Finding Stars: Mapping the Geography of the World's Scientific Elites

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Finding Stars: Mapping the Geography of the World's Scientific Elites

by

Andrés Rodríguez-Pose[§,֍,*], Leiboyu Xiang[§] and Neil Lee[§]

Abstract

This paper presents the first systematic city-level mapping of global scientific talent, analysing the top 200,000 star scientists across 3,635 cities worldwide annually between 2019 and 2023. We use a novel Knowledge Generation Index (KGI) that combines researcher quantity with research impact to reveal extreme spatial concentration in knowledge production. Just four cities — New York, Boston, London and the San Francisco Bay Area — host 12% of the world's star scientists, while much of the Global South remains virtually excluded from frontier research. Beijing's ascent into the global top ten represents a rare challenge to established hierarchies. Our analysis uncovers striking disciplinary variations. Resource-intensive fields like clinical medicine cluster heavily and traditionally dispersed disciplines are increasingly gravitating toward major hubs. Despite these differences, concentration is intensifying across most scientific fields. Even the pandemic's remote collaboration experiment failed to level the playing field. Established innovation centres continued strengthening their advantages while peripheral regions fell further behind. Overall, we find that geography remains destiny, with profound implications for innovation policy confronting widening spatial inequalities in global scientific capacity.

Keywords: Star scientists; geography of knowledge; innovation agglomeration; spatial inequality

JEL Codes: O25; O31; R12

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1. Introduction

The gravitational pull of star scientists in driving knowledge generation, innovation, and economic growth is increasingly recognised (Romer, 1986; Moretti, 2014). These exceptionally talented researchers not only drive innovation directly through groundbreaking work but also boost the productivity of their peers by expanding knowledge networks, engaging in collaboration, and mentoring emerging talent (Schiller and Diez, 2010; Azoulay et al., 2017; McHale et al., 2023). Through knowledge spillovers, academic influence, and training of new researchers, star scientists generate long-run local benefits to innovation (Agrawal et al., 2011). They articulate the development of local innovation clusters by attracting additional scientific talent and resources. From this perspective, the presence of star scientists becomes a fundamental determinant of a place's innovation capacity (Hager et al., 2024).

Over the past decades, governments worldwide have vied to attract and retain these star innovators. Moretti and Wilson (2017) showed that differences in personal and corporate tax regimes across U.S. states significantly shaped the migration patterns of star scientists. In response, national and regional authorities have implemented a range of initiatives — from special tax incentives and targeted recruitment programmes to the establishment of research centres and science parks — aimed at overcoming scale disadvantages and seeding local innovation ecosystems. China's Thousand Talents Plan was one of such cases. Launched by the Chinese government, it aimed to lure high-level scientific talent back from abroad. Scientists recruited under this programme have demonstrated substantially higher productivity than their peers (Shi et al., 2023). Such policy efforts underscore the premium placed on star scientists as engines of innovation.

However, while the influence of star scientists on innovation has been well documented, significant gaps remain in our understanding of their spatial distribution and its evolution over time. Current research lacks a comprehensive global perspective on where star scientists are located and has not yet provided precise geographic mapping of these individuals. Many studies of scientific output focus on specific countries or regions, but systematic analysis of individual-level data on scientific elites at a worldwide scale is scarce. Consequently, fundamental questions remain unanswered: Where are star scientists concentrated globally?; How extreme are the geographic inequalities in the distribution of these top researchers?; Is the spatial concentration of star scientists intensifying over time?; And which locations and disciplines are experiencing the most pronounced effects?

Addressing these questions is crucial for understanding the geography of innovation breakthroughs and the spatial dynamics of human capital in knowledge production.

To fill this gap, we draw on a novel individual-level dataset encompassing the top 200,000 most-cited scientists — increasingly known as the Stanford/Elsevier list of the 2% most cited scientists (Ioannidis et al., 2019) or, for short, the world top 2% scientists — across 22 disciplines from 2019 to 2023. We identify and map the location of these researchers across cities worldwide and across scientific fields. Our analysis reveals pronounced spatial clustering of star scientists. Elite researchers concentrate disproportionately in established research hubs and economically dynamic regions. We also uncover substantial cross-disciplinary variation in agglomeration patterns, with some fields exhibiting intense geographic concentration while others show more dispersed distributions.

Moreover, we introduce a new global, city-region ranking of innovation agglomeration that we term the Knowledge Generation Index (KGI). The KGI captures both the quantity of star scientists in a city and their research impact. We find that major cities emerge as critical nodes in global innovation networks, distinguished not only by how many star scientists they host, but also by the exceptional influence of their work. These research hubs provide ecosystems highly conducive to high-impact research. Our findings suggest that historical, path-dependent advantages enable certain cities to continuously attract and concentrate elite human capital, thereby reinforcing regional innovation capacity and stimulating economic growth through cumulative talent agglomeration (Arthur, 1989; Krugman, 1991).

Our research contributes to existing knowledge on the geographical agglomeration and inequality of innovation in several ways. First, we provide the first systematic mapping of the global distribution of star scientists at the city level, highlighting stark regional disparities and agglomeration patterns across disciplines.

Second, we examine how major cities leverage persistent advantages to attract star scientists in both quantity and impact, using a composite index (KGI) that balances the number of star researchers with the impact of their work. This reveals the uneven distribution of both talent and influence across regions.

Finally, we advance existing understanding of how historical path dependencies, disciplinary differences, and agglomeration effects collectively shape the uneven spatial distribution of scientific talent. Top-tier "superstar" cities are shown not only to host larger numbers of researchers but also to nurture higher-impact science, underscoring the self-reinforcing nature of innovation hubs.

The remainder of the paper is structured as follows. Section 2 reviews the literature on star scientists' role in innovation and theoretical perspectives on the spatial concentration of knowledge creation. Section 3 details our data sources and methodological approach. Section 4 presents the empirical results, and Section 5 discusses key findings and concludes with policy implications.

2. Star scientists in innovation and spatial concentration

2.1 Star scientists matter for innovation

Star scientists are the centre of knowledge generation. They act both as primary producers of transformative research and as catalysts within broader innovation ecosystems. Defined by their exceptional citation impact and groundbreaking contributions (Agrawal et al., 2017; Zucker and Darby, 2007), these individuals drive scientific progress through high-impact publications, patents, and novel methodologies that redefine disciplinary paradigms (Moretti, 2014). Their research generates considerable knowledge spillovers, embedding foundational ideas into the scientific commons that fuel cumulative innovation across fields (Romer, 1990; McHale et al., 2023).

Empirical evidence underscores the outsized influence of star scientists on knowledge production. For instance, Azoulay et al. (2010) examined the impact of the unexpected deaths of elite life scientists and found that while they were alive, these stars had far-reaching effects that shaped entire research trajectories well beyond their immediate collaborators. Star scientists also tend, by definition, to be vastly more productive than average researchers. In a classic study, Lotka (1926) showed that a small minority of scientists produced a majority of published papers in physics. This pattern of concentration has since been confirmed across multiple disciplines. Similarly, the arrival of a single star scientist to an institution has been shown to dramatically increase that department's output. One study found a 66.5% increase in annual research publications after recruiting a star, highlighting these scientists' dual capacity to innovate individually while improving the performance of those around them (Agrawal et al., 2017).

Beyond their direct and indirect research output, star scientists generate powerful network effects. Oettl (2012) found that the loss of a "highly helpful" star (i.e. one who frequently assists collaborators) led to declines in the publication quality of that star's co-authors, even if the quantity of output remained unchanged. Hence, star scientists enhance the conceptual depth and methodological rigour of collaborative research. This finding, however, contrasts with Waldinger's (2012) analysis of the dismissal of Jewish scientists in Nazi Germany, which found little impact on the remaining faculty's productivity after these scientists were forced out. The discrepancy likely reflects shifts in the organization of science over time. Earlier academic environments, such as 1930s Germany, placed greater emphasis on individual scholarship, whereas contemporary science is increasingly characterised by specialised, interdependent research networks and team-based collaboration (Bercovitz and Feldman, 2011; Conti and Liu, 2015). Star scientists today often serve as key nodes of expertise and collaboration, meaning their presence (or absence) can substantially sway the productivity and innovation capacity of entire teams or departments.

2.2 Star scientists and the geography of innovation

The influence of star scientists extends beyond individual institutions to shape the geography of innovation. By concentrating top-level human capital in particular places, star scientists magnify knowledge production in those locations (Akcigit et al., 2018). Their presence helps establish self-reinforcing clusters through several mechanisms. First, they enhance local productivity by fostering vibrant collaboration networks, mentoring younger researchers, and raising the reputation of their host institutions. This, in turn, attracts additional resources and talent. These dynamics generate cumulative, self-reinforcing patterns of geographic clustering (Rodríguez-Pose and Crescenzi, 2008; Baruffaldi and Raffo, 2017). Innovation hubs such as Silicon Valley exemplify how physical proximity triggers knowledge spillovers via dense networks of informal interaction, collaboration, and shared infrastructure. Storper and Venables (2004) famously describe this localised knowledge milieu as "local buzz," wherein face-to-face exchanges facilitate tacit knowledge transfer. Such a process is difficult to replicate at a distance. Star scientists reinforce this local buzz. For example, Azoulay et al. (2017) found that biomedical scientists working in close proximity (in the same metropolitan area) produced 30% more high-impact papers than those in more isolated locations. Likewise, Moretti and Wilson (2017) observed productivity premiums for researchers located in larger urban agglomerations. These findings align with a broader understanding that agglomeration confers advantages: thick labour markets, knowledge spillovers, and shared infrastructure all enhance output for co-located talent.

The geographic clustering of star scientists creates powerful feedback loops that simultaneously advance innovation in core regions and entrench spatial inequalities. Regions that manage to attract these stars forge ecosystem advantages, reducing "social filters" (Rodríguez-Pose, 1999). This facilitates the translation of knowledge generation into further innovation and economic growth. Over time, this cumulative advantage means that established hubs strengthen their lead, while research peripheries struggle to catch up. Indeed, the very forces that make star clusters so productive also make them hard to emulate elsewhere. Csomós (2018) identified distinctive spatial patterns in scientific output, showing that growth often concentrates in already-advanced regions, thereby widening regional disparities. Major cities like New York and Boston benefit from historical path dependencies — pre-existing top universities, thick venture capital networks, and supportive policy frameworks — which help sustain their dominance as innovation hubs (Moretti and Wilson, 2017; Pardy, 2025). These entrenched advantages lead to "sustained innovation superstars": cities that enjoy prolonged high output and impact, often at the expense of areas lacking such endowments. Pinheiro et al. (2022) call this as the "dark side" of the geography of innovation: improvements in knowledge systems disproportionately benefit well-positioned regions, while less endowed areas remain left behind.

In summary, existing research identifies star scientists as critical for global innovation ecosystems. They advance knowledge through exceptional research productivity and, in doing so, heavily shape the spatial organisation of scientific activity. Ample evidence shows that star scientists have a strong tendency to cluster in established research hubs, particularly in North America and Western Europe, yielding substantial spillover benefits for nearby researchers (Azoulay et al., 2010; Oettl, 2012). However, this high degree of concentration exacerbates core-periphery divides in innovation. As elite talent piles into a few locations, those places reap cumulative advantages that strengthen their lead, while remaining regions lag further behind (Rodríguez-Pose, 2001; Roper and Jibril, 2024). Tacit knowledge, dense collaborative networks, and reputational capital remain sticky, diffusing slowly beyond established centres of excellence (Crescenzi et al., 2007; Nathan and Lee, 2013). Thus, although clustering star scientists in key hubs can strengthen innovation and scientific breakthroughs, it simultaneously entrenches spatial disparities. This dynamic poses a fundamental tension for policymakers between harnessing agglomeration benefits and promoting a more geographically inclusive innovation landscape.

3. Data and methodology

3.1 Defining star scientists in knowledge generation

Conceptually, star scientists are individuals at the forefront of research who shape the trajectory of their scientific fields through consistently influential work. In operational terms, we identify star scientists using a comprehensive individual-level dataset compiled by Ioannidis et al. (2019) annually since 2019. This dataset ranks scientists by citation impact of scientific articles published in Scopus-indexed journals in 22 major scientific disciplines. We focus on the annual lists of "the top 100,000 scientists by c-score [...] or a percentile rank of 2% or above in the sub-field" (Ioannidis, 2024).[1] This yields an annual list of around 200,000 scientists globally (by a citation composite score, excluding self-citations) (Ioannidis et al., 2019). Merging these criteria results in a panel of 757,500 author-year observations spanning 2019–2023. The dataset includes detailed information on each scientist's institutional affiliation and their citation impact rank. To our knowledge, this is the first application of this rich dataset in the field of economic geography.

The paper's definition of "stardom" — balancing prolific output with high-impact quality — aligns only partially with how geographers have traditionally debated what 'counts' as research excellence. A consistent theme in debates within geography is that true

[1] Throughout the analysis we rely on the career-long version of the Stanford/Elsevier citation database, which reports the citations a researcher received in their careers. We do not use the companion dataset that aggregates single-recent-year citation counts. See Ioannidis (2024) for full documentation.

scholarly excellence is multifaceted, not reducible to raw productivity alone. Geographers underscore that quality, influence and relevance must temper any mere counting of publications (although citations themselves are considered in many ways an indicator of impact and quality). For example, the UK's formal Research Excellence Framework (REF) explicitly balances quantity with quality-based criteria: research outputs are assessed alongside measures of impact beyond academia and the research environment that supports work (Loo, 2024). This broadened view reflects an understanding that publishing means little unless those publications advance knowledge or society in meaningful ways. Phillips (2010) already made this point in the context of the UK's emerging impact agenda, warning against valuing only immediate utilitarian outcomes at the expense of curiosity-driven inquiry. In short, what geographers consider 'excellent' research hinges on a combination of rigorous productivity and the intellectual or societal value of that work. This is precisely the balance our definition of star scientists seeks to capture, albeit in a way that many geographers would abhor.

Geographers also frequently remind us that the pursuit of excellence can be a double-edged sword. On one hand, a shared definition of excellence steers scholars toward impactful, high-quality work. On the other, narrow or metrics-obsessed regimes may skew academic priorities. Barnes (2025), reflecting wryly on the UK's decades of research assessment exercises, observes that the competitive fervour they instilled twisted research agendas without necessarily, in his opinion, raising scholarly quality. His Canadian vantage point — in a system with no national research audit — suggests that quality research might thrive just as well under a kinder, less audit-driven climate. In contrast, Loo (2024), examining recent REF proposals, highlights the increasing weight given to engagement and impact, suggesting a structural shift towards rewarding research with direct societal contributions. Yet, on the whole, geographers are not calling for complacency, but rather for meaningful excellence. Jeffrey et al. (2024) point out that today's REF culture carries an expectation that research should engage public issues, with real-world impact now an important token of excellence. The success of any discipline depends on its ability to reinvent itself and tackle emerging challenges, noting that a new, more globally diverse generation of geographers is poised to do exactly that (Yeung, 2023). Taken together, these perspectives echo the notion that excellence in geography is not about lionising raw output for its own sake but about nurturing influential, innovative scholarship that stands up both in quality and in its value to science and society.

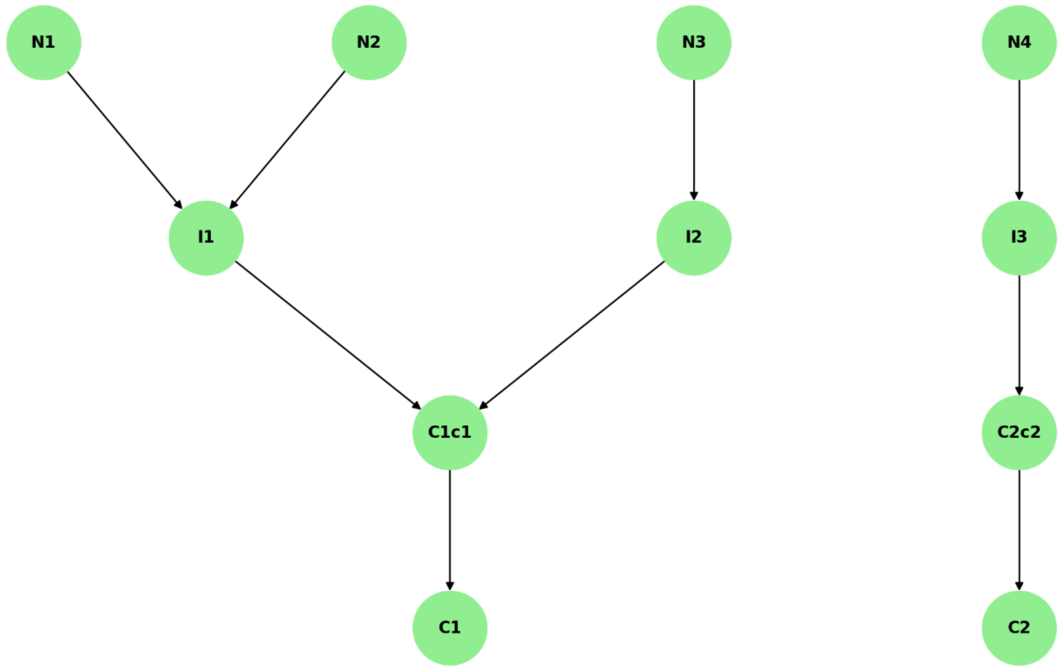
In any case, the individual-centric approach which we adopt in the paper to measure star scientist provides a uniquely granular view of global research capacity. It improves on traditional measures of regional research and innovation by incorporating an impact dimension. Previous studies often proxy local innovation output by the number of publications or patents (Dittmar and Meisenzahl, 2022; Lerner et al., 2024). However, counting outputs alone has well-known limitations for capturing the impact of knowledge generation (Bornmann and Leydesdorff, 2011; Csomós, 2018). For example, Qiu et al. (2024) find that some Chinese cities with very high publication volumes still have citation impacts far below the world average. In other words, pumping out more papers does not guarantee that those papers are influential or drive new knowledge. By contrast, Ioannidis et al. (2019) star scientist data inherently weights more influential work, since inclusion is based on citation impact. This allows us to verify geographic patterns at a finer scale and with a focus on influence on other research outputs, not just output quantity. Moreover, our career-long citation metrics mitigate fluctuations arising from short-term attention or individual breakthrough papers compared to single-year datasets. This approach provides a more robust measure of the entrenched, structural geography of global innovation. In sum, the dataset employed in this paper offers a more nuanced and dynamic indicator of local research capacity — one that balances productivity and impact — compared to traditional volume-based metrics.

3.2 Geocoding and spatial allocation

To analyse the geography of star scientists, we must accurately assign each scientist to a location. The dataset provides the institutional affiliation(s) of each researcher (based on their most recent publications). We geocode these affiliations and aggregate them to the city level (and, for some analyses, to regions and countries). This process involved several steps. First, we adopted consistent definitions of what constitutes a "city" across different countries. Administrative boundaries and city definitions can vary widely, so for global consistency we used the geographic definitions of ADM-2 level from the Global Administrative Areas (GADM) database, e.g., London in the UK and Beijing in China. A limitation is that, in the United States, ADM-2 corresponds to counties, which are not comparable to city units elsewhere. We therefore use the U.S. Census Bureau's Combined Statistical Areas (CSAs) to represent U.S. city-regions. Applying these definitions yielded a universe of 44,250 standardized urban units globally, providing a consistent framework for comparing cities across countries.

Each star scientist was then assigned to a city based on the location of their primary institutional affiliation. In cases where a scientist had multiple affiliations, the most prominent or primary affiliation was used. Figure 1 illustrates this hierarchical allocation process: individual scientists (N1, N2, etc.) are linked to their institutions (I1, I2, etc.), which are in turn mapped to specific cities and countries. For example, a scientist affiliated with Harvard University would be mapped to the Boston metropolitan area (USA), whereas one at Tsinghua or Peking Universities would map to Beijing (China).

Fig.1. Allocation of scientists to institutions, cities, and countries



We undertook data cleaning to address ambiguous or incomplete affiliation information. A small number of observations listed only a department or lacked a clear institution name (e.g. "Cardiology Department" with no university specified); these could not be reliably geocoded and were excluded. Given the very large sample, such exclusions were randomly distributed and constituted a negligible fraction of the data, so their omission is unlikely to bias the results. After geocoding and cleaning, our final panel comprises 757,500 scientist-year records, covering 59,162 unique institutions across 3,635 cities in 201 countries over the 2019–2023 period. This dataset provides an unprecedented level of geographical detail for determining where top scientific talent is located.

3.3 Knowledge generation index (KGI) and inequality measures

With individual star scientists assigned to cities, we construct aggregate metrics to compare cities' research strength. A straightforward measure is the count of star scientists in each city. Another is the average citation rank of those scientists (a proxy for their average research impact). However, using either measure alone can be misleading because cities differ on both dimensions. Some cities have a large number of star scientists, but those scientists might on average have relatively lower citation impact; other cities may have fewer star scientists, but those individuals are among the very top-ranked in influence. We observe substantial disparities in both the number of scientists and their average ranks across cities. For example, in 2023 London (UK) hosted 4,466 star scientists with an average citation-based rank of 118,127, whereas Zaqaziq (Egypt) had only 19 star scientists with an average rank of 232,286. Likewise, Beijing had more star scientists than the Chicago metro area (2,571 vs. 2,460), yet Beijing's scientists had a much lower average influence rank (196,440) compared to Chicago's (111,020). In these cases, a simple headcount would favour Beijing, while an average-quality metric would favour Chicago. This would result in two very different stories about which city is "ahead." These examples illustrate how focusing on only quantity or quality risks providing an incomplete picture.

To address this, we develop a composite Knowledge Generation Index (KGI) that balances both scientist quantity and impact for each city. The KGI construction follows a two-step process:

1. **Standardise Score:** For each city–year, we construct two inputs: (i) the average c-score rank of that city's star scientists, and (ii) the city's position in scale, measured by its standing in the global distribution of star-scientist counts (e.g., its share of the total or its percentile among cities). To smooth idiosyncratic spikes and reduce skew across the long tail of cities, we apply logarithmic transformations to both inputs: we take the natural log of the city's average c-score rank and, symmetrically, the natural log of its star-scientist headcount (using a log-plus-one where counts can be zero).
2. **Composite Index (KGI):** To align the directions of quantity and impact, we treat citation rank — where a smaller number denotes higher impact — as the denominator of the indicator, so improvements in rank mechanically raise the measure and increases in headcount also raise it. We use each city's average citation rank to temper the influence of extreme individual cases and produce a stable signal of typical impact. We then place both components on a common scale: each year, we convert a city's number of star scientists and its denominator-based impact measure into percentiles across all cities and divided by the mean rank of the city level star-scientists as the Knowledge Generation Index.

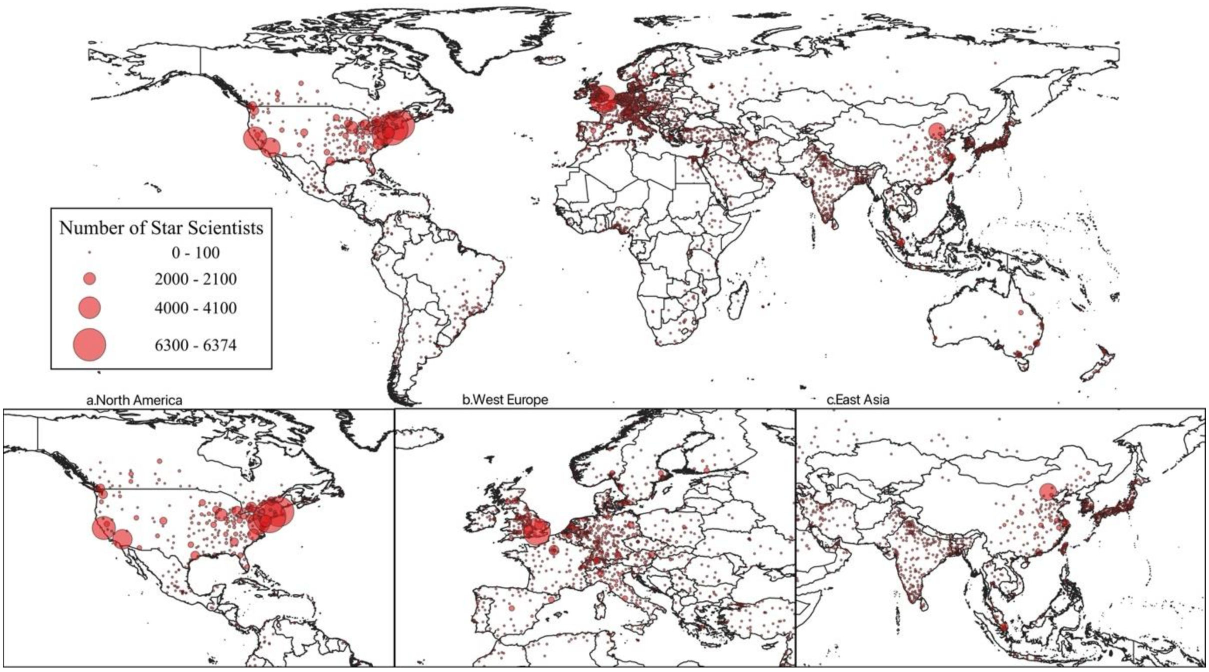
This approach yields a balanced index that rewards cities for attracting more star scientists and for hosting highly influential scientists. The use of percentile normalisation also reduces the influence of extreme outliers (such as the very largest or very smallest cities), facilitating more meaningful comparisons across the full spectrum of cities. For example, in 2020, Beijing counted 1,503 star scientists (12th globally) and Toronto 1,496 (13th). However, Toronto's scientists had a higher average global rank (99,477.61) than Beijing's (182,680.91). After applying the KGI, Beijing's city rank shifts to 16th, while Toronto rises to 11th. The KGI thus not only depends on the number of star scientists in a city but also captures the sensitivity of their scientifical impact. The use of a percentile scaling improves comparability and limits the impact of outliers (see Appendix 1 for details). In addition to the KGI, we calculate Gini coefficients to quantify the degree of concentration or inequality in star scientist counts at various scales: globally, within countries, and across disciplines. The Gini coefficient (ranging from 0 to 1) provides a summary measure of how unequally star scientists are distributed: a higher Gini indicates that a small number of units (cities or countries) hold a large share of the scientists, whereas a lower Gini would suggest a more even spread. These inequality measures will help us assess the extent and evolution of geographic concentration in scientific talent.

4. Results and discussion

4.1 Global distribution of star scientists

We begin by examining the global distribution of star scientists by providing a world map of the city-level concentration of star scientists in 2023 (Figure 2). It is immediately apparent that top scientific talent is highly geographically clustered. Consistent with earlier, more limited observations of star scientist clustering (Moretti, 2014; Agrawal et al., 2017), the map shows that the greatest star researcher hubs are found in a few major cities in North America and, to a much lesser extent, in Western Europe and East Asia.

Fig. 2. Geographical distribution of star scientists in cities in 2023



Notes: Data are aggregated at metropolitan area (MSAs) in the US, NUTS3 level in the EU and equivalent administrative units around world.

In North America, the eastern seaboard of the United States forms an immense “supercluster” of star scientists. The Boston–New York–Washington corridor alone accounts for more than 18,200 scientists just in its four main hubs. This corridor contains multiple Ivy League and other elite universities, top research hospitals, government labs, and R&D-intensive industries, which together create an unparalleled constellation scientific talent. Other significant U.S. concentrations appear on the West Coast (centred on the San Francisco Bay Area and Southern California) and around major research universities in the Midwest (e.g., Chicago), though these are smaller than the Northeast cluster.

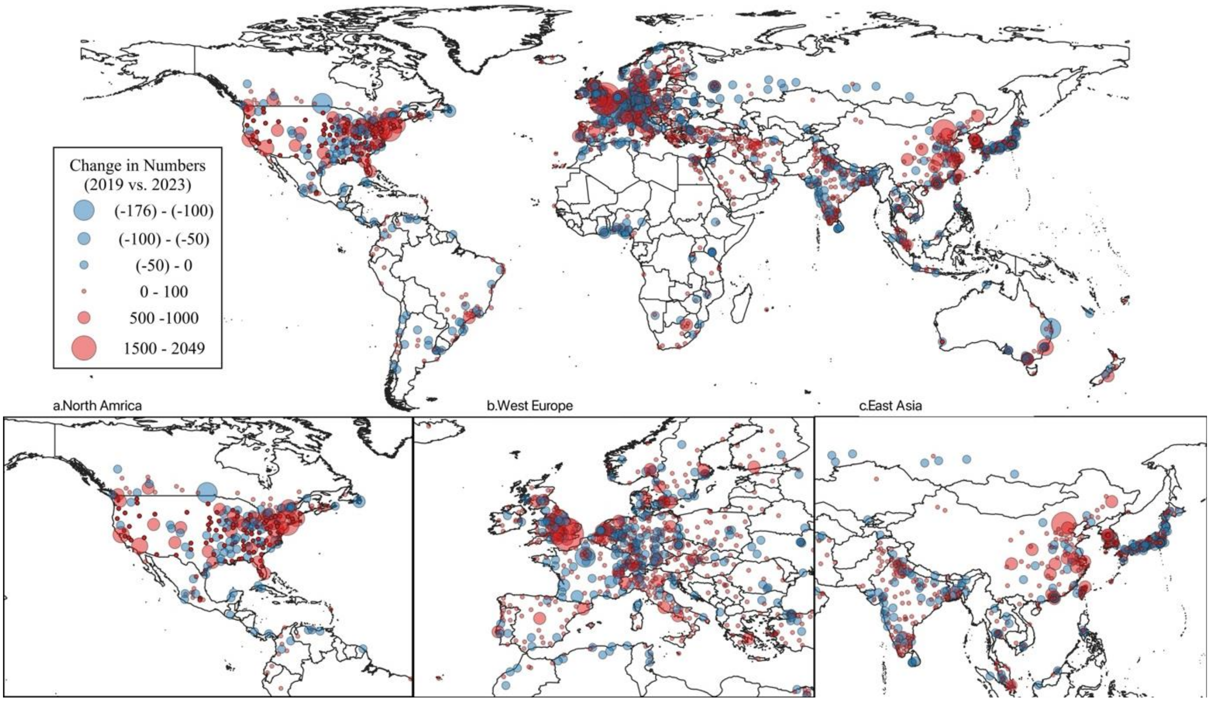
In Europe, London stands out as the dominant European hub with 4,466 star scientists in 2023, reflecting the city’s role as a global research centre. A secondary concentration is visible in the Paris region and additional notable clusters include major university centres such as Oxford and Cambridge in the UK, and Munich and Berlin in Germany. Beyond these hubs, Europe’s distribution is somewhat more evenly spread than the U.S., with a network of medium-sized clusters rather than giant mega-clusters. Nonetheless, a London-Paris axis clearly emerges as a core of European science.

Asia shows a similarly concentrated dynamic focused on a few rising megacities. Beijing has surged to become the pre-eminent Asian science hub, hosting 2,571 star scientists. Other notable Asian centres include Shanghai, Hong Kong, Singapore and Tokyo, each with substantial star scientist communities. Outside these top-tier Asian cities, however, much of the continent has relatively few star scientists.

By contrast, vast swathes of the globe have negligible representation among star scientists. Particularly in Africa, but also in Latin America and much of the developing world, only a handful of cities host more than a dozen star scientists. Many countries in these regions have no city reaching that threshold. The map thus paints a picture of extreme concentration: the global knowledge economy’s elite researchers are predominantly located in a small set of “superstar” cities in advanced economies, with only a few emerging challengers elsewhere.

To explore dynamics over time, Figure 3 maps the changes in star scientist counts by city between 2019 and 2023, a period of unusual churn as a result of the COVID pandemic (the annual maps are provided in Figure A1 in appendix). Despite overall growth in scientific output globally, a majority of cities lost star scientists over this five-year period. The gains in numbers of star scientists mainly accrued in a select few major hubs. Hence, recent years have witnessed a growing spatial concentration of scientific talent: the strongest cities are capturing even more top researchers, while mid-tier and smaller centres are often seeing declines.

Fig. 3. Changes of star scientists in cities



Among the big winners, Beijing stands out with the highest growth. Beijing more than doubled its star scientists, from 1,157 in 2019 to 2,571 in 2023 (Figure 4); a 122.2% increase. This catapulted Beijing into the top tier of global science cities by size. London also registered a significant rise of 41.4% (adding roughly 1,300 star scientists to reach 4,466). In North America, established hubs like New York, Boston, Washington, D.C., and Los Angeles saw the largest absolute gains, alongside a few notable additions such as Montreal.

The steepest declines were seen in mid-sized research centres in advanced economies. For example, Brisbane lost 176 star scientists from its 2019 count, while Essonne lost 164 and Winnipeg 151 (Figure 4). Four French regions were among the top ten decliners, suggesting increased spatial concentration and broader challenges within the French innovation ecosystem during this period. The consistent pattern is that nearly all rapidly gaining cities already had substantial star scientist populations (over 1,000 in 2019), whereas all the major losers started with fewer than 1,000. This points to a strong path dependence in star scientist agglomeration: established hubs with critical mass are pulling yet further ahead, while smaller centres without sufficient critical mass are falling behind (Figure 5). Advantages seem to compound over time in the big clusters, whereas disadvantages compound in the periphery.

Fig.4. Changes in numbers of star scientists by agglomeration (2023 vs. 2019)

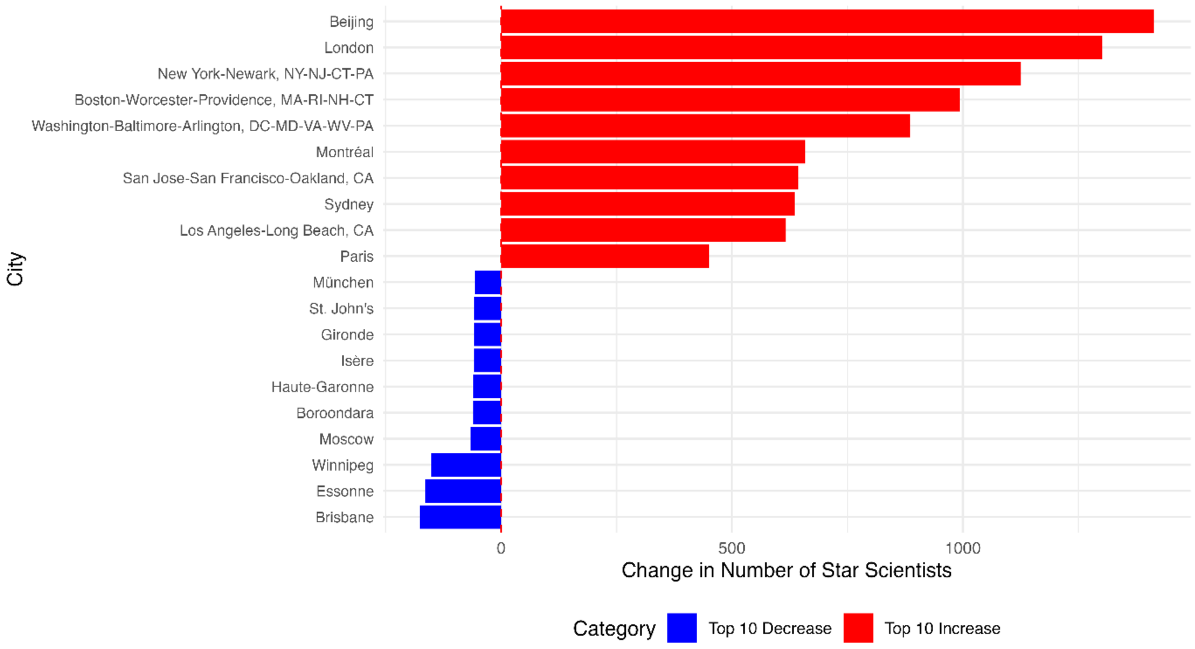
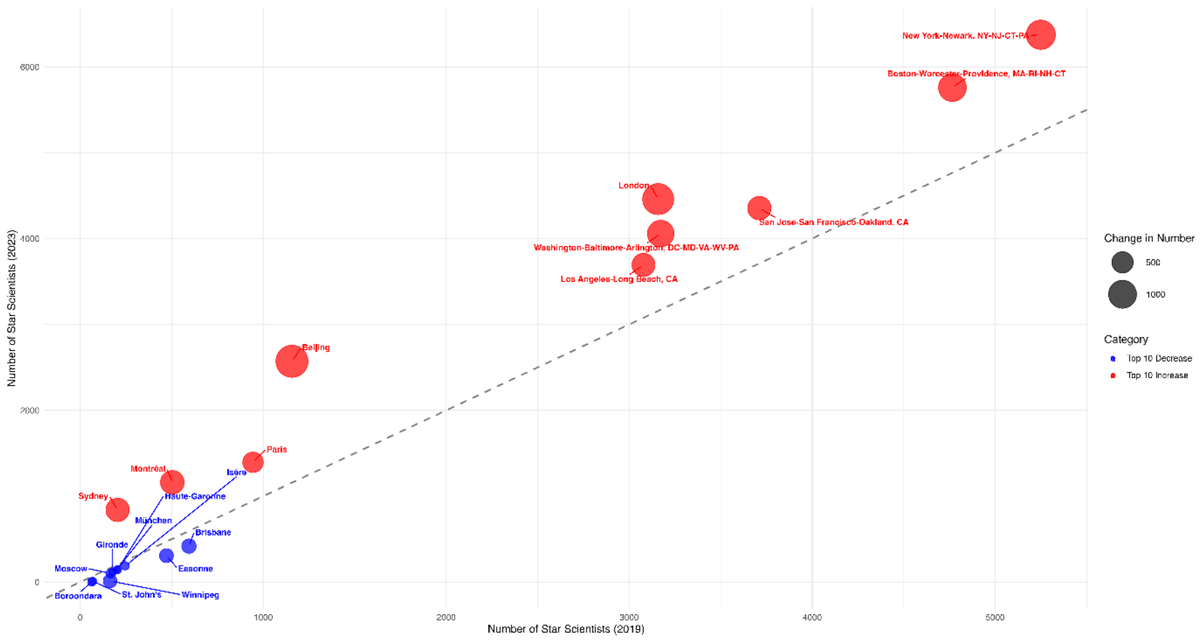


Fig.5. Number of the stars scientists by urban agglomeration in 2019 and 2023.



The global hierarchy of star scientist concentrations is detailed in Table 1, which lists the top 50 cities by number of star scientists in 2023. New York tops the list with 6,374 star scientists, followed by Boston with 5,759, London with 4,466, and the San Francisco Bay Area with 4355. Together, New York and Boston alone account for more than 7% of these top scientists in the dataset, underscoring the extraordinary weight of just two U.S. metropolitan areas in global science. Indeed, American cities dominate the upper echelons of the ranking: 11 of the top 15 and 26 of the top 50 cities are in the United States, and these U.S. cities alone collectively host 63.5% (48,248) of all the star scientists found in the top 50 centres. This concentration is even more pronounced than patterns observed in other domains like high-tech entrepreneurship, where European and Asian hubs often play a larger role (Crescenzi et al., 2007).

Table.1. Top 50 cities in the number of star scientists in 2023

Country	City	Number	Rank	Pct.
USA	New York-Newark, NY-NJ-CT-PA	6374	1	3.68%
USA	Boston-Worcester-Providence, MA-RI-NH-CT	5759	2	3.32%
GBR	London	4466	3	2.57%
USA	San Jose-San Francisco-Oakland, CA	4355	4	2.51%
USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	4058	5	2.34%
USA	Los Angeles-Long Beach, CA	3694	6	2.13%
CHN	Beijing	2571	7	1.48%
USA	Chicago-Naperville, IL-IN-WI	2460	8	1.28%
USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD	2069	9	1.19%
USA	Raleigh-Durham-Chapel Hill, NC	1941	10	1.12%
USA	Detroit-Warren-Ann Arbor, MI	1758	11	1.01%
CAN	Toronto	1607	12	0.87%
USA	Seattle-Tacoma, WA	1485	13	0.86%
USA	Houston-The Woodlands, TX	1435	14	0.83%
FRA	Paris	1394	15	0.80%
CHN	Hong Kong	1359	16	0.78%
USA	Atlanta--Athens-Clarke County--Sandy Springs, GA	1348	17	0.78%
GBR	Oxford	1254	18	0.72%
USA	Pittsburgh-New Castle-Weirton, PA-OH-WV	1176	19	0.68%
CAN	Montréal	1161	20	0.67%
GBR	Cambridge	1141	21	0.66%
USA	Denver-Aurora, CO	1122	22	0.65%
CAN	Greater Vancouver	1078	23	0.62%
SGP	Singapore	988	24	0.57%
USA	Madison-Janesville-Beloit, WI	973	25	0.56%
CHN	Shanghai	935	26	0.54%
USA	Minneapolis-St. Paul, MN-WI	901	27	0.52%
AUS	Melbourne	892	28	0.51%
DEU	München (Kreisfreie Stadt)	881	29	0.51%
USA	Cleveland-Akron-Canton, OH	864	30	0.49%
NLD	Amsterdam	848	31	0.49%
AUS	Sydney	840	32	0.48%
USA	Sacramento-Roseville, CA	838	33	0.48%
DEU	Berlin	826	34	0.48%
USA	St. Louis-St. Charles-Farmington, MO-IL	784	35	0.45%
GBR	Manchester	779	36	0.45%
USA	Columbus-Marion-Zanesville, OH	755	37	0.44%
USA	Dallas-Fort Worth, TX-OK	748	38	0.43%
USA	Gainesville-Lake City, FL	741	39	0.43%
AUT	Wien Stadt	739	40	0.43%

USA	Ithaca-Cortland, NY	727	41	0.42%
GBR	Edinburgh	717	42	0.41%
ESP	Barcelona	709	43	0.41%
DNK	København	699	44	0.39%
USA	State College-DuBois, PA	649	45	0.37%
FIN	Uusimaa	643	46	0.37%
JPN	Bunkyō, Tokyo	642	47	0.37%
USA	Salt Lake City-Provo-Orem, UT	633	48	0.36%
GBR	Glasgow	603	49	0.35%
USA	Nashville-Davidson--Murfreesboro, TN	601	50	0.35%

Looking at continental patterns, we see distinct geographies. Europe exhibits a dual-core pattern, with London and Paris as the dominant hubs (a combined 5,860 star scientists). They are followed, at some distance, by a set of secondary European nodes such as Munich and Berlin (Germany), Amsterdam (the Netherlands), or Milan (Italy) which have substantial but smaller star scientist populations. In Asia, the landscape is currently dominated by Beijing, which has leapfrogged into the global top ten. Hong Kong, Singapore and Shanghai also rank among the top 30 globally. Many other Asian cities, however, still lag far behind.

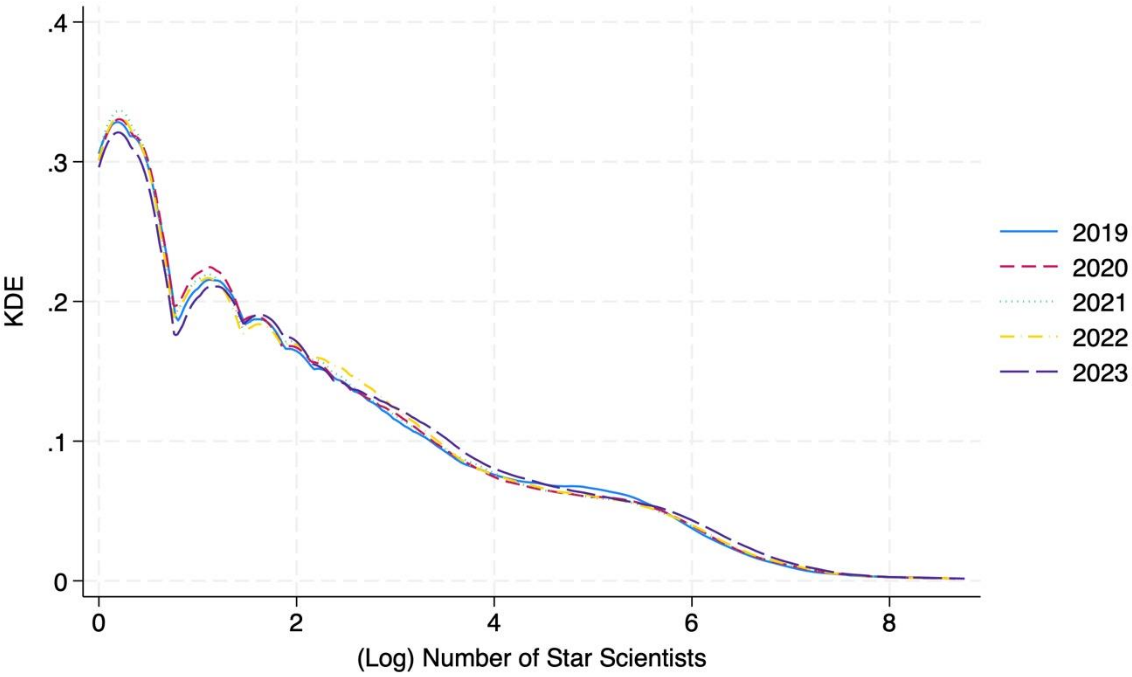
The Global South overall remains remarkably underrepresented. As of 2023, no city in the Global South (outside China) ranks in the top 50 for star scientists. Most countries in Africa, Latin America, and large parts of Asia have no city with more than 1,000 star scientists. For example, Luanda — the thriving capital of Angola — had only 12 star scientists in 2023. Even where there are pockets of excellence, they tend to be isolated individuals rather than clusters. In Bangalore, India's leading science city, the count rose only modestly from 187 in 2019 to 213 in 2023. But these numbers pale in comparison to the thousands concentrated in Boston or Beijing. We observe a scattered mini-stars phenomenon across the Global South: individual researchers may achieve global prominence, but they are too few and too dispersed locally to form self-sustaining research clusters. Factors like underdeveloped research infrastructure, unstable funding, and brain drain continue to impede the formation of dense scientific communities in these regions. In essence, many developing countries are witnessing some talented scientists reach world-class level, yet those scientists often remain lone stars rather than seeding vibrant local ecosystems. This stands in stark contrast to places like Boston or San Francisco, where star scientists benefit from — and continuously reinforce — a dense local network of elite peers, abundant resources, and supporting industries. The Global South's challenge is moving from sporadic excellence to critical mass. Without sufficient concentration of talent and resources, even brilliant researchers struggle to have an impact locally.

Additional detail on the persistence of leading cities can be found in Appendix Tables A1, which list the top 50 cities by star scientists on an annual basis over 2019–2023. The usual suspects — New York, Boston, San Francisco, London, Los Angeles — consistently top the rankings. New York and Boston maintained the number 1 and 2 positions every year between 2019 and 2023. London was 5th in 2019 and 4th from 2020 to 2022; in 2023 it moved up to 3rd, surpassing the San Francisco Bay Area. These subtle shifts (London overtaking Washington and San Francisco, Beijing climbing the ranks) highlight that while the overall geography of scientific excellence is stable, there are meaningful movements within the elite group. One remarkable trend is the rising prominence of Chinese cities. As noted, Beijing jumped from 14th place in 2019 to 7th by 2023. Similarly, Shanghai climbed from 39th to 26th. This reflects China's rapid expansion of research capacity and the impact of heavy public and private R&D investments in its top universities and institutes. By contrast, most cities in lower-income countries made only marginal gains in rank, if any. For example, Delhi moved up from 162nd to 123rd between 2019 and 2023 (from 181 to 325 star scientists). This represents a considerable improvement but the Indian capital remains still far outside the top tier. And the long tail of cities with minimal star presence is huge: 65.8% of all cities in our data had fewer than 10 star scientists in 2019 and by 2023 this share only inched down to 64.1%. In other words, nearly two-thirds of cities in our sample host a minimal number of star scientists and this has not substantially changed in recent years. The global geography of scientific talent thus remains highly uneven and stubbornly so, with most of the developing world essentially a negligible player in frontier knowledge production.

4.2 Intensifying inequality: Global and national patterns

To quantify the degree of spatial inequality in star scientist distribution, we calculate the kernel density of city-level star scientist counts and the Gini coefficient across various groupings. Figure 6 presents kernel density estimates of the (logarithm of) the number of star scientists per city for each year 2019 through 2023. Several consistent features emerge. Across all years, the distribution of cities by star scientist count is bimodal.

Fig.6. Kernel Density Estimation



There is a primary peak at the very low end (around a value of 0.3, which corresponds to two star scientists). Hence, a very large number of cities included in the sample host only a handful of star scientists. Then there is a secondary, much smaller peak around 1.5 (about 5-6 star scientists). This suggests a persistent bifurcation in the global scientific landscape: a broad base of cities with virtually no star scientists, and a select subset with modestly higher but still limited concentrations. The distribution's long right tail, extending to 8 on the log scale, reveals extreme concentration; the minimal kernel density at this range indicates that very few cities host over 2,900 star scientists.

Importantly, these distributions are remarkably stable over the period. The different yearly curves almost overlap for every year considered (Figure 6), implying that the overall structure of global talent distribution changed little. There are minor signs of change — for example, the secondary peak (representing the small clusters) may have grown slightly denser or shifted marginally, and the upper tail might have lengthened as top cities accumulated even more scientists. Such subtle changes could reflect the impact of economic shifts, new policies, or, most likely, the COVID-19 pandemic on specific cities. But the big picture is one of structural persistence: the world's scientific talent distribution remains entrenched, with a vast majority of cities stuck at very low levels and only a tiny fraction managing to host large communities of star scientists. This aligns with theories in economic geography that emphasise how difficult it is to alter established spatial hierarchies of innovation (Krugman, 1991; Crescenzi et al., 2014). In essence, global scientific hierarchies are resilient and self-reinforcing.

Another way to measure inequality in the location of star scientists is the Gini coefficient. Globally, the Gini for the distribution of star scientists across cities is extremely high (close to 0.90 in our data, depending on year, see Fig.A2 in appendix), confirming high concentration. We also compute Gini coefficients within individual countries and within disciplines to see how concentration varies at those levels. Figure 7 displays the distribution of star scientists among cities each year, stressing the persistent dominance of a few urban centres over time. Figure 8 shows the Gini indices for the top 20 countries over the five-year period. Among leading countries, inequality is somewhat less extreme than the global level, but still very high. Moreover, in many countries the Gini is increasing over time, indicating growing internal concentration of talent. Star scientists are not just unevenly distributed across the world, their location is also highly uneven within individual countries.

Fig.7. Distribution of star scientists in cities (2019-2023).

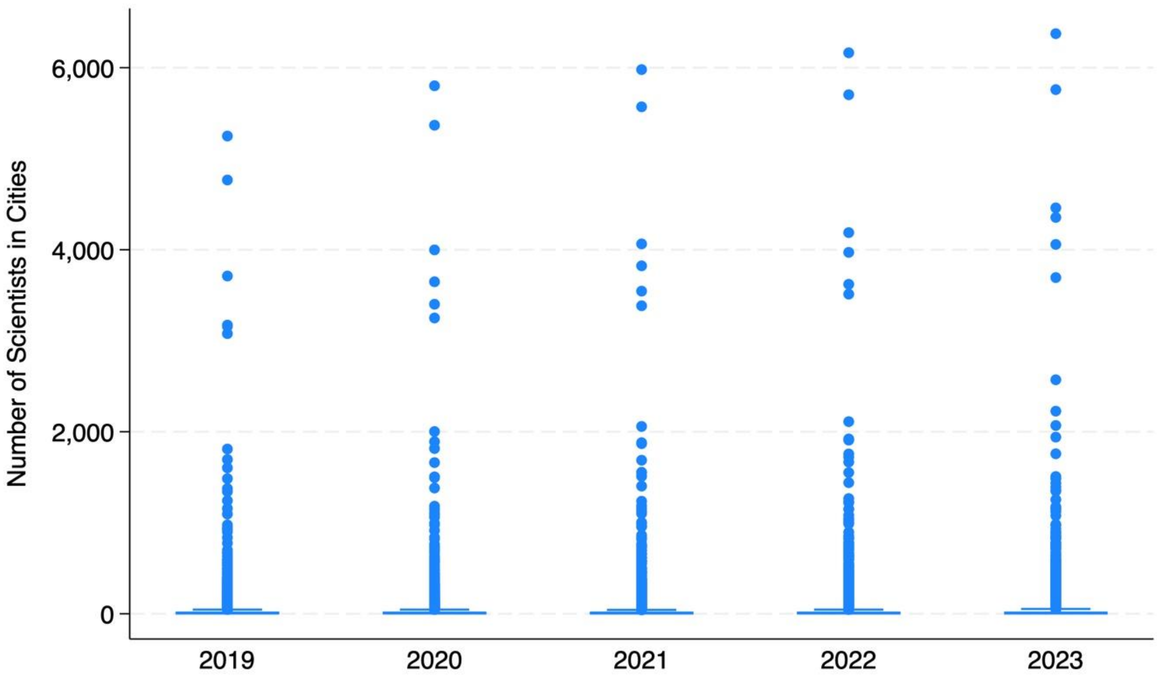
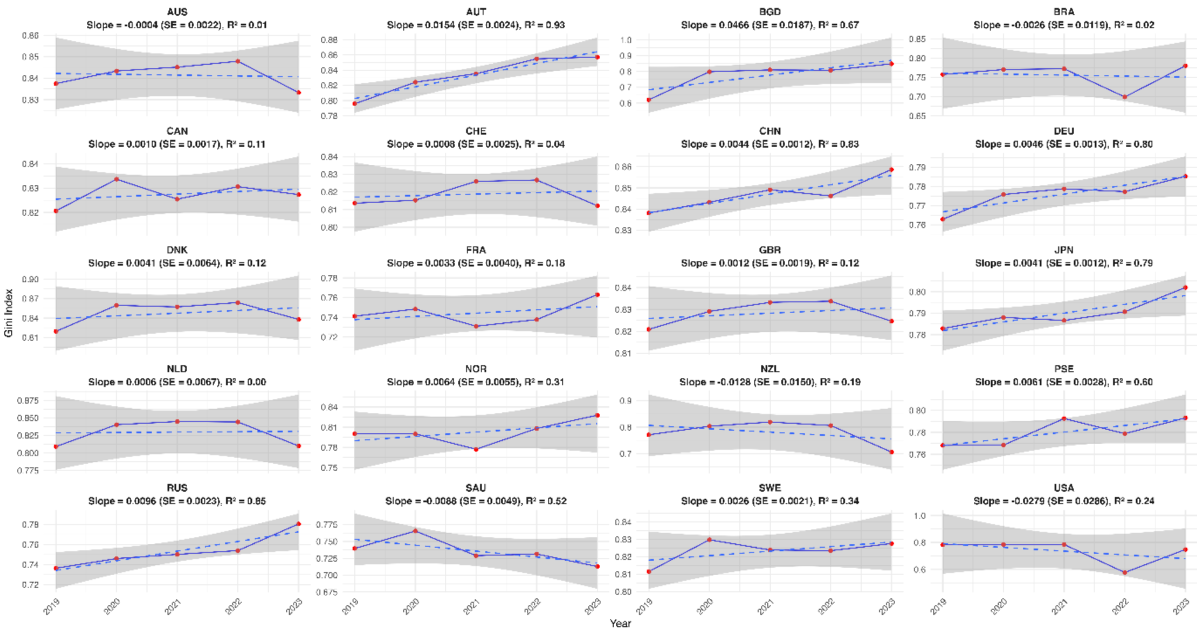


Fig.8. Top 20 countries Gini Index (2019-2023).



For example, Switzerland, a country with a high concentration of star scientists, also shows one of the highest levels of internal inequality. Between 2019 and 2023 its Gini coefficient rose from 0.81 to 0.86. Hence, Swiss-based star scientists became slightly more concentrated in its top cities — mainly in Zürich — while relatively fewer were found in the rest of the country by 2023. Another striking case is Bangladesh, a country with an emerging research sector: its city-level Gini jumped from 0.62 to 0.82 in just five years. This suggests that Bangladesh's modest increase in star scientists is heavily skewed towards Dhaka, with almost all new star scientists agglomerating there. In contrast, Canada maintained a high but stable Gini (0.82–0.83). Canada's scientific talent is known to be split primarily between Toronto, Montreal, and Vancouver, and that multi-polar structure did not change much. Internal disparities neither widened nor narrowed appreciably. These examples reflect how national contexts differ.

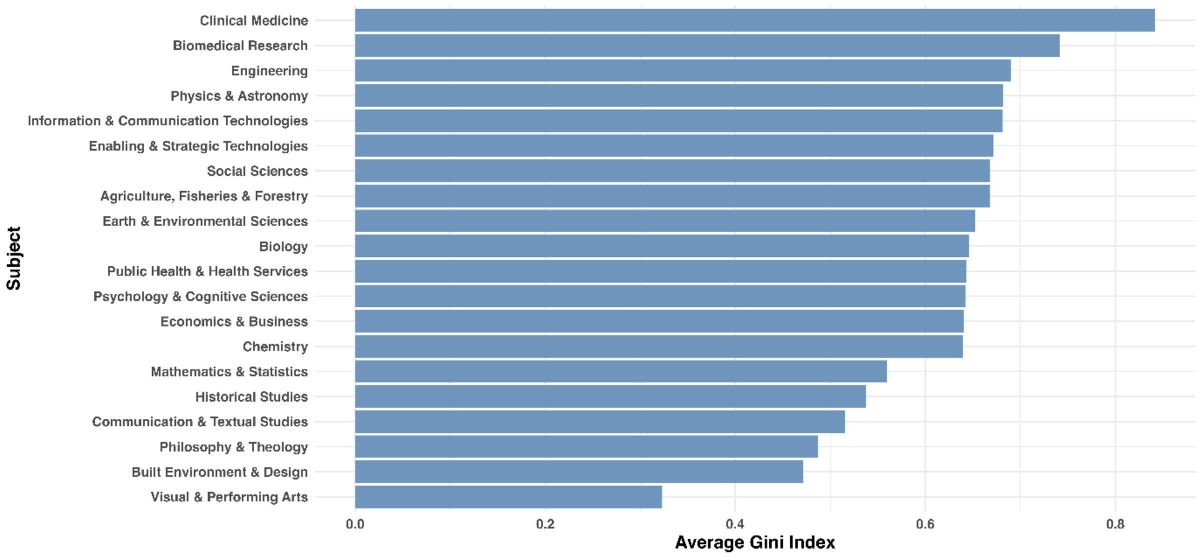
The pattern across countries is one of highly concentrated innovation. Even when we look within the 20 most scientifically prolific countries, the average Gini is only slightly lower than the global Gini, meaning that inequality in scientific knowledge generation is pervasive at multiple scales. During 2019–2023, nearly all of these top countries experienced either persistently high or increasing concentration of their star scientists in one or a few cities, Saudi Arabia being the main exception (Figure 8). The dynamics, of course, vary: in some nations, a single mega-city dominates (e.g. nearly all of Argentina's star scientists are in Buenos Aires); in others, a few cities share (e.g. Italy's stars are divided among Rome, Milan, Bologna, Turin, Padua). But a common theme is that scientific talent does not spread out easily or evenly within countries, let alone globally.

Concentration forces — whether driven by historical institutions, funding patterns, or network effects — remain extremely strong.

4.3 Disciplinary disparities in concentration

We turn now to differences across scientific disciplines. Is the clustering of star scientists primarily a phenomenon of certain fields (perhaps those that require large labs or expensive equipment), or is it universal? To investigate this, we calculate Gini coefficients for the distribution of star scientists within each discipline (Figure 9). The results reveal substantial heterogeneity between fields. Some disciplines are much more geographically concentrated than others. For instance, Clinical Medicine stands out as one of the most unevenly distributed fields, with an average city-level Gini of 0.85. This indicates that a very small number of cities globally account for a disproportionately large share of top clinical researchers. Indeed, star clinicians tend to cluster in a few major medical hubs (e.g. Boston, New York, London) with leading hospitals, medical schools, and biotech industries. In contrast, fields like Philosophy & Theology, Built Environment & Design, or Visual & Performing Arts have far lower Gini coefficients — below 0.5 — implying a more dispersed distribution of star scholars. Leading research in these fields is more spread across a variety of universities worldwide rather than all packed into a handful of elite institutions.

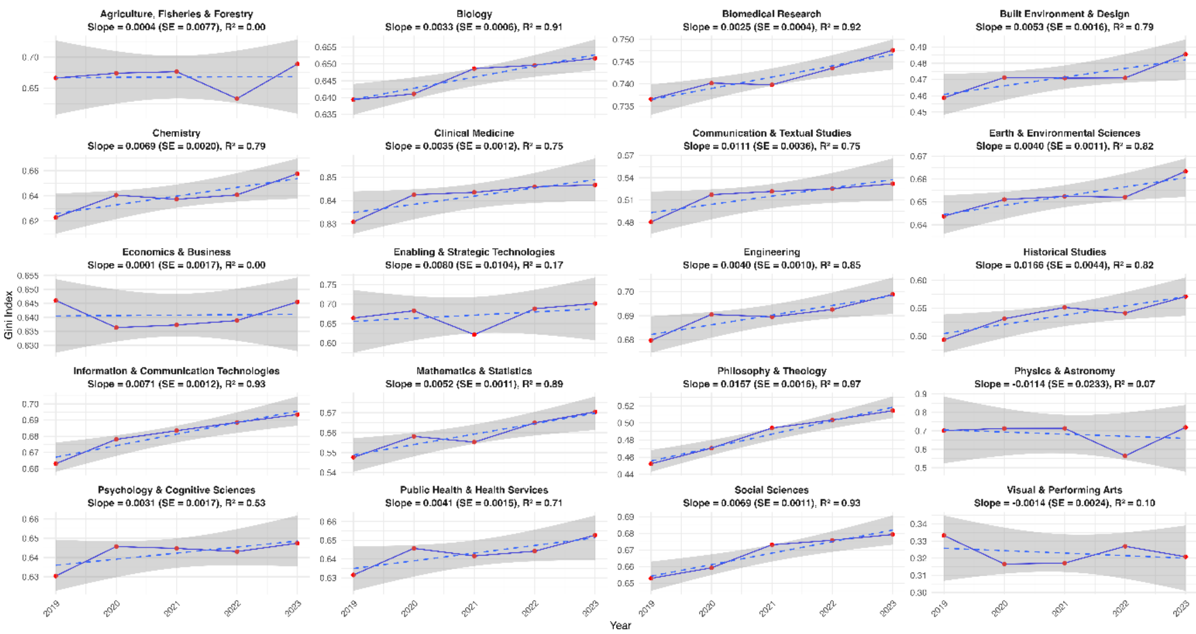
Fig.9. Gini Index of star scientists across subjects.



Most disciplines fall somewhere between these extremes. For example, Engineering, Biomedicine, and Physics/Astronomy exhibit Gini values in the 0.63–0.75 range. Fields like Mathematics and Social Sciences show moderate concentration (Gini in the high 0.5s to 0.6s), suggesting a somewhat broader distribution of talent. What drives these differences? It appears linked to the nature of research infrastructure and collaboration in each field. Clinical Medicine and biomedical sciences often require expensive laboratories, hospitals, and highly specialised equipment — resources typically available in only a few top locations — hence scientific stars congregate there. By contrast, scholars in humanities or theoretical fields can work from more varied locations (a brilliant philosopher can reside at a smaller university and still produce influential work), leading to less skewed geography.

We also examine how these disciplinary concentration patterns have evolved over the period of analysis (Figure 10). A notable finding is that nearly all disciplines show a trend toward increasing concentration in recent years, although the magnitude of change varies. Even fields that traditionally were more geographically dispersed (like some social sciences or mathematics) have started to see more clustering of top cited researchers. For instance, Social Sciences saw its Gini inch up from 0.65 to 0.68 over 2019–2023, and Mathematics from 0.55 to 0.57. These are small rises but indicate movement towards greater agglomeration. On the other hand, a few disciplines experienced temporary dips or non-linear trends. Physics & Astronomy and Agriculture showed a sudden —possibly Covid induced— decline in Gini in 2022 , though this dip was in both cases reversed by 2023. Only Visual & and Performing Arts experienced an overall decline in concentration of star scientists over the period considered.

Fig.10. Gini Index of star scientists worldwide across subject areas (2019-2023).



In essence, while different fields have different propensities to cluster (due to their inherent resource and collaboration structures), the overall push in recent years has been toward more concentration across the board. Even disciplines once considered more location-agnostic are agglomerating. This suggests that broad systemic forces — such as the increasing returns to scale in research, global rankings and competition, concentration of funding, and the advantages of being in elite networks — are affecting all areas of science, not just the lab-heavy ones.

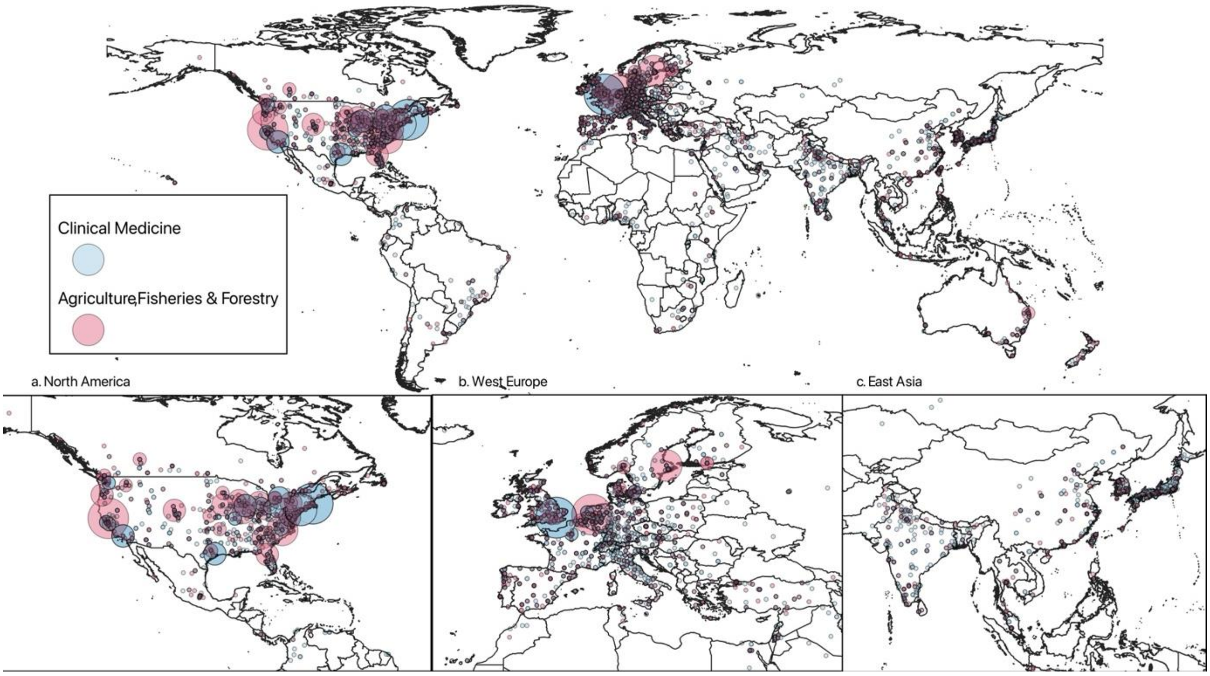
On top of the already mentioned costly infrastructure or unique facilities that are only available in certain places, two other factors can explain why some disciplines cluster more than others. First, disciplines differ in how research is organised and how credit is allocated. In some fields, collaboration is highly centralised. In others, it is distributed. High-energy physics, for instance, involves huge international collaborations (like CERN) with contributors spread globally, which can disperse star contributors geographically. By contrast, clinical medicine or biomedical science often operates via tightly knit lab groups under star principal investigators, concentrating recognition in certain institutions (Azoulay et al., 2010). The social sciences traditionally had more solo researchers or small teams, which were more spread out, though they too are gradually becoming more collaborative. Thus, the nature of collaboration influences spatial concentration: fields with big, centralised projects can allow stars to be anywhere, whereas fields with lab-centric or hierarchical team structures tend to concentrate stars where the top labs are.

Second, there is historical path dependence. The current geography of each discipline also reflects historical accumulations of expertise and reputation. Leading innovation clusters today often benefit from decades (or even centuries) of prior advantage: top universities, established funding streams, and prestigious journals or departments that are hard to replicate elsewhere. Once a city becomes known as a hub of excellence in a field, it attracts more talent and resources in that field, creating a lock-in effect (Arthur, 1989; Krugman, 1991). For example, the biggest math or economics departments have often been leading for a long time, making it difficult for a new city to suddenly rival them. These path dependencies mean that cities which gained an early edge in a particular discipline often maintain it. Even in disciplines theoretically less tied to location (like pure mathematics), we observe surprising geographic stability: social and professional networks, along with the reputational halo of certain institutions, create invisible barriers to entry for new locations. On the flip side, emerging interdisciplinary fields or newer disciplines without entrenched "old guard" centres show more flexibility for new cities to rise via targeted investment.

These factors interact in shaping disciplinary geographies. For instance, Clinical Medicine has all three factors pushing toward concentration: heavy infrastructure needs, hierarchical team science, and historically renowned hubs (e.g. the institutional legacies of Harvard Medical School and University of California, San Francisco have maintained their positions as the top two institutions by number of top 2% cited scientists in Clinical Medicine throughout 2019-2024). It is, therefore, no surprise then that star clinicians cluster overwhelmingly in a few cities. Conversely, Agricultural Sciences have less of each factor: research can be done in various environments (in fact it might benefit from diverse locations), collaborations can be field-based or spread, and historically it may not be as dominated by a few schools. Hence, stars scientists in agriculture are more geographically spread. Understanding these differences is important for crafting policy: strategies to promote a discipline in a new location need to address the specific constraints of that field (e.g. building a major facility or fostering international collaborations).

To visualise these differences, Figure 11 compares the location of star scientists for two disciplines: one highly concentrated and one relatively dispersed. The maps reveal distinct geographical distribution patterns between these fields. In Clinical Medicine, star scientists cluster in the world's premier biomedical centres — Boston, New York, London, Los Angeles, and Houston — with far smaller presence elsewhere globally. In contrast, Agriculture, Fisheries & Forestry exhibits a more dispersed pattern, with stars distributed across numerous cities and countries. Even within the same regions, agglomeration patterns differ markedly: in Europe, Agriculture, Fisheries & Forestry scientists concentrate at specialised institutions like Wageningen University & Research (WUR) in the Netherlands and Sveriges lantbruksuniversitet (SLU) in Sweden, while Clinical Medicine researchers cluster at comprehensive research universities like UCL in the UK. These comparisons demonstrate how the spatial logic of knowledge production varies fundamentally across disciplinary domains.

Fig.11. Geographical distribution of star scientists in clinical medical and Agriculture, Fisheries & Forestry in 2023



Despite these variations, an overarching trend is clear: almost every discipline is gradually concentrating more in established hubs. This concentration manifests in divergent patterns. Some cities develop as multidisciplinary powerhouses leveraging advantages across multiple fields (e.g., Boston, New York, London), while others evolve into highly specialised centres of excellence in specific domains (e.g., Wageningen and Uppsala in Agriculture, Fisheries & Forestry). However, the forces of funding concentration, network effects, and institutional prestige are increasingly cutting across all fields, even those once thought relatively location-independent. Evidence from the Gini index trends (Figure 10) and temporal changes in star scientist distributions (Figure 3) reveals that as science becomes ever more competitive and globalised, the advantages of being in a top research cluster (access to collaborators, funding, visibility) are growing, and even scholars in traditionally far-flung fields gravitate toward the major centres. This raises important questions about the future diversity of intellectual contributions and whether important ideas might be missed if they do not emanate from the usual places.

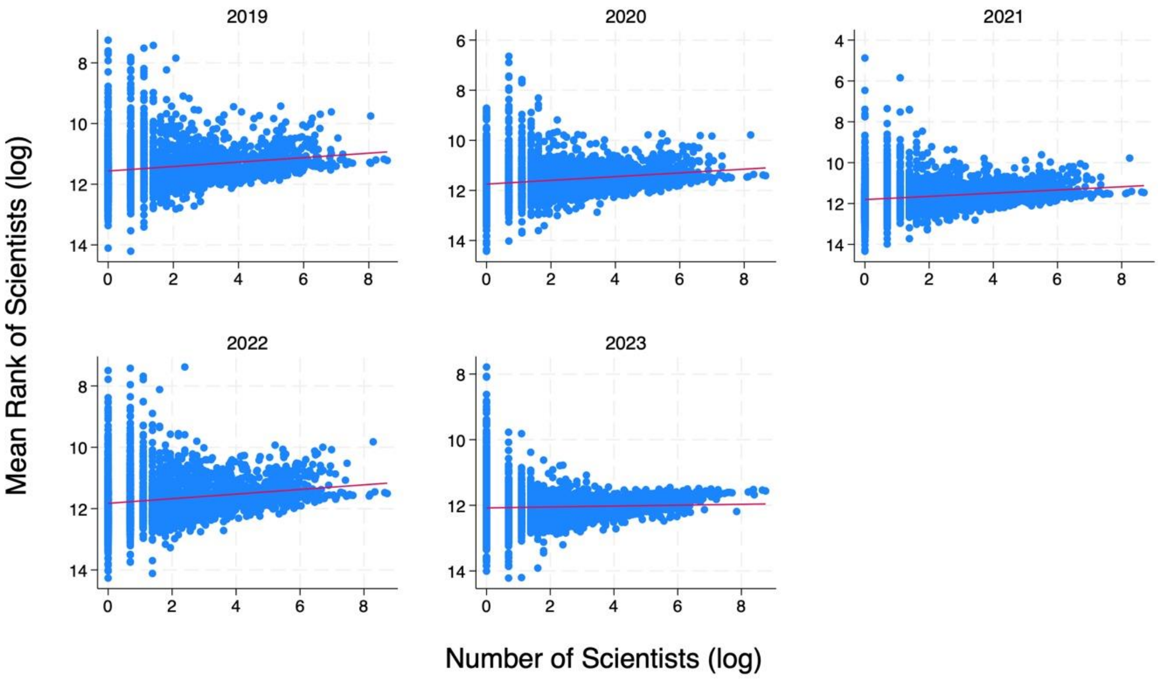
4.4 Quantity and impact: The KGI and superstar cities

Having examined the distribution of star scientists, we now bring together the quantity and impact dimensions using the Knowledge Generation Index (KGI). Figure 12 plots cities in a two-dimensional space: the horizontal axis is the number of star scientists (a measure of scale) and the vertical axis is the average citation impact rank of those scientists (a measure of impact, where higher means better average performance). Each city's five-year trajectory (2019–2023) can be visualised in this space, but for simplicity we focus on general trends. There is a robust positive correlation between a city's scale of scientific talent and the average impact of that talent. In other words, cities with more star scientists also to have higher average-impact researchers. Scale and excellence are mutually reinforcing in knowledge production, not a trade-off. This pattern holds consistently across the years of analysis.

What drives this correlation? It is likely to reflect several mechanisms. In large scientific communities, there are abundant opportunities for both formal collaboration and informal knowledge exchange (coffee-room discussions, lunch meetings, brown-bag seminars), which can spark new ideas and inspire research. Big hubs also enjoy shared infrastructure — whether that is cutting-edge labs, supercomputing facilities, or simply efficient administrative support — which individual researchers can leverage for higher productivity. Furthermore, prestige is a factor: top researchers are often attracted to places with other top researchers. An elite university in a big city can recruit star faculty who then win major grants, train outstanding students, and push the institution's reputation even higher, thereby attracting the next generation of talent. These self-reinforcing dynamics create what in science is known as a Matthew effect (Merton, 1968), where the rich get richer, although here operating at the city scale. Once a city becomes known as a leading centre, it draws in yet more high-performing scientists, creating an upward spiral of talent agglomeration and achievement.

In the bottom-left of the Figure 12 plot (low scale, low impact) are cities that have only a few star scientists and those scientists are, on average, of more modest impact. In the top-right (high scale, high impact) are the "superstar cities": places like Boston, New York, and London that dominate on both counts. These cities combine exceptional quantity and impact of scientific talent. They illustrate how historical advantages can compound to create seemingly insurmountable leads. For instance, Boston's combination of Harvard, MIT, other world-class universities, research centres and hospitals, and abundant research-driven firms means it has thousands of star scientists whose work is collectively among the most influential in the world. New York and London similarly leverage their massive academic and medical ecosystems to host both large numbers of stars and very prominent ones.

Fig.12. Correlations between number of star scientists and mean rank of scientist by cities from 2019 to 2023



Notes: The vertical axis represents the average rank of star scientists based on the citation score, where lower values denote higher rank (i.e., superior research influence or performance). The horizontal axis represents the number of star scientists at the city level, reflecting the quantitative concentration of elite researchers within urban areas.

Over the 2019–2023 period, these superstar cities not only grew their star scientist counts by sizeable margins (often 20–35% increases) but also improved the average citation ranking of their scientists. Leading cities are thus not just getting bigger in terms of talent, they are getting better too. They are adding star scientists at a faster pace than lesser cities, and the newcomers are often high-impact researchers themselves, which pushes the average impact up. This dual enhancement — more stars and higher impact per star — underscores how agglomeration benefits operate on both extensive (quantity) and intensive (impact) margins.

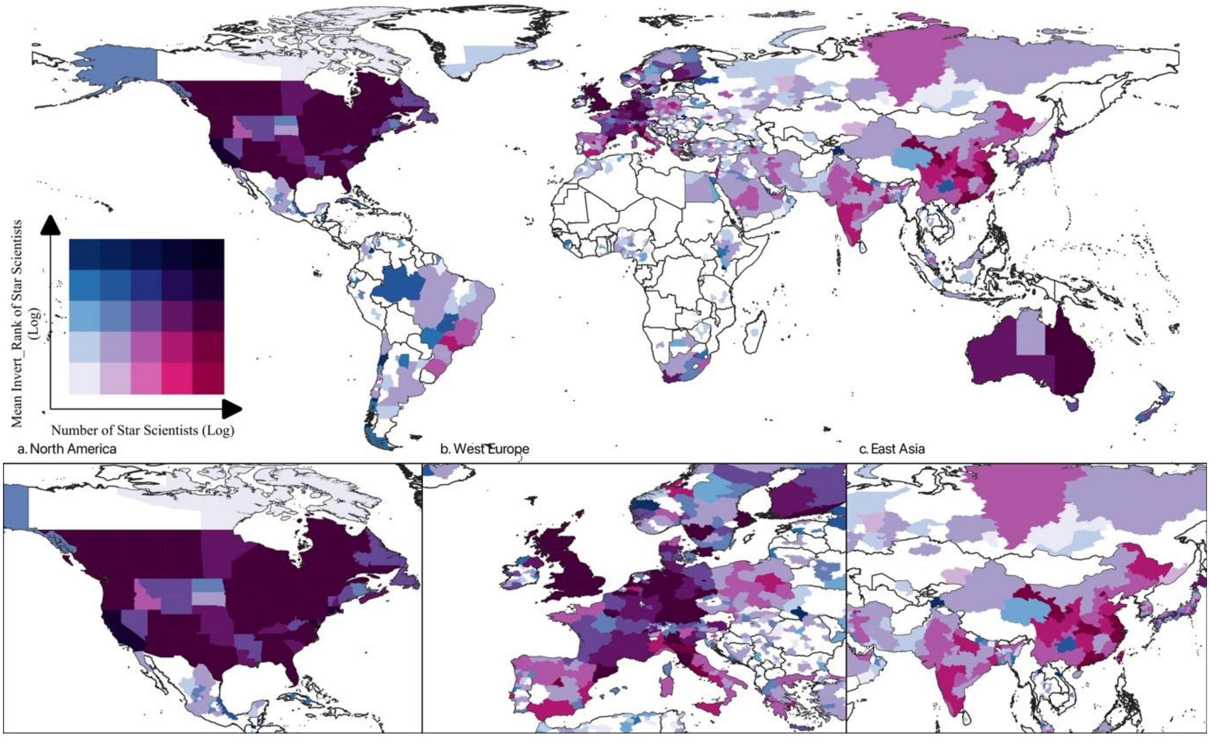
The persistence of these hierarchical differences is striking (Tables A2). Despite various policy interventions around the world aimed at nurturing new innovation hubs, very few cities manage to break into the elite club. The barriers to entry are formidable. Existing superstar cities benefit from dense local networks (making it easy to find collaborators or specialised services), proximity to investors and industry, and the branding that confers credibility in grant and publication processes. These accumulated advantages create high hurdles for up-and-coming cities. It is not impossible to join the ranks — as evidenced by the rise of several Chinese cities in recent years — but it requires extraordinary and sustained effort (as well as favourable national conditions).

Moreover, the correlation between city size (number of stars) and average impact appears to have strengthened over time. In many countries, the relationship in 2023 is tighter than it was in 2019. We computed correlation coefficients within countries and found they increased in most cases. This means the largest clusters are pulling further ahead in average impact as well, and smaller clusters are relatively lagging on impact. In China, for example, the trend is dramatic: Beijing and Shanghai saw huge gains in both the count and impact of star scientists (thousands added and average ranks up by 150–200 positions). Meanwhile, China's second-tier cities also increased their star counts but did not see comparable improvements in average impact. Essentially, simply adding more bodies in those cities did not raise their influence proportionately; they remain well behind Beijing/Shanghai in impact. This suggests that quantity alone cannot overcome impact deficits without the complementary advantages that top hubs have (e.g. stronger institutions, funding, networks).

We also considered whether the COVID-19 pandemic, which forced a global experiment in remote collaboration, disrupted these agglomeration dynamics. Initially, in 2020, the shift to remote work and virtual conferences had the potential to reduce the importance of physical colocation for researchers. We looked for signs of any geographic dispersion of star scientists during or after the pandemic. However, our data indicate that any such effects were minimal or short-lived. By 2023, the concentration trends in star scientist distribution look much the same as the pre-pandemic trajectory. If anything, the established hubs bounced back quicker. Top universities and labs resumed in-person activities and the appeal of being in a major cluster did not diminish. The resilience of these clusters suggests that the benefits they offer (tacit knowledge exchange, face-to-face mentoring, or lab access, among others) cannot be entirely substituted by remote interaction. In sum, the pandemic did not substantially level the playing field; geography's pull remains as strong as ever for scientific collaboration and innovation.

To visualise the relationship between quantity and impact, we classify regions across the world into KGI quadrants (Figure 13). The lower-right quadrant (many star scientists but lower average citation count) includes some very large but not top-impact research systems. The upper-left quadrant (fewer star scientists but very high average impact) includes smaller specialized hubs. Notably, the most policy attention often goes to trying to move cities into the coveted upper-right quadrant (high concentration of high-impact scientists). As our results show, that quadrant is currently dominated by the same few superstar regions, with strong performance in the US and Canada, parts of Western Europe, Australia, and, increasingly East Asia.

Fig.13. Relationship between the quantity and impact of star scientists in 2023 at a regional level.



Overall, the KGI analysis reinforces our earlier findings: the geography of star scientists is characterised by cumulative advantage. Figure 13 tells a familiar story of scientific power. Across North America, a research belt stretches along the eastern seaboard from Boston through New York to Washington, city-regions that have mastered the art of attracting star scientists whilst ensuring their work actually matters. The West Coast offers a respectable supporting act, with San Francisco, Los Angeles, and Seattle forming their own constellation of excellence.

Europe presents a rather different portrait, with London and Paris reigning over a more democratic landscape of secondary players. Munich, Frankfurt and the Randstad in the Netherlands each punch above their weight in specialised fields. This is a reflection of Europe's preference for nationally-rooted research systems loosely bound by Brussels bureaucracy.

In East Asia Beijing's, Shanghai's, and Guangdong's transformation from scientific also-rans to heavyweight contenders represents perhaps the most remarkable shift in modern research geography. China's strategic gamble on scientific leadership — massive infrastructure spending, systematic talent poaching — has paid off spectacularly. Tokyo and Seoul continue to be important and mature scientific ecosystems, but far less dynamic than their Chinese counterparts.

The Global South, however, remains stubbornly pale on our map. Indian cities like Bangalore present a particular puzzle: plenty of scientists, but only modest impact. Something — perhaps inadequate funding, institutional weakness, or a persistent brain drain westward — prevents quantity of researchers achieving greater research impact.

Sub-Saharan Africa barely registers, save for South Africa and Nigeria. Latin America's major cities such as São Paulo, Buenos Aires, Mexico City are the meagre representation of an underrepresented continent.

Perhaps most telling is what happens over time. The research-wealthy stay rich. City-regions with deep scientific talent in 2019 have only grown darker by 2023, while the pale rarely achieve meaningful transformation (Figures A3 in appendix). Beijing proves that change is possible, but its very exceptionalism underscores just how entrenched these hierarchies have become.

Moreover, cities and regions that lead on one dimension tend to lead on the other and, over time, those leads are growing. This paints a challenging picture for regions aspiring to become new knowledge leaders. It is not enough to simply produce more PhDs or lure a few experts. Places need to foster an environment that simultaneously grows the size of their research community and the impact of its output. Without both, they remain second-tier in the global hierarchy.

5. Conclusion: The resilience of “star” cities and emerging challengers

Our research yields an uncomfortable truth: scientific excellence worldwide is far more geographically concentrated than wealth itself. The KGI we have developed reveals that success in science requires both scale and impact. This is a combination that proves devilishly difficult to replicate outside a handful of superstar cities.

The numbers tell a stark story. Just four cities — New York, Boston, London and the San Francisco Bay Area — command 12% of the world's star scientists. Meanwhile, the vast majority of cities globally host fewer than ten such researchers. This is not merely clustering; it is a form of scientific clustering that rivals the most extreme forms of economic inequality documented elsewhere (Storper et al., 2015), and another example of the clustering of leading edge science and innovation (Carlino and Kerr, 2015).

What makes our findings particularly striking is the universality of concentration forces. Even disciplines once considered location-agnostic — e.g., philosophy, mathematics, agriculture— are gravitating toward major hubs. The romantic notion of the scholar working productively in intellectual isolation appears increasingly obsolete. As science becomes more collaborative and resource-intensive, the advantages of being embedded in dense networks of excellence compound relentlessly.

Beijing's and other Chinese cities meteoric rise offers the sole compelling counter-narrative. Its leap from scientific periphery to global scientific hubs represents perhaps the most dramatic shift in the modern geography of knowledge. Yet China's success — achieved through massive state intervention and strategic talent recruitment (Shi et al., 2023) — only underscores how entrenched these hierarchies have become. The exception proves the rule: without extraordinary commitment and resources, challenger cities remain trapped in the scientific equivalent of the middle-income trap.

The policy implications are profound. Attempts to build research capacity through quantity alone — expanding universities, hiring more faculty — consistently fail without commensurate gains in size, quality, and global connectivity (Atta-Owusu et al., 2021). Several cities in the Global South have discovered this harsh reality, generating modest increases in research outputs that barely register in international citations. Impact and quantity in science operate as complements, not substitutes. And this has profound implications for regional development strategies. As Fitjar (2025) shows, public funding for R&D tends to favour more economically developed regions, meaning it becomes an 'anti-regional' policy. We come to similar conclusions, highlighting the dilemma faced by policymakers. Our results provide more evidence of the 'dark side' of innovation, where concentration in core regions means that innovation can exacerbate spatial inequality (Boschma et al., 2025) and ignite discontent (Rodríguez-Pose et al, 2025).

Our longitudinal analysis reveals an equally troubling dynamic: advantages compound over time. Cities strong in 2019 have only grown stronger by 2023, whilst the also-rans fall further behind. Even the pandemic's forced experiment with remote collaboration failed to level the playing field, suggesting that tacit knowledge exchange and face-to-face interaction remain irreplaceable ingredients in frontier research.

Yet while our results show how hard it is for policy to encourage star scientists to move, the example of Beijing shows that it is not impossible. But Beijing's success has not been simply the result of a single policy, but a complex, long-term economic development strategy with technology and innovation at its core. If anything, this example indicates that policy for science can only succeed when integrated into a wider development strategy. Moreover, leading edge science is not the only route to economic growth. Other regions may seek to focus on incremental innovation or more marginal policy in specialised niches (Lee, 2024; Rodríguez-Pose and Wang, 2025). There are other routes to economic growth than leading science.

Our analysis comes with important caveats that future research must address. The definitional challenges alone are formidable. What constitutes a "city" varies wildly across continents. European cities are typically compact affairs. Asian "urban agglomerations" can, in contrast, sprawl across territories larger than entire European nations (Alessandrini et al., 2024). These inconsistencies inevitably distort our concentration measures and may inflate apparent clustering in some regions while understating it in others.

Our five-year window, captures, however, only a snapshot of what are inherently decades-long processes. Innovation ecosystems rise and fall over generational timescales. Witness Detroit's decline from automotive powerhouse or the gradual eclipse of once-mighty industrial cities across the American Rust Belt. A longer time lens might reveal different patterns of persistence and change, particularly if extended back to capture the post-war emergence of Silicon Valley or the earlier scientific pre-eminence of German universities.

Perhaps more fundamentally, our focus on individual star scientists misses the broader networks through which knowledge actually flows. Cities can punch above their weight by serving as connectors or brokers between larger hubs, channelling ideas across otherwise disconnected regions (Kauffeld-Monz and Fritsch, 2013). Some smaller cities may play outsized roles as bridges in the global knowledge web. This is a dynamic our researcher- and city-centric approach cannot capture.

Moreover, the reliance on citation metrics as the arbiter of scientific impact may be standard in the field but inevitably privileges certain forms of knowledge production over others. The entrepreneur who translates basic research into world-changing products, the mentor whose influence shapes generations of scientists, or the researcher whose work transforms policy rather than accumulating citations, all remain invisible in our framework. This Anglo-American bias in citation patterns may systematically undervalue contributions from non-English speaking researchers or those working on locally relevant problems.

In any case, our contribution of mapping star scientists at the city level using our composite KGI opens new avenues for understanding the geography of scientific research and innovation. Unlike traditional patent counts or publication volumes, our approach captures the dual challenge of attracting talent and ensuring impact, thus providing a more nuanced view of scientific competitiveness than previous studies (Kemeny et al., 2022; Pinheiro et al., 2022).

The concentration trends we document should concern anyone interested in the geography of innovation. As scientific challenges become more complex — from climate change to artificial intelligence safety — the world cannot afford to have cutting-edge research confined to a few privileged enclaves. The geography of knowledge may indeed be destiny, but it need not be immutable. Beijing's transformation demonstrates that strategic intervention can rewrite scientific hierarchies, though such victories remain frustratingly rare.

Without concerted efforts to democratise access to scientific excellence, we risk a future where global innovation resembles a few brilliant constellations against vast expanses of darkness. And this is an outcome that should concern us all.

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APPENDIX

1. Knowledge generation index

We estimate a measurement to balance both numbers and ranks.

$$Knowledge\ generation\ index = \frac{N_s}{\bar{R}}$$

The model rewards both the number of scientists (N_s) in institutions or cities and their average rank ($\bar{R}$) by their scientists. It implies that while more scientists are generally beneficial in knowledge generation, having top-tier scientists carries equal weight. As mentioned above, due to the large diversity on absolute number in bother rank and number, we created measurement to reduce the sensitives of number. By calculating number of scientists (N_s) divided by total number of scientists (TN), we find the position of institution or cities in numbers.

$$Knowledge\ generation\ index = \frac{\frac{N_s}{TN}}{\frac{R}{N_s}} = \frac{N_s^2}{R \times TN}$$

Also, it compresses extreme values and makes the model less sensitive to outliers. This model balances the importance of numbers and ranks in our model. The logarithmic functions compress extreme values, making the system less sensitive to outliers or very large numbers of scientists. By expand this equation we can get:

$$Knowledge\ Generation\ Index = \frac{Ln(N_s^2 + 1)}{Ln(R \times TN + 1)}$$

By examine researchers' data in overall and 20 sub-filed scientific we created city level maps and analyze the distribution and agglomeration of knowledge generation. Besides, we also construct Gini Index of distribution of scientists across countries and subjects.

Figure.A.1.1. Geographical distribution of star scientists in cities in 2022

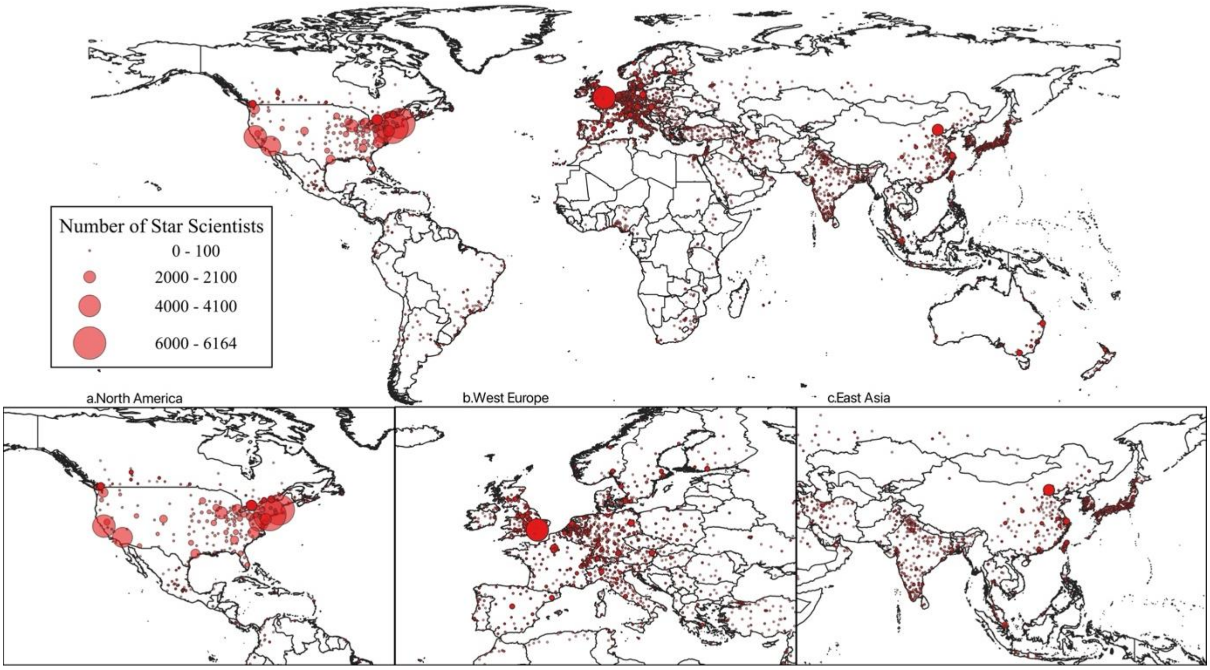

Figure.A.1.2. Geographical distribution of star scientists in cities in 2021

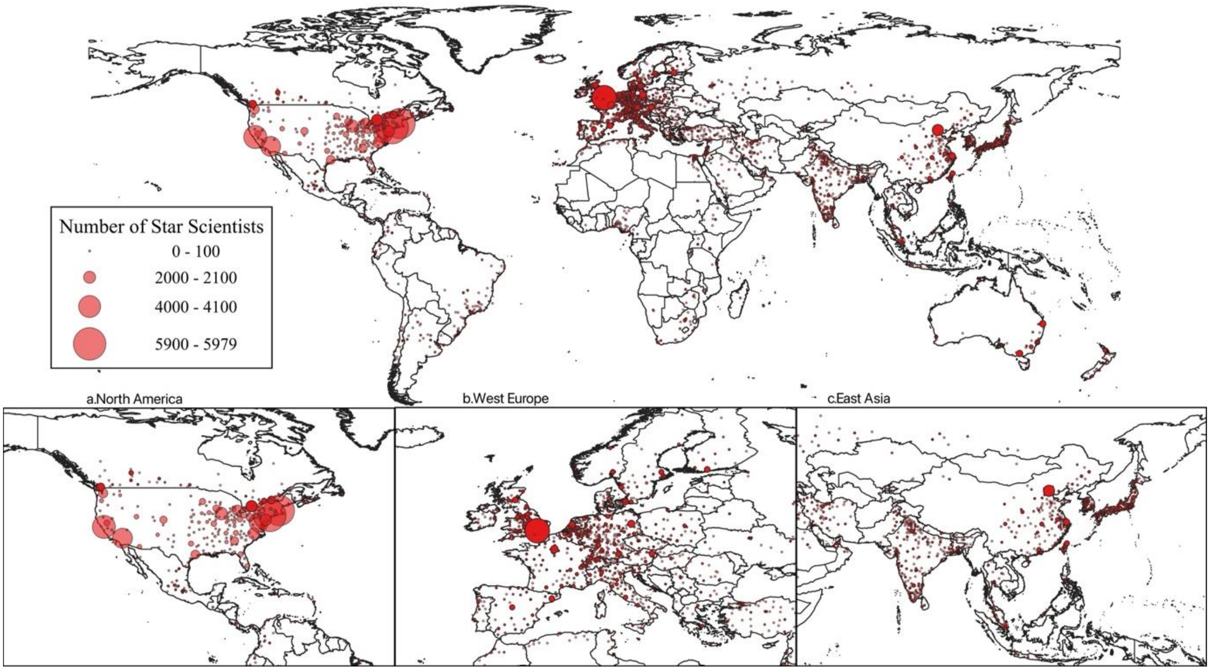

Figure.A.1.3. Geographical distribution of star scientists in cities in 2020

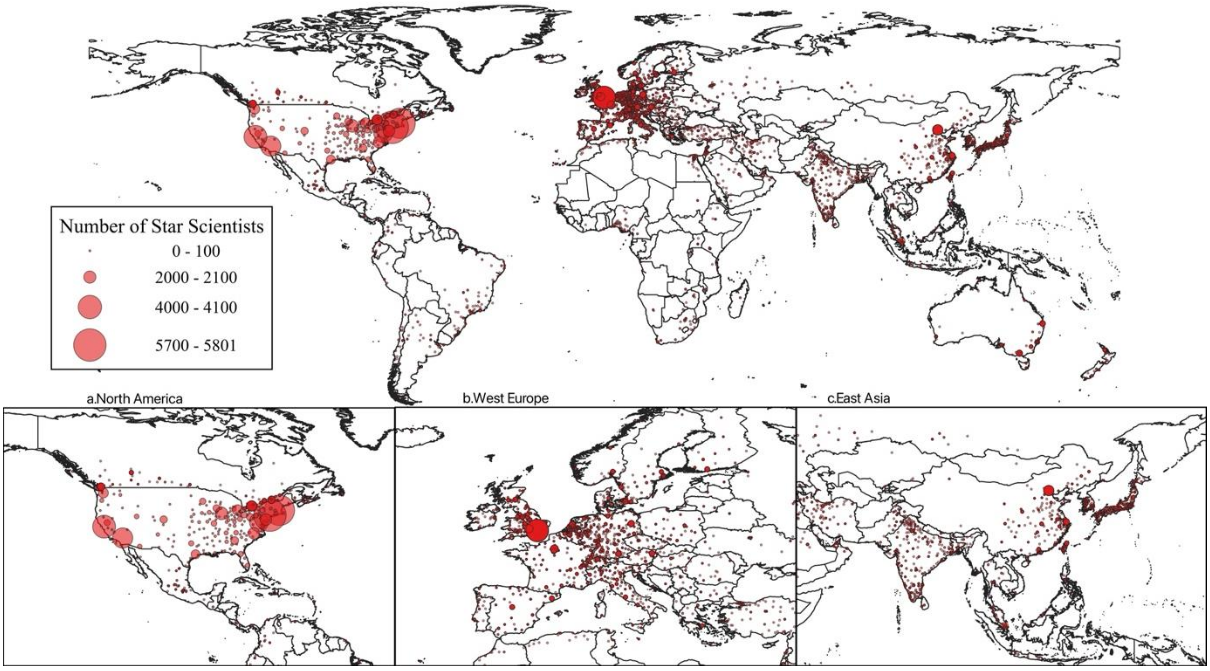

Figure.A.1.4. Geographical distribution of star scientists in cities in 2019

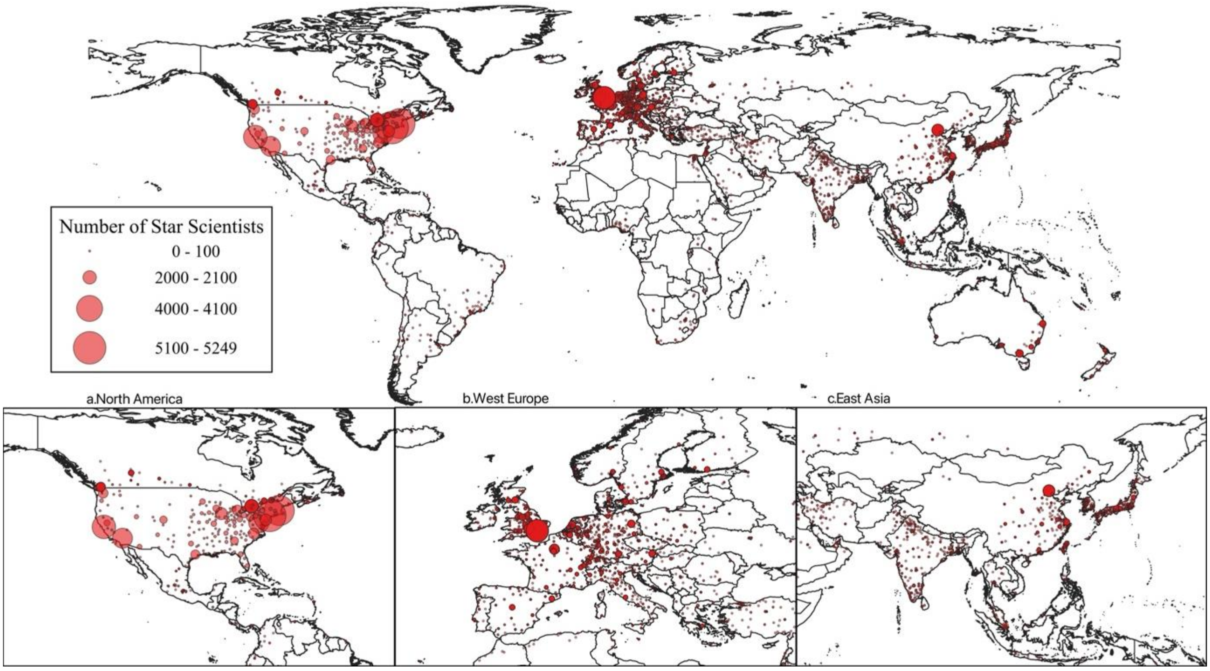

Table.A.1.1. Top 50 cities in the number of star scientists in 2022

Country	City	Number	Rank	Pct.
USA	New York-Newark, NY-NJ-CT-PA	6164	1	3.86%
USA	Boston-Worcester-Providence, MA-RI-NH-CT	5703	2	3.57%
USA	San Jose-San Francisco-Oakland, CA	4188	3	2.62%
GBR	London	3917	4	2.48%
USA	Los Angeles-Long Beach, CA	3620	5	2.26%
USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	3512	6	2.20%
USA	Chicago-Naperville, IL-IN-WI	2111	7	1.32%
USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD	1921	8	1.20%
USA	Raleigh-Durham-Chapel Hill, NC	1908	9	1.19%
CHN	Beijing	1756	10	1.10%
USA	Detroit-Warren-Ann Arbor, MI	1723	11	1.08%
CAN	Toronto	1667	12	1.04%
USA	Seattle-Tacoma, WA	1552	13	0.97%
USA	Houston-The Woodlands, TX	1441	14	0.90%
USA	Atlanta-Athens-Clarke County-Sandy Springs, GA	1266	15	0.79%
CHN	Hong Kong	1232	16	0.77%
GBR	Oxford	1221	17	0.76%
USA	Denver-Aurora, CO	1150	18	0.72%
USA	Pittsburgh-New Castle-Weirton, PA-OH-WV	1149	19	0.72%
FRA	Paris	1082	20	0.68%
CAN	Montréal	1046	21	0.65%
GBR	Cambridge	1025	22	0.64%
USA	Madison-Janesville-Beloit, WI	1001	23	0.63%
CAN	Greater Vancouver	989	24	0.62%
USA	Minneapolis-St. Paul, MN-WI	897	25	0.56%
USA	Cleveland-Akron-Canton, OH	860	26	0.54%
SGP	Singapore	838	27	0.52%
USA	Sacramento-Roseville, CA	838	27	0.52%
CHN	Shanghai	830	28	0.52%
DEU	Berlin	824	29	0.52%
AUS	Brisbane	782	30	0.49%
AUS	Melbourne	781	31	0.49%
DEU	München (Kreisfreie Stadt)	780	32	0.49%
NLD	Amsterdam	762	33	0.48%
DNK	København	757	34	0.47%
USA	Columbus-Marion-Zanesville, OH	743	35	0.46%
USA	St. Louis-St. Charles-Farmington, MO-IL	734	36	0.46%
USA	Dallas-Fort Worth, TX-OK	717	37	0.45%
USA	Gainesville-Lake City, FL	707	38	0.44%
AUT	Wien Stadt	697	39	0.44%
USA	Ithaca-Cortland, NY	668	40	0.42%
FIN	Uusimaa	661	41	0.41%
ESP	Barcelona	656	42	0.41%
GBR	Edinburgh	642	43	0.40%
USA	Knoxville-Morristown-Sevierville, TN	640	44	0.40%

ESP	Madrid	638	45	0.40%
USA	Miami-Fort Lauderdale-Port St. Lucie, FL	631	46	0.39%
USA	State College-DuBois, PA	618	47	0.39%
USA	Salt Lake City-Provo-Orem, UT	602	48	0.38%
CAN	Ottawa	601	49	0.38%
USA	Tucson-Nogales, AZ	601	49	0.38%
JPN	Bunkyō, Tokyo	596	50	0.37%

Table.A.1.2. Top 50 cities in the number of star scientists in 2021

Country	City	Number	Rank	Pct.
USA	New York-Newark, NY-NJ-CT-PA	5979	1	3.93%
USA	Boston-Worcester-Providence, MA-RI-NH-CT	5570	2	3.66%
USA	San Jose-San Francisco-Oakland, CA	4064	3	2.67%
GBR	London	3823	4	2.51%
USA	Los Angeles-Long Beach, CA	3545	5	2.33%
USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	3384	6	2.22%
USA	Chicago-Naperville, IL-IN-WI	2058	7	1.35%
USA	Raleigh-Durham-Chapel Hill, NC	1880	8	1.24%
USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD	1869	9	1.23%
USA	Detroit-Warren-Ann Arbor, MI	1687	10	1.11%
CHN	Beijing	1555	11	1.02%
CAN	Toronto	1551	12	1.02%
USA	Seattle-Tacoma, WA	1510	13	0.99%
USA	Houston-The Woodlands, TX	1403	14	0.92%
USA	Atlanta-Athens-Clarke County-Sandy Springs, GA	1237	15	0.81%
GBR	Oxford	1186	16	0.78%
CHN	Hong Kong	1157	17	0.76%
USA	Pittsburgh-New Castle-Weirton, PA-OH-WV	1128	18	0.74%
USA	Denver-Aurora, CO	1101	19	0.72%
CAN	Montréal	1004	20	0.66%
GBR	Cambridge	996	21	0.65%
USA	Madison-Janesville-Beloit, WI	965	22	0.63%
FRA	Paris	958	23	0.63%
CAN	Greater Vancouver	958	23	0.63%
USA	Minneapolis-St. Paul, MN-WI	863	25	0.57%
USA	Cleveland-Akron-Canton, OH	845	26	0.56%
DEU	Berlin	823	27	0.54%
USA	Sacramento-Roseville, CA	822	28	0.54%
SGP	Singapore	805	29	0.52%
CHN	Shanghai	765	30	0.50%
AUS	Brisbane	754	31	0.50%
NLD	Amsterdam	751	32	0.49%
AUS	Melbourne	744	33	0.49%
DNK	København	739	34	0.49%
USA	Columbus-Marion-Zanesville, OH	728	35	0.48%
USA	St. Louis-St. Charles-Farmington, MO-IL	724	36	0.48%
USA	Dallas-Fort Worth, TX-OK	700	37	0.46%
USA	Gainesville-Lake City, FL	692	38	0.45%
DEU	München (Kreisfreie Stadt)	664	39	0.44%
AUT	Wien Stadt	660	40	0.43%
GBR	Edinburgh	660	40	0.43%
USA	Ithaca-Cortland, NY	646	42	0.42%
ESP	Barcelona	623	43	0.41%
USA	Knoxville-Morristown-Sevierville, TN	614	44	0.40%
USA	State College-DuBois, PA	612	45	0.40%

FIN	Uusimaa	610	46	0.40%
ESP	Madrid	582	47	0.38%
FRA	Essonne, Paris	582	48	0.38%
USA	Tucson-Nogales, AZ	582	49	0.38%
USA	Miami-Fort Lauderdale-Port St. Lucie, FL	581	50	0.38%
JPN	Bunkyō, Tokyo	575	51	0.38%
USA	Salt Lake City-Provo-Orem, UT	575	51	0.38%
GBR	Manchester	551	53	0.36%
CAN	Ottawa	548	54	0.36%
SWE	Uppsala	510	55	0.34%

Table.A.1.3. Top 50 cities in the number of star scientists in 2020

Country	City	Number	Rank	Pct.
USA	New York-Newark, NY-NJ-CT-PA	5801	1	3.97%
USA	Boston-Worcester-Providence, MA-RI-NH-CT	5468	2	3.67%
USA	San Jose-San Francisco-Oakland, CA	3998	3	2.73%
GBR	London	3648	4	2.49%
USA	Los Angeles-Long Beach, CA	3401	5	2.33%
USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	3250	6	2.22%
USA	Chicago-Naperville, IL-IN-WI	2002	7	1.37%
USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD	1891	8	1.29%
USA	Raleigh-Durham-Chapel Hill, NC	1816	9	1.24%
USA	Detroit-Warren-Ann Arbor, MI	1661	10	1.14%
USA	Seattle-Tacoma, WA	1504	11	1.03%
CHN	Beijing	1503	12	1.03%
CAN	Toronto	1496	13	1.02%
USA	Houston-The Woodlands, TX	1382	14	0.95%
USA	Atlanta-Athens-Clarke County-Sandy Springs, GA	1182	15	0.81%
GBR	Oxford	1148	16	0.79%
CHN	Hong Kong	1105	17	0.76%
FRA	Paris	1096	18	0.75%
USA	Pittsburgh-New Castle-Weirton, PA-OH-WV	1087	19	0.74%
USA	Denver-Aurora, CO	1061	20	0.73%
CAN	Montréal	995	21	0.68%
GBR	Cambridge	983	22	0.67%
CAN	Greater Vancouver	980	23	0.67%
USA	Madison-Janesville-Beloit, WI	916	24	0.63%
USA	Sacramento-Roseville, CA	839	25	0.57%
USA	Minneapolis-St. Paul, MN-WI	836	26	0.57%
USA	Cleveland-Akron-Canton, OH	824	27	0.56%
SGP	Singapore	803	28	0.55%
DEU	Berlin	762	29	0.52%
CHN	Shanghai	743	30	0.51%
AUS	Melbourne	733	31	0.50%
NLD	Amsterdam	731	32	0.50%
USA	St. Louis-St. Charles-Farmington, MO-IL	716	33	0.49%
AUS	Brisbane	709	34	0.48%
DNK	København	708	35	0.48%
USA	Columbus-Marion-Zanesville, OH	699	36	0.48%
USA	Gainesville-Lake City, FL	684	37	0.47%
USA	Dallas-Fort Worth, TX-OK	670	38	0.46%
USA	Ithaca-Cortland, NY	626	39	0.43%
AUT	Wien Stadt	620	40	0.42%
DEU	München (Kreisfreie Stadt)	614	41	0.42%
ESP	Barcelona	604	42	0.41%
GBR	Edinburgh	595	43	0.41%
USA	State College-DuBois, PA	592	44	0.40%
GBR	Manchester	591	45	0.40%

FIN	Uusimaa	585	46	0.40%
JPN	Bunkyō, Tokyo	573	47	0.39%
FRA	Essonne, Paris	572	48	0.39%
USA	Salt Lake City-Provo-Orem, UT	571	49	0.39%
USA	Knoxville-Morristown-Sevierville, TN	569	50	0.39%

Table.A.1.4. Top 50 cities in the number of star scientists in 2019

Country	City	Number	Rank	Pct.
USA	New York-Newark, NY-NJ-CT-PA	5249	1	4.17%
USA	Boston-Worcester-Providence, MA-RI-NH-CT	4766	2	3.79%
USA	San Jose-San Francisco-Oakland, CA	3711	3	2.95%
USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	3172	4	2.52%
GBR	London	3158	5	2.51%
USA	Los Angeles-Long Beach, CA	3078	6	2.45%
USA	Chicago-Naperville, IL-IN-WI	1810	7	1.44%
USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD	1695	8	1.35%
USA	Raleigh-Durham-Chapel Hill, NC	1604	9	1.28%
USA	Detroit-Warren-Ann Arbor, MI	1485	10	1.18%
USA	Seattle-Tacoma, WA	1376	11	1.09%
CAN	Toronto	1343	12	1.07%
USA	Houston-The Woodlands, TX	1243	13	0.99%
CHN	Beijing	1157	14	0.92%
USA	Atlanta-Athens-Clarke County-Sandy Springs, GA	1096	15	0.87%
CHN	Hong Kong	992	16	0.78%
USA	Pittsburgh-New Castle-Weirton, PA-OH-WV	976	17	0.75%
GBR	Oxford	945	18	0.75%
FRA	Paris	944	19	0.74%
GBR	Cambridge	927	20	0.74%
USA	Denver-Aurora, CO	925	21	0.74%
CAN	Greater Vancouver	901	22	0.72%
USA	Madison-Janesville-Beloit, WI	837	23	0.67%
USA	Sacramento-Roseville, CA	776	24	0.62%
USA	Cleveland-Akron-Canton, OH	700	25	0.56%
USA	Columbus-Marion-Zanesville, OH	683	26	0.54%
SGP	Singapore	683	26	0.54%
DEU	Berlin	672	28	0.53%
NLD	Amsterdam	665	29	0.53%
USA	Minneapolis-St. Paul, MN-WI	664	30	0.53%
USA	St. Louis-St. Charles-Farmington, MO-IL	630	31	0.50%
AUS	Melbourne	630	31	0.50%
GBR	Manchester	599	33	0.48%
AUS	Brisbane	594	34	0.47%
USA	Gainesville-Lake City, FL	593	35	0.47%
USA	Ithaca-Cortland, NY	584	36	0.46%
DEU	München (Kreisfreie Stadt)	570	37	0.45%
JPN	Bunkyō, Tokyo	566	38	0.45%
DNK	København	564	39	0.45%
USA	Dallas-Fort Worth, TX-OK	556	40	0.44%
CHN	Shanghai	552	41	0.44%
USA	State College-DuBois, PA	541	42	0.43%
GBR	Edinburgh	536	43	0.43%
USA	Tucson-Nogales, AZ	529	44	0.42%
AUT	Wien Stadt	527	45	0.42%
CAN	Montréal	503	46	0.40%
ESP	Barcelona	502	47	0.40%

USA	Salt Lake City-Provo-Orem, UT	495	48	0.39%
FIN	Uusimaa	492	49	0.39%
USA	Miami-Fort Lauderdale-Port St. Lucie, FL	477	50	0.38%
FRA	Essonne, Paris	471	51	0.37%
USA	Nashville-Davidson--Murfreesboro, TN	462	52	0.37%

Fig.A.2 Gini Index across cities (overall)

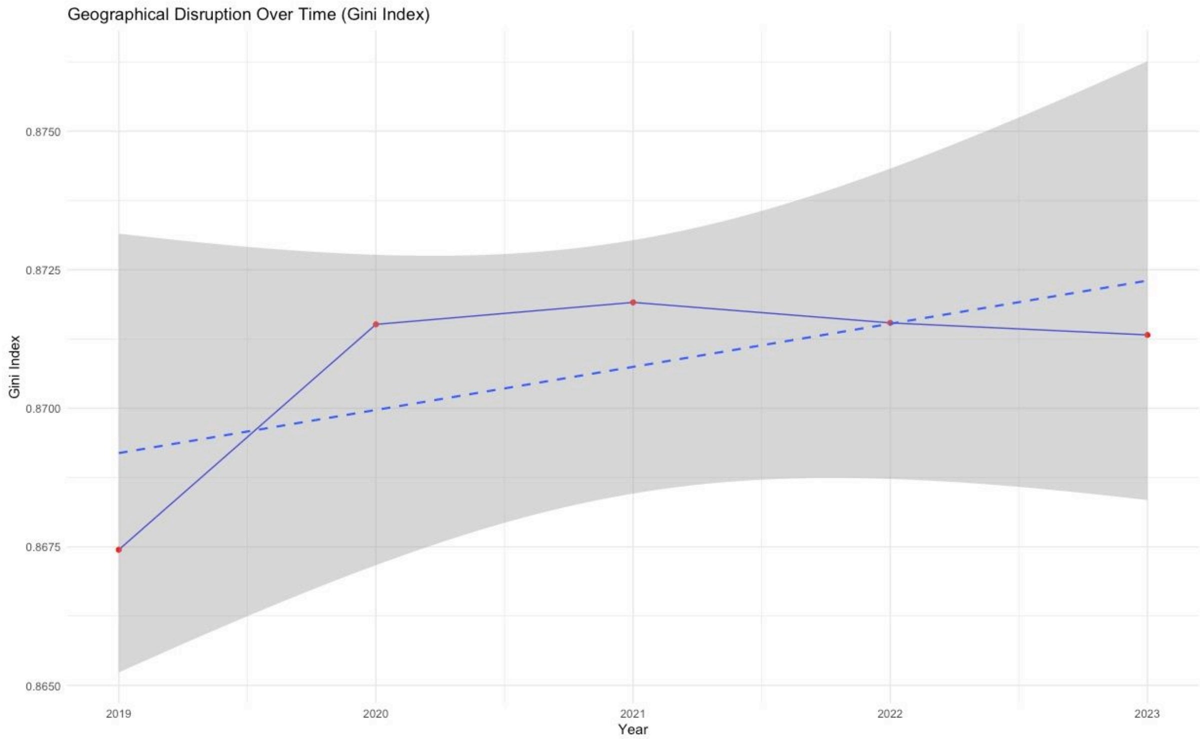

Table.A.2.1. Top 50 cities in the KGI in 2023

KGI Rank	Country	City
1	USA	New York-Newark, NY-NJ-CT-PA
2	USA	Boston-Worcester-Providence, MA-RI-NH-CT
3	USA	San Jose-San Francisco-Oakland, CA
4	GBR	London
5	USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
6	USA	Los Angeles-Long Beach, CA
7	USA	Chicago-Naperville, IL-IN-WI
8	CHN	Beijing
9	USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD
10	USA	Raleigh-Durham-Chapel Hill, NC
11	USA	Detroit-Warren-Ann Arbor, MI
12	USA	Seattle-Tacoma, WA
13	CAN	Toronto
14	USA	Houston-The Woodlands, TX
15	FRA	Paris
16	USA	Atlanta--Athens-Clarke County--Sandy Springs, GA
17	CHN	Hong Kong
18	GBR	Oxford
19	GBR	Cambridge
20	USA	Pittsburgh-New Castle-Weirton, PA-OH-WV
21	USA	Denver-Aurora, CO
22	CAN	Montréal
23	CAN	Greater Vancouver
24	USA	Madison-Janesville-Beloit, WI
25	SGP	Singapore
26	USA	Minneapolis-St. Paul, MN-WI
27	DEU	München (Kreisfreie Stadt)
28	NLD	Amsterdam
29	AUS	Melbourne
30	USA	Sacramento-Roseville, CA
31	USA	Cleveland-Akron-Canton, OH
32	USA	St. Louis-St. Charles-Farmington, MO-IL
33	CHN	Shanghai
34	AUS	Sydney
35	DEU	Berlin
36	GBR	Manchester
37	USA	Dallas-Fort Worth, TX-OK
38	USA	Ithaca-Cortland, NY
39	USA	Columbus-Marion-Zanesville, OH
40	USA	Gainesville-Lake City, FL
41	AUT	Wien Stadt
42	GBR	Edinburgh
43	ESP	Barcelona

44	DNK	København
45	USA	State College-DuBois, PA
46	USA	Salt Lake City-Provo-Orem, UT
47	FIN	Uusimaa
48	JPN	Bunkyō, Tokyo
49	USA	Tucson-Nogales, AZ
50	USA	Miami-Fort Lauderdale-Port St. Lucie, FL

Table.A.2.2. Top 50 cities in the KGI in 2022

KGI Rank	Country	City
1	USA	New York-Newark, NY-NJ-CT-PA
2	USA	Boston-Worcester-Providence, MA-RI-NH-CT
3	USA	San Jose-San Francisco-Oakland, CA
4	GBR	London
5	USA	Los Angeles-Long Beach, CA
6	USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
7	USA	Chicago-Naperville, IL-IN-WI
8	CHN	Beijing
9	CAN	Toronto
10	USA	Raleigh-Durham-Chapel Hill, NC
11	USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD
12	FRA	Paris
13	USA	Detroit-Warren-Ann Arbor, MI
14	USA	Seattle-Tacoma, WA
15	GBR	Oxford
16	USA	Houston-The Woodlands, TX
17	CAN	Montréal
18	DEU	Berlin
19	GBR	Cambridge
20	USA	Atlanta--Athens-Clarke County--Sandy Springs, GA
21	CHN	Hong Kong
22	USA	Pittsburgh-New Castle-Weirton, PA-OH-WV
23	SGP	Singapore
24	USA	Denver-Aurora, CO
25	CAN	Greater Vancouver
26	CHN	Shanghai
27	AUT	Wien Stadt
28	NLD	Amsterdam
29	DEU	München (Kreisfreie Stadt)
30	USA	Madison-Janesville-Beloit, WI
31	AUS	Melbourne
32	ESP	Madrid
33	ESP	Barcelona
34	DNK	København
35	USA	Minneapolis-St. Paul, MN-WI
36	USA	Cleveland-Akron-Canton, OH
37	AUS	Brisbane
38	USA	Sacramento-Roseville, CA
39	CAN	Ottawa
40	FIN	Uusimaa
41	USA	St. Louis-St. Charles-Farmington, MO-IL
42	GBR	Edinburgh
43	USA	Columbus-Marion-Zanesville, OH

44	USA	Dallas-Fort Worth, TX-OK
45	USA	Gainesville-Lake City, FL
46	USA	Ithaca-Cortland, NY
47	SWE	Göteborg
48	JPN	Bunkyō, Tokyo
49	FRA	Essonne, Paris
50	SWE	Uppsala

Table.A.2.3. Top 50 cities in the KGI in 2021

KGI Rank	Country	City
1	USA	New York-Newark, NY-NJ-CT-PA
2	USA	Boston-Worcester-Providence, MA-RI-NH-CT
3	USA	San Jose-San Francisco-Oakland, CA
4	GBR	London
5	USA	Los Angeles-Long Beach, CA
6	USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
7	CHN	Beijing
8	USA	Chicago-Naperville, IL-IN-WI
9	USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD
10	USA	Raleigh-Durham-Chapel Hill, NC
11	CAN	Toronto
12	USA	Detroit-Warren-Ann Arbor, MI
13	USA	Seattle-Tacoma, WA
14	FRA	Paris
15	USA	Houston-The Woodlands, TX
16	GBR	Oxford
17	CAN	Montréal
18	USA	Atlanta--Athens-Clarke County--Sandy Springs, GA
19	GBR	Cambridge
20	DEU	Berlin
21	CHN	Hong Kong
22	USA	Pittsburgh-New Castle-Weirton, PA-OH-WV
23	USA	Denver-Aurora, CO
24	CAN	Greater Vancouver
25	CHN	Shanghai
26	USA	Madison-Janesville-Beloit, WI
27	AUT	Wien Stadt
28	SGP	Singapore
29	NLD	Amsterdam
30	DEU	München (Kreisfreie Stadt)
31	AUS	Melbourne
32	DNK	København
33	ESP	Madrid
34	USA	Minneapolis-St. Paul, MN-WI
35	ESP	Barcelona
36	USA	Cleveland-Akron-Canton, OH
37	USA	Sacramento-Roseville, CA
38	AUS	Brisbane
39	FIN	Uusimaa
40	USA	St. Louis-St. Charles-Farmington, MO-IL
41	CAN	Ottawa
42	GBR	Edinburgh
43	USA	Columbus-Marion-Zanesville, OH

44	USA	Dallas-Fort Worth, TX-OK
45	USA	Gainesville-Lake City, FL
46	USA	Ithaca-Cortland, NY
47	SWE	Göteborg
48	JPN	Bunkyō, Tokyo
49	USA	Knoxville-Morristown-Sevierville, TN
50	SWE	Uppsala

Table.A.2.4. Top 50 cities in the KGI in 2020

KGI Rank	Country	City
1	USA	New York-Newark, NY-NJ-CT-PA
2	USA	Boston-Worcester-Providence, MA-RI-NH-CT
3	USA	San Jose-San Francisco-Oakland, CA
4	GBR	London
5	USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
6	USA	Los Angeles-Long Beach, CA
7	USA	Chicago-Naperville, IL-IN-WI
8	USA	Raleigh-Durham-Chapel Hill, NC
9	USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD
10	USA	Detroit-Warren-Ann Arbor, MI
11	CAN	Toronto
12	GBR	Cambridge
13	USA	Seattle-Tacoma, WA
14	GBR	Oxford
15	USA	Houston-The Woodlands, TX
16	CHN	Beijing
17	CHN	Hong Kong
18	FRA	Paris
19	USA	Atlanta--Athens-Clarke County--Sandy Springs, GA
20	USA	Pittsburgh-New Castle-Weirton, PA-OH-WV
21	USA	Denver-Aurora, CO
22	CAN	Greater Vancouver
23	CAN	Montréal
24	USA	Madison-Janesville-Beloit, WI
25	DEU	Berlin
26	USA	Minneapolis-St. Paul, MN-WI
27	USA	Cleveland-Akron-Canton, OH
28	USA	Sacramento-Roseville, CA
29	SGP	Singapore
30	NLD	Amsterdam
31	AUS	Melbourne
32	DNK	København
33	USA	Gainesville-Lake City, FL
34	USA	St. Louis-St. Charles-Farmington, MO-IL
35	AUS	Brisbane
36	USA	Dallas-Fort Worth, TX-OK
37	USA	Ithaca-Cortland, NY
38	USA	Columbus-Marion-Zanesville, OH
39	CHN	Shanghai

40	DEU	München (Kreisfreie Stadt)
41	USA	State College-DuBois, PA
42	AUT	Wien Stadt
43	ESP	Barcelona
44	GBR	Edinburgh
45	FIN	Uusimaa
46	GBR	Manchester
47	USA	Miami-Fort Lauderdale-Port St. Lucie, FL
48	USA	Salt Lake City-Provo-Orem, UT
49	JPN	Bunkyō, Tokyo
50	FRA	Essonne, Paris

Table.A.2.5. Top 50 cities in the KGI in 2019

Rank	Country	City
1	USA	New York-Newark, NY-NJ-CT-PA
2	USA	Boston-Worcester-Providence, MA-RI-NH-CT
3	USA	San Jose-San Francisco-Oakland, CA
4	GBR	London
5	USA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
6	USA	Los Angeles-Long Beach, CA
7	USA	Chicago-Naperville, IL-IN-WI
8	USA	Raleigh-Durham-Chapel Hill, NC
9	USA	Philadelphia-Reading-Camden, PA-NJ-DE-MD
10	USA	Detroit-Warren-Ann Arbor, MI
11	USA	Seattle-Tacoma, WA
12	CAN	Toronto
13	USA	Houston-The Woodlands, TX
14	USA	Atlanta--Athens-Clarke County--Sandy Springs, GA
15	GBR	Oxford
16	CHN	Beijing
17	GBR	Cambridge
18	USA	Pittsburgh-New Castle-Weirton, PA-OH-WV
19	CHN	Hong Kong
20	USA	Denver-Aurora, CO
21	FRA	Paris
22	CAN	Greater Vancouver
23	USA	Madison-Janesville-Beloit, WI
24	USA	Sacramento-Roseville, CA
25	DEU	Berlin
26	SGP	Singapore
27	NLD	Amsterdam
28	USA	Cleveland-Akron-Canton, OH
29	USA	Columbus-Marion-Zanesville, OH
30	AUS	Melbourne
31	USA	Minneapolis-St. Paul, MN-WI
32	USA	St. Louis-St. Charles-Farmington, MO-IL
33	USA	Ithaca-Cortland, NY
34	GBR	Manchester
35	USA	Gainesville-Lake City, FL
36	DEU	München (Kreisfreie Stadt)
37	AUS	Brisbane
38	DNK	København
39	USA	Dallas-Fort Worth, TX-OK

40	AUT	Wien Stadt
41	GBR	Edinburgh
42	JPN	Bunkyō, Tokyo
43	USA	State College-DuBois, PA
44	ESP	Barcelona
45	FIN	Uusimaa
46	CAN	Montréal
47	SWE	Solna
48	CHN	Shanghai
49	USA	Salt Lake City-Provo-Orem, UT
50	USA	Tucson-Nogales, AZ

Fig.A.3.1. Relationship between the quantity and impact of star scientists in 2022 at a regional level.

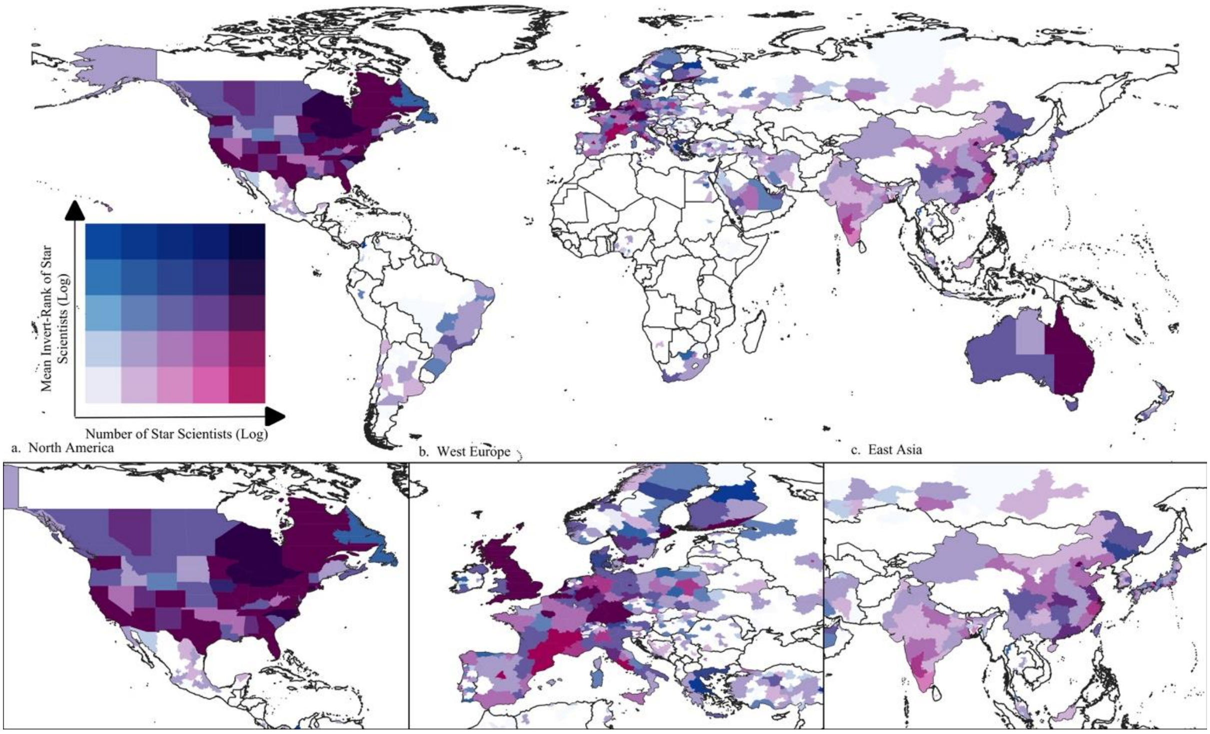

Fig.A.3.2. Relationship between the quantity and impact of star scientists in 2021 at a regional level.

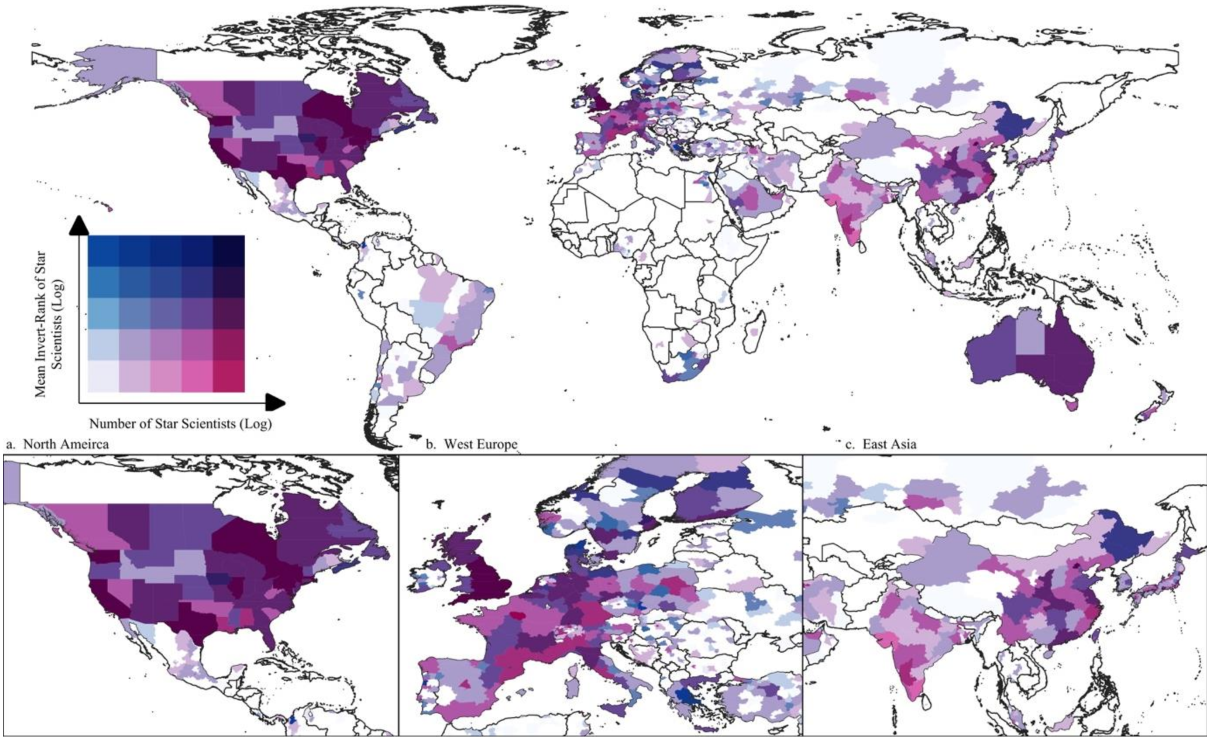

Fig.A.3.3. Relationship between the quantity and impact of star scientists in 2020 at a regional level.

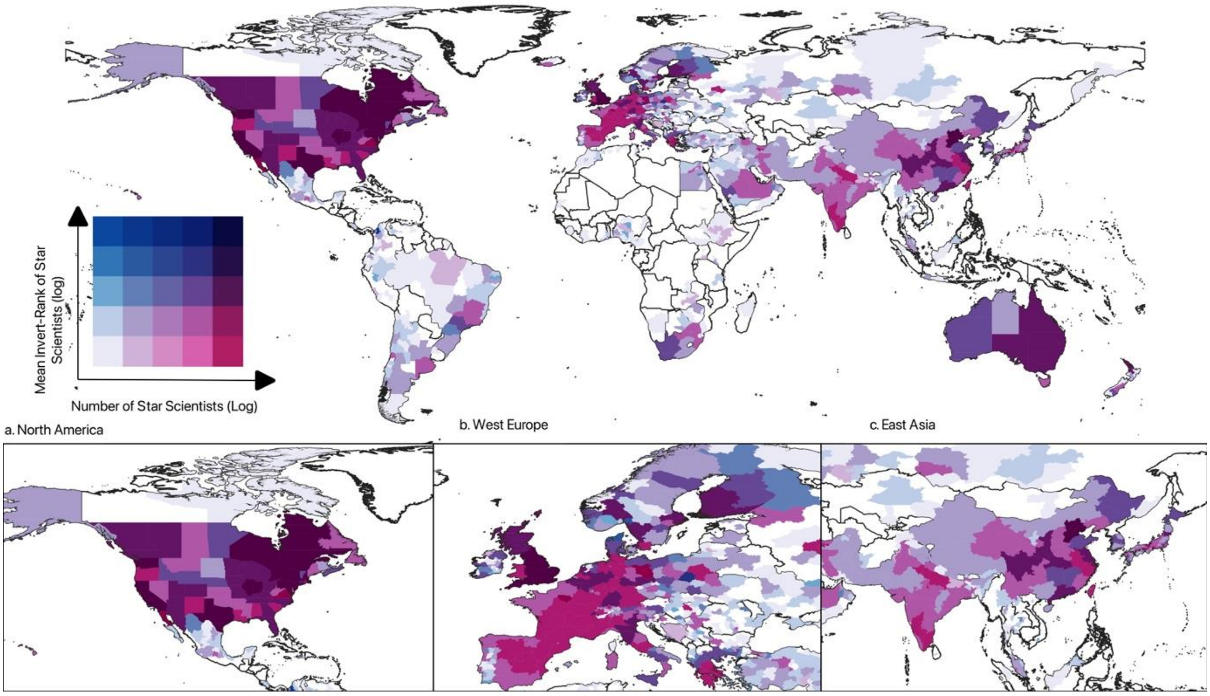

Fig.A.3.4. Relationship between the quantity and impact of star scientists in 2019 at a regional level.