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PH.D. PUBLICATION PRODUCTIVITY:
THE ROLE OF GENDER AND RACE IN SUPERVISION IN SOUTH AFRICA

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Ph.D. Publication Productivity: The Role of Gender and Race in Supervision in South Africa
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ABSTRACT

We study whether student-advisor gender and race composition matters for publication productivity of Ph.D. students in South Africa. We consider all Ph.D. students in STEM graduating between 2000 and 2014, after the recent systematic introduction of doctoral programs in this country. We investigate the joint effects of gender and race for the whole sample and looking separately at the sub-samples of (1) white-white; (2) black-black; and (3) black-white student-advisor couples. We find significant productivity differences between male and female students. These disparities are more pronounced for female students working with male advisors when looking at the joint effects of gender and race for the white-white and black-black student-advisor pairs. We also explore whether publication productivity differences change significantly for students with a high, medium, or low "productivity-profile". We find that female productivity gaps are U-shaped over the range of productivity. Female students working with male advisors have more persistent productivity gaps over the productivity distribution, while female students with a high (or low) "productivity-profile" studying with female advisors are as productive as male students with similar "productivity-profile" studying with male advisors.

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1. Introduction

Inequalities across gender and racial lines are ubiquitous and persistent. In academia, while recent changes in the composition of student bodies have seen increasing involvement of women and people of color in many countries (Snyder et al., 2019; Cloete and Mouton, 2015), at the faculty level these groups remain under-represented, particularly in STEM (Science Technology Engineering and Mathematics) fields and at higher levels of seniority (Snyder et al., 2019; Herman, 2017).

Acknowledging the numerous and complex reasons behind the persistence of these imbalances, past research on scholars' scientific productivity has looked at the productivity differences between male and female scientists. The gender gap in publishing has been well documented. While details depend on the context, discipline, geography or era, female scientists have been found to produce fewer papers per year than their male colleagues (Allison and Stewart, 1974; Cole and Zuckerman, 1984; Fox and Faver, 1985; Mairesse and Pezzoni, 2015; Pezzoni et al., 2016; Holman et al., 2018; Lerchenmueller and Sorenson, 2018; Mairesse et al., 2019). Given the nature of promotion and advance in an academic career, those productivity differences are among the main constraints on the careers of female and black scholars (Evans and Cokley, 2008).

So far, however, few studies have focused on doctoral student publication productivity and ask whether gender and race productivity gaps are already present at the start of a possible academic career, and, if so, to what extent they are related to their advisor characteristics. Advisors act in fact both as role models and academia gatekeepers for their students. Past research in education has shown that doctoral students tend to be productive with advisors of the same gender and race than them (Bettinger and Long, 2005; Lockwood, 2006; Aguinis et al., 2018). In this paper we investigate whether and, to what extent, the gender and racial pairing of Ph.D. students with their advisors influence positively their publication productivity.

Our contribution is unique in four ways. First, we have been able to construct an original and rich data set, practically covering all Ph.D. students in STEM disciplines in South Africa, with information on their advisors, over the decade

Second, while past research has generally been based on publication records in Web of Science (WOS) or SCOPUS, we rely on register data of Ph.D. students' enrollment, and thus we account for students who have not published, or have only published in outlets not listed in WOS or SCOPUS.

Third, while in the past science of science literature, gender and race issues have been studied separately, we investigate them jointly, which is particularly relevant in the South African case where doctoral students and professors case is particularly interesting since we are black and female scientists are present in the system in similar proportions; as we shall see.

Fourth, we complement provide new insights for the literature on scientific productivity by complementing the OLS results with a quantile regression that opens a more complex and nuanced understanding of the issues related to productivity gaps in science and serves to the identification of these gaps across the productivity distribution.

In studies of the gender gap, it has been common to observe that age plays a role in publishing productivity and that the gap can change with age (Kelchtermans and Veugelers, 2011). This observation, combined with the well-known Matthew Effect (Merton, 1988), suggests that productivity gaps might originate very early in the career and grow over time. An important open issue, then, is whether we observe publishing productivity gaps early in the career (David, 1993; Conti and Visentin, 2015), and if so how to under-stand them. Are under-represented groups disadvantaged by the scarcity of women and black professors (who can act as supervisors and mentors) during their Ph.D. training? We can get at this issue by examining publication of scientists during the course of their doctorates, looking at productivity of students while controlling for the gender or racial composition of student-advisor couples.

While the gender gap is defined in terms of single scientists, it must be acknowledged that much publishing involves more than the focal author (Wager et al., 2015; Chuang and Ho, 2014; Larivière, 2012). Not only co-authors, but research assistants, co-workers, technicians, conference participants, and many others contribute with work, ideas, and suggestions. Of course, when we are considering Ph.D. students as a (co-)authors, the thesis advisor is very likely to provide important inputs.

Often the thesis advisor is the first person with whom a student co-authors, but additionally, supervisors play a key role in introducing students into the profession. It seems very likely that the properties of the supervisor matter for a student's early success (Li et al., 2019). A priori, there are some obvious traits of the supervisor that will matter: extent of supervision, publishing record, status in the profession, quality, and so on. But other literature suggests gender (race) might also matter. For example, subtle gender and racial biases can distort the meritocratic evaluation of the students. An experiment in a sample of 127 biology, chemistry, and physics professors in the USA, asked academics to evaluate the CVs of students for a laboratory manager position, where gender was randomly assigned to CVs. It found that both male and female faculty judged female students as less competent. Consequently, females would be less likely to be hired than an identical male student, and would be offered a smaller salary and less mentoring (Moss-Racusin et al., 2016). Such biases can also reduce a student's access to relevant information. A similar randomization experiment found that black students were less likely to receive warning information from academic advisors than are white students, when race was randomly assigned to student academic records (Crosby and Monin, 2007). Along the same lines, past research has found that supervisors provide more psychological support to protégés of the same gender (Koberg et al., 1998; Aguinis et al., 2018).

Gender (or racial) bias can also play a role through the student side of the relationship (Rossello and Cowan, 2019). In education and learning the gender of the advisor can affect performance and beliefs (Gaule and Piacentini, 2018; Breda et al., 2018; Rossello and Cowan, 2019). For example, female students are often more inspired by female than by male ole models (Bettinger and Long, 2005; Lockwood, 2006; Aguinis et al., 2018). A recent French experiment among senior high school students found a reduction of stereo-types associated with jobs in science, after students were exposed to a female scientist (Breda et al., 2018). In the same study, enrolment in a selective science program increased by 30% among the higher achieving students; and in particular, the share of female (male) students in STEM programs were 38% (28%) higher than that in classes that did not receive the intervention. Thus, we might expect to see female students performing better with female advisors.

Exploring the relationship between gender (race) and productivity in the student-supervisor pair is a step towards understanding productivity differences among different groups within academia. Past research, generally focusing on STEM, is mostly available for the USA. Pezzoni et al. (2016) studied all fields in STEM with data based on 933 Ph.D. graduates and 204 advisors at the California Institute of Technology (Caltech) US, between 2004 and 2009, did not found productivity difference between the female-female and the male-male couples but they did find differences in cross-gender groups. In particular, they found that compared to the male-male student-advisor couples, female students working with male advisors published 8.5% less, and male students working with female advisors published 10% more.

In contrast, Gaule and Piacentini (2018) explored a single field, looking 20,000 Ph.D. graduates between 1999 and 2008 in the US chemistry departments. They found that same-gender couples tended to be more productive during their Ph.Ds., and that female students working with female advisors were more likely to become faculty members compared with female students working with male advisors.

Contrary to these previous analyses, our research here focusses on an emerging economy, namely South Africa, where resource constraints in the science system in general, and universities in particular, are much more severe than they are in developed countries.

We observe that the academic science system in South Africa is relatively small: in 2020 there were only 2 318 full professors, and 3 453 Ph.Ds. granted.[1] And the production of Ph.D.s is concentrated in a relatively small number of institutions (Cowan and Rossello, 2018).[2] These features are typical of many developing countries (Nchinda, 2002; González-Sauri and Rossello, 2022). While the concern with gender inequality in science is very important today in most countries, in South Africa, in view of the history of apartheid and its on-going legacy, race inequalities in science are also a crucial matter. Given that academic appointments are heavily based on performance during graduate studies, understanding gender and race effects on Ph.D. students' publication productivity is of great importance.

Though restricting attention to STEM disciplines, our analysis can be considered as representative of national trends and effects for the entire South African academic science system. Our statistical analysis is different from previous studies in three important respects. First, we consider early career productivity of students not in isolation but controlling for advisor characteristics. Second, our original data allows us to examine and decompose the intersection of gender and race, running regressions for three separate sub-samples of student-advisor couples: (1) white-white; (2) black-black; and (3) black-white. Third, we control for students' "ability" implementing a quantile regression analysis, in order to explicitly test whether gender differences vary depending on students' "productivity-profile": high, medium or low.

Besides usual regressions, we also implement quantile regressions approach to investigate the gender productivity gap. Past research has either measured average differences between male and female scientists or has tried to address potential bias using a three stage estimation correcting for promotion bias and scientist's non-publishing "idle periods", possibly related to motherhood (Mairesse and Pezzoni, 2015; Rivera León et al., 2017). A quantile regression approach can help quantify where the gender productivity gap is larger, and help identify targets to better close the gender gap.

Our main findings are the following. First, there is a gender-based publishing productivity gap in South Africa. Second, on average the productivity gap is smaller (or non-present) in inter-racial student-advisor couples. In same-race student-supervisor pairs there is no (statistically significant) productivity gap for female students with female advisors. For female students with male advisors, however, a gap exists. This suggests that the gap, as measured on the entire population is driven largely by female students working with male advisors in white-white and black-black pairs. Finally, using quantile regressions to consider the productivity distribution underlying the average differences, we observe that gender publication productivity differences are U-shaped over student productivity. In particular, female students with high (or low) productivity profile are as productive as male students (with similar productivity) working with male advisors.

In spite of its specificity and limits, our study lends itself to some important science policy recommendations. Because of cumulative advantage in science, as well as the well-known Matthew effect of citations, we know that early career productivity differences tend to grow over time.

Our results underline the importance of supervision, suggesting that female role models and inter-racial couples might mitigate early career publication differences between female and male students in STEM. These findings are of particular importance in the South African context, where many students do not complete their university studies. Our sample comprises an "elite" part of the South African university system, representing students who complete their education and become independent scientists. Hopefully, addressing productivity gender differences at the Ph.D. level may increase the (success and) proportion of female professors in the population and create an inclusive and productive working environment for all. It may, in turn, create positive feedbacks for students of lower levels.

2. Materials

2.1 The context

The context of our analysis is the South African university system. South Africa has a population of roughly 60 million people where 80% are black Africans. It is a country undergoing rapid social transformations where social, political, and economic conditions have been changing rapidly since 1994. South African society, including the university system, was segregated across racial lines by apartheid until 1994. Black universities were systematically underfunded, specialized in teaching and technical education, and not considered producers of new knowledge (Herman, 2017). In 1994 the university system began a process of integration, aiming to make both the student body and the faculty reflect the ethnic composition of the overall population. Progress has definitely been made, but the goal has not yet been achieved. It remains the case, though, that today South Africa is an important hub for African science and indeed is at the world frontier in many disciplines (aspects of biology, medicine, astronomy and agricultural science to name a few).

However, the system is relatively small, comprising 24 public universities and around 2300 full time permanent full professors in 2020.[3] Tuition costs can limit access to higher education for much of the population: the average annual tuition fee is high, between 30000 and 64000 ZAR.[4] (approximately 1500-3200 Euro), where GDP per capita in 2020 is estimated by the IMF at 6611 Euro.[5] Improvements notwithstanding, imbalances and racial inequalities are still present in the South African university system. This provoked two large student protests in 2015 *Rhodes Must Fall* and *Fees Must Fall* demanding racial transformations and equal access and opportunities.[6,7] *Rhodes Must Fall*, in particular, migrated to universities outside South Africa, in particular in the UK and the US.[8] The international echo made many think of *Rhodes Must Fall* as a precursor of the social movement *Black Lives Matter*.[9] The South African case of discrimination at universities is important not only for South Africa but for the world at large.

2.2 Data

Our data originates from the National Research Foundation (NRF) database of South African Academia. The NRF has a system in which academics at South African universities apply to be "rated". [10] This rating has (until recently) financial and prestige incentives, so most academics in South Africa who pursue a research career do apply. Overall, rated scholars comprise about 30% of South African scholars who produce roughly the 90% of the country peer reviewed output. The STEM fields have been part of the system longer than have SSH fields, and in these fields coverage appears to be almost complete. Consequently, we restrict attention to this group, where the agency has a primary role in funding research of individuals (including early in the career) as well as of universities. We create a unique dataset using information supplied by researchers in the rating application process. The raw data include three datasets, the first contains information about STEM Ph.D. students and their advisors from 2000 to 2014, the second has all individual employment information, and the third collects all publication data supplied to the NRF from 1961 to 2014.

From student and supervisor characteristics (i.e. name, surname, graduation year, scientific field and university) we match both students and advisors to their employment records and then match each individual to his or her NRF publication record.

This method avoids the problems associated with methods dependent on name disambiguation. Additionally, to be confident that our publication data are complete, we include in the analysis only Ph.D. students in STEM who became active scholars in the NRF system. We also create publication records for each student and advisor over time we carry forward for each student the time from enrollment year up to two years after graduation. In this way we obtain a total of 6049 observations corresponding to 924 PhD students and 549 PhD advisors. Our final sample covers the Ph.D. students enrolled during the period 2000-2012 and with a graduation date up to 2014. In our sample, Ph.D. students graduate on average after 3.8 years after enrollment.

Table 1: Descriptive statistics of Ph.D. students and advisors by gender and race
(Study sample –STEM disciplinary fields)

	Adv_ MaleWhite	Adv_ FemaleWhite	Adv_ White	Adv_ MaleBlack	Adv_ FemaleBlack	Adv_ Black
Stud_MaleWhite	179	53	232	13	4	17
	55%	*37%*	*49%*	*54%*	*36%*	*49%*
Stud_FemaleWhite	149	92	241	11	7	18
	45%	*63%*	*51%*	*46%*	*64%*	*51%*
Stud_White	328	145	473	24	11	35
	100%	*100%*	*100%*	*100%*	*100%*	*100%*
Stud_MaleBlack	123	45	168	97	17	114
	71%	*64%*	*69%*	*64%*	*81%*	*66%*
Stud_FemaleBlack	51	25	76	54	4	58
	29%	*36%*	*31%*	*36%*	*19%*	*34%*
Stud_Black	174	70	244	151	21	172
	100%	*100%*	*100%*	*100%*	*100%*	*100%*

Table 1 shows our study sample composition in terms of Ph.D. student and advisor couples by gender and race. [11] Ph.D. students in our study sample are 58% male (249 white and 282 black) and 42% female (259 white and 134 black). Advisors are 73% male (298 white and 104 black) and 27% female (130 white and 17 black). Overall 54% of Ph.D. students are supervised by white male advisors, 23% by white females, 19% black males, and only 3% black females.

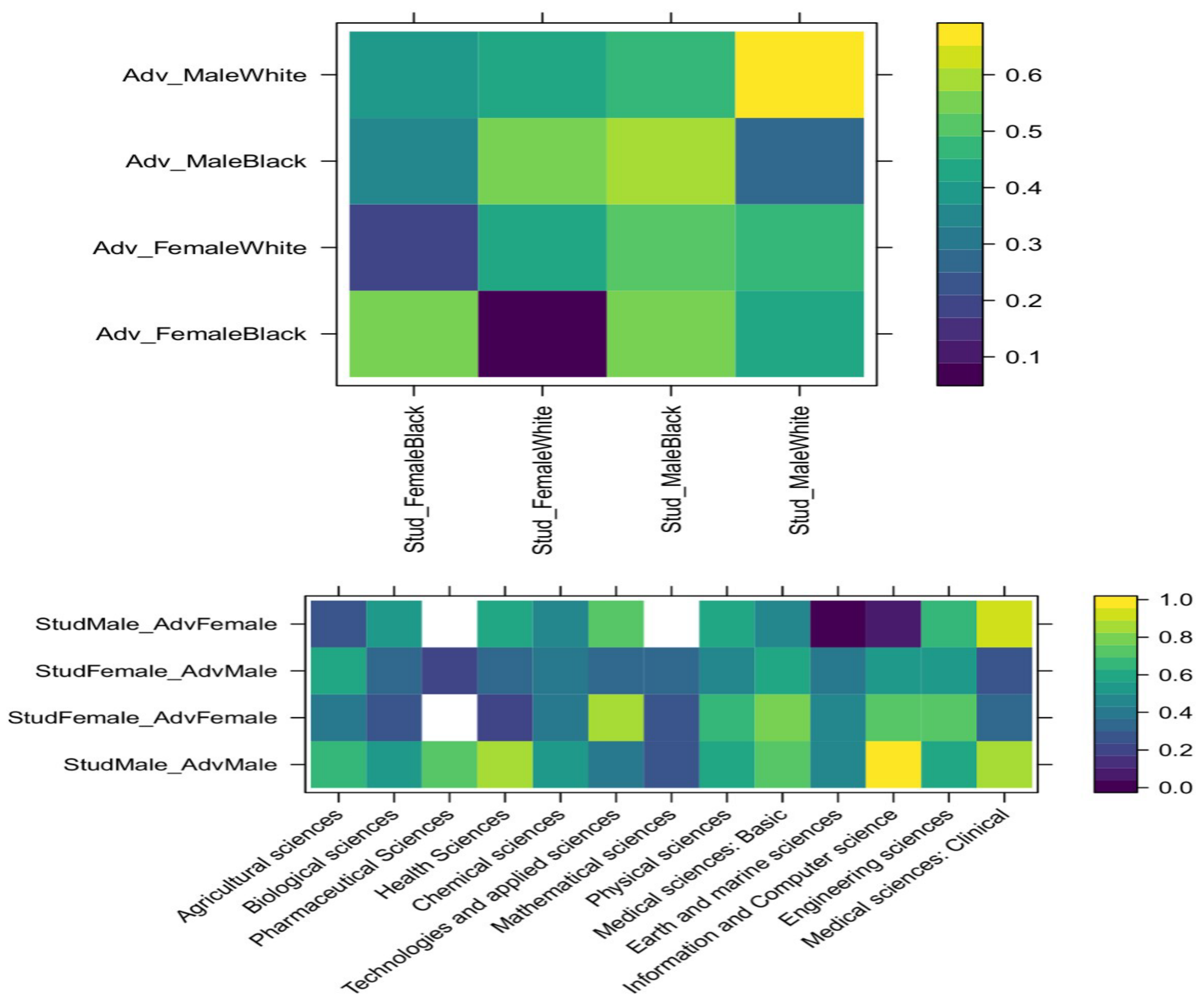
Our whole study sample (ALL) has 5115 observations. The three study subsamples with enough observations to be considered separately are the White Ph.D. students with White advisors (WW) with 2635 observations, the Black Ph.D. students with White advisors (BW) with 1421 observations, and the Black Ph.D. students with Black advisors (BB) with 877 observations.

2.3 Variables

Looking at three year moving windows between enrollment and graduation plus 2 years, the annual average number of published articles per Ph.D. student is close to one. The most productive are white male students who on average produce 1.58 articles, followed by black males with 1.37 articles, and white females with 1.21 articles. Black females are the least productive with an average of 0.75 articles. However, not surprisingly, the distribution of number of articles across of individual Ph.D. student is skewed, with close to zero median values for all groups, and with 44% (410) of them Ph.D. student publishing zero articles between their years of enrollment and two years after graduation. As we already stressed, being able to use register data of Ph.D. students' enrollment is particularly relevant in contrast to most previous studies which rely on Web of Science (WOS) or SCOPUS publication records and ignore Ph.D. students with zero published articles.

The Heat-Map of doctoral average annual for student and advisor gender and racial combinations of Figure 1-upper panel highlights important productivity differences between the sixteen groupings of the four gender*race types of Ph.D. students (columns) with the four gender*race types of advisors (rows). It suggests complex productivity effects of gender and race. Overall, which may not be surprising, it also appears that the productivity of the (WW) subsample is higher than the productivity of the (BW) subsample, in turn higher than the productivity of the (BB) subsample.[12]

Figure 1: Productivity Heat-Map of Ph.D. students and advisors by gender and race in upper panel and by disciplinary fields in lower panel



Legend: Darker colors indicate lower Ph.D. student productivity, and lighter colors higher productivity. See Section 3 for the definition and measurement of Ph.D. productivity.

Lower Panel B of Figure 1 shows average productivity across student-advisor gender differentiated by discipline. In 5 out of 13 fields the couple female student with female advisor has the highest average productivity.[13] In two fields, Mathematics and Medical: clinical, cross gender ties are those with the highest averages. In the remaining 6 fields the couple male student with male advisors has the highest average productivity. Finally, female students with male advisors have the lowest average productivity for 6 out of 13 fields.

3. Methods

Table 1 descriptive statistics and Figure 1 Productivity Heat-Map show that female and black Ph.D. students publish less than male and white students, but also depend on the race and gender of their advisors. But these differences could be driven by many other factors and in our analysis we control for a variety of factors. We also implement both a usual panel regression approach and a quantile regression approach. [14]

3.1 Regression approach

We estimate a number of panel data regressions with the following specification: clustered standard errors as follows.

$$Y_{iw} = \alpha_\tau + \gamma_\tau Z_i + \beta_\tau X_{i,t-1} + \varepsilon_{it} \tag{1}$$

where

- the dependent variable Y_{iw} is the productivity of Ph.D. student. $'i'$ in three year moving average windows (w) ranging from the year of his year of enrollment and to that of his year of graduation plus two years, considering that this windows covers the articles he has published out of his Ph.D.
- pub_{iw} is the number of articles published Ph.D. student $'i'$ in the three year moving average windows (w)
- Y_{iw} is measured as: $Y_{iw} = \log(1 + pub_{iw})$
- Z_i stand for the vector of control variables characterizing the Ph.D. student-advisor gender and race couples. We thus include the four following binary indicators: $StudFemale\_AdvFemale$ is equal to one if both student and advisor are females, $StudFemale\_AdvMale$ equals one if the student is female and the advisor is male, $StudMale\_AdvFemale$ is one if the student is male and his advisor is female, $StudMale\_AdvMale$ is one if both the student is male and his advisor are male
- $X_{i,t-1}$ are time variant, lagged controls. We thus include a dummy indicator equal to one when the Ph.D. student had published previously starting the Ph.D. and zero otherwise: $Stud\_Published\_Previously$.[15] To account for the quality of student Ph.D.s we include as control $Average\ Scimago\ Journal\ Ranking$. This variable is defined as the year of publication average of the 'Scimago Journal' rankings of the journals where Ph.D. students' articles are published. The Scimago Journal Ranking is a metric indicator of the number of citations received by articles published in academic journals.[16]
- To control for advisor publication productivity, we use the advisor's past cumulative average productivity $Adv\_LogAverage\_\ Previous\_Productivity$.[17]

- To account for advisor's "quality", we also rely on *Adv_NRF_Ratings* based on NRF.
- We further control for team size using *More_Adv*., a dummy variable equal to one if the student has more than one advisor and zero otherwise.[18]
- We control for the number of Ph.D.s supervised by the advisor (*Number_Adv_Stud*), as well as for the $Time\_to\_Stud\_Graduation$ the number of years t takes for a Ph.D. to student graduate.
- Finally, we include as additional controls field and student enrollment year dummies, lastly ε_{it} is the usual idiosyncratic error term.

We run the regressions including all these indicators and variables for our overall sample (ALL) and for our three subsamples (WW), (BB) and (BW).[19] The results are presented in Table 2 (Subsection 4.1)

3.2 Quantile regression approach

Compared to usual regressions, the quantile regression approach has the advantage of identifying Ph.D. students' ability profiles across productivity percentiles. It thus allows to compare these different profiles between male and female, and black and white.

The quantile regression formulation is:

$$Q_\tau\left(Y_t|Z_i, X_{i,t-1}\right) = \alpha_\tau + \gamma_\tau Z_i + \beta_\tau X_{i,t-1} + \varepsilon_{it} \tag{2}$$

We use the same specification as before, where $Q_\tau$this e regession function, Z_i are the dummies rep resenting the different student-advisor gender couples $StudFemale\_AdvFemale$, $StudFemale\_AdvMale$, $StudMale\_AdvFemale$ where the baseline category is the pair male students with male advisors. $X_{i,t-1}$ are the controls described before, and εit is the error term.[20] We run 40 quantile regressions each covering 2.5 percent of the student productivity distribution. To show these results we plot the estimated coefficients with their 95% confidence interval of the dummies of interest $StudFemale\_AdvFemale$, $StudFemale\_AdvMale$, $StudMale\_AdvFemale$; which compare the couples with the baseline ($StudMale\_AdvMale$).

4. Results

4.1 OLS regression results

Table 2 explores average productivity differences between student-advisor gender pairs compared to the baseline StudMale_AdvMale. It gives the results of OLS estimations of the model for the whole sample (ALL, column 1) and for same- (WW column 2, BB column 3) and cross- racial sub-samples (BW column 4). Overall, column 1 shows that female students working with male advisors ($StudFemale\_AdvMale$) have the largest gap compared with the male-male couple: they produce on average 14% fewer papers; while it is 13% fewer for female students working with female advisors ($StudFemale\_AdvFemale$). Male students working with female advisors ($StudMale\_AdvFemale$) do not differ in productivity compared to the baseline male–male pair ($StudMale\_AdvMale$).

However, disaggregating to take into account the racial composition of the pairs suggests a slightly different story. Here, in the same-race supervisions (WW and BB) we again observe a significant gap for female students with male advisers ($StudFemale\_AdvMale$) (columns 2 and 3). However, in these racial groupings we do not see a significant gap for female students with female advisors ($StudFemale\_AdvMale$) (again columns 2 and 3). In particular, when student and advisor are both white, (column 2) female students working with male advisors ($StudFemale\_AdvMale$) produce 14% fewer papers than male students working with male advisors. Similarly, among black-black supervision pairs (column 3) female students working with male advisors ($StudFemale\_AdvMale$) produce on average 24% fewer papers than do male students working with male advisors. By contrast, looking at the cross-racial sub-sample (column 4) the group of black students (of either gender) working with white advisors (of either gender) displays no significant productivity gaps with male-male couples for any gender combination. These figures suggest that there is a strong interaction between race and gender in determining student productivity.[21]

Table2: Pooled OLS Panel Regression

The dependent variable is log of 1+ average productivity (number of publications between t and t +2 inclusive divided by 3). Column (1) is the estimation on the whole sample; column (2) is the sub-sample White Students with White Professors; column (3) is the sub-sample Black Students with Black Professors; column (4) is the sub-sample Black Students with White Professors.

	(1)	(2)	(3)	(4)
	ALL	**WW**	**BB**	**BW**
StudFemale_AdvFemal	-0.128 *	-0.053	-0.605	-0.135
	(0.065)	*(0.079)*	*(0.419)*	*(0.150)*
StudFemale_AdvMale	-0.138	-0.141 *	-0.241 *	-0.123 *
	(0.045) **	*(0.060)*	*(0.115)*	*(0.089)*
StudMale_AdvFemale	-0.061	-0.023	0.195	-0.121
	(0.061)	*(0.093)*	*(0.198)*	*(0.094)*
More Adv.	0.039	0.125	0.090	-0.127
	(0.047)	*(0.067)*	*(0.129)*	*(0.076)*
Adv. Log Average	0.037	0.056	-0.054	0.113
	(0.022)	*(0.030)*	*(0.041)*	*(0.059)*
Adv. NRF Ratings	-0.003	-0.013	0.015	0.000
	(0.006)	*(0.007)*	*(0.014)*	*(0.016)*
Stud. Published	0.777 ***	0.822 ***	0.579 ***	0.770 ***
	(0.048)	*(0.065)*	*(0.133)*	*(0.099)*
Avarage Scimago	0.054 *	0.049	0.089	0.067 *
	(0.024)	*(0.034)*	*(0.075)*	*(0.034)*
Time to Graduation	-0.045 ***	-0.047 **	-0.033	-0.021
	(0.013)	*(0.018)*	*(0.041)*	*(0.026)*
Number of Adv. Stud	0.056 ***	0.059 ***	0.060 ***	0.063 ***
	(0.008)	*(0.014)*	*(0.014)*	*(0.018)*
Field	Yes	Yes	Yes	Yes
Enrolment Year	Yes	Yes	Yes	Yes
N	5 115	2 635	877	1 421
R^2	0.287	0.368	0.233	0.251

Note: Robust Standard errors Clustered at Student id level are in parenthesis
Significance code: * p<0.05 ** p<0.01 *** p<0.001

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This is particularly relevant in the South African context where the formerly white institutions are becoming more racially inclusive and the participation of black students is increasing. Indeed, while the sub-samples of same-race couples (models 2 and 3) account for potential segregation effects within departments and fields, the sub-sample of black students working with white advisors (column 4) may describe the "intermediate future" of the South African university system envisioning black graduates entering as Ph.D. students the formerly white departments, which will still be largely populated by white faculty.

Besides our main regressors, looking at the common controls used in the literature studying scholar

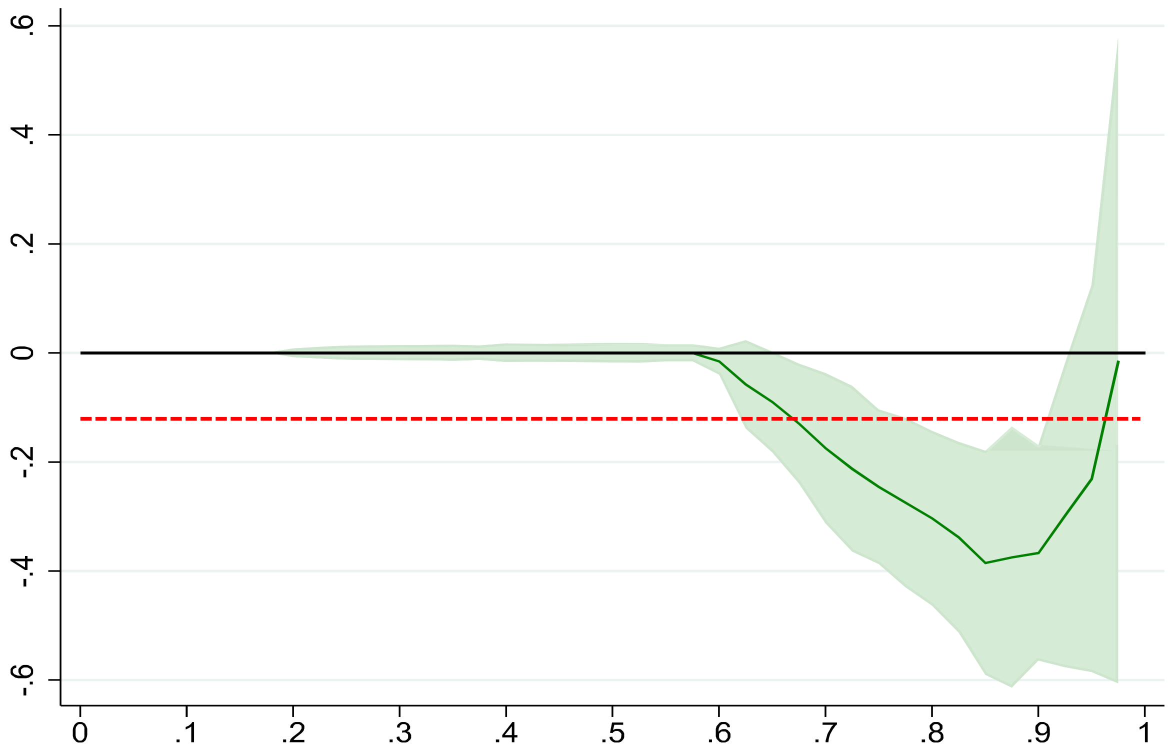
publication productivity, overall our results are consistent with others' results: the best predictor of future productivity is the past productivity — students who had published in the previous years (Stud. Published Previously) produce between 58% and 82% more papers than those who did not. Publication quality is also relevant in aggregate, (though not significantly so for same-race pairs): a one unit increases *Average Scimago Journal Ranking* increases student productivity between 5% and 7%. The team size plays a role and student productivity increases 6% for each additional student super-vised by her/his advisor (Number of Adv. Stud). These results highlight the role of past productivity in determining future productivity of scholars. This observation, coupled with gender imbalances in early productivity, might create a lock-in effect that systematically disadvantages female scholars.

4.2 Quantile regression results

To go beyond average differences, controlling for students' "ability", and to allow for te the skewness and fat tails of the dependent variable, in this subsection we examine the quantile regression results. In this way we are able to look at the origins of gender productivity differences, and ask whether discrepancy between groups is stronger or weaker for different sections of the population representing students with different "abilities".

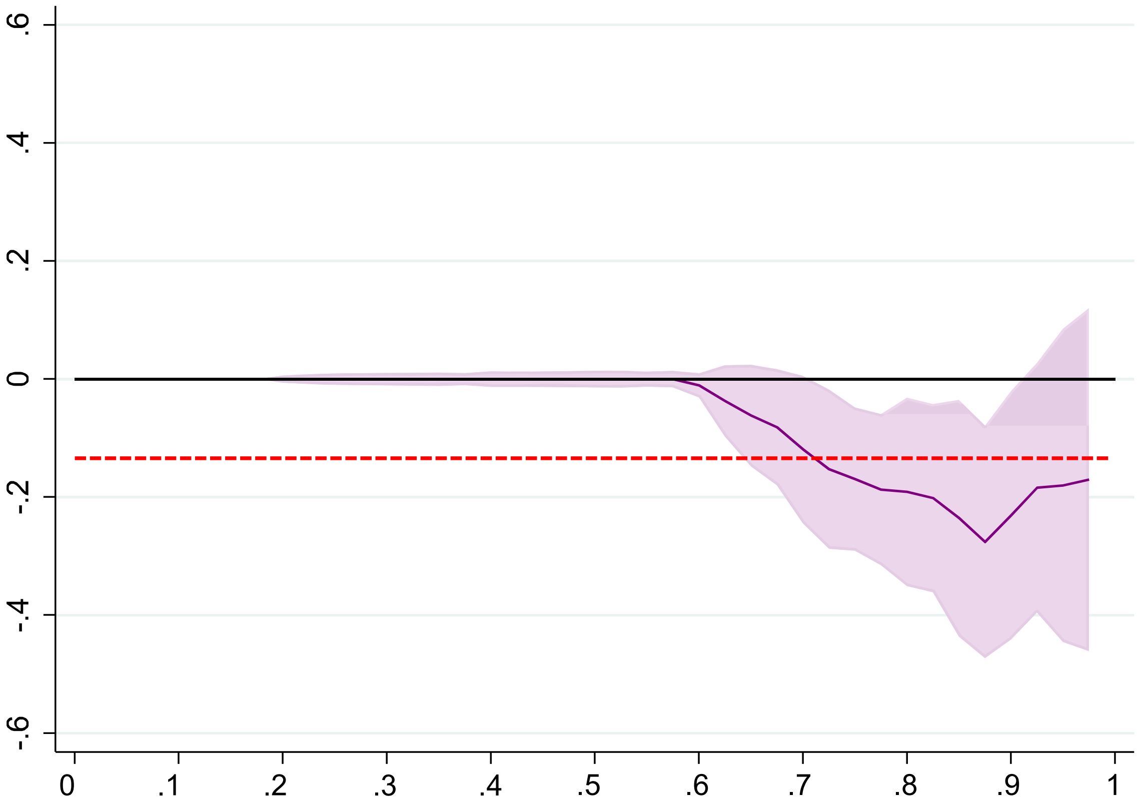
Figures 2, 3, and 4 plot the coefficients and 95% confidence intervals estimated respectively for $StudFemale\_AdvFemale$, $StudFemale\_AdvMale$ and $StudMale\_AdvFemale$ gender couples compared to the baseline ($StudMale\_AdvMale$). The figures collect results from 40 quantile regressions, estimated each 2.5% percentiles of the student productivity distribution. The 40 quantile regressions use the same controls as before: $More\ Adv.$, $Adv.Log\ Average\ Previous\ Productivity$, Adv. NRF Ratings, $Student\ Published\ Previously$, $Average\ Scimago\ Journal\ Ranking$, $Time\ to\ Graduation$, $Number\ of\ Adv.Student$, $Field$, $Enrolment\ Year$ and $Year\ dummies$. We report the corresponding regression table for selected percentiles in table A2 in the Appendix.

Figure 2: Quantile Regressions Coefficients and 95% confidence intervals of StudFemale_AdvFemale compared to baseline StudMale_AdvMale



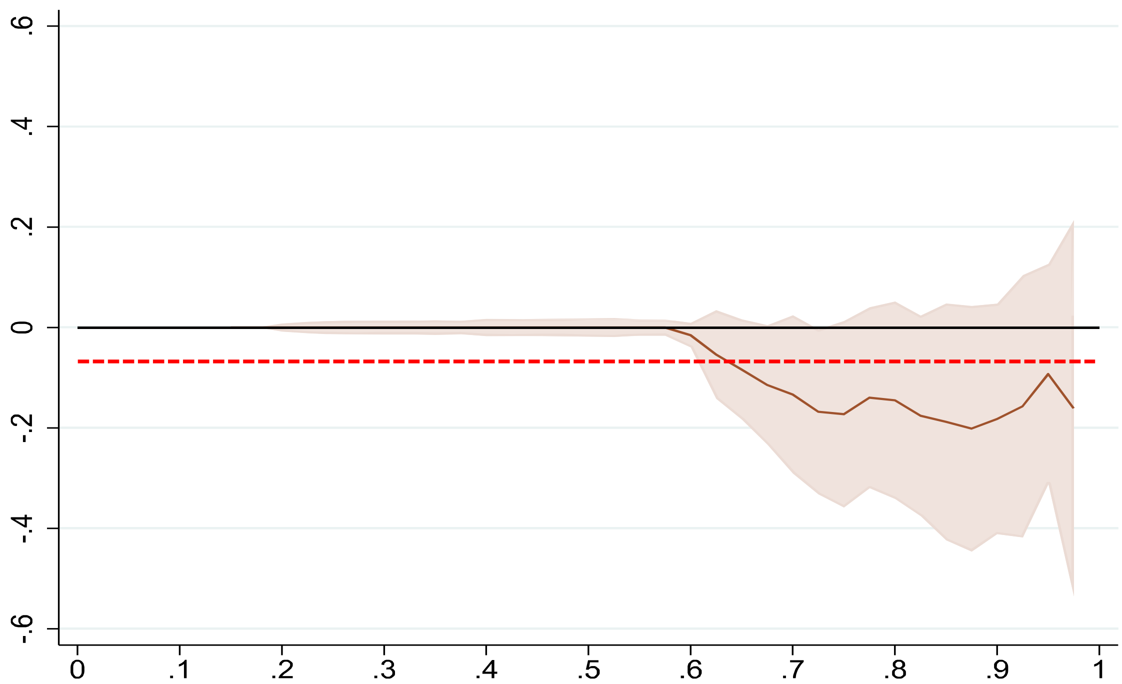
Legend: Quantile regressions are done for each 2.5 percentile following Machado et al. (2011). The solid black line is zero, dashed red line is the (non-quantile) panel OLS estimation for the overall study sample (Table 2 first column).

Figure 3: Quantile Regressions Coefficients and 95% confidence intervals of StudFemale_AdvMale com-pared to baseline StudMale_AdvMale



Legend: Same as Figure 2.

Figure 4: Quantile Regressions Coefficients and 95% confidence intervals of StudMale_AdvFemale com-pared to baseline StudMale_AdvMale



Legend: Same as Figure 2.

In the figures the black line at zero represents the baseline comparison with $StudMale\_AdvMale$; when the confidence intervals overlap the zero line the difference between the coefficient estimated of the gender couples and the baseline is not statistically different than zero. Otherwise, the coefficient of the productivity gap with the baseline is different than zero at 5% confidence level. Additionally, we indicate with the red dotted line the previous OLS estimation (model 1 of table 2, that is, not disaggregated by racial combination).

Figure 2 shows that productivity differences of female student working with a female advisor ($StudFemale\_AdvFemale$) are U-shaped over student productivity. The gap is largest among students with a productivity around the 85th productivity percentile. In-deed, female students working with female advisor with low (<70th percentiles) and high (>90th percentiles) productivity profiles are as productive as male students with similar profiles working with male advisors.

Similarly, figure 3 shows the estimated difference in productivity across percentiles between female students working with male advisors ($StudFemale\_AdvMale$) and male-male student-advisor couples ($StudMale\_AdvMale$). Again we observe a U-shaped tendency, but less pronounced. Between the 70th and 90th percentile female students working with a male advisors have a lower productivity than male students working with male advisors. A striking observation from these two figures is how the two gaps respond to the quantile. The gap observed for the ($StudFemale\_AdvFemale$) group is very clearly U-shaped, with the gap entirely disappearing at the higher productivity levels. By contrast, for the ($StudFemale\_AdvMale$) group increases from the 60th percentile and plateaus. There is only a small recovery at the top percentile. The gap is for this group more persistent over productivity levels.

Finally, figure 4 shows the quantile results for the difference in productivity between male students working with a female advisor ($StudMale\_AdvFemale$) and those working with a male advisor ($StudMale\_AdvMale$). In this case, as in the OLS results, we found no significance difference in productivity across student-advisor gender couples.

In aggregate the gender productivity gap shows a U-shape over productivity levels. It is weak for the least and the most productive students, but strong for students between the 70th and 90th percentile. But the "recovery" as productivity increases is not uniform across sub-groups. In fact, the recovery is driven almost exclusively by female students with female advisors. Among female students with male advisors, the gap appears around the 60th percentile and increases rapidly to the 80th percentile, as it does for those with female advisors. But for those with male advisors the gap does not close, but stays high for the upper tail of the distribution.

5. Conclusion

In STEM subjects, in South Africa, the gender composition of the student-advisor pair matters for students' early career productivity. In general, there is a productivity gap between male and female Ph.D. students. Dis-aggregating on the basis of the gender composition of the student-supervisor pair, we find that there are productivity gaps both for female-female and female-male student-supervisor pairs, with a slightly higher gap for female-male pairs. However, when we dis-aggregate further, considering also the racial composition of the pair, we find that female students working with female advisors display no productivity gap with male-male couples when student and supervisor are of the same racial group. And we find no gender gaps at all for couples in cross-racial ones. Where we do observe significant gender gaps in the same-race groups is in the StudFemale_AdvMale student supervisor pairs. Supervision teams that are either cross-race or are same-gender seem to have the same productivity.[22] This result points to the importance of the level of (dis-)aggregation at which the analysis is pursued. Focus solely on the effects of gender can generate mis-leading results, as the racial composition of the student-supervisor pair is important in determining gender effects. Gender effects that we seem to observe in the aggregate are not present in identifiable sub-groups.

Further, investigating the gender productivity differences across students' "ability", we find that the gap in productivity between male and female students is largest between the 85th and 90th percentile of the productivity distribution. In general, we find that the gap is U-shaped over student productivity, suggesting that the average productivity gap is driven by the moderately-productive students. But again this is sensitive to which sub-population we are observing.

Our results suggest that female students have smaller productivity gaps with male-male couples when coupled with female advisors: female students perform slightly better when coupled with female advisors. It would follow that the scarcity of female advisors (which is not unique to South Africa) might create a negative lock-in effect for female students. This is, potentially, the start of a vicious circle at the system level: because there are few female advisors, female students tend to be less productive. The Matthew effect drives this into the future, implying fewer females are promoted, perpetuating the situation in which female students cannot find female supervisors.

The reasons underlying the smaller gaps for females working with female advisors are numerous, but might be linked to a positive role model effect, or may suggest that female students with male advisors may receive lower quality (or quantity) supervision than do male students. We should remark, however, that our estimation of student productivity is in terms of statistical significance, not necessarily in economic or educational learning terms.

We do not attempt to give the ultimate explanation for the differences we observe, but our results open several important lines of future research.

In general terms, an additional potential avenue for future research would be to con-duct similar studies in other countries. The research of science of science in emerging economies is thin, which is unfortunate since improving the performance of science and higher education in these countries is often considered an important part of the catch-ing up agenda. It seems likely that the general patterns will be similar, but also likely to differ in details. Middle income countries in general face common challenges: scientific activity is often concentrate in specific topics, budget constraints are often more severe, and funding is more volatile and uneven. But the details beneath these general issues differ from country to country, and are thus likely to impinge on issues of (young researcher) productivity in different ways. It remains the case, though, that productivity gaps in emerging economies are potentially more problematic and extreme compared to those in more mature systems.

In more specific terms, our analysis looked at productivity differences in the short-run. It would be interesting to test whether there are any long-run effects. The Matthew effect suggests that in general there are, but the way this is manifest may vary across gender or race. A female scientist might not have the peak of productivity in her mid-career but later, and her productivity distribution might not be unimodal. To observe Ph.D. cohorts over a long period of time, relating future success to initial success, perhaps moderated by supervisor properties is an important direction for future research. While we examined the relation between the Ph.D. student and her/his main advisor, we must consider that they are located in a larger environment. In some disciplines (many natural sciences or medicine for example) research is very much team-based, with different lab members contributing different parts of the project. But even where that is not the case, spillovers among colleagues can affect research success or productivity. In addition, more "social" forces may be at play: for example, political power within a department, local and international networks of collaborators, the likelihood of experiencing discrimination, to name a few. How this local environment affects a student's productivity is essentially unexplored in the literature. Thus, an open, but potentially very important and influential question is how the relation between student and his/her advisor is affected by the larger environment in which they are embedded.

The observed differences in early career productivity could be due to student-supervisor personal relations; access to resources; differences in the career paths; different nature of the research output in terms of content (for example between basic or applied research which can translate into differential 'publishability'). The personal relations hypothesis is compatible with results in Rossello and Cowan (2019), which finds a same-gender (same-race) bias in supervision-tie formation. Bias in tie formation relates with group behavior and socialization in the working environment which may disadvantage female students working with males (Blackburn et al., 1981; Van den Brink and Benschop, 2014; Zinovyeva and Bagues, 2015). More in general, social relations are embedded in networks which are found both to vary with gender and to enhance or restrict access to resources, information, and collaborations (Jadidi et al., 2018).

Differences in productivity are often explained by differences in career paths induced by motherhood (Pezzoni et al., 2016). Past research has found that female productivity has a negative shock during the first 3 years of a newborn (Mairesse et al., 2019). In South Africa fertility rates peak at age 25-29 which corresponds to doctoral years (Lehohla, 2015). Such a shock may be accommodated differently depending on whether the female student works with a male or with a female supervisor.

A further explanation, explaining why the female-male couple has the lowest productivity, can relate with the two-world hypothesis. This hypothesis states that there exists a gender or racial specialization in specific sub-disciplines (Moore et al., 2018). Thus, cross-gender couples may re-combine different (sub-)fields and knowledge. More in general, the management literature has found that diversity is associated with novelty and innovation because it is more likely to recombine distant knowledge and expertise (Rzhetsky et al., 2015; Shi et al., 2015; Uzzi et al., 2013; Chen et al., 2009; Fleming, 2001). In science novelty is often a risk, particularly for a younger scientist, and may have slower returns (Wang et al., 2017; Boudreau et al., 2016; Verhoeven et al., 2016; Azoulay et al., 2011). Taking risks early in the career may slow down productivity in the short-run affecting 'publishability' of the research. Different gender composition pairs may differently mitigate the risk.

All these mechanisms may individually and jointly explain our findings and contribute to an early career gender gap in science. Our work aims at quantifying and identifying the origins of some of the gender and/or race differences in the publication productivity of early career scientists.

In spite of its specificity and limits, our study suggests important policy recommendations to close the gender productivity gap. It highlights the role of female advisors and of cross-race supervision and their potential role in mitigating initial productivity imbalances between male and female students. Additionally, our results suggest that if intervention is to be aimed at closing the gap, there are specific parts of the productivity distribution that should be targeted. The "strongest" and "weakest" students show no productivity gaps across gender, so interventions targeting the "productive but not super-productive" are likely to be more effective and efficient than targeting the entire population. Hopefully, addressing productivity gender differences at the Ph.D. level would increase the proportion of female professors in the population and create an inclusive and productive working environment for all. A similar goal, in turn, may create positive feedbacks, contrasting the mentioned negative lock-in effect generated by early career productivity imbalances which constrain the career of African woman in STEM.

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Appendix Table A1

	ALL	WW	BB	BW	POISSON	PUBLISHED	LOGIT
StudFemale_AdvFemale	-0.128	-0.0758	-0.541	-0.142	-0.339	-0.126	-1.531**
	(0.0663)	(0.0811)	(0.325)	(0.120)	(0.227)	(0.0958)	(0.491)
StudFemale_AdvMale	-0.130**	-0.125*	-0.239*	-0.132	-0.418**	-0.143*	-0.818*
	(0.0447)	(0.0596)	(0.109)	(0.0887)	(0.151)	(0.0588)	(0.385)
StudMale_AdvFemale	-0.0428	-0.0162	0.234	-0.0977	0.0319	-0.00192	-0.187
	(0.0633)	(0.0965)	(0.178)	(0.101)	(0.220)	(0.0804)	(0.498)
More Adv.	0.0512	0.143*	0.122	-0.129	0.0490	-0.0441	1.007*
	(0.0482)	(0.0689)	(0.128)	(0.0756)	(0.151)	(0.0564)	(0.428)
Adv. Log Average Previous Productivity	0.0346	0.0575	-0.0715	0.110	0.124	0.146***	-0.434*
	(0.0225)	(0.0302)	(0.0421)	(0.0589)	(0.0760)	(0.0356)	(0.205)
Adv. NRF Ratings	-0.00418	-0.0116	0.0154	-0.00864	-0.00608	-0.00316	-0.0169
	(0.00621)	(0.00750)	(0.0146)	(0.0162)	(0.0249)	(0.00889)	(0.0515)
Stud. Published Previously	0.760***	0.790***	0.500***	0.785***	1.558***	0.252***	8.390***
	(0.0486)	(0.0650)	(0.135)	(0.0982)	(0.125)	(0.0531)	(0.762)
Average Scimago Journal Ranking	0.0551*	0.0477	0.0958	0.0621	0.180**	0.0954**	-0.255
	(0.0240)	(0.0339)	(0.0763)	(0.0342)	(0.0575)	(0.0301)	(0.141)
Time to Graduation	-0.0470***	-0.0486**	-0.0704	-0.0196	-0.151***	-0.0988***	0.0132
	(0.0133)	(0.0180)	(0.0459)	(0.0241)	(0.0431)	(0.0169)	(0.111)
Number of Adv. Stud	0.0566***	0.0607***	0.0634***	0.0626***	0.126**	0.0526***	0.483***
	(0.00815)	(0.0145)	(0.0145)	(0.0179)	(0.0459)	(0.0127)	(0.0872)
Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enrolment Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes	No	No	No
N	5115	2635	877	1421	5115	1975	5115

Note: Robust Standard errors Clustered at Student id level are in parenthesis
Significance code: * p<0.05 ** p<0.01 *** p<0.001

Where column (1) is the estimation in the whole sample column (2) is the sub-sample White Students with White Professors; column (3) is the sub-sample Black Students with Black Professors; column (4) is the sub-sample Black Students with White Professors, and column (6) is the estimation excluding zeros. Column 1-4 additional controls for institutions. Column (5) is a Poisson Panel Regression with robust clustered standard error. The dependent variable is the number of publications of the student between the period t and t+2. Column (7) is a Logit Panel Regression with robust clustered standard error. The dependent variable is a dummy, equal to one if the number of publications of the student between the period t and t+2 is greater than zero and zero otherwise

Appendix Table A2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Percentiles				
	25th	*50th*	*70th*	*75th*	*80th*	*85th*	*90th*	*95th*	*99th*
StudFemale_AdvFemale	8.38e-16	6.87e-15	-0.175*	-0.246***	-0.303***	-0.385***	-0.367***	-0.231	-0.0397
	(0.00661)	(0.00928)	(0.0703)	(0.0727)	(0.0817)	(0.105)	(0.101)	(0.181)	(0.0618)
StudFemale_AdvMale	1.33e-15	2.61e-15	-0.119	-0.169**	-0.191*	-0.236*	-0.231*	-0.180	-0.240***
	(0.00493)	(0.00734)	(0.0637)	(0.0622)	(0.0814)	(0.102)	(0.107)	(0.135)	(0.0554)
StudMale_AdvFemale	1.05e-15	4.58e-15	-0.133	-0.173	-0.145	-0.188	-0.182	-0.0926	-0.0896
	(0.00652)	(0.00951)	(0.0803)	(0.0948)	(0.100)	(0.120)	(0.117)	(0.112)	(0.0878)
More Adv.	-2.53e-15	1.29e-15	0.0141	0.0202	0.0274	0.00420	0.0144	-0.00600	-0.261***
	(0.00543)	(0.00838)	(0.0465)	(0.0575)	(0.0717)	(0.111)	(0.0857)	(0.0958)	(0.0588)
Adv. Log Average Previous Productivity	2.66e-15	1.73e-16	0.0976**	0.128**	0.152***	0.192***	0.221***	0.243***	0.185***
	(0.00299)	(0.00452)	(0.0329)	(0.0413)	(0.0457)	(0.0532)	(0.0544)	(0.0594)	(0.0279)
Adv. NRF Ratings	-2.17e-18	-1.84e-16	0.00521	0.00819	0.00754	0.00601	0.00402	0.00866	0.00513
	(0.000673)	(0.00102)	(0.00711)	(0.00817)	(0.00987)	(0.0153)	(0.0157)	(0.0137)	(0.00720)
Stud. Published Previously	0.462***	0.847***	0.941***	0.885***	0.818***	0.767***	0.799***	0.796***	0.782***
	(0.0411)	(0.0628)	(0.0787)	(0.0779)	(0.0910)	(0.109)	(0.0972)	(0.149)	(0.0382)
Average Scimago Journal Ranking	0.124***	0.346***	0.482***	0.514***	0.492***	0.500***	0.398***	0.443***	0.292***
	(0.0334)	(0.0521)	(0.0651)	(0.0708)	(0.0841)	(0.118)	(0.0857)	(0.122)	(0.0623)
Time to Graduation	1.03e-15	7.90e-16	-0.0108	-0.0197	-0.0377	-0.0528*	-0.0956***	-0.131***	-0.186***
	(0.00151)	(0.00244)	(0.0164)	(0.0198)	(0.0211)	(0.0212)	(0.0229)	(0.0299)	(0.0106)
Number of Adv. Stud.	1.06e-16	3.16e-15	-0.00295	-0.00881	-0.0151	-0.0110	-0.0120	0.000487	-0.0114
	(0.00107)	(0.00160)	(0.0143)	(0.0164)	(0.0188)	(0.0280)	(0.0288)	(0.0299)	(0.00772)
Field	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enrolment Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5115	5115	5115	5115	5115	5115	5115	5115	5115
R^2	0.290	0.271	0.323	0.329	0.335	0.333	0.331	0.318	0.224

Note: Robust Standard errors Clustered at Student id level are in parenthesis
Significance code: * p<0.05 ** p<0.01 *** p<0.001

Endnotes

1 Data from Department of Higher Education and Training, available at available at https://www.heda.co.za/PowerHEDA/dashboard.aspx, accessed January 2023.

To compare, Italy, with the same population, granted 31,500 Ph.D.s in 2020:

https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:Number_of_tertiary_education_students_by_sex_and_level_of_education,_2020_(1_000)_ET2022.png

2 For a further discussion on the South African system see Rossello (2021), and the report Mouton et al. (2015)

3 https://www.heda.co.za/PowerHEDA/dashboard.aspx, accessed January 2023.; based on data from the Ministry of Higher Education and Training.

4 https://businesstech.co.za/news/finance/293800/university-fees-2019-how-much-it-costs-to-study-in-south-africa/ , accessed May 9, 2022.

5 https://www.imf.org/en/Countries/ZAF#countrydata, accessed May 5, 2022.

6 For details see https://en.wikipedia.org/wiki/Rhodes_Must_Fall. Last access December 2021

7 For details, see https://en.wikipedia.org/wiki/FeesMustFall. Last access December 2021

8 Those protests took place in Oxford (UK), University of Edinburgh (UK), Harvard (USA), University of California (USA), Berkeley (USA), University of Cambridge (UK).

9 For details see https://harvardpolitics.com/rhodes-must-fall/

10 National Research Foundation (NRF) is a South African state agency whose mission is the promotion of research and the development of national research capacity. It administers a rating system which has five broad categories ranging from A – Leading international researchers to B – Internationally acclaimed researchers to C – Established researchers to P – Prestigious Awards; and Y – Promising young researcher (the first three of which have also a finer grained category). These ratings are based on the reports written by a group of usually five or six international experts in the scholar's field that have read the publications submitted by the candidate. Additional details of the rating process are available at https://www.nrf.ac.za/rating/. Last accessed January 2023.

11 Our study sample composition by race and gender of Ph.D. students and advisors in our study period is close to that of the academic system as a whole. See Rossello and Cowan (2019).

12 The group of White females (Stud_Female White) with Black advisors (Adv_Male Black and Adv_Female Black) is an exception, with a higher productivity than when they work with White Advisors (Adv_Male White and Adv_Female White). However, the difference cannot be statistically significant, since the first group has only 18 observations, while the second as 241 observations.

13 The five fields are: Technologies and applied sciences, Physical sciences, Medical science: basic, Earth and marine sciences, Engineering.

14 As a robustness check we estimated a Poisson Panel Regression with the PhD. number of published articles instead of productivity. This is reported in the Appendix Table A1 column 5.

15 Overall 28% of male students have already published before starting the Ph.D., while for female students this percentage is 25%. In a developing context this is not surprising: many of the persons starting a Ph.D. have already a faculty appointment, and they undertake a doctoral education as part of an effort to advance in their careers.

16 We considered lagged publication quality to account for endogeneity issues. Journal publication is often single blinded and sometimes editors and referees might want to create a follow-up on a specific subject in the journal. This implies that the first publication in a journal attracts in the short-run subsequent publications of similar articles by the same author. Our lagged variable accounts for this. We additionally run the analysis considering non lagged *Average Scimago Journal Ranking* thus a variable simultaneous with productivity.

To construct this variable, we scraped the website of the Scimago Journal Rank (https://www.scimagojr.com/) starting from the journal names in our publication data, downloading for each item the corresponding Scimago Journal Rank for the period 1999-2021. We then matched each article with its corresponding yearly Scimago Journal Ranking, obtaining a time-dependent journal quality assessment.

We found that the quantile regression results and OLS results of the sub-sample of WW and BB are identical. These results are available upon request. To construct this variable, we scraped the website of the Scimago Journal Rank (https://www.scimagojr.com/) starting from the journal names in our publication data, downloading for each item the corresponding Scimago Journal Rank for the period 1999-2021. We then matched each article with its corresponding yearly Scimago Journal Ranking, obtaining a time-dependent journal quality assessment.

[17] This is the log of (1+ the lagged cumulative average productivity of advisor). The average cumulative number of papers is computed since the year of the first record in the publication data to t-1 and divided by the number of years of advisor's scientific activity.

[18] The maximum number of Ph.D. student advisors is 3 and one third of them has more than one. In our data we consider only the student's main advisor but we use this dummy as proxy for team size.

[19] We also account explicitly for the institutional segregation inherited from apartheid in Appendix Table A1.

[20] For the estimation we use robust clustered standard errors to account for heteroscedasticity and intra-cluster correlation as described in Machado et al. (2011).

[21] We should be very circumspect here. While in either same-race group the differences in coefficient estimates (FF versus FM) are relatively large, (those for FM being 3 or 4 times as large as that for FF), the two estimates are not statistically significantly different from each other, based on a post estimation Wald test on the difference between the two coefficients. This observation is not inconsistent, though, with the former being different from MM and the latter not.

[22] Interestingly, female students are split almost 50-50 between the groups that show gender gaps and those that do not.