Quantifying Talent Space of Nations Based on Global Patterns of Mobility

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Abstract. This paper investigates the concept of scientific complexity by analyzing global talent mobility through the lens of a bipartite network connecting countries to scientific fields. We introduce a novel set of metrics based on the Revealed Comparative Advantage (RCA) of countries in specific talent fields, which enables the identification of talent mobility patterns and the classification of scientific fields by their relatedness. Drawing on the Method of Reflections (MR), we derive the Talent Complexity Index (TCI) to measure the sophistication of national talent spaces. We further explore the fitness index to capture the dynamic interplay between country-level capabilities and the complexity of scientific fields. Our findings suggest that the fitness index not only reveals the structural intricacies of scientific ecosystems but also serves as a reliable predictor of a country's future economic performance. These results underscore the importance of talent mobility and scientific complexity in shaping global economic success.

Keywords: Talent mobility · Talent complexity · Science of Science

1 Introduction

In recent years, the concept of economic complexity has garnered significant attention as a powerful framework for understanding the drivers of national economic performance. Originally developed to explain the diversity and sophistication of a country's export profile, economic complexity emphasizes the interplay between capabilities, resources, and knowledge [6]. However, while much of the existing literature focuses on material and technological complexity, there remains a notable gap in understanding the complexity of talent—the knowledge, skills, and expertise that flow across borders in the form of scientific mobility. Talent mobility plays a pivotal role in the global scientific and technological landscape, yet it has been underexplored as a distinct dimension of economic complexity.

The movement of scientists and researchers across borders is a key mechanism for knowledge diffusion and the dissemination of innovations [2,8,9]. As global

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networks of collaboration become increasingly interconnected, understanding the flow of scientific talent offers critical insights into the dynamics of scientific ecosystems, national capabilities, and long-term economic growth [7]. Despite this, most existing approaches to talent mobility focus primarily on individual-level migration or country-level statistics, with limited attention paid to the structural complexity of global talent networks and the implications for national economic performance.

This paper seeks to fill this gap by introducing the concept of scientific complexity—a multidimensional measure of a country's contribution to the global talent pool, informed by the movement of scientists across different scientific fields. Our approach builds on the bipartite network framework, commonly used in economic complexity studies [5,6], where countries are connected to scientific fields based on the mobility of their scientists. Through this framework, we introduce the Revealed Comparative Advantage (RCA) of countries in specific talent fields as a novel measure of national capabilities in science and technology. This measure enables us to trace the evolution of a country's scientific specialization and identify the fields where it excels relative to other nations.

The contributions of this paper are threefold: first, we expand the conceptualization of economic complexity by introducing the idea of scientific complexity; second, we develop innovative metrics, including the Talent Complexity Index (TCI) and fitness index, to capture the dynamics of global talent mobility; and third, we provide empirical evidence linking talent complexity to future economic outcomes, thereby offering a novel predictive tool for policymakers and researchers seeking to understand the long-term drivers of scientific and economic growth. In doing so, we highlight the critical role of talent mobility in shaping the global economy and scientific landscape in the 21st century.

2 Quantifying Talent Space of Nations

2.1 RCA

We focus only on scientist export data (i.e., the number of scientists moving to other countries) and do not disaggregate by country of destination. Our way to empirically estimate whether a country is a significant exporter of a talent is to calculate the Revealed Comparative Advantage (RCA) [1] that that country has in a particular talent field. RCA is a measure constructed to inform whether a country's share of talent fields' world market, is larger or smaller than the talent field s' share of the entire world market.

The Revealed Comparative Advantage of country c for field f in year t is defined as:

$$\hat{RCA}_{c,f,t} = \frac{P_T(c,f,t)/\sum_{f,t} P_T(c,f,t)}{\sum_{c,t} P_T(c,f,t)/\sum_{c,f,t} P_T(c,f,t)} \tag{1}$$

where: $P(c,f,t)$ is the total number of scientists "exported" by country c for field f in year t, $\sum_{f,t} P(c,f,t)$ is the total number of publications produced by

country c in year t, $\sum_{c,t} P(c,f,t)$ is the total number of publications produced globally in year t, $\sum_{c,f,t} P(c,f,t)$ is the total number of publications across all countries and disciplines in year t.

If the RCA value of a country in a particular field is greater than or equal to 1, it indicates that the country is exporting scientists in that field at a higher rate than would be expected based on the global distribution of talent and the size of its economy. This suggests that the country has a comparative advantage in that field.

Empirically, we can examine the number of talent fields where a country has an RCA greater than 1 as a function of the RCA threshold. Our analysis shows that the RCA=1 cutoff aligns with the phase transition of a softened step function, as depicted in Fig. 1a. Thus, the natural cutoff for determining whether a country has a revealed comparative advantage in a particular talent field is when RCA > 1.

$$RCA_{c,f,t} = \begin{cases} 1 & \text{if } \hat{RCA}_{c,f,t} \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Figures 1b-c illustrate that both the average RCA and the probability of RCA exceeding 1 have increased over time, with high-income countries exhibiting higher RCAs than low-income ones.

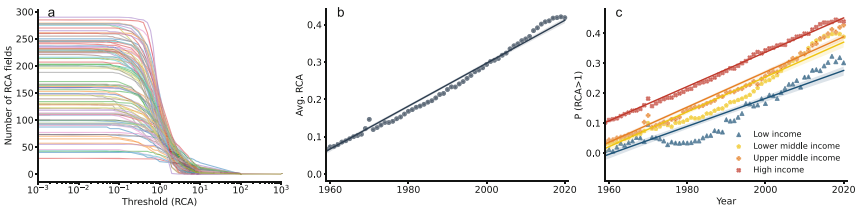


Fig. 1. Revealed Comparative Advantage (RCA) in Talent Export by Country and Field.

2.2 Global Talent Space

Economic complexity approaches typically rely on trade data organized into a bipartite network, which links exporters and talent fields, detailing both the presence and value of a country's exports in specific fields. Similarly, **scientific complexity** can be framed using talent mobility data, structured into a bipartite network that connects countries and talent fields, and provides information on whether and how much a country contributes to the global talent pool in a given scientific field.

The bipartite network is interpreted as the compact representation of the tripartite network constituted by countries-capabilities-talent fields (see Fig. 1a);

we follow existing studies [6] to take into account only the relevant exporters in the network, where the relevance is computed according to the Relative Comparative Advantage (RCA) [1].

Inspired by [4] and [6], here we introduce the level of sophistication of talent–the mix and diversity of a country's talent space–to the characterization of talent fields. Analyzing the network of relatedness between the fields of moving scientists, named talent space, which is built based on the international talent mobility data. Talent fields are considered to have high relatedness if they have a high probability to be co-exported by many countries in the international mobility. Formally, the proximity (ϕ_{ij}) between talent fields i and j is defined as:

$$\phi_{ij} = \min\{P(PCA_{x_i}|PCA_{x_j}), P(PCA_{x_j}|PCA_{x_i})\} \tag{3}$$

where $P(PCA_{x_i}|PCA_{x_j})$ is the conditional probability that country x is a significant exporter of talent field i given that it has been a significant exporter of talent field j. The significant exporter of a talent field is identified by the revealed comparative advantage (RCA, see Methods).

Larger proximity (ϕ_{ij}) means higher relatedness between talent fields i and j. Based on the proximity measure, the talent field space is generated and visualized (see Fig. 2). It can be seen that the talent field space has a core–periphery structure with more-sophisticated talent fields locating in the core and less-sophisticated talent fields occupying the periphery, and that "country-talent" bipartite networks are significantly nested, and the dynamics of nestedness can predict the evolution of scientific ecosystems [10].

Our talent space analysis shows that STEM fields occupy the core of the network, while social science and humanities fields are located at the edges (see Fig. 2d).

3 Talent Complexity Measures

3.1 TCI

To quantify the talent complexity of nations using international talent mobility data, we build upon the Method of Reflections (MR) to characterize the structure of the country-talent bipartite network. The resulting variables can be interpreted as indicators of economic complexity.

In this framework, the bipartite network is represented by an adjacency matrix M_{cf}, where $M_{cf} = 1$ if country c is a significant exporter ($\mathrm{RCA}_{c,f} \geq 1$) of talent field f, and $M_{cf} = 0$ otherwise. The talent complexity index (TCI) of country c is then defined as:

$$TCI_c = \frac{K_c - \langle \vec{K} \rangle}{std(\langle \vec{K} \rangle)} = \frac{N^2 K_c - N \sum_c K_c}{\sqrt{N \sum_c (N K_c - \sum_c K_c)^2}} \tag{4}$$

where N is the number of countries, $\vec{K}$ is the eigenvector associated with the 2nd largest eigenvalue of the matrix $\tilde{M}_{ccT}$, $\langle \vec{K} \rangle$ is the mean value of vector $\tilde{K}$, $std(\langle \vec{K} \rangle)$ is the standard deviation of vector $\vec{K}$. Here, the matrix $\tilde{M}_{ccT}$ is

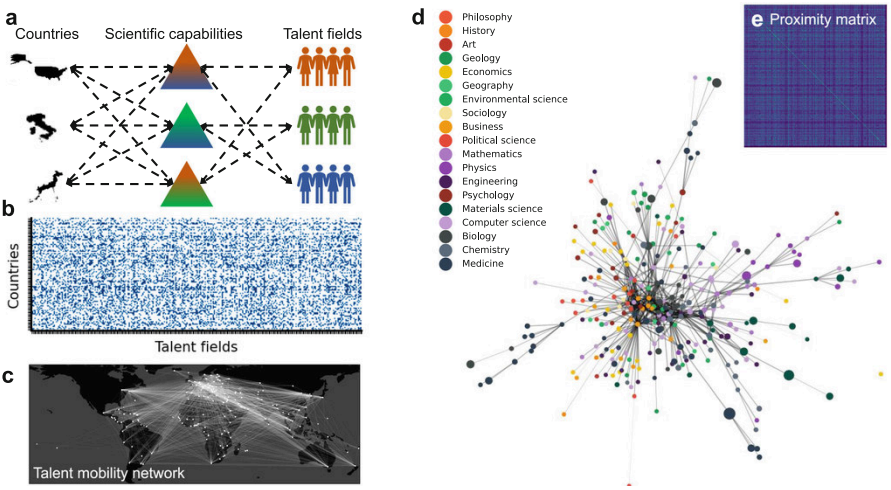


Fig. 2. Quantifying global talent space

defined through a set of linear iterative equations by connecting countries who have similar talent fields, weighted by the inverse of the ubiquity of talent space ($k_{f,0} = \sum_c M_{cf}$) and normalized by the diversity of country ($k_{c,0} = \sum_f M_{cf}$).

$$\tilde{M}_{cc'} = \sum_f \frac{M_{cf} M_{c'f}}{k_{c,0} k_{f,0}} \tag{5}$$

By putting the equation $k_{f,N} = \sum_c M_{cf} k_{c,N-1}/k_{f,0}$ (i.e., the average ubiquity of talent field) into the equation $k_{c,N} = \sum_f M_{cf} k_{c,N-1}/k_{c,0}$ (i.e., the average diversity of country) can generate $k_{c,N} = \sum_{c'} k_{c,N-2} \sum_f M_{cf} M_{c'f}/k_{c,0} k_{f,0}$, where $N > 1$ is the number of iteration. The talent complexity of country c is given by $TCI_c = \sum_{c'} \tilde{M}_{cc'} TCI_{c'}$, where $TCI_{c'}$ is the complexity of country c in the previous iteration step.

3.2 Fitness

In addition to the Talent Complexity Index (TCI), we also introduce a Fitness Index to quantify both the fitness of countries and the complexity of talent fields through coupled nonlinear maps. This approach uses a biased Markov chain process to rank countries in a more conceptually consistent manner, where a two-parameter bias is applied to account for the bipartite network structure. The Markov process is defined as follows:

$$\begin{cases} \omega_c^{N+1}(\alpha, \beta) = \sum_f G_{cf}(\beta) \omega_{f^N}(\alpha, \beta) \\ \omega_f^{N+1}(\alpha, \beta) = \sum_c G_{fc}(\beta) \omega_{c^N}(\alpha, \beta) \end{cases} \tag{6}$$

where ω_c is the fitness of country c, ω_f is the complexity of talent field f, N is the interaction step, and G is the Markov transition matrix given by:

$$\begin{cases} G_{cf}(\beta) = \frac{M_{cf} k_c^{-\beta}}{\sum_{c'} M_{c'f} k_c^{-\beta}} \\ G_{fc}(\alpha) = \frac{M_{cf} k_f^{-\alpha}}{\sum_{f'} M_{cf'} k_f^{-\alpha}} \end{cases} \tag{7}$$

where α and β are free parameters. Finally, in a vectorial formalism, the Fitness of country c fitness is $\omega_c^{N+1}(\alpha, \beta) = T(\alpha, \beta)\omega_c^N(\alpha, \beta)$, where the ergodic stochastic matrix T is defined as $T_{cc'}(\alpha, \beta) = \sum_f G_{cf}(\beta)\omega_f^N(\alpha, \beta)$.

Using data from 2020, we find a strong linear relationship between fitness and Economic Complexity Index (ECI) (see Fig. 3). Interestingly, while China exports a large number of scientists, it shows relatively low ECI and moderate fitness. The country with the highest ECI is the United Kingdom (GBR), while the highest fitness country is the United States (USA).

Additionally, our analysis reveals that developed countries generally exhibit higher fitness and ECI, while developing countries tend to have lower values in both indices (see Fig. 3b).

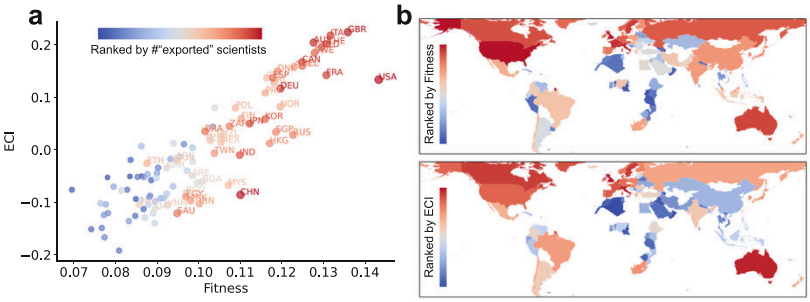


Fig. 3. Relationship and Geographical Distribution of Economic Complexity Index and Fitness.

4 Predicting Economic Success

Finally, we investigate whether talent complexity, as captured by the fitness index, can serve as a predictor of a country's future economic success. Specifically, we use the fitness of each country in 2015 to forecast a range of key economic and scientific indicators in 2020, including Purchasing Power Parity (PPP), Gross Domestic Product (GDP), Research and Development (R&D) expenditure, Foreign Direct Investment (FDI), paper productivity, and the number of researchers.

Our analysis, presented in Fig. 4, shows that all of these indicators are strongly and positively correlated with a country's fitness in 2015. In particular, we observe that countries with higher fitness in 2015 tend to exhibit superior economic performance and scientific output by 2020.

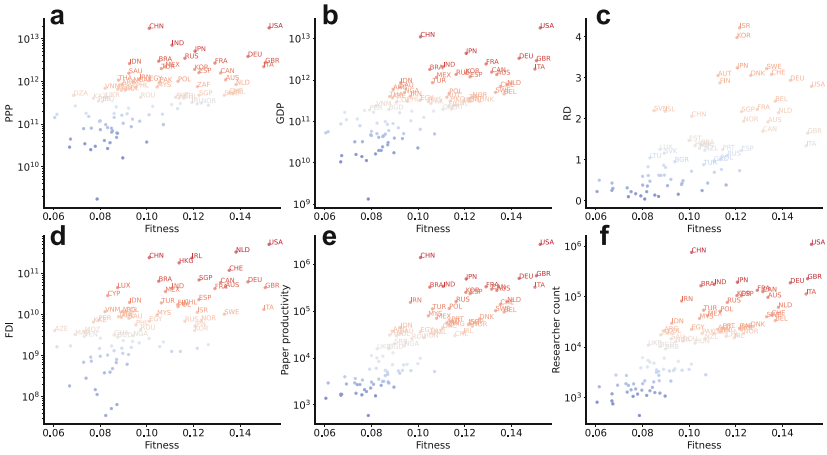


Fig. 4. Predicting Economic Success Using Fitness Data from 2015

5 Discussion

This study provides novel insights into the relationship between talent complexity and a country's economic and scientific performance. By analyzing international talent mobility data, we have framed talent space as a network linking countries and talent fields, and used this structure to derive indices of talent complexity and fitness for nations. The relationship between talent complexity and economic success underscores the importance of investing in talent mobility and fostering the global exchange of knowledge. Countries with high talent complexity are better positioned to leverage international scientific collaborations, attract FDI, and establish themselves as innovation hubs. Our findings suggest that talent complexity could serve as a valuable tool for policymakers aiming to predict and enhance their country's economic trajectory.

6 Data and Method

6.1 Bibliometric Dataset

This study leverages the Microsoft Academic Graph (MAG) dataset [13] to identify mobility of scientists. We utilize the MAG dataset as of December 6, 2021, encompassing a diverse compilation of over 20 million documents that include journal articles, conference proceedings, preprints, and other scholarly outputs spanning from 1800 to 2021.

MAG addresses the challenge of author name disambiguation through a hybrid approach combining machine learning, crowdsourcing, and web data [13]. The efficacy of MAG's disambiguation strategies is well-documented, with reports indicating a 100% accuracy rate and an 84% recall rate in a recent validation study [7].

Furthermore, MAG employs a data-driven methodology to accurately attribute authors to their respective affiliations and provides geographical coordinates (latitude and longitude) for these affiliations. This information has been integrated to associate affiliations with their corresponding countries, allowing for timely updates to reflect changes in affiliations and to facilitate the calculation of geographical distances.

6.2 Identifying Scientific Mobility

We identify mobility events by systematically tracking changes in authors' affiliations over time through an analysis of each author's publication corpus. Utilizing the disambiguated author data from MAG, we correlate the listed affiliations for each publication or patent to identify shifts in professional locations. This approach aligns with methodologies used in prior studies [3,11,12,14].

For our analysis of scientists, we curated data for 31,141,031 scientists who have each published at least two papers. This dataset comprises 182,278,076 observations, including detailed records of author-publication dates and affiliations. In these datasets, each author's papers or patents are meticulously arranged in chronological order. This organization enables the identification of mobility events, which we define as occurring when there is a change in an author's affiliation or location. A mobility event is recorded in the year of the publication or patent that documents the new affiliation or location. From this analysis, we have identified 25,072,692 instances of mobility among scientists between 1960 and 2020, with 15,857,556 of these instances representing international mobility (i.e., affiliation changes across different countries). These mobility events encompass affiliations across 198 countries.

References

1. Balassa, B.: Trade liberalisation and "revealed" comparative advantage. Manch. Sch. **33**(2), 99–123 (1965)
2. Czaika, M., Orazbayev, S.: The globalisation of scientific mobility, 1970–2014. Appl. Geogr. **96**, 1–10 (2018)
3. Deville, P., Wang, D., Sinatra, R., Song, C., Blondel, V.D., Barabási, A.-L.: Career on the move: geography, stratification and scientific impact. Sci. Rep. **4**(1), 4770 (2014)
4. Hausmann, R., Hwang, J., Rodrik, D.: What you export matters. J. Econ. Growth **12**(1), 1–25 (2007)
5. Hidalgo, C.A.: Economic complexity theory and applications. Nature Rev. Phys. **3**(2), 92–113 (2021)
6. Hidalgo, C.A., Hausmann, R.: The building blocks of economic complexity. Proc. Natl. Acad. Sci. **106**(26), 10570–10575 (2009)
7. Lin, Y., Frey, C.B., Wu, L.: Remote collaboration fuses fewer breakthrough ideas. Nature **623**(7989), 987–991 (2023)
8. Liu, L., Jones, B.F., Uzzi, B., Wang, D.: Data, measurement and empirical methods in the science of science. Nat. Hum. Behav. **7**(7), 1046–1058 (2023)

9. Mariani, M.S., Battiston, F., Horvát, E.Á., Livan, G., Musciotto, F., Wang, D.: Collective dynamics behind success. Nat. Commun. **15**(1), 10701 (2024)
10. Mariani, M.S., Ren, Z.-M., Bascompte, J., Tessone, C.J.: Nestedness in complex networks: observation, emergence, and implications. Phys. Rep. **813**, 1–90 (2019)
11. Murray, D., et al.: Unsupervised embedding of trajectories captures the latent structure of scientific migration. Proc. Natl. Acad. Sci. **120**(52), e2305414120 (2023)
12. Sanliturk, E., Zagheni, E., Dańko, M.J., Theile, T., Akbaritabar, A.: Global patterns of migration of scholars with economic development. Proc. Natl. Acad. Sci. **120**(4), e2217937120 (2023)
13. Wang, K., Shen, Z., Huang, C., Wu, C.-H., Dong, Y., Kanakia, A.: Microsoft academic graph: when experts are not enough. Quant. Sci. Stud. **1**(1), 396–413 (2020)
14. Zhao, X., Akbaritabar, A., Kashyap, R., Zagheni, E.: A gender perspective on the global migration of scholars. Proc. Natl. Acad. Sci. **120**(10), e2214664120 (2023)