An Advisor like me? Advisor Gender and Post-graduate Careers in Science

By Patrick Gaule and Mario Piacentini*

February 10, 2018

We investigate whether having an advisor of the same gender is correlated with the productivity of PhD science students and their propensity to stay in academic science. Our analysis is based an original dataset - combined from dissertation abstracts, faculty directories and bibliometric data - covering nearly 20,000 PhD graduates and their advisors from U.S. chemistry departments. We find that students working with advisors of the same gender tend to be more productive during the PhD; and that female students working with female advisors are considerably more likely to become faculty themselves. We suggest that the under-representation of women in science and engineering faculty positions may perpetuate itself through the lower availability of same-gender advisors for female students.

Keywords: Gender, Role models, Universities, Doctoral research

JEL Codes: O32, J16

* Patrick Gaule, Department of Economics, University of Bath, Claverton Down, Bath BA2 7AY, United Kingdom and CERGE-EI, a joint workplace of Charles University and the Economics Institute of the Academy of Sciences of the Czech Republic, Politických vězňů 7, 111 21 Praha 1, Czech Republic (patrickgaule@gmail.com); Mario Piacentini, Organisation for Economic Co-operation and Development (OECD), 2, rue André Pascal 75775 Paris Cedex 16, France (Mario.Piacentini@oecd.org).

1. Introduction

In the United States, women obtain half of all science and engineering degrees but remain underrepresented in science and engineering occupations. As of 2012, 50% of science and engineering bachelor's degrees in the United States were granted to women, but fewer than 30% of employed scientists and engineers were female (NSF 2015). Only 20% of full science and engineering professors in U.S. universities and 4-year colleges are female (ibid.). The discrepancy between degrees and employment partly reflects demographic inertia, resulting from the past, when fewer women received science and engineering degrees (National Research Council 2001, Hargens & Long 2002). However, it is also driven by a greater propensity for women to leave science and engineering (Preston 1994, Hunt 2010).

The underrepresentation of women among science and engineering professors raise both equity and efficiency concerns. The view that men and women should be equally represented (or at a minimum that they have equal opportunities to enter) in high-status professions has gained widespread acceptance. It would particularly troubling if high exit rates of women from science and engineering were driven by unequal opportunities to succeed, or discriminatory treatment. On the efficiency side, women who leave science and engineering after completing a university degree are forgoing the returns of large human capital investments. More generally, if talent matters for the production of knowledge (Agarwal & Gaule 2017), it is important for efficiency that talented women go to, and stay in, science and engineering. Hsieh et al. (2013) observe that there has been a large secular decline in the barriers faced by women (and blacks) in the U.S. labor and education market. Based on the calibration of a Roy occupational choice model, they suggest that this decline explains 15% of the U.S. overall wage growth from 1960 to 2008.

In scientific fields where only a small minority of faculty members are female, most female students will be matched with an advisor of the opposite gender. This could contribute to a higher rate of exit for women (and hence to persistence in the underrepresentation of women in science) either through a *productivity* channel or a *preference* channel. It is possible that students may be less productive when working with an advisor of the opposite gender, for a broad set of reasons ranging from gender differences in communication and work strategies to gender-biased expectations regarding competence. The lower productivity of female scientists during graduate studies (Pezzoni et al. 2016) could then translate into higher exit rates. Alternatively (or additionally) students may have a preference for working with an advisor of the same gender. In that case, the PhD experience is less enjoyable for students with advisors of the opposite gender (Eztkowitz et al. 2010, Robinson 2011), which could lead to higher drop-out after the PhD.

A natural starting point to understand the nexus between same-gender advisors, productivity and remaining in academia is to compare the career choices and research productivity of students with or without an advisor of their same gender. This is what we do in this paper. The results show that the research productivity during the PhD, and the propensity to become faculty after graduating, are both related to the gender of the advisor. Ideally, one would want to go one step further and identify whether these relations are driven by productivity effects stemming from interactions during the PhD, or by preference effects influencing the pairing of students with advisors. This is intrinsically difficult here, as the process by which students select advisors (or advisors select students) is not a random one. Moreover, students only do one PhD (mercifully perhaps) so there is little scope for the within-student comparisons that have often been used in the economics of education (Meghir & Rivkin 2011). However – and we will expand this point later - we see these descriptive results as useful, as they imply that students whose gender is underrepresented among faculty members are less likely to remain in academia, even if the association between an advisor's gender and students' outcomes arise through sorting rather than a causal effect of same gender on productivity.

Our works sits at the confluence of two related literatures. On the one hand, there is a literature on the effect of instructor gender on student performance and major choices at the undergraduate level (Bettinger and Long 2005, Hoffman and Oreopoulous 2009, Carrell et al. 2010). Carrell et al. (2010) find that having a (randomly assigned) female instructor increases female students' performance in math and science courses, as well as the likelihood of graduating with a STEM degree. Results along similar lines, though quantitatively small, are reported in Bettinger and Long (2005) and Hoffmann and Oreopoulos (2009). On the other hand, a couple of papers investigate the link between having female dissertation chairs and initial placement for female students in economics at the PhD level. Neither Neumark and Gardecki (1998) nor Hilmer & Hilmer (2007) find any statistical difference between female students working with female advisors and female students working with male advisors in the field of economics[1].

Relatively little work has been done on the advisor gender and student outcomes for STEM PhD students. One notable exception is a recent paper by Pezzoni et al. (2016) who study productivity (but not placement) differences among Caltech PhD graduates. They find that female students with female advisors are more productive than female students with male

[1] Hale and Regev (2014) find that the share of female faculty is correlated with the share of female students in top economics PhD programs.

advisors; but male students with a female advisor are more productive than male students with a male advisor. The generalizability of these findings may be limited by the fact that they have only 25 female advisors in the sample, and all students come from a single elite institution.

This paper fills a gap in this literature by focusing on the relationship between the advisors' gender and the academic outcomes of PhD students in science. Both the subject (whether it is male-dominated, such as mechanical engineering, or more gender-balanced, such as social sciences) and the study level (high school, undergraduate or PhD) may be important mediators of the link between a professor's gender on students' outcomes. Our analysis is based on an original dataset covering nearly 20,000 PhD graduates and their advisors, from U.S. chemistry departments. We measure productivity during the PhD by a quality-weighted count of publications; and proxy remaining in academic science by the likelihood of becoming faculty in a U.S. PhD-granting chemistry department.[2] We regress these two outcomes on an indicator variable for having an advisor of the same gender. We do this separately for male and female students. The richness of our data allows us to control for a set of advisor characteristics, including age and productivity.

We first document that female students are considerably more likely to be advised by female advisors than male students. We then report that students with advisors of the same gender tend to be more productive during the PhD than students with advisors of the opposite gender. The

[2] The competition for faculty positions in chemistry is intense given that the number of doctoral students far exceeds the number of new faculty openings, and virtually all new faculty hires have been through several years of postdoctoral training. We estimate that fewer than 5% of chemistry PhD students of either gender eventually become faculty in a U.S. PhD-granting chemistry department.

difference is quantitatively modest (with point estimates corresponding to a difference between 10% and 20%) and is more robust for male students than for female students. However, we find quantitatively large effects on placement limited to women: female students with female advisors are more than 50% more likely to become faculty themselves than female students with male advisors.[3]

In light of the literature on female instructors and STEM students, it seems plausible that having an advisor of the same gender may have a causal effect on graduate student productivity and the likelihood of becoming faculty. Alternatively the positive correlation between having a female advisor of the same gender and productivity/becoming faculty may reflect the sorting of more talented and academically oriented students to advisors of their same gender. In the latter case, one would expect that having more female faculty would enable departments to recruit more and better female doctoral students. While the relative importance of these "productivity" or "preference" effects of gender-pairing cannot be disentangled with our data, our results suggest that the underrepresentation of women among faculty members might influence the PhD experience of female students and might thus play a role in the propensity of female students to drop out of science and engineering.

The rest of this paper proceeds as follows. Section 2 briefly reviews the literature on the influence of gender on students' selection of a research team and on the quality of their PhD

[3] Only 2.8% of female doctoral students in our sample become faculty in a research-intensive U.S. chemistry department. Our point estimate for having a female advisor is 1.9 percentage point which corresponds to a 67% (=1.9/2.8) relative increase. We conduct robustness checks using a broader definition of staying in academia.

experience. Section 3 describes the data. Section 4 presents the empirical strategy and the findings. Section 5 concludes.

2. Framing the issue: how gender can influence students' doctoral experience and matching to research teams

How cognitive and behavioral differences between men and women intertwine with social forces to determine career outcomes is a subject of spirited debate (Carrell et al. 2010). Differences by gender in access to academic jobs are particularly large in science, and part of these differences might be rooted in early career choices, such as the selection of the research laboratory for the PhD. Several qualitative studies emphasize that male and female students often have different concerns and expectations as they approach their doctoral studies, and can be influenced by different factors when they decide which research team they want to join (Kemelgor and Etzkowitz, 2001). When students choose their advisors and lab more generally, they may want to maximize their productivity and postgraduate scientific careers opportunities. But they may also value having a pleasant work experience during the PhD. Similarly, advisors are likely to select students they expect to be productive and with whom they have a good social affinity.

Faculty members play a critical role in the socialization process of PhD students and their development of feelings of belonging to academia (Sallee, 2014). During their training, students learn not only the direct knowledge related to their field, but also the culture and the behaviors associated with success in their particular sphere of academia, reformulating their self-image, attitudes, and expectations (Austin 2002). Students who have positive relationships with their advisors have smoother trajectories through their graduate programs and develop higher expectations of success in academia (Golde, 1998). A caring and supportive advisor might be particularly important for young female scientists to acquire professional role confidence, defined as individuals' confidence in their ability to successfully fulfill the roles, competencies, and identity features of a profession (Cech et al., 2011). Using a longitudinal sample of engineering students, Cech et al. (2011) show that women's lack of this confidence, compared to men, reduces their likelihood of remaining in engineering majors and careers. Problematic relationships with advisors instead play a significant role in students' decisions to leave their doctoral programs and exit science (Golde, 2000). One of the largest qualitative reviews of the graduate experience in science was conducted by Etzkowitz et al. (2000), who interviewed over four hundred male and female postgraduates and faculty members across five scientific disciplines. Their study concludes that women are much less likely to have a positive doctoral study experience than men. Anxiety, feelings of helplessness, social exclusion as well as incidents of overt gender bias are often mentioned as serious hurdles the female graduates have to overcome to achieve academic status (Etzkowitz et al. 2010, Robinson 2011). These feelings are more common in more male-dominated disciplines, and in prevalently-male research groups (Hirshfield, 2017, Newsome 2008). Female students who anticipate that their life experience as PhD students is going to be more difficult in male-dominated environments may be expected to choose to work in a lab that is either led by a woman or has a strong representation of women.

Hirshfield (2010) argued that women's hypervisibility in male-dominated STEM fields, together with negative stereotypes about women in science (a consequence of the intensely 'masculine' culture of science departments), produces an identity threat – a concern that their perceived weaknesses are attributed both to themselves and to women as a group. In response, women seek out ‘friendlier,’ less identity-threatening environments, thereby clustering together in female-dominated work spaces. This perception might be reinforced by stereotypes or implicit biases against women in science. Moss-Racusin et al. (2012) sent science faculty members identical resumes for a laboratory manager position in which only the name and gender of the applicant were changed. The applicant with the male name was judged to be more competent and hireable and offered a larger starting salary than the female applicant. Female faculty were just as likely as male faculty to express an unintended bias against female students. In another experiment conducted by Milkman et al. (2014), professors at top U.S. universities were contacted by fictional prospective students seeking to discuss research opportunities prior to applying to a doctoral program. Faculty members were significantly more responsive to male students. Even if the landscape for women in science is changing, and direct discrimination in academic evaluations and selections is probably less important than in the past (Ceci et al. 2014), more subtle biases against the capacities of women to reach excellence in science might be fading more slowly. For example, Leslie et al. (2015) show that women are underrepresented in fields whose practitioners believe that raw, innate talent is the main requirement for success, because women are stereotyped as less likely to possess such talent.

Even in the absence of any discrimination against women, female scientists might opt out from male-led laboratories and from an academic career in science because their preferences and values differ from those of their male colleagues. The early career track in science typically involves long hours, intense competition and relative uncertainty about future placement, all of which may be less appealing to women. Women’s traditional responsibilities as caregivers can make female students perceive that they are less fit than male students to a work in an environment requiring total allegiance and dedication (Blair-Loy, 2003; Ceci and Williams, 2011). Female PhDs frequently cite marriage and childbirth as reasons to opt out of scientific careers (Goulden et al. 2011). Regarding competition, Buser et al. (2014) show that gender differences in willingness to compete account for a substantial portion of the gender difference in track choices for secondary school students in the Netherlands. Schiebinger (1999) found that women in science often see their working environment as highly competitive and rife with 'macho-ness'. While this culture of competition may be uncomfortable for both men and women, women may be more likely to fall victim to the weeding-out practices and competition in science than men because they are not socialized to be as comfortable with competition as men, and because this form of competition can lower their confidence (Niederle and Vesterlund, 2011). Experimental research has also shown that women tend to accept competition with other women, and to avoid competition with men (Gneezy et al., 2003; Datta Gupta et al. 2013).

These sorting processes can have durable implications on the likelihood of young scientists to remain in academia and achieve excellence as academic scientists. Female scientists are more likely than male scientists to work in smaller labs, a condition which puts them at a disadvantage in the race for grants, publications, patents, tenure, and promotions (National Research Council, 2001). Scheltzer and Smith (2014) argue that one cause of the leaky pipeline in biomedical research may be the low presence of women in high-achieving laboratories: in fact, they find that elite male faculty train significantly fewer women than other male faculty members.

3. Data

Standard sources of information on U.S. doctoral students-such as the Survey of Earned Doctorates- lack information on advisors as well as measures of student productivity. We thus assembled an original data set combining multiple sources: Proquest Dissertations and Abstracts to generate lists of students, the American Chemical Society Directory of Graduate Research for information on faculty and Scopus for publications. For students, we deduce gender from first names using a gender determination algorithm while gender is self-reported in the faculty data. Finally, we generate productivity measures by matching student names to publication data and placement measures by matching student names to the faculty data. The resulting analysis data covers nearly 20,000 PhD graduates and their advisors from U.S. chemistry departments. The rest of this section describes the data collection effort and resulting data in more detail.

We focus on chemistry for a number of reasons. First, it is a large component discipline of science, with about 30% of science PhDs graduating in chemistry. Second, this discipline is characterized by short publication cycles and an established hierarchy of journals, which enables us to measure research productivity during the PhD in a meaningful way. Third, chemistry is part of the physical science where the proportion of women among graduate students has steadily increased over time, reaching around 30% but the share of women among senior faculty members is still lower than 10% (see figure 1). As such, a focus on chemistry allows us to explore same-gender effects in a discipline where the share of women among students and potential advisors is markedly different.

(Insert figure 1 about here)

3.1. Sources and construction

Our source of information on students is Proquest Dissertations and Abstracts. This database lists dissertation abstracts, together with the names of the student and advisor, as well as the year and university of graduation. Using Proquest data, we built a list of students graduating with PhD degrees in chemistry, chemical engineering and biochemistry from U.S. universities between 1999 and 2008.[4]

We complement the data on students with data on faculty from the directory of graduate research from the American Chemical Society. Intended as a resource for prospective graduate students and published every two years, the directory lists names of faculty with gender, year of birth and education history for virtually all PhD-granting chemistry departments in the U.S. We use information from the directory (1999 to 2013 editions) in two ways. First, we match advisor names from Proquest to faculty names from the directory. This gives us information on gender and year of birth for the advisors of students in our sample. Second, we match PhD student names to faculty names from the directory, in order to determine which students become faculty.

Proquest does not list information on the gender of the student. Instead, we infer gender from first names.[5] The inference of students' gender is based on an algorithm that matches the first names of the students with an original database of around 175,000 first names defined as male or female, which expands the one used in Frietsch et al. (2009). Because of the difficulty in determining gender from Chinese and Korean first names, we exclude students with such

[4] For earlier work using this database and additional description see Gaule and Piacentini (2013).

[5] The database of names includes separate lists for specific countries, given that some names that are typically male in one country are typically female in another country. In a first iteration, we match the students' names to the list of first names for the United States, to identify the gender of all the students with a typical American name, and then match, in a second iteration, the remaining students to a larger list of international names.

ambiguous Chinese and Korean first names from the sample. We lose around 8% of students due to this restriction.

This methodology to infer gender from first names has been validated in different empirical applications (see OECD, 2012). However, we also assess its validity with scientists' names in the following manner. In the sample of chemistry advisors, we *know* the gender of advisors from the faculty directory. However, we can also use our algorithm to code their gender, and then compare the results of the algorithm to those reported in the faculty directory (which we take as the ground truth). The algorithm yields the correct gender in over 97% of cases.[6]

One of our main outcomes of interest is whether PhD students remain in academic research and become faculty members themselves. Coding this outcome using information from the faculty directory is conceptually appealing, as we are effectively measuring whether students end up in the same type of position as that which their advisors hold, i.e. a tenure-track (or tenured) appointment in a U.S. PhD-granting chemistry department. However, students could also become research academics by taking faculty positions outside the U.S. or in a non-chemistry departments, as well as non-faculty appointments in U.S. PhD-granting chemistry departments. To build a measure of becoming a research academic that encompass such positions, the only option available is to conduct manual web searches and code information from departmental websites, personal websites, LinkedIn, and similar sources. Given that collecting information this way is very time-intensive, we only collected this information for around 2,500 female students –

[6] The errors arise in a variety of ways; one of those is first names whose gender is inherently ambiguous (e.g. Kerry, Kendall or Robin).

all female students with female advisors, and a random sample of female students with male advisors.[7, 8]

Next, we match students to publication data from Scopus, one of the two major bibliometric databases (along with ISI Web of Science).[9] Our preferred productivity measure is the number of first-author papers, weighted by journal impact factor.[10] For this count we consider publications from 3 years before graduation to the year of graduation. We also match faculty to their publications, in order to build measures of productivity and specialization of advisors.

Finally, we define a set of ten elite schools based upon the 1995 ranking of U.S. chemistry doctoral programs by the National Research Council (National Research Council 1995). These are Berkeley, Caltech, Harvard, MIT, Stanford, Cornell, Illinois, UCLA, Wisconsin and Chicago.

---

[7] The search protocol to identify the placement of students is similar to that of Kahn & MacGarvie (2016) and Gaule (2014). Our research assistants were instructed to google the name of the student together with the keyword "Chemistry" and to inspect the first page of results. Once a possible match is identified, the RA was instructed to verify that it was in fact the right person (comparing the university of PhD study listed in the webpage and in our records, for instance).

[8] The fact that we sample students randomly ensures that this sample is representative of female PhD students in chemistry. An additional concern is that the limited sample size reduces statistical power, but we note that the current manual sample is half the size of the population and we obtain results that are significant at conventional levels even with the limited sample size.

[9] We match using last names, first initial and middle-initials, university and affiliation; as well as the advisor being one of the coauthors. In chemistry, PhD students are not expected to write papers independently; instead they almost invariably coauthor with a faculty member, typically their PhD advisor.

[10] The first authorship spot is highly meaningful in the life and physical sciences and is typically given to the junior scholar who has made the largest contribution to the paper. Weighting by journal impact factor is a standard way of (roughly) accounting for the quality of the paper. We obtain similar results when weighting for citations instead of journal impact factors.

3.2. Descriptive statistics

Our sample covers 19,335 students graduating with PhD degrees in chemistry from U.S. universities between 1999 and 2008.[11] Around 30% of students and 12% of advisors in our sample are female. Hence, the vast majority of male students have an advisor of the same gender, while only a small minority of female students are in this position. Female students are more likely to have female advisors (14%) than male students (9%) (cf table 1). Female students are similarly represented in the top 10 departments in terms of research productivity as in other less research intensive departments (table 3).

[Insert table 1, 2 and 3about here]

In terms of career outcomes, around 4% of students become faculty in a U.S. PhD-granting chemistry department (see table 2). This low number reflects how difficult it is to make an academic career in chemistry (as well as in the life and physical sciences more generally); however, one should also keep in mind that this percentage does not include placements in non-chemistry departments, department outside the U.S., or non-PhD granting departments. In the manually coded subsample of 2500 female students, we have about 20% of students who became research academics (which we define more broadly as any appointment in a research-intensive university as of January 2014).

In table 3 we report descriptive statistics across the four types of gender pairings between students and advisors. Students of both gender are more productive during the PhD and more

[11] Our sample is not far short ofthe population: NSF statistics indicates that there were 21,112 (NSF 2009: p141) doctorate recipients in chemistry from U.S. universities for the same period, 1999-2008.

likely to become faculty when paired with an advisor of the same gender. The prevalence of different types of gender pairing is similar in the elite schools and in the whole sample.

4. Empirical Specifications and Results

4.1 Empirical specifications

We have two main variables of interest – the productivity of students during the PhD and the likelihood of becoming faculty. We split the sample between female and male students and regress each dependent variable on an indicator variable for having an advisor of the same gender. While our results are qualitatively similar when pooling the sample and introducing interactions between the gender of the student and the advisor, we prefer to split the sample between female students and male students as the most straightforward and transparent way of presenting our results. Our specifications are one of the following types:

(1) $Y_{it} = \alpha + \beta^{*}\text{Female Advisor}_{it} + X_{it}\delta + \rho_t + \varepsilon_{it}$ (female students sample)

(2) $Y_{it} = \alpha + \beta^{*}\text{Male Advisor}_{it} + X_{it}\delta + \rho_t + \varepsilon_{it}$ (male students sample)

Where i indexes students; t indexes graduation years; Y_{it} is either productivity (i.e., the number of first-author papers published during the PhD, weighted by journal impact factor) or the likelihood of becoming faculty; Female Student_{it} is an indicator variable for female student; Female Advisor_{it} is an indicator variable for female advisor; Male Advisor_{it} is an indicator variable for male advisor; ρ is a set of graduation year fixed effects and X_{it} is a set of control variables.

Our control variables consist of fixed effects for the university of graduation, the area of specialization of the labs, the age of the advisor (dummies for decades), and the productivity of the advisor (indicator variables for 10 deciles of the distribution).[12] We will contrast results with and without control variables to examine whether results are sensitive to sorting of students across schools and labs. In the career regressions (with the likelihood of becoming faculty as outcome variable), we control for the productivity of students during the PhD. Given the importance of academic excellence in hiring decisions, we expect productivity during the PhD to be a strong predictor of becoming faculty. Controlling for productivity allows us to ask if having an advisor of the same gender is correlated with placement outcomes, on top of any effect that may arise from positive correlation between same-gender advisors and productivity. Productivity during the PhD is normalized in these regressions to have mean 0 and standard deviation 1 for ease of interpretation.We estimate the productivity regressions by Poisson Quasi-Maximum Likelihood and the career regressions by probit.

One important limitation of our empirical approach is that we only observe students who graduate. Our sample is thus potentially subject to sample selection if the gender pairing between students and advisors affect attrition during the PhD studies.

[12] One key determinant in the productivity of a PhD student is the quality of the advisor (Waldinger 2009), hence our control for advisor productivity and age. These are arguably two highly visible and relevant characteristics of the advisor that are likely to be related to the composition of his or her research lab. We cannot exclude, however, that other characteristics of the advisor we do not observe in our data (such as his or tenure in the current institution, or more difficult to measure character and attitudinal qualities) might also influence the pairing of students and advisors and the productivity of the research team. We attempt to further control for the quality of the environment, by including university fixed effects, and for differences across subdisciplines by controlling for the area of specialization of the lab. In our setting, we can only identify formal mentorships as reported in the students' thesis, and we cannot exclude that informal relationships with other faculty members also shape students' academic success.

4.2 Results

We first explore the relationship between having an advisor of the same gender and productivity. In the sample of female students, the point estimate for female advisor is positive, though it is only significant when we do not control for advisor characteristics (cf table 4a). The magnitude of the difference is relatively modest, with the point estimate corresponding (roughly) to a 10% or 20% difference, depending on the specification; the upper bound of the confidence interval does not exceed 30%. In the sample of male students, having an advisor of the same gender is more robustly associated with higher productivity (cf table 4b). The point estimate for male advisor is positive and significant irrespective of the choice of controls. The magnitude of the difference is comparable to that observed in the sample of female students.

[Insert table 4a and table 4b about here]

Overall we conclude that students matched to advisors of the same gender are more productive than those matched to advisors of the opposite gender. The differential productivity could be due either to the initial sorting of high ability students in laboratories run by advisors of their same gender or to a causal effect of having an advisor of the same gender on student productivity.

[Insert table 5a and 5b about here]

We examine next how the gender pairing between student and advisor affects the likelihood of becoming faculty in a U.S. PhD-granting chemistry department. Reassuringly, scientific productivity during the PhD is a strong predictor of who becomes faculty (cf table 5a and table 5b), and we control for it in all specifications. For male students, the coefficient on male advisor is positive but not significant (cf table 5b). For female students, having an advisor of the same gender is positively and significantly associated with becoming faculty (cf table 5a). The point estimate for female corresponds to a 1 or 2 percent point increase in the likelihood of becoming faculty, depending on the specification. Though that may appear in small, it is in fact considerable given that fewer than 3% of female students (and roughly 4% of male students) become faculty in our sample.[13] The magnitude of the female advisor coefficient is also comparable to a one standard deviation increase in scientific productivity during the PhD. With the caveat that this magnitude is imprecisely estimated, we note the striking correlation for female students between having an advisor of the same gender and becoming faculty.

[Insert table 6 about here]

We extend this analysis by looking separately at students in elite schools versus the rest. To do this, we split the sample into top 10 schools (as defined in the 1995 NRC ranking of chemistry PhD programs) versus not top 10 schools. We report the regressions with the full set of controls (year and school fixed effects as well as advisor characteristics) in table 6. While the results are noisy given the smaller sample size, it appears that the correlation between same gender advisor

[13] One reason the percentage is so low is that we do not observe tenure track appointment outside the United states or in non-chemistry departments; as well as postdoctoral or non-tenure track appointments. We also have some truncation bias, as some students may yet become faculty. To address these limitations, we use a different proxy for continuing in academia.

and becoming faculty is stronger in the top 10 schools, possibly reflecting a more competitive environment in these schools..

Finally, we investigate how the gender pairing affects the likelihood of female students remaining in academia after their doctoral studies, using a more comprehensive measure of academic transitions. The outcome variable in these regressions encompasses any research position in chemistry or non-chemistry departments, with or without a tenure-track appointment. Given the cost of collecting this data, results are only available for a random sample of female students.

[Insert table 7 about here]

We find that female students with female advisors are around 5 percentage points more likely to remain in academia than female students with male advisors (cf table 7). The point estimates are highly significant and very similar across the specifications with and without advisor characteristics.

5. Discussion and Conclusions

This paper investigates the relationship between having a same gender supervisor, productivity and post-graduate careers for a large sample of chemistry PhD graduates. We report that students working with advisors of the same gender tend to be more productive during the PhD; and that female students working with female advisors are considerably more likely to become faculty themselves.

Our results for PhD students in chemistry stand in contrast to earlier studies (Hilmer & Hilmer 2007; Neumark and Gardecki 1998), that found no such effects for economics PhD graduates.

However, they are in line with a series of studies (Bettinger & Long 2005, Hoffman & Oreopoulos 2009, Carrell et al. 2010, Pezzoni at al. 2016) finding that having female professors is beneficial for performance of female students in STEM fields. A candidate for explanation of that discrepancy is that that the doctoral experience and the nature of the collaboration between student and advisor is different in chemistry (and the life and physical sciences more generally) than in economics. Chemistry students typically work on research questions and projects suggested by advisors, work with equipment provided by the advisor, and are often financially supported by the grant of the advisor; none of which is common in economics. In the life and physical sciences, a student and his/her advisor can be thought of as jointly producing knowledge to a greater extent thant in economics.[14] The closer nature of the student-advisor collaboration in chemistry may potentially make the gender pairing more salient. Science may also be different from economics in terms of (masculine) culture: the cultural association between success in science and masculine traits could be a factor behind the relationship between gender pairing and career outcomes that we observe in our sample of chemistry students. However, given our focus on a single discipline –chemistry- we must remain agnostic about the existence of same-gender effects in other scientific disciplines.

We observe the fact that female students advised by a female faculty member are more likely to remain in academic science as consistent with female faculty members acting as role models for them, for instance by showing them that it is possible to successfully combine full-time careers with satisfying personal and family lives (Schlegel, 2000, National Research Council 2000). Male students have less need for role models, so their transitions to academic careers are

[14] This is reflected in authorship of papers: the vast majority of publications by life and physical science students are coauthored with the advisor; whereas in economics only a minority are.

shaped by other factors than the gender of their advisors. Besides role-model effects, this finding can also be explained by female students living a more positive doctoral experience or gaining more professional role confidence when advised by women, and thus developing during their PhD stronger preferences for continuing in academic science (Cech et al. 2011, Hirshfield, 2010).

An alternative interpretation for our findings is that they reflect sorting on ability or academic preferences. More talented female students may be more likely to match with female advisors; and more talented male students may be more likely to match with male advisors. If such sorting exists, it must reflect underlying preferences for working with an advisor of the same gender (or for working with a student of the same gender from the advisor's point a view).

We are unable to distinguish between these two interpretations; and more research into the doctoral experience of both male and female students would be useful to shed further light on the mechanisms shaping the motivations for a career in university, the choice of and the selection into different research laboratories, and the transitions out of science. However, we note that either interpretation – whether female students develop lower preferences for an academic career as they work in a research team led by a man, or whether academically-oriented female students prefer working with female advisors and compete for a limited number of places in female-led laboratories - implies that the underrepresentation of women among faculty members puts female students at a disadvantage, and hence contributes to the lower propensity for female students to remain in academia.

Limitations. The findings of our study are subject to multiple limitations. First, as already discussed, we are unable to separate a causal effect of advisor gender from selection effects. Second, we are unable to ascertain whether the selection into different types of advisors is driven by the preferences of the students, those of the advisors or possibly other factors. Third, we were able to control only for a limited set of advisor characteristics (age, productivity) while others may also be relevant. Fourth, we can only identify formal mentorships as reported in the students' thesis, and we cannot exclude that informal relationships with other faculty members also shape students' academic success. Fifth, due to the difficulty in inferring gender from names for Chinese and Korean students, we had to exclude them from the sample even though they represent a sizeable and productive part of the population of PhD students in U.S. universities (Gaule & Piacentini 2013). Students from East Asian countries may have different gender attitudes. Finally, our sample covered only chemistry students and may not extend to the rest of the life and physical sciences.

Nonetheless, our findings suggest that increasing the number of potential female advisors may increase the share of female students eventually pursuing academic careers. Hence, hiring more women faculty members may not just have a direct effect on faculty gender ratio, but also indirectly raise future female representation through influencing the career choices of female students. This provides an additional rationale for an initiative such as the creation at Princeton of a $10 million fund to hire and promote women faculty in science and engineering departments (Wilson, 2003). Another type of policy that could be considered is the provision of programs where junior female researchers receive mentoring and advice from senior female faculty members of other institutions. Such programs have been found to be effective in economics (Blau et al. 2010) and are increasingly common in science (Karukstis et al. 2010).

Acknowledgements

This project was financed by GACR grant 16-05082S. We thank Alena Bicakova, Ina Ganguli, Alexander Lembcke, Francesco Avvisati, Paula Stephan and three anonymous referees for suggestions and comments. Natalia Kobylkina and Tetiana Holets provided excellent research assistance. We are grateful to Andrew Downing of CERGE-EI's Academic Skill Center for careful professional editing. All errors are our own.

REFERENCES

Agarwal, R. & Gaule, P., 2017. Talent Matters: Evidence from Mathematics. Mimeo, University of Bath

Austin, A.E., 2002. Preparing the Next Generation of Faculty: Graduate School as Socialization to the Academic Career. The Journal of Higher Education 73(1):94–122.

Bettinger, E. P., & Long, B. T., 2005. Do faculty serve as role models? The impact of instructor gender on female students. American Economic Review, 152-157.

Blau, F. D., J. M. Currie, R. T. A. Croson, and D. K. Ginther, 2010. Can Mentoring Help Female Assistant Professors? Interim Results from a Randomized Trial. American Economic Review, 100(2): 348-52.

Buser, T., Niederle, M. & Oosterbeek, H., 2014. Gender, Competitiveness and Career Choices. Quarterly Journal of Economics, 129(3):1409-1447

Carrell, S. E., Page, M. E., & West, J. E., 2010. Sex and Science: How Professor Gender Perpetuates the Gender Gap. Quarterly Journal of Economics, 125(3), 1101-1144.

Ceci S.J., W.M. Williams, 2011. Understanding current causes of women's underrepresentation in science. Proceeding of the National Academy of Science of the United States of America,108:3157–3162

Ceci S.J, D. K. Ginther, S. Kahn, & W. M. Williams, 2014. Women in Academic Science: A Changing Landscape. Psychological Science in the Public Interest, 2014; 15 (3): 75

Cech, E., Rubineau, B., Silbey, S., & Seron, C., 2011. Professional role confidence and gendered persistence in engineering. American Sociological Review, 76(5), 641-666.

Etzkowitz, H., Kemelgor, C., & Uzzi, B., 2000. Athena unbound: The advancement of women in science and technology. Cambridge University Press.

Frietsch, R., I. Haller, M.F. Vrohlings and H. Grupp, 2009. Gender-specific Patterns in Patenting and Publishing. Research Policy, Vol. 38, No. 4, pp. 590-599.

Gaule, P., & Piacentini, M., 2013. Chinese graduate students and US scientific productivity. Review of Economics and Statistics, 95(2), 698-701.

Gaule, P., 2014. Who comes back and when? Return migration decisions of academic scientists. Economics Letters. 124(3):461-464

Golde, C. M., 1998. Beginning graduate school: Explaining first-year doctoral attrition. In M. S. Anderson (Ed.), The experience of being in graduate school: An exploration. New Directions for Higher Education, No. 101. San Francisco: Jossey-Bass.

Golde, C.M., 2000, Should I stay or should I go? Student descriptions of the doctoral attrition process, The Review of Higher Education, Vo. 23 No. 2, pp. 199-227.

Goulden M., Mason M.A., Frasch K, 2011, Keeping women in the science pipeline. Annual of the American Academy of Political and Social Sciences, 638(1):141–162

Hale, G., & Regev, T., 2014. Gender ratios at top PhD programs in economics. Economics of Education Review, 41, 55-70.

Hargens, L. L., & Long, J. S., 2002. Demographic inertia and women's representation among faculty in higher education. The Journal of Higher Education, 73(4), 494-517.

Hilmer, C., & Hilmer, M., 2007. Women helping women, men helping women? Same-Gender mentoring, initial job placements, and early career publishing success for economics PhDs. American Economic Review Papers and Proceedings, 97(2):422-426.

Hirshfield, L. E., 2010. "She Won't Make Me Feel Dumb": Identity Threat in a Male-Dominated Discipline. International Journal of Gender, Science and Technology, [S.l.], v. 2, n. 1, feb. 2010.

Hirshfield, L. E., 2017. I Don't Know Everything, But Ethan Would Know: Language, Expertise, and the Cultural Mismatch for Women Scientists, NASPA Journal About Women in Higher Education, 10:1, 118-137

Hoffmann, F., & Oreopoulos, P., 2009. A professor like me the influence of instructor gender on college achievement. Journal of Human Resources, 44(2), 479-494.

Hsieh, C., E. Hurst, C.I. Jones and P. Klenow, 2013. The Allocation of Talent and U.S. Economic Growth, NBER Working Paper No. 18693.

Hunt, J., 2010. Why do women leave science and engineering? (No. w15853). National Bureau of Economic Research.

Kahn, S., & MacGarvie, M. J., 2016. How Important is US Location for Research in Science? Review of Economics and Statistics, 98(2), 397-414.

Karukstis, K. K., Gourley, B. L., Wright, L. L., & Rossi, M., 2010. Mentoring Strategies to Recruit and Advance Women in Science and Engineering. Journal of Chemical Education, 87(4), 355-356.

Kemelgor, C., & Etzkowitz, H., 2001. Overcoming isolation: Women's dilemmas in American academic science. Minerva, 39(2), 153-174.

Leslie, S.J., Cimpian, A., Meyer, M., & Freeland, E., 2015. Expectations of Brilliance Underlie Gender Distributions Across Academic Disciplines. Science, 347(6219), 262-265.

Meghir, C., & Rivkin, S., 2011. Econometric methods for research in education. Handbook of the Economics of Education, 3, 1-87.

Milkman, K., Akinola, M., Chugh, D., Cachon, G., Caruso, E., Fernandez, R. & Pallais, A., 2014. Discrimination in the Academy: A Field Experiment. Available at SSRN 2063742.

Moss-Racusin, C. A., Dovidio, J. F., Brescoll, V. L., Graham, M. J., & Handelsman, J., 2012. Science faculty's subtle gender biases favor male students. Proceedings of the National Academy of Sciences, 109(41), 16474-16479. Chicago

Neumark, D., & Gardecki, R., 1998. Women Helping Women? Role Model and Mentoring Effects on Female Ph. D. Students in Economics. Journal of Human Resources, 33(1):220-246.

Newsome, J. L., 2008. The chemistry PhD: the impact on women's retention. A report for the UK Resource Centre for Women in SET and the Royal Society of Chemistry, 1-38.

Niederle, M. and L. Vesterlund, 2011. Gender and competition. Annual Review of Economics 3.1 (2011): 601-630.

National Research Council, 1995. Research Doctorate Programs in the United States: Continuity and Change. National Academies Press.

National Research Council, 2000. Women in the chemical workforce: a workshop report to the Chemical Sciences Roundtable. National Academies Press.

National Research Council, 2001. From scarcity to visibility: Gender differences in the careers of doctoral scientists and engineers. National Academies Press.

NSF, 2009. Doctorate Recipients from U.S. Universities: Summary Report 2007-2008. Arlington, Virginia: NSF Division of Science Resource statistics

NSF, 2015. Women, Minorities, and Persons with Disabilities in Science and Engineering. NSF 15-311. Arlington, Virginia: NSF Division of Science Resource statistics

OECD, 2012. Closing the Gender Gap: Act Now. OECD Publishing, Paris.

Pezzoni, M., Mairesse, J., Stephan, P., & Lane, J., 2016. Gender and the Publication Output of Graduate Students: A Case Study. PloS One, 11(1), e0145146.

Preston, A. E., 1994. Why have all the women gone? A study of exit of women from the science and engineering professions. American Economic Review, 1446-1462.

Robinson C.V. (2011). Women in science: In pursuit of female chemists. Nature 476, 273–275 (18 August 2011)

Sallee M. W., 2014. Performing masculinity: considering gender in doctoral student socialization. International Journal for Researcher Development, Vol. 5 Issue: 2, pp.99-122

Schiebinger, L., 1999. Has Feminism Changed Science? Cambridge, MA: Harvard University Press

Schlegel, M., 2000. Women Mentoring Women. Monitor on Psychology 31(10)

Sheltzer, J. M., & Smith, J. C., 2014. Elite male faculty in the life sciences employ fewer women. Proceedings of the National Academy of Sciences, 111(28), 10107-10112.

Waldinger, F., 2010. Quality matters: The expulsion of professors and the consequences for PhD student outcomes in Nazi Germany. Journal of Political Economy, 118(4), 787-831.

Wilson, R., 2003. Duke and Princeton Will Spend More to Make Female Professors Happy. Chronicle of Higher Education, 10 October 2003

TABLES AND FIGURES

Table 1: Students by gender and advisor gender

		Female advisor		
		0	1	
Female student	0	12,379 (64.02)	1,238 (6.4)	13,617 (70.43)
	1	4,893 (25.31)	825 (4.27)	5,718 (29.57)
		17,272 (89.33)	2,063 (10.67)	

Notes: Cell percentage in parenthesis

Table 2: Descriptive statistics

	Sample Mean	Standard Deviation
Student level information (19,335 students)		
Female student	0.30	0.45
Productivity during PhD- number of first-author papers weighted by journal impact factor	5.69	8.24
Became faculty (in a US PhD-granting chemistry department)	0.04	0.19
Became research academic (subsample of 2,523 female students only)	0.20	0.40
Top 10 school (according ot the 1995 NRC ranking of chemistry doctoral programs)	0.19	0.40
Year of graduation	2003.2	2.73
Advisor level information (5,119 advisors)		
Female advisor	0.12	0.32
Advisor year of birth	1952	11
Advisor productivity	6.84	12.49
Specialization		
Biochemistry	0.21	0.41
Physical chemistry	0.21	0.41
Organic chemistry	0.20	0.40
Material science	0.11	0.31
Inorganic chemistry	0.09	0.29
Analytical chemistry	0.08	0.27
Chemical engineering	0.07	0.26
Other	0.01	0.10

Table 3: Descriptive statistics by gender pairing

	Male students with male advisors (n=12,379)	Male students with female advisors (n=1,238)	Female students with female advisors (n=825)	Female students with male advisors (n=4,893)
Productivity during PhD- number of first-author papers weighted by journal impact factor	5.9 (8.6)	5.4 (7.5)	6.1 (8.3)	5.0 (7.5)
Became faculty (in a US PhD-granting chemistry department)	0.044 (0.205)	0.033 (0.179)	0.041 (0.199)	0.026 (0.159)
Became research academic (subsample of 2,523 female students only)	n/a	n/a	0.24 (0.43)	0.19 (0.39)
Year of graduation	2003.1 (2.7)	2003.6 (2.7)	2003.4 (2.8)	2003.3 (2.7)
Share among all students	0.64	0.06	0.04	0.24
Share among students from top 10 programs	0.64	0.07	0.04	0.25

Table 4a: Advisor gender and student productivity for female students

Productivity during the PhD	(1)	(2)	(3)
Female advisor	0.1997**	0.1693**	0.0928
	(0.0520)	(0.0651)	(0.0675)
University fixed effects	no	yes	yes
Graduation year fixed effects	no	yes	yes
Advisor characteristics	no	no	yes
Nb. of Obs.	5,718	5,680	5,680
Sample	Female students	Female students	Female students

Robust standard errors in parentheses. Estimation by Poisson QML. The dependent variable is "Productivity during the PhD", which is defined as the number of first-author papers published from 3 years before graduation to the year of graduation, weighted by the impact factor of the journal. Column 1 has no controls, column 2 controls for university and year of graduation; column 3 also controls for the age, productivity and specialization of the advisor.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4b: Advisor gender and student productivity for male students

Productivity during the PhD	(1)	(2)	(3)
Male advisor	0.0866*	0.1264**	0.1962**
	(0.0411)	(0.0434)	(0.0480)
University fixed effects	no	yes	yes
Graduation year fixed effects	no	yes	yes
Advisor characteristics	no	no	yes
Nb. of Obs.	13,617	13,591	13,591
Sample	Male students	Male students	Male students

Robust standard errors in parentheses. Estimation by Poisson QML. The dependent variable is "Productivity during the PhD", which is defined as the number of first-author papers published from 3 years before graduation to the year of graduation, weighted by the impact factor of the journal. Column 1 has no controls, column 2 controls for university and year of graduation; column 3 also controls for the age, productivity and specialization of the advisor.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5a: Advisor gender and becoming faculty for female students

Became faculty	(1)	(2)	(3)
Female advisor	0.0106^{+}	0.0131^{+}	0.0186^{*}
	(0.0055)	(0.0077)	(0.0082)
Productivity during PhD	0.0151^{**}	0.0175^{**}	0.0169^{**}
(normalized)	(0.0018)	(0.0024)	(0.0024)
University fixed effects	no	yes	yes
Graduation year fixed effects	no	yes	yes
Advisor characteristics	no	no	yes
Mean of dependent variable	0.028	0.028	0.028
Nb. of Obs.	5,718	3,968	3,895
Sample	Female students	Female students	Female students

Robust standard errors in parentheses. Estimation by probit, reporting marginal effects. “Became faculty” is defined as being listed as a faculty member in the ACS directory of graduate research (which covers U.S. PhD granting departments). Productivity during the PhD is defined as the number of first-author papers published from 3 years before graduation to the year of graduation, weighted by the impact factor of the journal, and normalized to have mean 0 and standard deviation 1. Column 1 has no controls besides productivity during the PhD, column 2 controls for university and year of graduation; column 3 also controls for the age, productivity and specialization of the advisor. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5b: Advisor gender and becoming faculty for male students

Became faculty	(1)	(2)	(3)
Male advisor	0.0095	0.0077	0.0049
	(0.0064)	(0.0068)	(0.0070)
Productivity during PhD	0.0205^{**}	0.0195^{**}	0.0188^{**}
(normalized)	(0.0013)	(0.0014)	(0.0015)
University fixed effects	no	yes	yes
Graduation year fixed effects	no	yes	yes
Advisor characteristics	no	no	yes
Mean of dependent variable	0.043	0.043	0.043
Nb. of Obs.	13,617	12,401	12,383
Sample	Male students	Male students	Male students

Robust standard errors in parentheses. Estimation by probit, reporting marginal effects. The dependent variable is "Becoming faculty" which is defined as being listed as a faculty member in the ACS directory of graduate research (which covers U.S. PhD granting departments). Productivity during the PhD is defined as the number of first-author papers published from 3 years before graduation to the year of graduation, weighted by impact factor of the journal, and normalized to have mean 0 and standard deviation 1. Column 1 has no controls besides productivity during the PhD, column 2 controls for university and year of graduation; column 3 also controls for the age, productivity and specialization of the advisor. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Advisor gender and becoming faculty in top 10 versus other programs

Became faculty	(1)	(2)	(3)	(4)
	Female students		Male students	
	Top 10	Not top 10	Top 10	Not top 10
Same gender advisor	0.0390*	0.0147	0.0447*	-0.0052
	(0.0197)	(0.0093)	(0.0217)	(0.0067)
Productivity during PhD (normalized)	0.0199**	0.0164**	0.0282**	0.0167**
	(0.0050)	(0.0031)	(0.0034)	(0.0016)
University Fixed Effects	Yes	Yes	Yes	Yes
Graduation Year Fixed Effects	Yes	Yes	Yes	Yes
Advisor characteristics	Yes	Yes	Yes	Yes
Mean of dependent variable	0.047	0.023	0.083	0.033
Nb. of Obs.	901	2,778	2,672	9,711
Sample	Female students in top 10 progams	Female students outside top 10 progams	Male students in top 10 programs	Male students outside top 10 programs

Robust standard errors in parentheses. Estimation by probit, reporting marginal effects. The dependent variable is "Becoming faculty" which is defined as being listed as a faculty member in the ACS directory of graduate research (which covers U.S. PhD granting departments). Productivity during the PhD is defined as the number of first-author papers published from 3 years before graduation to the year of graduation, weighted by impact factor of the journal, and normalized to have mean 0 and standard deviation 1. All columns control for university and year of graduation; as well as the age, productivity and specialization of the advisor. Top 10 schools are defined according to the 1995 NRC ranking of chemistry doctoral programs. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

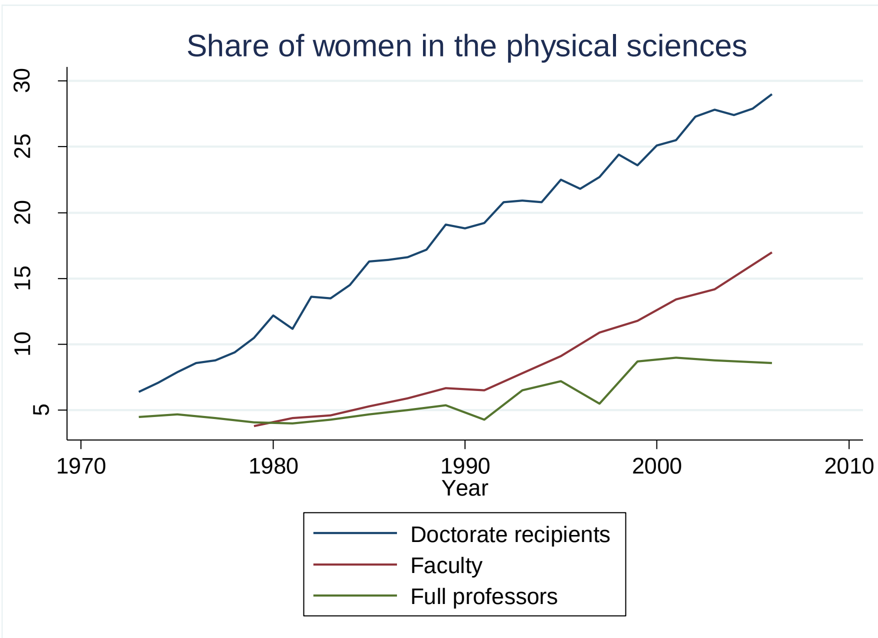
Table 7: Advisor gender and staying in academia for female students

Stayed in academia	(1)	(2)	(3)
Female advisor	0.0491**	0.0479**	0.0490*
	(0.0167)	(0.0178)	(0.0191)
Productivity during PhD (normalized)	0.0399**	0.0416**	0.0430**
	(0.0077)	(0.0082)	(0.0084)
University fixed effects	no	yes	yes
Graduation year fixed effects	no	yes	yes
Advisor characteristics	no	no	yes
Mean of dependent variable	0.205	0.205	0.205
Nb. of Obs.	2,523	2,425	2,423
Sample	Female students - manual sample	Female students - manual sample	Female students - manual sample

Robust standard errors in parentheses. Estimation by probit, reporting marginal effects. The dependent variable is "Stayed in academia" and is defined as being employed as faculty, postdoc or other researcher in a research-intensive university as of January 2014. Productivity during PhD is defined as the number of papers published from 3 years before graduation to the year of graduation, weighted by the impact factor of the journal, and normalized to have mean 0 and standard deviation 1. Column 1 has no controls besides productivity during the PhD, column 2 controls for university and year of graduation; column 3 also controls for the age, productivity and specialization of the advisor. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figures

Figure 1. Share of women among doctorate recipients, faculty and full professors in the physical sciences, United States



Source: Authors' calculations based on NSF data