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Does experiencing international research collaboration permanently affect the impact of scientific production? Evidence from Africa

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Keywords: Collaboration, Citation, Research Impact, Science Policy

Abstract

This paper examines the effect of experiencing a research collaboration between African scientists and their international partners on the African scientists' research impact, measured by scores based on the number of citations and journal impact factor. Using a difference in difference regression analysis on publication data of African scientists, the results show that international research collaboration in a given year has a positive and significant effect on research impact which lasts in the subsequent years. The presence of such permanent effect suggests a sort of "permanent learning by international collaboration". The positive effect of international collaboration on research impact, however, does not necessarily imply that the scientists with only local research collaboration are lesser scientists.

Introduction

One may claim that performing research or contributing to the advancement of science is a collaborative endeavour. This claim is also of particular relevance in Africa which benefits from numerous international aid and research support programs. In addition, administrative bodies and policy makers aim to get the maximum effect of research for the public purse. Considering the importance of research impact in science policy issues, investigating the determinants of citation count or impact factor of journals in which research is published is of high relevance. Various factors have been mentioned in the literature to explain the number of citations. Among them, national and international collaboration play an increasingly important role. This may even take a greater degree of importance when collaboration spans different systems of research and education.

In reviewing the collaborative research patterns in Africa, it is imperative to identify the flow of knowledge across the African continent as well as between African countries and the rest of the world. More specifically, a better understanding of the role of international collaboration and its incidence on research impact could help African policy makers to manage their science system. This paper contributes to advancing knowledge on collaborative research and its effect on research impact by focusing on the publication data from African scientists. Estimating difference in difference regression models, this paper shows that experiencing an international collaboration would result durable effect on research impact in subsequent years, which is measured by scores based on citation count and journal impact factor. The remainder of this article goes as follows: Section 2 reviews the relevant spans of the literature; Section 3 introduces the data set and explains the research methodology; Section 4 presents the regression analyses; and finally, Section 5 discusses the results and concludes.

Section 1 - Theoretical framework

Research impact can be measured by different indicators, but whether these are appropriate measuring tools is a pertinent question to ask. Any well-designed measure is at risk of manipulation due to the fact that scientists optimize indicators instead of performance. In addition, a single measure may even have different interpretations and functionalities. For instance, Amsterdamska and Leydesdorff (1989) argued that a cited article is used to either make a linkage with the current literature or to be used as evidence to complete a justification: i.e. for different purposes and with different implications.

The number of citations by itself may be mistakenly considered as measure of research quality. Moed et al. (1985) claimed that citations highlight the research impact and are not a good proxy for research quality, which implicitly suggests that every publication has a minimum quality. Furthermore, Olson et al. (2002) claimed that even publishing does not guarantee the minimum research quality since in some disciplines like Medicine there is a bias for publishing only research with positive results.

The impact factor of the journal may also not be a good choice for measuring research quality. Seglen (1997) argued that citation rates determine the journal impact factor, but that the reverse is not necessarily correct. Impact factors are field dependent: they are high in basic research as such journals cover large areas of basic research with a "rapidly expanding but short lived literature that use many references per article" (pp. 498).

Acknowledging plausible limitations of measures like citations in their comprehensive study, Retzer and Jurasinski (2009) concluded that a smart protocol of assessing citation counts can alleviate its plausible risks such as database-related problems, inflated citation records, as well as bias in citation rates and crediting of multi-author papers. In addition, Kostoff (1998) examined the theory of citations and proposed that every article can be cited either because of the real component of intellectual heritage or random components of self-interest. The author claimed that the random element disappears in time.

In more detailed guidelines, Kostoff (2002) suggested that citation-based evaluation of scholarly publications requires normalization against a control group of similar papers, which should have the following items in order to mitigate bias and subjectivity: using multiple technical experts to decrease deviation, comparing research with a normalization base of similar papers, and manual evaluation of base papers to reach high thematic similarity. No indicator is indeed perfect.

Despite the fact that citation indicators do not properly reflect the solidity/plausibility, originality, and societal value of research output, numerous studies like Aksnes et al. (2019), Wilsdon (2016), Martin (1996), Mirnezami et al. (2015), and Bornmann (2013) argued that citation indicators are appropriate proxies for scientific impact. Assuming that measures related to citation count are proper indicators for research impact, this research investigates the link between citation and research collaboration. Research collaboration by itself is a complex concept, depending on different factors like academic fields. Abramo et al. (2009a) showed that within interdisciplinary fields, there are more collaborations than in intramural fields and that collaboration with foreign organizations occur more often in the basic fields than in the applied fields.

Although imperfect, a useful proxy of scientific collaboration is co-authorship (Glänzel and Schubert, 2004, Abramo et al., 2009b, Butcher and Jeffrey, 2005, He, 2009). For instance, to emphasize that co-authorship and collaboration are not the same, Melin and Persson (1996) argued that some collaboration does not necessarily generate papers and some co-authored articles are not the result of concrete scientific collaboration. Katz and Martin (1997) seconded this argument by claiming that co-authorship is just a partial indicator of collaboration. They argued that collaboration is a kind of a social relationship for which it is not possible to identify the commencement and the termination and hence it is different from co-authorship that has definite and clear-cut product.

While Kumar (2018) supported the justification for studying co-authorship as a common approach to investigate research collaboration at micro, meso, and macro levels, the author also warned that some research contributors (research collaborators) are denied their place in the authors' list due to particular guidelines or lead researcher's decisions. Considering the importance of the authors' list composition in the reward system at the very basis of career promotion, tenure, performance reviews, and other incentives, such decisions may have unfortunate consequences. Conducting a survey on US academics, Ponomariov and Boardman (2016) distinguished amongst the relationship between authors (like mentorship) and the level of resource contributions: the results suggest the importance of informal and relational collaboration compared to intellectual and/or other resource contributions. The paper concluded that co-authorship is more likely to be characterized with (1) a pattern of lengthy history amongst co-authors, (2) frequent communication, (3) some level of mutual trust and support extending beyond the direct objects of the collaborations, and (4) shared socialization or educational history.

Assuming the social nature of collaboration, the literature found that it varies depending on institutions, fields, sectors, countries, and time. For example, the effectiveness and dimension of research collaboration vary in countries/institutions. Ynalvez and Shrum (2011) indicated that in a resource-constrained developing country, scientific collaboration does not significantly affect research productivity in a timely manner, but most scientists there benefit from the by-products of coordination and collaboration such as professional learnings and scientific updating for researchers.

Assuming dissimilar consequences of research collaboration in different countries and considering the progressive path of scientific development in Africa, which highlights the importance of research impact, this research intends to look into the effect of collaborating with a co-author outside the country (international collaboration) on research impact. Having reviewed the literature about the impact of collaboration, the hypothesis of our study is the following:

Hypothesis: *Experiencing an international collaboration permanently increases research impact measure by a) normalized citation score, b) normalized journal score, and c) the likelihood of being the author of on of the top 10% most cited articles.*

Section 2 - Data and methodology

Data

To test the hypothesis of this article, we first need to collect information on the scientific production of every scientist per year (subject to availability) and to identify international collaboration from the list of co-author affiliations. We then have to investigate the effect of the said collaboration on the scientific impact of the research published in scientific journals.

To identify African scientists, all publications that had at least one African affiliation was extracted from the Centre for Science and Technology Studies (CWTS), Leiden University, in-house version of the Web of Science for the period 2000-2015. The resulting data comprise a total number of 333,814 papers to which 248,868 African scientists have contributed. This database was disambiguated by the Leiden scientists according to the algorithm proposed by Caron and van Eck (2014) and Ruiz-Castillo and Costas (2014). The resulting database provides a unique author ID for each scientist. As databases are never perfect, we manually checked all records for which we had multiple similar names or multiple email addresses for the same surname – first-name or surname – initials groupings by searching for these individuals on the Internet in order to further disambiguate author names and correct any mistakes in the unique ID. On average, authors have published 3.5 articles over the period, and a total number of 121,090 African scientists (out of 248,868) have co-published with international colleagues (about half of our sample).

The data include three different measures of research impact: the normalized citation score (*ncs*) of each article compared to all publications in that year in that subject category[1] excluding self-citations, the top cited paper score indicating whether the article is in the top 10% most cited of its subject category in that year (*ptop10*), and the normalized journal score in which the article is published (*njs*). As the number of citations depends on the research fields, such a normalization contributes to eliminate discipline-specific effects (for instance, the pace of publication and the volume of citation are field dependent) and renders the measures comparable across subject categories. The normalized citation score (*ncs*) is the number of citations received by an article divided by the total number of citations received worldwide by the articles published in that subject category in that year. The same rationale is applied to the normalized journal score (*njs*) to correct for the discipline-specific differences regarding journal impact. Normalized journal score (*njs*) is the sum of the normalized citation score of the articles published in that journal in that year divided by the number of articles.

Methodology and econometric model

This paper is interested in the time effect of international collaboration. The model chosen for this research therefore needs to account for the change in performance subsequent to such collaboration. In other words, our model should consider experiencing international collaboration as a kind of treatment in a quasi-experimental study. A useful model for that purpose is the standard difference in difference framework that allows controlling all unobserved characteristics of hidden determinants that possibly or plausibly affect research impact. In principle, this method mimics an experimental research design using observational study data (quasi-experimental design), by measuring and comparing the average change over time in the outcome variable for the treated group (here, the scientists that have experienced international collaboration), and the average change over time for the

[1] The Leiden database includes the normalized citation score calculated for each of the 252 subject categories: https://www.leidenranking.com/Content/CWTS%20Leiden%20Ranking%202020%20-%20Main%20fields.xlsx .

control group (the scientists that have not experienced such international collaboration). This method also controls for unobserved characteristics of scientists. The idea behind the method is relatively simple. One assumes that both the control and the treatment groups would evolve similarly if both were left untreated (Y_{C1} to Y_{C2} for the control group and Y_{T1} to Y_{T2} for the treatment group). Because of the treatment, the treated group evolves to Y_{T2}, and the difference between Y_{T2} and Y_{UT2} is attributed to the treatment (see Figure 1).

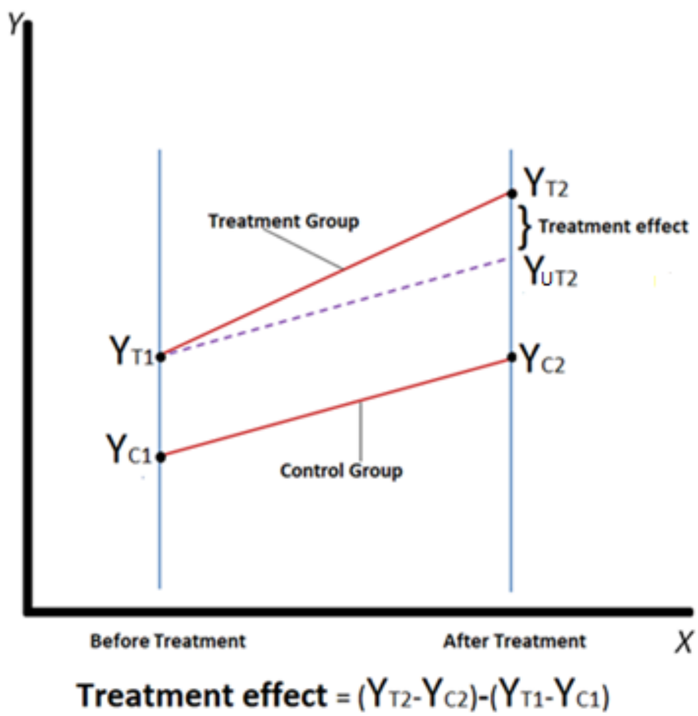


Figure 1 - Schematic explanation of difference in difference method

Simply measuring the treatment effect as a comparison between the after-treatment values of the control and treatment groups ($Y_{T2} – Y_{C2}$) yields false results as it does not account for the distinction between initial conditions, i.e. before the treatment ($Y_{T1} – Y_{C1}$). By subtracting the difference between the pre-treatment conditions, the difference in difference method mitigates the effects of extraneous factors and selection bias, resulting from initial conditions and inherent differences between the two groups. Figure 1 graphically shows how subtracting one difference from another one 'purifies' the effect of the treatment on outcome. The dataset includes scientists with different characteristics (age, gender, experience, field, etc.) that affect the dependent variable. These are not measured as independent variables in the right hand side of regression equation due to research limitations, and hence, randomization of treatment is out of our control. In other words, there are undoubtedly omitted variables which would normally imply the need for proxies or instruments, but this is not possible with the data at our disposal. The difference in difference technique relaxes the necessity of including control and proxy variables in the regression equation to ensure robust and significant results. The difference in difference model can be expressed as follows:

$$y_{it} = \alpha_0 + \alpha_1\, treatment_{it} + \alpha_2\, after_{it} + \alpha_3\, treatment_{it} \bullet after_{it} + u_{it}$$

In above equation, $treatment_{it}$ means that scientist *i* experienced an international collaboration in year *t* (as measured by co-publication with at least one international co-author) and $after_{it}$ is a dummy variable which takes the value 1 for scientist *i* in the treatment year *t* and afterwards, and the value 0 otherwise. Treated scientists did not experience international collaboration in the same year, i.e. in our study, the 'treatment' has occurred in different years. We have two types of scientists in our database: those who have published with international collaborators and others who did not. Because experiencing international collaboration (the treatment) did not happen in the same year for all scientists, there is a difficulty in defining the treatment time. To address this issue, the difference in difference analysis must be estimated for each year separately, indicating that the treatment has occurred at a specific point of time.

The resulting design estimates one difference in difference regression per year, for scientists who experienced international collaborators in that specific year for the first time, and for control groups of all scientist without any international collaboration. The scientists who experienced international collaborators in years other than that specific year are therefore not included in the regression analysis of that particular year. In such a setting, we do not have only two periods of time, but have different years before and after the treatment for each of the regressions. To control for unobserved characteristic of scientists' academic performance in different years, we add year dummy variables (see for instance: (Mummolo and Peterson, 2018, Sberna and Olivieri, 2014, Drago et al., 2015)). The updated version of the regression equation is as follows (d_{jit} is dummy variable for each year: j varies from 2001 to 2015). Because South Africa is likely to behave differently from the rest of the continent (site relevant papers that have found such a difference), we add a dummy variable to control for this difference.

Finally, because the unit of observation is the individual scientist, we need to transform the performance measures which are calculated at the level of the article. For this purpose, we calculate the mean normalized citation score (*mncs*) and the mean normalized journal score (*mnjs*) by taking the mean value of *ncs* and *njs* for all the papers published by an individual scientist in a given year. To satisfy the normality condition of these variables for the regression analysis, both *mncs* and *mnjs* are transformed using the natural logarithm. Lastly, the likeliness of being in the top 10% of the most cited papers in the subject category (*ptop10*) is a dummy taking the value 1 if any of the articles published by the individual scientist is in the top 10% most cited, and 0 otherwise. The final model is as follows:

$$y_{it} = \beta_0 + \beta_1\, treatment_{it} + \beta_2\, after_{it} + \beta_3\, treatment_{it} \bullet after_{it} + \beta_4\, dSouthAfrica + \beta_J\, d_{jit} + u_{it}$$

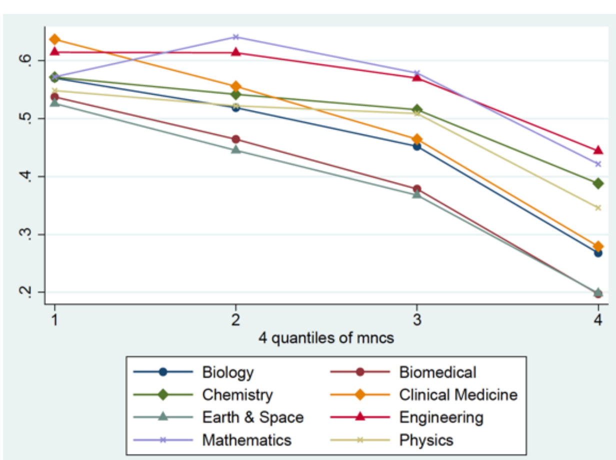
Section 3 – Descriptive statistics

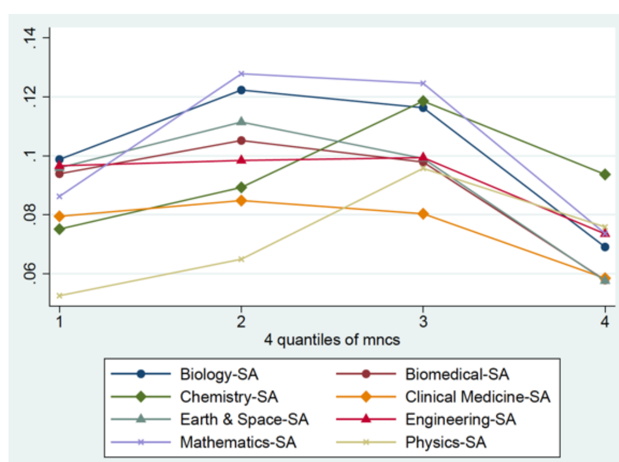
Table 1 summarizes the descriptive statistics of the main variables of interest: *ncs*, *ptop10*, and *njs*. Using this information at the journal article level, we aggregated the data at the individual scientist-year level calculating average measures for all mentioned variables. The result is a classic panel database.

Table 1 – Descriptive statistics for the three impact measures: *ncs, ptop10,* and *njs*

Variable	Description	Mean	Std. Dev.	Min	Max
ncs	Normalized citation score	0.832	1.987	0	301.718
ptop10	Dummy taking the value 1 if the article is in the top 10% most cited of the subject category, and 0 otherwise	0.068	0.224	0	1
njs	Normalized journal score	0.841	0.826	0	23.099

Before turning presenting the results, it is pertinent to graphically review the state of African scientists in terms of scientific impact. Because South Africa is the major producer of research papers in Africa, we separated its contribution from that of the rest of the continent, to provide a more nuanced understanding of the region. This separation will be also replicated by adding a dummy variable in regression analysis. Considering publications with at least one African affiliation, Figure 2 shows that African scientists (excluding those whose affiliation is in South Africa) are less present among the top cited scientists as measured by their mean normalized citation score (*mncs*) separated into four quartiles. The three domains where African scientists remain present in a relatively high proportion are Engineering, Mathematics and Chemistry. South African scientists follow a similar trend in the top quartile, but are less present in the bottom quartile, and that for all domains.





(a) (b)

Figure 2 – Proportion of a) African and b) South African scientists per quartile of mean normalised citation score (1, 2, 3 and 4 correspond to the first, second, third and fourth quartiles respectively)

The proportion of scientists from African countries other than South Africa with respect to South Africa in different quartiles in terms of number of publications (see Figure 3) magnifies the role of South Africa as this proportion decrease in top quartiles – in Mathematics for instance, there is about seven times more non South Africans in the bottom three quartiles, while this drops to about 3 in the top quartile. Both figures indicate that South Africa plays an important role in scientific production and research impact, which should be addressed in the regression analysis. The proportions in Figure 2 also show that the number of authors from outside continent is not negligible (in different quartiles/domains), and there are significant pattern of collaboration with scientists outside continent.

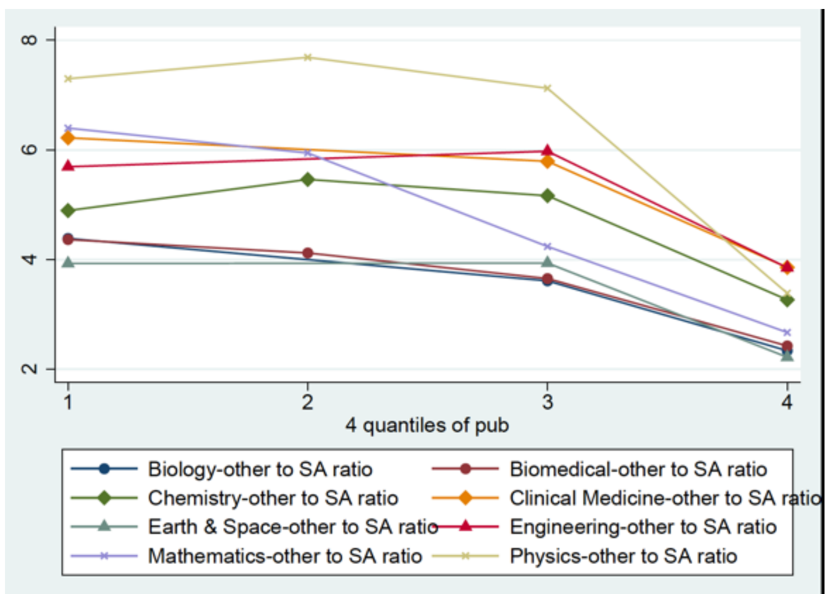


Figure 3 - Ratio of the number of African scientists excluding South Africans with respect to the number of South African scientists per quartile of the number of publications

In order to have an idea on the size of control and treatment group, Figure 4 summarizes the number of authors for each year when international collaboration is experienced.

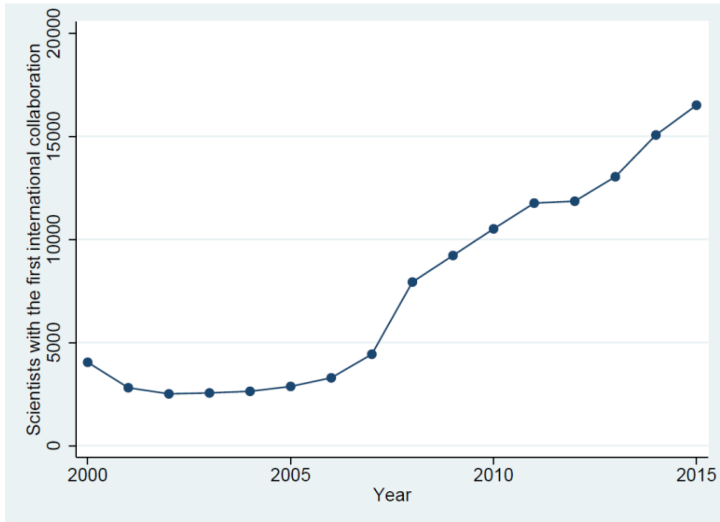


Figure 4 - The number of authors with international collaboration for each treatment year (The aggregate number of treated authors is 121,090 compared to 113,736 authors who did not have international collaboration at all, called as control group)

Section 4 - Results and discussion

As described in the methodology section, for each measure of research impact, the difference in difference analysis estimates a regression for each year. The results show that experiencing international collaboration has a positive and significant effect on the research impact of a scientist. The measures of research impact include the mean normalized journal score in which articles are published (*mnjs* in Appendix 1 table), mean normalized citation score of each article compared to all publications excluding self-citations (*mncs* in Table 2[2]), and the top cited paper score indicating whether the article is in the top 10% most cited of its field in that year (*ptop10*[3] in Appendix 2 table). The insights from the coefficients of β_1, β_2, and β_3 in three said tables are discussed accordingly.

[2] It should be noted that Table 2 drops the paper with no citations to only focus on scientific production with a minimum quality/effect. Just to show that our results are robust enough, we replicated Table 2 by keeping the papers with no citation in regression (by using ln(mncs+1) instead of ln(mncs)) and our target variable, which is coefficient of treatment*time (i.e. coefficient of α_3 in our difference-in-difference identification), is still significant. For robustness check evidence, we added that table as Appendix 3.

[3] Presumably, this is 1 if the individual has had at least 1 paper in the top 10% most cited

The generally positive sign of β_1 across all three regression models shows that scientists in the treatment group (those that have experienced international collaboration at some point of time) always, even before international collaboration, have a better performance compared to other scientists. This inherently means that the initial conditions of researchers or their capabilities/competencies (Pavitt, 1998), resulted in better performance and this may also have led to them experiencing international collaboration. This method does not measure researchers' capabilities/competencies by proxies or instruments, but by the dummy variable of the treatment group using the difference in difference method that controls for the initial difference between the two groups.

While the coefficient of β_1 compares the scientists who publish with international coauthors with those who did not, the coefficient of β_2 measures the performance difference in period 2 compared to period 1 (after and before treatment) regardless of whether they are in the treatment group or not. The positive sign of β_2 in all regressions shows that scientists produce research work of a higher impact after the treatment. Because it is a general point for all scientist (treatment group or not), we may conclude that scientists gain a greater level of academic experience in time to produce works with a higher impact (Kaiser et al., 2018) or that previous works may give more visibility to academic papers (Tahamtan et al., 2016, Shu et al., 2018).

Table 2 - Difference in difference analysis for the effect of experiencing international collaboration on the mean normalized citation score (*mncs*)

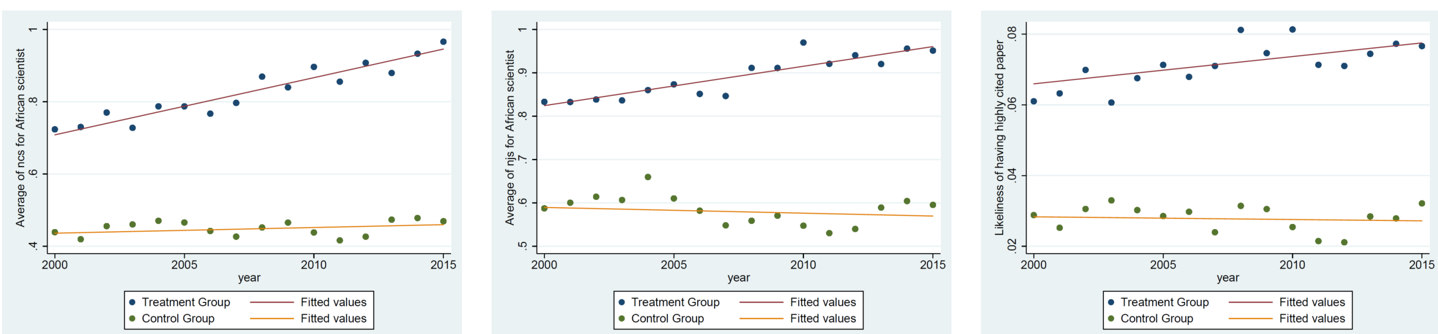
Variable	mncs2000	mncs2001	mncs2002	mncs2003	mncs2004	mncs2005	mncs2006	mncs2007	mncs2008	mncs2009	mncs2010	mncs2011	mncs2012	mncs2013	mncs2014	mncs2015
dSouthAfrica	0.22***	0.24***	0.23***	0.24***	0.23***	0.24***	0.24***	0.23***	0.23***	0.23***	0.23***	0.23***	0.23***	0.23***	0.23***	0.24***
treat	0.47***	0.24***	0.28***	0.32***	0.28***	0.23***	0.29***	0.32***	0.25***	0.35***	0.29***	0.25***	0.27***	0.22***	0.16***	0.19***
d2001		1.03***														
treatd2001		0.24***														
d2002			1.04***													
treatd2002			0.16***													
d2003				1.04***												
treatd2003				0.14***												
d2004					1.04***											
treatd2004					0.20***											
d2005						1.04***										
treatd2005						0.23***										
d2006							1.04***									
treatd2006							0.20***									
d2007								1.03***								
treatd2007								0.14***								
d2008									1.03***							
treatd2008									0.22***							
d2009										1.02***						
treatd2009										0.07***						
d2010											1.02***					
treatd2010											0.17***					
d2011												1.03***				
treatd2011												0.13***				
d2012													1.03***			
treatd2012													0.08***			
d2013														1.03***		
treatd2013														0.07***		
d2014															1.04***	
treatd2014															0.11***	
d2015																1.07***
treatd2015																0.07***
constant	-0.80***	-1.41***	-1.41***	-1.41***	-1.41***	-1.41***	-1.41***	-1.40***	-1.41***	-1.40***	-1.41***	-1.40***	-1.41***	-1.40***	-1.40***	-1.41***
Nb. o.	161966	150445	147621	147016	146958	146935	147834	149637	154383	155246	156148	156441	153760	152906	151382	147477
LogLikelihood	-238390	-219448	-215298	-214354	-214427	-214180	-215362	-218420	-225353	-226617	-227733	-228062	-223364	-221738	-219681	-213291
F	513.16***	748.07***	734.48***	744.80***	757.44***	751.94***	770.56***	768.13***	794.06***	795.99***	832.30***	826.09***	850.89***	897.87***	952.48***	1224.75***

Notes: *** shows the significance level at 0.05, 0.02, and 0.01 respectively; Year dummies are all significant.

The β_3 coefficient measures the interactive effect of time and treatment dummy variables. As discussed in the methodology section, the difference in difference method measures the effect of time and treatment separately in order to measure the interactive effect (treatment effect) free from time effect or the treatment group initial conditions. It is thus possible to read the treatment effect as robust and reliable. In other words, if there are any effect due to scientists' initial conditions/ability or time-specific characteristics, those have been reflected in β_1 and β_2 respectively. The positive and significant effect of β_3 indicates that experiencing international collaboration consequently results in conducting research that yields a higher impact. For instance, at the average level of mean normalized citation score (*mncs*=0.735), international collaboration permanently increases the mean normalized citation score by 0.4 unit.

The high level of significance of the year dummy variables (coefficient of β_J) imply the presence of year specific characteristics. The sign of the effect is not worth reporting as we just wanted to control the effect of different years in the regression analysis and to show that all scientists in each specific year have a sort of constant under/over-performance compared to other years. The effect of South Africa dummy variable (β_4 coefficient) is also positive and significant clearly showing that scientists from that country receive more citations and publish in high rank journals (a result compatible with the data description in Figure 2 and Figure 3). The significance of both types of dummy variables let us claim that the difference in difference analysis investigating the effect of international collaboration is robust and unbiased. Furthermore, we tested our hypothesis for three different measures of scientific impact: mean normalized citation score, likeliness of publishing an article in the top 10% most cited of the field, and mean normalized journal score. This strategy also helped us to minimize the risk of data measurement/collection concerns. The three mentioned measure differently point to the same concept (scientific impact), which helped us to reach an adequate robustness level in our analysis. The findings of papers like Bertrand et al. (2004), Donald et al. (2007) and Goodman-Bacon (2018) verify that our strategy to consider variation in treatment timing, and to have large number of observations specifically for control group, makes the analysis robust and reliable.

Reproducing the model stylized in Figure 1 with our results, Figure 5 clearly indicates that scientists' impact increases in time for the treatment group, hence emphasizing the significant effect of international collaboration. The graphs show the trend for the three measures of scientific impact, highlighting that the treatment positively affects the impact over time. The graphs provide an aggregate picture of the trend, which complements our regression analysis focusing on each treatment year separately.



(a) **(b)** **(c)**

Figure 5 – Trend for African Scientists that experienced any international collaboration (treatment group = 135,132 authors) versus no collaboration (control group = 113,736 authors) for a) mean normalized citation score; b) mean normalized journal score; and c) the likeliness of having a highly cited paper

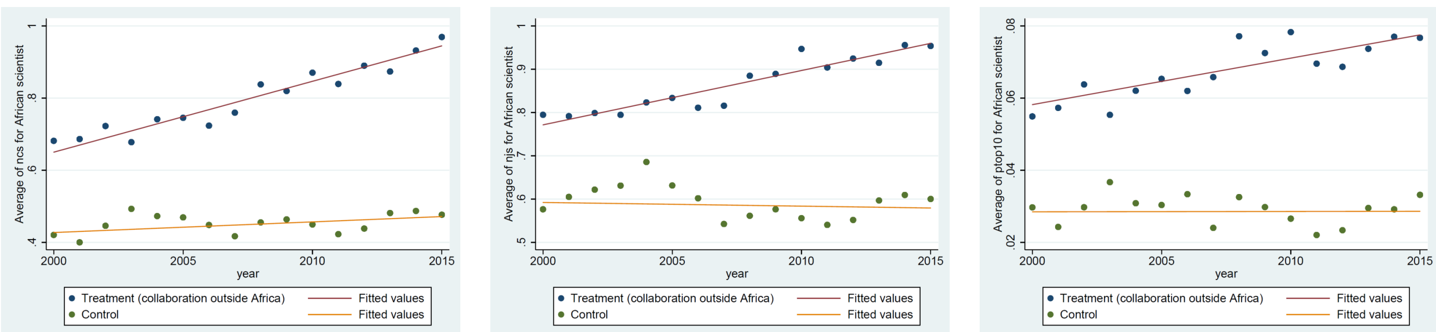
Let us explore some plausible explanations for these observations. First, benefitting from a partnership with good research group and access to research funds are motives for international collaboration. Scientist hence develop tacit or implicit capabilities to conduct research with higher impact in subsequent years. To provide evidence for this claim, Confraria et al. (2020) showed relational patterns between African scientists' share in international funding and international collaboration. Commenting on the evidence from higher education academics in sub-Saharan Africa, Eduan (2019) showed that studying abroad, as indicator of earning qualification for conducting research, is correlated with the chance of being involved in international collaboration.

Second, it is possible to argue that coauthored articles are more novel because highly diverse groups are expected to have scientific production with a higher impact. From this standpoint, Uzzi et al. (2013) constructed the concept of atypical knowledge which is rooted in conventional knowledge but with added innovativeness and impact. The authors argued that atypical papers are twice as likely to receive a greater number of citations and highlighted the importance of teamwork/co-authorship in the development of such works.

The third explanation is the emergence of multi-disciplinary fields, producing high impact research work but which needs or depends on collaborative work and international collaboration more specifically. Coccia and Bozeman (2016) observed the acceleration of the internationalization of research collaborations across all research fields but highlighted the relative higher growth in applied and multidisciplinary fields, particularly in the medical sciences and allied medical fields, as well as psychology.

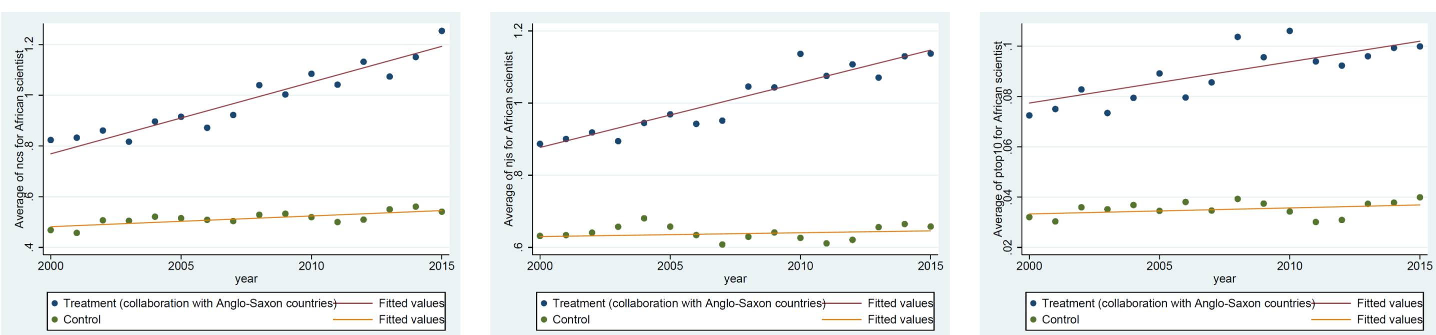
A fourth explanation may lie in the particular location of the collaborators. To disentangle the potentially different effects from collaborating with scholars and scientists from various parts of the world, as discussed by Confraria et al. (2018) and Smith et al. (2014), we replicated the graphs for research collaborations with scientists outside of the African continent (see Figure 6) and for research collaborations with scientists in Anglo-Saxon countries (see Figure 7). Out of a total number of

333,814 articles, 167,533 articles include international collaboration, 11,632 of which (7%) are within the African continent, i.e. 93% of international collaboration involve co-authors from outside of the African continent. Out of those, 41,442 articles (25%) stem from collaboration with scientists from Anglo-Saxon universities. The graphs suggest that international collaborations with Anglo-Saxon universities significantly boost the research impact of scientists. It's noteworthy that regression analysis is also compatible and well-matched with these graphs but we did not report it to save the article space.



(a) **(b)** **(c)**

Figure 6 – Trend for African Scientists that experienced any international collaboration outside of the African continent (treatment group = 128,469 authors) versus no collaboration outside of the African continent (control group = 120,399 authors) for a) mean normalized citation score; b) mean normalized journal score; and c) the likeliness of having a highly cited paper



(a) **(b)** **(c)**

Figure 7 – Trend for African Scientists that experienced any international collaboration with Anglo-Saxon universities (treatment group = 61,204 authors) versus no collaboration with Anglo-Saxon universities (control group = 187,664 authors) for a) mean normalized citation score; b) mean normalized journal score; and c) the likeliness of having a highly cited paper

This raises the question of the role played by the African authors and their international collaborators. Boshoff (2009) argued that researchers experiencing international collaboration are rarely the leading authors in papers published after that collaboration and they are highly likely to play a relatively passive role within international consortiums, by performing non-leading roles and therefore not learning and gaining capabilities. We compared the trend in number of articles in which an African scientist is the leading author. Both control and treatment groups exhibit increasing trends, but the gap between them becomes greater in time, indicating that the treatment group may benefit from international collaboration and then play a pivotal and significant role in publishing scientific articles in the future.

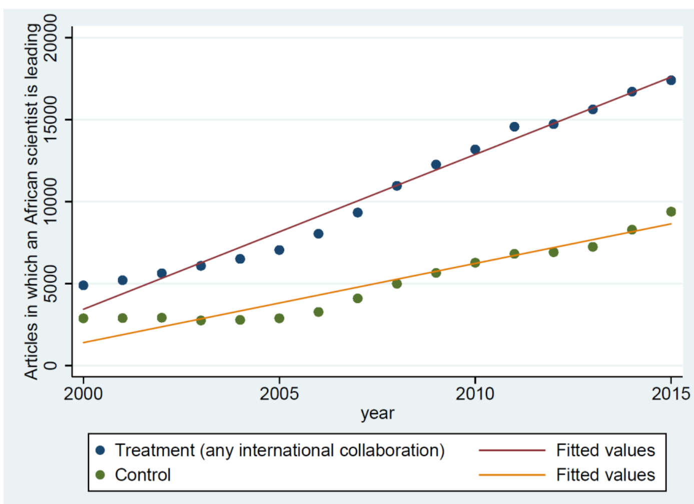


Figure 8 – Trends for the number of articles in which an African scientist is the leading author for those that experienced any international collaboration (treatment group) versus no collaboration (control group)

Conclusion

In this article, a difference in difference regression analysis was used to show that experiencing an international collaboration has a positive effect on the research impact measured by citation score, journal score, and the likeliness of publishing a top cited paper. In addition, scientists in different years may experience different institutional settings all of which can be controlled and represented by year dummy variables (as verified by their significant effect). The results of our analysis convincingly show that experiencing international collaboration has a deep and long lasting impact on the quality of research published by these 'treated' scientists. Considering the significant and positive effect of experiencing international collaboration, the main and most obvious policy advice is to set more incentives for such collaboration that may positively affect academic impact through different channels.

Assuming that international collaboration is a good contributor to conducting research with higher impact, as our results seem to show, here are a set of recommendation to increase the likeliness of shaping this sort of collaboration. First and foremost, incentivising and facilitating any sort of contact is the first step for collaboration. This can be achieved by regularly and systematically incentivizing researchers to take sabbatical leave abroad or by supporting scientists in attending high level academic conferences to help them build and maintain a strong network of international collaborators. Preparing the ground for such sort of contact may also be pursued by hosting international scientists for short or long research visits. It is noteworthy to mention that the target 4-b of the United Nation Sustainable Development Goals encourages scholarships available to low- and middle-income countries, which is also another avenue for shaping international collaboration if students who received those scholarship plan to come back to their home country.

The second approach is not necessarily related to physical contact, but focuses on empowering scientists in Africa to benefit from larges sums of international research funds for development, such as the International Research and Science Programs in the US, the International Development Research Centre (IDRC) in Canada, or the Global Challenges Research Fund (GCRF) in UK.

In terms of the validity of the abovementioned interpretations, we highlight a number of limitations in this study. First, this study only covers African scientists and the database time coverage is limited. For future research, one may suggest redefining two concepts of "international" and "collaboration". As discussed, there may be some better proxy for collaboration than co-authorship. In addition, all international collaborations do not have the same effect hence one may investigate the taxonomy of international collaboration. Intertwined in the international collaboration impact is that of the international mobility of scientists. Unfortunately, scientific mobility could not be tracked in the data at our disposal. The algorithm used assigned each author to the most probable country over the years and mobility was not taken into consideration, i.e. we have only one affiliation for the time interval based on the most probably affiliation. As a consequence, we cannot disentangle the impact of international collaboration from that of mobility. This is an important limitation to our study. In our recommendation to set up programs to help build and maintain a strong network of international collaborators, we cannot state whether going to conferences, short research trips or longer term sabbatical leave are more beneficial to establishing and maintaining one's network.

The second suggestion for future studies is about different research methods. Conducting qualitative research by gathering data from interviews could focus on how international collaboration shape the ability and competency of scientists. The point of Pouris and Ho (2014) about the necessity of having a regional research and innovation systems in Africa can be another subject for investigation, especially when there is a significant increasing collaborative research pattern.

Appendix 1 - Difference in difference regression results for the effect of experiencing international collaboration on the mean normalized journal score (*mnjs*)

Variable	mnjs2000	mnjs2001	mnjs2002	mnjs2003	mnjs2004	mnjs2005	mnjs2006	mnjs2007	mnjs2008	mnjs2009	mnjs2010	mnjs2011	mnjs2012	mnjs2013	mnjs2014	mnjs2015
dSouthAfrica	0.24***	0.25***	0.25***	0.25***	0.25***	0.25***	0.25***	0.25***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.25***
treat	0.66***	0.29***	0.28***	0.26***	0.30***	0.22***	0.21***	0.27***	0.25***	0.25***	0.28***	0.22***	0.28***	0.28***	0.24***	0.23***
d2001		0.14***														
treatd2001		0.33***														
d2002			0.14***													
treatd2002			0.29***													
d2003				0.14***												
treatd2003				0.33***												
d2004					0.14***											
treatd2004					0.30***											
d2005						0.14***										
treatd2005						0.37***										
d2006							0.13***									
treatd2006							0.41***									
d2007								0.14***								
treatd2007								0.33***								
d2008									0.13***							
treatd2008									0.36***							
d2009										0.13***						
treatd2009										0.33***						
d2010											0.13***					
treatd2010											0.34***					
d2011												0.13***				
treatd2011												0.39***				
d2012													0.14***			
treatd2012													0.33***			
d2013														0.14***		
treatd2013														0.21***		
d2014															0.14***	
treatd2014															0.24***	
d2015																0.15***
treatd2015																0.26***
constant	-0.95***	-1.06***	-1.06***	-1.05***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***	-1.06***
Nb. obs.	216077	204021	200968	200372	200356	200482	201420	203515	209003	210094	211440	212014	209466	209325	209028	207358
LogLikelihood	-296140	-282627	-278542	-278273	-278492	-278558	-279736	-282797	-289768	-291303	-292992	-293605	-290441	-290279	-289751	-288193
F	548.66***	323.51***	303.93***	293.97***	291.43***	293.58***	317.36***	312.11***	363.93***	404.78***	470.14***	456.12***	466.20***	463.22***	507.36***	462.90***

Notes: *** shows the significance level at 0.05, 0.02, and 0.01 respectively; Year dummies are all significant.

Appendix 2 - Difference in difference analysis for the effect of experiencing international collaboration on publishing an article that is in the top 10% most cited (ptop10)

Variable	ptop2000	ptop2001	ptop2002	ptop2003	ptop2004	ptop2005	ptop2006	ptop2007	ptop2008	ptop2009	ptop2010	ptop2011	ptop2012	ptop2013	ptop2014	ptop2015
dSouthAfrica	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
treat	0.05***	-0.01	0.00	0.02***	0.01***	0.01**	0.01**	0.03***	0.03***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
d2001		0.00*														
treatd2001		0.05***														
d2002			0.00													
treatd2002			0.04***													
d2003				0.00**												
treatd2003				0.02**												
d2004					0.00*											
treatd2004					0.04***											
d2005						0.00*										
treatd2005						0.04***										
d2006							0.00*									
treatd2006							0.04***									
d2007								0.00								
treatd2007								0.02***								
d2008									0.00							
treatd2008									0.02***							
d2009										0.00						
treatd2009										0.03***						
d2010											0.00					
treatd2010											0.04***					
d2011												0.00				
treatd2011												0.03***				
d2012													0.00*			
treatd2012													0.03***			
d2013														0.00		
treatd2013														0.03***		
d2014															0.00	
treatd2014															0.04***	
d2015																0.00**
treatd2015																0.03***
constant	0.03***	0.02***	0.03***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.02***	0.02***	0.03***	0.02***
Nb. obs.	216434	204374	201320	200727	200711	200834	201773	203870	209362	210451	211801	212371	209825	209682	209396	207747
LogLikelihood	96353.4	95180	95443.4	95136.2	93554.4	94836.3	92375.8	92162.2	90334	90736.3	87810.4	90664.4	91050.2	91332.4	89907.5	90557
F	66.09***	38.14***	33.77***	32.3***	35.95***	35.66***	40.76***	41.53***	55.42***	57.52***	69.43***	56.84***	50.17***	58.18***	60.42***	57.05***

Notes: *, **, and *** show the significance level at 0.05, 0.02, and 0.01 respectively; Year dummies are all significant.

Appendix 3 - Difference in difference analysis for the effect of experiencing international collaboration on the mean normalized citation score (*mncs*) – similar to Table 2 but papers with no citation are not dropped.

Variable	lncs2000	lncs2001	lncs2002	lncs2003	lncs2004	lncs2005	lncs2006	lncs2007	lncs2008	lncs2009	lncs2010	lncs2011	lncs2012	lncs2013	lncs2014	lncs2015
d_South_Africa	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
treat	0.22***	0.08***	0.09***	0.10***	0.10***	0.07***	0.08***	0.11***	0.09***	0.11***	0.10***	0.09***	0.10***	0.09***	0.08***	0.09***
d2001		-0.01														
treatd2001		0.12***														
d2002			-0.01													
treatd2002			0.10***													
d2003				0.00												
treatd2003				0.09***												
d2004					0.00											
treatd2004					0.11***											
d2005						0.00										
treatd2005						0.12***										
d2006							-0.01									
treatd2006							0.13***									
d2007								-0.01								
treatd2007								0.09***								
d2008									-0.01							
treatd2008									0.12***							
d2009										-0.01						
treatd2009										0.09***						
d2010											-0.01					
treatd2010											0.12***					
d2011												-0.01				
treatd2011												0.12***				
d2012													0.00			
treatd2012													0.10***			
d2013														-0.01		
treatd2013														0.10***		
d2014															-0.01	
treatd2014															0.11***	
d2015																0.00
treatd2015																0.09***
constant	0.26***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***	0.27***
N_observation	216434	204374	201320	200727	200711	200834	201773	203870	209362	210451	211801	212371	209825	209682	209396	207747
LogLikelihood	-86408	-78642	-77005	-76527	-77352	-76897	-78017	-79523	-83816	-83615	-86286	-86512	-85162	-84487	-88365	-87432
F	156.74	101.38	88.06	92.00	94.59	100.09	113.92	122.70	160.34	179.84	200.34	185.95	169.65	179.42	154.42	114.24

Notes: *** shows the significance level at 0.05, 0.02, and 0.01 respectively; Year dummies are all significant.

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