sector electronics patent	3,904	7528.0	12574.2	2	35879
agglomeration		application counts.	3,904	7528.0	12374.2	2	55679
Innovation	INST	Regional private-sector precision instruments	3,904	4211.4	7223.0	2	21592
agglomeration		patent application counts.	3,904	4211.4	1225.0	Z	21392
Innovation	MECHA	Regional private-sector mechanical engineering	3,904	5084.5	7580.0	5	22254
agglomeration		patent application counts.	3,904	5064.5	7380.0	5	22234
Institutional type	ΤΟΚΥΟ	Binary indicator for whether the university is	3,904	0.181	0.385	0	1
institutional type		located in Tokyo.	3,904	0.101	0.385	0	1
Institutional type	MEDICAL	Binary indicator for whether the university has a	3,904	0.101	0.302	0	1
institutional type		medical school.	3,904	0.101	0.302	0	1
Institutional type	NATUNIV	Binary indicator for national university status.	3,904	0.110	0.313	0	1
Institutional type	PRIUNIV	Binary indicator for private university status.	3,904	0.767	0.422	0	1

Note: EXT_INV, EXT_HR, and EXT_KIBS measure the number of types of external linkages established. EXT_INV can take a maximum value of 3, corresponding to connections with venture capital firms, accelerators, and other financial institutions. EXT_HR can take a maximum value of 2, capturing linkages to general human resource agencies and specialized managerial talent matching services. EXT_KIBS measures licensed business service linkages, such as those to accountants, lawyers, and patent attorneys. These variables reflect the diversity of linkage types rather than the total number of individual partnerships.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
RESEAR	(-)	(_)	(5)	\' /	(5)			(9)	(~)	(10)	(**)	()	(10)	(21)	()
HER	-0.0003	-0.0004	-0.0004*	-0.0003	-0.0003	-0.0004*	-0.0003	-0.0004	-0.0004*	-0.0003	-0.0003	-0.0004*	-0.0003	-0.0004	-0.0004*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KAKEN HIPJ	0.0007***	0.0008***	0.0007***	0.0007***	0.0008***	0.0007***	0.0007***	0.0008***	0.0007***	0.0008***	0.0008***	0.0006***	0.0008***	0.0008***	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PATAPP	0.0016	0.0019	0.0017	0.0016	0.0018	0.0017	0.0016	0.0018	0.0017	0.0015	0.0018	0.0018	0.0015	0.0018	0.0017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FTESTA FF	0.0363**	0.0243	0.0325**	0.0345**	0.0253*	0.0318**	0.0342**	0.0284*	0.0330**	0.0348**	0.0284*	0.0326**	0.0338**	0.0265*	0.0337**
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)
INCU	-0.1484	-0.1328	-0.1950	-0.1428	-0.1256	-0.1867	-0.1355	-0.1168	-0.1755	-0.1346	-0.1214	-0.1700	-0.1407	-0.1265	-0.1878
	(0.229)	(0.228)	(0.234)	(0.229)	(0.230)	(0.234)	(0.227)	(0.228)	(0.232)	(0.227)	(0.229)	(0.231)	(0.228)	(0.228)	(0.232)
USOFUN	0.0000	0.0101	0.0025	0.0007	0.0101	0.0025	0.0006	0.0096	0.0027	0.0007	0.0094	0.0030	0.0014	0.0097	0.0035
DS	0.0000	0.0101	0.0025	0.0007	0.0101	0.0025	0.0006	0.0096	0.0027	0.0007	0.0094	0.0050	0.0014	0.0097	0.0035
	(0.015)	(0.015)	(0.014)	(0.016)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)

Table 2 Estimated Fixed-effects Negative Binomial Models with Lagged Independent Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
CONSUL	0.0094 (0.095)	-0.0116 (0.095)	0.0048 (0.095)	0.0144 (0.096)	-0.0031 (0.096)	0.0174 (0.097)	0.0125 (0.095)	-0.0056 (0.095)	0.0053 (0.096)	0.0167 (0.094)	-0.0011 (0.094)	0.0080 (0.095)	0.0104 (0.095)	-0.0136 (0.095)	-0.0098 (0.096)
BIO	-0.0004* (0.000)	-0.0003 (0.000)	-0.0004** (0.000)												
EXT_IN V	0.0877			0.0964			0.1121			0.1184			0.0913		
	(0.105)			(0.103)			(0.102)			(0.102)			(0.104)		
BIO#EX T_INV	-0.0000														
EXT_HR		-0.1511 (0.172)			-0.1401 (0.171)			-0.1447 (0.169)			-0.1426 (0.170)			-0.1443 (0.172)	
BIO#EX T_HR		0.0002***													
		(0.000)													

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
EXT_KI	()	()											< - <i>y</i>		
BS			-0.1793			-0.1514			-0.1924			-0.1904			-0.2456
			(0.244)			(0.244)			(0.250)			(0.249)			(0.258)
EXT_KI			0.0004**												
BS#BIO															
			(0.000)												
CHEM				-0.0001	-0.0001	-0.0001*									
				(0.000)	(0.000)	(0.000)									
CHEM#E				0.0000											
XT_INV				-0.0000											
				(0.000)											
CHEM#E					0.0001***										
XT_HR					(0.000)										
					(0.000)										
CHEM#E															
XT_KIB						0.0001**									
S															
						(0.000)									

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ELE							-0.0000 (0.000)	-0.0000 (0.000)	-0.0000** (0.000)						
ELE#EX T_INV							-0.0000								
ELE#EX T_HR								0.0000*** (0.000)							
EXT_KI BS#ELE									0.0000**						
INST										-0.0001 (0.000)	-0.0000 (0.000)	-0.0001** (0.000)			
INST#EX T_INV										-0.0000					

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
INST#EX											0.0000***				
T_HR															
											(0.000)				
EXT_KI												0.0001***			
BS#INST															
												(0.000)			
MEGUA													0.0001#	0.0000	0.0001##
MECHA													-0.0001*	-0.0000	-0.0001**
													(0.000)	(0.000)	(0.000)
MECHA#															
EXT_IN													-0.0000		
V													-0.0000		
v													(0.000)		
													(0.000)		
MECHA#															
EXT_HR														0.0000***	
														(0.000)	
EXT_KI															
BS#MEC															0.0001**
HA															

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
															(0.000)
CONS	1.9543**	1.8884***	2.1414***	1.7283**	1.6681***	1.8779***	1.8835**	1.8076***	2.0398***	1.7969***	1.7342***	1.9750***	1.9404***	1.8344***	2.1358***
	(0.775)	(0.706)	(0.745)	(0.678)	(0.626)	(0.651)	(0.755)	(0.681)	(0.717)	(0.682)	(0.625)	(0.657)	(0.742)	(0.680)	(0.701)
LL	-512.0574	-509.2516	-509.1947	-512.7203	-509.6659	-509.9594	-512.1342	-509.1759	-509.3424	-511.9394	-509.1175	-509.0651	-512.0034	-509.1893	-509.1455
AIC	1052.1148	1046.5032	1046.3894	1053.4406	1047.3319	1047.9189	1052.2684	1046.3518	1046.6848	1051.8788	1046.2350	1046.1302	1052.0068	1046.3785	1046.2909
BIC	1114.5315	1108.9199	1108.8062	1115.8574	1109.7486	1110.3356	1114.6851	1108.7685	1109.1015	1114.2955	1108.6518	1108.5469	1114.4235	1108.7953	1108.7077
CHI2	42.7970	52.6201	47.1711	42.2217	53.2737	46.3200	42.5810	53.4810	47.3524	42.6446	53.5346	47.2583	43.3323	53.2301	48.0882

Notes

N=638.

Dependent variable: number of startups created.

Level of significance: *** 1%, ** 5%, * 10%

Standard errors are in parentheses.

Table 3 Summary

Interaction terms: University external linkages × Technology-specific innovation agglomerations	Entire sample	Subsample: non-Tokyo	Subsample: medical	Subsample: private	Subsample: national
Investor linkage \times Biotechnology agglomeration	n.s.	++	n.s.		n.s.
Investor linkage × Chemical agglomeration	n.s.	n.s.	n.s.		n.s.
Investor linkage × Electronics agglomeration	n.s.	++	n.s.		n.s.
Investor linkage × Precision instruments agglomeration	n.s.	++	n.s.		n.s.
Investor linkage × Mechanical agglomeration	n.s.	++	n.s.		n.s.
HR agent linkage × Biotechnology agglomeration	+++	n.s.	++	+	n.s.
HR agent linkage × Chemical agglomeration	+++	n.s.	++	++	n.s.
HR agent linkage × Electronics agglomeration	+++	+	++	+	n.s.
HR agent linkage × Precision instruments agglomeration	+++	n.s.	++	+	n.s.
HR agent linkage × Mechanical agglomeration	+++	n.s.	++	+	n.s.
KIBS linkage × Biotechnology agglomeration	+++	n.s.	n.s.	n.s.	n.s.
KIBS linkage × Chemical agglomeration	++	n.s.	n.s.	n.s.	n.s.
KIBS linkage × Electronics agglomeration	++	n.s.	n.s.	n.s.	n.s.
KIBS linkage × Precision instruments agglomeration	+++	n.s.	n.s.	n.s.	n.s.
KIBS linkage × Mechanical agglomeration	++	n.s.	n.s.	n.s.	n.s.

Notes

All estimates are based on fixed-effects negative binomial regression models, using lagged independent variables to mitigate simultaneity bias.

"+++", "++", and "+" indicate statistically significant positive effects at the 1%, 5%, and 10% levels, respectively.

"n.s." indicates results that are not statistically significant at the 10% level.

Table 4 Estimated CRE models

	(1)	(2)	(3)
L.CENTERED_RESEARCHER	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
L.CENTERED_KAKENHIPJ	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
L.CENTERED_PATAPP	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
L.CENTERED_FTESTAFF	0.036**	0.028*	0.033**
_	(0.014)	(0.014)	(0.014)
L.CENTERED_INCUBATOR	0.078	0.147	0.113
_	(0.226)	(0.218)	(0.225)
L.CENTERED_USOFUNDS	0.005	0.008	0.008
	(0.014)	(0.013)	(0.014)
L.CENTERED_CONSULT	0.042	0.022	0.043
	(0.092)	(0.092)	(0.093)
L.CENTERED_EXT_INV	0.082		
	(0.076)		
MEAN_RESEARCHER	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)
MEAN_KAKENHIPJ	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
MEAN_PATAPP	-0.006*	-0.006*	-0.005
	(0.004)	(0.004)	(0.004)
MEAN_FTESTAFF	0.089	0.113	0.111
	(0.081)	(0.092)	(0.087)

	(1)	(2)	(3)
MEAN_INCUBATOR	1.913***	1.989***	1.904***
	(0.242)	(0.248)	(0.247)
MEAN_USOFUNDS	-0.069*	-0.030	-0.044
	(0.040)	(0.039)	(0.037)
MEAN_CONSULT	1.051***	1.042***	1.097***
	(0.228)	(0.224)	(0.221)
MEAN_EXT_INV	0.402**		
	(0.188)		
ТОКҮО	0.376*	0.425**	0.352
	(0.215)	(0.216)	(0.218)
MEDICAL	0.498	0.604*	0.576*
	(0.318)	(0.318)	(0.319)
NATUNIV	0.340	0.278	0.523**
	(0.265)	(0.272)	(0.262)
L.CENTERED_EXT_HR		0.234*	
		(0.133)	
MEAN_EXT_HR		0.765**	
		(0.371)	
L.CENTERED_EXT_KIBS			0.030
			(0.212)
MEAN_EXT_KIBS			0.751*
			(0.414)
CONSTANT	-1.930***	-1.845***	-1.977***
		(0.292)	(0.268)

LN_R 1.537*** 1.615*** 1.492*** (0.192) (0.208) (0.187) LN_S -0.242 -0.280 -0.267 (0.185) (0.182) (0.180) LL -1167.390 -1167.129 -1168.651 AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996 CHI2 419.063 411.203 412.033		(1)	(2)	(3)
LN_S -0.242 -0.280 -0.267 (0.185) (0.182) (0.180) LL -1167.390 -1167.129 -1168.651 AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996	LN_R	1.537***	1.615***	1.492***
LL -1167.390 -1167.129 -1168.651 AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996		(0.192)	(0.208)	(0.187)
LL -1167.390 -1167.129 -1168.651 AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996				
LL -1167.390 -1167.129 -1168.651 AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996	LN_S	-0.242	-0.280	-0.267
AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996		(0.185)	(0.182)	(0.180)
AIC 2384.780 2384.258 2387.301 BIC 2535.475 2534.953 2537.996				
BIC 2535.475 2534.953 2537.996	LL	-1167.390	-1167.129	-1168.651
2000.110 2001.000 2001.000	AIC	2384.780	2384.258	2387.301
CHI2 419.063 411.203 412.033	BIC	2535.475	2534.953	2537.996
	CHI2	419.063	411.203	412.033

Notes

N=3065.

Dependent variable: number of startups created. Level of significance: *** 1%, ** 5%, * 10%

Standard errors are in parentheses.



