



Become a better you: Correlation between the change of research direction and the change of scientific performance



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ABSTRACT

It is important to explore how scientists decide their research agenda and the corresponding consequences, as their decisions collectively shape contemporary science. There are studies focusing on the overall performance of individuals with different problem choosing strategies. Here we ask a slightly different but relatively unexplored question: how is a scientist's change of research agenda associated with her change of scientific performance. Using publication records of over 14,000 authors in physics, we quantitatively measure the extent of research direction change and the performance change of individuals. We identify a strong positive correlation between the direction change and impact change. Scientists with a larger direction change not only are more likely to produce works with increased scientific impact compared to their past ones, but also have a higher growth rate of scientific impact. On the other hand, the direction change is not associated with productivity change. Those who stay in familiar topics do not publish faster than those who venture out and establish themselves in a new field. The gauge of research direction in this work is uncorrelated with the diversity of research agenda and the switching probability among topics, capturing the evolution of individual careers from a new point of view. Though the finding is inevitably affected by the survival bias, it sheds light on a range of problems in the career development of individual scientists.

1. Introduction

The availability of large scale data set and computational tools makes it easier than ever to quantitatively probe the science at different scales, from papers (Chen et al., 2021a; Hu et al., 2020; Mukherjee et al., 2017; Wang et al., 2013) to individual scientists (Bu et al., 2018; Liu et al., 2018; Way et al., 2017; Zhang et al., 2017), and from research teams (AlShebli et al., 2018; Ma et al., 2020; Wu et al., 2019) to institutions and nations (Chen, Zhu, & Jia, 2021c; Huang et al., 2020a; King, 2004; Liu, Yu, Huang, Xia, & Jia, 2020; Zhao et al., 2020; Zuo & Zhao, 2018). As the development of science is driven by scientists' involvements in different research topics, it is crucial to understand how they decide their research directions and what are the consequences of their collective decisions. Such choices affect not only individual careers but also collectively shape contemporary science. The conflict in topic choosing is vividly depicted as "The essential tension" (Kuhn, 1977) that scientists often need to decide whether to explore a new field or to exploit familiar topics (Foster et al., 2015).

By carefully selecting the control group or by comparing a group of elites with the average, quantitative studies have provided us with a consistent conclusion. Those who focus on a narrow research agenda tend to secure a steady scientific output and gain more

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overall citations (Amjad et al., 2018; Pramanik et al., 2019; Zeng et al., 2019) whereas those who take the risk to change topics are likely to produce “hit” papers or highly innovative outcomes (Azoulay et al., 2011; Foster et al., 2015; Leahey et al., 2017). However, existing works usually focus on a group of selective individuals whose scientific achievements are beyond a certain threshold. It is still unclear what would happen to a typical scientist who crosses the boundary and enters a new field. Moreover, the comparison is usually based on the overall performance and made between two distinct groups of individuals. The change of performance, measured by the past and current performance of one’s own, is rarely investigated.

Here, we ask a set of simple but relatively unexplored questions: If one changes the research agenda and succeeds in the new field, is she going to publish better research works than she used to do? Is she going to publish faster or slower compared with her past publication speed? Furthermore, if she were to venture further, would her benefits/disadvantages increase or decline? These questions focusing on the change of the scientific performance of an individual are not fully addressed in existing works, to the best of our knowledge. We understand that individual scientists are inherently different from each other, affected by confounding factors such as scientific training (Clauset et al., 2015), gender (Huang et al., 2020b; Mauleón and Bordons, 2006), age (Jones and Weinberg, 2011; Petersen et al., 2011), mobility (Petersen, 2018; Robinson-Garcia et al., 2019; Zhao et al., 2020), prestige of institution in which they work (Way et al., 2019), and more. While some factors can be controlled, many of them are hard to control. Therefore, we choose to use a large size of samples which may allow us to balance out other factors and reach preliminary answers to these questions. We use data about the publication in the American Physical Society (APS) journals and apply the approach by Aleta et al. (2019); Jia et al. (2017) to quantitatively measure the extent of research direction change. The method does not just provide a binary classification that tells if a scientist changed the research direction or not. Instead, it gauges the distance between two vectors characterizing the topics of a paper set, giving rise to a continuous measure of the direction change. Using the publication records of over 14,000 scientists, we find that the research direction change is positively correlated with the increase of impact: those with a bigger change in the research direction demonstrate not only a higher probability to increase citations of the publications, but also the relative magnitude of the citation gain. In contrast, the relationship between the research direction change and productivity change is neutral. Scientists who stay on the same topic do not produce faster than their colleagues venturing into new areas. We observe similar patterns when varying the criteria of data filtering, which supports the robustness of our conclusion.

We also carefully compare our results with some recent findings. We provide evidence that the metric used in our study is totally uncorrelated with the one in Zeng et al. (2019) and the quality associated with the direction change is also different. Hence, the two studies quantify the effects of direction change from two distinct perspectives. We compare the direction change with the diversity change of an individual’s research agenda (Leahey et al., 2017; Wang et al., 2015) and find that these two quantities are uncorrelated. Therefore, the gain of citation is not from the benefit of conducting diverse or interdisciplinary research. We also control the field citation and find that our conclusion still holds. In other words, the positive correlation between direction change and impact change is not from the move to a hot field. Taken together, we show the correlation between the research direction change and the performance change among a large number of physicists, which advances our understanding of the career development of individual scientists.

2. Materials and methods

2.1. Data set

The APS publication data is publicly available at <http://journals.aps.org/datasets>, which consists of around 300,000 scientific papers authored by around 200,000 scientists together with their citation records covering years from 1976 to 2009. The information includes a paper’s author list, its publication time, its reference list, and more. To classify papers belonging to each author, we perform the name disambiguation following procedures in previous works Aleta et al. (2019); Deville et al. (2014); Zeng et al. (2019). The name disambiguated data are roughly the same as one we used in another work Jia et al. (2017). Still, some author names are so general that individual authors can hardly be distinguished. For this reason, we calculate the Shannon entropy of topics in an author’s publications and filter out those outliers who participate in unexpected highly diverse topics. We first find the topic vector g based on the all papers under one author (see below for composing topic vector) and then calculate Shannon entropy as $H = -\sum_{j=1}^{67} x_j \log(x_j)$ where x_j is the j^{th} element of the vector g . Following Jia et al. (2017), we set $H = 2.5$ as the cutoff value.

2.2. Composing topic vector

We make use of the Physics and Astronomy Classification Scheme (PACS) code firstly proposed by the American Institute of Physics in 1975. The PACS code contains 6 digits in a format like “ab.cd.ef” that points to a specific and specialized area in physics. The order of these digits is related to the hierarchical structure of the topics. For example, the code “82.39.Rt” corresponds to “Reactions in complex biological systems” which is a subtopic under the first level topic “82”: physical chemistry and chemical physics. Totally, there are 67 topics given by the first two digits of the PACS code, representing 67 sub-disciplines in modern physics. Over 90% of papers published after 1985 are labeled by one to three PACS codes.

For each paper, we count the occurrence of the first level topic given by the first two digits of a PACS code. The number of occurrences is further normalized by the total number of PACS codes in a paper. Then for this paper, we can build a vector $A = (a_1, a_2, \dots, a_j, \dots, a_{67})$ where the element a_j is the fractionalized occurrence of each topic in this paper. For a set of m papers, we can average the m vectors of each paper and reach a topic vector g representing the weight coverage of 67 topics that the set of m papers demonstrates. If the m papers are authored by one scientist, the topic vector g then provides a good proxy of her research direction,

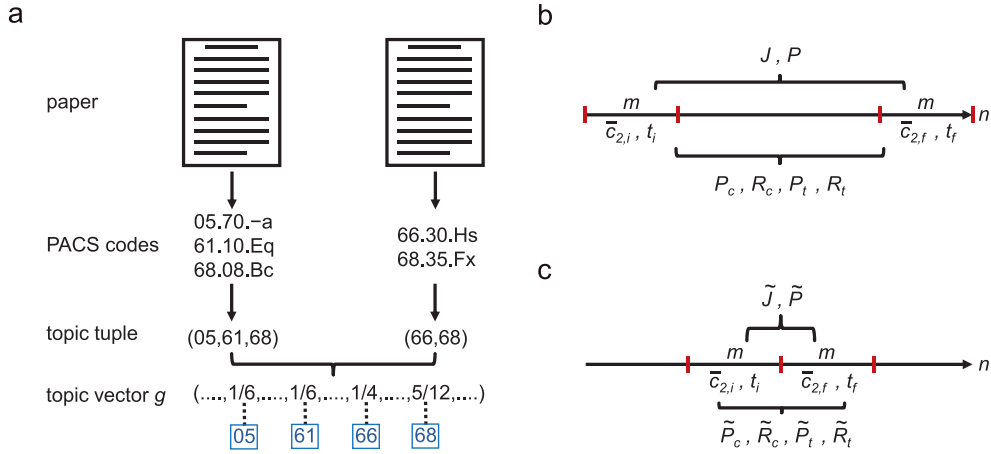


Fig. 1. (a) An example demonstrating the procedure to compose topic tuple and topic vector g . For two topic tuples (66, 68) and (05, 61, 68), the element value in g of topic 66 is calculated as $\frac{1/2+0}{2} = \frac{1}{4}$, as it appears once in one topic tuple and is not included in the other. The element value in g of topic 68 is calculated as $\frac{1/2+1/3}{2} = \frac{5}{12}$, as it appears once in each of the topic tuples. Similarly, the element values in g of topic 05 and 61 are calculated as $\frac{0+1/3}{2} = \frac{1}{6}$. (b) The scenario that takes the first and the last m papers in a scientist's publication sequence to obtain the direction change J , its distribution P , the growth fraction and growth rate of the scientific impact and productivity P_c, R_c, P_t , and R_t . (c) The scenario that uses two adjacent sequences of m papers randomly chosen from a scientist's publication sequence. Correspondingly, the quantities obtained are denoted by $\tilde{J}, \tilde{P}, \tilde{P}_c, \tilde{R}_c, \tilde{P}_t$, and \tilde{R}_t .

capturing not only the collection of topics but also the level of involvements she studies in the m papers. An example of composing a topic vector is illustrated in Fig. 1a.

2.3. Measuring the research direction change

We sequence a scientist's n papers according to their publication time. We then select two sets of papers, each with size m , in a scientist's early and late career, from which we can build two topic vectors. Denote g_i by the topic vector of the early publications and g_f by the late publications. Comparing the difference between these two vectors allows us to quantify the degree of research direction change J_o . Using cosine similarity, we have

$$J_o = 1 - \frac{g_i \cdot g_f}{\|g_i\| \|g_f\|}. \quad (1)$$

J_o varies between 0 and 1, where $J_o = 0$ means the author studies the same topic in the early and late career with identical involvements, $J_o = 1$ corresponds to the largest change as the topics in the two sets of papers have no overlap.

To make sure that the results are not affected by how the two sets of papers are selected, we consider two distinct scenarios. First, we select two series of m papers maximally separated in a scientist's publication sequence, i.e. the first and last m papers, capturing the change across the whole recorded career (Fig. 1b). The corresponding direction change is denoted by J . As one publication sequence defines one unique career, we only have one measure of J for each author.

Additionally, we also consider two consecutive sets of papers beginning at a random choosing paper to eliminate potential effects caused by the gap between the two sets of publications (Fig. 1c). The direction change measured is denoted by \tilde{J} . As an author may have published more than $2m$ papers, there are multiple measures of \tilde{J} for each author. Therefore, for all measures associated with this scenario, we randomly pick a beginning paper for each author, get the measures needed (such as \tilde{J}, \tilde{P} and so on), and calculate the statistics across the population. Then we repeat this procedure 2000 times. We report the mean value and the error bar that corresponds to the standard deviation. Though the value and the exact distribution of J and \tilde{J} are different, it is also noteworthy that the two quantities are highly correlated. The Pearson correlation between J and the average value $\langle \tilde{J} \rangle$ of an individual scientist is over 0.99 (Fig. S1 in Supplementary material). It implies that the big research direction change is likely carried out incrementally throughout one's career.

Due to the way we quantify the research direction change, only authors with no fewer than $2m$ papers can be included in our analysis. In the main text, we report results based on $m = 8$, corresponding to 14,726 scientists who authored at least 16 papers. We repeat the same analysis with different m values ($m = 7$ and $m = 9$, Section S2 in Supplementary material). The same pattern is observed, suggesting that our findings do not depend on the choice of m .

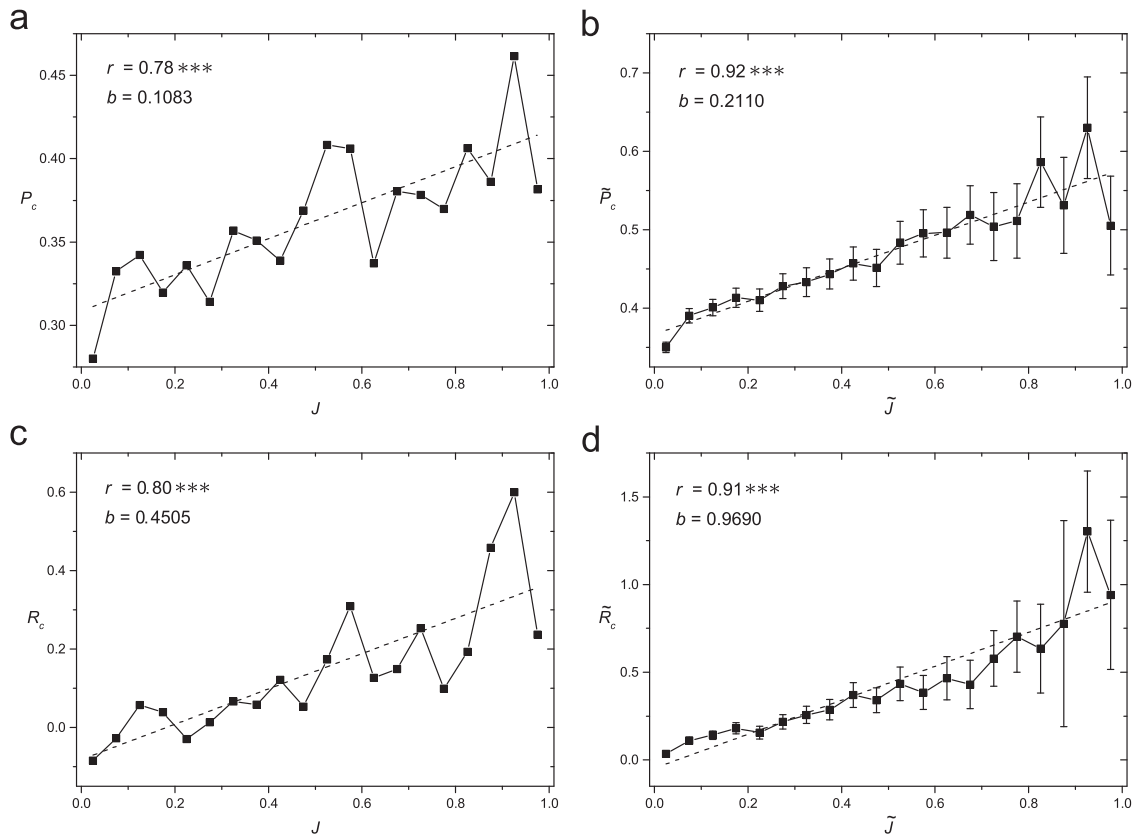


Fig. 2. (a) P_c conditioning on the range $(J - 0.025, J + 0.025]$ is positively correlated with J . The dashed line represents the linear regression. (b) The average \bar{P}_c conditioning on the range $(\bar{J} - 0.025, \bar{J} + 0.025]$ is positively correlated with \bar{J} . (c) The average R_c conditioning on the range $(J - 0.025, J + 0.025]$ is positively correlated with J . (d) The average \bar{R}_c conditioning on the range $(\bar{J} - 0.025, \bar{J} + 0.025]$ is positively correlated with \bar{J} . At the boundary $J = 0$ and $\bar{J} = 0$, the range $[0, 0.05]$ is used, and the same boundary condition applies in all the analyses of J and \bar{J} . The scatter plots of P_c , \bar{P}_c , R_c , and \bar{R}_c are displayed in Fig. S2 in Supplementary material. The value of b is defined as the slope of the corresponding linear regression function (The dashed line). *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$ (t -test for Pearson coefficient r). Error bars represent the one standard deviation of the mean.

3. Results

3.1. Correlation between the direction change and impact change

We apply two distinct approaches to quantify the impact change. First, we group scientists whose direction changes fall into a small range ($J \in (0.025, 0.075]$ for instance) and measure the percentage of scientists within this group whose research impact have increased. In particular, we count the number of citations a paper receives within two years after its publication and normalize this value by the average citations of papers published in the same year, giving rise to a normalized citation measure c_2 that takes into account the citation inflation (Huang et al., 2020b; 2020c; Petersen et al., 2019; Radicchi et al., 2008; Sinatra et al., 2016) (Section S1 in Supplementary material). We then measure the average value of c_2 for the m papers in an author's early and late publication list which is used to quantify research direction change. Denote $\bar{c}_{2,i}$ and $\bar{c}_{2,f}$ by the average citation of the two paper sets, respectively (Fig. 1b-c). If an author's late publications on average receive more citations than her early ones ($\bar{c}_{2,f} > \bar{c}_{2,i}$), we consider this author's research impact has increased. The percentage P_c is then calculated as the ratio between the number of authors whose $\bar{c}_{2,f} > \bar{c}_{2,i}$ and the number of authors whose direction change fall within the range $(J - 0.025, J + 0.025]$. For the direction change \bar{J} , we obtain \bar{P}_c with a similar approach.

The interpretation of these two measures of P_c and \bar{P}_c can be rather intuitive: for those who choose to venture into a new topic, how many of them are going to produce better research works than they used to? Our results demonstrate a strong positive correlation between J and P_c , as well as between \bar{J} and \bar{P}_c , where the Pearson correlation coefficient r 0.78 for J and 0.92 for \bar{J} (Fig. 2a-b). The positive correlation indicates that those who leave the current research field are more likely to produce works of more impact than their previous work. More importantly, it also implies that the further one leaves the original area, the higher this likelihood will be.

The P_c and \bar{P}_c provide a binary check on whether or not an author's works are on average better than her previous ones. They do not, however, quantify the extent of the improvement or the decline. It could be the case, for example, that the gain is small but the

loss is big associated with a certain direction change. For this reason, we measure the relative impact change $(\bar{c}_{2,f} - \bar{c}_{2,i})/\bar{c}_{2,i}$, which quantifies the extent that the impact of the later research differs from the early ones. We calculate $(\bar{c}_{2,f} - \bar{c}_{2,i})/\bar{c}_{2,i}$ for each author and get the average value R_c and \bar{R}_c of scientists with similar research direction change J and \bar{J} , respectively (for few scientists whose $\bar{c}_{2,i} = 0$, we assign a default value 2 to their relative impact change). We again observe a strong and positive correlation between J and R_c , as well as \bar{J} and \bar{R}_c (Fig. 2c-d). Taken together, those who exhibit a larger change of research direction demonstrate a higher extent of impact improvement. The larger the change, the more impact the work would receive.

A scientist may move to a “hot” field where the publication’s average citation is higher than others. To explore if this can explain the positive correlation observed, we calculate the field-normalized citation of each paper (Section S3 in Supplementary material). The positive correlation preserves when taking the difference of each field into account. Finally, to make sure our results are not affected by the sample sizes in calculating citations, we perform similar analyses using different citation measures. Besides, we also test the case when the citation time window is 3 years. The corresponding results are presented in Section S4 in Supplementary material. In all cases, a strong positive correlation is observed between the research direction change and the impact change.

3.2. Correlation between the direction change and productivity change

Another quantity associated with scientific performance is productivity, typically quantified by the time needed to complete a certain number of papers. Here we use the time interval t between the publications of the first and m^{th} paper in a given series of papers. Similar to the above analyses, we identify the fraction of scientists P_t (and \bar{P}_t) whose productivity are increased ($t_f < t_i$), and calculate the average change rate R_t (and \bar{R}_t) of scientists’ productivity by averaging $(\frac{1}{t_f} - \frac{1}{t_i})/\frac{1}{t_i}$ of individual scientists whose research direction change are within the same range (Fig. 1b-c).

The direct correlation measure shows two seemingly contradictory pictures. On one hand, based on two adjacent sets of papers, the research direction change \bar{J} is not correlated with the probability to increase productivity \bar{P}_t (Fig. 3a), nor the change of productivity rate \bar{R}_t (Fig. S3a in Supplementary material). On the other hand, if the change is measured based on two sets of papers that are at the two ends of a career, J is positively correlated with both P_t (Fig. 3b) and R_t (Fig. S3b in Supplementary material). Does it mean that switching to new topics at the latter career would associate with advanced productivity?

To have a right understanding of the correlation between J and P_t as well as J and R_t , we have to first control their inherent correlation. As J depends on the two sets of papers that are maximally separated in one’s publication list, the more publications one produces, the less likely it that the publications on one end of the list would contain similar topics with those on the other end. Therefore, it is expected and also empirically confirmed that J is positively correlated with the number of publications n in a career (Fig. 3c). Furthermore, the growing number of publications may enrich a scientist’s experiences, skills, and collaboration networks, which in return would benefit productivity. It can be expected that the chance to surpass the publication rate at the beginning of the career (which usually corresponds to the graduate training period) would grow as one’s publication list gets longer. Indeed, we observe empirically that P_t and R_t are positively correlated with n (Fig. 3d, and Fig. S3c in Supplementary material).

The positive correlation between J and n as well as P_t and n leads to an inherent correlation between J and P_t . In other words, given the way that J is measured and the various values of the hidden variable n , J is expected to correlate with P_t . Indeed, if we control the number of publications by focusing on $16 \leq n \leq 20$ or $21 \leq n \leq 25$, the correlation disappears (Section S5 in Supplementary material).

To control this inherent correlation, we can first identify the dependence between J and P_t from their pairwise dependence with n (Section S6 in Supplementary material). The result gives $P_t \sim b \times J$, which is the expected dependence between J and P_t (red line in Fig. 3b). We then subtract the increase from P_t , yielding a measure $P'_t = P_t - b \times J$ in which P_t ’s natural dependence with J is excluded. When the inherent correlation is properly controlled, we find that P'_t and J are uncorrelated (Fig. 3e). The same analyses can also be performed on R_t , which leads to similar results (Fig. S3d in Supplementary material).

Taken together, by properly control the effect of publication number n in our measure, we reach consistent results that the research direction change is not correlated with the probability to increase productivity nor the average change rate of productivity. This is contrary to our common perception that changing research direction is likely to hurt productivity. But we have to keep in mind that there may be a survivor bias. A scientist can contribute to the statistics only when she successfully changes the direction. Those who take the risk to explore a new area but fail to publish enough are not included in our data. Therefore, the interpretation of the results needs more caution. Finally, the hidden variable n leads us to two contradictory relationships because it strongly and positively correlates with P_t as well as R_t . In terms of impact change analyzed in the above section, we find that n is weakly and slightly negatively correlated with P_c and R_c (Fig. S4 in Supplementary material). This is in line with some previous findings that simply publishing a lot does not necessarily enhance the scientific impact of individual papers (Hanssen and Jørgensen, 2015; Kolesnikov et al., 2018; Larivière and Costas, 2016; Sarewitz, 2016). Therefore, although the dependence between J and n preserves, it does not play a role in our conclusion about impact change.

3.3. Extended discussions

It is a conventional narrative that scientific productivity tends to grow rapidly at the early stage of a career and then slowly declines. Such narrative is highlighted in some recent studies (Li et al., 2020; Sinatra et al., 2016) explaining why elite scientists tend to produce the most significant works at their early career stage: because their productivity declines when they get older. This pattern seems to be against our finding that P_t and n are positively correlated, which plays a crucial role in explaining the discrepancy in the initial results

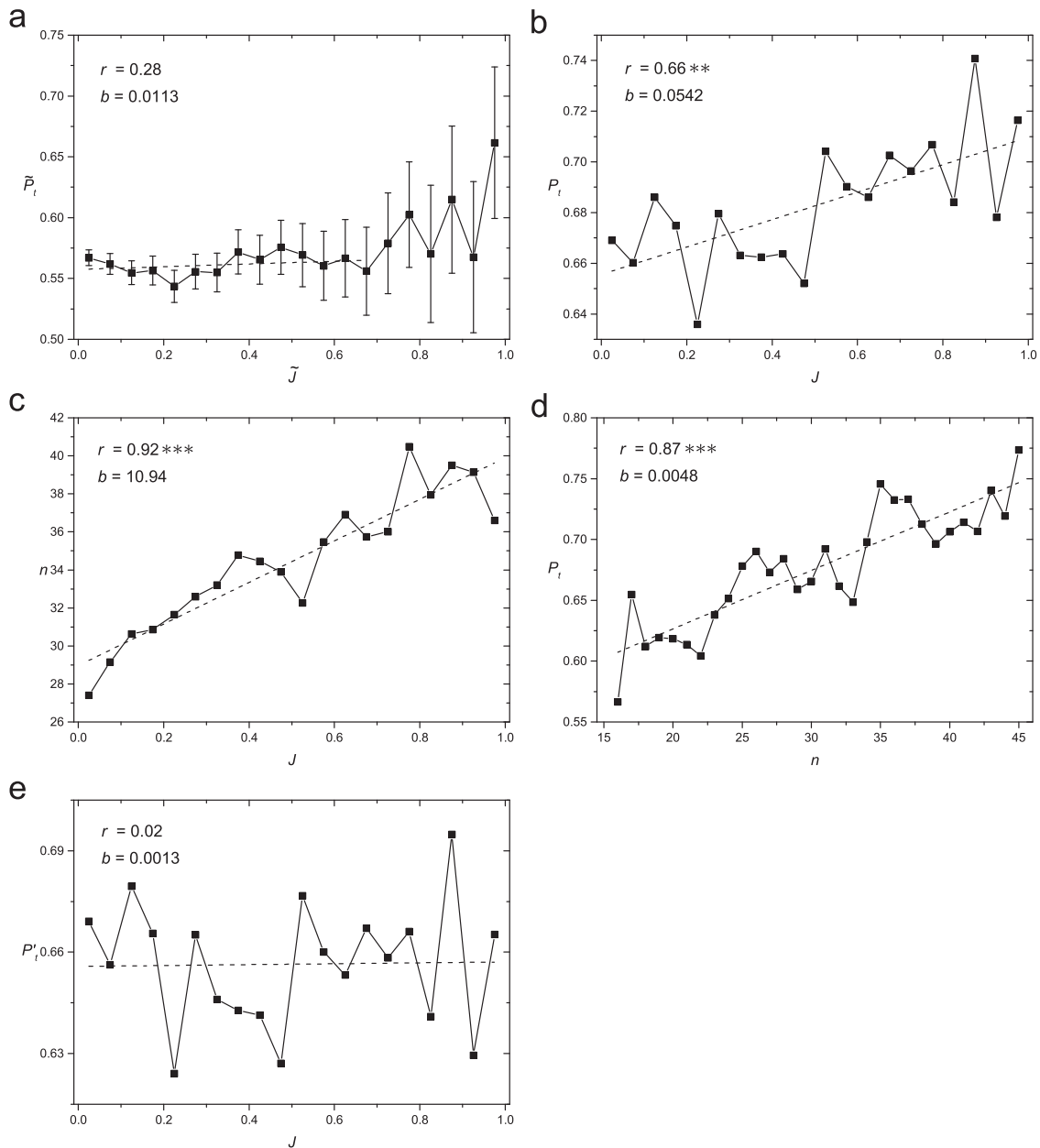


Fig. 3. (a) \tilde{P}_t is not correlated with \tilde{J} for a range of values ($0 \leq \tilde{J} \leq 0.725$) with over 97% of the sample size and small standard deviations. Due to the relatively small sample size (no more than 100) and high standard deviation for each group of J in the range ($0.725 < \tilde{J} \leq 1.0$), we do not take this range into discussion. (b) P_t increases with J , the slope of which is almost the same as the one predicted by the correlations between P_t and n as well as n and J (Section S6 in Supplementary material). (c) The average output n conditioning on the range of direction change ($J - 0.025, J + 0.025$) is positively correlated with J . (d) P_t is positively correlated with the output n . (e) After subtracting the increase induced by the pairwise dependence between n and J as well as n and P_t , the result indicates that P'_t and J are uncorrelated. The value of b is defined as the slope of the corresponding linear regression function (The dashed line). *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$ (t -test for Pearson coefficient r).

of the productivity change. Indeed, if we are not only interested in elite scientists, the productivity change can be diverse and the jump-decline pattern is not the only typical one (Way et al., 2017). Even in the work that implies a jump-decline pattern, we can still observe in the vast majority that the productivity declines at the very early career (typical schooling and training period) followed by a steady increase as the career unfolds (Fig. 1E in Sinatra et al. (2016)). For a typical scientist, it may hold that the productivity at the end of the career, though has declined from the peak, is still higher than when she starts the career. Indeed, when we turn to a more comprehensive data set by the Web of Science, we still observe P_t (R_t) and n are positively correlated (Fig. S5a-b in Supplementary material). Another potentially important factor is the career length, which is not controlled in the above analyses. Therefore, those

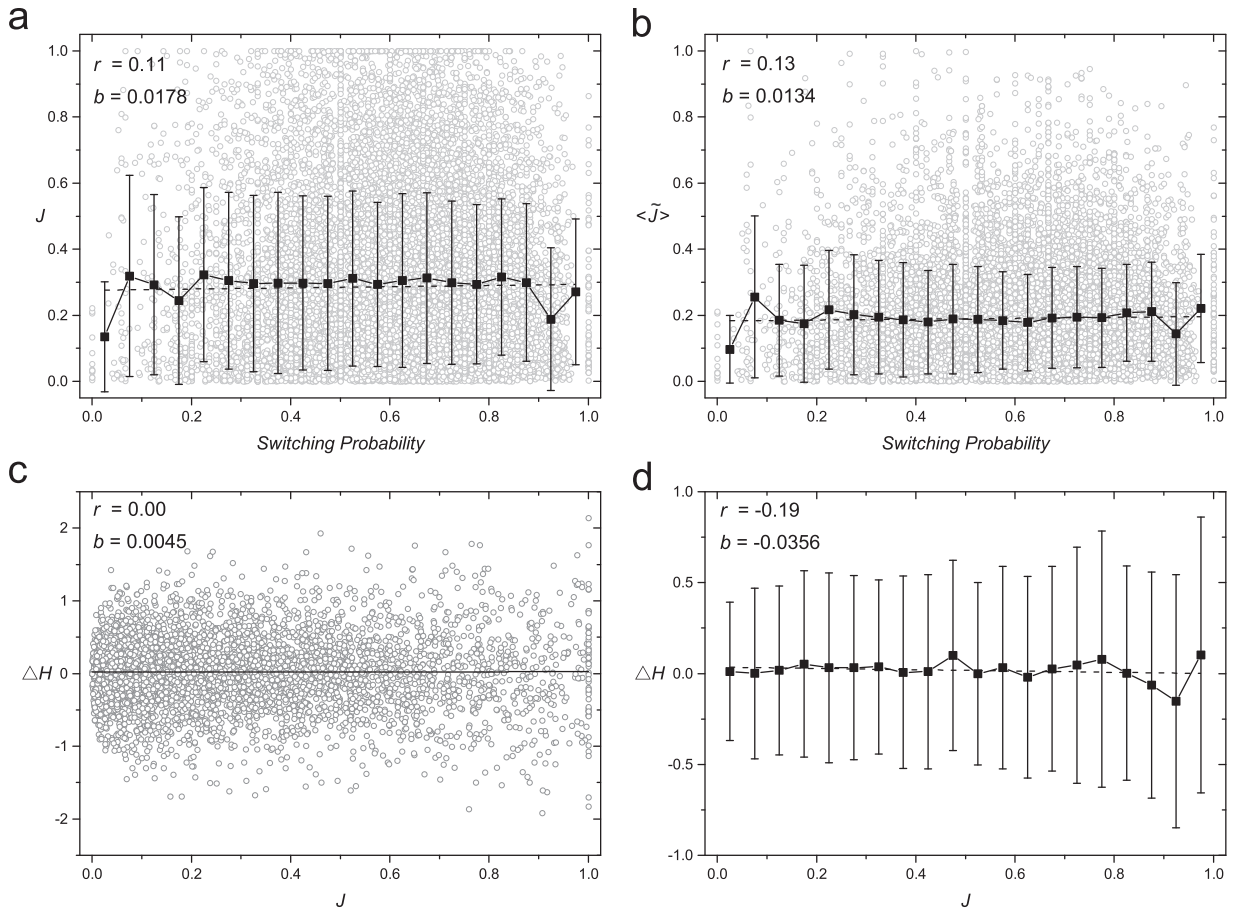


Fig. 4. (a) For each scientist, we plot her J versus switching probability (grey circle), and the mean value of J conditioning on the range of (switching probability - 0.025, switching probability + 0.025] (scatter with line). The result shows that switching probability is not correlated with J on the individual level ($p > 0.1$). (b) For each scientist, we calculate the average value (\tilde{J}) of her $n - 1$ \tilde{J} . Then we plot her (\tilde{J}) versus switching probability (grey circle), and the mean value of (\tilde{J}) conditioning on the range of (switching probability - 0.025, switching probability + 0.025] (scatter with line). The result shows that switching probability is not correlated with (\tilde{J}) at the individual level ($p > 0.1$). (c) For scientists whose impact has increased ($\bar{e}_{2,f} > \bar{e}_{2,i}$), we plot their J versus the change of Shannon entropy ΔH (grey circle). The result shows that ΔH and J are not correlated ($p > 0.1$). The average ΔH is close to 0, indicating that diversity change is not associated with the impact increase. (d) Similar to (c), but the mean value of ΔH is taken for individuals with ($J - 0.025, J + 0.025$). The value of b is defined as the slope of the corresponding linear regression function (The dashed line). Error bars represent the one standard deviation of the mean.

who are on the rising stage may outnumber those in the gloaming. Nevertheless, when the career length is controlled, the same positive correlation remains (Fig. S5c-d in Supplementary material). Moreover, the study by [Sinatra et al. \(2016\)](#) and [Liu et al. \(2018\)](#) suggest that the work with the highest impact may appear randomly in one's publication sequence. But this pattern is not contradictory to the positive correlation between the direction change and impact change, which implies that the work with the highest impact may appear in the later career. The “random impact rule” by [Liu et al. \(2018\)](#); [Sinatra et al. \(2016\)](#) is based on all samples without any control, whereas the correlation measured is conditioned on a certain research direction change.

Another work we wish to discuss more is the recent advances by [Zeng et al. \(2019\)](#) which also utilizes the APS data to quantify topic change patterns of scientists. In this pioneering work, the authors measure the probability to switch between topics in an individual career. The results demonstrate that compared with typical scientists, the top 10% of productive scientists have a lower switching probability in the early career and higher switching probability in the later career. Moreover, the top 10% most cited scientists have an overall lower switching probability than normal scientists. The relationship discovered seems contradictory to our findings. However, as a matter of fact, our work and the work by [Zeng et al. \(2019\)](#) are different in terms of the quantification of the direction change and the quality that the change is associated with. Hence, the two conclusions can be both valid.

First, in this work, we are interested in the change of performance, not the performance itself. In other words, we investigate how likely a scientist can publish works with more impact or within less time as the career develops, regardless if she is in the top 10% elite group or not. The focus, and consequently the findings are different from that in [Zeng et al. \(2019\)](#). More importantly, the switching probability quantifies the likelihood that the current topic would be different from the subsequent one, which only depends

on the topic of two papers. The direction change applied in this study compares the averaged topics of two sets of papers. Therefore, they reflect two distinct aspects in an individual's research topic selection. As an example, assume a scientist who has published 16 papers within which the first 8 papers are on topic A and the next 8 are on topic B. The direction change J of this scientist would be 1, as she explores totally different topics in the early and late sets of publications. The switching probability, however, is very low because this scientist only switches the topic once, which occurs in the 9th paper. Likewise, assume another scientist who has also published 16 papers on either topic A or topic B. She publishes following a pattern that if her current publication is on topic A, then the next paper will be on topic B, and vice versa. In this case, the direction change J would be 0 as this scientist equally devotes herself to topics A and B throughout the career. But the switching probability would be very high as she constantly switches the topic. The two examples vividly depict the difference between these two measures. Indeed, when we try to associate a scientist's direction change and switching probability together, we find that they two are independent of each other (Fig. 4a-b). Therefore, we believe that this work and the work by Zeng et al. (2019) are complementary rather than contradictory. As they reveal two essential patterns underlying the scientific careers of individuals, it would be interesting to check in future studies if a combination of they two is a more comprehensive predictor for an individual career.

Finally, we also wish to point out that our finding is different from that on research diversity, though they both suggest a positive citation gain (Alfredo, Ismael, Pablo, & Wolfgang, 2015; Chen, Arsenault, & Larivire, 2015; Chen, Qiu, Arsenault, & Larivire, 2021b; Leahey, Beckman, & Stanko, 2017). Indeed, the direction change and diversity change are two different things. Take the above example again, a scientist who has published the first 8 papers on topic A and the next 8 papers on topic B. The direction change is 1. But the diversity change is 0, as she always focuses on one topic only. Another example is when a scientist only focuses on topic A at the beginning and then changes the agenda with 80% of topic A and five other topics each with 4% of weight. As the main focus is still on topic A, the direction change is very small. But because there are five other topics added to the agenda, the diversity change is high. Here, we use Shannon entropy to quantify the diversity of one's research agenda as $H = -\sum_{j=1}^{67} x_j \log(x_j)$ where x_j is the j^{th} element of the vector g (the other two types of diversity index are reported in Section S7 in Supplementary material). We focus on scientists whose impact has increased ($\bar{c}_{2,f} > \bar{c}_{2,i}$) and plot their change of entropy ΔH with their change of research direction. We find these two quantities are not correlated (Fig. 4c-d and Fig. S15 in Supplementary material). The fact that the change of diversity is close to 0 on average indicates that the increased impact is not from a more interdisciplinary or more narrow research agenda. Instead, it is likely a result of bringing existing expertise to the new field and solving the field problem by a new approach.

4. Conclusions

To summarize, by utilizing PACS codes to classify topics in physics publications, we quantify the degree of the research direction change in an individual career. Instead of considering the overall scientific performance, we associate this direction change of an individual with the change of her performance. On one hand, we find that the direction change is strongly and positively correlated with the change of impact. Those who demonstrate a larger change on research topics are more likely to receive more citations than they used to. The magnitude of the relative improvement also tends to be higher. On the other hand, the direction change is not correlated with the productivity change. The likelihood that one increases or decreases productivity may be associated with many factors in an individual's career, but the change of research direction alone is not associated with it. We perform supplementary analyses to demonstrate the robustness of the conclusion. We also discuss in detail the difference between our findings and findings reported by others. Our study provides another point of view not fully captured in previous studies.

The statistics provide an encouraging prediction for scientists who venture into a new field. Once they are established in the new field, they are likely to become better scientists. What is not mentioned, however, is the risk associated with the direction change (Azoulay et al., 2011; Bromham et al., 2016; Foster et al., 2015; Goldstein and Kearney, 2020). Indeed, our analyses are based on scientists who have published enough papers in the new field. Those who try to change but fail to have the new research published are not included. This naturally poses a survival bias in the result, which motivates further studies on failures across a career (Wang et al., 2019b; Yin et al., 2019). There are also many factors that the correlation measure alone can not explain. For example, a scientist may be forced to leave the old field because it shrinks and can not yield interesting results, and another scientist finds a way to combine her prior knowledge with the new problem which leads to fruitful results (Pramanik et al., 2019). In both cases, a citation gain and a direction change would be observed. Yet, in the current study we can not distinguish them nor identify which causes the other. Given confounding factors in an individual career, it is difficult but important to check other explanations of the observation. Moreover, our study is based on APS publication data. Despite the intensive usage (Chinazzi, Gonçalves, Zhang, & Vespignani, 2019; Liu, Nanetti, & Cheong, 2017), this data set only covers a small part of the science. The classification scheme provided by the PACS code has certain limitations as well. Given the availability of large scale data sets, such as Microsoft Academic Graph (Wang et al., 2020) and advances in machine learning tools to identify and classify topics from papers (Chinazzi et al., 2019; Palmucci et al., 2020; Qian et al., 2020; Shen et al., 2019), it would be important to check if similar patterns can be observed in other data set. Finally, we adopt the whole counting in this study that gives equal credit to all co-authors. This approach may lead to inflation when calculating the impact of a scientist's work and her productivity (Huang et al., 2011; Yu et al., 2021). It may be worthwhile to try other counting or credit allocation method (Shen and Barabási, 2014; Sivertsen et al., 2019; Wang et al., 2019a).

Author contributions

Xiayao Yu: Conceived and designed the analysis, Contributed data or analysis tools, Performed the analysis, Wrote the paper, Writing Reviewing and Editing. **Boleslaw K. Szymanski:** Conceived and designed the analysis, Collected the data, Wrote the paper,

Writing Reviewing and Editing. **Tao Jia:** Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper, Writing Reviewing and Editing.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.joi.2021.101193.

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