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Scientific Travelers Associated with Less Disruption but Better Scientific Novelty

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Abstract

Building on the framework of facilitymetrics and the features of big science facilities, this study provides a more micro method to identify the scientific mobility procedure, named scientific travels hereafter, and associated with scientific performance at the author level and paper level. We classify external users of big science facilities into two types (travelers and locals) by measuring the number of facilities the focal scientist's used, measured by co-authored publications, during a specific period (one year, previously, and career level), visualize their gap in scientific performance, which is measured by a five-year disruption index and novelty score, and validate the impact relationships by causal inference respectively in paper-level and author-level. Results show that locals might produce more disruptive knowledge while travelers perform better in novel knowledge production. Paper-level and author-level regressions validate the results that the participation of travelers in teams leads to better novelty but lower disruption, and the performance gaps between travelers and locals surely exist. However, from a long-term perspective, the disruptive ability could increase significantly as a traveler is fully localized and gradually surpasses his or her peers' ability. The novelty ability of travelers might decrease slowly but insignificantly since they are always ahead of locals and their peers. This study contributes to understanding the performance evaluation and science policy in big science facilities, which enriches the research in scientific mobility, and the results could be a reference for those short periods of scientific activity related to mobility without visible information to map and quantify.

Introduction

Scientific mobility is highly motivated by the development of transportation and the trends of globalization (Lin, Frey, & Wu, 2023), especially since the 21st century. Scientists, with their knowledge, can travel around the globe easily, communicate with distant peers, collaborate for new progress, and chase career success (Wang, Hooi, Li, & Chou, 2019). High mobility has already transformed the paradigms of knowledge production by several approaches, for instance, local knowledge could flow to a wider academia easily, and knowledge from different regions could be highly connected for global scientific progress (Franzoni, Scellato, & Stephan, 2012; Söderström, 2023a). As for a scientist, he or she could serve as a carrier of regional knowledge outflows to global academia. Similarly, scientists could be trained in multi-regions and eventually bring his or her diverse knowledge to in-flow regions (Thelwall & Maflahi, 2022).

In the science of science, the performance of scientific mobility receives great attention, and many studies are demonstrating the benefits of scientific mobility (Aykac, 2021; De Filippo, Casado, & Gómez, 2009). Even though temporary performance loss at individual and collective levels (so-called brain drain) is reported (Abramo, D'Angelo, & Di Costa, 2022; Verginer & Riccaboni, 2021) and types of inequality exist concurrently (Deville et al., 2014; Gu, Pan, Zhang, & Chen, 2024; Momeni, Karimi, Mayr, Peters, & Dietze, 2022), scientific mobility is still considered an effective way to improve individual performance in impact and productivity and is beneficial to returnees' regions for a long-term perspective (Holding, Acciai, Schneider, & Nielsen, 2024; Liu & Hu, 2022).

Thus, we suppose that the identifications of scientific mobility are not able to keep up with the increasingly evaluating demands in short-term scientific travels for communication and collaboration. Concurrently, most identifications based on the changing information in individuals' affiliations and the related data are always extracted from their published records, scholar identity, and self-disclosing Curriculum vitae (CV). Such methods are still at a coarse-grained level since they might neglect several short-term scientific movements, which might also influence individual performance. We collected a unique dataset from the publications of global big science facilities, which could be used to fill this knowledge gap.

Big science is considered one of the basic features of modern science, and big science facilities are research infrastructures for modern science. National or supranational bodies began the investments during World War II and are expecting these big machines to assist cutting-edge knowledge discoveries with advanced analytical technologies, especially in science-related disciplines (Hallonsten, 2014). Nowadays, big science facilities are operated as user-oriented experimental platforms, which requires users, considered as external scientists, from global academia to submit their research proposals and conduct their experiments on-site if users' proposals are permitted successfully (Heinze & Hallonsten, 2017; Silva, Schulz, & Noyons, 2019; Söderström, 2023b).

The utilization model of big science facilities provides us with a novel perspective to identify scientific mobility in a more micro way, and we suppose that "scientific travel" is a more suitable concept (Söderström, 2023a). Therefore, we demonstrate that those co-authored external scientists of the facility could be defined as scientific travelers if they are recorded in more than one facility during a specific period, and they are considered as scientific locals if they are only recorded in one facility. After the classification, we could compare the performance gaps between two types of external users at the author level and paper level by measuring the disruptive and novel abilities.

This study contributes to current knowledge in several ways. Firstly, we proposed a more micro way to identify scientific mobility and named such level movements as scientific travelers, enriching the current research on the relationships between scientific performance and scientific mobility from a novel and unique perspective based on the research context in big science facilities. Secondly, we contribute to expanding the framework of facilitymetrics by providing significant evidence related to the performance gaps between different types of users (diverse or concentrated) to facilitate the practices of brain gain and science policy in the era of big science. Thirdly, the results from the micro perspective could be extrapolated to those short-term scientific activities full of knowledge communication and peer collaborations but concurrently hard to be identify in the level of scientific big data, for instance, attending international conferences, the plans of visiting scholars, and other on-site collaborations with cross-regional co-authors.

We review the extant literature related to big science facilities and scientific mobility, introduce our methods of data collection, indicator construction, and quantitative predisposition, display our main results and supporting results, and discuss the potential implications of our results to science policy in the following sections.

Literatures Review

Big Science Facilities and Facilitymetrics

Big science is a concept that has already existed for at least several decades since World War II, which gave birth to a group of research infrastructures with advanced experimental technologies and unique scientific circumstances for cutting-edge knowledge discoveries in science disciplines (Hallonsten, 2016; Heinze & Hallonsten, 2017). Such research infrastructures, named big science facilities, are commonly invested by national or supranational bodies since the processes of construction and maintenance require too much vast investment, huge network resources, and collective efforts to be afforded by one or several universities and institutions (D'Ippolito & Rüling, 2019). Therefore, the nature of big science facilities contain the concept of shared and are ready to open for scientific progress (Hallonsten & Christensson, 2017; Lauto & Valentin, 2013), known as user-oriented, and should be responsible to their taxpayers since they are public investment goods. Under such context, one cutting-edge discipline, so-called facilitymetrics, arose and has already developed for a decade to apply, revise, and update quantitative methods from scientometrics to evaluate the scientific performance of big science facilities. Facilitymetrics is first proposed by Hallonsten (2013) with suitable indicators (Hallonsten, 2014), for instance, Facility Immediate Index and Facility Impact Factors (Heidler & Hallonsten, 2015), applied to evaluate these machines' performance based on the scientific publications supported by them.

The development of facilitymetrics originated from the special features of big science facilities, leading to the evaluations of scientific performance should consider those hidden factors. For instance, the extreme number gap between investments and productivity might lead to absurd evaluative results (Lauto & Valentin, 2013). Moreover, in the context of big science facilities, knowledge production is highly depended on collaborations and the collaboration between communities should be highlighted since there are two unique communities of scientists related to big science facilities, named external scientists (users) and internal scientists (staff), respectively. With respect to previous studies in theories and the user orientation in practices, such a collaboration paradigm might damage the research chances of internal scientists and emphasize their functions of supporting and serving, which placed them in an underrepresented condition

(D'Ippolito & Rüling, 2019; Silva et al., 2019; Söderström, 2023b). However, in our previous work, results demonstrated that the paper-level performance would be significantly improved if external users collaborate with those internal scientists, ensuring the indispensable effects of internal scientists. From the theories of team science (Katz & Martin, 1997; van Knippenberg & Schippers, 2007), we supposed that it might be the heterogeneous knowledge, for instance, technology manipulation or data interpretation, that internal scientists possess that makes collaborative users conduct their experiments easier, more effective, and more standardized (Xu et al., 2024; Yang, Tian, Woodruff, Jones, & Uzzi, 2022). Eventually, succeed in scientific performance.

The utilization of most big science facilities is on-site (Söderström, 2023a), but these facilities are still suffering from the shortages of beamtime and research resources since the booming demands from global users and the annual experimental volumes in one facility are limited by natural reasons (D'Ippolito & Rüling, 2019). Therefore, potential users are required to submit research proposals to compete and await to be permitted by facilities (Hallonsten & Christensson, 2017). Those successful users need a short period to visit the facility and finish their research on-site during the limited beamtime. Such a mechanism enables us to identify whether the focal author traveled or not during a specific period.

After all, big science facilities are considered experimental platforms for scientific research, especially important for those disciplines that highly depend on advanced analytical technologies such as X-rays, Particle accelerators, Free-electron lasers, and Neutrino detectors. Therefore, there are different types of big science facilities, and Synchrotron Radiation Lightsource (SLS) is one of the most attractive facility types in the framework of facilitymetrics. It is reported that about 50 SLSs are operating, and some of them are still under construction around the world concurrently (Conroy, 2024; Wild, 2021), and most of them have already produced considerable scientific knowledge with several Nobel prizes related to (Hand, 2010; Heinze & Hallonsten, 2017; Jiménez, 2010). Therefore, we mainly focus on the performance of SLSs in this study and confine our focal scientists to the community of external scientists for high accuracy to define travelers and locals with respect to the unique features abovementioned in the context of a big science facility.

Scientific Mobility and Individuals' Performance

One of the features of modern science that benefited from the development of transportation is that scientific individuals could move around the globe more easily than before to communicate and collaborate with their peers (Franzoni et al., 2012; Lin et al., 2023; Söderström, 2023a; Van Noorden, 2012). Many studies have provided evidence to demonstrate the impacts of scientific mobility, and such influences could be divided into two aspects approximately. One focuses on evaluating the socio-economic impacts and the future of in-flow and out-flow regions (Verginer & Riccaboni, 2021) and the other attempts to discover the variation of individuals' scientific performance (De Filippo et al., 2009).

In the science of science, scientific mobility is tightly associated with the evaluations of scientific performance (De Filippo et al., 2009). Moving to another place might bring several risks and challenges (Deville et al., 2014), leading to a temporary productivity loss (Abramo et al., 2022), disconnecting with previous colleagues in the former affiliations gradually (Wang et al., 2019), and eventually damaging individuals' performance. However, from a further perspective, specifically at the career level, the main viewpoint of scientific mobility demonstrates that mobility offers more improvements in performance for individuals as returns (Holding et al., 2024; Tartari, Di Lorenzo, & Campbell, 2020). It is reported that individuals' social networks are supposed to be expanded since new connections will be set up as scientists move to another scientific affiliation while the previous connections will not disappear suddenly (Jiang, Pan, Wang, & Ma, 2024; Liu & Hu, 2022; Wang et al., 2019). Moreover, several studies have demonstrated scientific mobility could eventually improve individuals' performance in productivity and impact by comparing those moving scientists with their peers without moving experiences (Chen, Wu, Li, & Sun, 2023; Momeni et al., 2022; Uhlbach, Tartari, & Kongsted, 2022). The chances of collaboration, the probability of producing high-quality articles, and the internationalized impact are also discovered to be improved due to scientific mobility (Aykac, 2021; Gu et al., 2024).

Previous research highlighted the importance of scientific mobility. However, we supposed that the methods of mobility identification and performance evaluation are still at a coarse-grained level. As to mobility identifications, most studies depended on the changes in affiliated relationships to justify whether a focal scientist moved or not, and the information on affiliations is commonly extracted from published records (Aykac, 2021; Deville et al., 2014; Holding et al., 2024; Jiang et al., 2024; Liu & Hu, 2022; Momeni et al., 2022). Several studies also collected the mobility information by analyzing the author-level identifications, for instance, ORCID, Scopus ID, and Web of Science ID, or picking up affiliations information from individuals' curriculum vitae (CV) (Abramo et al., 2022; De Filippo et al., 2009; Tartari et al., 2020; Wang et al., 2019). Such methods might lack of strengths in interpreting how those short-term scientific activities, without changing affiliation information, could influence the scientists' performance in return. However, the gradually connective scientific communities and increasingly facilitating scholarly communications require demonstrations on whether short-term scientific activities, such as scientific visits, attending conferences, moving around for face-to-face collaboration, and conducting scientific experiments in another lab or facility abovementioned, will benefit or hurt scientists' performance. It is also a question attracting great attention from academia, policymakers, and the public.

Additionally, as to author-level performance evaluations, several studies took the mean value or positive probability of paper-level performance as a representation (Li, Tessone, & Zeng, 2024; Zeng, Fan, Di, Wang, & Havlin, 2022). However, we suppose that in the context of widespread collaborations, paper-level performance might need to be credited to co-authors respectively by measuring their contributions (Thelwall & Maflahi, 2022). Therefore, we introduced a cost-benefit perspective in this study and considered that all scientists' efforts during a specific period should be limited, dispersing to his or her scientific publications unevenly (Jones, 2021; Leyan Wu, Yi, Bu, Lu, & Huang, 2024). Therefore, the benefits of one scientist attained from each publication depend on the costs he or she has invested (Zhang et al., 2024), and the volume of investment is measured by author sequence and based on the methods of proportional count (VanHooydonk, 1997).

Summary

Those short-term scientific activities without varying affiliations are named by us as Scientific Travels. They are increasingly common, but academia still knows little about scientific travels' impact on individuals' performance since, at the level of scientific big data, it is challenging to define and identify these activities with credit accuracy. However, the features of big science facility utilizations provide a valuable perspective and make such micro-identification possible. Based on the publications supported by worldwide big science facilities, the SLSs, it is easy to identify external scientists' global scientific activities and their flows during a specific period. Therefore, we are motivated to shrink this knowledge gap, provide important evidence on the impact of scientific travels, and support the decisions of science policy.

In the following sections, the analysis associates the travel experiences with scientists' performance, adjusted by individuals' contributions, and eventually offers a novel insight for related research in scientific mobility and enriches the framework of facilitymetrics.

Data & Method

Publication Library and Open Dataset

The scientific published data collection processes in the framework of Facilitymetrics are quite different since the special features of Big Science Facilities and should be noted. The traditional method, the retrieval query, was proved unsuitable due to lack of coverage and accuracy. If the published data were retrieved from Web of Science Core Collections (WoSCC) or Scopus, the fields of Affiliation Address and Funding Text should be applied. However, retrieving by Addresses might only lead to those publications at least authored by one staff who is affiliated with the focal facility while retrieving by Funding Text shall lead to those publications authored by external users, but the expressions of acknowledgments are not identical, and not all users acknowledged the focal facility in their publications (Silva et al., 2019; Söderström, 2023a, 2023b).

However, almost all Big Science Facilities around the globe have constructed their own bibliographic library to index their supporting scientific publications, and these libraries can be found and accessed on their official websites. Such libraries are considered one of the ways to make the scientific performance of big science facilities public and visible, responding to the concerns of policymakers, governments, and the public as taxpayers. Moreover, these libraries served an entrance for globally potential users to know the technological abilities and previous knowledge explored by the focal facility. Correspondingly, these libraries are considered self-constructed databases in the framework of Facilitymetrics, which highly facilitates the procedures of data collection.

We selected SLSs as our focal type of big science facilities in this work, a widely discussed type to be explored in Facilitymetrics, as abovementioned. SLSs are considered scientific platforms with advanced experimental technologies for almost all disciplines of science, especially material science, biology, physics, and chemistry. Concurrently, about 50 SLSs are operating or under construction around the world. Based on the expertise from China Big Science facilities and the guidance of the LightSources website[1], we constructed a publication dataset including about 240,000 scientific articles supported by 41 SLSs by exporting or crawling their self-constructed databases one by one. The remained 9 facilities have not constructed a mature database or have not been applied to support scientific research, and therefore, our dataset excluded them. For those collected facilities, not every SLS has operated for decades and possesses enough beamtime and experimental volume for global users. Therefore, in this study, we only considered the Top 20 SLSs (covered about 80% of publications) in productivity as analytical cases for better data quality. The selected big science facilities with their location, beginning year, and productivity (Final results after cleaning and matching with supplemental database by Python 3.11) are shown in Table 1.

Table 1. Selected Big Science Facilities (Top 20) and the Details of Publications.

No.	*Facility*	*Located Country/Region*	*Begin Year*	*Number of Publications*
1	ESRF	France	1986	26,544
2	APS	USA	1970	25,492
3	PETRA	Germany	1986	25,115
4	SPring-8	Japan	1999	12,922
5	ALS	USA	1991	12,733
6	PF	Japan	1972	11,091
7	Diamond	UK	2001	9,844
8	NSLS-II	USA	1984	9,005
9	SSRF	China	2000	8,207
10	MLS	Germany	1964	7,336
11	SSRL	USA	1983	5,731
12	AS	Australia	2006	5,659
13	NSRRC	Taiwan (China)	2003	5,629
14	BESSY	Germany	1992	5,621
15	PLS	Korea	2008	5,585
16	ELETTA	Italy	1994	5,182
17	NSRL	China	1984	4,821
18	LNLS	Brazil	1987	4,514
19	SOLEIL	France	2012	3,692
20	MAXIV	Sweden	1983	3,199
		Total Data		197,618

[1] https://lightsources.org/

It should be noted that every self-constructed database provides different structures of metadata, and the data framework is also differentiated, which highly challenges further data processing and limits our perspectives if we do not introduce bibliographic databases as supplemental data sources. Therefore, we used the OpenAlex database as a supplement to introduce more metadata by matching DOI and Title of published records collected from Top20 facilities' self-constructed databases. OpenAlex is a fully open database of the global research system with advantages in terms of inclusivity, affordability, and availability, and it is widely used in current research related to the science of science (Priem, Piwowar, & Orr, 2022).

Measures

We applied a 5-year Disruptive Index (DI_5) and Novelty Metrics, mainly Novelty Score (NS), as dependent variables to measure the scientific performance with the positive probabilities and Author Contribution (AC) adjusting mean value quantified. Moreover, we defined a new metric named the cutting-edge ability, which tells the boundaries-pushing by users' research to a focal facility by measuring the similarity with previous knowledge based on the Jaccard Similarity. Additionally, we set up a framework including several potential indicators to measure the correlations and regression relationships, for instance, the number of Traveled places, Traveled Times, resources of the network, and several involved knowledge topics. Details of our measurements are introduced as follows.

Scientific Performance

The Disruptive Index was proposed by Funk and Owen-Smith (2017) as CD-index and received a update by Lingfei Wu, Wang, and Evans (2019). It quantifies how one paper disrupts the current knowledge system according to the citation relationship. The illustration and formula are shown as follows:

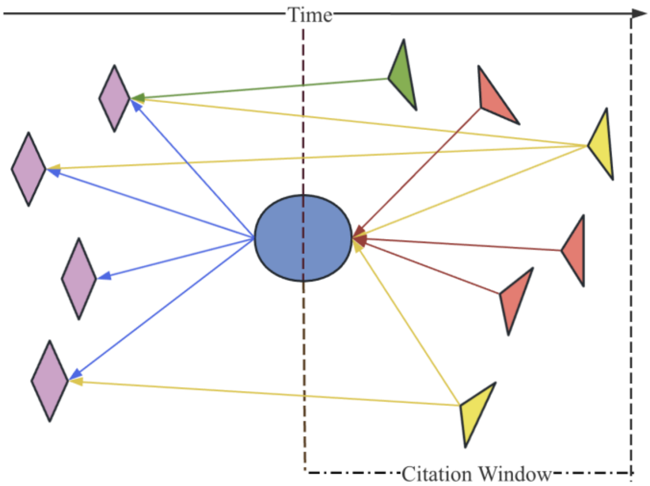

Figure 1. Illustration of Disruption Index.

$$(1)\text{Disruption Index} = \frac{\mathrm{N_r} - \mathrm{N_y}}{\mathrm{N_r} + \mathrm{N_y} + \mathrm{N_g}}$$

For every focal paper (blue node in Figure 1), N_r represents the number of red triangles in Figure 1, measuring the citing publications that only cite the focal paper but do not cite its references, and the references of focal paper are displayed by purple rhombuses. N_y records the number of yellow triangles, telling those citing publications not only cite the focal paper but also cite its references while N_g means the number of citing publications that only cite the references of focal paper and colored in green in Figure 1. According to the formula, we could tell that the value should range from [-1, 1], and all red triangles lead to 1, indicating that the focal paper might create a new orientation in the current knowledge system, while all yellow triangles lead to -1, meaning that the focal paper might be a consolidative or developmental for its focal knowledge field. Therefore, if the value of DI was no less than zero, the focal paper was supposed to be disruptive. Otherwise, the focal paper was considered consolidating.

It is also obvious that DI might be influenced by the number of references, times cited, and the citation window. Therefore, we have set a 5-year citation window with at least five references and five citations as thresholds to ensure stability.

Novelty Metrics, consisting of Novelty Score and Conventionality Score, was proposed by Uzzi, Mukherjee, Stringer, and Jones (2013). It has introduced the concept of cited journal combinations to measure the focal paper's knowledge novel degree from the knowledge input perspective. The key step of the Novelty Score is the calculation of the Z-score, and the formula is shown as follows:

$$(2)\mathrm{Z} = \frac{(\mathrm{obs} - \exp)}{\sigma}$$

Every cited journal combination could be calculated a Z-score, and obs is the observed frequency of the focal cited journal pair while exp is the mean frequency of all cited journal pair and σ Represents the standard deviation of the number of journal pairs obtained from 10 randomized simulations of paper-to-paper citation network. Therefore, for one focal paper, its references and corresponding cited journal combinations could be found, and the Z-score of each combination could be sorted from the lowest to the highest, 10^{th} percentile Z-score is selected to represent the Novelty Score while the median Z-score is used to represent Conventionality Score.

Both Indicators, DI and NS, are widely explored and applied concurrently, and we applied them as two aspects of scientific performance to quantify the differences between scientific travelers and locals.

Author Contribution

We introduce a coefficient to adjust the evaluations of the author-level's scientific performance since this work mainly focuses on the scientific performance at the author-level (Zhang et al., 2024). We suppose that it is unsuitable to simply take the paper-level performance of an author in one specific year or during the total career as his or her performance, especially concurrently, scientific collaborations are widespread, and scientists have a higher possibility to produce more than one papers in a year than before, leading to a situation that one scientist might distribute his or her efforts into several works simultaneously but unevenly. Therefore, we first filtered our data to retain those publications of teamwork and calculated the author contribution as an adjusting coefficient based on the method of proportional count and the hypothesis of cost-benefit perspective by measuring one author's rank in the team considered (VanHooydonk, 1997). The formula for Author Contribution is shown as follows:

$$(3)\text{Author Contribution} = \frac{(\mathrm{N}+1) - \mathrm{AS_a}}{\sum_1^{\mathrm{N}} \mathrm{AS}}$$

In formula (3), denoted N is the number of co-authors in one scientific team, while AS is the focal authors' sequence. If four authors collaboratively published one paper, the first author's credit should be 0.4, the last author's credit should be 0.1, and the two middle authors' credit should be 0.3 and 0.2, respectively. It is noted that this indicator is based on author sequence, which might overlook the contributions of corresponding authors of scientific teams. However, we suppose that the overlook might not cause heavy variations, and it is the most suitable choice. Firstly, the role of corresponding authors is difficult to identify in the level of publication data, and not all corresponding authors are always placed at the last. Moreover, corresponding authors usually have a higher tendency to publish more articles in one year or during the career than the first author and other authors, which well-matched our hypothesis that the efforts of the last author (if he or she is the corresponding author of his or her team) might be further distributed. If not, the last authors might be the lowest contribution author in the team.

We applied this coefficient to paper-level indicators of scientific performance and considered the mean values and positive probability of scientific performance adjusted by author contribution as the scientific performance of the focal author in one-year, total career, or for a specific time stage. The formulas of mean value and positive probability are as follows:

$$(4)\mathrm{Mean_j} = \frac{\sum_{\mathrm{i}}^{\mathrm{N}} (\mathrm{AC} \times \mathrm{P_i})}{\mathrm{N}}$$

$$(5)\mathrm{Prob_j} = \frac{\mathrm{N_{positive}}}{\mathrm{N}}$$

In formulas (4) and (5), denoted j is the period of scientific performance and AC is the focal author's credit in one paper and P_i is the scientific performance of corresponding paper. N should be the number of published articles of the focal author during the period j. $N_{positive}$ refers to the situation that $DI_5 \geq 0$ or $NS \leq 0$ and the probability does not need to be adjusted by author contribution since the sign will not change.

Traveled Places

The dataset of big science facilities' publications collected by us previously offers an even micro perspective to define the processes of scientific mobility since every facility requires users to conduct their experiments on-site. This context assists us in defining the role of scientific travelers and locals. We firstly confined that the focal authors should be external users of big science facilities, and if they have used more than one facility in a specific period, they should be scientific travelers. Otherwise, they are locals. The identification of the used facility is according to the relationships of focal author's publications with self-constructed databases. If one author's publication during a specific period is collected from more than one self-constructed database of facilities, we can tell that he or she should be a traveler since more than one facility is used. Therefore, the number of traveled places is considered as the number of used facilities in one year or during a specific period.

It should be noted that, according to our previous studies, the co-utilization between or among these big science facilities is uncommon but possible. Given that there is a co-utilized author who only published one publication but could be observed to use more than one facility. Such a situation is complicated and out of our research range, therefore, during the data cleaning, we have already dropped out those publications supported by more than one facility. It also means that Travelers should publish at least two articles in the focal period.

Other Important Indicators

We also define other indicators to finish further processes of visualization, correlations, and regression. Firstly, we proposed the volume of one author's network resources and involved knowledge topics from paper-level indicators by measuring the number of collaborative peers and published topics in a specific period. Secondly, we considered the productivity and the mean values of AC adjusted scientific impacts in one year and ten years to describe their impacts immediately and in the long term.

Furthermore, based on the Jaccard Similarity, we define the AC adjusted knowledge similarity by measuring the number of new topics in one publication compared with the using facilities' previously published topics numbers and considered the mean values to represent the performance of the focal author. The formula is shown as follows:

$$(6)\text{Knowledge Similarity} = \frac{\left|\overline{\mathrm{T}}_{\mathrm{i,j}} \cap \overline{\mathrm{T}}_{\mathrm{k,j-1}}\right|}{\left|\overline{\mathrm{T}}_{\mathrm{i,j}} \cup \overline{\mathrm{T}}_{\mathrm{k,j-1}}\right|}$$

Denoted paper i published in j year supported by facility k, and $\bar{T}_{i,j}$ refers to the research topics of focal paper while $\bar{T}_{k,j-1}$ refers to research topics the focal facility has researched. Both sets of topics are provided by OpenAlex. Then, the paper-level similarity with pervious knowledge could be calculated and after adjusting by AC, the mean values are used to indicate author-level performance during a specific period.

Additionally, we define the level of localization for travelers by measuring the ratio of local productivity and global productivity. Formulas are shown as follows:

$$(7-1)\text{Localization Ratio}_{\mathrm{j}} = \frac{\text{Local Productivity}_{\mathrm{j}}}{\text{Total Productivity}_{\mathrm{j}}}$$

$$(7-2)\text{Divide Thresholds}_{\mathrm{n1}} = \min_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} + (\max_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} - \min_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}})/3$$

$$(7-3)\text{Divide Thresholds}_{\mathrm{n2}} = \max_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} - (\max_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} - \min_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}})/3$$

$$(7-4)\text{Localization Level} = \begin{cases} \text{Low}, & \min_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} \leq \mathrm{LR}_{\mathrm{j}} \leq \mathrm{DT}_{\mathrm{n1}} \\ \text{Moderate}, & \mathrm{DT}_{\mathrm{n1}} < \mathrm{LR}_{\mathrm{j}} < \mathrm{DT}_{\mathrm{n2}} \\ \text{High}, & \mathrm{DT}_{\mathrm{n2}} \leq \mathrm{LR}_{\mathrm{j}} \leq \max_{\mathrm{n}} \mathrm{LR}_{\mathrm{j}} \end{cases}$$

We first calculate the focal traveler's Localization Ratio in every used facility during the period j, and then find the lowest ratio and highest ratio of localization with the number of traveled facilities (denoted n in the formula 7-2 and 7-3) for all focal travelers during the period j considered. The divide thresholds could be found, and all focal travelers could be classified into different groups of Low, Moderate, and High according to the formula (7-4).

Results

We provided several perspectives related to the performance gap between scientific travelers and locals with multiple classifications applied to verify the robustness of our results. In the section of Results, we mainly classify external users into travelers or locals at the yearly level. The results by classifying at the level of total career or the level of past experiences are shown in the appendix, and all results are consistent, indicating the robustness of our discoveries and contributions. Moreover, the appendix also contains several figures for data distribution, which assisted us in setting thresholds for data filtering for better data quality.

Scientific Performance Gaps Between Travelers and Locals

According to Figure A1(A) and the definition of travelers abovementioned, the productivity of travelers and locals mainly distribute less than 15 articles, and therefore, we only considered those scientists' yearly productivity range from 2 to 15. From Figure A1(B), we can tell most scientists' career age is no more than 30 years, which leads to another threshold. Figure A1(C), displays the annual average credit differences between travelers and locals, and the value of author contribution is highly related to team size that we have confined that the number of co-authors in one article should be less than 45.

Figure A2 shows the tendency of modern science that the connections in global academia are increasingly close. As time goes on, more scientists tend to travel around, and concurrently the ratio of travelers in one year has reached 0.4. Figure A2(A) and A2(C) show similar results that middle-aged scientists have a higher possibility to travel to more than one facility, and junior scientists might lack travel chances.

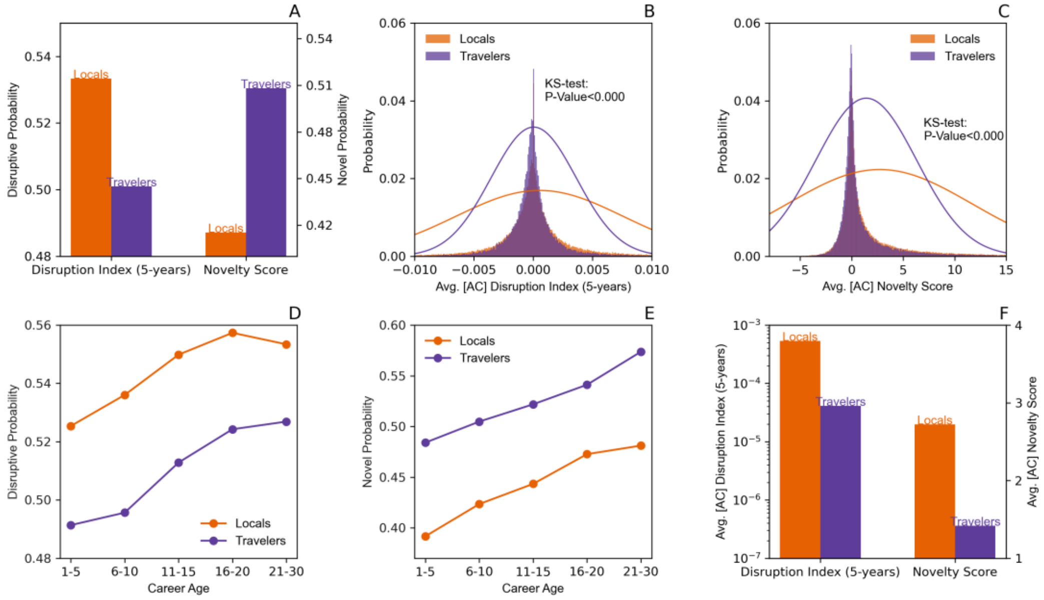

Figure 1. Travelers Associated with Better Novelty while Locals Produce More Disruption. Travelers and Locals are classified at the yearly level.

Under such context, Figure 1 mainly shows the basic results of this study that scientific travelers negatively related to disrupting the current knowledge systems while their works possess higher scientific novelty than locals. Figure 1(A) shows the gap of positive probability (K-S Test, $p<0.000$) between locals and travelers in scientific performance (103,359 Locals and 40,854 Travelers in the Sample of DI_5 while 142,420 Locals and 61,522 Travelers in the Sample of NS), and 1(B) and 1(C) display the mean value distribution of scientific performance indicators while 1(F) records the significant differences (K-S Test, $p<0.000$) of mean values between travelers and locals that locals still perform better at disruption but lack of knowledge novelty (Samples are consistent). 1(D) and 1(E) show the positive relationships between positive probability and career age.

Consistent results are also displayed in Figure A3 and Figure A4. Figure A3 classified all external users into "Never Traveled" and "Traveled" according to their travel experiences at career level, while Figure A4 identified "Un-Traveled" and "Over-Traveled" by yearly measuring whether the focal scientists have traveled or not in the past. For instance, given that there is one user (U) and he or she first traveled in 2000, leading to he or she is considered as an "Un-Traveled" before 2000, as an "Over-Traveled" current and after 2000. The results of the three classifications with their positive probabilities and mean values are consistent.

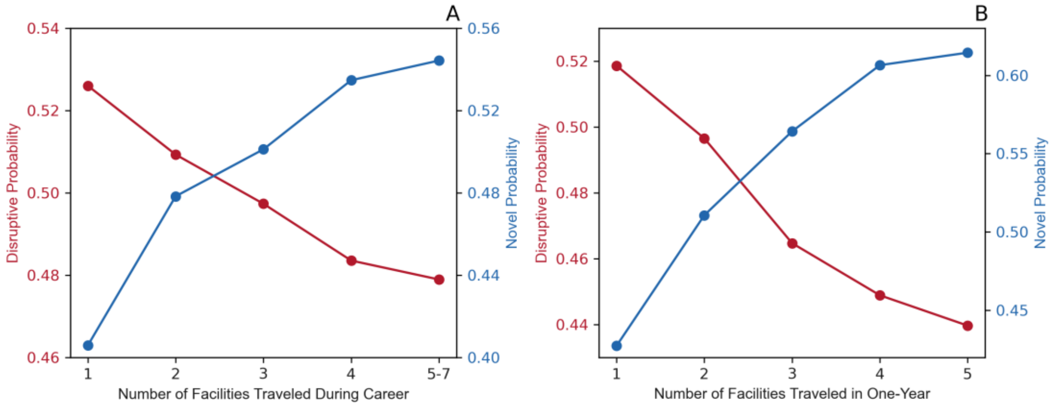

Figure 2. More Travels Lead to Negative Disruptive Ability but Positive Scientific Novelty.

Figure 2 displays relationships between the number of traveled facilities for scientists during their total career and in one year. The red color represents the variation of Disruptive Probability while the blue color shows the variation of Novelty. From the perspective of academic career, those locals might suffer from a low probability of novelty (about 0.4) but benefit from a high disruptive probability. The thresholds of traveled facilities numbers were selected by referring to Figure A5.

The Impacts of Localization

Denoted that the ratio of localization level describes the degree of concentration and dispersion of scientific travelers by measuring their local productivity and global productivity. If one traveler is observed with extremely skewed productivity in the minor facility, he or she might be a highly localized traveler. Here, we mainly classified scientists by their annual productivity, and the results of career-level productivity are shown in Figure A6.

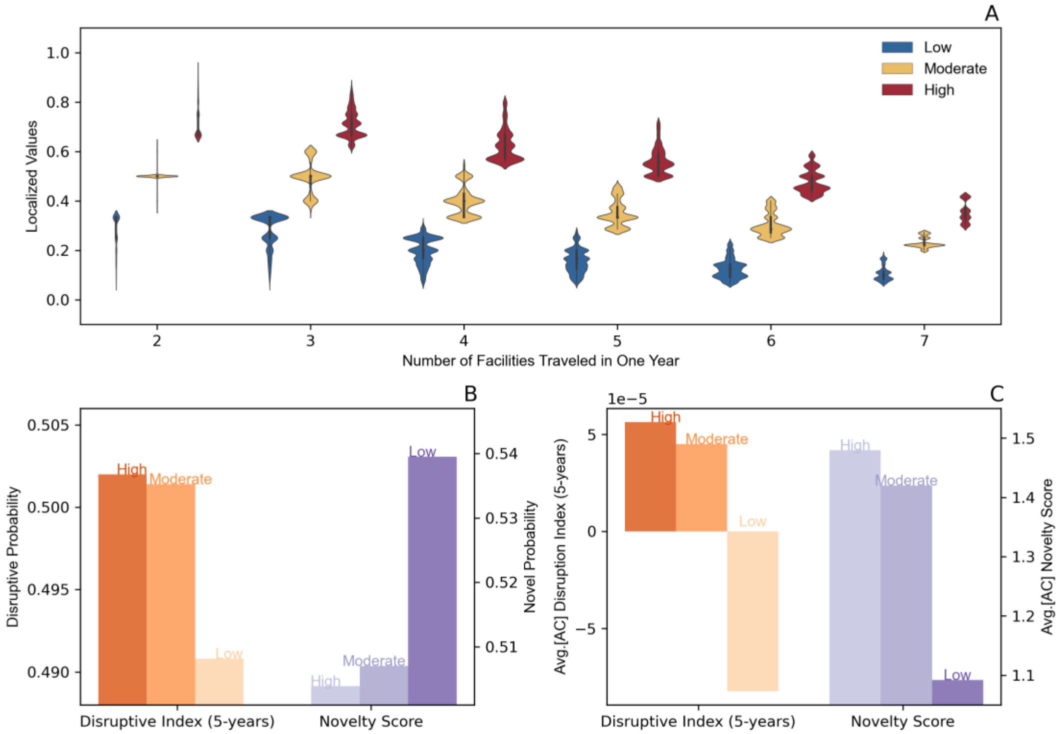

Figure 3. High Localization Travelers Produce More Disruption while Low Localization Travelers Associated with More Novelty.

Figure 3(A) displays the classifications of localization level with the number of traveled facilities considered. The threshold of traveled facilities numbers is also referred to in Figure A5. If one traveler's productivity ratio in any facility he or she used in the focal year drops in the red range, he or she is classified into high localization. Similarly, moderate and low levels of localization could be identified. In the sample of DI_5, 14,100 year-level Travelers are classified as High, 24,224 are classified as Moderate group, and 2,529 are classified as Low group. In the sample of NS, 20,418 year-level travelers are high localized, 37,023 are moderate, and 4,078 are low localized. In Figure 3(B) and Figure 3(C), results indicate that high localized travelers are associated with better disruptive performance than low localized counterparts while opposite results of novelty score. The performance gaps between different levels of localization are significant according to the K-S Test ($p<0.000$ for High-Moderate and Moderate-Low test when considering the positive probabilities of DI_5 and NS and the mean value of NS; $p<0.1$ for Moderate-Low test and $p<0.05$ for High-Moderate test when considering the mean values of DI_5). Figure A6 shows similar results that those scientists who traveled to several facilities during their career but have extremely skewed preferences might produce more disruptive knowledge while those who are not skewed in productivity might produce more novel knowledge. These two figures record the performance gap between travelers and if we take corresponding locals as controls to compare with, results support that highly localized scientists produce less disruption knowledge but still better novelty than totally localized scientists.

The Impacts of Travel Experiences

In this subsection, we mainly focus on those scientists with travel experiences, and for the sake of improving the inclusive, we also included those travelers who have already localized and annually produced only one article in the local year.

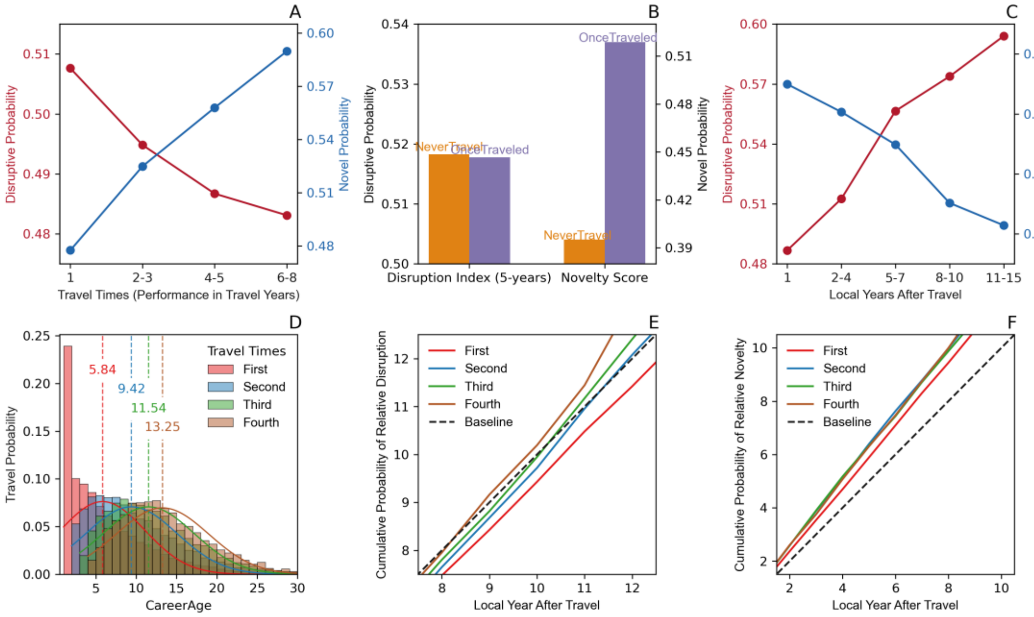

Figure 4. Travel Experience Damage Locals' Disruptive Ability but Increase Novelty.

Figure 4 displays evidence to understand how travel experiences will affect scientists' scientific performance. Firstly, Figure 4(A) shows the concurrent yearly performance variation of travelers in the travel year, indicating that more traveled experiences might decrease the probability of disruption but increase the novelty probability. Comparing the career-level performance of those scientific travelers when they are locals (Never Traveled to another facility, 62,480 year-level scientists for DI_5 and 65,997 for NS) and once traveled (at least traveled to two facilities previously, 42,114 year-level scientists for DI_5 and 75,717 for NS), and the results of comparisons are recorded in Figure 4(B). It is shown that the probability of disruption suffers from slight damage (KS-test: $p<0.000$, T-test: $p=0.854$) while novelty probability is observed a significant improvement (KS-test: $p<0.000$). The following figures could assist in understanding such a situation in Figure 4(C), we observed that for those travelers, once they have finished a one-year travel and are back to local scientists, their disruptive probabilities will increase as the local year goes on, but their probability of novelty might slowly decrease since total localization. However, the novel ability of these fully localized travelers is still much better than that of those locals without travel experiences. To better display the variations, ensure data quality, and compare with those travelers' counterparts, we mainly focus on the impact of the first four times travel experience and display travelers' average travel career age as shown in Figure 4(D). Later, we take these mean values as the representative travel career ages by rounding down, considering the next year should be the first local year of those travelers who finished scientific travel, and select those locals with identical career ages as the control group to compare the subsequent years' performance whether a scientist chose to travel or not. Results are shown in Figure 4(E) and Figure 4(F), with the cumulative probability of relative disruption and novelty visualized. We consider those corresponding years' performance of locals as a baseline and compare it with the travelers' yearly scientific performance after their travels at different times. Then, the relative probability of positive scientific performance could be calculated, and eventually, the cumulative value could be found. From the abovementioned results, it is reported that scientific travel might decrease scientists' disruptive ability, and their disruption might increase gradually as they localized. However, Figure 4(E) argues that those scientists with travel experiences might slowly surpass their peers without travel experiences in disruptive ability as time goes on, especially those scientists with more than one-time travel experience, and the surpass year will become earlier if one traveler has traveled around for times. Figure 4(F) indicates that those scientists with travel experiences could significantly outperform their peers in producing novelty knowledge.

Alternative Indicators Differences between Travelers and Locals

Several factors might affect the performance gaps between travelers and locals with respect to previous knowledge. We aim to shrink such potential impacts and validate our results. Therefore, we visualized differences between travelers and locals in alternative indicators.

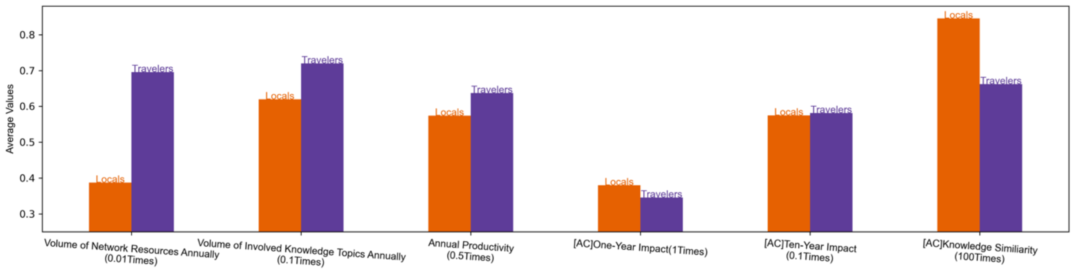

Figure 5. Alternative Indicators Differences Between Locals and Travelers.

Figure 5 tells the scientific input gaps between travelers and locals in annual network resources and involved knowledge topics and displays the output-level gaps in productivity, short-term and long-term impact, and the similarity with previous local knowledge. The values are normalized by us to reach a better visualization, and the times of normalizations are recorded following all indicators in the Figure. Locals might receive more short-term citations, while in the long term, travelers might have higher scientific impacts. Travelers might also perform better in expanding the knowledge edge for the facility they are using since they have lower similarity with previous knowledge than locals.

Note that the annual volume of network resources represents the number of collaborators for a focal scientist in one year, and the annual volume of involved knowledge topics records the number of research topics the focal scientists have published. Both are reported to affect the scientific performance at the paper level and therefore, we put emphasis on them to avoid potential impacts on author-level performance and the results are shown in Figure 6.

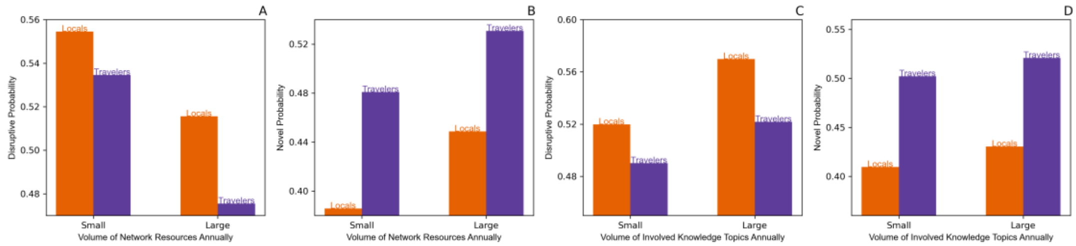

Figure 6. The Effects of Network and Involved Knowledge Topics on Scientific Performances.

Figure 6(A) and Figure 6(B) record the impact of small or large volumes of network resources on the scientific performance of travelers and locals, respectively. The classifications of small or large volumes refer to the distributions shown in Figure A7(A), and we take mean values (locals: 12 and travelers: 16) as boundaries. Even though a large volume of network resources might influence disruptive ability negatively and positively related to novel knowledge, the performance gaps between locals and travelers could still be observed that locals perform better in disruption while travelers could produce more novel knowledge. Similar tendencies could be discovered in Figure 6(C) and Figure 6(D) that if we control the impacts of involved knowledge topics (boundaries could be referred to in Figure A6(B)), locals still perform better in disruption, and travelers possess advantages in novelty.

Regression Analysis to validate

To validate the main results of this study, we conduct the Paper-level and author-level Ordinary Least Squares (OLS) regression to ensure the impacts of scientific travels on scientific performance. Table 2 displays the paper-level results with two corresponding indicators considered as independent variables respectively (the ratio of travelers and the total contribution of travelers in the focal academic team) and potentially influential variables controlled.

Specifically, we select Team Size (at least two co-authors), Number of References (at least five references), and Cited Topics as control variables for disruption index and novelty score according to our previous visualizations. Times Cited_5, a widely demonstrated impactful indicator on DI_5, is considered a unique control variable for disruptive index with a five-year citation window and at least five citations confined while the published year is customed for novelty score since the ability to advance knowledge might be affected by the level of scientific development. Moreover, we consider the supporting facility of each publication as a dummy variable to avoid potential influence caused by different levels among technologies.

In the paper level, Table 2 demonstrates the negative impact of Travelers participating in the scientific team on disruptive ability as their ratio (β=-0.007, p<0.001) or contribution (β=-0.006, p<0.001) improving. The results in Table 2 also ensure the positive effects of Travelers on producing more novel knowledge, given that the lower value of Novelty Score represents better Novelty, and the increasing ratio and contribution of travelers could significantly improve research novelty. All regression models are significant according to F-scores and corresponding significances.

Table 2. Paper-level OLS regression with Indicators Related to Travelers in Teams Considered as Independent Variables.

Models	*(1)* DI_5	*(2)* DI_5	*(3)* *NS*	*(4)* *NS*
Travelers Ratio	-0.007^{***}		-17.229^{***}	
	(0.001)		(0.790)	
Travelers Contribution		-0.006^{***}		-16.007^{***}
		(0.001)		(0.815)
Team Size	-0.000^{***}	-0.000^{***}	-0.029	-0.032
	(0.000)	(0.000)	(0.037)	(0.037)
Number of References	-0.000^{***}	-0.000^{***}	-0.125^{***}	-0.127^{***}
	(0.000)	(0.000)	(0.009)	(0.009)
Cited Topics	0.000^{***}	0.000^{***}	-0.292^{***}	-0.290^{***}
	(0.000)	(0.000)	(0.012)	(0.012)
Times $Cited_5$	0.000^{***}	0.000^{***}		
	(0.000)	(0.000)		
Published Year			0.153^{***}	0.139^{***}
			(0.029)	(0.029)
Constant	0.008^{***}	0.008^{***}	-271.957^{***}	-245.150^{***}
	(0.000)	(0.000)	(57.477)	(57.435)
Dummy	Big science facility			
Adj. R^2	0.064	0.064	0.036	0.036
F-score	208.9^{***}	207.3^{***}	156.3^{***}	152.5^{***}
Obs.	72,896	72,896	99,425	99,425

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Author-level regressions could help to understand how scientific travels will influence scientific performance, as shown in Table A1 and Table A2. Both tables record the OLS regression results in the author-level performance evaluations but different from yearly and career perspectives, respectively, with a binary variable (Travelers: 1, Locals: 0) considered as the independent variable and career age, productivity, network resources, and involved topics controlled according to previous visualizations.

In Table A1, we conduct a yearly analysis which is consistent with our main figures, and results demonstrated that travelers negatively related to disruptive knowledge (β=-0.022, $p<0.001$ in $ProDI_5$ and β=-0.041, $p<0.001$ in $MeanDI_5$) but positively related to novel knowledge (β=0.037, $p<0.001$ in ProNS and β=-1.107, $p<0.001$ in MeanNS). Table A2 applied a career perspective that validate the robustness of our result that travelers still disadvantage in producing disruptive knowledge (β=-0.024, $p<0.001$ in $ProDI_5$ and β=-0.051, $p<0.001$ in $MeanDI_5$) but associated with more novelty (β=0.044, $p<0.001$ in ProNS and β=-1.544, $p<0.001$ in MeanNS).

Discussion and Conclusion

This study provides a more micro and, therefore, more novel perspective to identify the impacts of short-term scientific travels on individuals' scientific performance, quantified by disruptive index and novelty score, discovered that travelers might disturb scientists' ability to produce disruptive knowledge but enhance their novelty ability in return. The micro identification is beneficial from the features of utilizing big science facilities, mainly the characters of external users and on-site experiments. Results classified two types of external users (travelers and locals) by multi-approaches from yearly, previous, and career perspectives, and all results are consistent to show locals associated with higher disruption while travelers perform better in novel knowledge production. Further results indicate that the performance loss of travelers in disruption is mainly short-term, and the last of the period averagely depends on their travel times. We observed that their disruptive ability might increase and even surpass those peers without travel experiences since they have finished their scientific travels and become local users as time goes by. The novel abilities of Travelers are observed to be significantly higher than those of locals in different classifications. Additionally, we conduct OLS regressions at the paper level and author level, respectively, to validate the robustness and consistency of our results. The results of causal inference provided further evidence to support our main conclusions.

The micro-level identification has enriched the extant research in scientific mobility associated with scientific performance since our methods make use of the features in big science facilities context, and the results could be extrapolated to similar situations such as visiting scholars, attending conferences, and any other activities for scientific communication and collaboration without affiliated information to be identified. After all, we propose positive evidence to those policies encouraging scientific mobility and scientific communication, and we demonstrate that in long-term scientific' careers, those travelers could produce novel knowledge easier than those scientists without travel experiences but insignificantly suffer from the loss of disruptive ability.

This study also has several limitations. Firstly, the loss of data should be noted, and the volume of published records is limited by the operating years and experimental volumes of big science facilities for external users. The process of data collection also receives lots of challenges due to one facility having one customed database, and some of them provide low-quality publication data. Therefore, we only take about 210,000 articles as the sample, which might shrink the applied scope of results.

Secondly, concurrently, most advanced facilities located in developed countries or regions and open to their citizens might be the priorities, leading to the scientific contributions from global south might be overlooked potentially. We highly recommend future research focusing on related issues and providing more solutions.

Acknowledgments

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Appendix

Table A1. OLS Regression of Scientific Performance at the Level of Publish Year.

Models	*(1)* *$ProDI_5$*	*(2)* *$MeanDI_5$*	*(3)* *ProNS*	*(4)* *MeanNS*
T1L0	-0.022^{***}	-0.041^{***}	0.037^{***}	-1.107^{***}
	(0.001)	(0.003)	(0.001)	(0.039)
Career Age of the year	0.003^{**}	-0.020^{***}	0.029^{***}	-0.068^{***}
	(0.001)	(0.003)	(0.001)	(0.003)
Annual Productivity	-0.066^{***}	-0.072^{***}	-0.031^{***}	0.276^{***}
	(0.002)	(0.005)	(0.002)	(0.017)
Annual Network Resources	0.009^{***}	0.019^{***}	-0.008^{***}	0.000^{***}
	(0.001)	(0.003)	(0.001)	(5.83e-05)
Annual Involved Topics	0.084^{***}	0.095^{***}	0.032^{***}	-0.177^{***}
	(0.002)	(0.005)	(0.001)	(0.010)
Constant	0.524^{***}	0.000	0.443^{***}	3.498^{***}
	(0.001)	(0.003)	(0.001)	(0.042)
Adj. R^2	0.017	0.004	0.020	0.011
F-Score	486.6^{***}	130.6^{***}	854^{***}	460.1^{***}
Obs.	144,213	144,213	203,942	203,890

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All Independent variables are standardized to mean zero and S.E. 1, and for better discoveries in data, we also standardized the dependent variables of $MeanDI_5$. T1L0 is a binary variable that denoted Travelers as 1 while Locals as 0

Table A2. Robustness Check of Scientific Performance at the Level of Author Career Age.

Models	*(1)* *$ProDI_5$*	*(2)* *$MeanDI_5$*	*(3)* *ProNS*	*(4)* *MeanNS*
T1L0	-0.024^{***}	-0.051^{***}	0.044^{***}	-1.544^{***}
	(0.002)	(0.004)	(0.001)	(0.060)
Career Age	0.005^{**}	0.005	-0.007^{***}	-0.013^{*}
	(0.002)	(0.004)	(0.001)	(0.007)
Total Productivity	-0.028^{***}	-0.029^{***}	-0.015^{***}	0.018^{***}
	(0.002)	(0.006)	(0.002)	(0.004)
Total Network Resources	-0.004^{**}	0.012^{**}	-0.015^{***}	0.000^{***}
	(0.001)	(0.004)	(0.001)	(2.15e-05)
Total Involved Topics	0.041^{***}	0.048^{***}	0.020^{***}	-0.023^{***}
	(0.002)	(0.006)	(0.002)	(0.003)
Constant	0.525^{***}	0.000	0.430^{***}	3.521^{***}
	(0.001)	(0.004)	(0.001)	(0.044)
Adj. R^2	0.008	0.003	0.018	0.011
F-Score	110.1^{***}	43.89^{***}	327.8^{***}	201.9^{***}
Obs.	67,441	67,441	89,963	89,911

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All Independent variables are standardized to mean zero and S.E. 1, and for better discoveries in data, we also standardized the dependent variables of MeanDI$_5$. T1L0 is a binary variable that denoted Travelers as 1 while Locals as 0

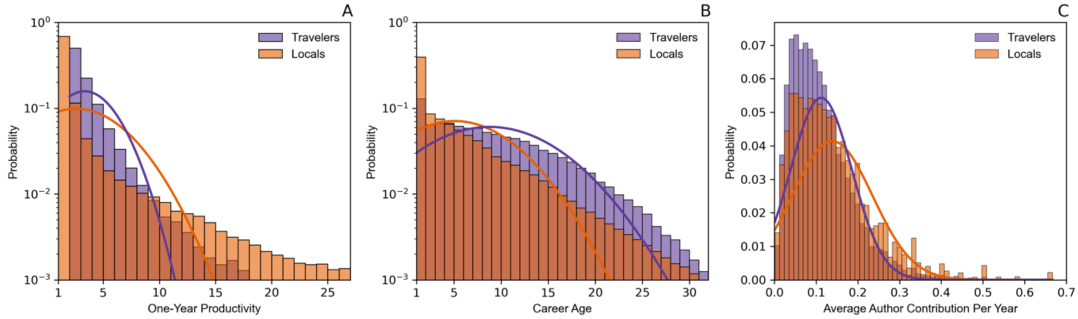

Figure A1. Probability of Travelers and Locals Yearly Productivity, Career Age, and Averagely Collaborative Contribution. Therefore, we selected those authors whose one-year productivity no more than 15, career age no more than 30 and limited the team size of published records less than 45 due to credits of Author Contribution.

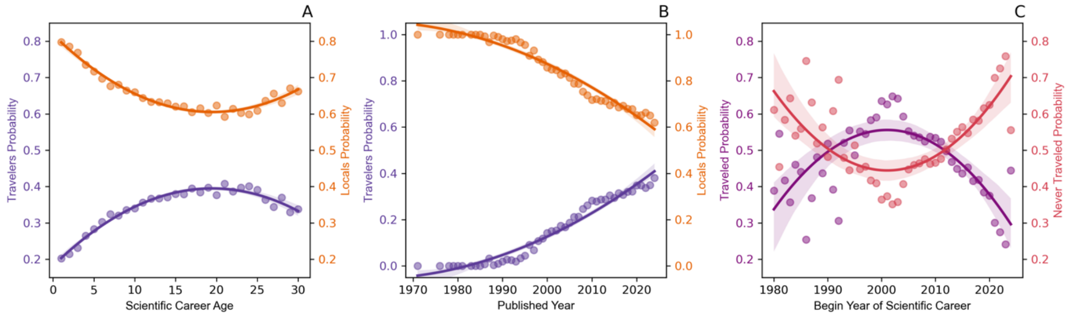

Figure A2. Probability of Traveler and Locals/Non-Travelers.

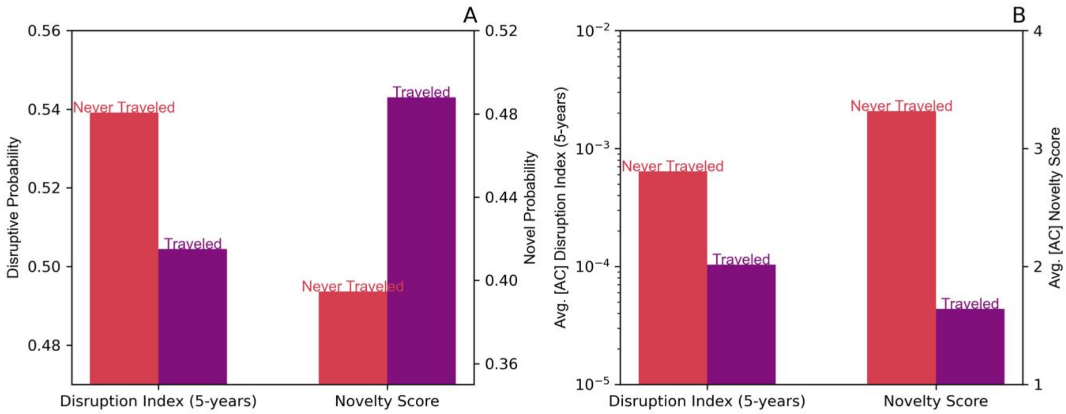

Figure A3. Identical Differences in Performance Between Locals and Travelers in Career Scale. Denoted "Never Traveled" represents those scientists who used only one facility during the career while "Traveled" means those scientists who used at least two facilities during the career.

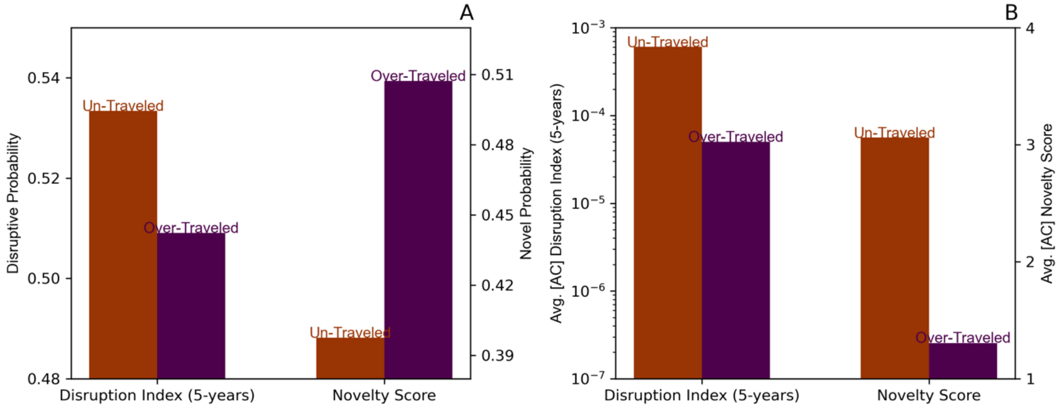

Figure A4. Identical Differences in Performance Once Scientific Travel Appeared. Denoted "Un-Traveled" represents those scientists have not used more facilities and "Over-Traveled" represents those scientists have used more facilities. Once the author used more than one facility, the author would be considered from "Un-Traveled" to "Over-Traveled".

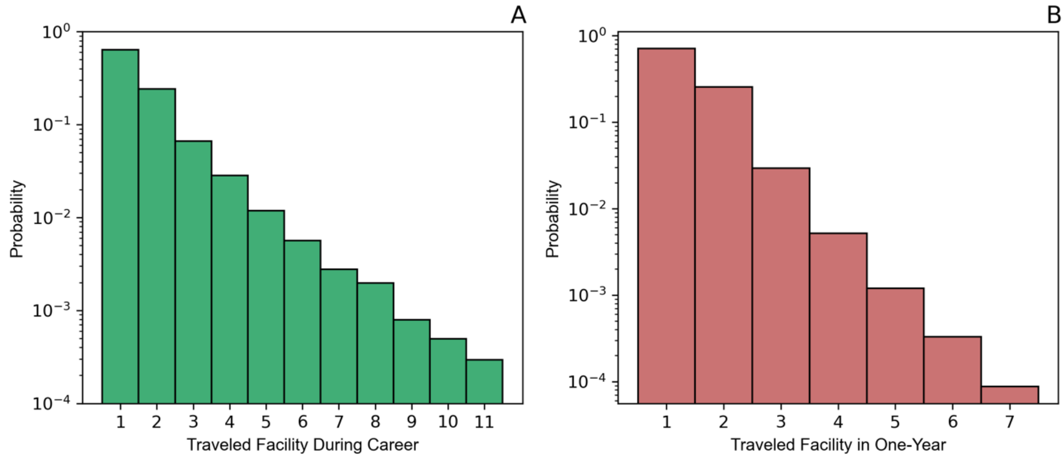

Figure A5. Probability of Traveled Facility Numbers for Scientists during Career and Yearly. We selected the thresholds as no more than seven facilities during career and no more than five facilities in One-Year.

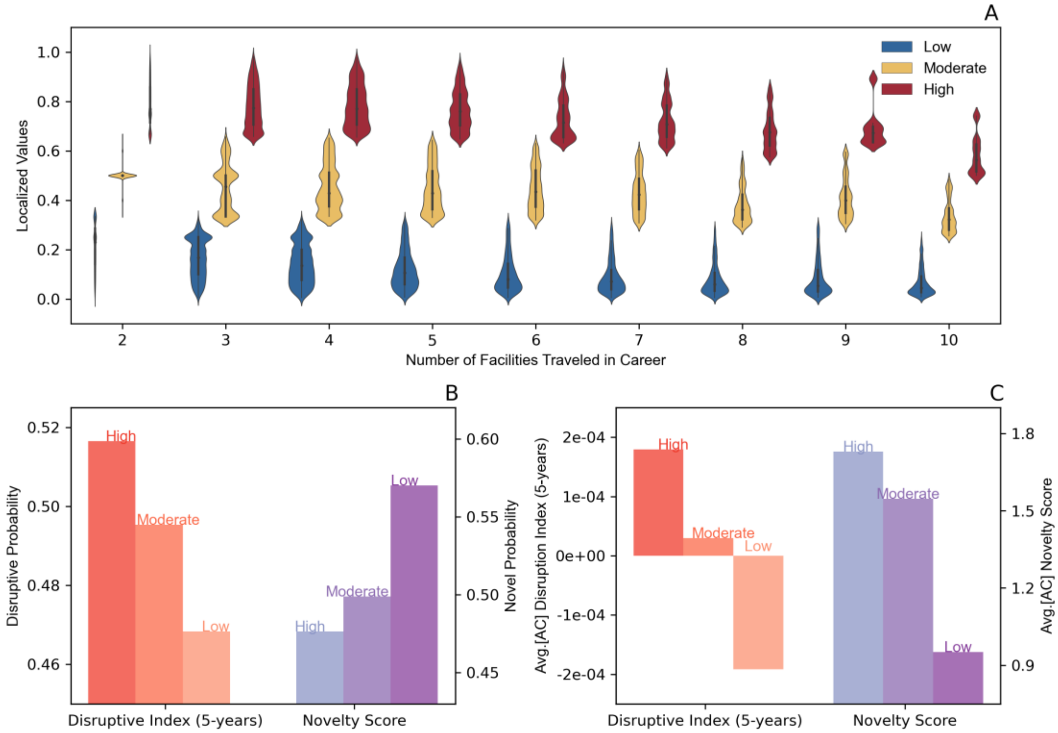

Figure A6. Performance of Travelers with Different Localization Levels in Career Scale. Performance gaps are consistent and more obvious in the career scale and high localized travelers associated with better disruption but lower novelty.

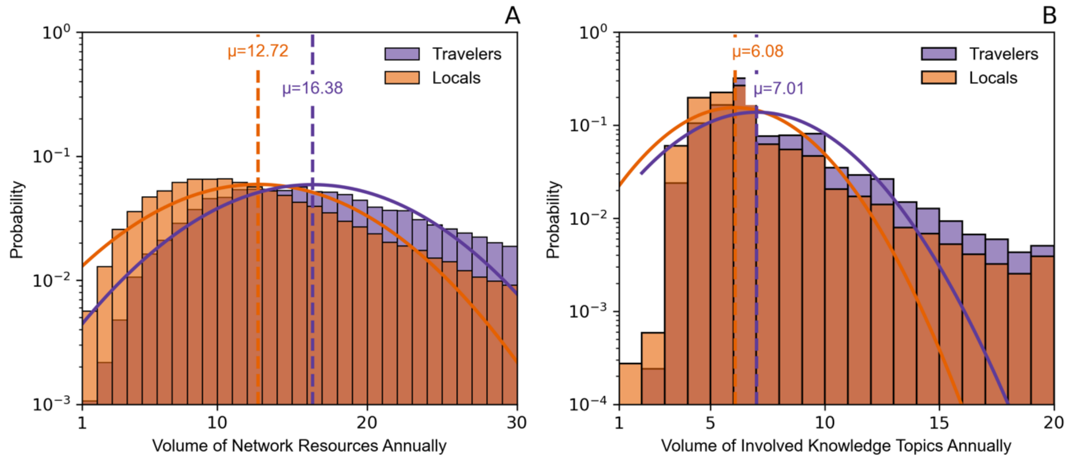

Figure A7. Performance of Travelers with Different Localization Levels in Career Scale. We considered 12 and 16 respectively for locals and travelers as thresholds to divide their volume of network resources. Six and Seven are respectively take as thresholds to divide the annually volume of involved knowledge topics for locals and travelers.