Ethnic Diversity Increases Scientific Impact

Bedoor K AlShebli*, Talal Rahwan*, Wei Lee Woon*

Department of Computer Science, Masdar Institute, Khalifa University of Science and Technology, Abu Dhabi, United Arab Emirates

Email: {bedoor.alshebli, talal.rahwan, wei.woon}@ku.ac.ae

Abstract

Inspired by the numerous social and economic benefits of diversity [1, 2, 3, 4, 5, 6], we analyze over 9 million papers and 6 million scientists spanning 24 fields of study, to understand the relationship between research impact and five types of diversity, reflecting (i) ethnicity, (ii) discipline, (iii) gender, (iv) affiliation and (v) academic age. For each type, we study group diversity (i.e., the heterogeneity of a paper’s set of authors) and individual diversity (i.e., the heterogeneity of a scientist’s entire set of collaborators). Remarkably, of all the types considered, we find that ethnic diversity is the strongest predictor of a field’s scientific impact ($r$ is 0.77 and 0.55 for group and individual ethnic diversity, respectively). Moreover, to isolate the effect of ethnic diversity from other confounding factors, we analyze a baseline model in which author ethnicities are randomized while preserving all other characteristics. We find that the relationship between ethnic diversity and impact is stronger in the empirical data compared to the randomized baseline model, regardless of publication year, number of authors per paper, and number of collaborators per scientist. Finally, we use coarsened exact matching to infer causality, whereby the scientific impact of ethnically diverse papers and scientists are compared with closely-matched control groups [7]. Impact gains of 11.64% and 55.45% were observed between the top and bottom 10% group and individual diversities, respectively. This provides further evidence that ethnic diversity leads to higher scientific impact.

Diversity is highly valued in modern societies [8, 9, 10]. Social cohesion, tolerance and integration are linked to tangible benefits including economic vibrancy [4, 11] and innovativeness [9, 12, 13, 14]. Far from being an abstract ideal, this conviction has guided many governmental and hiring policies and can have broad and long-lasting effects on society [15, 16]. However, diversity is a complex issue that can be viewed from multiple perspectives including ethnicity, gender, age and socioeconomic background. It is also unclear if all forms of diversity are beneficial. For instance, the existence of a critical mass of minority groups has been associated with positive outcomes in terms of health [17, 18] and economic growth [19],
which suggests that the impact of diversity is non-monotonic. Furthermore, diversity can be a divisive topic that is clouded by emotion, partisan loyalties and political correctness, all of which can hinder impartial discussions [20]. The factors above strongly motivate an objective study on the value of diversity, and on whether more diverse groups achieve greater success.

One domain in which this question can be effectively addressed is academia [3, 6]. The structure of academic collaboration is observable via co-authorships, which frequently involve scientists from different locations, disciplines and backgrounds [21, 22]. Furthermore, academic output has an objective, widely-accepted measure—citation count [23, 24]. This amenability to analysis has already attracted attempts at identifying the factors which underlie success in academia, an enterprise known as the “science of science” [25]. Although many such factors have been studied, including gender [26], academic age [27], team size [28], interdisciplinarity [29], ethnicity [30], and affiliation [31, 32], several questions remain unanswered, some of which are addressed in our study. In particular, we are the first to (i) compare different types of diversity, (ii) examine the relationship between the diversity and research impact at the level of scientific fields, (iii) study diversity from the perspective of groups and individuals, (iv) study the evolution and effect of diversity over time, team size and number of collaborators, and (v) estimate the causal effect of diversity on scientific impact. The results of these multiple angles of analysis are combined to form a far richer picture of diversity than has been possible in the past.

We use the Microsoft Academic Graph dataset¹, and analyze 1,045,401 multi-authored papers, authored by 1,529,279 scientists, spanning 8 main fields and 24 subfields of science. Moreover, for each such scientist with at least 10 collaborators, we analyze his/her entire set of collaborators, amounting to a total of 5,103,877 collaborators over 9,472,439 papers (Sections S1.1 through S1.6). We analyze diversity with regards to five aspects of scientific collaborations: (i) ethnicity, denoted by “eth”; (ii) discipline, “dsp”; (iii) gender, “gen”; (iv) affiliation, “aff”; and (v) academic age, “age” (Section S2.1). These types reflect many technical and social factors that influence teamwork and collaboration. Affiliation is reflective of geographic location, and may even reflect the way collaborative work is carried out—from the style and culture of collaboration to its mundane details, such as the medium used to collaborate, e.g., face-to-face interactions vs. telecommunication or email. Academic age is not only indicative of the amount of experience that a scientist has, but is also typically associated with actual age. Discipline may reflect a scientist’s substantive knowledge and his/her acquired skills through training, as well as the culture in which collaborative work is carried out. Ethnicity and gender may play a role in shaping scientists’ social identities, unconscious biases, and knowledge that likely applies to social situations. For each diversity type, we distinguish between group diversity, where the unit of analysis is the paper’s set of authors, and individual diversity, where the unit of analysis is a scientist’s entire set of collaborators. In both cases, we use Gini Impurity [33] to quantify diversity (Sections S2.2 through S2.4).

As a proxy for scientific impact, we consider the number of citations received within five years of publication, denoted by $c_G^G$ (Section S1.7). We use this to study the relationship between a subfield’s diversity and its academic impact (Figure 1). Specifically, for each subfield, Figure 1A depicts the mean group diver-

¹https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/
sity indices, \( \langle d_{eth}^G \rangle, \langle d_{age}^G \rangle, \langle d_{gen}^G \rangle, \langle d_{dsp}^G \rangle \) and \( \langle d_{aff}^G \rangle \), against the mean five-year citation count, \( \langle c_5^G \rangle \), taken over papers in that subfield. Similarly, for each subfield, Figure 1B depicts the mean individual diversity indices, \( \langle d_{eth}^I \rangle, \langle d_{age}^I \rangle, \langle d_{gen}^I \rangle, \langle d_{dsp}^I \rangle \) and \( \langle d_{aff}^I \rangle \), against the mean five-year citation count, \( \langle c_5^I \rangle \), taken over scientists in that subfield (notation summary and formal definitions are in Table S5 and Section S2, respectively). Remarkably, from both the group and individual perspectives, we find that a subfield’s ethnic diversity is the most strongly correlated with impact \( (r = 0.77 \text{ and } 0.55 \text{ for } d_{eth}^G \text{ and } d_{eth}^I, \text{ respectively}) \). The positive correlations persist even when the subfields are studied in isolation, as shown in Figures S6 and S7. While these findings do not imply causation, it is still suggestive that one can largely predict scientific impact based solely on average ethnic diversity, especially given that ethnic diversity is unrelated to technical competence.

Intrigued by these findings, we further explore the phenomenon of ethnic diversity by analyzing a randomized baseline model in which the scientists’ ethnicities are shuffled. This process is akin to creating a universe in which ethnicity is eliminated as a criterion in the selection of co-authors while preserving other factors. Importantly, for every paper \( p \) in the real dataset, there exists a matching paper \( p' \) in the randomized dataset that may differ from \( p \) in terms of ethnic diversity, but is identical to \( p \) in terms of gender, discipline, affiliation, academic age, citations, publication year, number of authors per paper and number of collaborators per author. Furthermore, while such a baseline model may produce ethnically homogeneous groups, the emergence of such groups is purely the result of random chance, rather than homophily [34]. As such, by comparing the real dataset with this baseline model, we can quantify homophily, and understand how it is related to academic impact.

Figures 2A and 2B compare the cumulative distributions of \( d_{eth}^G \) and \( d_{eth}^I \) in our real dataset with that of the randomized baseline model. As can be seen, groups with low \( d_{eth}^G \) and individuals with low \( d_{eth}^I \) are both more common in reality than would be expected by random chance, highlighting the fact that homophily does indeed exist in academia. These observations persist, regardless of the publication year (Figures 2C), the number of authors per paper (Figure 2D) and the number of collaborators per scientist (Figures 2E). Next, we study the relationship between homophily and impact in the randomized universes where, as noted earlier, ethnicity is excluded as a criterion for selecting co-authors while the other factors are preserved. Hence, it stands to reason that any differences in field impact between the randomized and real datasets can be attributed to ethnic diversity. To examine these differences, we plotted in Figures 2F and 2G the correlation between \( \langle c_5^G \rangle \) and \( \langle d_{eth}^G \rangle \) and between \( \langle c_5^I \rangle \) and \( \langle d_{eth}^I \rangle \), respectively. As can be seen from both the group and individual perspectives, these correlations are significantly greater in the case of the real datasets, suggesting that both group and individual ethnic diversities can have a positive influence on research impact.

Having studied the differences between the real and randomized datasets at the level of scientific fields, we now study these differences at the level of papers and scientists (Figure 3). Here, the papers were partitioned into two categories which we label as “diverse” \( (d_{eth}^G > \tilde{d}_{eth}^G) \) and “non-diverse” \( (d_{eth}^G \leq \tilde{d}_{eth}^G) \) where the tilde denotes the median. The scientists were similarly partitioned into “diverse” \( (d_{eth}^I > \tilde{d}_{eth}^I) \) and “non-diverse” \( (d_{eth}^I \leq \tilde{d}_{eth}^I) \). Plotting the publication year against the mean impact, \( \langle c_5^G \rangle \), reveals that
the diverse consistently outperform the non-diverse (Figure 3E). We replicated the plot using the random-ized dataset (Figure 3F), and measured the relative impact gain, \( \left( \frac{\langle I^G_{\text{diverse}} \rangle - \langle I^G_{\text{non-diverse}} \rangle}{\langle I^G_{\text{non-diverse}} \rangle} \right) \), of the diverse over the non-diverse in both datasets (Figure 3G). These results show that, for almost all of the cases investigated, the competitive edge of being diverse is greatly reduced in the baseline model. Furthermore, the competitive edge holds regardless of the number of authors per paper (Figures 3H to 3J), and the number of collaborators per scientist (Figures 3K to 3M).

In an effort to establish a causal link between ethnic diversity and scientific impact, we use coarsened exact matching [7], a technique used to infer causality in observational studies. Specifically, it matches the control and treatment populations with respect to the confounding factors identified, thereby eliminating the effect of these factors on the phenomena under investigation. In our case, when studying group ethnic diversity, the treatment set consists of papers for which \( d^G_{\text{eth}} > P_{100-1}(d^G_{\text{eth}}) \), and the control set of papers for which \( d^G_{\text{eth}} \leq P_i(d^G_{\text{eth}}) \), where \( P_i(d^G_{\text{eth}}) \) denotes the \( i \)th percentile of \( d^G_{\text{eth}} \). This process is repeated using \( i = 10, 20, 30, 40, 50 \), corresponding to progressively larger gaps in ethnic diversity between the two populations. Thus, if ethnic diversity does indeed increase scientific impact, we would expect to find a significant difference in impact between the two populations, and that it increases in tandem with the aforementioned gap in diversity. We identified the following confounding factors: (i) year of publication; (ii) number of authors; (iii) field of study; (iv) affiliation ranking; and (v) authors’ impact prior to publication. The same process was carried out for individual ethnic diversity, with the following confounding factors: (i) academic age; (ii) number of collaborators; (iii) discipline; and (iv) affiliation ranking; see Section S3 for more details. Tables 1 and 2 summarize the results for group and individual ethnic diversities, respectively. As can be seen, increasing the diversity gap between the control and treatment populations broadly increases the impact gain between the two populations. For example, papers and scientists above the median witnessed an average increase of about 5% and 19% respectively, compared to those below the median. In contrast, papers and scientists above the 90th percentile witnessed an average increase in impact of about 12% and 55% respectively, compared to their counterparts below the 10th percentile. Notice how these impact gains are significantly greater than in the previous case.

Finally, we investigate the interplay between group ethnic diversity, \( d^G_{\text{eth}} \), and individual ethnic diversity, \( d^I_{\text{eth}} \). To this end, for each of the 1,045,401 papers in our dataset, we calculate \( d^I_{\text{eth}} \) averaged over the authors in that paper; we denote this as \( \langle d^I_{\text{eth}} \rangle_{\text{paper}} \). This allows us to study the ways in which the two notions of diversity vary in the same paper. Indeed, as illustrated in Figure 4, a paper can have high \( d^G_{\text{eth}} \) and at the same time have low \( \langle d^I_{\text{eth}} \rangle_{\text{paper}} \), and vice versa. With this in mind, we studied the impact, \( \langle I^G \rangle \), of papers falling in different ranges of \( d^G_{\text{eth}} \) and \( \langle d^I_{\text{eth}} \rangle_{\text{paper}} \); see the matrix at the bottom-right corner of Figure 4. Here, if we denote the matrix by \( A \), and label the bottom row and leftmost column as “1”, we find that \( \sum_{i=1}^4 A_{i,1} < \sum_{i=1}^4 A_{i,4} \) and \( \sum_{i=1}^4 A_{i,4} > \sum_{i=1}^4 A_{i,1} \). Hence, while it appears that both group and individual diversities can be valuable, the former seems to have a greater effect on scientific impact. This matters as it implies that an author’s open-mindedness and inclination to collaborate across ethnic lines is not as important as the mere presence of co-authors of different ethnicities on a paper.

Our results illuminate some unexpected connections between diversity and scientific collaboration. The
preeminence of ethnicity over the other types of diversity is especially surprising since ethnicity is not as related to technical competence as some of the other types. These findings have significant implications. For one, recruiters should always strive to encourage and promote ethnic diversity, be it by recruiting candidates who complement the ethnic composition of existing members, or by recruiting candidates with proven track records in collaborating with people of diverse ethnic backgrounds. Another implication is that, while collaborators with different skill sets are often required to perform complex tasks, multidisciplinarity should not be an end in of itself. Conversely, our results suggest that bringing together individuals of different ethnicities, with the attendant differences in culture and social perspectives, could ultimately produce a large payoff in terms of performance and impact. This would imply that intangible factors such as team cohesion and a sense of esprit de corps should be considered in addition to technical alignment.

The underlying message is an inclusive and uplifting one. In an era of increasing polarization and identity politics, our findings may contribute positively to the societal conversation and reinforces the conviction that good things happen when people of different backgrounds, cultures, and yes, ethnicities, come together to work towards shared goals and the common good.

Acknowledgments

We thank Steven Skiena and his team for providing access to their Name Ethnicity Classifier tool [?, ?]. We also thank Kinga Makovi for suggesting the use of coarsened exact matching for causal inference.

References

[1] Wagner, C. S. & Jonkers, K. Open countries have strong science. *Nature* 550, 32–33 (2017).

[2] Puritty, C. et al. Without inclusion, diversity initiatives may not be enough. *Science* 357, 1101–1102 (2017).

[3] Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N. & Malone, T. W. Evidence for a collective intelligence factor in the performance of human groups. *Science* 330, 686–688 (2010).

[4] Levine, S. S. et al. Ethnic diversity deflates price bubbles. *Proceedings of the National Academy of Sciences* 111, 18524–18529 (2014).

[5] Page, S. E. *The difference: How the power of diversity creates better groups, firms, schools, and societies* (Princeton University Press, 2008).

[6] Hong, L. & Page, S. E. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences of the United States of America* 101, 16385–16389 (2004).
[7] Iacus, S. M., King, G. & Porro, G. Causal inference without balance checking: Coarsened exact matching. Political analysis 20, 1–24 (2012).

[8] Ager, P. & Brückner, M. Cultural diversity and economic growth: Evidence from the US during the age of mass migration. European Economic Review 64, 76–97 (2013).

[9] Lee, N. Migrant and ethnic diversity, cities and innovation: Firm effects or city effects? Journal of Economic Geography 15, 769–796 (2014).

[10] Suedekum, J., Wolf, K. & Blien, U. Cultural diversity and local labour markets. Regional Studies 48, 173–191 (2014).

[11] Herring, C. Does diversity pay?: Race, gender, and the business case for diversity. American Sociological Review 74, 208–224 (2009).

[12] Paulus, P. B., van der Zee, K. I. & Kenworthy, J. Cultural diversity and team creativity. In The Palgrave Handbook of Creativity and Culture Research, 57–76 (Springer, 2016).

[13] Parrotta, P., Pozzoli, D. & Pytlikova, M. The nexus between labor diversity and firms innovation. Journal of Population Economics 27, 303–364 (2014).

[14] Østergaard, C. R., Timmermans, B. & Kristinsson, K. Does a different view create something new? the effect of employee diversity on innovation. Research Policy 40, 500–509 (2011).

[15] Brown, G. K. & Langer, A. Does affirmative action work: Lessons from around the world. Foreign Aff. 94, 49 (2015).

[16] Arcidiacono, P., Lovenheim, M. & Zhu, M. Affirmative action in undergraduate education. Annu. Rev. Econ. 7, 487–518 (2015).

[17] Alvarez, K. J. & Levy, B. R. Health advantages of ethnic density for african american and mexican american elderly individuals. American journal of public health 102, 2240–2242 (2012).

[18] Das-Munshi, J., Becares, L., Dewey, M. E., Stansfeld, S. A. & Prince, M. J. Understanding the effect of ethnic density on mental health: multi-level investigation of survey data from england. BMJ 341, c5367 (2010).

[19] Montalvo, J. G. & Reynal-Querol, M. Ethnic diversity and economic development. Journal of Development economics 76, 293–323 (2005).

[20] Galinsky, A. D. et al. Maximizing the gains and minimizing the pains of diversity: A policy perspective. Perspectives on Psychological Science 10, 742–748 (2015).

[21] Jia, T., Wang, D. & Szymanski, B. K. Quantifying patterns of research-interest evolution. Nature Human Behaviour 1, 0078 (2017).
[22] Deville, P. et al. Career on the move: Geography, stratification, and scientific impact. *Scientific reports* **4** (2014).

[23] Sinatra, R., Wang, D., Deville, P., Song, C. & Barabási, A.-L. Quantifying the evolution of individual scientific impact. *Science* **354**, aaf5239 (2016).

[24] Wang, D., Song, C. & Barabási, A.-L. Quantifying long-term scientific impact. *Science* **342**, 127–132 (2013).

[25] Fortunato, S. et al. Science of science. *Science* **359** (2018). URL http://science.sciencemag.org/content/359/6379/eaao0185. http://science.sciencemag.org/content/359/6379/eaao0185.full.pdf.

[26] Nielsen, M. W. et al. Opinion: Gender diversity leads to better science. *Proceedings of the National Academy of Sciences* **114**, 1740–1742 (2017).

[27] Jones, B. F. & Weinberg, B. A. Age dynamics in scientific creativity. *Proceedings of the National Academy of Sciences* **108**, 18910–18914 (2011).

[28] Wuchty, S., Jones, B. F. & Uzzi, B. The increasing dominance of teams in production of knowledge. *Science* **316**, 1036–1039 (2007).

[29] Uzzi, B., Mukherjee, S., Stringer, M. & Jones, B. Atypical combinations and scientific impact. *Science* **342**, 468–472 (2013).

[30] Freeman, R. B. & Huang, W. Collaborating with people like me: Ethnic coauthorship within the united states. *Journal of Labor Economics* **33**, S289–S318 (2015).

[31] Jones, B. F., Wuchty, S. & Uzzi, B. Multi-university research teams: Shifting impact, geography, and stratification in science. *Science* **322**, 1259–1262 (2008).

[32] Adams, J. Collaborations: The fourth age of research. *Nature* **497**, 557–560 (2013).

[33] Bishop, C. M. *Pattern recognition and machine learning* (Springer, 2013).

[34] McPherson, M., Smith-Lovin, L. & Cook, J. M. Birds of a feather: Homophily in social networks. *Annual review of sociology* **27**, 415–444 (2001).
Figure 1: Mean group and individual diversity indices against mean paper impact in each subfield. In each subplot, the color indicates the main field, while the solid line and the shaded area represent the regression line and the 95% confidence interval, respectively. Each regression has also been annotated with the corresponding Pearson’s $r$ and $p$ values. (A) For each subfield, the subplots depict the mean group diversity indices, $\langle d_{G_{eth}} \rangle$, $\langle d_{G_{age}} \rangle$, $\langle d_{G_{gen}} \rangle$, $\langle d_{G_{dsp}} \rangle$ and $\langle d_{G_{aff}} \rangle$, against the mean five-year citation count, $\langle c_{I_{5}} \rangle$, taken over papers in that subfield. (B) For each subfield, the subplots depict the mean individual diversity indices, $\langle d_{I_{eth}} \rangle$, $\langle d_{I_{age}} \rangle$, $\langle d_{I_{gen}} \rangle$, $\langle d_{I_{dsp}} \rangle$ and $\langle d_{I_{aff}} \rangle$, against the mean five-year citation count, $\langle c_{I_{5}} \rangle$, taken over scientists in that subfield.
Figure 2: Real vs. randomized data: evidence of homophily and its effect on scientific impact. (A) Cumulative distribution of $d_{eth}^G$ for real and randomized data (Figure S4 shows the same information, but for each subfield separately). (B) Cumulative distribution of $d_{eth}^I$ for real and randomized data (Figure S5 shows the same information, but for each subfield separately). (C) Publication year against mean group ethnic diversity, $\langle d_{eth}^G \rangle$ in real and randomized data. (D) Number of authors against $\langle d_{eth}^G \rangle$ in real and randomized data. (E) Number of collaborators per author against $\langle d_{eth}^I \rangle$ in real and randomized data. (F) $\langle d_{eth}^G \rangle$ against $\langle c_{G5} \rangle$ in the real and randomized data, where $R = 0.0355$ for the randomized data and $R = 0.77$ for the real data, which was significantly greater ($p < 0.0001$). (G) The same as in Figure 2F, but where $\langle d_{eth}^G \rangle$ and $\langle c_{G5} \rangle$ are replaced with $\langle d_{eth}^I \rangle$ and $\langle c_{I5} \rangle$, respectively. Here, $R = 0.0376$ for the randomized data and $R = 0.55$ for the real data, which was also significantly greater ($p < 0.0001$).
Figure 3: The relationship between ethnic diversity and impact. (A) Distribution of $d_{eth}^G$ in real data. Papers were partitioned into two categories: “diverse” (highlighted in red, with $d_{eth}^G > \tilde{d}_{eth}^G$) and “non-diverse” (highlighted in yellow, with $d_{eth}^G \leq \tilde{d}_{eth}^G$), where the tilde denotes the median. (B) The same as Figure 3A, but for randomized data. (C) and (D) The same as Figures 3A and 3B, respectively, but with $d_{eth}^I$ instead of $d_{eth}^G$. (E) $\langle c_S^G \rangle$ against publication year in real data. (F) $\langle c_S^G \rangle$ against publication year in randomized data. (G) The relative impact gain of diverse over non-diverse papers, i.e., $(\langle c_S^G \rangle_{\text{diverse}} - \langle c_S^G \rangle_{\text{non-diverse}}) / \langle c_S^G \rangle_{\text{non-diverse}}$, against publication year. (H) $\langle c_S^G \rangle$ against number of authors per paper in real data. (I) $\langle c_S^G \rangle$ against number of authors per paper in randomized data. (J) The relative impact gain of diverse over non-diverse papers against number of authors. (K) $\langle c_S^G \rangle$ against number of collaborators per scientist in real data. (L) $\langle c_S^G \rangle$ against number of collaborators per scientist in randomized data. (M) The relative impact gain of diverse over non-diverse scientists against number of collaborators.
Figure 4: The interplay between group and individual ethnic diversity in a given paper. The top part of the figure illustrates an example of 4 papers. The authors of paper A have different ethnicities, but each has ethnically-homogeneous collaborators. Then, one could argue that paper A has high $d_{et\text{h}}^G$, but low $\langle d_{et\text{h}}^I \rangle_{\text{paper}}$. Similarly, paper B has low $d_{et\text{h}}^G$ and low $\langle d_{et\text{h}}^I \rangle_{\text{paper}}$, paper C has low $d_{et\text{h}}^G$ and high $\langle d_{et\text{h}}^I \rangle_{\text{paper}}$, and paper D has high $d_{et\text{h}}^G$ and high $\langle d_{et\text{h}}^I \rangle_{\text{paper}}$. The matrix at the bottom-right corner, denoted by $A$, represents the mean citation counts, $\langle c_{5,\text{G}} \rangle$, of papers falling in different ranges of $d_{et\text{h}}^G$ and $\langle d_{et\text{h}}^I \rangle_{\text{paper}}$. Labeling the bottom row and leftmost column as “1”, we find that $\sum_{i=1}^4 A_{1,i} < \sum_{i=1}^4 A_{4,i}$ and $\sum_{i=1}^4 A_{4,i} > \sum_{i=1}^4 A_{1,i}$, implying that group diversity has a greater effect on scientific impact than individual diversity.
Table 1: **Results of coarsened exact matching on group ethnic diversity.** $T$ and $C$ are the treatment and control populations respectively; $T'$ and $C'$ are the populations of matched treatment and matched control papers respectively; $L_1$ is the multivariate imbalance statistic [7]; $\delta$ is the relative impact gain of $T'$ over $C'$, i.e., $\delta = 100 \times (\langle c_{G}^{T'} \rangle - \langle c_{G}^{C'} \rangle)/\langle c_{G}^{C'} \rangle$. A t-test shows that $\delta$ is statistically significant; see the resulting $p$-values. For more details, see Section S3.

| $T$ | $C$ | $T'$ | $C'$ | $L_1$ | $\delta$ | $p$ |
|-----|-----|------|------|-------|---------|-----|
| $\displaystyle T: \ d_{G}^{T} > P_{90}(d_{G}^{T})$   
$\displaystyle C: d_{G}^{C} \leq P_{10}(d_{G}^{C})$ | 45,710 | 17,802 | 16,477 | 16,322 | 0.37 | 11.64 | 0.001 |
| $\displaystyle T: \ d_{G}^{T} > P_{80}(d_{G}^{T})$   
$\displaystyle C: d_{G}^{C} \leq P_{20}(d_{G}^{C})$ | 45,710 | 24,827 | 16,546 | 22,855 | 0.37 | 12.97 | 6.85e-06 |
| $\displaystyle T: \ d_{G}^{T} > P_{70}(d_{G}^{T})$   
$\displaystyle C: d_{G}^{C} \leq P_{30}(d_{G}^{C})$ | 58,889 | 56,662 | 39,934 | 55,250 | 0.22 | 7.43 | 6.14e-05 |
| $\displaystyle T: \ d_{G}^{T} > P_{60}(d_{G}^{T})$   
$\displaystyle C: d_{G}^{C} \leq P_{40}(d_{G}^{C})$ | 78,340 | 63,129 | 59,370 | 61,834 | 0.27 | 7.42 | 1.28e-05 |
| $\displaystyle T: \ d_{G}^{T} > P_{50}(d_{G}^{T})$   
$\displaystyle C: d_{G}^{C} \leq P_{50}(d_{G}^{C})$ | 127,629 | 63,129 | 72,376 | 62,121 | 0.25 | 5.03 | 0.003 |

Table 2: **Results of coarsened exact matching on individual ethnic diversity.** The notation is as per Table 1.

| $T$ | $C$ | $T'$ | $C'$ | $L_1$ | $\delta$ | $p$ |
|-----|-----|------|------|-------|---------|-----|
| $\displaystyle T: \ d_{I}^{T} > P_{90}(d_{I}^{T})$   
$\displaystyle C: d_{I}^{C} \leq P_{10}(d_{I}^{C})$ | 139,822 | 84,270 | 31,500 | 48,801 | 0.61 | 55.46 | 7.38e-18 |
| $\displaystyle T: \ d_{I}^{T} > P_{80}(d_{I}^{T})$   
$\displaystyle C: d_{I}^{C} \leq P_{20}(d_{I}^{C})$ | 168,575 | 168,475 | 67,686 | 152,379 | 0.40 | 43.26 | 8.87e-145 |
| $\displaystyle T: \ d_{I}^{T} > P_{70}(d_{I}^{T})$   
$\displaystyle C: d_{I}^{C} \leq P_{30}(d_{I}^{C})$ | 252,801 | 251,423 | 174,457 | 237,525 | 0.36 | 30.51 | 1.11e-165 |
| $\displaystyle T: \ d_{I}^{T} > P_{60}(d_{I}^{T})$   
$\displaystyle C: d_{I}^{C} \leq P_{40}(d_{I}^{C})$ | 346,137 | 336,570 | 231,951 | 320,815 | 0.34 | 26.80 | 3.70e-224 |
| $\displaystyle T: \ d_{I}^{T} > P_{50}(d_{I}^{T})$   
$\displaystyle C: d_{I}^{C} \leq P_{50}(d_{I}^{C})$ | 437,600 | 404,782 | 322,820 | 391,162 | 0.27 | 18.63 | 2.39e-194 |
Supplementary Materials for

Ethnic Diversity Increases Scientific Impact

Bedoor K AlShebli, Talal Rahwan, Wei Lee Woon
correspondence to: {bedoor.alshebli, talal.rahwan, wei.woon}@ku.ac.ae

June 12, 2018

Contents

S1 The Data
  S1.1 The Collaboration Network ........................................ 2
  S1.2 Acquiring the Field of Science of Each Publication Venue .......... 2
  S1.3 Classifying the Ethnicity of Each Scientist ........................... 3
  S1.4 Identifying the Gender of Each Scientist ............................. 4
  S1.5 Controlling for Countries ............................................ 5
  S1.6 Excluding Review Papers .............................................. 6
  S1.7 Scientific Impact: Citation Counts .................................... 6

S2 Quantifying Diversity
  S2.1 Types of Diversity .................................................. 8
  S2.2 Measuring Diversity ................................................ 10
  S2.3 Group Diversity Index ............................................... 11
  S2.4 Individual Diversity Index ......................................... 13

S3 Coarsened Exact Matching ............................................. 15

S4 Supplementary Figures .................................................. 17

S5 Supplementary Tables .................................................... 23
S1 The Data

S1.1 The Collaboration Network

The data used for this study was obtained on October 2015 from the Microsoft Academic Graph (MAG) database. This is a dataset consisting of scientific publications, their citation records, date of publication, information regarding the authorship (such as name and affiliation), publication venue and more. The dataset also contains a citation network in which every node represents a paper and every directed link represents a citation. While the number of citations of any given paper is not provided explicitly by the dataset, it can easily be calculated from the citation network. More important, the dataset specifies the keywords in each paper, as well as the position of each such keyword in a field-of-study hierarchy, the highest level of which is comprised of 19 disciplines.

Unfortunately, the dataset suffers from three limitations: (i) it does not specify the publication venue’s field of science; (ii) it does not specify the ethnicity of each scientist; and (iii) it does not specify the gender of each scientist. In the following three subsections, we show how to overcome these limitations.

S1.2 Acquiring the Field of Science of Each Publication Venue

To address limitation (i) of Microsoft Academic Graph, we refer to Google Scholar Metrics. Here, journals are categorized into 8 main fields of science, and each such field is divided into multiple subfields. A list of the top 20 publication venues are listed for each subfield. We considered five top journals from 3 randomly selected subfields from each of the 8 main fields, resulting in a total of 24 subfields and 120 journals. For each journal, we extracted the data

1https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/
2Note that some keywords fall under multiple disciplines. For instance, according to the dataset, the keyword “Fast fission” has a 50% match with Physics and a 50% match with Chemistry.
3https://scholar.google.com/citations?view_op=top_venues
on all papers published therein, and applied four filtering steps: (i) removed all single-authored papers (because we are interested in studying collaborations), (ii) controlled for English speaking countries (explained further in Section S1.5), (iii) removed review papers (explained further in Section S1.6), and (iv) extracted data only up to 2009 (the reason behind this is explained in Section S1.7). This yielded a final set of 1,045,401 papers, authored by 1,529,279 unique authors.

Lastly, to avoid any potential confusion between a scientist’s area of science, and a paper’s area of science, we will use the term “discipline” when referring to the former, and use the term “field” when referring to the latter.

S1.3 Classifying the Ethnicity of Each Scientist

To address limitation (ii) of Microsoft Academic Graph, we used the Name Ethnicity Classifier$^4$ (1, 2) to identify the ethnicity of each scientist. In particular, this classifier uses various machine-learning techniques to classify any given name into the following 13 ethnic groups (any unresolved names are marked as “unknown”):

1. Asian, Greater East Asian, East Asian (or “East Asian” for short);
2. Asian, Greater East Asian, Japanese (or “Japanese” for short);
3. Asian, Indian Sub-Continent (or “Indian Sub-Continent” for short);
4. Greater African, Africans (or “Africans” for short);
5. Greater African, Muslim (or “Muslim” for short);
6. Greater European, British (or “British” for short);
7. Greater European, East European (or “East European” for short);
8. Greater European, Jewish (or “Jewish” for short);
9. Greater European, West European, French (or “French” for short);

$^4$http://www.textmap.com/ethnicity/
10. Greater European, West European, Germanic (or “Germanic” for short);
11. Greater European, West European, Hispanic (or “Hispanic” for short);
12. Greater European, West European, Italian (or “Italian” for short);
13. Greater European, West European, Nordic (or “Nordic” for short).

As can be seen, the term “ethnicity” is used here in its broader sense, where an ethnic group is defined as “a social group that shares a common and distinctive culture, religion, language, or the like”. The Name Ethnicity Classifier (1–3) has an overall accuracy\(^6\) of 80%, which is quite impressive given that the classifier depends solely on the individual’s name. Importantly, this accuracy is measured over 20 million distinct names, comprising over 100 million individual entity references (1). Admittedly, an accuracy of 80% means that some names will be misclassified. Nevertheless, unlike conventional methods where ethnicity is identified manually, this classifier allows for conducting studies at an unprecedented scale, e.g., involving millions of names. In our case, we were able to obtain the ethnicity of every single scientist in our study.

**S1.4 Identifying the Gender of Each Scientist**

To address limitation (iii) of Microsoft Academic Graph, we needed to identify the gender of each scientist in our dataset. To this end, a number of alternative methods have been proposed in the literature to identify the gender (either male or female) of any given individual based solely on his/her first name (4–6). Out of all those alternatives, a software tool called “‘Genderize.io’”, which is available at: https://genderize.io/, was shown to be the most reliable (4). Note that gender identification based solely on first name is indeed very challenging (if not impossible, in some cases), due mainly to the fact that some names are unisex. As such, it is per-

\(^5\)http://www.dictionary.com/browse/ethnicity?s=t

\(^6\)While the authors report the results of each ethnicity independently, the overall accuracy can easily be computed from these results.
haps not surprising that 47.71% of the names tested on Genderize.io were unclassified, i.e., the tool returned “unknown” for each such name (4). Nevertheless, this tool outperformed the alternative methods, for which the number of unclassified names exceeded 84%. As for the names that were classified, the “error rate” represents the percentage of names whose classification was incorrect. While the alternative methods had an error rate greater that 32%, Genderize.io had an error rate of just 7%, which is impressive given that the input to this gender-identification tool is merely the first name of the individual in question. Admittedly, an error rate of 7% means that some genders will be misclassified. Nevertheless, unlike conventional methods where gender is identified manually, this automated tool allows for conducting studies at an unprecedented scale, covering thousands, or even millions of names. Using Genderize.io, we were able to classify the gender of 3,183,911 scientists. To further increase our confidence of the gender classification, we considered only the 2,046,359 names that were classified with at least 90% confidence.

S1.5 Controlling for Countries

To control for countries, we consider papers of which the majority of the authors’ affiliations belong to any of the following countries: USA, UK, Canada and Australia. The rationale behind this choice is threefold:

1. These are predominantly English-speaking countries.⁷ As English is widely considered the universal language of science,⁸ limiting our study to English-speaking countries should cover a wide range of cultural, ethnic and national backgrounds.

2. These countries have ethnically diverse populations and higher-education systems that attract large numbers of international students and faculty members. In contrast, universi-

---

⁷Although Canada has two official languages, namely English and French, 56.9% of the Canadian population report English as their mother tongue; see: www.statcan.gc.ca.
⁸https://www.researchtrends.com/issue-31-november-2012/the-language-of-future-scientific-communication/
ties in many other countries (such as Japan and China) have student populations of which the vast majority are of a single ethnic group.

3. Universities from those four countries form a significant proportion of the world’s leading institutions (as reported in the Times Higher Education 2018 rankings, 95% of the world’s top 20, and 63% of the top 100 universities are from these four countries

To put it differently, most papers (co)authored in these four countries are arguably (i) written in the same language, (ii) produced in environments that permit the formation of diverse teams and (iii) relatively more likely to produce high-impact research. The above factors help to ensure that the papers studied are, in general, highly impactful and comparable. Of all the affiliations present in the Microsoft Academic Graph dataset, 5,899 (out of a total of 19,788) were manually verified to be based in one of the aforementioned four countries.

S1.6 Excluding Review Papers

Review papers exhibit different statistics (7–9), and could bias our results. As such, we excluded from our analysis any review papers that we could find based on tell-tale words that could be found in the keywords of the paper, such as “literature review”, “literature”, or “survey”. Following this process, 11,367 review papers were found and removed from our dataset.

S1.7 Scientific Impact: Citation Counts

In their expansive study on scientific impact, Sinatra et al. (10) studied the number of citations that a paper accumulates 10 years after publication, denoted by \( c_{10} \); the same impact measure was later on used in (?). We follow a similar approach, but focus on 5 rather than 10 years. This way, we incorporate more recent papers in our study, which is particularly important since the majority of the papers in our study were published in recent years (Figure S1). Based on this, as

\[ \text{https://www.timeshighereducation.com/world-university-rankings/2018/world-ranking#!/} \]
well as the fact that our dataset was obtained in October 2015, we only calculate $c_5$ for papers published between 1958 and 2009.

We distinguish between the number of citations that a paper accumulates, and the number of citations that a scientist accumulates. To this end, we introduce the following notation:

1. $c_5^G(p_j)$: The number of citations that paper $p_j$ accumulates 5 years after publication, where “G” stands for “Group”;

2. $c_5^I(s_i)$: The average number of citations that scientist $s_i$ accumulates from a paper 5 years after its publication, where “I” stands for “Individual”. More formally:

$$c_5^I(s_i) = \frac{\sum_{p_j \in Papers(s_i)} c_5^G(p_j)}{|Papers(s_i)|}.$$  

(1)

To improve readability, we will often write $c_5^G$ instead of $c_5^G(p_j)$ whenever the paper is clear from the context. Similarly, we will write $c_5^I$ instead of $c_5^I(s_i)$ when there is no risk of confusion.

Various studies have demonstrated that the average number of citations per paper changes over time (7, 10–12). To mitigate this temporal effect, we follow the approach proposed by Sinatra et al. (10), and consider an alternative, normalized measure of impact, defined as:

$$\tilde{c}_5^G = \frac{c_5^G(p_j)}{\langle c_5^G \rangle_{year(p_j)}},$$

where $\langle c_5^G \rangle_{year(p)}$ denotes the average $c_5$ taken over all papers published in the same year as $p_j$.

Similarly, when analyzing the impact of a scientist $s_i$, we considered an alternative, normalized version of $c_5^I(s_i)$, defined as follows:

$$\tilde{c}_5^I(s_i) = \frac{\sum_{p_j \in Papers(s_i)} \tilde{c}_5^G(p_j)}{|Papers(s_i)|}.$$  

(2)

Considering every paper in the entire MAG dataset, we found that $c_5^G$ and $\tilde{c}_5^G$ are very strongly correlated, with Pearson’s $r = 0.965$ and $p < 0.0001$ (Figure S2 depicts $c_5^G$ against $\tilde{c}_5^G$.
S2 Quantifying Diversity

This section starts by discussing the five types of diversity that are considered in our study (Section S2.1). After that, Sections S2.3 and S2.4 discuss the group and individual diversity indices, respectively. A summary of all notation is provided in Table S3.

S2.1 Types of Diversity

When exploring diversity in research collaborations, we investigate five types of diversity:

1. Ethnic diversity: This type of diversity takes into consideration the ethnic background of each scientist. As described in Section S1.3, we use the Name Ethnicity Classifier to identify the ethnicity of each scientist.

2. Gender diversity: This type of diversity takes into consideration the gender of each scientist, which is identified using Genderize.io. When studying gender diversity, we only include a paper if the gender of each of its author is identified by Genderize.io; see Section S1.4 for more details.

3. Age diversity: Here, “age” refers to the academic age of a scientist, which we measure by subtracting the year of the scientist’s first paper from the year 2009 (see Section S1.7 for more details). The resulting dataset is then divided into the following bins:
   - Academic age group 0 : 0-9 years of experience;
• Academic age group 1: 10-19 years of experience;
• Academic age group 2: 20-29 years of experience;
• Academic age group 3: 30-39 years of experience;
• Academic age group 4: 40-49 years of experience;
• Academic age group 5: \( \geq 50 \) years of experience.

4. **Discipline Diversity:** This type of diversity takes into account the co-authors’ area of expertise. We determine the discipline of each scientist based on the keywords that are specified in his/her papers. This is made possible by the fact that the MAG dataset specifies the probability of each keyword belonging to any of the following 19 disciplines:

(1) Art  
(2) Biology  
(3) Business  
(4) Computer Science  
(5) Chemistry  
(6) Economics  
(7) Engineering  
(8) Environmental science  
(9) Geography  
(10) Geology  
(11) History  
(12) Materials Science  
(13) Mathematics  
(14) Medicine  
(15) Philosophy  
(16) Physics  
(17) Political Science  
(18) Psychology  
(19) Sociology

Formally, the probability of scientist \( s_i \) belonging to discipline \( x_j \) is calculated as follows:

\[
P(dsp(s_i) = x_j) = \frac{\sum_{p \in Papers(s_i)} \sum_{w \in Keywords(p)} P(dsp(w) = x_j)}{\sum_{x_k \in Disciplines} \sum_{p \in Papers(s_i)} \sum_{w \in Keywords(p)} P(dsp(w) = x_k)}
\] (3)

where \( Papers(s_i) \) denotes the set of papers of scientist \( s_i \), \( Keywords(p) \) denotes the set of keywords of paper \( p \), \( P(dsp(w) = x_j) \) denotes the probability that the keyword \( w \) belongs to the discipline \( x_j \), and \( Disciplines \) denotes the set of the 19 disciplines in MAG. Then,
the discipline of scientist \( s_i \) is determined as follows:

\[
dsp(s_i) = \begin{cases} 
\arg \max_{x_k \in \text{Disciplines}} P(dsp(s_i) = x_k) & \text{if } \max_{x_k \in \text{Disciplines}} P(dsp(s_i) = x_k) > 0.5 \\
\text{“unknown”} & \text{if } \max_{x_k \in \text{Disciplines}} P(dsp(s_i) = x_k) \leq 0.5
\end{cases}
\]

where \( P(dsp(s_i) = x_k) \) is calculated as in Equation (3). We exclude from our analysis any paper of which the discipline of an author is “unknown”.

5. **Affiliation Diversity:** This type of diversity takes into consideration the affiliations of the co-authors of a paper. Note that a scientist’s affiliation may vary from one paper to another. We exclude any papers where an author has more than one affiliation or no affiliation at all. This way, having multiple affiliations on a paper indicates that it is the result of collaboration across different research entities.

### S2.2 Measuring Diversity

The diversity of any given group reflects the degree to which its members differ from one another. To study the relationship between this property and the success of the associated group, a numerical measure of group diversity is required. To this end, several metrics have been proposed, the majority of which fall into two main categories:

1. Metrics that measure diversity by quantifying the uncertainty in predicting the type of an element drawn randomly from the set in question. Such a metric is commonly known as the Shannon entropy or the Shannon-Wiener Index. Formally, given \( k \) types, and a set \( S \), the Shannon entropy is computed as follows, where \( p_i(S) \) denotes the proportion of the elements of \( S \) that are of the \( i^{th} \) type:

\[
\text{Shannon}(S) = - \sum_{i=1}^{k} p_i(S) \ln p_i(S).
\]
2. Metrics that are designed to reflect the degree of concentration when the group members are classified into types (13). Such a metric is commonly known as the Simpson index in ecological literature, and as the Herfindahl-Hirschman index in the economic literature (14). It can also be found, with slight variations, in other fields under different names, including the probability of interspecific encounter (15), the Gini-Simpson index (16), and the Gini impurity (17). The formula for the Gini impurity can be found in Section S2.3.

For every paper in the entire MAG dataset, we measured the ethnic diversity in the group of authors using the Shannon entropy and using the Gini impurity. The two measures are plotted against each other in Figure S3. As can be seen, the two are strongly correlated, with Pearson’s $r = 0.93$ and $p < 0.0001$. Based on this, throughout the remainder of our study, we focus on just one of those measures, namely the Gini impurity, which will be explained in more detail in the following subsection.

**S2.3 Group Diversity Index**

In this subsection, we explain how the Gini impurity (18) is used to measure the diversity in any given paper. To this end, we need to introduce some additional notation. Let $S$ and $P$ denote the set of scientists and the set of papers under consideration, respectively. Furthermore, let $Authors(p_j) \subseteq S$ denote the set of authors of paper $p_j$. Now, for any given scientist $s_i \in S$, let $eth(s_i)$, $gen(s_i)$, $dsp(s_i)$, and $age(s_i)$ denote the ethnicity, the gender, the discipline and the academic age of $s_i$, respectively. Similarly, let $aff(s_i, p_j)$ denote the affiliation of scientist $s_i$ on paper $p_j$.\(^\text{10}\) For details on how the ethnicity, gender, discipline, academic age, and affiliation are identified, see Section S2.1. Note that for any given paper, $p_j$, any set $\{x(s_i) : s_i \in Authors(p_j)\}$ such that $x \in \{eth, gen, age, dsp\}$ is actually a

---

\(^\text{10}\)The affiliation of $s_i$ is denoted by $aff(s_i, p_j)$ rather than $aff(s_i)$ because the affiliation of a scientist may vary from one paper to another.
multiset. Likewise, the set \( \{ \text{aff}(s_i, p_j) : s_i \in \text{Authors}(p_j) \} \) is also a multiset. When dealing with multisets, we will use square brackets instead of curly ones. For instance, for any given paper, \( p_j \), we could have: [\( \text{eth}(s_i) : s_i \in \text{Authors}(p_j) \)] = [Japanese, British, British], and have: [\( \text{aff}(s_i, p_j) : s_i \in \text{Authors}(p_j) \)] = [Harvard, Harvard, Stanford]. For any given multiset, \( M \), let \( |M| \) denote the cardinality of \( M \), let \( \text{under}(M) \) denote the underlying set of \( M \), and let \( \text{multi}(m, M) \) denote the multiplicity of element \( m \) in \( M \). For example, given \( M = [\text{Harvard}, \text{Harvard}, \text{Stanford}] \), we have: \( |M| = 3 \), \( \text{under}(M) = \{\text{Harvard, Stanford}\} \), \( \text{multi}(\text{Harvard}, M) = 2 \) and \( \text{multi}(\text{Stanford}, M) = 1 \). The Gini impurity of a multiset, \( M \), is then defined as:

\[
Gini(M) = 1 - \sum_{m \in \text{under}(M)} \text{proportion}(m, M)^2,
\]

where

\[
\text{proportion}(m, M) = \frac{\text{multi}(m, M)}{|M|}.
\]

With this notation in place, we are now ready to formally define our group diversity index. In particular, for any given paper, \( p_j \in P \), the group diversity index of \( p_j \) is defined as follows, where the “\( G \)” in \( d^G_x \) stands for “Group”:

\[
d^G_x(p_j) = \begin{cases} 
Gini ([x(s_i) : s_i \in \text{Authors}(p_j)]) & \text{if } x \in \{\text{eth}, \text{gen}, \text{dsp}, \text{age}\} \\
Gini ([x(s_i, p_j) : s_i \in \text{Authors}(p_j)]) & \text{if } x = \text{aff} 
\end{cases}
\]

We will often omit the paper, \( p_j \), from the notation \( d^G_x(p_j) \) and simply write \( d^G_x \) whenever the paper itself is clear from the context.

Next, we summarize our five group diversity indices, and specify the papers that were considered for each such index (out of all 1,045,401 papers published in our dataset):

1. \( d^G_{\text{eth}} \)—the “group ethnic diversity index”; we calculated this for all papers in our dataset.

2. \( d^G_{\text{gen}} \)—the “group gender diversity index”; for any paper, we calculate this index only if the gender of each of author has been identified by Genderize.io.
3. $d_{age}^G$—the “group age diversity index”; this was calculated for all papers in our dataset.

4. $d_{dsp}^G$—the “group discipline diversity index”; for this index, we exclude every paper of which an author’s discipline is “unknown” according to Equation (4).

5. $d_{aff}^G$—the “group affiliation diversity index”; we calculated this index for every paper whose authors each have exactly one affiliation on the paper (i.e., we exclude papers of which an author has more than one affiliation, or no affiliation at all).

### S2.4 Individual Diversity Index

For any given scientist, $s_i \in S$, the individual diversity index of $s_i$ is defined as follows:

$$d^I_x(s_i) = \begin{cases} 
\text{Gini} \left( \biguplus_{p_j \in \text{Papers}(s_i)} \left[ x(s_k) : s_k \in \text{Authors}(p_j) \setminus \{s_i\} \right] \right) & \text{if } x \in \{\text{eth, gen, dsp, age}\} \\
\text{Gini} \left( \biguplus_{p_j \in \text{Papers}(s_i)} \left[ x(s_k, p_j) : s_j \in \text{Authors}(p_j) \setminus \{s_i\} \right] \right) & \text{if } x = \text{aff}
\end{cases}$$

(7)

where “I” in $d^I_x$ stands for “Individual”, Papers($s_i$) denotes the set of papers of which scientist $s_i$ is an author, $\uplus$ denotes the multiset sum operation, and Gini is defined as in Equation (5).

We will clarify the notation through an example. Suppose that scientist $A$ is an author of just two papers, $p_1$ and $p_2$, such that:

- $\text{Authors}(p_1) = \{A, B, C\}$;
- $\text{Authors}(p_2) = \{A, C, D\}$;
- the ethnicities of $B$, $C$, and $D$ are Japanese, British, and French, respectively.

Then we would have:

$$\biguplus_{p_j \in \text{Papers}(A)} \left[ \text{eth}(s_k) : s_k \in \text{Authors}(p_j) \setminus \{A\} \right] = \left[ \text{eth}(B), \text{eth}(C) \right] \uplus \left[ \text{eth}(C), \text{eth}(D) \right]$$

$$= \left[ \text{Japanese, British} \right] \uplus \left[ \text{British, French} \right]$$

$$= \left[ \text{Japanese, British, British, French} \right].$$
We will overload the notation by letting $d_I^x(p_i)$ denote the average individual diversity of the authors of paper $p_i$. More formally:

$$d_I^x(p_i) = \frac{\sum_{s_i \in \text{Authors}(p_i)} d_I^x(s_i)}{|\text{Authors}(p_i)|}, \quad (8)$$

where $x \in \{ \text{eth}, \text{gen}, \text{age}, \text{dsp}, \text{aff} \}$. To improve readability, we may write $\langle d_{\text{eth}}^I \rangle_{\text{paper}}$ instead of $d_I^x(p_i)$ when $p_i$ is clear from the context. Moreover, when dealing with individual scientists, we will often write $d_I^x$ instead of $d_I^x(s_i)$ when $s_i$ is clear from the context.

To summarize, our five individual diversity indices are as follows:

1. $d_{\text{eth}}^I$—the “individual ethnic diversity index”;

2. $d_{\text{gen}}^I$—the “individual gender diversity index”;

3. $d_{\text{age}}^I$—the “individual age diversity index”;

4. $d_{\text{dsp}}^I$—the “individual discipline diversity index”;

5. $d_{\text{aff}}^I$—the “individual affiliation diversity index”.

Out of the 1,529,279 scientists in our dataset, we calculated the individual diversity index for those with at least ten collaborators each; this yielded a total of 766,338 scientists with 5,103,877 collaborators taken from 9,472,439 different papers. Furthermore, when studying the average individual diversity in each subfield, we excluded any scientist whose name appears in more than one subfield in our dataset. This led to the exclusion of 6.8% of the scientists.
S3 Coarsened Exact Matching

To establish a causal link between ethnic diversity and scientific impact, we use coarsened exact matching, a technique used to infer causality in observational studies. Specifically, it matches the control and treatment populations with respect to the confounding factors identified, thereby eliminating the effect of these factors on the phenomena under investigation. In our case, we identified the following confounding factors when studying a paper’s group ethnic diversity:

- **year of publication**: 5 bins, the first of which contains papers published before 1990; the remaining 4 bins reflect 5-year intervals between 1990 and 2010.
- **number of authors**: Each bin corresponds to a single number.
- **field of study**: 8 bins, one for each of the main fields of science.
- **affiliations rankings**: 2 bins, one for all universities ranked in the top 500, and one for the rest.
- **authors’ impact prior to publication**: This is measured using the average citation count per year of authors at date of publication. 2 bins, one containing papers where the average of the authors’ impact is in the top 25% percentile.

In contrast, when studying an author’s individual ethnic diversity, we identified these confounding factors:

- **academic age**: 10 bins, with boundaries set to the sample percentiles.
- **number of collaborators**: 10 bins, with boundaries set to the sample percentiles.
- **discipline**: 8 bins, one for each of the main fields of science.
- **affiliation ranking**: 2 bins, one for universities ranked in the top 500, and one for the rest.

11http://www.shanghairanking.com/ARWU2017.html
Next, we filter the dataset and retain only papers and scientists for which the above confounding factors are known. Throughout the remaining steps of CEM, we will only deal with this filtered dataset. We now move on to selecting the treatment set, $T$, and the control sets, $C$. To this end, let $P_i(d^G_{eth})$ be the $i^{th}$ percentile of $d^G_{eth}$. Then, when studying group ethnic diversity:

- the treatment set consists of papers with $d^G_{eth} > P_{90}(d^G_{eth})$, yielding 45,710 papers;
- the control set consists of those with $d^G_{eth} \leq P_{10}(d^G_{eth})$, yielding 17,802 papers.

Similarly, when studying individual ethnic diversity:

- the treatment set consists of papers with $d^I_{eth} > P_{90}(d^I_{eth})$, yielding 139,822 scientists;
- the control set consists of those with $d^I_{eth} \leq P_{10}(d^I_{eth})$, yielding 84,270 scientists.

The results of the CEM have already been presented in detail in Tables 1 and 2 in the main paper. For the group diversity, we observe an 11.64% increase in number of citations compared to the matched control set. For individual diversity, an impact gain of 55.46% was observed. To demonstrate the robustness of our findings, we then perform sensitivity analysis where, in addition to the initial experiment using $i = 10$, we also consider different percentile groupings, using $P_i(d^G_{eth})$ and $P_{100-i}(d^G_{eth})$ as the lower and upper thresholds respectively, and where $i = 20, 30, 40, 50$. The results of these subsequent experiments are also included in Tables 1 and 2, and show that not only was the overall effect preserved, the impact gain increased in tandem with the diversity gap.
Figure S1: The distribution of papers published each year in the Microsoft Academic Graph corpus. The inset shows the distribution of our sample set, consisting of 1,045,401 papers.
Figure S2: $c_{G5}$ against $\tilde{C}_{G5}$ for 500,000 papers sampled uniformly at random from the entire MAG dataset. As can be seen, the two are very strongly correlated (over the entire dataset, Pearson’s $r = 0.965$ and $p < 0.0001$).

Figure S3: For every group of scientists that coauthored a paper in the Microsoft Academic Graph dataset, we measured the ethnic diversity using the Shannon entropy, and using the Gini index. The two are plotted against each other, showing a clear correlation ((Pearson’s $r = 0.93$ and $p < 0.0001$).
Figure S4: Distribution of group ethnic diversity, $d_{eth}^G$, for the real and randomized data. In most of the 24 subfields, the probability masses corresponding to the randomized data appear shifted to the right compared to the real data. Furthermore, in the real dataset, the frequency of teams with absolute homophily (i.e., where $d_{eth}^G = 0$) is clearly greater than expected by random chance; this is consistent across all subfields.
Figure S5: Distribution of individual ethnic diversity, $d_{eth}^I$, for the real and randomized data. In nearly all 24 subfields, the probability masses corresponding to the randomized data appear shifted to the right compared to the real data. Furthermore, in the real dataset, the frequency of teams with absolute homophily (i.e., where $d_{eth}^I = 0$) is clearly greater than expected by random chance; this is consistent across all subfields.
Figure S6: Group diversity against $c_G^5$ in each of the 24 subfields, which are grouped into the 8 main fields in Google Scholar. In the case of group ethnic diversity and group age diversity, every significant correlation with $c_G^5$ is positive, and nearly all correlations were significant. This, however, does not hold for the remaining group diversity indices (see the corresponding p-values in Table S1).
Figure S7: Individual diversity against $c_I^f$ in each of the 24 subfields, which are grouped into the 8 main fields in Google Scholar. In the case of individual ethnic diversity, every correlation with $c_I^f$ is significantly positive. The same holds for individual age diversity, with the exception of two subfields (Philosophy and Drama) for which the correlations are positive but not significant. This, however, does not hold for the remaining individual diversity indices (see the corresponding p-values in Table S2).
S5 Supplementary Tables

Table S1: Pearson’s $r$ and $p$ values corresponding to each subfield in Figure S6.

| Field                   | $r_{eth}$ | $p_{eth}$ | $r_{age}$ | $p_{age}$ | $r_{dsp}$ | $p_{dsp}$ | $r_{aff}$ | $p_{aff}$ | $r_{gen}$ | $p_{gen}$ |
|-------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Sustainable Energy      | 0.06      | 0.00      | 0.06      | 0.00      | 0.09      | 0.00      | -0.05     | 0.00      | -0.01     | 0.14†     |
| Mechanical Engineering  | 0.06      | 0.00      | 0.04      | 0.00      | 0.04      | 0.00      | -0.06     | 0.00      | -0.02     | 0.04      |
| Bioinformatics          | 0.01      | 0.56†     | 0.02      | 0.00      | 0.02      | 0.00      | 0.00      | 0.68†     | -0.03     | 0.00      |
| Cardiology              | 0.03      | 0.00      | 0.24      | 0.00      | 0.05      | 0.00      | -0.02     | 0.12†     | 0.05      | 0.00      |
| Psychiatry              | 0.03      | 0.00      | 0.24      | 0.00      | 0.05      | 0.00      | -0.02     | 0.12†     | -0.00     | 0.93†     |
| Nursing                 | 0.04      | 0.00      | 0.02      | 0.00      | 0.04      | 0.00      | -0.02     | 0.12†     | -0.00     | 0.93†     |
| Accounting              | 0.07      | 0.00      | 0.03      | 0.02      | -0.02     | 0.26†     | -0.02     | 0.44†     | -0.01     | 0.66†     |
| Marketing               | 0.09      | 0.00      | 0.02      | 0.00      | 0.02      | 0.06†     | 0.02      | 0.51†     | -0.00     | 0.92†     |
| Educational Administration | 0.02   | 0.00      | 0.07      | 0.00      | 0.07      | 0.00      | 0.06      | 0.04      | 0.04      | 0.05      |
| Language & Linguistics  | 0.07      | 0.00      | 0.07      | 0.00      | 0.03      | 0.02      | 0.02      | 0.47†     | 0.06      | 0.00      |
| Philosophy              | 0.08      | 0.03      | 0.07      | 0.00      | 0.03      | 0.03      | -0.04     | 0.21†     | 0.00      | 0.84†     |
| Drama                   | 0.10      | 0.35†     | 0.22      | 0.00      | -0.14     | 0.00      | 0.01      | 0.90†     | 0.04      | 0.51†     |
| Mathematical Optimization | 0.07    | 0.00      | 0.02      | 0.02      | 0.03      | 0.00      | 0.00      | 0.73†     | -0.00     | 0.80†     |
| Fluid Mechanics         | 0.02      | 0.02      | -0.01     | 0.18†     | 0.02      | 0.00      | -0.02     | 0.01      | -0.04     | 0.00      |
| Mathematical Physics    | 0.03      | 0.00      | 0.02      | 0.00      | 0.01      | 0.15†     | 0.04      | 0.00      | -0.04     | 0.00      |
| Political Science       | 0.05      | 0.00      | 0.08      | 0.00      | 0.05      | 0.00      | -0.04     | 0.03      | -0.01     | 0.47†     |
| Sociology               | 0.03      | 0.22†     | 0.04      | 0.00      | -0.01     | 0.23†     | -0.02     | 0.34†     | 0.04      | 0.00      |
| History                 | 0.20      | 0.00      | 0.04      | 0.00      | 0.05      | 0.00      | -0.04     | 0.17†     | 0.01      | 0.14†     |
| Oil, Petroleum & Nat. Gas | 0.15      | 0.00      | 0.05      | 0.00      | -0.07     | 0.00      | 0.14      | 0.00      | -0.02     | 0.30†     |
| Nanotechnology          | 0.11      | 0.00      | 0.05      | 0.00      | 0.06      | 0.00      | -0.02     | 0.12†     | -0.01     | 0.22†     |
| Materials Engineering   | 0.02      | 0.00      | 0.02      | 0.00      | 0.05      | 0.00      | 0.00      | 0.76†     | -0.01     | 0.04      |
| Geology                 | 0.04      | 0.00      | 0.00      | 0.65†     | 0.06      | 0.00      | 0.02      | 0.14†     | -0.03     | 0.00      |
| Environmental Sciences  | 0.05      | 0.00      | 0.04      | 0.00      | 0.05      | 0.00      | 0.01      | 0.22†     | -0.01     | 0.00      |
| Ecology                 | 0.01      | 0.29†     | 0.06      | 0.00      | 0.02      | 0.00      | -0.00     | 0.84†     | -0.02     | 0.00      |

† $p \geq 0.05$
Table S2: Pearson’s $r$ and $p$ values corresponding to each subfield in Figure S7.

| Field                          | $r_{eth}$ | $p_{eth}$ | $r_{age}$ | $p_{age}$ | $r_{ds}p$ | $p_{ds}p$ | $r_{aff}$ | $p_{aff}$ | $r_{gen}$ | $p_{gen}$ |
|-------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Sustainable Energy            | 0.05      | 0.00      | 0.04      | 0.00      | -0.02     | 0.55†     | -0.03     | 0.51†     | 0.00      | 0.50†     |
| Mechanical Engineering        | 0.06      | 0.00      | 0.07      | 0.00      | 0.01      | 0.79†     | -0.06     | 0.15†     | 0.00      | 0.39†     |
| Bioinformatics                | 0.02      | 0.00      | 0.01      | 0.00      | -0.02     | 0.23†     | -0.16     | 0.00      | -0.00     | 0.01      |
| Cardiology                    | 0.06      | 0.00      | 0.05      | 0.00      | 0.05      | 0.12†     | 0.07      | 0.00      | 0.00      | 0.75†     |
| Psychiatry                    | 0.03      | 0.00      | 0.04      | 0.00      | 0.05      | 0.37†     | 0.10      | 0.08†     | 0.02      | 0.00      |
| Nursing                       | 0.03      | 0.00      | 0.04      | 0.00      | 0.06      | 0.32†     | -0.34     | 0.00      | 0.02      | 0.00      |
| Accounting                    | 0.06      | 0.00      | 0.04      | 0.00      | -0.01     | 0.86†     | 0.03      | 0.61†     | -0.02     | 0.11†     |
| Marketing                     | 0.01      | 0.05      | 0.04      | 0.00      | 0.12      | 0.13†     | 0.10      | 0.28†     | 0.00      | 0.81†     |
| Educational Administration    | 0.10      | 0.00      | 0.06      | 0.00      | 0.23      | 0.00      | -0.29     | 0.00      | 0.05      | 0.00      |
| Language & Linguistics        | 0.07      | 0.00      | 0.08      | 0.00      | 0.14      | 0.20†     | 0.10      | 0.34†     | 0.03      | 0.01      |
| Philosophy                    | 0.06      | 0.00      | 0.03      | 0.08†     | 0.27      | 0.04      | -0.34     | 0.00      | 0.01      | 0.75†     |
| Drama                         | 0.13      | 0.00      | 0.11      | 0.05†     | 0.07      | 0.70†     | 0.02      | 0.91†     | 0.02      | 0.79†     |
| Mathematical Optimization     | 0.06      | 0.00      | 0.05      | 0.00      | 0.07      | 0.20†     | -0.09     | 0.07†     | -0.00     | 0.62†     |
| Fluid Mechanics               | 0.06      | 0.00      | 0.04      | 0.00      | 0.07      | 0.26†     | -0.04     | 0.53†     | -0.01     | 0.00      |
| Mathematical Physics          | 0.04      | 0.00      | 0.01      | 0.00      | 0.04      | 0.42†     | 0.07      | 0.17†     | -0.01     | 0.00      |
| Political Science             | 0.08      | 0.00      | 0.06      | 0.00      | 0.25      | 0.02      | -0.14     | 0.21†     | -0.01     | 0.65†     |
| Sociology                     | 0.06      | 0.00      | 0.04      | 0.00      | 0.05      | 0.67†     | 0.09      | 0.42†     | 0.03      | 0.02      |
| History                       | 0.04      | 0.00      | 0.07      | 0.00      | -0.03     | 0.88†     | -0.40     | 0.29†     | 0.01      | 0.25†     |
| Oil, Petroleum & Nat. Gas     | 0.14      | 0.00      | 0.10      | 0.00      | 0.02      | 0.78†     | 0.16      | 0.02      | -0.03     | 0.00      |
| Nanotechnology                | 0.06      | 0.00      | 0.04      | 0.00      | 0.09      | 0.13†     | 0.01      | 0.89†     | 0.01      | 0.00      |
| Materials Engineering         | 0.02      | 0.00      | 0.02      | 0.00      | -0.05     | 0.32†     | 0.05      | 0.29†     | 0.01      | 0.00      |
| Geology                       | 0.03      | 0.00      | 0.06      | 0.00      | 0.03      | 0.57†     | 0.09      | 0.15†     | 0.03      | 0.00      |
| Environmental Sciences        | 0.08      | 0.00      | 0.07      | 0.00      | -0.04     | 0.51†     | 0.09      | 0.19†     | -0.01     | 0.00      |
| Ecology                       | 0.04      | 0.00      | 0.05      | 0.00      | 0.11      | 0.05†     | 0.07      | 0.19†     | -0.00     | 0.90†     |

† $p \geq 0.05$
| Notation      | Description                                                                                                                                 |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| $S$          | The set of scientists under consideration                                                                                                  |
| $P$          | The set of papers under consideration                                                                                                       |
| $Papers(s_i)$| The set of papers of scientist $s_i$                                                                                                         |
| $Authors(p_j)$| The set of authors of paper $p_j$                                                                                                           |
| $Keywords(p_j)$| The set of keywords in paper $p_j$                                                                                                          |
| $Gini(M)$    | $Gini$ impurity of multiset $M$; see Equation (5)                                                                                            |
| $Disciplines$| The set of 19 scientific disciplines in Microsoft Academic Graph (MAG)                                                                       |
| $dsp(s_i)$   | Discipline of scientist $s_i$ according to Microsoft Academic Graph; see Equation (4)                                                        |
| $eth(s_i)$   | Ethnicity of scientist $s_i$ according to the Name Ethnicity Classifier                                                                    |
| $gen(s_i)$   | Gender of scientist $s_i$ according to Genderize.io                                                                                        |
| $age(s_i)$   | Academic age of scientist $s_i$, measured by subtracting the publication year of the first paper of $s_i$ from the year 2009                 |
| $aff(s_i,p_j)$| Affiliation of scientist $s_i$ in paper $p_j$ according to Microsoft Academic Graph                                                         |
| $d^{G}_{x}$  | Group discipline diversity index; see Equation (6), where $x$ = $dsp$                                                                        |
| $d^{G}_{eth}$| Group ethnic diversity index; see Equation (6), where $x$ = $eth$                                                                           |
| $d^{G}_{gen}$| Group gender diversity index; see Equation (6), where $x$ = $gen$                                                                           |
| $d^{G}_{age}$| Group age diversity index; see Equation (6), where $x$ = $age$                                                                           |
| $d^{G}_{aff}$| Group affiliation diversity index; see Equation (6), where $x$ = $aff$                                                                       |
| $d^{I}_{x}$  | Average $d^{G}_{x}$ taken over a set of papers, where $x$ $\in$ $\{eth, gen, age, dsp, aff\}$                                              |
| $d^{I}_{x}$  | Individual discipline diversity index; see Equation (7), where $x$ = $dsp$                                                                   |
| $d^{I}_{eth}$| Individual ethnic diversity index; see Equation (7), where $x$ = $eth$                                                                     |
| $d^{I}_{gen}$| Individual gender diversity index; see Equation (7), where $x$ = $gen$                                                                      |
| $d^{I}_{age}$| Individual age diversity index; see Equation (7), where $x$ = $age$                                                                       |
| $d^{I}_{aff}$| Individual affiliation diversity index; see Equation (7), where $x$ = $aff$                                                                   |
| $\langle d^{I}_{x}\rangle_{paper}$ | Average $d^{I}_{x}$ taken over all authors of $p_j$, where $x$ $\in$ $\{eth, gen, age, dsp, aff\}$; see Equation (8) |
| $c^{G}_{5}(p_j)$ | Number of citations that paper $p_j$ accumulates 5 years after publication                                                                   |
| $\langle c^{G}_{5}\rangle$ | Average $c^{G}_{5}$ taken over a set of papers                                                                                               |
| $c^{I}_{5}(s_i)$ | Number of citations that scientist $s_i$ accumulates on average from his/her papers 5 years after publication; see Equation (1)            |
| $\langle c^{I}_{5}\rangle$ | Average $c^{I}_{5}$ taken over a set of individuals                                                                                          |
| $P_i(d^{G}_{eth})$ | The $i^{th}$ percentile of $d^{G}_{eth}$                                                                                                   |
References

1. Ambekar, A., Ward, C., Mohammed, J., Male, S. & Skiena, S. Name-ethnicity classification from open sources. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge Discovery and Data Mining, 49–58 (ACM, 2009).

2. Ye, J. et al. Nationality classification using name embeddings. arXiv preprint arXiv:1708.07903 (2017).

3. Chen, S. A.i. research is in desperate need of an ethical watchdog. Wired.

4. Wais, K. Gender prediction methods based on first names with genderizer. R Journal 8 (2016).

5. West, J. D., Jacquet, J., King, M. M., Correll, S. J. & Bergstrom, C. T. The role of gender in scholarly authorship. PloS one 8, e66212 (2013).

6. Larivière, V., Ni, C., Gingras, Y., Cronin, B. & Sugimoto, C. R. Bibliometrics: Global gender disparities in science. Nature News 504, 211 (2013).

7. Radicchi, F., Fortunato, S. & Castellano, C. Universality of citation distributions: Toward an objective measure of scientific impact. Proceedings of the National Academy of Sciences 105, 17268–17272 (2008).

8. Radicchi, F. & Castellano, C. Testing the fairness of citation indicators for comparison across scientific domains: The case of fractional citation counts. Journal of Informetrics 6, 121–130 (2012).

9. Stringer, M. J., Sales-Pardo, M. & Amaral, L. A. N. Statistical validation of a global model for the distribution of the ultimate number of citations accrued by papers published in a
scientific journal. *Journal of the Association for Information Science and Technology* **61**, 1377–1385 (2010).

10. Sinatra, R., Wang, D., Deville, P., Song, C. & Barabási, A.-L. Quantifying the evolution of individual scientific impact. *Science* **354**, aaf5239 (2016).

11. Bornmann, L. & Daniel, H.-D. What do citation counts measure? a review of studies on citing behavior. *Journal of documentation* **64**, 45–80 (2008).

12. Althouse, B. M., West, J. D., Bergstrom, C. T. & Bergstrom, T. Differences in impact factor across fields and over time. *Journal of the Association for Information Science and Technology* **60**, 27–34 (2009).

13. Simpson, E. H. Measurement of diversity. *nature* **163**, 688 (1949).

14. Herfindahl, O. C. *Concentration in the steel industry*. Ph.D. thesis, Columbia University New York (1950).

15. Hurlbert, S. H. The nonconcept of species diversity: a critique and alternative parameters. *Ecology* **52**, 577–586 (1971).

16. Jost, L. Entropy and diversity. *Oikos* **113**, 363–375 (2006).

17. Rokach, L. & Maimon, O. Top-down induction of decision trees classifiers-a survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* **35**, 476–487 (2005).

18. Bishop, C. M. *Pattern recognition and machine learning* (Springer, 2013).