# Collaboration and Gender in Science: Evidence from STAR METRICS Data ${ }^{1}$ 

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Teams have been shown to affect productivity, be it that of soccer players, supermarket checkers, or fruit pickers. Science is no exception (Jones et al., 2008). In science, however, much of the study of teams has focused on the interactions of Principal Investigators in publications and patents. Yet scientific teams are largely populated by graduate students and postdoctoral fellows (Black and Stephan, 2010), an increasing proportion of whom are female. Understanding how graduate students and postdoctoral fellows participate in research teams is important because it sheds light on an additional dimension of productivity: a trainee's work on a research team reflects an implicit contract with a university in which she works with faculty to produce research at the same time that she learns by doing. Thus, knowledge is disseminated not

[^0]only through publication and patents, but also through the learning and subsequent placements of the trainees.

Despite the important role that teams play in both producing science and in training the next generation of scientists, our understanding of the effect of teams on productivity mostly concern the analysis of patterns of co-authorship on papers and co-invention on patents (Azoulay et al., 2010; Wuchty et al., 2007). The examination of these after-the-fact collaborations limits the analysis; individuals who do not publish or patent are analytically invisible. And, even though women have been participating in science in increasing numbers, we know very little about how the gender composition of scientific teams affects productivity and virtually nothing about how the gender composition of teams relates to the productivity of graduate students. Yet the little research that there is suggests that a relationship may exist, although the evidence as to its direction of the relationship is mixed. Apesteguia et al., for example, find that groups composed exclusively of women underperform groups of other gender configurations in terms of performance (Apesteguia et al., 2012) while Woolley et al.’s research suggests that the presence of women increases productivity through an increase in collective intelligence (Woolley et al., 2010). Work by Fox and Fonseca finds the productivity of male advisors to be an increasing function of the number of male students they work with(Fox and Fonseca, 2006).

In this paper we examine how the productivity of graduate students relates to: (1) their gender; (2) the gender composition of the team and (3) the gender of the advisor. We focus on graduate students, given the key role that productivity at the time of training plays in subsequent placement outcomes and career trajectories. We examine the role of gender by making use of STAR METRICS data that enables us to construct detailed measures of teams at the project level and which includes data on trainees. The particular dataset is derived from detailed payroll data
of an elite U.S. university. It captures longitudinal quarterly data on all individuals (and their occupations) who were paid on federal grants for the period 2000-2012. The data also enable us to generate direct measures of research productivity by linking the personnel records to subsequent research outcomes. ${ }^{3}$

## SAMPLE AND VARIABLES

We study graduate students in ,biology, chemistry, engineering, geology, mathematics and physics ) who received their PhD by 2012 and who were supported on one or more federal grants for a month or longer. All told we have 8,697 student-year observations for 1,654 unique students.

We are able to capture data on team collaborations in two ways. First, because we are able to observe all individuals paid on all federally funded grants, we can observe which grants each student is working on and how many other graduate students and postdoctoral fellows are working on the same grant at every time period (t) that the student is working on a grant. We can thus construct measures of team size by calculating the number of graduate students and postdoctoral researchers who are paid in years $t, t-1, t-2, t-3$ by the principal investigators on

[^1]whose grants the focal student is supported in time t . Second, since we have information on all graduate student dissertations, we are able to link students to their advisors.

We are also able to determine the gender of almost all individuals in the dataset, and thus construct a measure of the gender composition of each team. We use a two-pronged approach to determine gender. First we match the first name and approximate date of birth to Social Security Administration data to determine the probable gender. Second, and for the instances where we cannot determine gender using this method (often because the trainee has an Asian name not contained in the Social Security records) we searched the university website to visually determine the gender of the individual. ${ }^{4}$ Among the 1654 student/advisor pairs of our study sample, 77 (4.6\%) have a female student and female advisor and 1,065 (64.4\%) a male student and male advisor, while 118 (7.1\%) have a male student and a female advisor and 394 (23.8\%)a female student and a male advisor.

The share of women on the team is calculated as the percent of the team, as defined above, who are women, excluding the focal student. While the average proportion of females was $28 \%$, there is substantial variation in the proportion of women in the team. Some teams had no women; others consisted of all women. However, $90 \%$ of teams had more males than females.

The picture of collaboration is not static. PhD recipients on average were supported on 3.6 grants during the course of their training. The size of the team with which they worked in any given year varied substantially - from single person teams to teams with almost 500

[^2]participants; the median team size was 38 . Although many measures of productivity are possible, and in later work we will explore placement outcomes, as well as career trajectories, in this paper we use a generally accepted measure of research productivity: we count the number of publications each student coauthors with a senior researcher (either their advisors and/or a faculty member who was associated with any grant on which they were supported while in graduate school). We measure the average number of articles published over the two years $\mathrm{t}+1$ and $t+2$, in order to smooth the time profile of student publication from changes which could result from adopting an exact one year publication lag. While the average number of publications over the two year period relative to the base period $(\mathrm{t})$ is .81 , with a standard deviation of 1.23 , no publications are observed in about $44 \%$ of the observations .

## Results

Regression results are presented in Table 1. Our dependent variable is the log of publications. ${ }^{5}$ Our key right hand side variables of interest are gender, the size and gender composition of the team, the gender of the advisor, and interactions between these variables and the gender of the student. We also include a dummy variable to capture when the student is working on a grant without other graduate students/doctoral fellows (i.e. no team). We include a dummy variable indicating whether the student had at least one publication or not during their first year of study in order to proxy for her iniatial productivity. This is preferable than using

[^3]fixed effects which would also proxy for all time invariant variables (such as gender) and would also take out too much variability from the dependent variable.

We are fortunate to be able to control for many factors which might confound the analysis. The effect of differential access to resources and quality of the training environment is muted because we are examining data for one highly elite university. We include controls for the number of years it takes to earn the PhD, and the discipline of the student. Since we have data on the advisor, we also control for the advisor's productivity and experience by including the moving average, centered on time $t$, of the number of theses that the advisor has supervised, the moving average of the number of grants the advisor has and the moving average of the number of articles that the advisor has published ${ }^{6}$. It is well known that the number of publications varies substantially by field of study; we control for this by means of dummy variables for the major fields - Biology, Chemistry, Geology, Mathematics and Physics.

Our central finding is that women graduate students publish approximately 4.6 percent fewer papers than do men (column 1). The variable is significant at the 1 percent level. The gender effect is minimal compared to the average of 19.6 percent reported by Cici et al. ${ }^{7}$ We find that male students who write with a female advisor publish 5.2 percent more than those who write with male advisor (column 2). There is no evidence that the premium is shared by women students.

We also find significant effects related to the gender composition of the team. In particular, a ten percent increase in the share of females on a team is associated with a 1.7

[^4]percent increase in publications (column 3). The variable is significant at the 1 percent level. We find no evidence to suggest that the benefits to working with teams populated by women are shared differentially by gender. We find that research productivity is negatively and significantly related to the size of the team and to working alone (column 5). We note that the benefits to working with female teams are cut approximately in half once we control for team size and whether the individual works alone (column 5). We find no evidence that there is a diminution in productivity for women who work alone (column 6). Students who publish their first year in graduate school are more productive and publications increase up to the fourth year in the program. Compared to engineers, students in biology, math and "other" fields publish less.

Some of the effects we observe may be due to individuals working on very large grants and with very large teams. In order to further investigate this possibility, we re-estimate the model reported in column 6 , limiting the measure of team size and team composition to teams supported on grants of $\$ 500,000$ or less. We report the results in column 7. We find the positive effects of having a female advisor and working with a team populated with women persist after we eliminate teams supported on extremely large grants. We also find that the team effect is not shared by women. Indeed, the interaction term, which is significant at the 5 percent level, indicates that there is a substantial productivity reduction if women work with other women. We find, however, that there is no apparent diminution in productivity for women who work alone.

Table 1: Selected Regression results: Dependent Variable log of Publications

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Female advisor |  | 0.052*** |  |  |  | 0.041*** | 0.035** |
|  |  | (0.019) |  |  |  | (0.016) | (0.015) |
| Female student | $-0.046 * * *$ | -0.046*** |  | -0.032* | -0.027 | -0.013 | 0.0057 |
|  | (0.011) | (0.012) |  | (0.019) | (0.019) | (0.025) | (0.030) |
| Female student and |  | -0.015 |  |  |  |  |  |
| female advisor |  | (0.031) |  |  |  |  |  |
| Share of females in |  |  | 0.17*** | 0.20*** | 0.11*** | 0.11*** | 0.11** |
| the team |  |  | (0.028) | (0.034) | (0.039) | (0.041) | (0.046) |
| Female student * |  |  |  | -0.071 | -0.076 | -0.12 | -0.20 ** |
| Share of females in |  |  |  |  |  |  |  |
| the team |  |  |  | (0.058) | (0.058) | (0.071) | (0.081) |
| Dummy no team |  |  |  |  | -0.16*** | -0.15*** | -0.062** |
|  |  |  |  |  | (0.023) | (0.025) | (0.025) |
| Female student * |  |  |  |  |  | -0.035 | -0.052 |
| Dummy no team |  |  |  |  |  | (0.038) | (0.033) |
| Log(team size) |  |  |  |  |  |  | 0.018** |
|  |  |  |  |  | (0.0045) | (0.0045) | (0.0089) |
| PhD years | yes | yes | yes | yes | yes | yes | yes |
| Discipline | yes | yes | yes | yes | yes | yes | yes |
| Advisor's |  |  |  |  |  |  |  |
| productivity and | yes | yes | yes | yes | yes | yes | yes |

experience

| Constant | $0.37 * * *$ | $0.37^{* * *}$ | $0.32^{* * *}$ | $0.33^{* * *}$ | $0.41^{* * *}$ | $0.40^{* * *}$ | $0.37 * * *$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $(0.015)$ | $(0.015)$ | $(0.016)$ | $(0.017)$ | $(0.022)$ | $(0.022)$ | $(0.027)$ |
| Observations | 8,697 | 8,697 | 8,697 | 8,697 | 8,697 | 8,697 | 8,697 |
| R-squared | 0.160 | 0.161 | 0.162 | 0.164 | 0.169 | 0.169 | 0.176 |

## CONCLUSION

This paper uses new data at the project level to examine the effects of gender - that of the individual, her team and her advisor - on the research productivity of a graduate student. We find the direct relationship between gender and publications to be modest: women PhD students write approximately $5.0 \%$ percent fewer papers than their male counterparts during their doctoral studies. This is approximately 75 percent less than the gender differential of $20 \%$ that has recently been reported among faculty (Ceci et al., 2014). But this does not mean that gender does not play a distinctive role. Indeed, we find that students who work with a female advisor and who participate in female intensive teams populated by other students and postdoctoral researchers are significantly more productive in terms of publications.

Several caveats accompany our research. First, we measure team size by counting the number of postdoctoral researchers and graduate students supported on grants on which the student worked. This undercounts team size, since it excludes other members of the team such as staff scientists and technicians. Second, we only attribute publications to a student if they are shared with a faculty member; sole-authored papers or those co-authored with other students or faculty who do not support students on grants are excluded. Third, our results are for an elite institution and are not necessarily generalizable to other institutions. Finally, we only use one measure of research productivity - publications. Richer measures, such as job placements and
career trajectories are currently being developed. We hope that other researchers will take up the issue of gender differences among doctoral students; STAR METRICS data, including links to Census data on placement and earnings, will become available to the research community through the new Institute for Research on Innovation and Science at the University of Michigan and through Census Research Data Centers.

## REFERENCES

Apesteguia, J., Azmat, G., Iriberri, N., 2012. The impact of gender composition on team performance and decision making: evidence from the field. Manage. Sci. 58, 78-93.

Azoulay, P., Graff Zivin, J., Wang, J., 2010. Superstar Extinction. Q. J. Econ. 125, 549-589.
Black, G., Stephan, P.E., 2010. The Economics of University Science and the Role of Foreign Graduate Students and Postdoctoral Scholars., in: Clotfelter, C. (Ed.), American Universities in a Global Market. University of Chicago Press, Chicago, p. 12961.

Ceci, S.J., Ginther, D.K., Kahn, S., Williams, W.M., 2014. Women in academic science: Explaining the gap. Psychol. Sci. Public Interes.

Fox, M.F., Fonseca, C., 2006. Gender and mentoring of faculty in science and engineering: individual and organizational factors. Int. J. Learn. Chang. 1.

Jones, B.F., Wuchty, S., Uzzi, B., 2008. Multi-university research teams: Shifting impact, geography, and stratification in science. Science (80-. ). 322, 1259-1262.

Lane, J., Owen-Smith, J., Rosen, R., Weinberg, B., 2013. New Linked Data on Science Investments, the Scientific Workforce and the Economic and Scientific Results of Science.

Weinberg, B.A., Owen-Smith, J., Rosen, R.F., Schwarz, L., Allen, B.M., Weiss, R.E., Lane, J., 2014. Science Funding and Short-Term Economic Activity. Science (80-. ). 344, 41-43.

Woolley, A.W., Chabris, C.F., Pentland, A., Hashmi, N., Malone, T.W., 2010. Evidence for a collective intelligence factor in the performance of human groups. Science (80-. ). 330, 686-688.

Wuchty, S., Jones, B.F., Uzzi, B., 2007. The Increasing Dominance of Teams in Production of Knowledge. Science (80-. ). 316, 1036-1039. doi:10.1126/science. 1136099


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[^1]:    ${ }^{3}$ The STAR METRICS data draws transaction data from the Human Resources system in each research institution to capture on a monthly or quarterly basis, the universe of individuals (Principal Investigators (PIs), co-PIs, postdoctoral researchers graduate and undergraduate students, lab technicians, staff scientists, science administrators, etc.) paid from all federal grants. Earlier success with the U.S. Longitudinal Employer-Household Dynamics Program (LEHD) have demonstrated the value of using payroll records as a source for administrative data, and served as a model for the design and development of STAR METRICS (see Lane, Owen-Smith, Rosen, \& Weinberg, 2013; Weinberg et al., 2014 for a more detailed discussion).

[^2]:    ${ }^{44}$ We were not able to determine the gender of $4 \%$ of trainees and $2 \%$ of advisors; these were excluded from the study sample.

[^3]:    ${ }^{5}$ Specifically, the left hand side variable is the $\log (1+$ average number of articles in $t+1, t+2)$. The results are substantially unchanged if we restrict the time period to year $t+1$, or expand it to year $t, t+1$ and $t+2$, if we use a Poisson regression, and also if we exclude from the sample those observations with no publications.

[^4]:    ${ }^{6}$ In the interest of conserving space, we do not report regression coefficients for these variables.
    ${ }^{7}$ The result is based on self-reported publications for the previous five years for data collected in 2008.

