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Research university assortativity conditions the integration of regional innovation systems

Alexander Michael Petersen*, Andrea Montaño Ramirez

Department of Management of Complex Systems, School of Engineering, University of California at Merced, Merced, California, United States of America

* apetersen3@ucmerced.edu

Abstract

Substantial policy efforts to develop regional innovation systems (RIS) highlight the importance of understanding the institutional factors that promote integration and synergy at the regional scale. To this end, we analyzed historical patterns of research co-production within and across California (CA) and Texas (TX), two US regions that account for >5% of global research publication. This predominance is largely attributed to the University of California and the University of Texas, two multi-campus university systems (MUS) that feature distinct configurations of institutional research specialization. We exploit these differences to analyze four institutional assortativity channels that foster RIS synergy: institutional proximity, prestige, homophily, and specialization. Descriptive analysis reveals that institutional co-publication rates differ within and across RIS and are influenced by external socio-economic shocks, such as the 2007-08 financial crisis, which intensified institutional clustering within these research university ecosystems. We also develop institutional specialization profiles for exploring the structure and role of institutional alignment within RIS. Results indicate that regional integration is mediated by the alignment of institutional specialization and moderated by institutional homophily. These findings underscore the critical role of the MUS backbone that supports RIS integration and generates resiliency to socio-economic shocks. Moreover, MUS provide institutional redundancy and variation that generates a broad combinatorial space fostering multi-university research synergies. All together our framework can help address the innovator's dilemma of whether to exploit institution-specific capabilities or to strategically identify and invest in novel multi-institutional synergies that leverage the complex configurational space of institutional specializations that uniquely characterize each RIS.

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Author summary

We analyze the structure and dynamics of regional scientific integration in California and Texas, two U.S. states with distinct research university (RU) ecosystems. By leveraging these differences, we develop a framework for understanding how institutional assortativity – defined as similarities that sustain research partnerships across time and space – drives integration and defines the structure of regional innovation systems (RIS). Our analysis offers practical insights for research development offices working to identify strategic research priorities and foster multi-university collaborations, particularly in the face of the organizational innovator's dilemma: whether to focus on existing institutional strengths or pursue new, cross-institutional opportunities. It also provides guidance for national agencies making place-based investments in specialized infrastructure and institutional partnerships that support emerging technologies. From a systems science perspective, we highlight the vulnerability of RU ecosystems to large-scale socioeconomic shocks, such as the 2007-08 financial crisis, and underscore the critical roles of institutional diversity and redundancy in promoting structural resilience – features that are defining characteristics of multi-campus university systems (MUS), such as the University of California and University of Texas systems. Importantly, our findings show how MUS enhance regional integration by enabling resource sharing, supporting knowledge co-production, and generating network effects in human and intellectual capital that reach beyond RIS boundaries.

"The whole is greater than the sum of its parts."
– widely attributed to Aristotle (384-322 B.C.E.)
"Specialize less, systematize more." – Madhaven, Poste and Rouse [1]

Introduction

Regional innovation systems (RIS) are the foci of substantial science policy initiatives aimed at strategically integrating national and pan-national innovation systems [2–11] by supporting the co-production of knowledge and the circulation of high-skilled labor [12–18]. In addition to representing local sources of specialized industrial inputs and labor market pooling that contribute to innovation economy agglomeration [19,20], structurally resilient innovation systems are essential to generating effective solutions for addressing both regional and global challenges [21–24]. At the sub-national scale, RIS are characterized by a myriad of historical, cultural, geographic, industrial and other factors that condition the prospects for economic growth [3,10,22,25–28]. Chief among the institutional and geographic fixtures that define a given RIS are its research universities (RU) [29–33], which represent "sources, anchors and hubs" [22] across vast multi-level networks of human, social and intellectual capital [34–37]. Yet despite longstanding policy efforts advancing regional integration [9,13,38,39] via public investment into university education, research and infrastructure [30,32,40], our understanding of how the composition of RU ecosystems promotes regional integration and synergy is limited.

Against this backdrop, we develop a framework for measuring *institutional assortativity* – broadly defined as the tendency for similar institutions to co-produce research – and for understanding how it promotes RU ecosystem integration and the emergence of RIS structure. In this context, assortativity refers to both the selective sorting according to shared institution-level attributes (e.g., the propensity for collaboration among researchers from a common multi-campus university systems or a common state). Moreover, assortativity also refers to how entities within a network tend to preferentially connect based on shared connectivity. Examples include the tendency for hubs to connect to other hubs [41], and as in the present context, how institutions tend to preferentially form stronger subnetworks aligned around common research specialization. To this end, we analyze four distinct channels of institutional assortativity: proximity, prestige, homophily, and specialization. By quantifying the relative contributions of these distinct channels, we seek to analyze how institutional variation manifests in operational synergies that enhance the productive capacity of the RIS as a whole.

Our study is thus motivated by Aristotle's sum-of-the-parts argument, which guides the development of our framework for analyzing the structure and dynamics of RU ecosystem integration – proxied in this work according to rates of research co-production between institutions. As such, our analysis addresses four research questions (RQs) in sequence:

RQ1: What is the structure of institutional research co-production – within and across regions?
RQ2: What are the structural dynamics of RIS integration – are they characterized by steady growth or fluctuating regimes?
RQ3: How do institutional specialization and homophily condition RIS integration?
RQ4: How do the different assortativity channels contribute to RIS integration, and to what extent are the roles of institutional homophily and prestige sensitive to socio-economic shock?

Our results contribute to the understanding of how positive externalities generated by regional integration support the national innovation system at large [2,6,42], and highlight the importance of public investment in multi-campus university systems (MUS) [24,25], which generate the backbone of the California (CA) and Texas (TX) research ecosystems. From an institutional perspective, our framework may provide valuable insights for research development offices tasked with specializing in strategic research areas and identifying multi-university funding opportunities that target specific research problems (regional and global), as well as national funding agencies charged with strategically investing in critical infrastructure and emerging technologies. Finally, from a systems science perspective, our analysis highlights the systemic risks exposed by periodic disruptions to socio-economic stability [21]. In particular, our longitudinal analysis of the ecosystem structure before, during, and after the 2007-08 global financial crisis provides timely and relevant analysis of how innovation systems respond to economic shocks affecting the availability of financial and other resources critical to scientific activity.

Background and motivation

Research universities form the backbone of regional innovation systems

The U.S. state is a regional scale that aligns with the governance, funding and related agenda of state governments. At this scale, research institutions operate under policies shaped by regional agencies that coordinate funding and resource distribution to address region-specific challenges – such as wildfire, illicit wildlife trade, invasive species, and deforestation [43–45] – by promoting collaborative solutions, and fostering a more integrated approach to regional development and innovation.

Accordingly, we analyze the composition and structure of multi-institutional collaboration within and between two prominent US states – California and Texas – building on the tradition of two-region models in economic geography that serve as a foundation for studying more complex multi-region systems [19]. Notably, CA and TX represent geographically and politically distinct RIS within the US innovation system, each featuring extensive RU ecosystems that generate a sizable high-skilled workforce and attract investments into specialized R&D infrastructure that are critical to state and national research agendas.

Despite their strength, these innovation systems remain sensitive to disruptions at multiple scales – ranging from institutional changes (e.g., entry, exit, or mergers [46]) to large-scale macroeconomic shocks [47]. To investigate this sensitivity, we exploit the 2007-08 financial crisis to examine how the institutional ecosystem structure responds to external resource shock. This case-event analysis sheds light on how structural changes influence research outcomes, offering insights into the structure–function dynamics of innovation system.

In order to measure and evaluate the persistence of research co-production within and between innovation systems over time, we selected the most prominent research-oriented institutions within each state. As such, a principal component of our institutional sample are the research-oriented multi-campus university systems (MUS) in each state: the University of California (UC) system comprised of 10 distinct institutions (or 'campuses'), and the University of Texas (UT) system comprised of 12 institutions (7 traditional university campuses offering multi-disciplinary graduate education, and 5 specialized health science centers). We complement these MUS institutions with six prominent private universities that form a non-MUS comparison group – see Fig 1A. Due to the labor intensive collection of disambiguated institutional profiles from our primary data source, the Clarivate Analytics Web of Science Core Collection (WOS), we focus on the largest single MUS along with the three most prominent private universities in each RIS. Together the 28 select institutions in our sample are affiliated with roughly 3 million distinct WOS publications – see Fig 1B – alltogether accounting for >5% of all publications indexed by WOS over our focal sample period.

A configurational perspective on university ecosystems

According to evolutionary principles applied to organizational and industrial dynamics, the knowledge economy can be understood as a dynamic system in which organizations and institutional environments co-evolve over time [48]. Drawing from Durham's prescription of the model of evolutionary change [48,49], knowledge takes the role of the unit of transmission. Accordingly, we then consider institutional environments – encompassing (research and researcher) governance, culture, legacy, policy and norms – as endogenous sources of variation. Meanwhile, the localization of institutions to particular regions and cities generates sources of isolation that shape how knowledge develops and diffuses across space over time.

Given the multi-disciplinary composition of research universities, then the variation in institutional research area profiles within a given region is a fundamental determinant of its distinct *configurational space* – the set of all possible configurations of a system. At a more granular level, the configurational space reflects the various ways that subcomponents (such as researchers, research labs, specialized infrastructure, strategic industry partnerships, etc.) can be arranged and interact within the system.

In reality, we only observe the subset of realized ecosystem configurations that emerge as a result of constraints (financial, geographic, etc.) and related selection mechanisms. By analyzing the relative magnitude and persistence of realized institutional relationships and overall system structure, we are able to evaluate various dimensions of variation and selection – i.e., assortativity channels that promote research synergies that persist within and across the university ecosystem. From this perspective, the configurational space uniquely characterizes each university ecosystem and conditions the integration of regional innovation systems.

Yet the configurational space is also subject to principles of strategic design, which thereby confronts these institutions with the organizational innovator's dilemma of whether to focus on existing institutional strengths or pursue new, cross-institutional opportunities. As a relevant scenario pertaining to multi-campus systems, consider a breakthrough research area or technological breakthrough such as quantum computing: should a MUS invest in a new research center at a particular campus, or should it develop a cross-cutting consortium that distributes critical investment resources more broadly

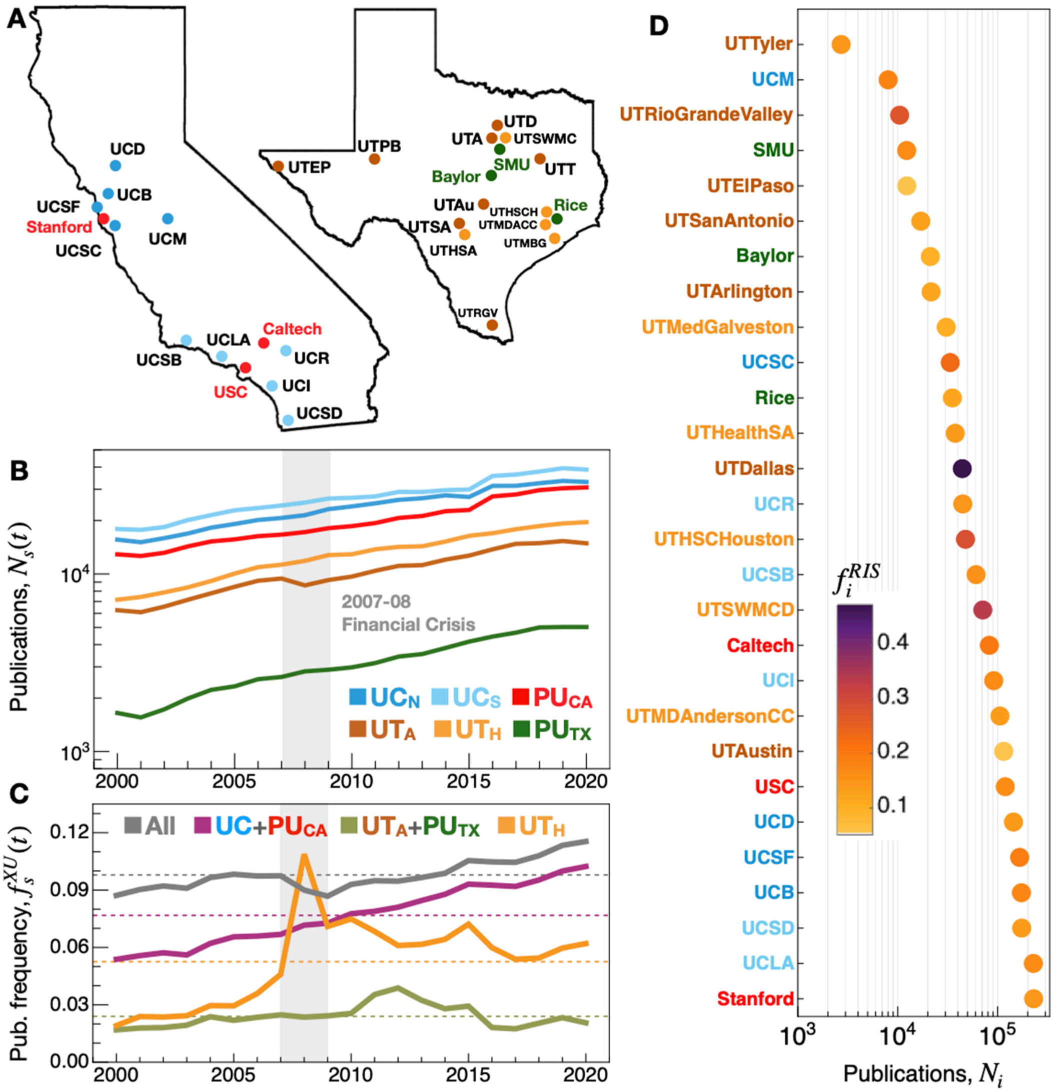

Fig 1. **Framework for evaluating RIS according to the integration of research university ecosystems. (A)** Geographic distribution of universities and health science centers belonging to the University of California (UC) and University of Texas (UT) systems, along with the three most prominent private research universities within CA and TX (approximate locations to avoid overlaps). The outline of each state administrative boundary was generating using public-domain U.S. Census Bureau TIGER shape files from https://catalog.data.gov/. **(B)** Research output $N_s(t)$ of six university subgroups. UC_N are the 5 UC campuses located in the greater Bay Area mega-region: the exponential growth rate over the 21-year period shown is $g_{UC_N} = 0.042(1)$; UC_S are the UC campuses located in southern California: $g_{UC_S} = 0.040(1)$. PU_{CA} represents Stanford, USC and Caltech combined: $g_{PU,CA} = 0.046(1)$. UT_A denotes the 7 UT campuses: $g_{UT_A} = 0.047(2)$; and UT_H denotes the 5 UT health science centers: $g_{UT_H} = 0.051(2)$. PU_{TX} represents Rice, SMU and Baylor combined: $g_{PU,TX} = 0.060(2)$. For each g value reported, the digit in parenthesis is the standard error in the last digit shown. **(C)** Base rate $f_s^{XU}(t)$ of multi-university research co-production, for three non-overlapping university subgroups and all 28 universities considered together. Distinct levels observed for $UC + PU_{CA}$ and $UT_A + PU_{TX}$ reflect different degrees of co-production (dashed lines indicate mean values), and show that CA features higher levels of RIS integration than TX. **(D)** Universities ranked according to the total number of research articles N_i co-produced by scholars at each university i over 2000-2020. As an indicator of regional embeddedness, each data point is colored according to the fraction f_i^{RIS} of the N_i articles that involved multi-university collaboration within its RIS (home state); the mean and standard deviation across these RU are 0.17 ± 0.09.

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across the system? To this end, the University of California established the Multicampus Research Programs and Initiatives (MRPI) as a dedicated funding mechanism designed to strategically channel financial resources towards system-level synergies.

Four assortativity channels that contribute to ecosystems structure

Conceptually, configurational entities that are more closely related tend to be more 'proximal' within the configuration space. From a configurational perspective, this principle means fewer and smaller changes are required to align one entity with another. This concept is generalizable across various domains, including cognitive, organizational, institutional, and geographical contexts [50–52]. Within the present context, assortativity channels refers to particular institution-level factors that generate different pathways for alignment, thereby fostering persistent research co-production between institutions. The following four channels reflect both latent and observable characteristics of research universities.

(i) Institutional location and spatial proximity. Geographic location is a core institutional factor that generates relatively stable characteristics, such as cultural diversity, historical legacy, natural environment, and proximity to other places. Implicit distances shape the relative influence of diffusive versus ballistic dynamics, which operate on different time scales (e.g. diffusive dynamics spread as the square root of time, whereas ballistic is proportional to time) and depend on the characteristics of the innovation. To this latter point, for example, prior work shows that the diffusion of technological knowledge depends on their underlying complexity [53]. While spatial proximity is fixed, the ability to overcome that distance, virtually or physically, depends on advances in technology and transportation infrastructure [54] that enable more direct, or "ballistic," forms of transmission. In this way, institutional location can promote or restrict the formation of institution-spanning collaborations, and contributes to the wide variation in rates of research production extending across regional and global scales over the last half century [42].

Consequently, theories of spatial agglomeration [3,5,8,9,19,20,51] have contributed to our understanding of how the spatial distribution and concentration of knowledge sources shape innovation. A key insight from this literature is that institutional concentration enhances a region's innovation capacity by facilitating spontaneous knowledge diffusion and team formation, increasing the chances of collaboration and idea exchange without requiring the costs (financial and otherwise) associated with deliberate coordination. In order to track the evolution of research outcomes that overcome the burdens of spatial and institutional boundaries, previous studies measured the rate of multi-university collaboration (denoted by XU) and found that this mode of collaboration has increased significantly over time [55]. Within our data sample, the frequency $f^{XU}(t)$ of XU research co-production between the 28 RU in our sample ranges between 2% and 10% depending on the regions and institution type, and indicates that CA has significantly higher levels of XU activity compared to the TX ecosystem – see Fig 1C. Moreover, since $f^{XU}(t)$ is dominated by within-state research co-production, it is notable that the CA trends exhibits steady growth, whereas the TX trends are relatively flat.

When the distance between institutions exceeds a certain threshold – such as the size of a U.S. state – researcher mobility increasingly depends on rapid transportation options, such as air travel or trains, to overcome barriers that impede the formation of research collaborations spanning multiple institutions [54] and industrial sectors [5,7]. Hence, in large states such as CA and TX, the physical distance between two cities is an inconsistent indicator of the actual time and effort needed for travel between two locations. For this reason, we classify the varying distances between institutions according to three categories:

Within-City: Denoting institutions belonging to a common metropolitan area. This distance implies a preference for face-to-face interaction;

Within-RIS: Denoting institutions belonging to common state (but not a common metropolitan area). This distance implies a relatively low barrier to frequent interaction through a mix of in-person and virtual meetings.

Across-RIS: Denoting institutions belonging to different states. In the case if CA and TX, this distance corresponds to a two-hour time-zone difference for virtual meetings, and a full day of air travel for in-person meetings.

Further upscaling to the national and global scale, the geographic embedding of our publication sample features a balanced mix of research extending within and across state and national borders. As documented in a companion study focusing on geographic embedding and institutional competitiveness, we find that 1 in 4 publications feature *XU* collaboration extending across different US states, and 1 in 3 publications feature collaborations extending internationally [56].

(ii) Institutional prestige. The legacy and size of research institutions are key factors associated with institutional prestige and the stratification of faculty mobility networks [37], as well as access to critical labor and other physical resources that are essential to both basic and breakthrough research [40,57]. As a result, prior research often focuses on premier universities, as they tend to produce research in higher volumes [55,58].

However, university ecosystems also encompass many public universities that, while less prolific on their own, collectively play a substantial role in advancing research and education [1,59–61]. Because our analysis focuses on the spatial scale of individual US states, we thus encounter a broad distribution of institutional sizes. In particular, we observe considerable variation in total research production N_i among UC and UT institutions, largely attributable to year-of-establishment and surrounding population density variability across campuses – see Fig 1D. This size variation contributes to the stratification of university ecosystems, which manifests in prestige hierarchies in science that extend across national and international systems [36,37,55]. This stratification may reinforce "best-with-best" institutional interactions, thereby limiting the identification and investment into regional synergies. Henceforth, moderating the tendency for institutions to align based on prestige alone necessitates ambidextrous research development strategies that strike a balance between exploitation and exploration within the multi-organizational configuration space [62,63].

While larger institutions often tend to be more prominent, size alone does not determine institutional prestige, many prestigious institutions are relatively small (e.g, Caltech and Rice University are notable examples). In our analysis, we define institutional prominence by considering both N_i, which reflects both institutional size and researcher productivity, as well as international prestige indicated by the widely known ARWU "Shanghai" university rankings (https://www.shanghairanking.com/rankings/arwu/2024) [32]. This dual criterion allows us to isolate a subset of institutions that are both highly productive and internationally reputable. As such, we measure institutional prestige by distinguishing a set of 11 prominent and internationally reputable institutions in our sample, comprised of Stanford, USC, Caltech, Rice, UCSF, UCB, UCLA, UCSD, UTAustin, UTMDAndersonCC, UTSWMCD. These premier institutions are distinguished by their persistently high centrality within the networks of research co-production network over time – see S1 Fig.

(iii) Institutional homophily. We define institutional homophily to represent the propensities for scholarly collaboration that arise from membership within a multi-campus university system (MUS). A related but more top-down mechanism that gives rise to the same propensity for within-MUS co-production is institutional isomorphism [64]. This concept describes how institutions converge toward similar policies, structures, and norms in response to both explicit directives from system-level governance bodies and implicit mixing derived from scholarly and administrative mobility within each MUS.

As a case example, consider the University of California (UC), which is the largest such multi-campus system, generating roughly 10% of research published across the US [65]. As a conglomerate entity, MUS feature common institutional policies, educational mission and values, and brand equity, which together foster knowledge diffusion and researcher circulation within the system [66]. As such, the multiplicity of MUS campuses fosters regional integration by the very design of its spatial distribution, and thereby offers a wide range of configurational options for addressing the organizational innovator's dilemma [62,63]. Another key characteristic of MUS is the replication of organizational principles and policies across various locations (e.g. tenure and promotion policy), such that certain aspects of institutional environment can be considered approximately fixed across the different campuses.

Such organizational commonalities promote homophily, whereby social groups tend to initiate and persist via the identification of shared attributes, values and experiences [67]. We expect the role of homophily to be substantial when considering the extent to which curriculum vitae in academia are headlined by an individual's educational history. The great number of graduates generated by MUS generates several distinct avenues that signal and reinforce institutional homophily, including but not limited to collaboration, employment, student admissions and brand equity [66]. Thus, the direct and indirect network effects generated within and across MUS campuses create interconnected educational and research pathways, such that it is relatively common for careers to span multiple MUS institutions. This combinatorial capability thereby provides a significant organizational advantage of MUS for achieving a key objective of university administrators – namely, optimizing the professional environment to attract and retain highly productive scholars [32]. In this way, the full extent of MUS accommodates talent absorption at higher levels than any single campus would be able to achieve, and thus contributes to Aristotle's sum-of-the-parts argument promoting integration within regional university ecosystems. In this regard, it is also worth noting the increasing variety of multi-university consortia constructed from institutions that do not necessarily share common organizational governance, principles and policies. These consortia represent a variation on the objectives and advantages of MUS, and represent a potential avenue for future comparative analysis.

(iv) Institutional research specialization. The body of research generated by an institution largely reflects its research mission and the disciplinary composition of the scholars in residence. A notable example is the University of Texas MD Anderson Center, which employs a strikethrough to emphasize its core research mission and differentiate its brand equity [66]. Research specialization (or conversely, research diversity) is thus a defining, albeit latent, institutional feature that has eluded the prior literature, which largely focused on diversity indicators based upon educational and structural features [68].

In this regard, we exploit the different organizational configurations of the UC and UT systems to understand how institutional specialization conditions the combinatorics of institutional alignment. Notably, the UT is comprised of a 7 campuses representing traditional multi-disciplinary RU, coupled with 5 campuses that are specialized biomedical and health science centers. Conversely, 9 out of 10 UC campuses are traditional RU, the exception being UCSF which specializes in biomedical and health science research and graduate-level educational programs, akin to UT health science centers. From an organizational standpoint [69], the bureaucratic complexity of managing diversified RU compounds in MUS, especially where resource allocation and investments across the system are guided by principles of competitiveness, equity and transparency. The varying levels of institutional specialization among MUS members create trade-offs between redundancy and diversity, especially concerning the effectiveness of a uniform governance approach. As such, institutional specialization represents a fourth channel of institutional assortativity that conditions the research alignment between institutions, and also represents an intriguing degree of freedom underlying the strategic design of MUS.

The 2007-08 global financial crisis: An exogenous shock to research production

The 2007-08 financial crisis extended globally, generating a significant shock to the international economy that lasted for several years. While not the principal focus of this study, it is worth describing the contextual backdrop behind the major socio-economic shock occurring during the focal period of our analysis and how it impacted academic research institutions, and why its signatures would be evident in our analysis.

The pervasiveness of the financial crisis strained academic institutions by triggering rapid and significant endowment losses at private universities [70,71]. While also true for public universities, they additionally faced severe state budget cuts that generated hiring freezes, furloughs and staff cuts, raised student-faculty ratios, and limited research capacity. Together, these sudden resource constraints generating funding allocation gaps can be expected to directly affect faculty research output, graduate student funding resources, and general morale.

A sudden shift toward fiscal austerity occurred across the US and Europe, marked by unexpected reductions in public and private R&D spending as well as cuts to educational expenditures [47,72]. At the same time, there was significant reduction to industrial research productivity as firms pivoted available resources away from basic research towards product development [73], likely mirroring adjustments within the academic sector. In the US, stimulus response measures like the American Recovery and Reinvestment Act (ARRA) provided temporary relief to mitigate the immediate effects of this shock [74–76]. Among academic institutions, labor markets proved particularly susceptible, with public universities experiencing sharper declines in new faculty hires and salary growth compared to private institutions [77]. Accordingly, in what follows we observe the response dynamics of this socio-economic shock and therefore examine how this socio-economic shock reshaped the institutional ecosystem, in particular regarding patterns of institutional stratification relating to homophily and prestige.

Related literature

A substantial body of research has mapped international collaboration and mobility networks, highlighting how the flow of human and intellectual capital across borders shapes the globalization of science [12,13,17,18,78–83]. However, accounting for variations in regional and institutional contexts poses significant challenges for studies conducted on a global scale.

To address this limitation, some studies downscale by aggregating counts at the level of national regions [9,13,14,38,53,84]. Here we further downscale the focal unit of analysis to the level of institutions, which aligns with a resource-based view on the relationship between institutional environment and scientific productivity [57,85]. Another motivation for focusing on regional ecosystems is to support the literature developing diagnostic and place-based policy guidance for seeding and incubating innovation hubs, which often develop and evolve around universities that draw investment into specialized facilities and equipment [3,4,8,10,20,25,38,39,86]. A relevant study on patent co-production found that higher levels of regional integration, measured by the size of the largest network component, played a crucial role in driving the development of innovation hubs in Silicon Valley and Boston in the 1990s [87]. Against this backdrop, our work contributes to the longstanding economics and science policy literature on research universities [22,29–33,86] and university systems [8,24,25] as potent vehicles for direct investment.

Mapping institutional interactions reveals key insights into the organizational ecology of complex systems tasked with collective problem-solving [8,22,88]. In particular, our analysis contributes to the literature on social homophily, whereby shared backgrounds, attributes, values, and experiences promotes the formation of lasting in-group propensities [67] that can be readily quantified using network metrics, such as the assortativity coefficient and the clustering coefficient [41,89,90]. Homophily is particularly relevant in the academic context, where educational pedigree is widely emphasized. For example, scholars find that sharing common educational histories is an important factor supporting entrepreneurial team formation [91], and that institutional homophily is a key factor driving the digital media co-visibility of research institutions [66]. Extending to other sectors, another study found that non-governmental organizations are more likely to develop partnerships with peers sharing common funding sources and common consultative agreements with intergovernmental organizations [92]

In addition to institutional-specific factors, multi-university (*XU*) research co-production is also sensitive to exogenous economic shocks. In particular, the 2007-08 financial crisis generated a sudden decline in public funding for research and development (R&D) that extended from the national to regional scale, which translated into significant university budget reductions. One particularly relevant study of R&D appropriations in Spain before and after the global crisis showed that the adverse effects of the crisis extended well into the early 2010s [47]. Interestingly, we observe a rapid reaction to the crisis at the regional level, with *XU* research among TX health science centers (UT_H) exhibiting a sudden burst during the 2007-08 financial crisis, indicative of within-MUS resource-sharing during this period of resource constraints. Contrariwise, rates of *XU* research observed among all 28 universities exhibited a downturn during the same period, indicative of the sensitivity of across-region activity to heightened financial constraints and uncertainty – see Fig 1C.

Our focus on institutional networks at the regional scale complements prior work analyzing multi-university collaboration at the global scale. In particular, in their seminal study on *XU* research over the period 1975-2005, Jones et al. [55] found that multi-university collaborations tend to occur between scholars at prestigious universities; they also found that roughly 90% of multi-university collaborations involve just 2 distinct universities, which supports our choice of a pairwise measure of research co-production developed in what follows. Another perspective focusing on the global scale analyzes the increasing prevalence of multi-national collaborations [42,78,79]. A recent study found that research produced by scholar extending across 2-4 countries to be the largest growth mode, which accounted for roughly 17% of research in 2010, whereas mono-national research accounted for roughly 80% [81].

Materials and methods

Data collection

We collected 2,965,198 records published between 1970-2020 from the Clarivate Analytics Core Collection (WOS) using their in-house institutional disambiguation tool to identify publications with at least one author from a particular campus. Exploiting the WOS “Affiliation Index” (available only within the WOS web portal search interface) specifically addresses limitations in the availability and consistency of the C1 “Author Address” WOS field tag in the raw data, which we found to be largely void prior to 1997 in our downloaded data records. The publication counts and metrics used in our analysis reflect the same journal selection process as WOS, which periodically reviews and updates its journal coverage to maintain a focus on high-quality, reputable sources.

Why not extend beyond these 28 RU? Due to limited access to the WOS database, we manually collected data through their web portal, which restricts downloads to 500 publications at a time. These constraints are the primary reason for limiting our sample to 28 RUs, selected to represent the most prominent institutions in each state, which together represent roughly 5% of global research indexed in the entire WOS database, and 10% of US research. While there are numerous RU and other research-generating institutions in each state that were not included in our representation of each RIS, these 28 institutions represent the majority of research produced in each state – i.e., 70% of all publications produced by CA, with the largest excluded institution being San Diego State; and 55% in the case of TX, with the largest excluded institution being Texas A&M Univ. at College Station.

While our analysis is restricted to these two states, this focused approach provides a practical foundation for extending to more regions, as in the tradition of extending two-region to multi-region spatial models [19]. Extending to other regions would need to account for the variable levels of institutional concentration that occur, especially in large megacities globally. Another institutional dimension that would need to be accounted for is the nature and extent of satellite campuses that are increasingly prevalent, as in the case of New York University (NYU) Abu Dhabi and NYU Shanghai.

As this institutional sample includes the most prominent research producers in each region, it also captures the most prominent sources of co-production in each region. In terms of the connectivity generated by these institutions, we find that roughly ∼6% of the articles feature two or more universities from our sample – see S2 Fig. For a base rate comparison, our companion study analyzing the brand co-visibility among the same set of institutions across a comprehensive collection of 2 million digital media articles published between 2000-2020 identifies ∼10% of the articles featuring two or more institutions [66].

Quantifying the intensity of institutional research co-production

As a proxy for regional integration, we analyze the principal mode of institution-specific knowledge (co-)production, which is peer-reviewed scientific research. While patents, grants and other formal multi-institutional agreements and products may offer complementary information that enhances the representation of innovative activities in a particular region, their metadata are less available in standardized formats that extend across substantial time periods on the order of decades. Moreover, in the particular case of patents, federal grants and other forms of joint R&D contracts, the research teams and thus the number of distinct assignee institutions tend to be much smaller than in the domain of academic publication [93], which would limit the resolvability of persistent multi-institutional relationships and their cofactors. Hence, in this study we exploit the consistent data generated by research scholars that constitute the principal data source in the science of science [34].

Regarding the generating mechanisms contributing to institutional co-production, there are two principal contributions: collaboration by scholars at two distinct institutions; and individual scholars with multiple affiliations. Recent analysis has identified an increasing prevalence of the latter multi-affiliation mode, rising to roughly 16% of authors in 2019, on average, albeit with substantial national and disciplinary variation [94,95]. While we do not distinguish between the two mechanisms, as we are focused on the institutional layer of science, we expect that the number of individual scholars with multiple affiliations at the particular set of institutions we analyzed to make a marginal contribution to the overall rate of institutional co-production relative to the mechanism of distinct scholars collaborating across institutional boundaries. Indeed, additional analysis is merited to analyze the relative contributions of these two author-level mechanisms to measures of institutional co-production.

To facilitate accounting for both institutional attributes (MUS membership, research specialization, and prestige) and relational attributes (spatial proximity and research area alignment), we adopt a pairwise (dyadic) representation of the institutional ecosystem. We test the fidelity of this representation by tabulating the frequency of research articles featuring N_c individual MUS campuses – see S2 Fig. for the frequency distribution $P(N_c)$. Results indicate that the vast majority of multi-university publications feature $N_c = 2$ MUS campuses, consistent with prior work extending across a larger sample of universities [55].

We quantify the intensity of research co-produced by universities i and j in a given time period t by way of the Jaccard similarity index,

$$J_{ij,t} = \frac{N_{ij,t}}{N_{i,t} + N_{j,t} - N_{ij,t}} \in [0, 1] \ , \tag{1}$$

where the quantity $N_{i,t}$ is the total number of publications by i in a given period t, and $N_{ij,t}$ is the number of publications featuring authors from both i and j during the same period. J_{ij} measures the intersection over union of the two publication sets, corresponding to the fraction of the total possible research articles that were co-produced by those two entities.

This quantity is preferred over N_{ij} for the following reasons. By construction, $J_{ij,t}$ is intensive (a fraction), and so its distribution is more stationary than the distribution of $N_{ij,t}$, which is instead an extensive quantity that is systematically biased by the persistent exponential growth of scientific publication output [96] – see Fig 1B. Thus, $J_{ij,t}$ supports analyzing relationships that persist and develop in excess of baseline secular growth patterns. At the same time, the denominator of J_{ij} explicitly controls for the wide variation in publication volume N_i across institutions – see Fig 1D. In the same way that traditional gravity model approaches control for the size of the units as explicit cofactors [5,7]), in what follows this cofactor (i.e., N_i) is implicitly incorporated into our dependent variable definition. Together, this dependent variable standardization accommodates cross-temporal regression analysis spanning multiple decades.

The Jaccard index is a valid proxy of intersection when the sample sizes N_i and N_j are sufficiently large, a condition that applies to most statistical metrics. Otherwise, the Jaccard index can be biased by the minimum-bound inequality $N_{ij,t} \leq \mathrm{Min}(N_i, N_j)$, which generates relatively small $J_{ij,t}$ values when $\mathrm{Min}(N_i, N_j) \ll \mathrm{Max}(N_i, N_j)$. This scenario can be difficult to distinguish from small $J_{ij,t}$ values reflecting genuinely weak intersection (i.e., $N_{ij} \ll N_i + N_j - N_{ij}$). A similar problem associated with sample sizes significantly smaller than the average ($N_i, N_j \ll \overline{N}$), is that relatively large $J_{ij,t} \approx 1$ can occur due to random chance. As our institutional sample focuses on research-intensive institutions, $N_{i,t}$ values are sufficiently large so as to avoid these small-sample issues – see Fig 1D. The average and standard deviation of J_{ij} in our data sample is 0.0051 ± 0.0072 with (min, max) values of (0.0001, 0.0955).

Quantifying the research area profile of institutions

A reliable classification of scientific research areas is essential for consistently measuring specialization across institutions and time. To this end, we exploit the longstanding classification of journals indexed by WOS according to research areas (corresponding to the SC field tag), which facilitates measuring the disciplinary profile of individual universities. This journal classification is comprised of 153 individual research areas that map onto 5 broad categories (denoted here by SC), with some journals featuring two compounded SC. As such, we focus on the six most frequent SC associated with co-produced research, which together span 87% of the entire data sample. Four of these categories are singular SC, and two represent compound SC (e.g."Life Sciences & Biomedicine × Physical Sciences"). Thus, for a given set of publications, we denote the proportion of publications featuring a particular SC distribution by the vector $\vec{f}^{SC} = \{f_{SC1}, f_{SC2}, ..., f_{SC6}\}$, where individual components are bounded $0 \leq f_{SCx} \leq 1$ and the vector is normalized, $\sum_{x=1}^{6} \vec{f}_{SCx} = 1$.

For each institution i, we calculate a research area profile (denoted by $\vec{f}^{SC}$) for two non-overlapping sets of publications: the first being mono-university research affiliated with i; and the second being multi-university research affiliated with each institutional pair ij. Each set of publications is useful for calculating a measure of research area diversity by way of the Herfindahl-Hirschman index (HHI), $d^{SC} = 1 - \vec{f}^{SC} \cdot \vec{f}^{SC}$. In the first case, we use $\vec{f}^{SC}_{i,M}$ defined by mono-university research to calculate the disciplinary diversity of a particular institution, denoted by $d^{SC}_{i,M} = 1 - \vec{f}^{SC}_{i,M} \cdot \vec{f}^{SC}_{i,M}$. And in the second case, we use $\vec{f}^{SC}_{ij}$ to calculate the disciplinary diversity of the research co-produced by universities i and j, denoted by $d^{SC}_{ij} = 1 - \vec{f}^{SC}_{ij} \cdot \vec{f}^{SC}_{ij}$. The minimum value $d^{SC} = 0$ corresponds to a maximally concentrated distribution dominated by a single SC, connoting an extremely specialized institution; and the maximum value $5/6 = 0.8\overline{3}$ corresponds to a uniform distribution of SC more representative of a traditional multi-disciplinary RU.

To further explore how institutional similarity moderates RIS integration, we define the pairwise institutional alignment

$$A^{SC}_{ij,t} = \vec{f}^{SC}_{i,t,M} \cdot \vec{f}^{SC}_{j,t,M} \in [0, 1] \tag{2}$$

calculated using each institution's mono-university publications. Institutions with little overlap in their research area profiles will generate small values, with $A^{SC}_{ij} = 0$ indicating no overlap at all. Two institutions that are maximally concentrated in the same single SC will generate the maximum value $A^{SC}_{ij} = 1$. And institutions with mixed research area profiles will generate intermediate values of A^{SC}_{ij}, which empirically tend to cluster around $A^{SC}_{ij} \sim 0.26$ when the institutions i and j are both traditional research universities (i.e. offering undergraduate and graduate education programs across a multi-disciplinary array of fields). The average and standard deviation of A_{ij} is 0.26 ± 0.17 with (min, max) values of (0.053, 0.95).

Research co-production model specification

In order to systematically evaluate the relative contributions of the four institutional assortativity channels on the structure and dynamics of institutional research co-production (quantified by $J_{ij,t}$), we estimate the coefficients of the following linear regression model,

$$\begin{aligned} J_{ij,t} \quad = \quad & const. + \beta_{MUS} MUS_{ij} + \beta_{A|MUS}(A_{ij,t-1} \times MUS_{ij}) \\ & + \beta_R R_{ij,t-1} + \gamma_{\star} + \gamma_{Geo} + \gamma_t + \epsilon. \end{aligned} \tag{3}$$

We implemented the estimation using STATA 13 "reg" including robust standard errors. The full set of parameter estimates are shown in the model (7) column in Table 1; see the SI Appendix for complete model variable descriptive statistics.

This model specification accounts for factors such as distance and relative size of the entities as in the traditional gravity model (see for example [5,7]), while also accounting for each of the four assortative channels. The main distinction from the gravity model is that we do not assume a multiplicate relationship between the dependent variables, which is implied when the dependent variable enters as a logarithm. Second, because $N_{ij,t}$ and $N_{i,t}$ are extensive variables that are

Table 1. **Research co-production model – full set of parameter estimates.** We implemented the estimation using STATA 13 including year fixed-effects and robust standard errors; see Eq (3) for the model specification. The dependent variable in each model is the research co-production $J_{ij,t}$ between institutions i and j in year t calculated for publications in the 21-year period 2000-2020. We incorporate the alignment with a 1-year lag, $A^{SC}_{ij,t-1} = \vec{f}^{SC}_{i,t-1,M} \cdot \vec{f}^{SC}_{j,t-1,M}$, to account for inter-annual variation in research area profiles $\vec{f}^{SC}_{i,M}$; note that research area profiles are calculated using mono-university (denoted by M) publications of institution i, whereas $J_{ij,t}$ are calculated for co-produced publications. Below each point estimate is the associated p-value. See S3 Fig. for the corresponding descriptive statistics and covariance matrix. See Fig 5C for a plot of the interaction $\gamma_{MUS \times t}$ coefficients included in model (8) to identify the temporal trend associated with institutional homophily. See Fig 5D for a plot of the interaction $\beta_{\star\star \times t}$ coefficients generated by model (8) to identify the temporal trend associated with institutional prestige involving two premier universities ($Prem_{ij} = 2$).

	(1) $J_{ij,t}$	**(2)** $J_{ij,t}$	**(3)** $J_{ij,t}$	**(4)** $J_{ij,t}$	**(5)** $J_{ij,t}$	**(6)** $J_{ij,t}$	**(7)** $J_{ij,t}$	**(8)** $J_{ij,t}$
MUS pair, $MUS_{ij} = 1$	0.00242*** (0.000)		–0.0000974 (0.810)				–0.00144*** (0.000)	–0.00386*** (0.000)
Research alignment, $A^{SC}_{ij,t-1}$		0.00506*** (0.000)	0.000425 (0.388)					
Research alignment for !MUS pair, $A^{SC}_{ij,t-1} \vert MUS_{ij} = 0$							0.00170*** (0.002)	0.00154*** (0.000)
Research alignment for MUS pair, $A^{SC}_{ij,t-1} \vert MUS_{ij} = 1$			0.00878*** (0.000)				0.00846*** (0.000)	0.00859*** (0.000)
Co-located metro. area pair, G_{ij} =Metro (relative to G_{ij} =Within-RIS)				0.0150*** (0.000)			0.0142*** (0.000)	0.0142*** (0.000)
Across-RIS (XRIS) pair, G_{ij} =Across-RIS (relative to G_{ij} =Within-RIS)				0.00303*** (0.000)			0.00256*** (0.000)	0.00254*** (0.000)
Single premier Uni., $Prem_{ij} = 1$ (relative to $Prem_{ij} = 0$)					–0.000294 (0.190)		0.000354 (0.088)	0.000134 (0.900)
Premier Uni. pair, $Prem_{ij} = 2$ (relative to $Prem_{ij} = 0$)					0.00313*** (0.000)		0.00283*** (0.000)	0.000595 (0.611)
Institutional size ratio, R_{ij}						–0.000154*** (0.000)	–0.000101*** (0.000)	–0.000105*** (0.000)
Year (t) dummy	Y	Y	Y	Y	Y	Y	Y	Y
MUS-Year interaction, $MUS_{ij} \times t$	N	N	N	N	N	N	N	Y
Premier Uni.-Year interaction, $P_{ij} \times t$	N	N	N	N	N	N	N	Y
Constant	0.00262*** (0.000)	0.00181*** (0.000)	0.00234*** (0.000)	0.00127*** (0.000)	0.00282*** (0.000)	0.00453*** (0.000)	0.000774 (0.056)	0.00211 (0.066)
N adj. R^2	6364 0.044	6364 0.033	6364 0.064	6364 0.192	6364 0.051	6364 0.063	6364 0.257	6364 0.270

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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susceptible to temporal trends, we focus on the intensive variable $J_{ij,t}$ that appropriately standardizes the nominal integration measure $N_{ij,t}$ by the pairwise subsample size $(N_{i,t} + N_{j,t} - N_{ij,t})$. The coefficients in the resulting model measure the degree to which shifts in $J_{ij,t}$ are attributable to time-invariant (e.g. spatial variables) and time-dependent co-variates (e.g. institutional sizes). For the latter variable type, we account for potential causal relationships by implementing 1-year lags in the variables denoted by $R_{ij,t-1}$ and $A_{ij,t-1}$.

Considering the role of each co-variate more specifically, we start with the spatial factor variable $\gamma_{Geo} \equiv (\beta_{Metro}, \beta_{WRIS}, \beta_{XRIS})$, which classifies the institutional pair according to three non-overlapping categories denoted by the categorical variable G_{ij}. The first category is $G_{ij} = Metro$, corresponding to institutions that are co-located within a greater metropolitan area (e.g. UTD, UTA, UTSWMCD and SMU); the second is $G_{ij} = WRIS$, corresponding to institutions within the same state but extending across metropolitan areas; and the third is $G_{ij} = XRIS$, corresponding to institutions spanning across state boundaries. In what follows, we employ the second within-RIS group as the baseline category.

We measure institutional homophily via the binary indicator variable $MUS_{ij} \equiv \mathbb{1}_{MUS,ij}$, which represents institutional pairs where both institutions belong to a common MUS with the value 1, and 0 otherwise. We measure the role of institutional specialization as it manifests in the research area alignment of the two institutions, denoted by A_{ij}. Note that research area profiles are calculated using mono-university publications of institution *i*, whereas $J_{ij,t}$ is based upon co-produced research. Moreover, we include an interaction between A_{ij} and MUS_{ij} to explore the moderating role of institutional homophily on the contributions attributable to the alignment of institutional specialization.

To account for institutional prestige we employ two measures that control for institutional reputation as well as relative size variation. The first is a categorical variable that measures the combined reputation among the pair *ij* by counting the number of premier institutions, denoted by $Prem_{ij}$. This variable has three categories corresponding to 0, 1, or 2 institutions, and generates a set of corresponding coefficients denoted by $\gamma_{\star} \equiv (\beta_0, \beta_{\star}, \beta_{\star\star})$. In what follows, we employ the group with 0 premier institutions as the baseline category. The second quantity is the institutional size ratio $R_{ij,t} = Max[N_{i,t}, N_{j,t}]/Min[N_{i,t}, N_{j,t}] > 1$, which facilitates estimating the propensity for institutions to sort according to relative differences in total research production. Values of $R_{ij} \sim 1$ represent institutions of roughly similar size, whereas $R_{ij} \gg 1$ controls for institutional size asymmetry. The average and standard deviation of R_{ij} is 5.9 $\pm$ 9.8 with (min, max) values of (1.0, 150). And finally, γ_t represents annual fixed effects, such that estimates are measured in excess of idiosyncratic temporal shocks.

Temporal interaction model: To explore the temporal trends in the MUS_{ij} and $Prem_{ij}$ variables, we elaborate on the basic model by including temporal interactions,

$$\begin{aligned} J_{ij,t} \quad = \quad & const. + \gamma_{MUS\times t}(MUS_{ij} \times t) + \beta_{A|MUS}(A_{ij,t-1} \times MUS_{ij}) \\ & + \beta_R R_{ij,t-1} + \gamma_{\star\times t} + \gamma_{Geo} + \gamma_t + \epsilon. \end{aligned} \tag{4}$$

The interaction $MUS_{ij} \times t$ facilitates exploring the temporal evolution of this factor over time, which offers insights into the sensitivity of the MUS backbone to financial resource constraints characteristic of financial shocks such as the 2007-08 financial crisis. Similarly, the interaction $Prem_{ij} \times t$ generates a set of corresponding coefficients $\gamma_{\star\times t} \equiv (\beta_{0\times t}, \beta_{\star\times t}, \beta_{\star\star\times t})$. For both interaction terms we measure the temporal change relative to the baseline value in 2000. The full set of parameter estimates are shown in the model (8) column in Table 1, and are demonstrably robust with respect to model (7) which lacks the temporal interactions.

Results

Visualizing the structure and dynamics of RIS integration

Given the relatively high density of connections among institutions, we present the ensemble of co-production intensities quantified by $J_{ij,t}$ as an ordered matrix. This descriptive visualization strategy is sufficient to reveal the structure of RIS integration and also facilitates the identification of dynamical patterns. To this end, the two sequential $J_{ij,t}$ matrices shown in Fig 2 illustrate the structure and dynamics of these two RU ecosystems, showing significant levels of within-RIS and across-RIS integration. Visual inspection suggests that within-RIS co-production is strongly mediated by both institutional homophily prioritizing within-MUS collaboration, as well as stratification according to institutional prestige.

To more objectively identify RU clusters in each $J_{ij,t}$ matrix we employ a standard unsupervised (modularity maximizing) algorithm [97]. Results indicated along the border of each matrix confirm that clusters strongly correlate with spatial proximity largely corresponding to each RIS. The presence of notable community overlaps reflects the fact that $J_{ij,t}$ are constructed by aggregating publication data across disciplinary boundaries (i.e., *SC*). While it is outside the scope of the present analysis, we anticipate that co-occurrence matrices constructed conditionally upon certain research areas would show more distinct communities.

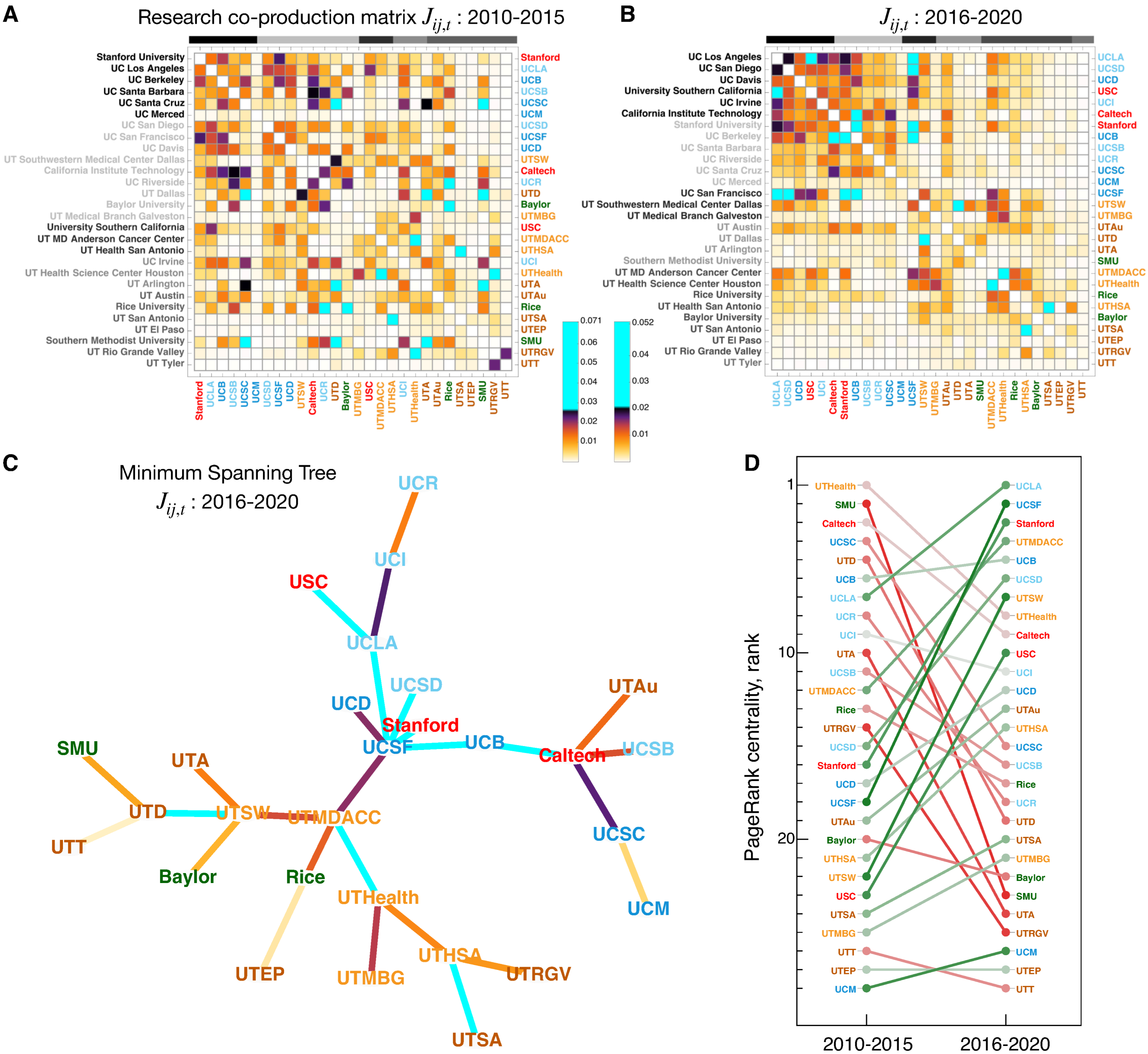

Fig 2. **Structure and dynamics of within-RIS and across-RIS research co-production (RQ1)**. **(A,B)** The matrix J_{ij} measures the fraction of research output co-produced by universities i and j by way of the Jaccard similarity index. We identify university clusters using a modularity maximizing algorithm [97], as indicated by the gray-scale border segments along the upper border; within each cluster, universities are ordered according to their research productivity, N_i. Comparison of $J_{ij,t}$ tabulated over two consecutive time periods indicates assortative regional integration mediated by spatial proximity, institutional prestige and biomedical & health science specialization. Each color-legend extends to the maximum value; the cyan segment begins at the value of the 10th-largest J_{ij} value to facilitate identifying the most prominent pairs. **(C)** Minimum spanning tree representation of $J_{ij,t}$ shown in panel (B). **(D)** Slope-graph showing the rank-changes according to the weighted PageRank centrality calculated for the two matrices shown in (A,B). Universities with increasing centrality tend to specialize in biomedical and health sciences. See S1 GIF for a dynamic visualization of $J_{ij,t}$ at the 1-year resolution from 1970-2020, and S1 Fig. for the PageRank centrality dynamics.

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Three commonalities among the most prominent $J_{ij,t}$ values (highlighted by cyan) are: they feature strong alignment in research area specialization (e.g. UT Austin most frequently co-produces with other premier engineering schools at Caltech and UCB); indications of prestige sorting among the most premier institutions (e.g. UCLA features relatively high $J_{ij,t}$ with UCSD, Stanford, UCB and UCSF); and the institutions are co-located within a single metropolis (e.g. UT Dallas and UTSW; UTMDACC and UTHealth; UCLA and USC). Across-RIS integration is most prevalent among the specialized UT health science centers, UCSF, and traditional multi-disciplinary research universities featuring prominent medical schools (e.g., Stanford, USC, UCLA, UCSD).

Comparison of $J_{ij,t}$ clusters calculated for 2010-2015 and 2016-2020 indicates an increasing role of institutional specialization and homophily contributing to RIS integration. This contextual regularity is reproduced by the minimum spanning tree representation of $J_{ij,t}$ shown in Fig 2C. This network representation indicates that the backbone of the RIS networks are universities with prominent medical schools and health science centers, and highlights the role of the most prominent hubs as mediators of both within- and across-RIS research co-production. In a similar vein, Fig 2D shows that institutions featuring the greatest cross-temporal increases in network centrality tend to be those specializing in biomedical and health sciences.

From a dynamic perspective, we analyze the information contained in the sequence of $J_{ij,t}$ matrices to understand how the system responds to exogenous resource shocks, in particular the 2007-08 global financial crisis, which impacted federal and private spending on R&D [47,73–76], as well as university financials and academic labor markets [66,70–72]. To this end, the average value $\overline{J}_t$ measures the characteristic level of pairwise integration, we note a dramatic decline at the onset of the financial crisis. Following a period of re-consolidation, the system features a second substantial negative shift from 2016-2020 – see Fig 3A. Thus, while it may be tempting to assume that RIS integration has increased by following secular trends of globalization [42], we find variation and departure from aggregate trends at the regional level.

Two complementary weighted network metrics yield additional insights into the dynamics of clustering and assortative mixing among institutions [41,89,90]. Treating $J_{ij,t}$ as a weighted network, we calculate the mean clustering coefficient which quantifies the degree to which the strongest co-producing institutions of a given institution also feature relatively high levels of research co-production between themselves. Fig 3B shows that the strength of prominent institutional triads started to increase at the onset of the financial crisis indicating the emergence of structural modularity [98]. Instead, the network assortativity coefficient measures the propensity for institutions to sort according to the relative magnitude of neighboring $J_{ij,t}$ values [89]. If institutions with relatively high (low) $J_{ij,t}$ tend to pair with other institutions featuring relatively high (low) $J_{ij,t}$, then the $J_{ij,t}$ configuration will generate positive values of network assortativity. Conversely, if institutions with relatively high (low) $J_{ij,t}$ tend to pair with other institutions featuring relatively low (high) $J_{ij,t}$, then such a configuration will generate negative values of network assortativity. Results indicate that network assortativity is largely negative and tracks the trend observed for $\overline{J}_t$. These three metrics are consistent with a general shift towards regional collaborations orienting around resource sharing and less about prestige sorting during the 2007-08 financial crisis. Yet we also observe a general fragmentation of $J_{ij,t}$, with the recovery of structural integrity extending well into the mid 2010s – see S1 GIF for a dynamic visualization of $J_{ij,t}$ at the 1-year resolution from 1970-2020. This finding is consistent with work studying the impact of this global financial shock on the research enterprise over the short and medium term [47,66].

Regional integration is mediated by the dichotomy of institutional diversity and specialization

We exploit the distinct multi-campus university system configurations in CA and TX to provide additional insights regarding the role of institutional specialization on regional integration. One the one hand, the UC features 9 campuses whose research profiles are variations on a multi-disciplinary theme. As such, researchers seeking to develop multi-university projects ranging from small collaborations to large consortia can strategically assemble expertise, access to equipment and other resources by coordinating within the system, as the organizational redundancy offers many options from which to choose. Contrariwise, if a large proportion of campuses are highly specialized and feature low redundancy, then there

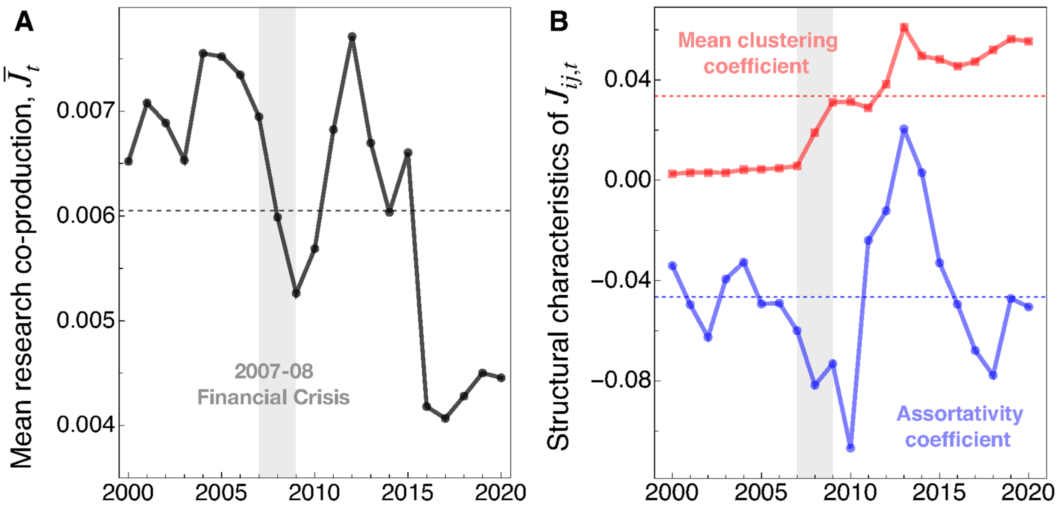

Fig 3. Structural dynamics of regional integration (RQ2). (A) Mean value of the co-production matrix $J_{ij,t}$ calculated from 2000-2020. **(B)** Two weighted network measures capturing the structural properties of $J_{ij,t}$. The weighted mean clustering coefficient measures the prevalence of prominent institutional triads [98], such that three institutions all feature relatively high co-production values, largely reflecting the emergence of modularity in the institutional ecosystem. The network assortativity measures the propensity for institutions to sort according to research co-production intensities, with negative values reflecting systems governed by resource constraints and zero-sum interactions [89]. Dashed lines indicate the mean value across each time series.

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are relatively fewer within-MUS combinations that offer sufficient multi-disciplinary alignment. This latter scenario is more representative of the UT system, where roughly half of the institutions are biomedical and health science oriented, and the remainder are more traditional multi-disciplinary institutions. (Note that UT Austin was the only campus prior to 2016 with a medical school; the UTRGV and UTT medical schools launched very recently, in 2016 and 2021, respectively).

To explore the combinatorial implications of MUS composition – both at the institutional and system levels – we leverage the WOS research area categories (denoted by *SC*) to define a research area profile for a given institution over a particular time period. Fig 4 shows the disciplinary signature of each institution according to the relative frequencies of six primary SC categories, as indicated by $\vec{f}^{SC}$. More specifically, we calculate two variants of $\vec{f}^{SC}$ according to two non-intersecting publication subsets. First, for each institution we calculate a research area profile based upon its mono-university research, denoted by $\vec{f}^{SC}_{i,M}$. And second, for each institutional pair we also calculate a research area profile $\vec{f}^{SC}_{ij}$ based upon research co-produced by institutions *i* and *j* (i.e., the subsample of size $N_{ij,t}$). Fig 4A and 4B show the frequency distributions $\vec{f}^{SC}_{i,M}$ and $\vec{f}^{SC}_{ij}$. The $\vec{f}^{SC}_{i,M}$ representations shown along the diagonal of each matrix indicate a wide range of research area distributions, both across and within each region and MUS. In the UC and UT, seven campuses feature the maximum observed $d_i = 0.75$ (UCB, UCSB, UCSC, UCM, UTAu, UTRGV and UTEP). Contrariwise, the specialized biomedical and health science centers feature relatively small diversity, $d_i < 0.16$.

Comparison of $\vec{f}^{SC}_{i,M}$ and $\vec{f}^{SC}_{ij}$ profiles for a given *i* indicate that co-produced research is mediated by the particular specialization of each university, such that more specialized institutions (e.g. Caltech) tend to co-produce research with other universities that align with their principal research area (i.e., “Physical Sciences”). This pattern indicates that research co-production is mediated by research-area alignment rather than complementarity. Moreover, it also suggests that regions comprised of institutions with a rich variety of *SC* profiles will foster higher levels of integration. Interestingly, a bi-product of this coupling mechanism are lower d^{SC}_{ij} levels observed for the co-produced research relative to distribution of $d^{SC}_{i,M}$ values calculated for mono-university research. Hence, while regional integration is supported by alignment, the co-produced

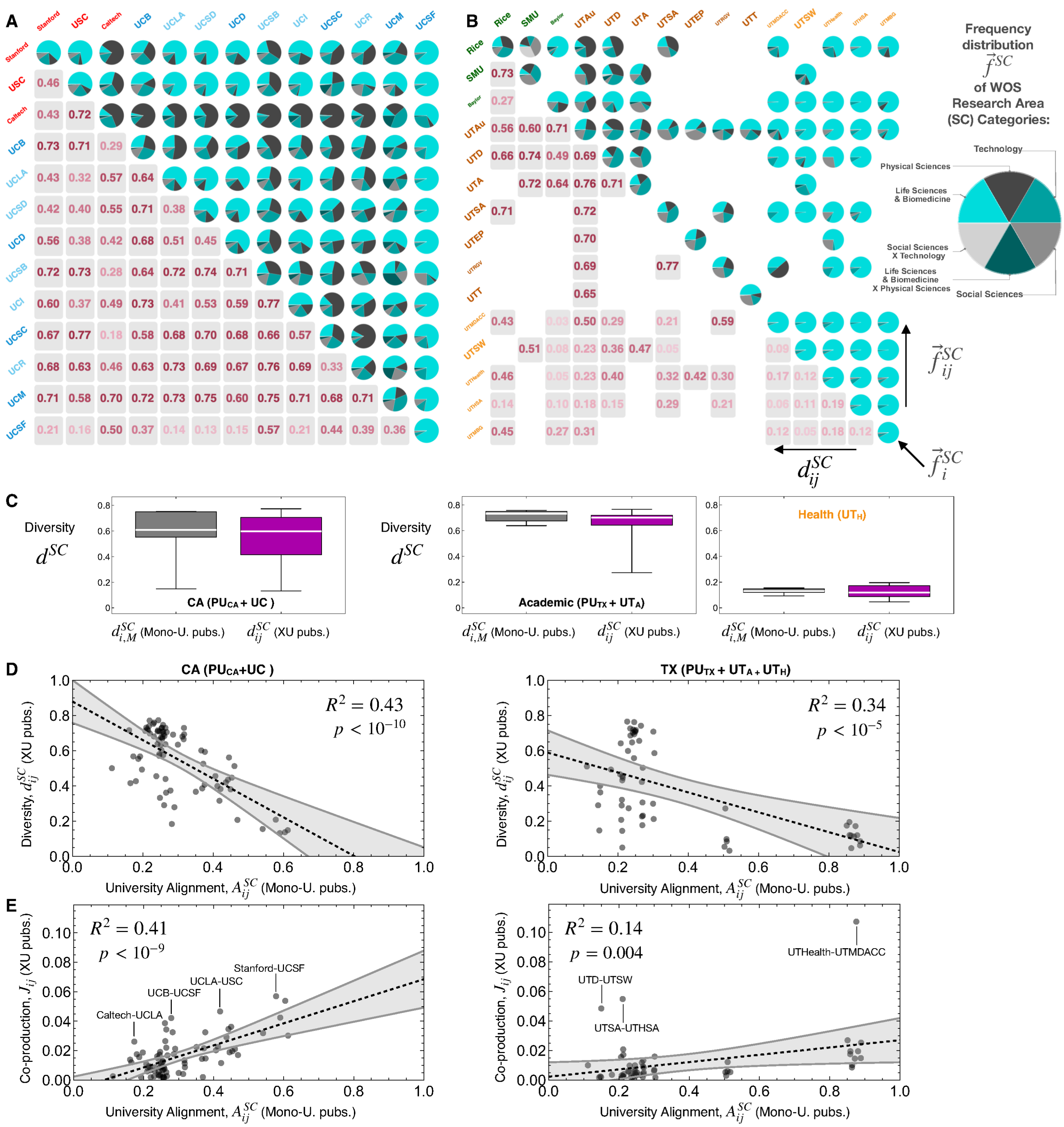

Fig 4. The composition and diversity of institutional research area profiles conditions the degree of regional integration (RQ3). Research area composition and diversity for **(A)** California and **(B)** Texas, calculated for research published between 2016-2020. For each matrix, the pie charts comprising the upper diagonal matrix show the relative frequency $\vec{f}_{ij}^{SC}$ of various WOS "Research Areas" across research co-produced by each

university pair *ij*. Pie charts along the diagonal show the SC distribution $\vec{f}_i^{SC}$ tabulated using mono-university research over the same period. To measure SC diversity we calculate $d_{ij}^{SC} = 1 - \mathrm{HHI}_{ij}$, where HHI is the Herfindahl-Hirschman index calculated across the six SC categories: small (large) d^{SC}values correspond to concentrated (diverse) SC profiles. Each d_{ij} value is shown in the cross-diagonal matrix element *ji*. University pairs with less than 50 co-publications are omitted from each matrix. **(C)** Below each matrix we show the interquartile range of d_{ij} values (purple) derived from co-produced research relative to the distribution of d_i derived from mono-university research (gray). The distribution of d_{ij} is shifted towards lower values, indicating that regional research co-production is mediated by university-level research area specialization. **(D)** Negative correlation between alignment of research areas between universities ($A_{ij}^{SC} = \vec{f}_{i,M}^{SC} \cdot \vec{f}_{j,M}^{SC}$) and the diversity of co-produced research, d_{ij}. This relationship explains a significant portion of within-RIS variation in d_{ij} exhibited in panel (C). **(E)** Positive correlation between university alignment and pairwise integration, J_{ij}. Comparing the characteristic levels of J_{ij} between regions highlights the higher degree of ecosystem integration in CA versus TX. Callouts indicate highly localized university pairs, indicating the role of spatial proximity in addition to institutional similarity.

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research outcomes tends to be more concentrated in specific research areas that are likely representative of institutional strengths – see Fig 4C.

Finally, comparison of d^{SC} distributions within and across regions demonstrate how institutional specialization conditions regional integration. The distributions of $d_{i,M}^{SC}$ shown in Fig 4C are more narrowly distributed in the UT, which in turn constrains the variation in d_{ij}^{SC}. These constraints represent hard limits on the combinatorial synergies that can be realized between institutions. Notably, a significant number of institutional pairs co-produce fewer than 50 publications, corresponding to empty cells in Fig 4A and 4B. These structural holes underscore the different levels of regional integration in CA versus TX. This result is only partly attributable to the distinct institution specialization in TX, as there are even notable weak links among the academic institutions (denoted by UT_A). Hence, one of our main findings is that maintaining a balance between institutional redundancy and variation is essential for creating a wide range of potential institutional synergies, and influences the degree to which regional ecosystems integrate.

We observe a negative relationship between d_{ij}^{SC} and A_{ij}^{SC} for both CA and TX – see Fig 4D. These trends exhibit the downside of redundancy. At the same time, they highlight the multidisciplinary advantage of regions featuring a diversity of institutional research area profiles. This latter point is reflected by the distribution of A_{ij}^{SC} values, which is more continuous for CA and more modal for TX. At the same time, we observe a positive relationship between A_{ij}^{SC} and J_{ij}, reinforcing the principle that institutional ecosystems integrate according alignment rather than complementarity, while also exhibiting a higher degree of integration in CA relative to TX – see Fig 4E. Notable J_{ij} outliers tend to be neighbors within the same metropolis, which points to the persistent advantages of co-location.

Multi-campus university systems promote regional integration

Research co-production affinities that persist over distance and time point to the factors that generate structural resiliency within innovation systems. In this regard, we exploit the annual variation in $J_{ij,t}$ over the period 2000-2020 to evaluate the relative strength of assortative channels as they relate to regional integration. We employ a panel regression specified in Eq (3) to simultaneously measure the relative contributions of four assortativity channels to rates of research co-production. As an indication of goodness-of-fit, our full model generates an adjusted $R^2 = 0.257$. See Fig 5A for a visual summary of the focal variable estimates; and see Table 1 for the full list of point estimates and demonstration of model specification robustness.

Whereas much of the research on global collaboration trends supports the 'death of distance' perspective [80,99], our results show that spatial proximity is still a dominant factor at the regional scale, as noted in other studies [42,53,100]. The coefficient β_{Metro} measures the contribution from agglomeration density by denoting institutional pairs that are acutely proximal corresponding to a <2 hour driving distance within a greater metropolitan area. By way of example, four institutions in our sample are located within the greater Dallas-Fort Worth area. Measured relative to the baseline within-RIS category, the coefficient $\beta_{Metro} = .014$ ($p < 0.001$; 95%CI = [0.012, 0.016]) quantifies the excess co-production attributable

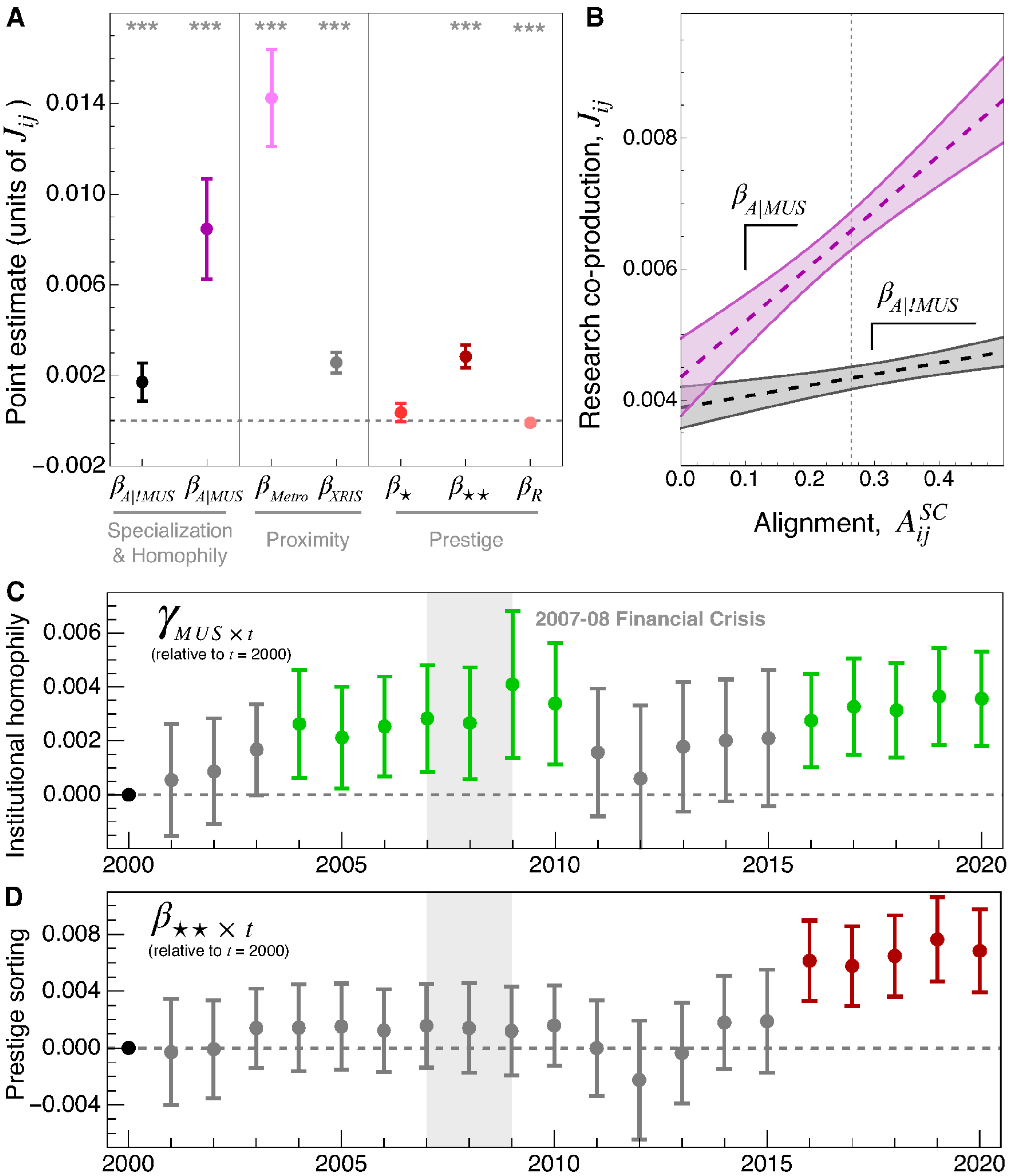

Fig 5. Sensitivity of multi-university research co-production to assortativity channels and exogenous socio-economic shocks (RQ4). (A) Regression model point estimates. The impact of institutional co-location on research co-production is roughly 5× stronger than both the impact attributable to institutional prestige affinity ($\beta_{\star\star}$) and the impact attributable to geo-political barriers affecting across-region collaboration (β_{XRIS}). Statistical significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; model adjusted $R^2 = 0.27$. **(B)** Marginal effect of institutional alignment A_{ij}^{SC} conditional on MUS homophily, holding all other regression model covariates at their mean values – see Eq (3) for the model specification. Differentiating between *ij* pairs belonging to a MUS from those that do not (!MUS) shows that institutional homophily (MUS) moderates regional integration. The vertical dashed line corresponds to the mean A_{ij}^{SC} value. **(C)** Plot of the temporal trend associated with institutional homophily, $\gamma_{MUS\times t}$. Green data points indicate years in which the coefficient significantly deviates from the baseline value in 2000 at the $p < 0.05$ level. Note a general increase in $\gamma_{MUS\times t}$ up until the period of global financial crisis in 2007-08. **(D)** Plot of point estimates indicating the temporal trend associated with "binary star" co-production between two premier universities, $\beta_{\star\star\times t}$. Red data points indicate years in which the coefficient significantly deviates from the baseline value in 2000 at the $p < 0.05$ level. The intensification of prestige sorting (2016-2020) follows the recovery period (2009-2012, during which the RU networks fragmented). See Table 1 for the full list of regression model point estimates.

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to co-location within the same metro area, which exceeds the characteristic co-production levels for many of the institutional pairs shown in Fig 2. Moreover, β_{Metro} is roughly 5.5 times larger in magnitude than coefficient representing across-RIS pairs, $\beta_{XRIS} = 0.0026$ ($p < 0.001$; 95%CI = [0.002, 0.003]), and is also 5 times larger than the prestige effect $\beta_{\star\star}$ reflecting pairs where both i and j are premier institutions.

On of our main results is the relation between research area alignment A^{SC}_{ij} and research co-production $J_{ij,t}$, and the degree to which it is moderated by institutional homophily. We operationalize this differential by measuring the coefficient associated with A^{SC}_{ij} conditional on the two institutions ij belonging to the same MUS or not, denoted by the binary variable MUS_{ij}. Fig 5B shows that institutional pairs belonging to a common MUS feature a marginal effect of alignment that is 5 times stronger than the counterfactual: $\beta_{A|MUS} = 0.0085$ ($p < 0.001$; 95%CI = [0.006,0.011]) and $\beta_{A|!MUS} = 0.0017$ ($p < 0.001$; 95%CI = [0.0009, 0.0025]). How consequential is this difference in terms of the net impact on research co-production levels? To assess the magnitude of this difference, we consider two institutions featuring the average level of alignment $\overline{A}_{ij} = 0.26$. At that level, the net differential $\beta_{A|MUS} - \beta_{A|!MUS} = 0.007$ ($p < 0.001$; 95%CI = [0.004,0.090]) corresponds to a 50% increase in $J_{ij,t}$ for MUS members relative to the counterfactual. This substantial difference reflects the advantages of access to common pool resources such as state and system-level funding initiatives, in addition to the relatively higher familiarity and mobility among scholars within multi-campus university systems that generate ecosystem network effects.

The degree to which institutions sort according to reputation is captured by the categorical variable $Prem_{ij}$, which counts the number of premier institutions among the pair ij. We do not identify a significant difference associated with institutional pairs involving 1 premier relative to the baseline of 0 premier institutions ($\beta_{\star} = 0.0004$; $p = 0.08$; 95%CI = [–0.0001, 0.0008])). However, we do identify a substantial increase in co-production attributable to “binary star” pairs featuring 2 premier institutions, $\beta_{\star\star} = 0.0028$ ($p < 0.001$; 95%CI = [0.0023, 0.0033]). This result is indicative of the prestige hierarchies that foster the emergence of rich clubs in science [36,37,55].

The degree to which institutions sort according to their size prominence is captured by the continuous variable $R_{ij} \geq 1$, which measures the ratio of the larger relative to the smaller institution size. A tendency for larger institutions to co-produce relatively more (relatively less) with smaller institutions corresponds to $\beta_R > 0$ (respectively, $\beta_R < 0$); and if there is no tendency for size-stratification, then $\beta_R = 0$. Additionally, this quantity controls for extensive variables associated with institutional size that generate larger $N_{i,t}$, such as the amount of research infrastructure and the researcher population. Results indicate a negative correlation, $\beta_R = -0.0001$ ($p < 0.001$; 95%CI = [–0.00011, –0.00009]), indicating a tendency for institutions to pair according to size. This results implies a comparative advantage among larger legacy institutions, as the preferential coupling may inadvertently generate barriers to entry for smaller regional counterparts.

Evolving roles of institutional homophily and prestige sorting. Having identified the relative contributions of the four assortativity channels, we next examine trends in two categorical variables that reflect dynamic relationships sensitive to social and economic change. First, we assess how multi-campus university systems have contributed to regional integration over time by analyzing the interaction term $MUS_{ij} \times t$ incorporated into the interaction model specified in Eq 4). Shown in Fig 5C, the set of coefficients $\gamma_{MUS\times t}$ capture the incremental change relative to the baseline year 2000. The results indicate a general increase in the strength of institutional homophily over the past two decades, interrupted by a sharp decline following the 2007-08 financial crisis. This trend digression highlights the sensitivity of institutional homophily and regional integration to the sudden emergence of resource constraints. These findings align with the structural metrics in Fig 3, which similarly suggest that institutions formed strategic partnerships prioritizing regional clusters while reducing emphasis on prestige-based stratification.

Second, we evaluate the evolution of institutional prestige stratification using the interaction term $Prem_{ij} \times t$. Fig 5D shows the “binary star” coeffiecients $\beta_{\star\star\times t}$, representing co-production between two premier institutions measured relative to the baseline category $Prem_{ij} = 0$ measured in the baseline year 2000. (For brevity we do not show the other time series for the $\beta_{\star\times t}$, for which none of the point estimates significantly deviate from the baseline level at the $p < 0.05$ level.) After a post-crisis decline, $\beta_{\star\star\times t}$ reversed course in 2012, and by 2016, exceeded its baseline value significantly. This resurgence reflects a parallel mechanism of fragmentation within the ecosystem, visible in the evolving network community structure of $J_{ij,t}$ – see S1 GIF.

While both MUS affiliation and prestige sorting contribute to the ecosystems structure, resilience to systemic shocks appears more strongly tied to the institutional redundancy and stability of MUS. However, the recent strengthening of prestige-based ties suggests that regional administrators must carefully balance investments that support both flagship institutions as well as the broader network connectivity representing foundational infrastructure that is fostered by MUS on the whole.

Discussion

We analyzed the structure and dynamics of regional university ecosystems, focusing on both institution- and system-level attributes that facilitate research co-production. Accordingly, our framework provides valuable insights and approaches for monitoring regional integration and institutional specialization that have been central to innovation system policy initiatives developed around the globe [9,10,13,38,39]. A key motivation is to identify pathways for enhancing university ecosystem synergies and foster increasing returns to scale owing to a principal advantage of systems of systems, à la Aristotle's "the whole is greater than the sum of its parts" principle. To this end, our analysis focuses upon four complementary dimensions of institutional assortativity that support research co-production that persists over distance and time. While our results are based upon two prominent US states (CA and TX) featuring established public university systems and elite private universities (Fig 1), our framework readily generalizes to other regions and geographic scales.

Our main results pertain to the mechanism by which institutional research diversity mediates research co-production and RIS integration. By juxtaposing institutional research area profiles calculated for mono-university (M) versus multi-university (XU) research ($\vec{f}^{SC}_{i,M}$ and $\vec{f}^{SC}_{ij}$, respectively), we contribute a detailed understanding of the relation between research co-production (J_{ij}, derived from XU research) and institutional alignment (A^{SC}_{ij}, derived from M research). Results show that RIS integration is conditioned by the distribution of institutional alignments, as the combinatorics of diversity favor institutional breadth over specialization – see Fig 4. More specifically, since less specialized institutions (larger $d^{SC}_{i,M}$) have more ways to align with other multi-disciplinary institutions, this configurational perspective explains the more complete system-level integration observed in CA, where many large universities feature relatively high $d^{SC}_{i,M}$ values. It follows that regional innovation systems featuring a broader range of multi-university configurations are well positioned to harness scientific and technological convergence [23,35,101] and to thereby address pernicious hybrid problems that pose substantial regional as well as global systemic risks [21]. Hence, these result also have implications for institutional investments in interdisciplinary initiatives [102,103], regional multi-campus funding programs (such as the UC system's internal Multicampus Research Programs and Initiatives (MRPI) that feature explicit multi-campus criteria), and the overall design of multi-campus university systems (MUS) aimed at optimizing the returns to specialization.

Exploiting the different organizational configuration of the UC and UT systems – in particular associated with specialized biomedical and health sciences institutions – was a principal motivation for focusing on CA and TX. The prominence and legacy of the UC and UT systems also facilitates analyzing the role of institutional homophily, defined as the affinity for within-MUS research co-production. Our results indicate that this affinity is substantial, generating a roughly 50% increase in research co-production rates among MUS members, net of spatial proximity and other factors – see Fig 5. This result is analog to the finding that the formation of collaborations across academic, industrial and governmental sectors – which involves bridging distinct organizational and cultural differences – is more sensitive to spatial proximity than within-sector collaboration [5,7].

Accordingly, we posit that the long-run contributions to regional integration by MUS owes to multi-institutional (structural) ambidexterity – an advantage gained by organizations capable of exploiting traditional paradigms while exploring new strategies [62,63]. In the present context, institutional ambidexterity can be leveraged via three dynamic capabilities: (i) diversity: achieved by implementing variations on the theme of conventional organizational and governance structures, and by investing in strategic specialization at both the individual RU and system level; (ii) adaptability: achieved by leveraging the combinatorics of strategic institutional configurations to address discipline-spanning regional and global challenges [21,23,24,103]; and (iii) scalability: achieved by periodically extending the system to serve a greater share of the region's population, thereby optimizing for returns to scale [104]. These capabilities are essential for casting a wide and deep net to attract and retain the skilled workforce that circulates across academia [17,18,36,37,105,106]. Consequently, MUS not only generate a resilient backbone supporting RIS integration, they also generate indirect network effects by supporting national (across-region) career pathways, as evident in the relatively high coupling between the UC and UT systems.

Our results also expose the impact of macro-economic shocks on integration within and across regions, as indicated by trends in research co-production during and after the 2007-08 financial crisis. We observe a significant burst of multi-university research among UT health science centers during this global economic downturn, indicative of increased within-MUS resource sharing within that subsystem, coupled with a sharp decline in research co-production within and across systems. These macro level trends are complemented by structural shifts in the $J_{ij,t}$ matrix, in particular a positive shift in the mean clustering coefficient and a negative shift in network assortativity. These trends together indicate that researchers adjusted to financial constraints and uncertainty by prioritizing within-region collaborations and de-prioritizing prestige hierarchies – see Fig 3. Notably, the re-organization of the $J_{ij,t}$ structure extended well into the 2010s, as evidenced by comparing the fragmented community structure during 2010-2015 to the more consolidated structure during 2016-2020 – see Fig 2 and the S1 GIF for a dynamic visualization of $J_{ij,t}$ at the 1-year resolution from 1970-2020.

While previous studies have studied the strength of prestige sorting across more comprehensive sample of universities [36,37,55], we focused on institutions concentrated in two regions in order to control for institutional environment, and to generate a more comprehensive representation of the breadth of institutions within each region. Yet certain limitations persist and arise at this scale and focus. First, we did not include the entire set of universities in each ecosystem. This choice was largely driven by data collection limitations. Furthermore, extending to larger number of institutions would involve visualization tradeoffs, and require additional institutional controls regarding the intensity of the research mission relative to the educational mission. Second, only a few states can support public university systems featuring the diversity and scale of the UC and UT, so extensions of this framework to greater numbers of regions should account for economy size and population density.

Third, our analysis does not account for varying propensities in problem selection and team design, which may depend on the individual and their research discipline. Consequently, multi-university collaborations may select into certain types of projects and problems, influencing the rate and impact of outcomes. By way of example, mega-projects that increasingly span the globe, such as the ATLAS and BABAR particle-physics collaborations, can explain a substantial portion of SMU research co-produced with UTA, UTD and UCSC during the period 2010-2015. While the contribution of large team projects is relatively small relative to the bulk of research produced, it tends to be magnified when the analysis is conditioned on *XU* research. Large international projects and other such latent drivers of institutional co-production represent omitted mechanisms not captured by our battery of controls, and offers avenues for improvement of the model specification. In our present study, this omitted variable bias manifests in manageable levels of heteroskedasticity observed in our assessment of OLS regression residuals – see S4 Fig. This issue is nevertheless addressed by our model estimation using robust standard errors and relatively large sample size.

Fourth, we do not account for other relevant assortativity channels specifically capturing variation in cultural diversity or governance structure, for example. Nevertheless, the public-private distinction and the common institutional policies shared among MUS campuses do reflect substantial variations in institutional governance and access to state funding that begin to account for culture and governance.

Finally, further research is needed to clarify the causal nature, effect size, and generalizability of the relationships identified between institutional assortativity and regional integration. For instance, while the tendency for within-MUS collaboration aligns with the expected role of homophily in multi-organization settings, further research is needed to evaluate the impact and effectiveness of system-level interventions (such as UC MRPI) in fostering sustained and impactful integration within MUS.

Conclusion

We conclude with an outlook for research enterprise management. Research universities are key sources of knowledge and skilled labor, forming the foundation for regional development and public investment. These multifaceted institutions are tasked with harnessing dynamic capabilities through strategic resource allocation, human capital development, critical R&D infrastructure, decision-making across multiple time horizons, institutional brand management, and multi-university initiatives [32,66,107,108]. Achieving and scaling these objectives across a complex multi-level organization is a challenge that is manifestly compounded in multi-campus university systems. Whereas our main results relate to institutional assortativity and RIS integration, our study also provides insights relevant to research development administrators.

Our findings suggest that MUS design should be tailored around both system integrity and flagship institution competitiveness [56]. Whereas system integrity is important for leveraging the network effects that promote a rich set of educational and research career pathways for attracting and retaining talented scholars within each RIS, supporting institutional competitiveness is critical for driving breakthrough innovation, securing large-scale infrastructure funding, attracting strategic boundary-spanning collaborations, and developing the brand equity that supports attracting student enrollment and alumni donations [11,40,57,66,85]. Results from the comparison of CA and TX further highlight the tradeoffs between institutional specialization and regional integration, as over-specialization reduces the possibilities for multi-institutional alignment. As such, weakly-integrated RIS may limit the extent to which institutions can benefit from the positive externalities generated by premier universities and the prominence they generate at the international level. Similarly, whereas our analysis does highlight metropolitan co-location as a particularly strong driver of institutional integration, MUS design should also consider the potential disadvantages of having too many campuses within a particular city. One possible downside of metropolitan agglomeration is that it may reduce the amount of regional integration that would have otherwise occurred if the campuses were more evenly distributed. Additionally, such concentration may lead institutions to over-exploit convenient local collaborations over exploring the diversity of potentially complementary partnerships across the region.

Another key insight for administrators, researchers, and funding agencies is how the development of regional integration can contribute towards solving wicked problems arising from networked risks at the nexus of socio-economic and environmental systems [21,23,24,103]. Further work is needed to assess the advantages that across-RIS integration may promote for addressing global challenges, and similarly, to what degree within-RIS integration is primed for addressing region-oriented issues. Yet independent of the institutional configuration and the spatial scale, our work underscores the value of regional integration in support of a modern corollary to Aristotle's postulate regarding the premium attributable to integration – which is to "specialize less, systematize more" [1].

Supporting information

S1 Fig. Prominence in co-published research: Dynamics of local connectivity and global centrality. Structural properties of the co-production matrix $J_{ij,t}$ constructed at the annual time resolution using Jaccard similarity to account for variable research production across i and t. **(A)** The clustering coefficient C_i measures the degree of connectivity among neighbors of university i. The table ranks universities according to the average annual growth rate over the 11-year period, as indicated by the color scale. UCSF featured the most prominent increase in $C_i(t)$ from 2010 to 2020, and SMU featured the most prominent decrease over the same period. **(B)** The Page-rank centrality index PR_i measures the relative prominence of i based upon the prominence of its most strongly connected peers. Each time series $PR_i(t)$ is scaled by the system size $N = 28$ to facilitate identifying those universities above or below the value expected of a uniform distribution, such $PR_i = 1/N$ values, being that the Page-rank values are normalized within each period, $\sum_i PR_i = 1$. As in

panel (A), the color scale indicates the average annual growth rate of each time series over the sample period, estimated using OLS regression.
(PDF)

S2 Fig. Intensity of within-MUS collaboration.
(A,B) The frequency distribution $P_{\alpha}(N_c)$ of the number of MUS campuses per article, N_c, is well-fit by the Borel distribution – a discrete distribution parameterized by the scalar α: $P(N_c) = (N_c!)^{-1} \exp[-\alpha N_c](\alpha N_c)^{N_c - 1}$, with distribution mean $1/(1-\alpha) \approx 1 + \alpha$ for $\alpha \ll 1$. We calculate each α value using the maximum likelihood estimator: $\alpha_{UC} = 0.066$ and $\alpha_{UT_{A+H}} = 0.091$. Sample averages are: $\overline{N}_c = 1.07$ (UC); 1.10 (UT_{A+H}); 1.02 (UT_A); 1.06 (UT_H). The UC system shows excess frequency for large N_c, indicative of system-level integration modes. Contrariwise, the UT system shows a dearth of activity for large N_c, as there is relatively less collaboration within the academic campuses (UT_A), and instead, much of the multi-campus activity derives from UT_A + UT_H (health center) collaboration, indicating that collaboration within UT_H is likely diminished according to the specialization of these centers. **(C,D,E)** Evolution of within-system collaboration since 2000, calculated over 3-year non-overlapping periods. **(C)** The Borel distribution parameter α is nearly indistinguishable from the frequency $P(N_c \geq 2)$ shown in **(D)**. Trends indicate differing levels and direction of integration within each MUS. The UC and UT_H subsystem show steady integration, whereas UT_A and the UT_{A+H} system do not. **(E)** Evolution of extreme N_c values, calculated as the 99.5th percentile of N_c, indicates that $N_c = 2$ is a characteristic level for evaluating within-MUS (multi-campus) integration.
(PDF)

S3 Fig. Descriptive statistics for the J_{ij} model analyzed in Table 1.
Upper-diagonal elements: bivariate histogram between row and column variables. Diagonal elements: histogram for variable indicated by the row/column labels. Lower-diagonal elements: bivariate cross-correlation coefficient: light-shaded squares indicate the Pearson's correlation coefficient between two variables that are both continuous measures; dark-shaded squares indicate the Cramer's V associate between two variables that are both nominal (categorical).
(PDF)

S4 Fig. Assessment of OLS regression residuals and robustness of parameter estimates to outliers.
(A) Residual scatter plot. Fitted line (red) does not indicate any strong trend in the residuals as a function of the predicted model estimate, supporting the linearity assumption and model specification. However, the presence of excessive residuals nevertheless is indicative of a localized sources of heteroskedasticity, likely arising from omitted variables that do not capture idiosyncratic mechanisms associated with institutional co-production. One such variable are large-scale grants funding high-energy physics experiments, which tend to produce many publications with many institutional affiliations, which generates J_{ij} values in excess of what other predictors can capture. **(B)** The distribution of residuals features substantial deviation from the baseline Normal distribution, in particular in the extreme tail of positive residuals. **(C)** Extreme residual values – those in excess of 1.5 times the inter-quartile range above (below) the upper (lower) quartile – corresponding to roughly 8% of the sample (N= 497 out of the total 6364 observations). These extreme residuals tend to concentrated in the positive tail. **(D)** Further confirmation via the quantile-quantile plot that the deviation from the normality assumption is constrained to the upper tail corresponding to roughly 8% of the total sample. In addition to these visual tests, we also tested for multicollinearity by computing the Variance Inflation Factor (VIF) for each model variable, and do not identify any problematic variables (i.e., the largest VIF value observed was 3.94 for the variable MUS_{ij}, which is well below the problematic heuristic value of 10; the average VIF value across all variables is 2.06). See S1 Table for the robustness of our regression model results with respect to residual outliers.
(PDF)

S1 Table. Regression model – Robustness check with respect to residual outliers.
Regression model parameters estimated with (first column – corresponding to column 7 of Table 1 in the main manuscript) and without (second column) the 497 observations (8% of total sample) that are residual outliers. The majority of individual coefficients are largely consistent in magnitude, sign and statistical significance level with the full model results, indicating that the residual outliers are not substantially biasing the parameter estimates. The main consequential differences are the estimates for $A^{SC}_{ij,t-1}|MUS_{ij} = 0/1$, which feature a smaller difference when calculated without outliers; and the $Prem_{ij} = 1$ coefficient becomes statistically significant and increases in magnitude when estimated without the outliers. Neither of these two differences alter the interpretation of the results or overall takeaways based upon the regression model estimated for all observations. Overall, the robustness of the results to residual outliers is attributable to the basic model specification, the inclusion of robust standard errors that account for heteroskedasticity, and a relatively large sample size.
(DOCX)

S1 GIF. Dynamic visualization of co-production matrix $J_{ij,t}$.
This image sequence highlights the sensitivity of regional integration to the 2007-08 financial shock manifesting in re-organization of $J_{ij,t}$ extending into the early 2010s. Shown are $J_{ij,t}$ matrices calculated at the 1-year resolution from 1970-2020. For each year we identify university clusters using the Louvain modularity maximizing algorithm, indicated by the gray-scale border segments along the upper border of the matrix. Clusters are sorted each year according to the total number of publications by all member universities; and within each cluster, we sort each university according to its individual total research production in that year. Hence, the clusters featuring strong inter-connectivity initially start in the upper left corner, and extend over time to the bottom right corner – this shift altogether represents the expansion of regional and across-regional integration over the last half century. Yet in 2008, there is a drastic fragmentation of clusters that had been consolidating over the prior decades, which do not re-emerge until 2013. We use a fixed color scale, whereby cyan identifies the most prominent pairs with $J_{ij} > 0.02$ in any given period.
(GIF)

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Author contributions

Conceptualization: Alexander Petersen, Andrea Montano Ramirez.

Data curation: Alexander Petersen, Andrea Montano Ramirez.

Formal analysis: Alexander Petersen.

Investigation: Alexander Petersen.

Methodology: Alexander Petersen.

Visualization: Alexander Petersen.

Writing – original draft: Alexander Petersen.

Writing – review & editing: Alexander Petersen, Andrea Montano Ramirez.

References

1. Madhavan G, Poste G, Rouse W. NAE: The bridge on complex unifiable systems. National Academies Press; 2020.
2. Mowery DC. The U.S. national innovation system: Origins and prospects for change. Res Policy. 1992;21(2):125–44. https://doi.org/10.1016/0048-7333(92)90037-5
3. Cooke P, Gomez Uranga M, Etxebarria G. Regional innovation systems: Institutional and organisational dimensions. Res Policy. 1997;26(4–5):475–91. https://doi.org/10.1016/s0048-7333(97)00025-5
4. Cooke P. Regional innovation systems, clusters, and the knowledge economy. Ind Corp Change. 2001;10(4):945–74. https://doi.org/10.1093/icc/10.4.945
5. Ponds R, Van Oort F, Frenken K. The geographical and institutional proximity of research collaboration. Pap Regional Sci. 2007;86(3):423–44. https://doi.org/10.1111/j.1435-5957.2007.00126.x
6. Fagerberg J, Srholec M. National innovation systems, capabilities and economic development. Res Policy. 2008;37(9):1417–35.
7. Ponds R, Oort F v., Frenken K. Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. J Econ Geogr. 2009;10(2):231–55. https://doi.org/10.1093/jeg/lbp036
8. Fealing KH. The science of science policy: A handbook. Fealing KH, editor. Stanford CA, USA: Stanford Business Books; 2011.
9. De Noni I, Ganzaroli A, Pilotti L. Spawning exaptive opportunities in European regions: The missing link in the smart specialization framework. Res Policy. 2021;50(6):104265. https://doi.org/10.1016/j.respol.2021.104265
10. Guzman J, Murray F, Stern S, Williams H. Accelerating innovation ecosystems: The promise and challenges of regional innovation engines. Entrepreneur Innov Policy Econ. 2024;3:9–75. https://doi.org/10.1086/727744
11. Carayol N, Henry E, Lanoë M. Stimulating collaborations: Evidence from a research cluster policy. Rev Econ Stat. 2023:1–38.
12. Owen-Smith J, Riccaboni M, Pammolli F, Powell WW. A comparison of U.S. and European university-industry relations in the life sciences. Manag Sci. 2002;48(1):24–43. https://doi.org/10.1287/mnsc.48.1.24.14275
13. Chessa A, Morescalchi A, Pammolli F, Penner O, Petersen AM, Riccaboni M. Science. 2013;339(6120):650–1.
14. Morescalchi A, Pammolli F, Penner O, Petersen AM, Riccaboni M. The evolution of networks of innovators within and across borders: Evidence from patent data. Res Policy. 2015;44(3):651–68. https://doi.org/10.1016/j.respol.2014.10.015
15. Geuna AE. Global mobility of research scientists. Academic Press; 2015.
16. Petersen AM, Puliga M. High-skilled labour mobility in Europe before and after the 2004 enlargement. J R Soc Interface. 2017;14(128):20170030. https://doi.org/10.1098/rsif.2017.0030 PMID: 28298610
17. Doria Arrieta OA, Pammolli F, Petersen AM. Quantifying the negative impact of brain drain on the integration of European science. Sci Adv. 2017;3(4):e1602232. https://doi.org/10.1126/sciadv.1602232 PMID: 28439544
18. Petersen AM. Multiscale impact of researcher mobility. J R Soc Interface. 2018;15(146):20180580. https://doi.org/10.1098/rsif.2018.0580 PMID: 30257927
19. Fujita M, Krugman PR, Venables A. The spatial economy: Cities, regions, and international trade. MIT Press; 2001.
20. Moretti E. The new geography of jobs. Houghton Mifflin Harcourt; 2012.
21. Helbing D. Globally networked risks and how to respond. Nature. 2013;497(7447):51–9. https://doi.org/10.1038/nature12047 PMID: 23636396
22. Owen-Smith J. Research universities and the public good: Discovery for an uncertain future. Stanford University Press; 2018.
23. Petersen AM, Ahmed ME, Pavlidis I. Grand challenges and emergent modes of convergence science. Humanit Soc Sci Commun. 2021;8(1). https://doi.org/10.1057/s41599-021-00869-9
24. National Research Council. Enhancing coordination and collaboration across the Land-Grant system. National Academies Press; 2022.
25. Kenney M, Mowery DC. Public universities and regional growth: Insights from the University of California. Stanford University Press; 2014.
26. Doehne M, Rost K. Long waves in the geography of innovation: The rise and decline of regional clusters of creativity over time. Res Policy. 2021;50(9):104298. https://doi.org/10.1016/j.respol.2021.104298
27. Balland P-A, Jara-Figueroa C, Petralia SG, Steijn MPA, Rigby DL, Hidalgo CA. Complex economic activities concentrate in large cities. Nat Hum Behav. 2020;4(3):248–54. https://doi.org/10.1038/s41562-019-0803-3 PMID: 31932688
28. Hidalgo CA, Klinger B, Barabási A-L, Hausmann R. The product space conditions the development of nations. Science. 2007;317(5837):482–7. https://doi.org/10.1126/science.1144581 PMID: 17656717
29. Mowery DC, Sampat BN. Universities in national innovation systems. The Oxford Handbook of Innovation. Oxford University Press; 2009. p. 209–39. https://doi.org/10.1093/oxfordhb/9780199286805.003.0008
30. National Research Council. Research universities and the future of America: Ten breakthrough actions vital to our nation's prosperity and security. National Academies Press; 2012.

31. Veugelers R, Del Rey E. The contribution of universities to innovation, (regional) growth and employment; 2014. p. 18.
32. Rouse WB. Universities as complex enterprises: How academia works, why it works these ways, and where the university enterprise is headed. John Wiley & Sons; 2016.
33. Rouse WB, Lombardi JV, Craig DD. Modeling research universities: Predicting probable futures of public vs. private and large vs. small research universities. Proc Natl Acad Sci U S A. 2018;115(50):12582–9. https://doi.org/10.1073/pnas.1807174115 PMID: 30530668
34. Fortunato S, Bergsrom CT, Borner K, Evans JA, Helbing D, Milojevic S, et al. Science of Science. Science. 2018;359(6379):eaao0185.
35. Petersen AM, Majeti D, Kwon K, Ahmed ME, Pavlidis I. Cross-disciplinary evolution of the genomics revolution. Sci Adv. 2018;4(8):eaat4211. https://doi.org/10.1126/sciadv.aat4211 PMID: 30116784
36. Clauset A, Arbesman S, Larremore DB. Systematic inequality and hierarchy in faculty hiring networks. Sci Adv. 2015;1(1):e1400005. https://doi.org/10.1126/sciadv.1400005 PMID: 26601125
37. Wapman KH, Zhang S, Clauset A, Larremore DB. Quantifying hierarchy and dynamics in US faculty hiring and retention. Nature. 2022;610(7930):120–7. https://doi.org/10.1038/s41586-022-05222-x PMID: 36131023
38. Di Cataldo M, Monastiriotis V, Rodríguez-Pose A. How ‘smart’ are smart specialization strategies?. JCMS: J Common Market Stud. 2022;60(5):1272–98.
39. Hidalgo CA. The policy implications of economic complexity. Res Policy. 2023;52(9):104863. https://doi.org/10.1016/j.respol.2023.104863
40. Stephan P. How economics shapes science. Cambridge MA: Harvard University Press; 2012.
41. Barabási AL. Network science. Cambridge University Press; 2016.
42. Montaño Ramirez A, Petersen AM. Transformation of Global Science core–periphery structure towards a multi-polar horizon: The rise of China and the Global South from 1980–2020. Res Policy. 2026;55(1):105370. https://doi.org/10.1016/j.respol.2025.105370
43. Balch JK, Abatzoglou JT, Joseph MB, Koontz MJ, Mahood AL, McGlinchy J, et al. Warming weakens the night-time barrier to global fire. Nature. 2022;602(7897):442–8. https://doi.org/10.1038/s41586-021-04325-1 PMID: 35173342
44. Arroyave FJ, Goyeneche OYR, Gore M, Heimeriks G, Jenkins J, Petersen AM. On the social and cognitive dimensions of wicked environmental problems characterized by conceptual and solution uncertainty. Adv Complex Syst. 2021;24(03n04). https://doi.org/10.1142/s0219525921500053
45. Arroyave FJ, Jenkins J, Shackelton S, Jackson B, Petersen AM. Research alignment in the U.S. national park system: Impact of transformative science policy on the supply and demand for scientific knowledge for protected area management. J Environ Manage. 2024;357:120699. https://doi.org/10.1016/j.jenvman.2024.120699 PMID: 38552516
46. Kang Y, Liu R. Does the merger of universities promote their scientific research performance? Evidence from China. Res Policy. 2021;50(1):104098. https://doi.org/10.1016/j.respol.2020.104098
47. Cruz-Castro L, Sanz-Menéndez L. The effects of the economic crisis on public research: Spanish budgetary policies and research organizations. Technol Forecast Social Change. 2016;113:157–67. https://doi.org/10.1016/j.techfore.2015.08.001
48. Murmann JP. Knowledge and competitive advantage: The coevolution of firms, technology, and national institutions. Cambridge University Press; 2003.
49. Durham WH. Coevolution: Genes, culture, and human diversity. Stanford University Press; 1991.
50. Hidalgo CA, Balland PA, Boschma R, Delgado M, Feldman M, Frenken K, et al. The principle of relatedness. In: Morales AJ, Gershenson C, Braha D, Minai AA, Bar-Yam Y, editors. Unifying themes in complex systems IX. Cham: Springer International Publishing; 2018. p. 451–7.
51. Balland P-A, Boschma R, Frenken K. Proximity and innovation: From statics to dynamics. Regional Stud. 2014;49(6):907–20. https://doi.org/10.1080/00343404.2014.883598
52. Frenken K. Geography of scientific knowledge: A proximity approach. Quant Sci Stud. 2020;1(3):1007–16. https://doi.org/10.1162/qss_a_00058
53. Abbasiharofteh M, Broekel T, Mewes L. The role of geographic distance and technological complexity in U.S. interregional co-patenting over almost two centuries. Environ Plan A. 2024;56(7):2003–22. https://doi.org/10.1177/0308518x241255525
54. Catalini C, Fons-Rosen C, Gaulé P. How do travel costs shape collaboration?. Manag Sci. 2020;66(8):3340–60. https://doi.org/10.1287/mnsc.2019.3381
55. Jones BF, Wuchty S, Uzzi B. Multi-university research teams: Shifting impact, geography, and stratification in science. Science. 2008;322(5905):1259–62. https://doi.org/10.1126/science.1158357 PMID: 18845711
56. Petersen AM. Institutional prestige, geographic embedding and competitiveness: A comparative analysis of research ecosystems in California and Texas. Elsevier BV; 2026. http://dx.doi.org/10.2139/ssrn.6030114
57. Zhang S, Wapman KH, Larremore DB, Clauset A. Labor advantages drive the greater productivity of faculty at elite universities. Sci Adv. 2022;8(46):eabq7056. https://doi.org/10.1126/sciadv.abq7056 PMID: 36399560
58. Adams JD, Black GC, Clemmons JR, Stephan PE. Scientific teams and institutional collaborations: Evidence from US universities, 1981–1999. Res Policy. 2005;34(3):259–85.
59. Brint S. Can public research universities compete?. Future of the American public research university. Rotterdam & Taipei: Sense Publishers; 2007. p. 91–118.
60. Oreskes N. The Ivy League gets attention, but public universities are far more important. Sci Am. 2023;329(5):86.
61. Kreth Q. Understanding faculty research productivity in striving research universities. Georgia Institute of Technology; 2025.

62. O'Reilly CA III, Tushman ML. Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. Res Org Behav. 2008;28:185–206. https://doi.org/10.1016/j.riob.2008.06.002
63. O'Reilly CA III, Tushman ML. Organizational ambidexterity: Past, present, and future. AMP. 2013;27(4):324–38. https://doi.org/10.5465/amp.2013.0025
64. DiMaggio PJ, Powell WW. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. Am Sociol Rev. 1983;48(2):147. https://doi.org/10.2307/2095101
65. Gaind N. Huge US university cancels subscription with Elsevier. Nature. 2019;567(7746):15–6. https://doi.org/10.1038/d41586-019-00758-x PMID: 30837729
66. Petersen AM. University digital media co-occurrence networks reveal structure and dynamics of brand visibility in the attention economy. Humanit Soc Sci Commun. 2025;12(1). https://doi.org/10.1057/s41599-025-04419-5
67. McPherson M, Smith-Lovin L, Cook JM. Birds of a feather: Homophily in social networks. Annu Rev Sociol. 2001;27(1):415–44. https://doi.org/10.1146/annurev.soc.27.1.415
68. Huisman J, Lepori B, Seeber M, Frølich N, Scordato L. Measuring institutional diversity across higher education systems. Res Eval. 2015;24(4):369–79. https://doi.org/10.1093/reseval/rvv021
69. Walsh JP, Lee YN. The bureaucratization of science. Res Policy. 2015;44(8):1584–600.
70. Geiger R. Impact of the financial crisis on higher education in the United States. IHE. 2015;(59). https://doi.org/10.6017/ihe.2010.59.8486
71. Brown KC, Tiu CI. The interaction of spending policies, asset allocation strategies, and investment performance at university endowment funds. How the financial crisis and great recession affected higher education. University of Chicago Press; 2013. p. 43–98.
72. Wolinsky H. The crash reaches the universities. The global financial crisis threatens private and public university funding in the USA and Europe. EMBO Rep. 2009;10(3):209–11. https://doi.org/10.1038/embor.2009.17 PMID: 19255575
73. Mezzanotti F, Simcoe T. Research and/or development? Financial frictions and innovation investment. w31521; 2023.
74. State Science & Technology Institute (SSTI). Recovery act helped maintain U.S. R&D spending during economic crisis. https://ssti.org/blog/recovery-act-helped-maintain-us-rd-spending-during-economic-crisis
75. Dinerstein MF, Hoxby CM, Meer J, Villanueva P. Did the fiscal stimulus work for universities?. How the financial crisis and great recession affected higher education. University of Chicago Press; 2014. p. 263–320.
76. Park H, Lee J (Jay), Kim B-C. Project selection in NIH: A natural experiment from ARRA. Res Policy. 2015;44(6):1145–59. https://doi.org/10.1016/j.respol.2015.03.004
77. Turner SE. The impact of the financial crisis on faculty labor markets. In: How the financial crisis and great recession affected higher education. University of Chicago Press; 2013. p. 175–207.
78. Glänzel W. National characteristics in international scientific co-authorship relations. Scientometrics. 2001;51(1):69–115. https://doi.org/10.1023/a:1010512628145
79. Glänzel W, Schubert A. Analysing scientific networks through co-authorship. Handbook of quantitative science and technology research: The use of publication and patent statistics in studies of S&T systems. Springer; 2004. p. 257–76.
80. Pan RK, Kaski K, Fortunato S. World citation and collaboration networks: Uncovering the role of geography in science. Sci Rep. 2012;2:902. https://doi.org/10.1038/srep00902 PMID: 23198092
81. Hsiehchen D, Espinoza M, Hsieh A. Multinational teams and diseconomies of scale in collaborative research. Sci Adv. 2015;1(8):e1500211. https://doi.org/10.1126/sciadv.1500211 PMID: 26601251
82. Miao L, Murray D, Jung W-S, Larivière V, Sugimoto CR, Ahn Y-Y. The latent structure of global scientific development. Nat Hum Behav. 2022;6(9):1206–17. https://doi.org/10.1038/s41562-022-01367-x PMID: 35654964
83. Dosso M, Cassi L, Mescheba W. Towards regional scientific integration in Africa? Evidence from co-publications. Res Policy. 2023;52(1):104630. https://doi.org/10.1016/j.respol.2022.104630 PMID: 36597459
84. Hoekman J, Frenken K, van Oort F. The geography of collaborative knowledge production in Europe. Ann Reg Sci. 2008;43(3):721–38. https://doi.org/10.1007/s00168-008-0252-9
85. Way SF, Morgan AC, Larremore DB, Clauset A. Productivity, prominence, and the effects of academic environment. Proc Natl Acad Sci U S A. 2019;116(22):10729–33. https://doi.org/10.1073/pnas.1817431116 PMID: 31036658
86. Gross DP, Sampat BN. America, jump-started: World War II R&D and the takeoff of the US innovation system. Am Econ Rev. 2023;113(12):3323–56. https://doi.org/10.1257/aer.20221365
87. Fleming L, King III C, Juda AI. Small worlds and regional innovation. Org Sci. 2007;18(6):938–54.
88. Gomez CJ, Lieberman D, Mäkinen EI. Hedgehogs, foxes, and global science ecosystems: Decoding universities' research profiles across fields with nested ecological networks. Res Policy. 2024;53(7):105040. https://doi.org/10.1016/j.respol.2024.105040
89. Newman MEJ. Assortative mixing in networks. Phys Rev Lett. 2002;89(20):208701. https://doi.org/10.1103/PhysRevLett.89.208701 PMID: 12443515
90. Shirado H, Iosifidis G, Christakis NA. Assortative mixing and resource inequality enhance collective welfare in sharing networks. Proc Natl Acad Sci U S A. 2019;116(45):22442–4. https://doi.org/10.1073/pnas.1911606116 PMID: 31636181
91. Gompers PA, Huang K, Wang SQ. Homophily in entrepreneurial team formation. National Bureau of Economic Research; 2017.

92. Atouba YC, Shumate M. International nonprofit collaboration. Nonprofit Voluntary Sector Q. 2014;44(3):587–608. https://doi.org/10.1177/0899764014524991

93. Petersen AM, Pavlidis I, Semendeferi I. A quantitative perspective on ethics in large team science. Sci Eng Ethics. 2014;20(4):923–45. https://doi.org/10.1007/s11948-014-9562-8 PMID: 24919946

94. Hottenrott H, Rose ME, Lawson C. The rise of multiple institutional affiliations in academia. Asso for Info Sci Tech. 2021;72(8):1039–58. https://doi.org/10.1002/asi.24472

95. Hottenrott H, Lawson C. What is behind multiple institutional affiliations in academia?. Sci Public Policy. 2021;49(3):382–402. https://doi.org/10.1093/scipol/scab086

96. Petersen AM, Pan RK, Pammolli F, Fortunato S. Methods to account for citation inflation in research evaluation. Res Policy. 2019;48(7):1855–65. https://doi.org/10.1016/j.respol.2019.04.009

97. Blondel VD, Guillaume J-L, Lambiotte R, Lefebvre E. Fast unfolding of communities in large networks. J Stat Mech. 2008;2008(10):P10008. https://doi.org/10.1088/1742-5468/2008/10/p10008

98. Barrat A, Barthélemy M, Pastor-Satorras R, Vespignani A. The architecture of complex weighted networks. Proc Natl Acad Sci U S A. 2004;101(11):3747–52. https://doi.org/10.1073/pnas.0400087101 PMID: 15007165

99. Cairncross F. The death of distance: How the communications revolution will change our lives. Harvard Business School Press; 2001.

100. von Graevenitz G, Graham SJH, Myers AF. Distance (still) hampers diffusion of innovations. Regional Stud. 2021;56(2):227–41. https://doi.org/10.1080/00343404.2021.1918334

101. Yang D, Pavlidis I, Petersen AM. Biomedical convergence facilitated by the emergence of technological and informatic capabilities. Adv Complex Syst. 2023;26(01). https://doi.org/10.1142/s0219525923500030

102. Leahey E, Barringer SN. Universities' commitment to interdisciplinary research: To what end?. Res Policy. 2020;49(2):103910.

103. Petersen AM, Arroyave F, Pavlidis I. Methods for measuring social and conceptual dimensions of convergence science. Res Eval. 2023;32(2):256–72. https://doi.org/10.1093/reseval/rvad020

104. Liu Q, Patton D, Kenney M. Do university mergers create academic synergy? Evidence from China and the Nordic Countries. Res Policy. 2018;47(1):98–107. https://doi.org/10.1016/j.respol.2017.10.001

105. Baruffaldi SH, Landoni P. Return mobility and scientific productivity of researchers working abroad: The role of home country linkages. Res Policy. 2012;41(9):1655–65. https://doi.org/10.1016/j.respol.2012.04.005

106. Lee E, Clauset A, Larremore DB. The dynamics of faculty hiring networks. EPJ Data Sci. 2021;10(1). https://doi.org/10.1140/epjds/s13688-021-00303-9

107. Eisenhardt KM, Martin JA. Dynamic capabilities: What are they?. Strategic Manag J. 2000;21(10–11):1105–21.

108. Teece DJ. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Manag J. 2007;28(13):1319–50. https://doi.org/10.1002/smj.640