Mentorship and the Gender Gap in Academia*

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Abstract

This paper examines how the presence of female professors impacts graduates from top-50 U.S. economics PhD programs. Combining rich data on advisor-advisee relationships and career trajectories with a research design leveraging quasi-random sabbatical timing, we find gendered effects. The absence of a female professor decreases third-year female Ph.D. students' likelihood of publishing papers and securing academic positions. Conversely, male Ph.D. students in the same cohort benefit from this absence, seeing an increase in their publishing and placement prospects. These divergent outcomes can be explained by gender homophily in mentorship, with female students 51 percent more likely than male students to have a female advisor. One additional female senior professor in each top-50 economics department would close one-third of the gender gap in representation among assistant professors at top-25 schools.

Keywords: gender gap, Economics, homophily, network

JEL Codes:

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1 Introduction

The second half of the twentieth century witnessed a significant increase in female labor force participation and a convergence between men and women in labor market outcomes. Despite this progress, notable gender differences remain in terms of representation in occupations, leadership positions, and high-status jobs (Blau and Kahn, 2017; England et al., 2020; Goldin, 2006, 2014).[1] This project focuses on one potentially important determinant: homophily in mentorship.[2]

We argue (and document) that mentor relationships are gendered: women and men are not equal in their likelihood to connect and have meaningful professional relationships. In turn, these relationships matter for human capital formation and career outcomes. We study the role of homophily in mentorship in the context of the field of Economics, focusing on the dynamics between Ph.D. students and their professors. We posit that if mentorship relationships are gendered, then the presence of female professors at a department should improve the early-career outcomes of female Ph.D. students.

Studying mentorship is challenging. Taking our context as an example, students select into Ph.D. programs (and choose their advisors) based on factors such as institutional reputation, desired specialization, faculty expertise, and gender, among others. Consequently, female students in departments with more female professors may inherently differ from those in departments with fewer, in ways that could affect their post-Ph.D. outcomes. To address these challenges, we use female professors' sabbatical leaves as a source of quasi-random variation. Sabbatical leaves offer three key advantages. First, professors on leave typically engage less with students and often visit other institutions, creating temporary variation in faculty presence. Second, because women economists remain significantly underrepresented among tenured faculty in research-intensive universities (Davies et al., 2022; Ginther and Kahn, 2004), their temporary absence induces a meaningful decline in available female faculty. Third, the timing of sabbaticals are unexpected by students and thus orthogonal to students' potential outcomes.

We begin by combining faculty records from course catalogs and university websites into a novel dataset covering nearly all top-50 US Economics departments from 1994 to 2019. Complemented by the faculty members' academic CVs, we identify top-50 faculty's sabbati-

[1] Existing investigations of these ongoing disparities have focused on discrimination and biases (Bertrand, 2020; Kahn and Ginther, 2017a), household constraints (Kleven et al., 2019; Le Barbanchon et al., 2021), differences in risk attitudes, competitiveness, and bargaining behavior (Buser et al., 2014; Charness and Gneezy, 2012; Shurchkov and Eckel, 2018), as well as societal norms affecting women's career choices and behaviors (Cortes and Pan, 2019).

[2] Homophily refers to the tendency of individuals to associate with others who are similar to them (McPherson et al., 2001a).

cal leaves. We match each of these 3,750 faculty members to their publications and network of co-authors from EconLit, CrossRef, and the Microsoft Academic Graph. We further compile the list of Ph.D. graduates from these departments during the same time period, and link these 14,000 students to their dissertations (which name academic advisors) from ProQuest and JEL; their publications and network of co-authors from EconLit, CrossRef, and the Microsoft Academic Graph; and their academic positions from department job placement records, CVs, and LinkedIn pages.

We establish three main results. First, third-year female Ph.D. students in a department with a female professor on leave, publish fewer papers in their early career than female Ph.D. students in unaffected cohorts, with a 15 percent lower probability of publishing any paper (relative to the sample mean of 0.53 for female Ph.D. students) and 33 percent fewer publications (relative to the sample mean of 1.8). Second, female Ph.D. students in departments where a female professor is on leave during their third year have a corresponding lower probability of securing academic positions after graduation, with the magnitude matching the decline in the probability of publishing. Third, the corresponding cohorts of male Ph.D. students are *more* likely to publish, have more publications, and are more likely to be placed in academia when a female professor is on sabbatical.

We argue that these effects are likely connected to the gender homophilous nature of professional and social networks in academia, where the absence of female professors hinders the development and placement of female students. To support this interpretation, we present evidence of gender homophily in advisor-advisee relationships: even after controlling for department-year-field fixed effects, we find that female students are 51 percent more likely than male students to have a female advisor, with the average probability for male students being 7 percent.[3] We next show that sabbatical leaves break advisor-advisee relationships and that female students are disproportionately affected, particularly in the third year of their Ph.D.[4]

We further examine publication and placement quality, focusing on three measures correlated with academic quality: the number of top-five publications, the number of citations per paper per year, and the ranking of the placement institutions. Third-year female students experience a significant decrease in top-tier journal publications, while male students see some improvements in publication quality. Although the individual male gains are smaller than the female losses, there is close to no aggregate effect at the institutional level due to the gender composition. In contrast, when we look at placement quality, the share of women

[3]In a different context, Gallen and Wasserman (2023) document significant gender homophily in student-alumni relationships, using data from an online college student-alumni mentoring platform.

[4]We further rule out alternative explanations, finding that the effects are not mediated by field of study or professor quality.

placed in top-25 institutions decreases by 55 percent, while the share of men in these same institutions remains the same, but they tend to secure positions at lower-ranked institutions.

How does it all matter? First, our results have equity implications. The above disparities suggest that female students face significant barriers in academia, likely due to the loss of female mentors and advocates which in turn benefits their male peers, possibly through reduced competition. From the point of view of a department, however, the losses for the affected cohort of female Ph.D. students mostly cancels out the gains for the male Ph.D. students. Second, our results suggest that the lack of female representation at the senior levels of academia (e.g., among associate and full professors) contributes to the "leaky pipeline" of female academics. If decision-makers, such as those responsible for hiring, promotion, and resource allocation, are predominantly men, and they tend to have stronger relationships with other men due to gender homophily, this can result in a bias towards promoting and supporting male academics. Consequently, women may face greater challenges in advancing to senior positions, leading to an asymmetry in female representation at each successive stage of the academic career ladder.[5] Indeed, a counterfactual exercise suggests that hiring one senior female professor at each of the top 50 schools could close one-third of the gender gap among assistant professors at the top 25 schools, which have a low average gender ratio of 0.278. This approach would also directly address the gap among senior professors, all while resulting in minimal losses in academic productivity among assistant professors – a common concern in diversity hiring. Moreover, as these female assistant professors achieve tenure and take on advisory roles, their influence could compound, shaping future generations of academics, amplified by the fact that conversion of Ph.D. students to professors is more likely to occur at top schools rather than at lower-ranked schools. Moreover, our results have plausible implications for the type of women who enter and succeed in the profession in a world that is male-dominated at the top. If relationships matter and decision-making is dominated by men, female Ph.D. students who tend to form relationships with men might be more likely to succeed. They may be more inclined to collaborate with male colleagues and navigate a male-dominated environment effectively, slowing down female representation in a work environment where relationships matter.

We are the first study to exploit the (temporary) absence of female professor induced by sabbatical leaves. Our findings contribute to three areas of literature. First, we contribute to the broader literature examining the asymmetric gender representation across fields, occupations, and industries (Bertrand, 2018; Blau and Kahn, 2017; Cortes and Pan, 2019). Studies

[5]Relatedly, Canaan and Mouganie (2021) find that first-year female undergraduates assigned to a female advisor in the economics department have lower dropout rates and are more likely to graduate with a degree in Economics.

have documented women's under-representation in technical fields like Engineering, Computer Science, and Economics (Cheryan et al., 2017; Ginther et al., 2020; Ginther and Kahn, 2004; Kahn and Ginther, 2017a,b; Kleemans and Thornton, 2023; Kulis and Sicotte, 2002). Our findings suggest that the under-representation of women at senior academic levels both limits the share of women in Economics and contributes to the "leaky pipeline." Our results are consistent with a world where mentorship affects promotion through human capital transmission and preferential treatment, and is homophilic (Athey et al., 2000). Academia, and in particular the Ph.D. years, being a hybrid between education and work environment (akin to an apprentice environment), helps us think through the role of mentorship and human capital formation in the labor market in the early career of an individual. As such, our work complements Blau et al. (2010) and Ginther et al. (2020), which evaluated the CeMENT mentorship program randomized control trial, connecting female assistant and senior professors. We focus on an earlier stage of the academic pipeline – the formative Ph.D. years. Most importantly, it explores a more universal relationship in the production of professors and their professional life: Not everyone has access to mentorship programs, but all Ph.D. students need an advisor. Furthermore, by analyzing the effects on male and female students separately, we reveal that the absence of female mentors may inadvertently benefit male students, with gains for men offsetting losses for women.

Second, prior research on gender disparities in Economics has documented various challenges faced by women, including biases in hiring and promotion (Ceci et al., 2014; Ginther and Kahn, 2004; Sarsons et al., 2021), publication disparities (Alexander et al., 2021; Card et al., 2020; Hengel, 2022; Paredes et al., 2020; Wu, 2018), and biased teaching evaluations (Boring, 2017; Mengel et al., 2019). These studies have primarily focused on later career stages, while we focus on the Ph.D. stage, shedding light on how gender disparities emerge and persist from the very start of academic careers. Our results contrast with Hilmer and Hilmer (2007) which explores the observed endogenous matched advisor-advisee relationship directly, and find that women with male advisor tend to do better.

Third, while gender homophily has been documented in job search networks (Torres and Huffman, 2002; Zhu, 2018), referral systems (Beaman, 2013; Zeltzer, 2020), and academic collaborations (Davies et al., 2022; Ductor and Prummer, 2024), its role in mentorship relationships during doctoral training remains understudied. Mentorship relationships in academia are often observed and individual level productivity can be measured, allowing us to construct a rich dataset following job placements, professional networks, and publication outputs.[6] We exploit this and show that gender homophily in Ph.D. mentorship has

[6] A few studies have made use of such data richness, investigating the role of mentorship and advisor-advisee relationships on the career outcomes of women in Economics, Blau et al. (2010), Ginther et al. (2020);

lasting career impacts.

2 Data description

To explore the role of female professors on sabbatical leave on the early career outcomes of Ph.D. students, we constructed and relied on four main datasets: faculty members in top-50 US Economics departments from 1994 to 2019, advisor-advisee relationships for these institutions, academic publications, and career output for both Ph.D. students and professors, including their co-authorship networks. We focus on top-50 US Economics departments as these institutions produce the bulk of academics coming from U.S. institutions and our data on advisor-advisee relationships primarily covers U.S. institutions.[7] We chose the longest the time frame we could (1994-2019) given data availability. Each dataset contributes to our analysis in the following ways: the faculty dataset identifies position for all faculty members and their sabbatical leaves, the advisor-advisee data captures mentoring relationships, and the publication and career datasets measure key outcomes of interest. In this section, we first outline the data collection process followed by the descriptive statistics of the final dataset.

2.1 Data collection

Our data collection begins with the identification of a list of top US Economics departments and the full roster of faculty members in these departments. For each department, we then collected the faculty members' sabbatical leave information along with the yearly list of Ph.D. graduates and their advisors. We finally matched the researchers and the Ph.D. students to their academic publications. We refer you to Appendix B for detailed information on the data collection.

Department-level data: To select the set of Economics departments for our main analysis, we used *RePEc* US department rankings from 2013 to 2015.[8] We included all departments ranked in top 50 in each of the three years, resulting in a total of 47 departments. For each department, we then scraped the list of all faculty members and their positions, focusing on

Ginther and Kahn (2004), Hilmer and Hilmer (2007), and Neumark and Gardecki (1998).

[7] There is a negative correlation between the rank of an institution and the number of Ph.D. students per department. The top 10-schools have 20 Ph.D. students per year on average and the 10 lowest ranked schools have 7 Ph.D. students in our sample. Looking at all schools, the same pattern holds, where the below top-50 schools that is producing Ph.D. students, produce on average 4 Ph.D. students. This is in line with Clauset et al. (2015), finding that roughly 80 percent of tenure-track faculty in the US received their Ph.D. from a top-50 department across various disciplines.

[8] These years correspond to the last three Ph.D. graduation years in our estimation sample. See https://ideas.repec.org/top/old/1505/top.usecondept.html for an example of the *RePEc* list.

the years 1994 to 2019. Hereafter, a year refers to an academic year, i.e., 2019 refers to the academic year 2019-2020. Our primary sources are the university course catalogs. Course catalogs are official university publications that provide comprehensive information about academic programs, policies, and faculty. We supplemented these with historical snapshots of department websites from the *Wayback Machine*.[9] The average department has 32 faculty members, with fewer than 2 full female professors, see Table 1.

Faculty sabbatical leave information: We manually collected data on faculty members' sabbatical leaves by combining information from university course catalogs, department websites, and Curriculum Vitae (CV).

We began with course catalogs and supplemented them with department websites, which often listed faculty members' leave status in the faculty directory or on individual professor pages. Together, course catalogs and department websites yielded 991 leave spells (45 percent of all the leaves collected). We also collected their list of visiting professors, which provided an alternative way of identifying an additional 406 leave events (19 percent of total leaves). We coded professors listed as visiting another department as on leave from their home institution. Finally, we collected CVs focusing on associate and full professors due to the time-intensive nature of the task and the focus of our analysis.[10] Our main analysis focus on the role of associate and full professors on Ph.D. students.[11] When defining leaves from CVs, we excluded visiting positions shorter than four months and those listed with only a generic calendar year. The CV collection added 783 additional leave events to our sample (36 percent of the total leaves). Our results are robust to including these leaves and alternative CV coding choices (see Appendix C).

To sum up, we define a professor on leave as one listed as on leave or visiting in any of these sources. In total, we identified 2,180 leave events between 1994 and 2019. The remainder of the paper focuses on the sabbatical leaves of female associate and full professors (204 leave spells, or 9.3 percent of the total leaves). To gauge the source of variation we are going to use, Appendix Figure B4 and Figure B5 report the number of female sabbatical events per department and per department-year. See Appendix B for a detailed description and coverage evaluation of our dataset. For a sensitivity analysis on the definition of sabbatical

[9]For most departments, we combined the two sources to cover as many years as possible. For about one-third of the departments, we relied solely on the websites, as the course catalogs did not provide information on faculty.

[10]We have CVs (or CV-like information) for 74 percent of the 2,351 associate and full professors in our sample: 89 percent of female faculty and 73 percent of male faculty at these ranks.

[11]Assistant professors have to navigate their own career and establish their own name, making them less suited to help the Ph.D. students establish in the profession. Indeed, only 6.5 percent of our Ph.D. students have an assistant professor as their main advisor (see Table 3).

leaves, ensuring the robustness of our main results, we refer you to Subsection C.2.

Ph.D. student-level data: We compiled data on Ph.D. students for each department by combining two sources: the Journal of Economic Literature (JEL) annual publication "Doctoral Dissertations in Economics" and ProQuest Dissertations & Theses Global. JEL provides information on dissertation fields (through JEL codes), while ProQuest contains advisor information.

Our main sample is compiled from the ProQuest dissertation database for the years 1990 to 2022 using ProQuest dissertation metadata from TDM studio.[12] ProQuest is a repository of dissertations, serving as the official archive for the US Library of Congress. It contains the authors' full names, their affiliated institutions, dissertation titles, and the composition of their advisory committees. We then digitized the corresponding JEL dissertations for the same years to get information on research fields. JEL invites contributions from all US and Canadian institutions awarding Ph.D. degrees in Economics, receiving responses from nearly all prominent Economics departments (Lundberg and Stearns, 2019). Each JEL entry includes the Ph.D. student's full name, dissertation title, JEL classification code used as research fields, graduation year, and university affiliation. Both JEL and ProQuest provide the graduation year but do not give information on the start year of the Ph.D.

We combine the two data sources by matching entries within university and year. We use the dissertation titles in the two datasets to identify false positive author matches (86 percent of JEL entries matched). For the remaining unmatched samples, we perform a second match within university and ± 1 year (additional 4 percent of JEL entries matched). Out of the 32,716 JEL dissertations (1990-2022), we matched about 90 percent to a ProQuest dissertation.

We then subset the sample to include only students if both their Ph.D. was granted by one of the universities of the top 50 departments and their advisor was from one of the top 50 departments in that same institution. We apply this sample criteria to identify students in Economics and to exclude Economics students from neighbouring schools within the same university. The criteria may miss students with an advisor in a department different from their Ph.D. department, and wrongly include students with an advisor from the department but doing the Ph.D. at a neighbouring school within the same university. For instance, a Ph.D. student from Harvard Kennedy School with an advisor in the Economics department could be miss-assigned to the Economics department. We refer you to Appendix Subsection C.4 for a robustness check against alternative criteria.

Finally, we started by genderizing all students and professors using the Genderize.io

[12] Although the database extends further back, advisor information is not available for earlier years.

database. We then manually verified the predicted gender, successfully assessing 97.2 percent of the students and 100 percent of the professors in our main sample. We excluded the 205 students (2.8 percent of the students) that we could not identify the gender. See Appendix Subsection B.4 for an evaluation of the gender prediction variable.

Our sample includes 13,948 Ph.D. students (with 78.2 percent appearing in the JEL dissertation list), covering 46 (out of the 47) Economics departments, with a graduation year between 1994 and 2019. The university missing is Dartmouth College, which does not have a Ph.D. program in Economics.

Academic publications, job placement and networks: To measure the early career output of Ph.D. students, we use a unique dataset on Economics academic publication output, combining three sources: EconLit database, Microsoft Academic Graph (MAG), and CrossRef. See Appendix Subsection B.3 for details. The publication dataset covers more than 2,302,565 unique papers across 1799 journals publishing Economics and Economics related papers from 1852 to 2021. MAG, developed by Microsoft Research,[13] contains information on academic publications including articles, conference papers, journals, authors, institutions, and citation relationships. CrossRef is a metadata retrieval system with more than 120 million metadata records. By combining CrossRef and Microsoft Academic Graph, the publication dataset allows to get citation data for a large sample of papers (2,033,825 combining both).[14] We also linked all the publication record of each author under a unique identifier (author ID). Detailed information on the process of assigning author IDs can be found in Appendix Subsection B.3.

We merged the publication dataset with the Ph.D. students and the faculty member datasets. In addition to information on publications (journal quality and citations), we also measured the number of unique coauthors as well as the number of female coauthors for both the Ph.D. students and the faculty members.

Finally, we collected information about the job placement of the Ph.D. students using a variety of sources, such as the student's LinkedIn page, their CV and the department placement records. We collected information about their placements up to three years after graduation as some students might take up short-term position right after graduation. See Appendix Subsection B.2 for details.

[13] As of December 31, 2021, Microsoft Academic services, including MAG, have been discontinued.

[14] With a large overlap between the two sources of 1,308,274 entries, MAG covers 1,702,622 entries and CrossRef covers 1,637,689

2.2 Final sample and descriptive statistics

The final sample covers the academic years 1994 to 2019, with 3,749 unique faculty members and 13,948 Ph.D. students in 46 departments. We focus primarily on students who earned their Ph.D. between 1998 and 2014. The start year of 1998 allows sufficient time after the first year of faculty data (1994) to study the effect of sabbatical leaves on all cohorts of Ph.D. students in a department, assuming an average completion time of five years (see Subsection 3.1). We chose the end year, 2014, given the last available year in the publication dataset (2019) and the focus on early-career outcomes, which we define as the first five years post-Ph.D., aligning with the average tenure-track evaluation period.

Figure 1 shows the evolution of the share of female Ph.D. students and faculty members over time. The share of women among full professors rose from 5 percent in 1994 to 13 percent in 2019, while female associate professors grew from 5 percent in 1995 to 22 percent in 2019. Among assistant professors, the share of women fluctuated, increasing from 22 percent in 1994 to nearly 29 percent in 2007, then returning to around 22 percent. This pattern mirrors the share of graduating female Ph.D. students, which started at a slightly higher level, averaging around 28 percent. These figures are consistent with previous findings (Auriol et al., 2022; Ductor et al., 2023; Kleemans and Thornton, 2023; Lundberg and Stearns, 2019). Ductor et al. (2023) reported an increase in the share of Economics research papers authored by women from 8 percent in 1970 to 29 percent in 2011. Similarly, Lundberg and Stearns (2019) observed a comparable pattern in top US Economics departments based on information from the Universal Academic Questionnaire.These gender gaps in representation, while present in both Europe and the U.S., are more pronounced in the U.S., where they tend to widen with seniority (Auriol et al., 2022).

Twenty-two percent of department-year observations had no female full professors, and 43 percent had no female associate professors, resulting in 12 percent of department-year observations with neither a female full nor a female associate professor. The median number of female full professors per department is only 1, with a mean of 1.77, while for associate professors, the median is also 1 but with a lower mean of 0.92, see Table 1. These statistics indicate a predominantly male professional environment.

The characteristics of the associate and full professors, shown in Table 2, reveal notable gender differences in faculty members' productivity, networks, and main research fields. While male faculty members have a higher average number of publications, female faculty members have a higher average number of top-five publications and citations per paper per year. These results contrast with Ductor et al. (2023), which shows that women have 43 percent fewer top-five publications. This difference is likely due to our focus on top departments and associate or full professors. Turning to their co-authorship practice, male faculty members have more unique co-authors overall, whereas female faculty members have more unique female co-authors. Additionally, female faculty members are more likely to specialize in Labor/Public Economics, while male faculty members tend to focus on Macro/Finance.[15] These patterns align with prior findings (Beneito et al., 2021; Chari and Goldsmith-Pinkham, 2017; Lundberg and Stearns, 2019). Lastly, the share of female professors taking sabbaticals is higher than that of male professors.[16]

Table 3 shows descriptive statistics for the Ph.D. students in our main estimation sample, and reveals similar gender differences in their advisors, productivity, networks, job placements, and dissertation fields. Female Ph.D. students are more likely than male students to have a female advisor (12% vs. 7%). In terms of productivity, male students have a slightly higher average number of publications and top-five publications within five years post-Ph.D. The difference in top-five publications contrast with the statistics for the associate/full professors and is in line with previous results (Ductor et al., 2023). However, both genders have similar average citations per paper per year. Conditional on publication, male Ph.D. students have more unique co-authors overall, while female Ph.D. students have more unique female co-authors. Regarding job placement, male Ph.D. students are slightly more likely to enter academia and secure positions in top-ranked Economics departments. Lastly, female Ph.D. students are more likely to specialize in Labor/Public Economics for their dissertations, while male Ph.D. students are more likely to focus on Macro/Finance.

3 From female professors to female Ph.D. students: Three early-career results

How does the presence of female professors during the Ph.D. years influence the career outcomes of female Ph.D. students? Answering this question presents empirical challenges. Various considerations determine the Ph.D. programs students end up at, including the

[15] For ease of interpretation, we follow Lundberg and Stearns (2019) in grouping the 20 *JEL* codes into seven broad fields: "Micro" for JEL code D; "Macro/Finance" for codes E, F, and G; "Labor/Public" for codes H, I, and J; "IO" for code L; "Environmental" for code Q; "History/Development" for codes N and O; and "Other" for the remaining codes A, B, C, K, M, P, R, Y, and Z. The field of a professor is based on the field information from their students and is defined as the field in which they have served as an advisor most often.

[16] One possible explanation for this difference is that our leave variable includes maternity leaves. However, given our focus on senior professors (associate and full professors) and the biological constraints associated with age, parental leaves might not constitute a significant enough share of the female sabbatical leaves in our sample to explain such difference. Supporting this view, 131 out of the 204 female leave spells in our data have a verified visiting institutions through CVs or faculty records, making them unlikely to be parental leaves. Among the remaining 73 leave spells, only 23 occurred involve a professor within 15 years of their graduation, indicating that these professors were likely over 40. Thus, it seems unlikely that parental leaves account for a substantial portion of female sabbatical leaves in our sample.

reputation of the institution, their desired specialization, the expertise of faculty members in those areas, and gender. Consequently, female students in departments with a higher number of female professors may differ from their counterparts in departments with fewer female professors, in ways inherently linked to their post-Ph.D. career outcomes.[17] To address these empirical challenges and examine the impact of female professors on the careers of female students, we propose using the timing of a professor's sabbatical leave as a source of quasi-random variation.

Most universities implement sabbatical policies that allow scholars to temporarily withdraw from their teaching and administrative duties. Sabbatical leaves offer three key advantages in our context. First, during sabbaticals, professors typically engage less with students and often visit other institutions, leading to a temporary variation in the presence of professors within a department. Second, because the mean number of female professors in our sample is less than two,[18] a female professor's temporary absence is likely to meaningfully reduce the number of female faculty members in a given year.

This decline is illustrated in Figure 2, which shows the relationship between the presence of female professors (full and associate) in a department in a given year and a female professor taking leave, using information from the top 50 departments from 1994 to 2019.[19] The figure reports the estimated yearly coefficients alongside their 95 percent confidence intervals from the following regression:

$$y_{d,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \gamma_s FemSabbat_{d,t-s} + \varepsilon_{d,t}, \tag{1}$$

where $y_{d,t}$ is one of two outcome variables, either a dummy variable for whether department d had *any* female professors present in year t (Figure 2a) or the share of female professors hired who are present in a given department d in a given year t (Figure 2b). $FemSabbat_{d,t-s}$ is a dummy variable equal to one if department d had any female professors on sabbatical in year $t-s$, and the coefficients γ_s capture the yearly impacts on the presence of female professors of a sabbatical leave s years before or after the leave. For $s \in \{-5, 5\}$, γ_s represents whether a sabbatical leave happened five years *or more* before or after year t, respectively. α_d and δ_t denote department and time fixed effect. Given that a department might have female

[17]A regression of the share of female students on the share of female faculty members in our sample shows a positive relationship with a coefficient equal to 0.11 (significantly different from zero at the 5 percent level).

[18]Remember from Subsection 2.2, the mean number of female professors is 1.77, with a median of 1.

[19]We focus on associate and full professors, as they are more likely to serve as advisors to Ph.D. students. In our sample, only 6 percent of Ph.D. students have an assistant professor as their advisor (see Table 3). Assistant professors, still navigating their own careers and establishing their reputations, may be less well-positioned to help Ph.D. students establish themselves in the profession compared to associate and full professors, who have more experience, visibility, and professional networks.

professors on leave in consecutive years, multiple time indicators could be simultaneously equal to one. In this type of event study regression, no reference category is required (see Keiser and Shapiro, 2019). Following Miller (2023), we normalize the figure by setting the average coefficient in the period $s \in \{-4, \dots, -1\}$ to zero, facilitating interpretation.

The results presented in Figure 2a show that departments with a female professor on leave experience an estimated 15 percentage point decline in the likelihood of having at least one female professor present in that year (with 87 percent of the department-year data having at least one female professor present in our sample). The figure shows no significant changes either before or after the leave year, suggesting that a female professor on leave does not correlate with recent hiring of female professors or with female professors leaving for other positions.

To further gauge how the female professor on leave translates in the presence of female professors, we restrict the sample to the department-year with at least one female professor, and run a regression on the share of female professors hired that are present in a department in a given year instead (where the baseline is 100 percent, i.e., all hired female professors hired are present). Figure 2b shows that the female professor on sabbatical translates to a 41 percentage point decrease in the pool of female faculty members in a department during that year. These sizeable declines in the availability of female faculty members can be attributed to the scarcity of female professors. By contrast, as shown in Appendix Figure A3, a male professor on leave results in a much smaller reduction in the presence of male professors in a department (a decline of less than 9 percentage point relative to the baseline of 100 percent of men present).

The third advantage of using sabbatical leaves as a source of variation is that sabbaticals are temporary, and the decline in female professor presence due to sabbaticals is unlikely to impact student selection into departments or departmental commitments to hire female professors. From the perspective of the students, these leaves can arguably be seen as a short-term exogenous shock to the "supply" of female professors. Consistent with this interpretation, we observe no changes in the gender composition of Ph.D. students around the years female professors take leave. Appendix Figure A1 illustrates this by plotting the estimated yearly coefficients from a regression similar toEquation 1, with the female share of Ph.D. students as the outcome. We next show three results related to the impact of female professors on sabbatical on Ph.D. students' early career outcomes.

3.1 Early-career outcomes

To examine the impact of female professors' presence on the career outcomes of Ph.D. graduates, we leverage the timing of sabbaticals interacted with the variation provided by the students' year in the Ph.D. program. While the absence of a female professor may affect all female Ph.D. students, we hypothesize that not all years are equal, and that students in their critical phase of academic research development – around their third year of the Ph.D. program – are more likely to be affected by the absence of a female professor.

The first year of a Ph.D. program is typically dedicated to core coursework, while the second year focuses on advanced field courses. In contrast, the third year students develop and build their research agendas. We argue that this year constitutes a critical phase for students' later academic careers, not only because students develop their research direction during this period, but also because they often engage with their advisor and other faculty, forging relationships and gaining insights into their quality as scholars. The final years are then spent on the dissertation, building on the direction and relationships established in earlier years. In our empirical model, we will use a flexible specification that allows for heterogeneity by year in the Ph.D. program and specifically test this hypothesis.

To explore this timing, we need to know which year students are in when a professor goes on leave. However, as mentioned in the data description (Subsection 2.1), we only observe a student's graduation year, not their entry year into the Ph.D. program. To deduce the start year, we assume a five-year Ph.D. completion time, defining each student's start year as their graduation year minus five. During our study period, the typical duration of an Economics Ph.D. program in the US was dominated by five years, with six years becoming more prevalent by the end of the sample (Stock et al., 2009; Stock and Siegfried, 2014).[20] Figure C1 illustrates this trend, showing the evolution of completion times for a subsample of students whose Ph.D. start and completion years we manually collected from their CVs. Our results remain robust to variations in the Ph.D. completion time, including adjustments for trends extending the Ph.D. duration from five to six years (see Appendix C.3). With this assumption, we categorize students relative to a professor's sabbatical year as follows: "first-year" students began their Ph.D. in the same year as the sabbatical, "second-year" students the year before, and "third-year" students two years prior, as shown in Figure 3. To illustrate, relative to Claudia Goldin's sabbatical at the Russell Sage Foundation in 1997, first-year students are those starting in the fall of 1997 (the sabbatical year) and graduating in the spring of 2003. Similarly, second-year and third-year students are those starting in the fall of 1995 and 1996 and graduating in the spring of 2001 and 2002, respectively.

[20] The same pattern also holds for European universities (Ábrahám et al., 2022).

Main specification: Using these imputed Ph.D. start years, we focus our analysis on early career outcomes measured at the individual level, aggregated over the first five years following graduation. To estimate the effect of female professors' sabbatical leave on students' publication and job placement outcomes, we use the following equation:

$$y_{id,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \gamma_s FemSabbat_{id,t-s} + \varepsilon_{id,t}, \tag{2}$$

where $y_{id,t}$ denotes one of three early-career outcomes: the probability that student i in department d graduating in year t publishes at least one paper up to five years post-Ph.D. (HasPubs), the number of papers published within the same time frame (#Pubs), or a dummy equal to one if the student was placed in academia and zero otherwise (Academia). $FemSabbat_{id,t-s}$ is a dummy variable equal to one if student i in department d had a female professor on sabbatical in year $t-s$. The coefficient γ_s captures the differential effect on students who were exposed to a female professor on leave s years before or after their graduation year t, relative to the students not exposed to a female professor on leave.

As in Equation 1, for $s \in \{-5, 5\}$, γ_s represents whether a sabbatical leave happened five years or more before or after year t. We include up to five years following the sabbatical to account for all student cohorts that could have plausibly overlapped with the female professor during her leave. In our setting, we do not expect cohorts to be affected beyond these years – neither before nor after – as each year represents a different cohort. However, we do expect heterogeneity in the treatment effect for the affected cohorts ($s \in \{0, \dots, 4\}$), which is supported by our results below. Finally, α_d and δ_t denote department and year fixed effects, respectively. To allow for differential gender dynamics, we estimate the regression separately for female and male students. Standard errors are clustered at the department-year level. The main results are presented in Figure 4, which reports the coefficients γ_s for the female (green triangle) and the male (orange square) students. We present point estimates for third-year students in Panel A of Table 4.

Result 1: A decline in the early-career publications of third-year female Ph.D. students. Starting with the female students, Figure 4a shows an estimated decline of 8 percentage points in the probability of publishing any paper during the five years post-Ph.D. for third-year students (i.e., those graduating two years after the leave). This decline represents approximately 15 percent of the sample mean of 0.54, and the effect is statistically significant at the 5 percent level. We find close to no effects for other cohorts of female Ph.D. students, including for those graduating before the sabbatical leave (the pre-treatment period). Looking at the number of publications instead, Figure 4b also shows a decline for third-year students with an estimated coefficient of -0.60. This effect is statistically significant at the 1 percent level and translates into a decline equal to approximately 33 percent of the sample mean of 1.81 publications. Again, we find essentially no impact on the other cohorts of Ph.D. students. This heterogeneity, with the effect concentrated among third-year students, aligns with our previous discussion: the absence of a female professor does not affect all students equally, and those in their critical early research development phase are the most likely to be impacted.

Result 2: A decline in the share of female Ph.D. students with an academic placement. Considering the importance of early-career publications for surviving in academia, the decline in publications (result 1) suggests that we should find a lower share of female economists in academic positions. We next show that this indeed is the case. Figure 4c shows estimated coefficients when estimating Equation 2 using instead a binary variable equal to one if a student was placed "in academia," meaning they obtained either an assistant professor or postdoctoral position at a university within one year of graduation.[21] The figure shows a clear decline in the probability of staying in academia for third-year female students, and the decline is in line with the magnitude of the decline in the probability of publishing with an estimated coefficient of -0.098 versus -0.080. Consistent with the publication outcomes, we do not observe any impacts statistically different from zero for the other cohorts of Ph.D. students at any conventional level.

Result 3: Zero-sum game – evidence from male students. Using the publication and the placement variables for the male Ph.D. students, we provide evidence of what looks like a zero-sum game between male and female Ph.D. students of the third year-students cohort. Starting with the probability of publishing at least one paper, we find an increase of 7.1 percentage points for male third-year students, corresponding to 13 percent of the sample mean of 0.56 (Figure 4a). For the number of publications, we find an increase of 0.43 papers for third-year students, corresponding to 19 percent of the sample mean of 2.27 publications (Figure 4b). Both estimates are significant at the 1 percent level. Lastly, for the probability of staying in academia, we find an increase of 3.5 percentage points for third-year students, significant at the 10 percent level (Figure 4c). Similar to the findings for female students, we observe no significant impact on other student cohorts, including those graduating before the sabbatical leave (the pre-treatment period). The contrasting results for male and female students – where female Ph.D. students lose from the absence of a female

[21]We obtain very similar results if we instead define academia as holding an assistant professor position at a university within three years post-Ph.D.

professor, while the male Ph.D. students gain – suggest a zero-sum dynamic between the affected students. Indeed, when estimating Equation 2 on a pooled sample of all male and female Ph.D. students in Figure A2, we find no statistically significant effects for any cohorts of students.

3.2 Robustness checks

Our setting has a number of empirical challenges related to the nature of the treatment, namely multiple leave events per department and variation in treatment timing across units. As a result, the event study regressions contain a large number of overlapping treatment events, meaning that a significant share of department-year observations have multiple time indicators switched on at the same time (due to different female professors taking leave at different times). These overlaps make it challenging to precisely estimate the various lead and lag coefficients jointly, as the indicators are correlated, sometimes strongly so. In this section we first engage with the event study literature in Econometrics (Roth et al., 2022) and discuss potential biases in the estimation of the average treatment effect that occur in the presence of treatment heterogeneity inherent to settings with variation in treatment timing.[22] Notice that our setting slightly differs from existing ones, which makes it difficult to apply existing solutions as is. We provide evidence showing that our results are not driven by these concerns. We then show that our results are robust to a variety of alternative specifications, treatment definitions and sample restrictions.

Leads and lags estimated separately: To alleviate concerns related to repeated leaves and time-varying treatment effects, we start by showing that the results are robust to estimating each lead and lag through separate regressions, using the following specification:

$$y_{id,t} = \alpha_d + \delta_t + \beta_s FemSabbat_{id,t-s} + \varepsilon_{id,t}, \tag{3}$$

which we run separately for $s \in \{-5, \ldots, 5\}$. The regression estimates the effect of female professors on sabbatical leave, s years before (or after) students' graduation year using *every* other year as the base category. We restrict the sample to be the same as the one in the baseline regressions.[23] As can be seen in Figure 5, we obtain almost exactly the same

[22] Recent econometric research has highlighted issues with standard two-way fixed effect models (controlling for group and time fixed effects) when treatment effects are heterogeneous and treatment timing varies. These models might make "forbidden" comparisons between earlier and later treated units, potentially combining heterogeneous treatment effects using weights that lack economic intuition, such as negative weights on observations that serve as both treated and controls (Goodman-Bacon, 2021).

[23] Since this specification does not include all lead and lag periods, the sample has approximately 20 percent more observations compared to the baseline regression, as the inclusion of leads and lags introduces

estimates as before, including no effect for students graduating prior to the leave (see point estimates in Panel B of Table 4). Since the control group differs from our main specification, yet the results remain consistent and confined to third-year students, this reduces concerns about heterogeneity and dynamic effects commonly raised in the event study literature.

To further alleviate concerns related to repeated leave events, we also run a stacked Difference-in-Difference specification where we apply more stringent sample restrictions than in our main specification to assure a "clean" control group. By stacking all treatment events, this approach mitigates potential issues related to the negative weighting of treatment events (Cengiz et al., 2019). This specification produces estimates comparable to our main results, Subsection C.1.

Other robustness checks. We also show that our results are robust to a variety of other alternative specifications, presented in Appendix C. These checks explore alternative definitions of our treatment variable, such as using the sum or share of female professors on leave, and varying the exclusion criteria for sabbatical leaves, such as excluding half-year sabbatical leaves. We also examine the sensitivity of our results to different assumptions about the start year of students' Ph.D. programs, and test for potential confounding effects of within-department time trends and the influence of individual departments on our estimates by adding department-five-year interacted fixed effects and throwing out one department at a time from our estimation sample. Our main findings remain robust across these various specifications and sample restrictions. The estimated effect of sabbatical leaves on the number of publications of third-year female students ranges from -0.37 to -0.85 across the 15 alternative estimates presented in Appendix C (compared to -0.60 using our main definition), and all coefficients are statistically different from zero at the 5 percent level.[24]

4 Publication and placement quality

We have provided evidence of a decline in publication and academic placement records for the cohort of affected female Ph.D. students, with apparent gains for their male counterparts. These changes resulted in negligible aggregate effects for the affected cohorts. In this section, we investigate the change in the representation of students at top-tier departments and top-tier academic journals.

missing values. To ensure comparability, the estimates in Figure 5 are based on the same sample as our main regressions. We also estimated the coefficients using the unrestricted sample (which includes the additional 20 percent observations), and the results are consistent with those from the main regressions.

[24] 11 of the 15 estimates are significant also at the 1 percent level.

Starting with the quality of research publications, we use two different measures to proxy for academic quality: the number of top-five publications[25] and the number of citations per paper per year. Table 5 shows the results of a regression similar to our main analysis, where the outcome variables are the mentioned quality measures, as well as the number of publications (Panel A) as a benchmark. Panel B, Column 1, shows that third-year female students experience a 60 percent decline in top-five publications relative to their average of 0.156. In contrast, column 2 shows that the effect for third-year male students is not statistically significant at any conventional levels and is much smaller, representing a 19 percent increase relative to their average of 0.243. Column 3, which aggregates data across genders, reveals no net decline in publications, a result driven by the gender composition of the student pool, where women make up only 30 percent of the total.

Further analysis of students who remain in academia (columns 4 and 5) shows that the decline in publications for women is not solely due to fewer women holding academic positions. Female students who stay in academia publish fewer papers overall (though these estimates are not statistically significant) and fewer papers in top-five journals, with the latter result being statistically significant at the 10 percent level. Interpreting our results with the opposite sign, as the effect of having a female professor present, the magnitude of our estimates – although not statistically significant – aligns closely with the observed gender gap in publication output. This gender gap in publication output has been well-documented in previous studies (Ductor et al., 2023), also reflected in our sample, where male graduates publish an average of 3.199 papers in their early career, compared to 2.672 papers for female graduates. Specifically, our findings suggest that male Ph.D. students placed in academia would have published an average of 2.953 papers in their early career (i.e., 3.199 − 0.246), while females would have published an average of 2.994 papers (i.e., 2.672 + 0.322). In contrast, the positive effects on publications for male students are no longer statistically significant at conventional levels, suggesting that the earlier increase was primarily driven by the extensive margin. Further, the affected cohort of male students who remain in academia do not publish higher-quality papers, as measured by the number of top-five publications, and produce fewer highly cited papers.

Mirroring the results on the quality of academic production for the female students, the affected cohort of female students are missing at top-tiered academic institutions. In contrast, the affected male cohort are filling positions at lower-ranked academic institutions. To rank placement institutions, we average the citation per papers of their assistant professors to define three distinct placement groups based on rankings: Group 1 includes the top-25

[25]The top-five journals include American Economic Review, The Quarterly Journal of Economics, Econometrica, The Review of Economic Studies, and Journal of Political Economy.

Economics departments;[26] Group 2 includes all other departments; group 3 represents not being in academia.

Table 6 displays the marginal effects of a multinomial regression model with the three placement categories, using Group 3 (out of academia) as the base category.[27] The affected female cohort is 3.9 percent less likely to be placed in a top-25 department. This decline accounts for 56 percent of the 7 percent of female Ph.D. students in our sample who end up in top-25 departments and 45 percent of the overall decline in female Ph.D. students entering academia, with placements at other institutions accounting for the remaining 55 percent. In contrast, the affected cohort of male students have an estimated coefficient very close to zero in these same top-25 departments, indicating they do not replace their female counterparts but instead take positions outside of the top-25 departments.

A natural question arises: is the decline in publications, particularly top-five publications, among the affected cohort of female students consistent with the change in placement rankings? If female Ph.D. students, regardless of their human capital formation, are placed in less prestigious institutions, they may encounter different tenure incentives, reduced support from colleagues, limited funding opportunities, and fewer connections to influential networks. These conditions could influence their publication and citation outcomes. To assess the contribution of the change in placement quality to the decline in publication, we estimate the same regression as above, substituting the average publications of the student placement group for individual publication records as the outcome variable. [28] The estimates in column 6 of Table 5 indicate that, had the affected female cohort published at the same rate as assistant professors at their average placement institutions, their decline in publications and top-five publications would be significantly smaller – only one-third of the observed decline in overall publications and half the decline in top-five publications. Yet, while male students publish more papers than the average number of publications of their placement groups (comparing Panel A, columns 2 and 7) – noting that they come from top schools but often secure positions at lower-ranked institutions – these same students do not produce

[26]The group consists of the following departments: Northwestern, Chicago Booth, Harvard Kennedy School, Harvard Business School, Columbia Business School, LSE, Harvard, Columbia, MIT, Dartmouth, UC Berkeley, MIT Sloan, Washington University in St. Louis, Princeton, Stanford Graduate School of Business, UPenn, Wharton School of Business, Haas School of Business, Boston, University of British Columbia, UCLA, Chicago, Arizona State University, NYU Stern and University of Houston.

[27]The remaining variables are defined as in our main regression in Equation 2. We refer you to Appendix D for the exact specification. We also refer you to Table D2 for an alternative classification based on the *RePec* Economics department ranking.

[28]We refer you to Appendix D for a detailed description of these groups. To keep the placement groups as comparable as possible, we use finer placement groups for this analysis by dividing departments into 7 groups based on average citations, and calculate the within-group average of each outcome within the groups, excluding each students' own value. See Appendix D for details on the placement groups and the within-group averages.

higher-quality papers, as measured by top-five publications (comparing Panel B, columns 2 and 7). This suggests that placements do not solely drive the effects on publications for female students. Instead, the Ph.D. training environment shapes a student's early career trajectory beyond the job market and initial placement.

Regardless of the primary mechanism, our findings underscore that a missing female professor significantly impacts the careers of affected Ph.D. students. The losses for women numerically balance the gains for men, with one important caveat: men tend to enter the profession from lower-ranked institutions, while women are notably absent from the upper-ranked institutions. The replacement from the point of view of the home institutions of these students is not of equal "placement quality".

Beyond the effects on home institutions, our results have implications for top schools, which have particularly low female representation. For example, within our sample period, the top 25 institutions have a gender ratio of 0.278 among their assistant professors, which increases to 0.37 for the bottom 25 institutions.

Consider a scenario where each of the top 50 schools in our sample hires one additional senior-level female professor, holding other factors constant; our estimates would imply an increase of the share of women assistant professors in the top 25 schools by 50 percent – from 21.5 percent to 32.4 percent. These calculations are based on the gender composition of our sample among Ph.D. graduates at each department, using the estimates from Table 6 and assuming that an assistant professor remains in the role for an average of six years.[29]

Of course, the real world is more complex. Hiring a female professor – whether full or assistant – might influence the composition of both the student and professor pools in dimensions that our exercise does not capture. Such shifts could generate selection effects or equilibrium adjustments, such as a decline in male assistant professors at these same institutions due to replacement. Moreover, this simple calculation does not account for long-term dynamic effects. As these female assistant professors achieve tenure and become advisors themselves, their influence could compound and shape future generations of academics.

In light of recent efforts to promote diversity in academia and improve gender representation among faculty, our analysis highlights the potential impact of hiring senior female professors. Specifically, this approach could achieve one third of the progress needed to reach gender parity among assistant professors while also improving gender balance among senior faculty. Moreover, our findings suggest that these advances come with minimal losses in

[29]Specifically, for each year, we calculate the number of graduating female Ph.D. students in our sample (average 146) and multiply it by 0.039, as derived from Table 6 which identifies the top-25 schools using the average citations of the schools. This gives an estimate of the extra number of assistant professors entering top departments by year (mean 5.7). We obtain a similar estimate when we use the estimates from Table D2 which uses the top-25 *RePec* departments instead.

academic productivity – a common meritocracy concern in diversity hiring.

5 Gendered professional relationships

A key question remains: How do we explain the apparent shift in opportunities from women to men within the affected cohort? One plausible explanation is that the positive effect on men is an unintended consequence of the adverse impact on women in a competitive job environment where relative positioning is crucial. We argue that these ripple effects stem from the intersection of two factors: the importance of professional relationships for career outcomes and the gendered nature of these relationships. Professional relationships matter for human capital formation, information sharing and extraction, career growth, and promotion.[30] For example, a supportive mentor may provide valuable guidance, share research ideas, or introduce their advisees to influential colleagues, all of which can significantly impact career trajectories.[31] While professionals benefit from having a mentor, a (strong) relationship cannot be forced, and we show that these relationships tend to be gendered. The lack of female mentors and advocates likely hinders the development and placement of female students, while unintentionally benefiting male students. In what follows, we present further evidence supporting this gender homophily mechanism.

Gendered affinity, cultural differences in communication styles, or sexual tension, inherent in gendered relationships, could lead male professors to connect more easily with male students and female professors with female students. This does not mean that all male students get along with male professors or all female students with female professors; rather, the likelihood of forming strong connections is higher within same-gender pairs. As such, the absence of a female professor might inadvertently disadvantage female Ph.D. students, and benefit the male students. Note that while these gendered relationship dynamics tend to be more pronounced in the academic setting, they are also present in most other work environments and can help explain gender differences in the workplace more broadly.

In what follows, we first provide evidence of gender homophily in advisor-advisee relationships – the tendency for individuals to associate with others who share similar characteristics – and demonstrate that a professor's leave affects the advisor-advisee relationship, particularly for third-year students.

[30] A series of papers have shown the importance of ones' network for job market outcomes, such as unemployment duration, job quality and wages (Cingano and Rosolia, 2012; Schmutte, 2014; Zimmerman, 2019).

[31] Descriptive evidence suggests that mentoring affects Ph.D. students career outcomes, (Paglis et al., 2006)

Gendered relationship. In line with previous research demonstrating homophily in various contexts, such as friendship formation (Currarini et al., 2009; McPherson et al., 2001b), job search networks (Hellerstein et al., 2011), mentoring relationships (Ginther et al., 2020; Ginther and Kahn, 2004; Hilmer and Hilmer, 2007; Ibarra, 1992), and social support (Mollica et al., 2003), we first show the presence of gender homophily in advisor-advisee relationships: female students are more likely to have a female advisor even after controlling for research field.

Figure 6 provides a first look at advisor-advisee relationship and shows that female students were more likely than male students to be matched with female advisors. The figure allows us to compare the evolution of 1) the share of female students with a female advisor, 2) the share of male students with a female advisor, and 3) the share that we would expect to observe if the matching of advisor-advisee were random, which serves as a benchmark.[32] Throughout the sample period, the share of male students with a female advisor is consistently about half that of the female students, with an average of 12.5 percent for the female students compared to 7.5 percent for the male students for the full sample period from 1994 to 2019. The share of female students with a female advisor closely follows this estimate for most of the sample period, with the exception of a short period between 2010 and 2015.

Figure 6 (although informative) potentially conflates gender differences in advisor choices with gender differences in field preferences. Table 7 shows the results of a regression of a dummy variable for whether a student has a female advisor on whether the student is identified as female. We gradually include fixed effects, starting with only year fixed effects (Column 1), adding department fixed effects (Columns 2-3), then field fixed effects (Column 4), and finally, we including the interaction of department-year-field fixed effects. Fields are measured using the JEL code of the dissertations.[33] Standard errors are clustered at the department-year level.

Consistent with the magnitude in Figure 6, Table 7 (Columns 1-2) shows that female Ph.D. students are about 5 percentage points more likely to have a female advisor compared to men. Controlling for field fixed effects reduces the estimate to 4.7 percentage points, while adding the triple interaction reduces it further to 3.6 percentage points. Still, even in the most stringent specifications, comparing male and female students from the same department, graduation year, and research field, female students are almost 4 percentage points (51 percent of the average share for male students, 0.07) more likely to have a female advisor, with all estimates statistically significant at the 1 percent level. These results suggest

[32] We compute this as the share of women among associate and full professors at each department-year and weight it by the number of students (at each department-year).

[33] We are missing JEL codes for close to 20 percent of our sample. We replicate the results with department and year fixed effects with the reduced sample in Column 3 for ease of interpretation.

that department and field choices explain only a small portion of the pattern in Figure 6. The homophily in advisor-advisee relationships align with existing results in economics and other fields.[34]

Sabbatical leaves break advisor-advisee relationships. We next explore how sabbatical leaves affect the matching of Ph.D. students to advisors, starting from the point of view of professors on leave. We show that a professor on leave experience a decline in the number of third-year students they advise.

Using all associate and full professors in our sample, we estimate the following specification at the professor-department-year level:

$$NbAdvisees_{jd,t} = \alpha_{jd} + \delta_t + \sum_{s=-5}^{s=5} \beta_s Sabbat_{jd,t-s} + \varepsilon_{jd,t}, \tag{4}$$

where $NbAdvisees_{ijt}$ is the number of graduating advisees of professor i in department d and year t; $Sabbat_{jd,t-s}$ is a dummy variable equal to 1 if professor j in department d went on sabbatical s periods before year t; α_{jd} denotes professor×department fixed effects, and δ_t denotes year fixed effects. The coefficient β_s captures the number of graduating students professor j had s years after (or before) the leave year. As in the main analysis, we estimate this equation for a sample of students graduating between 1998 to 2014, normalizing the coefficients to the average coefficient in the reference period $s \in \{-4, \ldots, -1\}$. Standard errors are clustered at the professor-department level.

The estimates, shown in Figure 7, reveal a drop in the number of advisees graduating two years after the leave year, with an estimate of -0.12. This decline corresponds to approximately 24 percent of the sample mean (0.49 graduating students per year). We find a decline of the same magnitude three years after the leave.

Sabbatical leaves influence advisor matching for female students: Fewer female advisors and advisors with more Ph.D. students. We have documented that professors on leave have fewer advisees in the years right after. But what about the students? How are the advisors of the affected students different from other cohorts of women? Using the main specification in Equation 2, we look at a series of outcomes related to the characteristics of the advisors of the Ph.D. students, including the gender of the advisor, the number of other Ph.D. students, the number of other female Ph.D. students, the number of publications and the citation count per paper of their advisors. The results are summarized

[34] For instance, Gallen and Wasserman (2023) documents gender homophily using data from an online college student-alumni mentoring platform.

in Table 8, which shows the estimates for the third-year students.[35]

Three points stand out. First, in column 1, the third-year female students are less likely to have a female advisor, with a decline of 8.1 percentage points, which corresponds to a 64 percent decrease from the sample mean. In contrast, the estimated effects for male students are negligible, with values close to zero. Second, female students are also more likely to have an advisor that is slightly more experienced (as measured by the number of years since its first publication) and that has a lot of other Ph.D. students, and in particular, other female Ph.D. students (columns 4 and 5). We do not find such effects for male students. Third, columns 6-8 suggest that female students are not more likely to match with a lower quality professor when a female professor goes on leave. This result indicates that our main findings cannot be explained by the quality of the female professor on leave.

Discarding alternative explanations While we argue and provide evidence for the gendered nature of mentorship and professional networks and their role in shaping the career trajectories of young economists, two alternative explanations could drive our results.

First, in Section 2 we showed that men and women are not equally distributed across fields: both female students and professors are relatively more likely to work in Labor/Public and less likely to work in Macro/Finance as compared to men. Could our findings be driven by the fact that the absence of female professors translated into a lower share of professors in fields where women are more likely to work, disproportionately affecting female Ph.D. students.

For each of the seven fields in our sample, we test whether having a professor on leave in that field affect the early-career outcome at the department-level. To be specific, for the male and female students separately, we run seven regressions – one per field, where the treatment variable is defined as having at least one professor on leave in a particular field in a given year, independently of the gender of the professor (details presented in Appendix Subsection E.1). The results reveal no systematic effects on early-career outcomes for third-year students (Appendix Figure E2), which we would expect to observe if field representation was a key characteristic of the missing professors.[36] Notably, we find no significant effects on the early-career outcomes when a professor in Labor/Public goes on leave. These results, therefore, do not support the interpretation that our main findings are driven by the absence of professors in fields where women are more represented.

[35]We refer you to the Appendix Figure A4 for the related figures and the coefficients for all other cohorts of Ph.D. students.

[36]The only statistically significant effect for female third-year students is an 5 percentage point increase in the estimated probability of staying in academia when a professor in Macro/Finance is missing. However, we find no significant impact of this absence on their publication outcomes.

The second alternative explanation for our findings is that male professors might take leave at times when female professors do not. Hence, the positive effect on male students could be due to their benefiting from the presence of male professors. To test this, we first estimate the baseline regression from Equation 2, using male professors on sabbatical leave instead of female professors on leave (Table A1). Second, we estimate the baseline regression while controlling for male professors on sabbatical leave, adding the same number of leads and lags as for female professors on leave (Table A2). We use two measures of male professors on sabbatical leave: (1) a binary variable indicating whether *any* male professor is on leave at the department level in a given year (Panel A), and (2) the *number* of male professors on leave (Panel B). The second measure accounts for the fact that 60 percent of department-year observations in our sample include at least one male professor on leave. The estimates for a male professors on leave on early-career outcomes are close to zero for both female and male Ph.D. students (Table A1). Furthermore, the estimated effects of female professors on leave remain almost identical to those observed previously Table A2). This suggests that our results are not driven by the timing of male sabbatical leaves negatively correlated with the timing of female leaves.

6 Conclusion

To sum up, our study provides evidence of gender homophily in advisor-advisee relationships, with female Ph.D. students being more likely to work with female advisors. However, the female professors on leave disrupts these relationships, leading to weaker ties and fewer collaboration opportunities for female students. This finding underscores the importance of same-gender mentorship in fostering the success of women in male-dominated fields like Economics.[37] Furthermore, our analysis of the placement of female Ph.D. students across school rankings shows that affected female students are missing from top-ranked institutions and are underrepresented in academia. This pattern suggests that female students are "ranked down" upon entering the job market, either due to lower human capital formation or other job market misallocation influenced by the absence of female mentors.

These dynamics of gendered relationships extend beyond academia, permeating most work environments. While academia often exacerbates these challenges, our findings can explain broader gender disparities in the workplace, including the underrepresentation of

[37] An alternative mechanism, rooted in gender homophily, suggests that students form relationships prior to their third year, with female students often investing in relationships with female professors. When a female professor is absent, this creates a one-year mentorship gap for the affected students. While this explanation also hinges on gender homophily, we demonstrate in Appendix Subsection E.2 that such a disruption alone is unlikely to account for our findings.

women in senior roles and specific job categories. Specifically, our research underscores the pivotal role of women in leadership positions in fostering gender diversity across occupations. Hiring more female associate and full professors can create a more inclusive and supportive academic environment, improving representation and retention of women in the profession. Senior female professors, as role models, mentors, and advocates, can counteract professional barriers, addressing the leaking pipeline (Casad et al., 2021).

Finally, our findings have implications for the feasibility of policies aimed at promoting an equitable and merit-based system in academia, in an environment where relationship matters and tend to be gendered.

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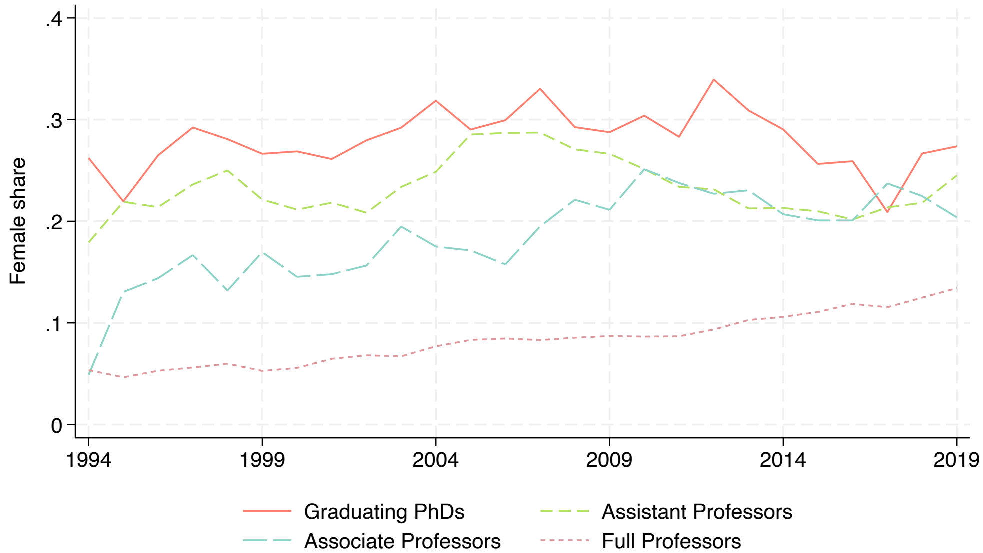
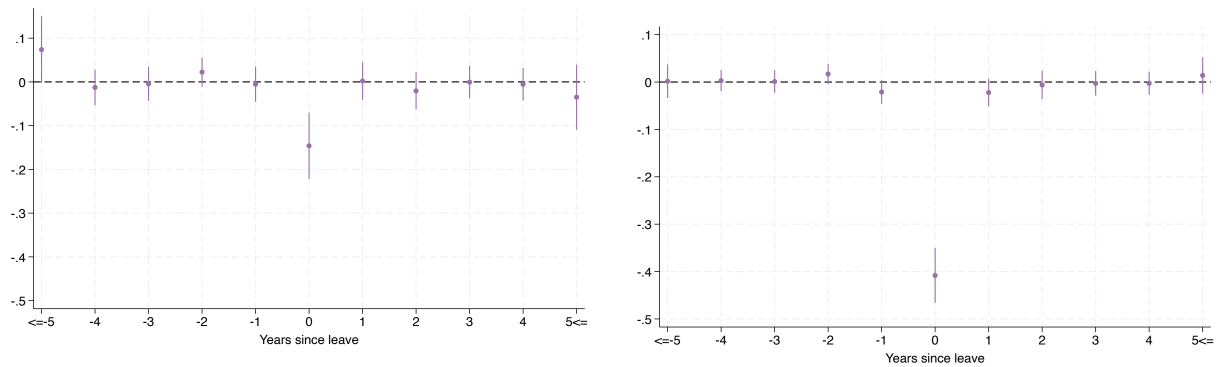
Figure 1: Female shares of Ph.D. students and faculty members



Note: The figure shows the evolution of the female share of graduating Ph.D. students (solid red), assistant professors (short dash green), associate professors (long dash blue), and full professors (dot pink) for the 46 Economics departments in our sample from 1994 to 2019.

Figure 2: Leave of absent and the presence of female professors



(a) Probability of at least one female professor present

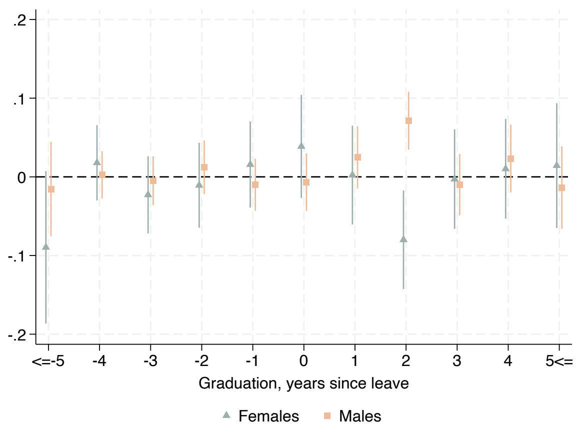
(b) Share of female professors present

Note: The figures show coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation 1. The outcome variable in Figure (a) captures whether departments have any female professor present, while the outcome in Figure (b) is the share of female professors present (i.e. the share of hired female professors not on leave). Standard errors are clustered at the department-year level.

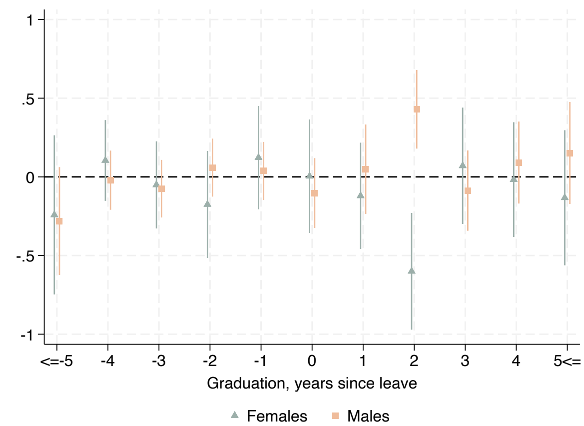
Figure 3: Timing of leave and classification of Ph.D. students

	Leave Year t^*				
Cohort	*First Year*	*Second Year*	*Third Year*	*Fourth Year*	*Fifth Year*
Start Year	t^*	t^*-1	t^*-2	t^*-3	t^*-4
Graduation Year	t^*+4	t^*+3	t^*+2	t^*+1	t^*

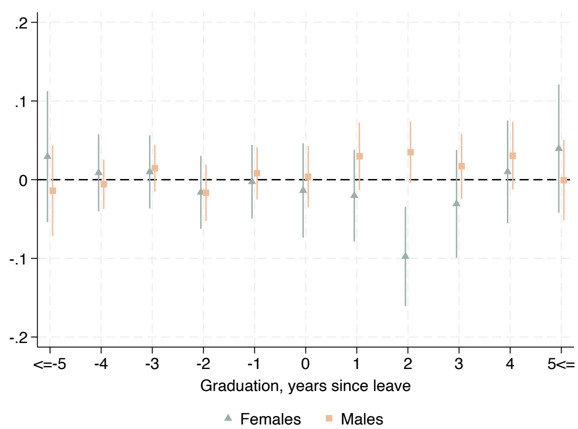
Figure 4: Female professors on sabbatical leaves and students' early-career outcomes



(a) Probability of publication



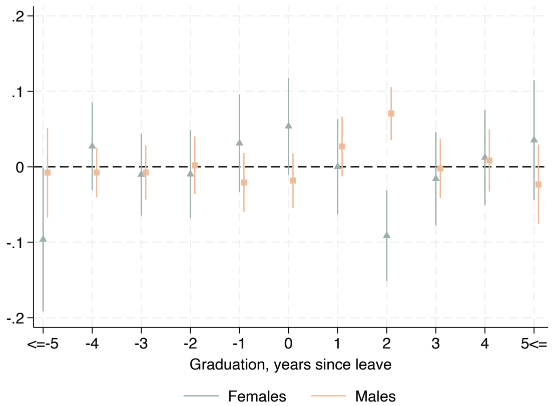
(b) Number of publications



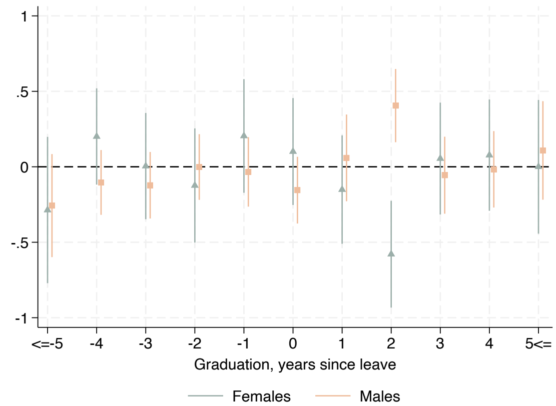
(c) Probability of staying in academia

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 2. The outcome variable in Figure (a) is a binary variable denoting whether students have any publications five years post-Ph.D. In Figure (b) the outcome is the number of publications five years post-Ph.D, and in Figure (c) the outcome is a binary variable denoting whether students stayed in academia. Standard errors are clustered at the department-year level.

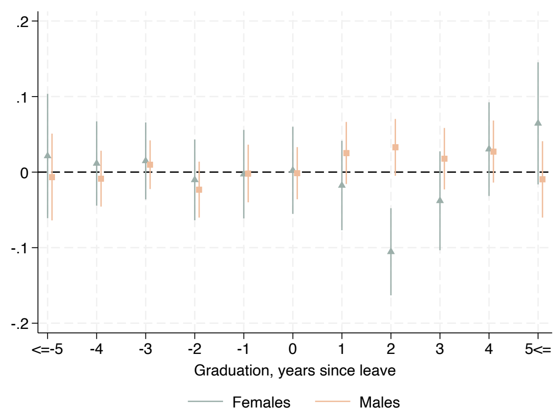
Figure 5: Robustness: Female professors on sabbatical leaves and students' early-career outcomes, leads and lags estimated in separate regressions



(a) Probability of publication



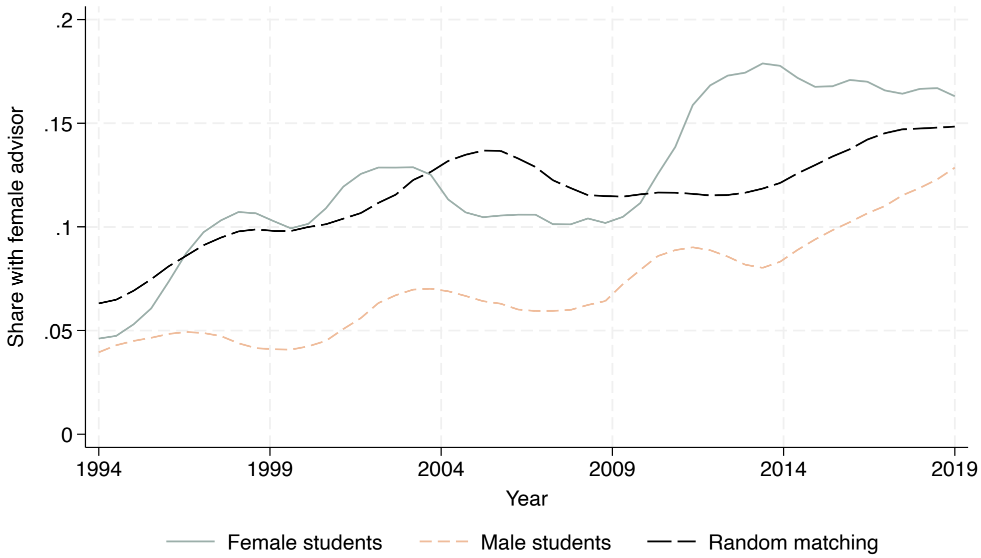
(b) Number of publications



(c) Probability of staying in academia

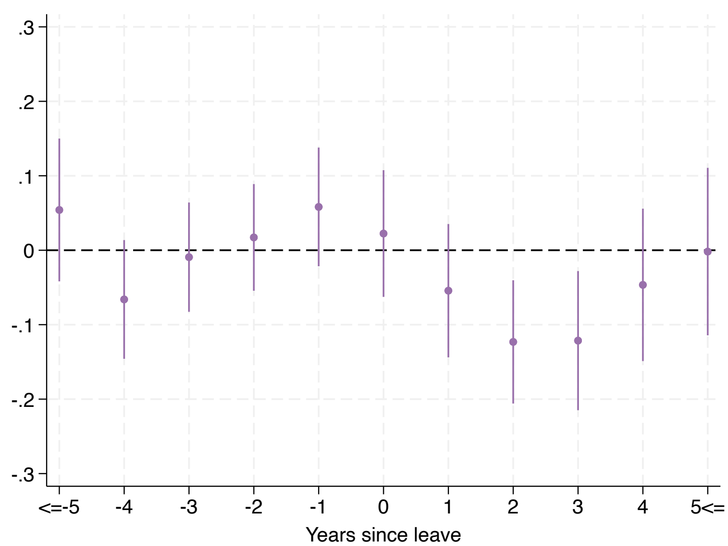
Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 3, where each of the time indicators are estimated through separate regressions. The outcome variables are the same as in Figure 4. Standard errors are clustered at the department-year level.

Figure 6: Share of Ph.D. students with a female advisor



Note: The figure shows the share of students with a female advisors, separately for female (solid green) and male students (dash orange). The line labelled "Random matching" (long dash black) shows the share of women among associate and full professors at each department-year, weighted by the number of students.

Figure 7: Sabbatical leaves and the number of graduating advisees



Note: The figure shows coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 4. The regression is estimated at the professor-year level and the outcome variable is the number of graduating advisees the professor had each year. Standard errors are clustered at the professor-department level.

Table 1: Descriptive statistics – Top-50 Economics departments, 1994-2019

	Total			Females			Males	
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)	Mean (7)	Median (8)
Panel A: Number of faculty and graduating Ph.D. students								
Graduating Ph.D. students	12.27	11	0.23	3.17	3	0.08	9.10	8
Faculty	32.47	31	0.38	4.56	4	0.07	27.83	26
Full professors	19.89	19	0.29	1.77	1	0.05	18.13	17
Associate professors	4.64	4	0.09	0.92	1	0.03	3.70	3
Assistant professors	7.94	8	0.12	1.88	2	0.04	6.00	6
Observations	1029			1029			1029	
Panel B: Share of faculty with a graduating Ph.D. student								
Full professors	0.36	0	0.0034	0.34	0	0.0111	0.36	0
	(n=20471)			(n=1818)			(n=18653)	
Associate professors	0.23	0	0.0060	0.19	0	0.0127	0.23	0
	(n=4773)			(n=942)			(n=3831)	
Assistant professors	0.08	0	0.0031	0.05	0	0.0050	0.09	0
	(n=8169)			(n=1930)			(n=6175)	

Note: The unit of observation in Panel A is department-year, while the unit in Panel B is professor-year. Panel A shows the number of graduating Ph.D. students and faculty by rank, while Panel B shows the share of faculty by rank that have at least one graduating Ph.D. student.

Table 2: Descriptive statistics – Faculty (associate and full), 1994-2019

	Total		**Females**		**Males**	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Panel A: Sabbatical leaves						
Sabbatical leave	0.06	0.0015	0.08	0.0051	0.06	0.0016
Observations	25244		2760		22484	
Panel B: Mentoring						
Advisees	0.28	0.0033	0.26	0.0097	0.28	0.0035
Female advisees	0.07	0.0015	0.10	0.0057	0.07	0.0015
Male advisees	0.21	0.0027	0.16	0.0072	0.21	0.0029
Observations	25244		2760		22484	
Panel C: Productivity (previous 10 years)						
Publications	8.73	0.0599	8.83	0.1695	8.72	0.0637
Top-five publications	1.29	0.0130	1.53	0.0430	1.26	0.0137
Average citations per paper and year	3.98	0.0338	5.47	0.1482	3.84	0.0350
Observations	25244		2760		22484	
Panel D: Networks (previous 10 years)						
Unique co-authors	6.43	0.0510	6.42	0.1580	6.43	0.0538
Unique female co-authors	1.13	0.0115	1.57	0.0450	1.08	0.0118
Unique male co-authors	5.25	0.0410	4.79	0.1194	5.29	0.0434
Observations	25244		2760		22484	
Panel E: Main research field (shares)						
Micro	0.18	0.0106	0.14	0.0300	0.18	0.0113
Macro/Finance	0.35	0.0132	0.23	0.0363	0.36	0.0141
Labor/Public	0.23	0.0117	0.41	0.0424	0.21	0.0119
IO	0.07	0.0069	0.05	0.0192	0.07	0.0074
Environmental	0.04	0.0055	0.03	0.0146	0.04	0.0059
Development/History	0.08	0.0073	0.07	0.0236	0.07	0.0077
Other	0.15	0.0098	0.13	0.0287	0.15	0.0104
Observations	1299		135		1164	

Note: The unit of observation is professor-year, except for Panel D which is at the professor level. Panel A shows the average number of graduating advisees per year and by gender. Panel B shows the average number of published papers, the number of top-five papers and citations per paper and year over the previous 10 years. Panel C shows the average number of unique co-authors over the previous 10 year by gender, and finally, Panel D shows the share of professors by their main research field. Fields are defined based on the most common JEL code from the dissertations of their advisees. The sample is restricted to the associate and full professors.

Table 3: Descriptive statistics – Ph.D. students, 1998-2014

	Total		**Females**		**Males**	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Advisor						
Female advisor	0.08	0.0033	0.12	0.0072	0.07	0.0035
Full professor	0.82	0.0050	0.82	0.0091	0.82	0.0060
Associate professor	0.11	0.0041	0.11	0.0076	0.11	0.0049
Assistant professor	0.06	0.0032	0.06	0.0057	0.06	0.0038
Observations	6999		2072		4927	
Panel B: Productivity (5 years post Ph.D.)						
Any publication	0.55	0.0059	0.53	0.0110	0.56	0.0071
Publications	2.13	0.0370	1.80	0.0605	2.27	0.0458
Top-five publications	0.22	0.0092	0.16	0.0131	0.24	0.0118
Average citations per paper and year	3.83	0.1253	3.79	0.2730	3.84	0.1360
Publications with advisor	0.20	0.0080	0.17	0.0119	0.21	0.0101
Observations	6999		2072		4927	
Panel C: Networks (conditional on publication)						
Unique co-authors	4.95	0.1361	4.88	0.2951	4.98	0.1496
Unique female co-authors	0.96	0.0362	1.19	0.0800	0.87	0.0392
Unique male co-authors	3.95	0.1075	3.64	0.2254	4.08	0.1204
Observations	3878		1108		2770	
Panel D: Job placement						
Academia	0.51	0.0060	0.49	0.0110	0.52	0.0071
Top-25 Economics department	0.08	0.0032	0.07	0.0056	0.08	0.0039
Observations	6999		2072		4927	
Panel E: Field of dissertation						
Micro	0.16	0.0049	0.14	0.0085	0.17	0.0060
Macro/Finance	0.29	0.0061	0.24	0.0107	0.31	0.0074
Labor/Public	0.21	0.0055	0.29	0.0114	0.17	0.0061
IO	0.06	0.0032	0.05	0.0056	0.06	0.0039
Environmental	0.03	0.0023	0.03	0.0043	0.03	0.0028
History/Development	0.09	0.0038	0.11	0.0077	0.08	0.0044
Other	0.16	0.0049	0.14	0.0086	0.17	0.0060
Observations	5507		1609		3898	

Note: Panel A shows the share of students with a female advisor, as well as the share of students with an advisor by different ranks. Panel B displays measures of productivity for the period five years post graduation. Panel C is based on the sub-sample of Ph.D. students that were placed in academia during the first three year post graduation and shows the average number of unique co-authors by gender. Panel D shows the share of the Ph.D. students that were placed in academia, as well as the share that were placed in a top 25 Economics department, defined based on the average citations of assistant professors (see Section 4). Finally, Panel E shows the share of students in different research fields, defined in terms of the JEL codes of the dissertations. The sample includes all the Ph.D. students graduating between 1998 and 2014.

Table 4: The effects of sabbatical leaves on early-career outcomes of third-year students, baseline specification and leads and lags estimated separately

	Female Ph.D. students			Male Ph.D. students		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
Panel A: Baseline estimates:						
FemSabbat, $t-2$	-0.080**	-0.600***	-0.098***	0.071***	0.430***	0.035*
	(0.032)	(0.189)	(0.032)	(0.019)	(0.127)	(0.020)
Observations	2072	2072	2072	4927	4927	4927
R^2	0.053	0.051	0.084	0.032	0.037	0.046
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518
Panel B: Leads and lags separately:						
FemSabbat, $t-2$	-0.091***	-0.579***	-0.105***	0.070***	0.405***	0.033*
	(0.031)	(0.180)	(0.029)	(0.018)	(0.124)	(0.019)
Observations	2072	2072	2072	4927	4927	4927
R^2	0.049	0.049	0.082	0.031	0.036	0.045
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518

Note: Panel A of the table presents estimates on early-career outcomes from the specification in Equation 2. The table only displays the coefficients for the cohort graduating 2 years after the sabbatical leave (corresponding to third-year students). See Figure 4 for the coefficients for the other cohorts of Ph.D. students. Panel B of the table presents estimates on the same outcomes using the specification in Equation 3, where we estimate each lead and lag through separate regressions. See Figure 5 for similar coefficients for the other cohorts of Ph.D. students. "Mean dep.var." displays the average values of the dependent variables. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Table 5: The effects of sabbatical leaves on measures of publication quality

	All students			In Academia		Placement average	
	Females (1)	Males (2)	All (3)	Females (4)	Males (5)	Females (6)	Males (7)
Panel A: Sum publications							
FemSabbat, $t-2$	-0.600***	0.430***	0.121	-0.322	0.246	-0.176***	0.072*
	(0.189)	(0.127)	(0.107)	(0.265)	(0.200)	(0.056)	(0.041)
Observations	2072	4927	6999	1022	2554	2072	4927
Mean dep.var.	1.805	2.27	2.132	2.672	3.199	1.805	2.27
Diff (1)-(6), p-value						0.013	
Diff (2)-(7), p-value							0.003
Panel B: Sum top-five publications							
FemSabbat, $t-2$	-0.094**	0.046	0.005	-0.133*	0.037	-0.052***	0.019
	(0.043)	(0.033)	(0.026)	(0.079)	(0.060)	(0.017)	(0.014)
Observations	2072	4927	6999	1022	2554	2072	4927
Mean dep.var.	0.156	0.243	0.217	0.279	0.424	0.156	0.312
Diff (1)-(6), p-value						0.324	
Diff (2)-(7), p-value							0.388
Panel C: Average citations							
FemSabbat, $t-2$	-0.020	-0.400	-0.294	0.919	-1.428***	-0.764***	0.143
	(0.772)	(0.355)	(0.327)	(1.536)	(0.546)	(0.270)	(0.122)
Observations	2072	4927	6999	1022	2554	2072	4927
Mean dep.var.	3.786	3.843	3.826	5.555	5.557	3.786	3.843
Diff (1)-(6), p-value						0.317	
Diff (2)-(7), p-value							0.129

Note: Panel A of the table presents estimates for the effects of sabbatical leaves on the sum of publications, Panel B for the sum of top-five publications, while Panel C shows estimates for the average number of citations per paper and year. The table only displays the coefficients for the cohort graduating 2 years after the sabbatical leave (corresponding to third-year students). All estimates are based on the specification in Equation 2. Columns 1-3 are based on the full sample, while columns 4-5 are restricted to students placed in academia. The estimates in columns 6-7 replace the individual outcome with placement group averages, excluding students' own values. Standard errors clustered on department-year are shown in the parentheses. ***p<0.01, **p<0.05, *p<0.10.

Table 6: The effects of sabbatical leaves on job placement, marginal effects from multinomial regression on placement categories

	Female Ph.D. students			Male Ph.D. students		
	Top-25 Economics department (1)	Other departments (2)	Out of academia (3)	Top-25 Economics department (4)	Other departments (5)	Out of academia (6)
FemSabbat, $t-2$	-0.039**	-0.047	0.086**	0.001	0.032*	-0.033*
	(0.017)	(0.035)	(0.034)	(0.011)	(0.019)	(0.020)
Observations	2072	2072	2072	4927	4927	4927
Share in category	0.070	0.423	0.507	0.084	0.435	0.482

Note: The table shows estimated marginal effects from a multinomial logistic regression using placement categories as the outcome. The categories are defined as follows: "Top-25" captures the top 25 departments with the highest number of average citations among students placed in the department, "Other departments" denotes other academic institutions, while "Out of academia" captures those without a job in academia during the three years post graduation. "Share in category" displays the share of the estimation sample in the particular job placement category. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Table 7: Homophily in advisor-advisee relationships

	Female advisor				
	(1)	(2)	(3)	(4)	(5)
Female student	0.053***	0.051***	0.057***	0.047***	0.036***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Observations	12419	12371	9725	9725	7980
R^2	0.018	0.133	0.145	0.172	0.384
Mean male students	0.07	0.07	0.07	0.07	0.07
Year FEs	Yes	Yes	Yes	Yes	No
Dept FEs	No	Yes	Yes	Yes	No
Field FEs	No	No	No	Yes	No
Year-Dept-Field FEs	No	No	No	No	Yes

Note: The table shows the results from regressing a dummy variable for whether a student had a female advisor on whether the student is a female. In Column 1, we only control for year fixed effects. The next columns gradually add more fixed effects: in Column 2 department fixed effects, in Column 4 field fixed effects, and in Column 5 the year-department-field fixed effects. The regression in Column 3 includes the same fixed effects as the regression in Column 2, but the sample is restricted to observations with information on research field. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Table 8: Female professors on sabbatical leaves and characteristics of the advisor students are matched with, third-year students

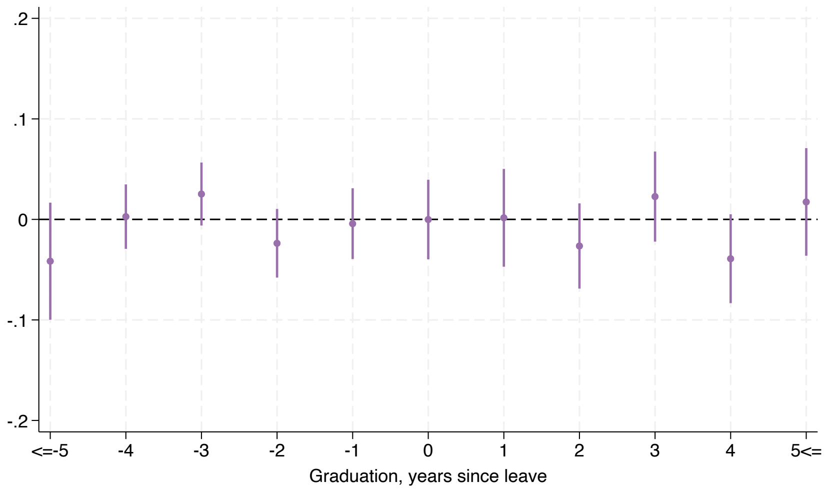
	Female	Full Prof.	Years since first pub	Other students	Other female students	Pubs	Top-five	Citations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Female Ph.D. students								
FemSabbat, $t-2$	-0.080***	0.000	0.974	0.397**	0.138	0.357	-0.418	-0.305
	(0.024)	(0.030)	(0.719)	(0.190)	(0.115)	(1.264)	(0.322)	(0.708)
Observations	2072	2072	1754	2072	2072	1822	1822	1822
Mean dep.var.	.121	.697	25.184	2.997	1.253	20.858	3.851	10.045
Panel B: Male Ph.D. students								
FemSabbat, $t-2$	0.000	-0.025	-0.410	0.018	-0.007	-0.935	0.221	0.484
	(0.011)	(0.026)	(0.567)	(0.157)	(0.060)	(0.855)	(0.177)	(0.534)
Observations	4927	4927	4136	4927	4927	4322	4322	4322
Mean dep.var.	0.065	0.688	24.496	2.899	0.697	20.337	3.985	10.662

Note: The table presents estimates from the specification in Equation 2, using characteristics of students' advisors as outcomes, as denoted by the headings. Column 1 captures whether the advisor is a female, Column 2 whether the advisor is a full professor, Column 3 the number of years since the advisor's first publication, Column 4 the number of other students graduating in year $t-1$ to $t+1$, where t is the graduation year of the student, Column 5 the number of other female students, measured over the same time period, Column 6 the number of publications the advisor had over the last 10 years, Column 7 the number of top-five publications the advisor had over the last 10 years, and Column 8 the advisor's average number of citations per paper and year over the last 10 years. Panel A presents estimates for female Ph.D. students, and Panel B for male Ph.D. students. "Mean dep.var." displays the average values of the dependent variables. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Online appendix

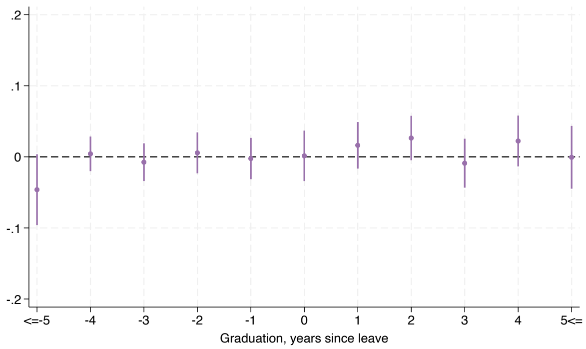
A Extra figures and tables

Figure A1: Female share of graduating Ph.D. students and female professors on sabbatical leave

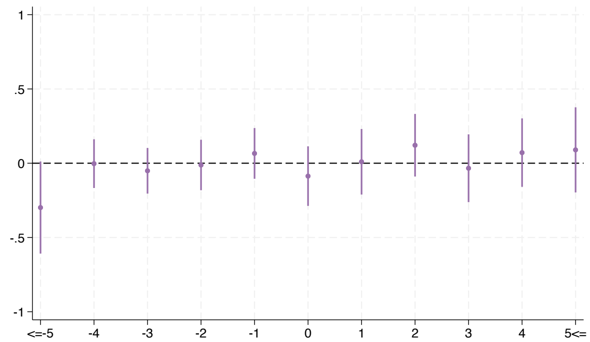


Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation 1. The outcome variable is an indicator variable denoting female Ph.D. students. Note that the regression includes one more lag than Equation 1, to capture the female share of students accepted during the leave year.

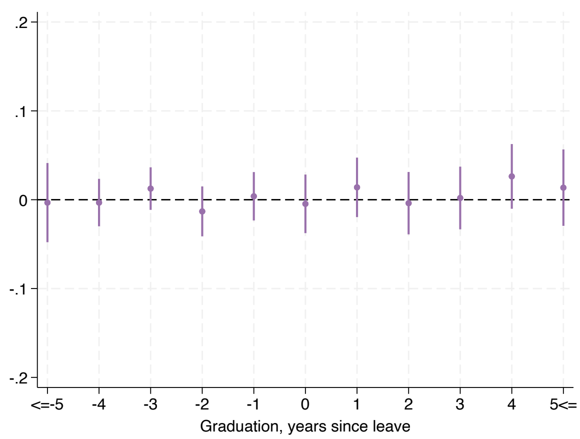
Figure A2: Zero-sum: Female professors on sabbatical and early-career outcomes, pooled sample



(a) Probability of publication



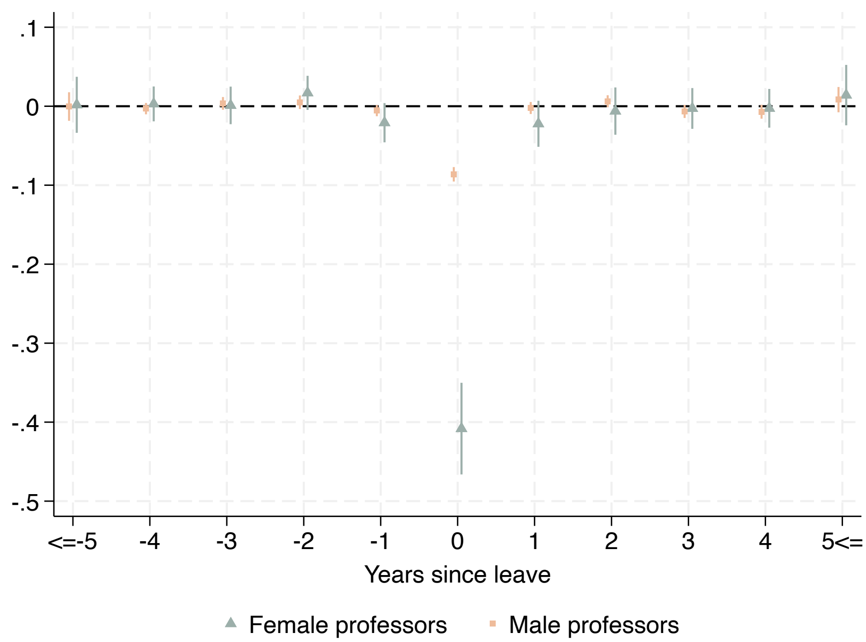
(b) Number of publications



(c) Probability of staying in academia

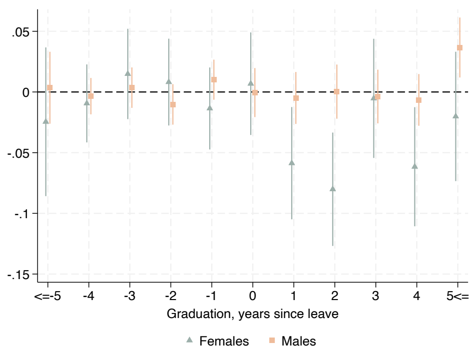
Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 2 estimated on a pooled sample of female and male Ph.D. students. The outcome variable in Figure (a) is a binary variable denoting whether students have any publications five years post-Ph.D. In Figure (b) the outcome is the number of publications five years post-Ph.D, and in Figure (c) the outcome is a binary variable denoting whether students stayed in academia. Standard errors are clustered at the level of department-year.

Figure A3: Sabbatical leaves and the presence of male and female professors

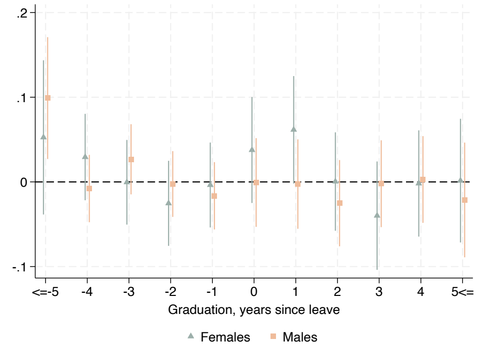


Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation 1, estimated separately for male and female professors. The outcome variable is the share of female or male professors present (i.e. the share of hired professors not on leave). The regression is estimated at the level of department-year.

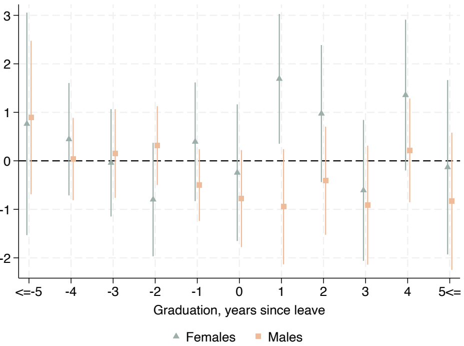
Figure A4: Female professors on sabbatical leave and advisor characteristics



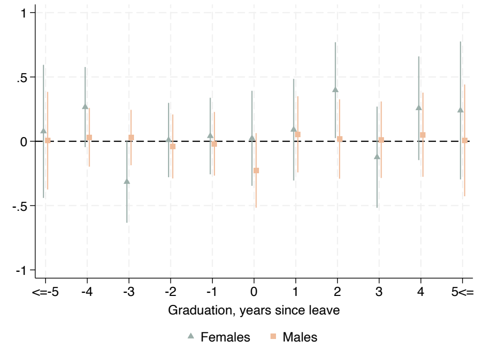
(a) Female



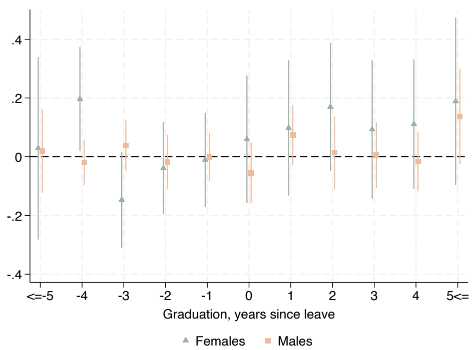
(b) Full professor



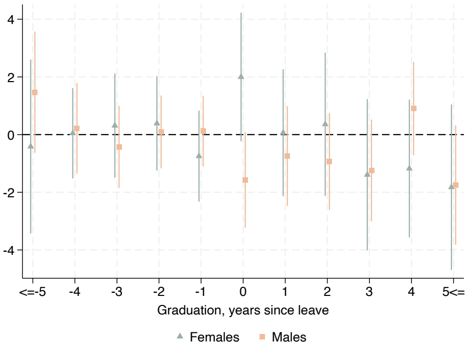
(c) Years since first publication



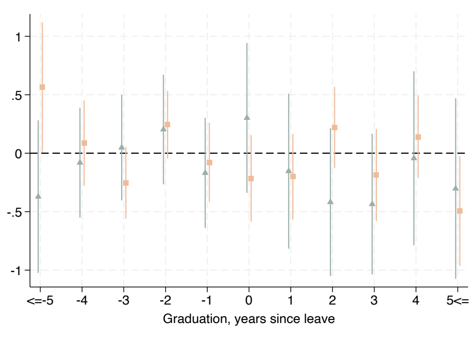
(d) Number of other students



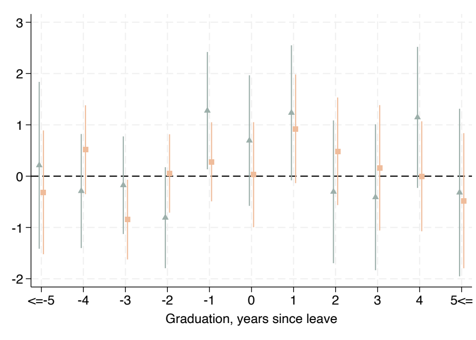
(e) Number of other female students



(f) Number of publications



(g) Number of top five



(h) Citations

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 2. See Table 8 for point estimates for third-year students, as well as explanations of the outcome variables. Standard errors are clustered at the level of department-year.

Table A1: The effects of male professors' sabbatical leaves on early-career outcomes of third-year students

	Female Ph.D. students			Male Ph.D. students		
	HasPub.	#Pubs.	Academia	HasPub.	#Pubs.	Academia
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Binary variable for male professors on leave:						
MaleSabbat, $t-2$	-0.033	-0.199	0.001	-0.003	0.013	0.007
	(0.027)	(0.148)	(0.027)	(0.017)	(0.102)	(0.017)
Observations	2072	2072	2072	4927	4927	4927
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518
Panel B: Sum of male professors on leave:						
MaleSabbat, $t-2$	0.000	0.043	0.002	0.005	-0.001	0.010**
	(0.010)	(0.056)	(0.009)	(0.005)	(0.032)	(0.005)
Observations	2072	2072	2072	4927	4927	4927
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518

Note: Panel A of the table presents estimates on early-career outcomes from the specification in Equation 2, replacing the binary variable for female professors on leave with a binary variable for male professors on leave. Panel B presents similar estimates using the sum of male professors on leave. The table only displays the coefficients for the cohorts graduating 2 years after the sabbatical leave (corresponding to third-year students). "Mean dep.var." displays the average values of the dependent variables. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Table A2: The effects of female professors' sabbatical leaves on early-career outcomes of third-year students, controlling for male professors' sabbatical leaves

	Female Ph.D. students			Male Ph.D. students		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
Panel A: Binary variable for men on leave:						
FemSabbat, $t-2$	-0.072**	-0.583***	-0.097***	0.074***	0.425***	0.037*
	(0.032)	(0.187)	(0.031)	(0.018)	(0.127)	(0.020)
Observations	2072	2072	2072	4927	4927	4927
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518
Panel B: Sum of male professors on leave:						
FemSabbat, $t-2$	-0.074**	-0.641***	-0.107***	0.062***	0.411***	0.029
	(0.032)	(0.192)	(0.032)	(0.020)	(0.132)	(0.020)
Observations	2072	2072	2072	4927	4927	4927
Mean dep.var.	0.535	1.805	0.493	0.562	2.27	0.518

Note: Panel A of the table presents estimates on early-career outcomes from the specification in Equation 2, while controlling for leads and lags of a binary variable capturing whether a department had any male professors on leave. Panel B presents similar estimates controlling for the sum of male professors on leave. The table only displays the coefficients for the cohorts graduating 2 years after the sabbatical leave (corresponding to third-year students). "Mean dep.var." displays the average values of the dependent variables. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

B Data collection

B.1 Faculty members and sabbatical leaves

We collect information on faculty members and sabbatical leaves from university course catalogs, historical versions of department websites and CVs of professors, as referenced in Section 2 of the main paper. In this section, we provide a detailed description, with examples from these data sources and discuss the coverage of the data.

As an example of how we use the course catalogs, Figure B1 displays a snapshot of the 2010-2011 catalog of Harvard University. This publication displays all faculty members of the Department of Economics, including their rank, whether they are visitors from other institutions or whether they are on sabbatical leave. In many cases, the university catalogs miss some, or all, of this information. Because of this, we supplement our data with information from the departments' own websites. To do this, we identify historical versions through the *Wayback Machine*. The *Wayback Machine* stores versions of websites with information on the archive date. We always tried to find a date at the end of calendar years, but this was not always possible as webpages are archived with a varying frequency. The criteria we used was that the date of the archived webpages had to lay within the relevant academic year.

Figure B2 shows an example of a department website, again using Harvard University. As can be seen, the faculty list on this website as of October 31, 2019 (which we use to identify Harvard faculty members for the academic year 2019-2020), provides information on names, rank and sabbatical leaves.[38] For instance, Dale Jorgensen was – according to the website – on sabbatical leave for the full academic year.

In Figure B3, we show for which departments and years we were able to identify a list of faculty members with information on rank (the squares), and for which department-year we have information on sabbatical leaves from the above department-level sources (the filled squares). In total, we identify 991 sabbatical leaves from the department webpages and the university course catalogs, and these leaves are spread over 184 department-year observations (18.3% of the department-year observations).

As described in Section 2 of the main paper, we extend our data using information on visiting professors from the other departments in our sample and by manually extracting information on leaves from the professors' CVs. These extensions give 1,189 additional leave spells. When using all sources combined, 72% of the department-year observations have at least one professor on leave in our data.

Evaluating coverage. To assess the coverage of female professors' sabbatical leaves in the sample, we proceed as follows. The department-level information on leaves (course catalogs and department websites) is likely to provide a reasonably accurate estimate of the actual number of faculty members on sabbatical leaves. For the 184 department-year observations with such information available, we find that 17% of the female associate and full professors are on leave in any given year. This number is consistent with the average female professor going on sabbatical once every sixth year. If we use this number as benchmark, we can

[38]It also provides information on visiting professors, although this is not seen from the screenshot.

induce that the full sample of 1005 department-years, covering 2671 female professor-year observations, *should have had* about 450 leave spells. In our data, however, we only observe 204 leave spells, meaning that we observe a little less than half of the expected number of leaves. Although the coverage of sabbatical leaves might be correlated with department characteristics, we show in Section C.2 that selection in terms of data availability is unlikely to explain our results.

B.2 Placement data

We collected information on job placement for all the Ph.D. students in our main estimation sample. We focused on this sample due to the time consuming nature of this task.

As a starting point, we searched for job placement records at the department-level. Some departments, such as the Department of Economics at Massachusetts Institute of Technology, only provide aggregate placement information. In total, we were able to find placement of individual students for 21 departments, and for 277 department-year observations.

As this department-level information is incomplete, and often lacks details on the timing of the job placements, as well as on the type of position (e.g. instructor, postdoc or assistant professor) we also searched for information online. Our primary sources were the CVs and the LinkedIn pages of the students. We collected information on jobs up to three years after graduation.

Overall, we were able to find job placement information for 87% of our main estimation sample. For the remaining 13% (916 students), we could not find their positions for the relevant time period in any of the above sources. We assume that these students did not get a job in academia. The assumption is consistent with the publication record of this group: five years post Ph.D. they have an average number of publications of 0.82 (and a median of 0) versus an average of 3.05 (and a median of 2) for the group *with* placement information that we have coded as not in academia.

B.3 Publication dataset and matching methods

In this section, we describe the publication dataset and our matching methodology.

The dataset covers over 2,302,565 unique papers published in 1,799 journals focused on Economics and related fields from 1852 to 2021. It was constructed by combining three primary sources: the JEL publications database, Microsoft Academic Graph (MAG), and CrossRef. MAG, developed by Microsoft Research, provides comprehensive information on academic publications, including articles, conference papers, journals, authors, institutions, and citation relationships. CrossRef, a metadata retrieval system, contains over 120 million metadata records. By integrating data from CrossRef and MAG, we compiled citation data for a substantial sample of 2,033,825 papers. Additionally, all publication records were linked to unique author identifiers (author IDs).

Our data collection process began with compiling a list of journals that publish Economics and related papers from 1852 to 2021. We standardized journal names and assigned a unique master ID to each, resulting in a total of 1,799 journals. Using this master list, we merged data from the three sources based on journal names, publication titles, and publication years. This process yielded a unified dataset of 2,302,565 unique publication entries.

Next, we focused on linking authors across publications. The MAG author IDs, though useful, presented challenges: each author had an average of ten IDs, and authors with similar names were sometimes grouped under a single ID. To address these issues, we initiated the matching process by using author names, aiming for an aggregation broad enough to minimize false negatives. We further refined the matches by incorporating additional information, such as fields of study and paper titles, to disambiguate entries. This allowed us to construct a robust panel dataset linking all papers authored by a single individual under a unified panel ID.

Finally, we integrated student and professor records into the publication dataset. For students, we first matched names and then used thesis title embeddings to associate them with publication records of potential matches. Similarly, professors were matched to publication records using the same approach.

B.4 Evaluating quality of gender predictions

We genderized all students and professors using the *Genderize.io* database. In addition to this, we manually checked the gender of all associate and full professors in the faculty data, and 90 percent of the students in our main sample. We excluded students that we could not identify with a gender prediction below 80 percent (resulting in 205 students, or 2.8 percent, being dropped from the main sample).

In Table B1, we display the share of correct gender predictions for different prediction probability bins, separately for faculty and Ph.D. students. As can be seen, the share of correct gender predictions is usually below the average gender probability. For the highest probability bins the difference is small: less than 0.05% of those with a gender probability equal to unit has an incorrect predicted gender. Among those with a gender probability between 90% and 100%, the share of correct predictions is about 1%-point smaller than what is suggested by the average probabilities. The difference is larger for the lower probability bins.

Figure B1: Example: Course catalog of Harvard University 2010-2011

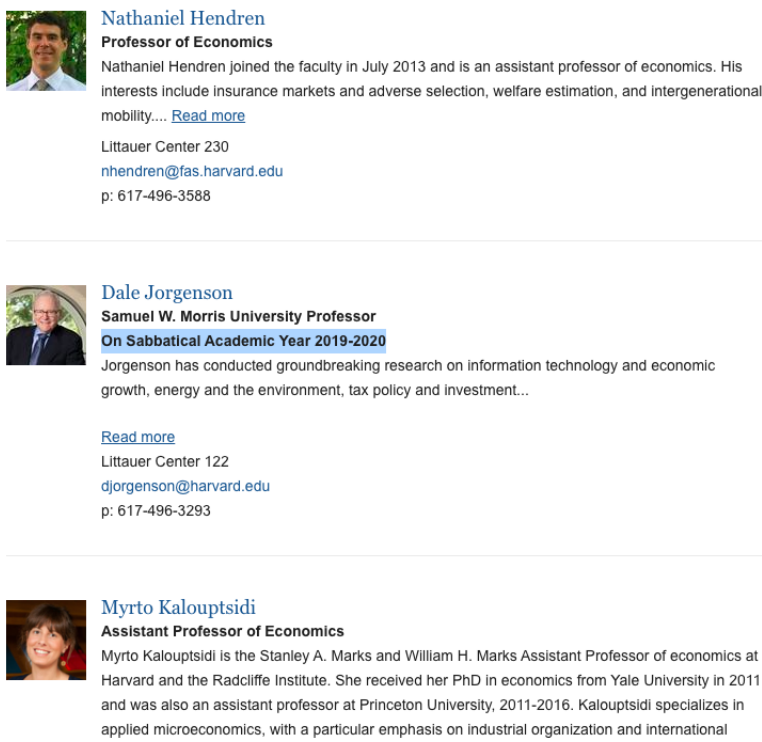
AN HISTORICAL EDITION OF FAS COURSES OF INSTRUCTION

Faculty of the Department of Economics

John Y. Campbell, Morton L. and Carole S. Olshan Professor of Economics, Harvard College Professor *(Chair)*
Philippe Aghion, Robert C. Waggoner Professor of Economics
Alberto F. Alesina, Nathaniel Ropes Professor of Political Economy
Attila Ambrus, Associate Professor of Economics
George-marios Angeletos, Visiting Professor of Economics
Pol Antràs, Professor of Economics *(on leave spring term)*
Susan Athey, Professor of Economics
Anthony Barnes Atkinson, Frank W. Taussig Research Professor of Economics *(University of Oxford)*
Robert J. Barro, Paul M. Warburg Professor of Economics
Efraim Benmelech, Frederick S. Danziger Associate Professor of Economics
Jeffrey Borland, Visiting Professor of Australian Studies (Economics)
Gary Chamberlain, Louis Berkman Professor of Economics
Eric Chaney, Assistant Professor of Economics
Raj Chetty, Professor of Economics *(on leave spring term)*
Richard N. Cooper, Maurits C. Boas Professor of International Economics
David M. Cutler, Otto Eckstein Professor of Applied Economics
Ulrich Doraszelski
Stanley Engerman, Visiting Professor of Economics *(University of Rochester)*
Emmanuel Farhi, Professor of Economics
Martin Feldstein, George F. Baker Professor of Economics
Erica M. Field, John L. Loeb Associate Professor of the Social Sciences
Christopher L. Foote, Visiting Lecturer on Economics *(Federal Bank of Boston)*
Richard B. Freeman, Herbert S. Ascherman Professor of Economics
Benjamin M. Friedman, William Joseph Maier Professor of Political Economy
Roland G. Fryer, Robert M. Beren Professor of Economics
Drew Fudenberg, Frederic E. Abbe Professor of Economics
Edward L. Glaeser, Fred and Eleanor Glimp Professor of Economics

Note: The figure displays a screenshot from the 2010-2011 university course catalog of Harvard University. The course catalog is available here.

Figure B2: Example: Economics department website, Harvard University, October 2019



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Samuel W. Morris University Professor
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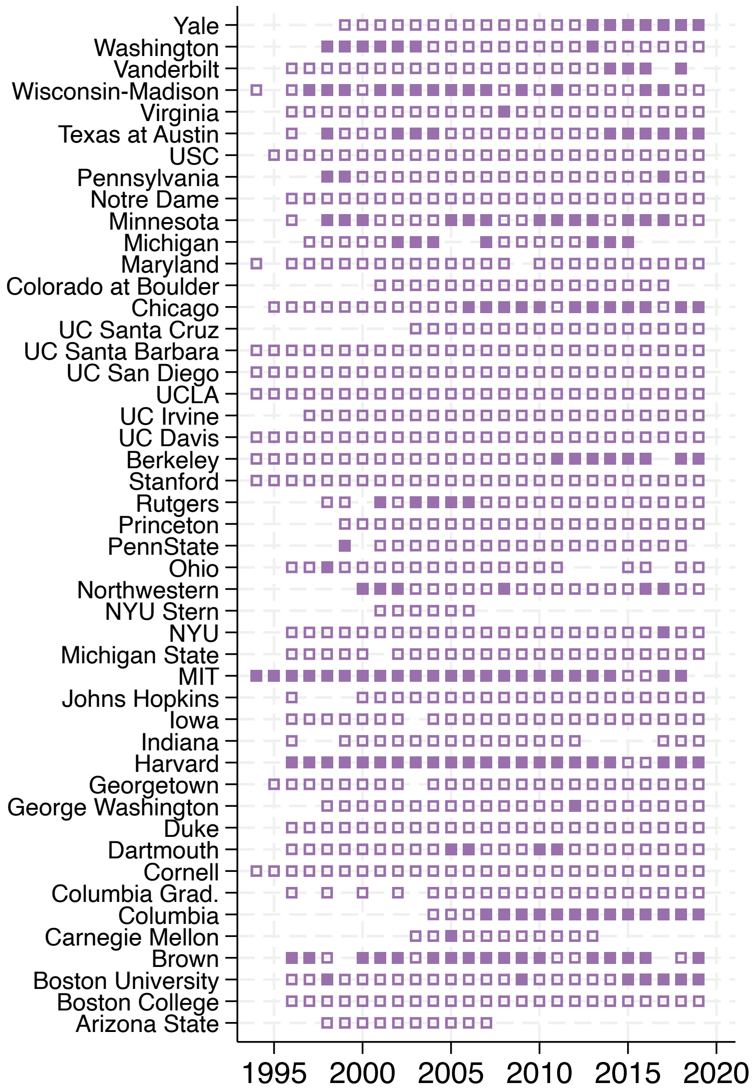
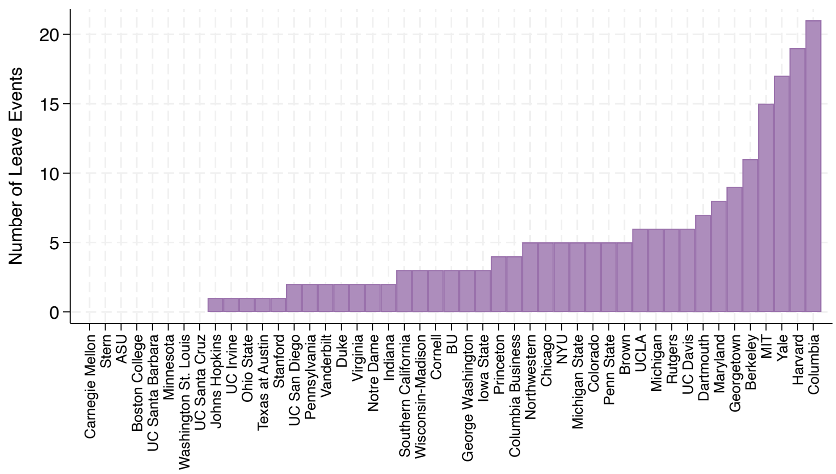
Note: The figure displays a screenshot from the website of the Department of Economics at Harvard University as of October 31, 2019. The website is available here.

Figure B3: Department-years with faculty data and department-level information on sabbatical leaves



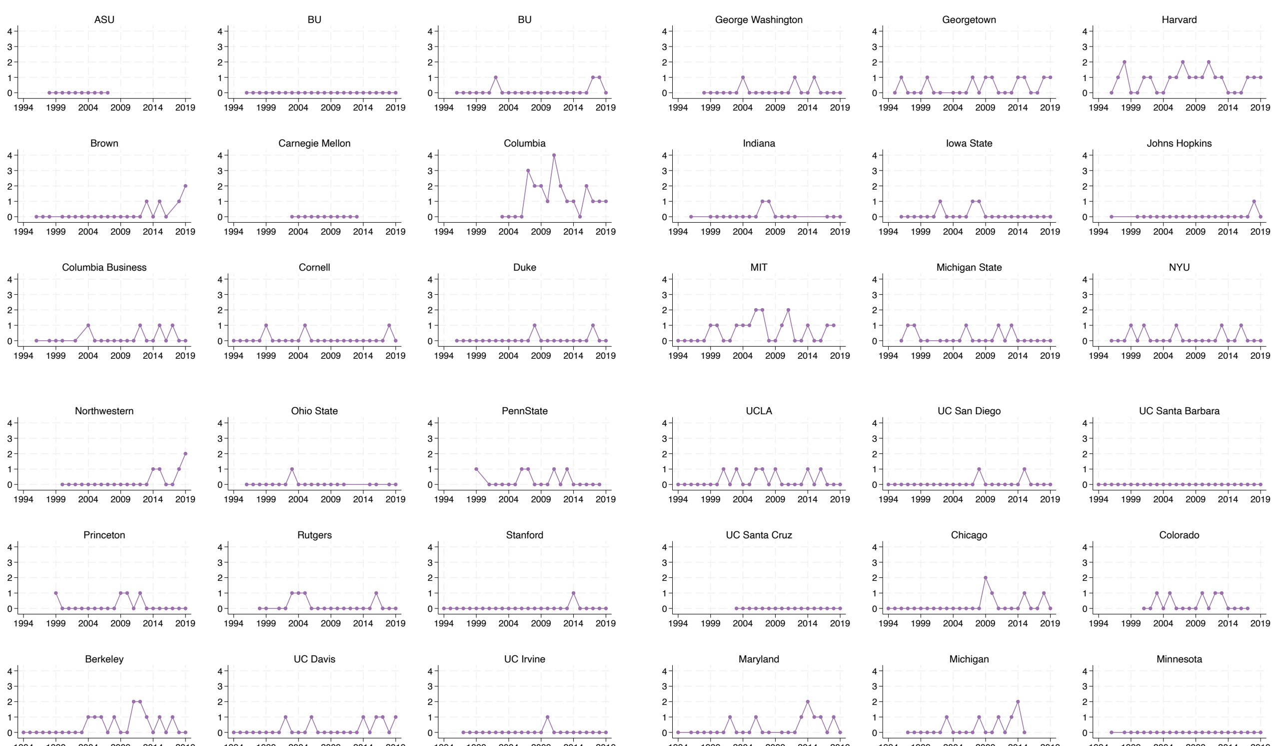
Note: The squares indicate for which department-years we have information on faculty members and their rank. The filled squares show for which of this department-year observation we have information on sabbatical leaves from the department-level data sources.

Figure B4: Number of female professors on leave per department



Note: The figure shows the aggregate number of female professors on leave per department for the period 1994 to 2019.

Figure B5: Number of female leave events per department-year



Note: The figure shows the number of female professors on leave per department-year for the period 1994 to 2019.

Table B1: Quality of gender variable

	$p = 1$ (1)	$0.95 \leq p < 1$ (2)	$0.9 \geq p < 0.95$ (3)	$0.85 \leq p < 0.9$ (4)	$0.8 \leq p < 0.85$ (5)	$p < 0.8$ (6)
Panel A: Faculty						
Correct gender	0.9977	0.9736	0.9348	0.8571	0.7500	0.5785
Mean gender probability	1.0000	0.9807	0.9252	0.8739	0.8200	0.6168
Observations	1741	265	46	28	28	121
Panel B: Ph.D. students						
Correct gender	0.9952	0.9728	0.9251	0.8438	0.7680	0.6224
Mean gender probability	1.0000	0.9837	0.9348	0.8783	0.8216	0.7012
Observations	4141	1067	227	192	125	437

Note: Panel A compares predicted gender with the manually collected gender for associate and full professors, while Panel B is based on the sample Ph.D. students for which we manually checked their gender. “Correct gender” displays the share in different gender probability bins with correct predicted gender.

C Robustness checks

In this section, we present several robustness tests of our main findings.

In Subsection C.1, we present a stacked Difference-in-Difference (DiD) specification where we apply more stringent sample restrictions than in our main specification to assure a "clean" control group. By stacking all treatment events, this setup avoids potential problems due to negative weighting of treatment events, which may occur in settings such as ours with varying treatment timing (Goodman-Bacon, 2021). We show that this regression provides estimates that are comparable to our main estimates.

In Subsection C.2, we explore alternative definitions of our treatment variable. We first replace the binary variable with the sum of female professors on leave and the share of female professors on leave to capture differences in the intensity of treatment. We also provide four additional variations in the definition of sabbatical leaves, such as including leaves with indeterminate/ambiguous length and excluding leaves of one semester. In addition to this, we conduct a robustness check related to the coverage of sabbatical leaves by restricting the treatment variable to leaves extracted from the professors' CVs only. Although this removes a large part of the treatment variation used in the main analysis, we still obtain estimates that are comparable to our baseline estimates, showing that our results do not arise from selection of department-year observations with information on leaves.

In Subsection C.3, we test the robustness to alternative assumptions on Ph.D. duration. One limitation of our analysis is that we do not know the start-year of students' Ph.D. programs. In our baseline analysis we assume that it took five years to complete a Ph.D during our study period and use this to impute start years. We allow for two variations in this assumption. First, based on the subsample of students for which we were able to find the start and the end year, we calculate the median Ph.D. duration per department and gender and use this to impute start year for the full sample. Second, we assume a five years completion time for all students graduating before 2011 and six years completion for students graduating thereafter. We show that our results are robust to these variations.

In Subsection C.4, we check whether our findings survive alternative sample restrictions. Ideally, we would like to identify all students doing a Ph.D. in one of the 46 Economics departments in our sample. We do not observe such a sample, however, as neither ProQuest nor JEL provide information on departments. Because of this, we restrict the baseline sample to students with at least one advisor from one of our Economics departments. We provide two alternative to this. First, we relax the restriction on advisors and instead restrict the sample to students appearing on the JEL dissertation list only. Second, we re-impose the baseline restriction on advisors while *also* restricting the sample to students appearing on the JEL's list of economics dissertations. For both of the alternative sample restrictions we find estimates that are very similar to our baseline estimates.

In Subsection C.5, we present robustness tests to alleviate concerns related to within-department time trends potentially correlated with students' publication or job placement outcomes. First, we add linear time-trends specific to each department, and second, we interact the department fixed effects with five year dummies. Our results are robust to these alternative specifications as well.

In Subsection C.6, we present a final robustness check where we drop one department at a time to test whether our results are driven by one particular department. We obtain estimates that are remarkable stable across the different subsamples.

C.1 Stacked regression with clean control group

To alleviate concerns related to repeated leaves and time-varying treatment effects, we run a stacked DiD specification with a clean control group (Cengiz et al., 2019). We start by identifying department-year observations with a female professor on leave but with no females on leave during the three previous years. This results in 46 leave events (out of the original 79 leave events used in the main analysis). We then construct event-specific datasets, each covering four cohorts of Ph.D. students. Based on the timing of our baseline estimates, we define the treatment group as the third- and fourth-year students at the time of the leave and the control group as the two cohorts graduating just before the treatment group. The sample criteria (three years without a leave followed by a leave) ensures that students in the control group did not experience a leave episode while being in their third or fourth year of the Ph.D. program. In this way, we avoid the overlapping of treatment events inherent in our main specification. We also add a pure control group from departments with no female professor on leave during the four-year time window.

Finally, we stack all the 46 datasets and estimate the following specification:

$$y_{ide,t} = \beta_1 FemSabbat_{ide,t-1} + \beta_2 FemSabbat_{ide,t-2} + \alpha_{de} + \delta_{te} + \varepsilon_{ide,t}, \tag{C.1}$$

where $FemSabbat_{ide,t-1}$ and $FemSabbat_{ide,t-2}$ denote a leave event one or two years before graduation (capturing fourth- and third-year students at the time of the leave), while α_{dh} and δ_{th} denote department and year fixed effects, now specific for each event dataset e. Because students in the pure control group could appear multiple times in the regression, we re-weight the regression accordingly (see e.g. Acemoglu et al., 2023). We cluster standard errors at the level of department-year.

The results are presented in Table C1. As can be seen, the standard errors are larger than in our baseline regressions due to the reduced sample size. However, most point estimates remain remarkably similar, suggesting that our main findings are unlikely to be driven by overlaps in treatment events or negative weighting of events used as both treated and control units.

C.2 Sabbatical Leaves: Possible selection and alternative definitions

In Section B.1, we documented that about 65% of the department-year observations in our sample have at least one professor on leave and that 18.3% of the department-year observations have information on leaves from the department-level sources (course catalogs and/or department websites). In this section, we show that our results are unlikely to be driven by selection of department-years with data coverage. We also show that our results hold for alternative definitions of leaves.

Data coverage. Note first that all our regressions include department-level fixed effects. Thus, the identifying variation we use comes from *within* departments, and as such, this should take care of any selection of departments with information on sabbatical leaves. Still, to further alleviate concerns related to this, we define the treatment variable based on sabbatical leaves extracted from the professors' CVs only. As compared to the leaves from the department-level sources, these leave spells are much more spread out across the different departments in our sample (as we searched for the CVs of *all* female professors). Hence, this approach extracts completely from the possible selection of department-year observations with department-level information on leaves. Estimates are shown in Table C2. For female students, we find impacts of somewhat greater magnitude as compared to our baseline, while the effects are weaker (and insignificant) for male students.

Alternative definitions of sabbatical leaves. We next show that our results are robust to alternative definitions of sabbatical leaves. We start by exploring intensity measures. In the baseline specification from Equation 2, we use a set of binary treatment variables to capture whether or not departments had *any* female professors on leave in particular years. In Panel A of Table C3, we show estimates for third-year students when we replace the binary variables with leads and lags for the *sum* of female professors on leave. All estimates are significant at the 5% level.

Note that we cannot directly compare these coefficients with our baseline estimates. The average number of females on leave – conditional on a department having at least one female on leave – is 1.26 (the average treatment intensity). If we scale the coefficients with this number, we derive an estimate of -0.082 for the probability of publishing a paper versus the baseline of -0.080, an estimate of -0.455 versus the baseline of -0.600 for the sum of publications and an estimate of -0.069 versus the baseline of -0.098 for the probability of staying in academia. The estimates thus suggest a somewhat weaker impact on the early-career outcomes as compared to our main estimates.

For male students, the estimates closely resemble our main results (when scaled as above) and the positive effects on both publications and on the probability of staying in academia are highly statistically significant.

In Panel B of Table C3, we use the *share* of female professors on sabbatical leave in different years. This measure is only defined for department-year observations with at least one female professor. Because of this, we also show an alternative version in Panel C where we include department-year observations without females by setting the share of females on leave equal to zero. As before, we find negative impacts on the early-career outcomes of female students and positive impacts on the early-career outcomes of male students. The average share of female professors on leave – conditional on any females on leave – is 0.40. If we scale the coefficients with this number, as above, we obtain magnitudes that are slightly smaller than our main estimates. Still, all estimates for both female and male students are statistically significant at the 5% level.

We provide four additional variations in the definition of sabbatical leaves. These results are presented in Table C4. First, in our baseline specification we exclude sabbatical leaves extracted from the CVs that have an indeterminate/ambiguous length. This could for instance be leaves denoted with just a calendar year. We start by including such sabbatical leaves (Panel A). Second, we exclude sabbatical leaves that lasted for just one semester, which are included in the main estimation (Panel B). Third, we exclude sabbatical leaves that are followed by the professor leaving the department (Panel C). 32 out of the 209 leaves by female professors in our sample are like this. Such leaves could be different than other leaves, as it might be clear for the students – at least in some cases – that the professor will not return. Fourth, in our main analysis we define "senior female economists" as associate and full professors. Yet, in some departments associate professors might not be tenured. As a last alternative, we therefore use information extracted from CVs and focus solely on sabbatical leaves of *tenured* professors (Panel D). As can be seen from the table, all these alternative definitions give estimates that are very similar to our baseline estimates.

C.3 Ph.D. Duration: Descriptive statistics and alternative assumption

One key limitation of our analysis is that we do not know the start-year of students' Ph.D. programs. Because of this, we need to impute the year the students are in when the professors go on leave. In our main analysis, we proceed by assuming a five-year Ph.D. completion time and by defining each student's start year as their graduation year minus five. In this section, we first present descriptive statistics on completion time from our own primary data and show that these statistics support our baseline assumption. We then show that our results are robust to plausible alternative assumptions on completion time.

Descriptive statistics. As part of our data collection efforts related to job placement, we collected Ph.D. start and end year for whomever we could find it for, covering about one-third of our sample. Most often we extracted the information from LinkedIn.[39] In Figure C1a, we plot the average and median Ph.D. duration by year of graduation.[40] As can be seen, the average duration is slowly (but steadily) increasing over time, from around 5.25 years in the beginning of the sample to slightly above 5.50 years towards the end of the sample. The median duration is five years for all academic years until 2014-2015. Note that these patterns are consistent with other evidence from the same time period (Ábrahám et al., 2022; Stock et al., 2009; Stock and Siegfried, 2014). In Figure C1b, we plot the average duration by gender, and as can be seen, female and male Ph.D. students do not differ much in terms of completion time. If anything, female students use slightly more time to finish the Ph.D. as compared to male students, with an average of 5.52 years versus 5.40 for the full sample.

Alternative assumptions. In the rest of this section, we present estimates on early-career outcomes under alternative assumptions on completion time. As a first alternative, we assume a common switch from five to six years from 2010, consistent with the descriptive statistics in Figure C1a. We implement this by adjusting the time indicators in our baseline specification such that $FemSabbat, t-1$ always represents fourth-year students, $FemSabbat, t-2$ represents third-year students and so fourth.[41] Estimates are presented in Table C5. Overall, the estimated effects on third-year students are somewhat smaller in

[39] Most of the CVs did not include information on start year.

[40] We present the figure in this way, as our analysis takes the graduation year as the starting point.

[41] I.e., for students graduating after the switch to a six years completion time, we replace $FemSabbat, t-1$ with $FemSabbat, t-2$, and $FemSabbat, t-2$ with $FemSabbat, t-3$ and so on.

magnitude than our baseline estimates. Yet, we still find negative impacts on the number of publications and job placement for female third-year students significant at the 5% level in this alternative specification. The effect on having any publication is however no longer significantly different from zero.

As a second alternative, we use the sub-sample of students with information on completion time (approximately one-third of the sample) to compute the median completion time for each department, separately for female and male students. We then impose these median durations on all students.[42] As above, we implement this by adjusting the time indicators according to the particular Ph.D. duration. We present the estimates in Panel B of Table C5. As can be seen, the results for female students are close to our baseline estimates, although the estimated effect on the probability of publishing is only significant at the 10% level. The other key coefficients are significant at the 5% level.

However, for male students we find weaker (but still positive) impacts compared to our baseline results. Still, taken together, the results presented in this section suggest that our main results are robust to alternative assumptions on Ph.D. completion time.

C.4 Alternative sample restrictions

The ProQuest and the JEL dissertation data both provide names of the Ph.D. granting universities, but they do not give information on departments. In our main analysis, we identify which departments students belong to by assuming that they have at least one advisor from their home department. Two types of error could occur. First, we will miss students if they only have an advisor outside of the department, and second, we might include students that do not belong to the Economics department but that have an advisor in the Economics department. This second type of error is likely to be particularly present for universities with business schools or public policy schools.

To get a sense of the importance of these errors, we randomly selected two sub-samples of students from Harvard University. We choose Harvard as the Economics department has several neighbouring schools with Economics and related fields, which is likely to make the errors more prevalent. To investigate the first type, we randomly extracted 100 students from the Economics department's website on earlier job placements, assuming that these students actually belonged to the department.[43] We then checked how many of these students we have in our sample. We were able to identify 92. Of the remaining 8, 2 had lacking information on advisors in the ProQuest database, while 6 had advisors that we could not match to any of the Harvard professors in our faculty data. To investigate the second type of error, we similarly extracted 100 random students from our estimation sample and manually checked their CVs and/or LinkedIn pages to get information on their Ph.D. We identify 89 as students of the Economics department. Of the remaining 11, 5 were students in Health Policy, 1 in Public Policy, 3 in Business Economics, and 2 we could not find information on. Thus, for the case of Harvard, the two errors seems to be around 10% each. Note that this is likely to

[42] Because of the low data coverage, and because the set of (former) students that have a detailed LinkedIn page, or a detailed CV posted online, is likely to differ from those without, we do not make use of the individual start years in the regressions.

[43] See the webpage here: https://economics.harvard.edu/placement.

be higher than for most of the other universities in our sample due to the many neighbouring schools at Harvard.

In the rest of this section, we show that our results are robust to alternative sample restrictions. As a first alternative, we focus on students appearing on the JEL dissertation list and put no restrictions on the institution of the advisors. This approach will likely minimize the first type of error, as students excluded from our main sample with an advisor outside their home department now will be included. In contrast, the second type of error is likely to be more severe with this approach, especially for departments with neighbouring economics departments within the same university. The results using this alternative sample restriction are shown in Panel A of Table C6. The estimates are similar to our main estimates, although the effect on the number of publications for female students is somewhat smaller (but still significant at the 5% level). Note that we did not collect data on job placement for the alternative sample used in Panel A due to the time required for this task.[44]

As a second alternative, we again focus on students appearing on the JEL's list of economics dissertations, but we now *also* impose the restriction on advisors. Because of this, this approach is likely to minimize the second type of error, as students in related fields with an economist as advisor will be excluded from the sample. The results are shown in Panel B of Table C6. We find estimates that are very similar to our baseline estimates. The only exception is for the probability of staying in academia for male third-year students, for which we do not find a significant effect.

In all, we conclude from these estimates that our results are unlikely to be an artifact of the particular sample restrictions imposed in our main analysis.

C.5 Within-department time trends

In this section, we show that our results are robust to the inclusion of within-department time trends, as well as department fixed effects interacted with dummies for five year periods.

In Panel A of Table C7, we estimate a version of Equation 2 where we include a linear time trend, specific for each department. This should help alleviate potential concerns related to differential trends in publication or job placement outcomes across the departments in our sample. In sum, the estimates are not much affected by the within-department time trends.

In Panel B, we show estimates from a specification where we interact each department fixed effect with dummy variables denoting five year periods.[45] This rather demanding specification gives estimates that are very similar to our baseline. This is reassuring, as it quite strongly suggests that our results are not caused by within-department time trends correlated with the timing of female professors on leave.

C.6 Leave out departments

Our estimation samples consist of a fairly small number of department-year observations (480 for female students and 513 for male students). Because of this, one might worry that

[44] The sample in Panel B, in contrast, is a sub-sample of our main estimation sample.

[45] We construct dummy variables capturing each of these three periods: the academic years 1998 to 2003, 2004 to 2008, and 2009 to 2014.

the results are driven by a particular department. In this section we show that this is not the case.

In Figure C2 we present estimates for third-year students based on Equation 2 and our three main outcomes when we exclude one department at the time in a rotating fashion. The bars in the figures show the estimates we obtain when we exclude observations from the department in the label and the lines show 95% confidence intervals. As can be seen, both the point estimates and the precision of the coefficients are relatively stable across the different subsets of the data. With the exception of the probability of staying in academia for male third-year students, all coefficients are also statistically significant at the 5% level in *all* of the sub-samples.

In all, the estimates in this section shows that the results are not driven by a single department or by outliers.

Table C1: Stacked regression with clean control group

	Female Ph.D. students			Male Ph.D. students		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
FemSabbat, $t-2$	-0.080*	-0.642***	-0.065	0.118***	0.716***	0.039
	(0.043)	(0.242)	(0.042)	(0.030)	(0.149)	(0.028)
Observations	9377	9377	9377	21601	21601	21601
Mean dep.var.	.534	1.74	.49	.543	2.145	.502

Note: The table presents estimates from the stacked regression specification in Equation C.1. The regressions are re-weighted to account for the fact that observations in the pure control group appear multiple times in the regressions. "Mean dep.var." displays the average values of the dependent variables. Standard errors clustered on department-year are shown in the parentheses.
***p<0.01, **p<0.05, *p<0.10.

Table C2: Robustness: Sabbatical leaves from CVs only

	Female Ph.D. students			Male Ph.D. students		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
FemSabbat, $t-2$	-0.089**	-0.572***	-0.136***	0.027	0.180	0.032
	(0.035)	(0.201)	(0.034)	(0.021)	(0.148)	(0.022)
Observations	2072	2072	2072	4927	4927	4927

Note: The table presents estimates from our main specification in Equation 2, but the treatment variable is restricted to leaves extracted from professors' CVs only. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Table C3: Robustness: Intensity measures of sabbatical leaves

	Female Ph.D. students			**Male Ph.D. students**		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (5)	#Pubs. (6)	Academia (7)
Panel A: Sum female professor on leave						
FemSabbat, $t-2$	-0.065**	-0.392**	-0.055**	0.054***	0.332***	0.036**
	(0.025)	(0.164)	(0.028)	(0.015)	(0.094)	(0.014)
Observations	2072	2072	2072	4927	4927	4927
Panel B: Share of female professor on leave						
FemSabbat, $t-2$	-0.160**	-0.928**	-0.125*	0.107***	0.662**	0.086**
	(0.066)	(0.390)	(0.071)	(0.040)	(0.262)	(0.037)
Observations	1697	1697	1697	3961	3961	3961
Panel C: Share of female professor on leave including zeros						
FemSabbat, $t-2$	-0.156***	-0.944***	-0.163**	0.112***	0.603**	0.071**
	(0.059)	(0.356)	(0.065)	(0.040)	(0.252)	(0.033)
Observations	2072	2072	2072	4927	4927	4927

Note: The table presents estimates on early career outcomes using intensive measures of female professors on sabbatical leave. In Panel A, the treatment variable is defined as the sum of professors on leave. In Panel B, the treatment is the share of female professors on leave. As this share only is defined for department-years with at least one hired female professors, Panel C displays similar estimates when we set the share equal to zero for department-years without female professors. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Table C4: Robustness: Alternative definitions of sabbatical leaves

	Female Ph.D. students			Male Ph.D. students		
	HasPub.	#Pubs.	Academia	HasPub.	#Pubs.	Academia
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Including leaves with indeterminate length						
FemSabbat, $t-2$	-0.071**	-0.554***	-0.073**	0.067***	0.431***	0.035*
	(0.031)	(0.183)	(0.031)	(0.019)	(0.121)	(0.019)
Observations	2072	2072	2072	4927	4927	4927
Panel B: Excluding semester-long leaves						
FemSabbat, $t-2$	-0.090**	-0.545***	-0.110***	0.033*	0.255*	0.032
	(0.035)	(0.181)	(0.031)	(0.019)	(0.137)	(0.019)
Observations	2072	2072	2072	4927	4927	4927
Panel C: Excluding leaves followed by quit						
FemSabbat, $t-2$	-0.082***	-0.564***	-0.098***	0.060***	0.418***	0.028
	(0.031)	(0.180)	(0.031)	(0.019)	(0.121)	(0.019)
Observations	2072	2072	2072	4927	4927	4927
Panel D: Excluding leaves by professors without tenure						
FemSabbat, $t-2$	-0.092***	-0.629***	-0.094***	0.058***	0.394***	0.042**
	(0.034)	(0.200)	(0.034)	(0.019)	(0.135)	(0.021)
Observations	2072	2072	2072	4927	4927	4927

Note: The table presents estimates on early career outcomes using alternative definitions of female professors on sabbatical leave. In Panel A, we include sabbatical leaves from CVs with indeterminate length (for instance those just listed with a generic calendar year); in Panel B, we exclude sabbatical leaves lasting for one semester only; in Panel C, we exclude leaves from professors that move to another department right after the leave; and in Panel D, we only include sabbatical leaves of tenured professors. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Table C5: Robustness: Alternative assumptions on Ph.D. duration

	Female Ph.D. students			Male Ph.D. students		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
Panel A: 6 years from 2011, 5 years before						
FemSabbat, $t-2$	-0.083***	-0.601***	-0.127***	0.054***	0.280**	0.042**
	(0.031)	(0.184)	(0.030)	(0.020)	(0.127)	(0.021)
Observations	2066	2066	2066	4897	4897	4897
Panel B: Median duration by gender-department						
FemSabbat, $t-2$	-0.062*	-0.496**	-0.072**	0.039*	0.220	0.041*
	(0.034)	(0.193)	(0.034)	(0.021)	(0.148)	(0.021)
Observations	2027	2027	2027	4796	4796	4796

Note: The table presents estimates on early career outcomes using alternative assumptions on Ph.D. duration. In Panel A, we assume a common switch from a 5 to 6 years completion time starting from 2011. In Panel B, we use the sub-sample for which we have data on start and end dates to calculate the median completion by gender, department and year, and impose this to all observations from the same department-year-gender. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Table C6: Robustness: Alternative sample restrictions

	Female Ph.D. students			Male Ph.D. students		
	HasPub.	#Pubs.	Academia	HasPub.	#Pubs.	Academia
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: On JEL list + no restriction on advisor						
FemSabbat, $t-2$	-0.080**	-0.480**		0.057***	0.414***	
	(0.035)	(0.213)		(0.020)	(0.133)	
Observations	1928	1928		4557	4557	
Mean dep.var.	.544	1.914		.5571	2.331	
Panel B: On JEL list + advisor in department						
FemSabbat, $t-1$	-0.027	-0.207	-0.036	0.029	0.026	0.022
	(0.037)	(0.196)	(0.031)	(0.021)	(0.164)	(0.025)
FemSabbat, $t-2$	-0.097***	-0.657***	-0.118***	0.061***	0.441***	0.025
	(0.037)	(0.222)	(0.035)	(0.020)	(0.147)	(0.023)
Observations	1609	1609	1609	3898	3898	3898
Mean dep.var.	.562	1.942	.513	.577	2.394	.53

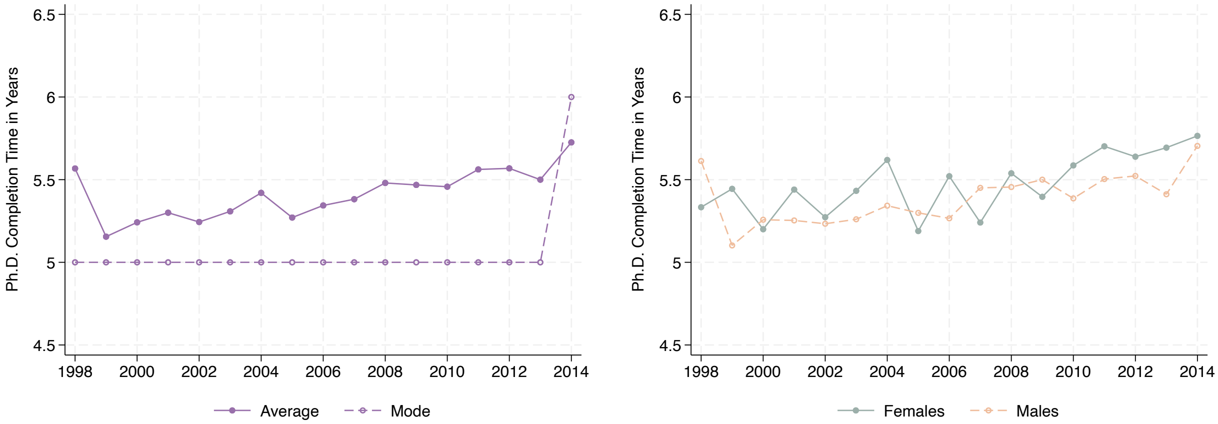
Note: The table present results on early career outcomes under alternative sample restriction. In Panel A, we restrict the sample to students appear on the JEL dissertation list (and put no restrictions on their advisors). In Panel B, we restrict the sample to the JEL list but also impose the baseline restriction on having an advisor from one of the department in our sample. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Table C7: Robustness: Within-department time trends

	Female Ph.D. students			Male Ph.D. students		
	HasPub.	#Pubs.	Academia	HasPub.	#Pubs.	Academia
	(1)	(2)	(3)	(5)	(6)	(7)
Panel A: Linear time trend						
FemSabbat, $t-3$	-0.068*	-0.602***	-0.101***	0.077***	0.556***	0.031
	(0.037)	(0.202)	(0.031)	(0.021)	(0.138)	(0.021)
Observations	2072	2072	2072	4927	4927	4927
Panel B: Five years-department fixed effects						
FemSabbat, $t-2$	-0.098**	-0.853***	-0.066*	0.114***	0.500***	0.043*
	(0.039)	(0.214)	(0.038)	(0.022)	(0.151)	(0.026)
Observations	2072	2072	2072	4927	4927	4927

Note: The table present results on early career outcomes controlling for within department time-trends. In Panel A, we include a linear department time-trend, and in Panel B, we interact the department fixed effects with five-year dummies. Robust standard errors clustered on department-year are shown in the parentheses.
*** $p < 0.01$,** $p < 0.05$,* $p < 0.10$.

Figure C1: Completion time of Ph.D. students

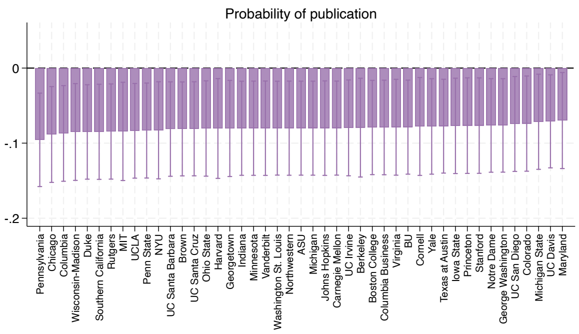


(a) Average and median

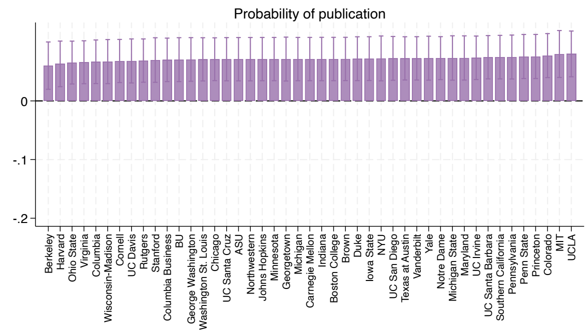
(b) Average by gender

Note: The figure shows Ph.D. duration by graduation year for the sub-sample of students for which we collected start and end dates of the Ph.D. The left panel displays average and median duration by year, while the right panel displays average duration by year and gender.

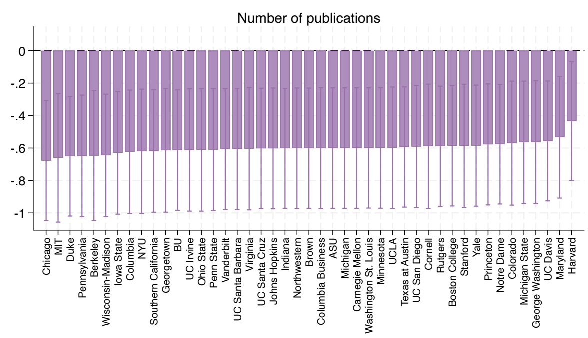
Figure C2: Robustness: Leave out departments one-by-one



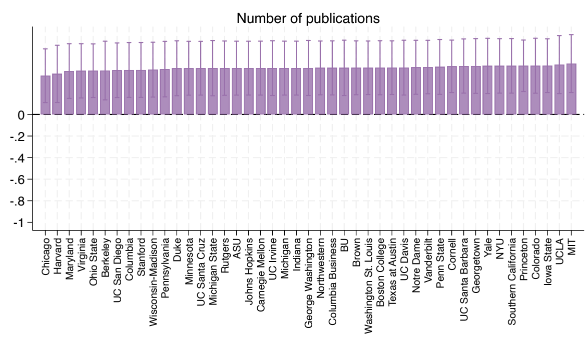
(a) Females



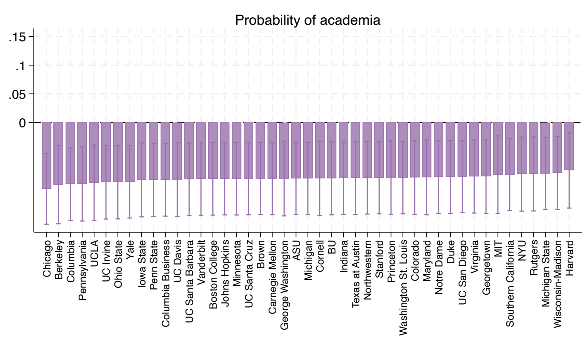
(b) Males



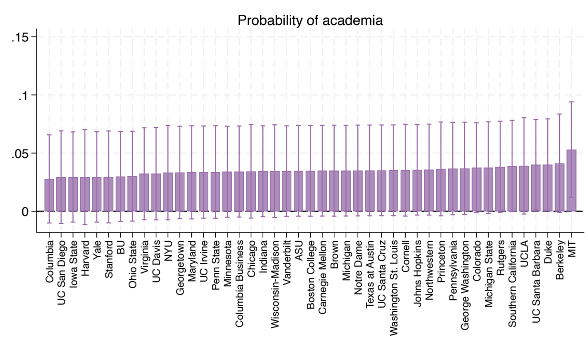
(c) Females



(d) Males



(e) Females



(f) Males

Note: The figures display estimates on our main outcomes when removing each of the departments from the estimation sample in a rotation fashion. Each bar represents a coefficient when the department in the legend is removed.

D Details on publication and placement quality

In this section we present some additional details on the analysis of Section 4 of the main paper.

First, in Table 5, we present a regression where we use the *placement group averages* of the research quality measures as outcomes. We construct these averages as follows. We first calculate average citations per paper and year over the five years post-Ph.D., by placement institution. When doing this, we limit the sample to institution with at least 10 student-placement observations. Note that we also include non-academic institutions. We next rank institutions and make 5 distinct groups: those ranked 1-10, 11-20, 21-31, 31-40 and 41-50. We also add two groups consisting of students not placed in any of the top-50 institutions, in academia or not in academia.[46] Finally, we calculate average values within each of these 7 groups, leaving out students' own value in the calculation.

Table D1 displays descriptive statistics: the number of students in each group, and the group average of sum of publications, sum of top-five publications and citations. The group averages for citations are mechanically falling in the first five groups. Note that the group averages are falling monotonically in the group ranking also for the sum of publications and for top-five publications.

Second, in Table 6 we present marginal effects from a multinomial logistic regression where the dependent variable is a categorical variable with three possible outcomes ($k = 1, 2, 3$), representing the placement group of a student. Group 1 is the set of top-25 Economics departments; group 2 includes all other departments; while group 3 represents not being in academia. We use the following specification:

$$P(y_{id,t} = k) = \frac{e^{\beta_k' X_{id,t}}}{\sum_{j=0}^{2} e^{\beta_j' X_{id,t}}}, k = 0, 1, 2 \tag{D.1}$$

where $P(y_{id,t} = k)$ equals the probability that student i graduating from department d at year t end up in placement group k. $X_{id,t}$ denotes the set of independent variables used in our baseline regression (see Equation 2). Standard errors are clustered at the level of department-year.

As an alternative, we also present estimates of Equation D.1 using the *RePEc* US Economics department ranking to make the three groups. Specifically, using the ranking as of 2015 we defined Group 1 as the set of top-25 departments on the ranking, Group 2 as all other departments and Group 3 as not in academia. Estimates are shown in Table D2. As can be seen, we find very similar estimates as in our main specification, presented in Table 6.

[46]This thus includes students placed in non-ranked institutions with less than 10 student-placement observations.

Table D1: Details on placement groups

Group	No students	Sum publications		Sum top-five		Citations	
		Mean	SE	Mean	SE	Mean	SE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ranked 1-10	253	4.30	0.23	1.48	0.13	17.56	1.73
Ranked 11-20	204	3.77	0.24	1.24	0.11	12.91	1.20
Ranked 21-30	216	3.92	0.30	1.07	0.11	10.00	1.05
Ranked 31-40	208	3.25	0.21	0.55	0.06	7.48	0.73
Ranked 41-50	196	2.89	0.22	0.41	0.05	5.92	0.74
Other, in academia	2525	2.79	0.07	0.13	0.01	3.18	0.14
Other, not in academia	3495	1.17	0.04	0.04	0.00	2.00	0.13

Note: The table display descriptive statistics by the placement groups used in the regression presented Table 5 of the main paper.

Table D2: The effects of sabbatical leaves on job placement, marginal effects from multinomial regression on placement categories, alternative rankings

	Female Ph.D. students			Male Ph.D. students		
	Top-25 Economics department	Other departments	Out of academia	Top-25 Economics department	Other departments	Out of academia
	(1)	(2)	(3)	(4)	(5)	(6)
FemSabbat, $t-2$	-0.043***	-0.044	0.087***	0.007	0.035*	-0.042**
	(0.016)	(0.033)	(0.033)	(0.013)	(0.019)	(0.020)
Observations	2072	2072	2072	4927	4927	4927
Share in category	0.074	0.419	0.507	0.085	0.434	0.482

Note: The table shows estimated marginal effects from a multinomial logistic regression using placement categories as the outcome. The categories are defined as follows: "Top-25" captures the top 25 departments on the *RePec* US Economic department ranking as of 2015, "Other departments" denotes other academic institutions, while "Out of academia" captures those without a job in academia during the three years post graduation. "Share in category" displays the share of the estimation sample in the particular job placement category. Standard errors clustered on department-year are shown in the parentheses. ***p<0.01, **p<0.05, *p<0.10.

E Discarding alternative explanations

In this section, we provide details on the analyses mentioned in Section 6 of the main paper, on plausible alternative explanations behind our results.

E.1 Can the field of the absent professors explain our findings?

In Section 2 we showed that men and women are not equally distributed across fields: both female students and professors are more likely than men to work in Labor/Public and less likely to work in Macro/Finance. In Figure E1 we display how the share of students and advisors in the different fields have developed over the period 1994 to 2019.[47] Consistent with the findings of Lundberg and Stearns (2019), the figure reveals that gender differences in field choice remained relatively stable over this time period.

One alternative mechanism behind our results – given these persistent gender differences in research fields – is that the absence of female professors leads to a lower share of professors in fields where women are more likely to work, disproportionately affecting female Ph.D. students. We test this alternative explanation by running seven different regressions, one for each of the fields:

$$y_{id,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \gamma_s Sabbat^{f}_{id,t-s} + \varepsilon_{id,t}, \tag{E.1}$$

where $y_{id,t}$, as before, denotes one of the three early-career outcomes and $Sabbat^{f}_{id,t-s}$ is a dummy variable equal to one if a professor (regardless of gender) working in field f went on sabbatical leave in year $t-s$. For $s \in \{-5, 5\}$, γ_s represents whether a sabbatical leave happened five or more years before or after year t. Standard errors are clustered at the level of department-year.

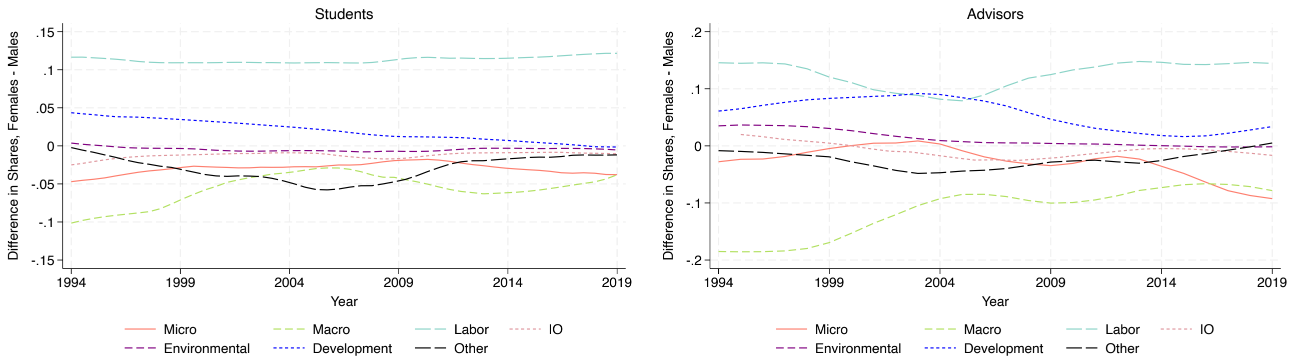
We present the estimates in Figure E2. For space consideration, we only present the coefficients for third-year students. Three of the 21 individual coefficients for male students are significantly different from zero at the 5% level: we find a negative impact on the number of publications of -0.54 when a professor in Environment economics goes on leave (but a positive and insignificant effect on the probability of staying in academia), and a positive impact on the probability of staying in academia of 0.05 when a professor in either IO or Macro/Finance goes on leave (but no effect on publications). For female third-year students, only one of the estimated coefficients is significantly different from zero at the 5% level: the probability of staying in academia increases by 5 percentage points when a professor in Macro/Finance goes on leave. As for males, we find no impact on their publication record.

In sum, therefore, we do not find any systematic effects of sabbatical leaves on the early-career outcomes of Ph.D. students when we define leaves in terms of the research field of the professors. For the fields for which we *do* find a statistically significant coefficient, we do not find similar effects for the other outcomes, which we would expect if field was the

[47] As noted in Section 2, we define the research field of students as the JEL code of their dissertation, aggregated into seven broad fields, and for professors, we define fields as the field in which they have served as advisors most often.

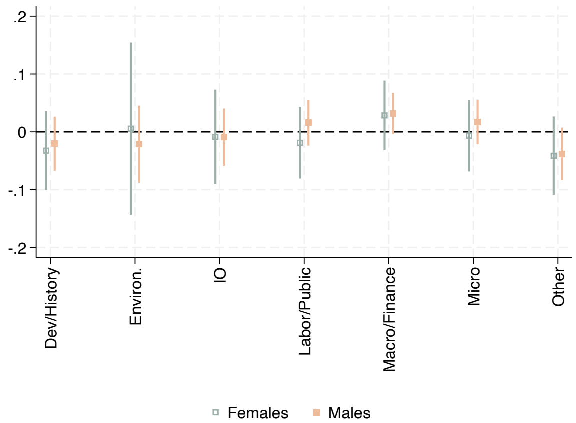
key characteristic of the missing professor. Thus, the results do not support the alternative interpretation that our main findings are caused by missing professors in certain fields.

Figure E1: Gender Differences in research fields: students and advisors

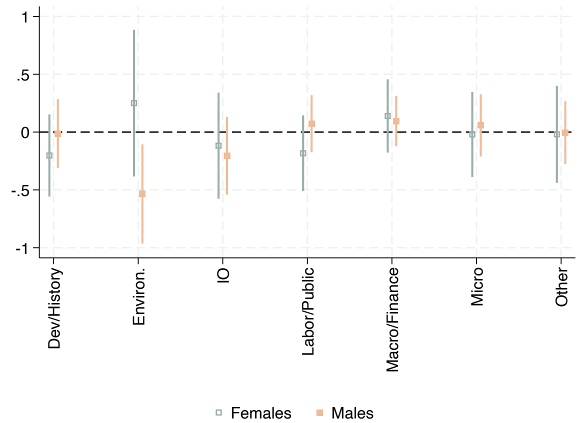


Note: The figure is based on the sample of students and advisors from the top-50 economics departments. The left panel plots the differences in shares of female Ph.D. students in different research fields and the share of male Ph.D. students in the same field, while the right panel plots the differences in the share of dissertations in different fields advised by a female professor and the share of dissertations in the same fields advised by a male professor.

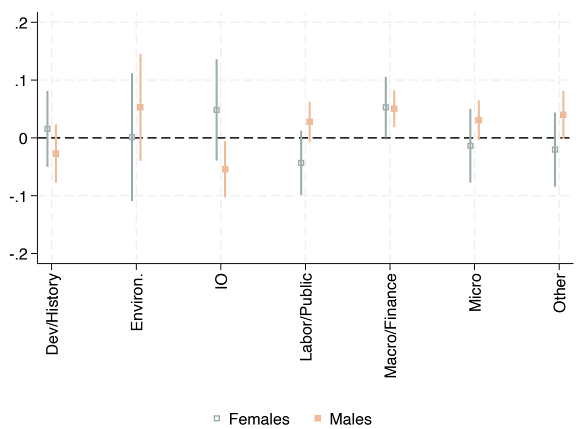
Figure E2: Early career outcomes and sabbatical leaves by professors in different research fields



(a) Probability of Publication



(b) Number of Publications



(c) Probability of Staying in Academia

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators from Equation E.1. The figure only presents estimates for third students. Standard errors are clustered at level of department-year.

E.2 Can our findings be explained by disturbances in advisor-advisee relationships, and not gender?

Another potential mechanism for our findings is the disturbance generated by the absence of female professors going on sabbatical leave. In particular, female third-year students might have expected to work with the missing professors, and if female Ph.D. students are more likely to work with female professors, the impact of the absence might be more pronounced for them than for male Ph.D. students.

To test whether this alternative explanation can explain our findings, and not gendered relationships per se, we first define the set of professors that are the most likely advisors for male and female students. We do this in two steps. In the first step, we identify professors with at least two advisees during the previous five years. Approximately 42% of the professor-year observations satisfies this criteria, where around 90% of these are full professors. Figure E3 shows the full density distribution for female and male professors.

In the second step, we categorize the subgroup of professors satisfying the first criteria as either "female concentrated" or "male concentrated", defined as having a share of female advisees higher or lower than the median of 26%. Figure E4 shows the density distribution of this object, separately for female and male professors. 688 advisors are defined as female concentrated by this definition (out of which 14% are females), while 608 advisors are defined as male concentrated (out of which 5% are females).

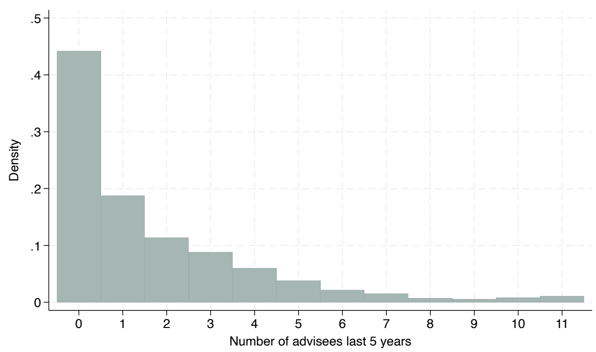
We then conduct separate analyses on the impact of sabbatical leaves taken by these two groups, using a specification similar to Equation 2:

$$y_{id,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \gamma_s Sabbat^g_{id,t-s} + \varepsilon_{id,t}, \tag{E.2}$$

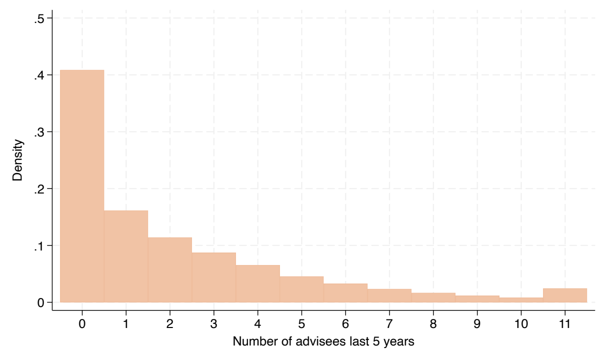
where $y_{id,t}$ denotes one of the three early-career outcomes and $Sabbat^g_{id,t-s}$ is a dummy variable equal to one if a professor (regardless of gender) defined as either female or male concentrated went on sabbatical leave in year $t-s$. For $s \in \{-5, 5\}$, γ_s represents whether a sabbatical leave happened five or more years before or after year t. Standard errors are clustered at the level of department-year.

Estimates are shown in Figure E5 and Figure E6 for leaves of female and male concentrated professors, respectively. As can be seen, sabbatical leaves taken by faculty with high female student representation have no systematic effect on either female or male students. Similarly, we find no effects of sabbatical leaves taken by professors with a high male student representation. These results are therefore inconsistent with an interpretation that our main results are only due to the disturbance generated by a professor's absence.

Figure E3: The number of advisees last 5 years, density distribution



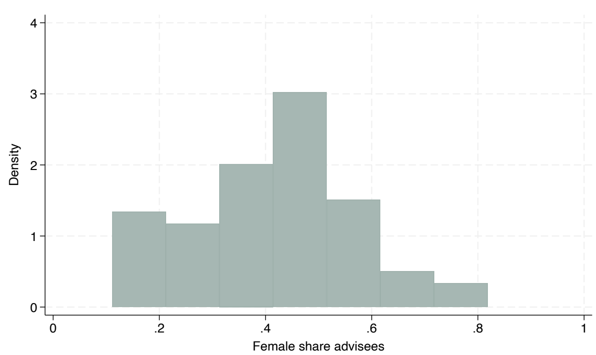
(a) Female professors (associate and full)



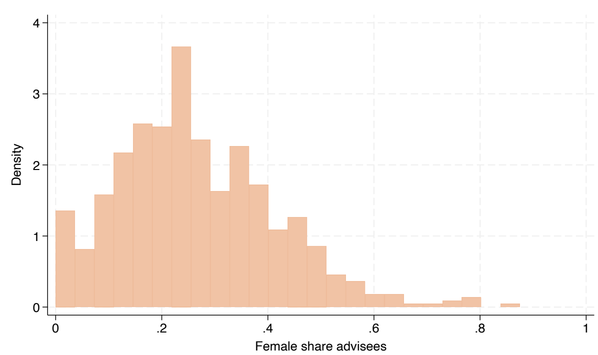
(b) Male professors (associate and full)

Note: The figures display the density function for the number of advisees over the last five years, separately for female associate and full professors (left panel) and male associate and full professors (right panel). The unit of observation is professor-year.

Figure E4: Share of female advisees, density distribution



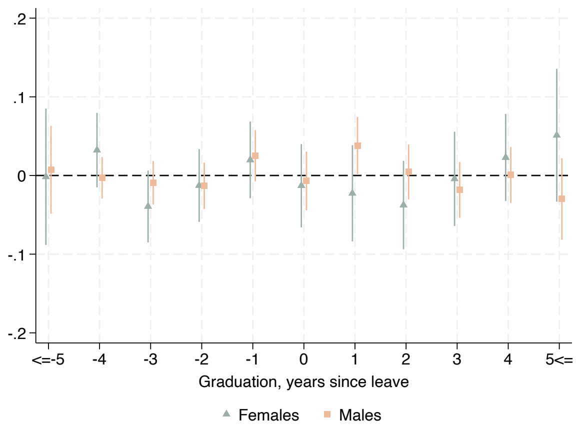
(a) Female professors (associate and full)



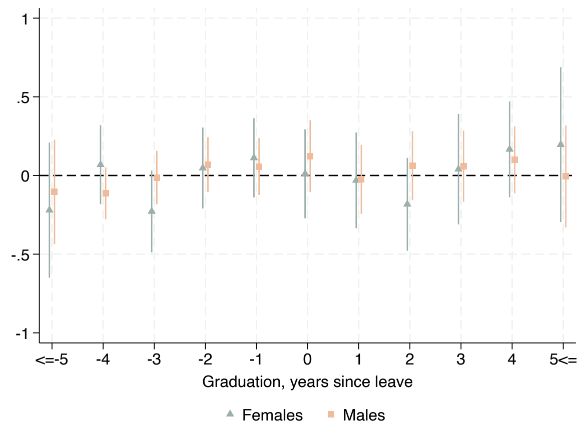
(b) Male professors (associate and full)

Note: The figures display the density function for female share of professors' advisees, separately for female associate and full professors (left panel) and male associate and full professors (right panel). The unit of observation is the professor-level.

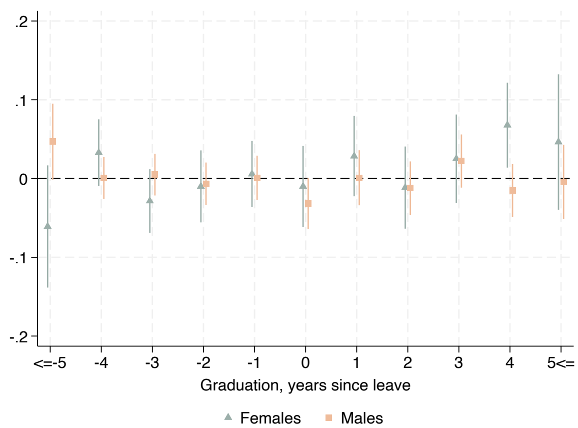
Figure E5: Early-career outcomes and sabbatical leaves by female concentrated advisors



(a) Probability of publication



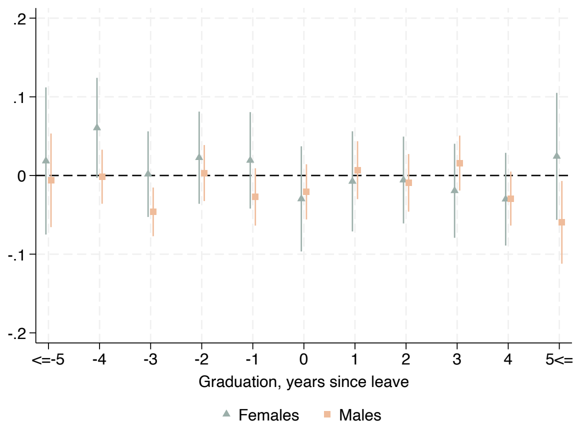
(b) Number of publications



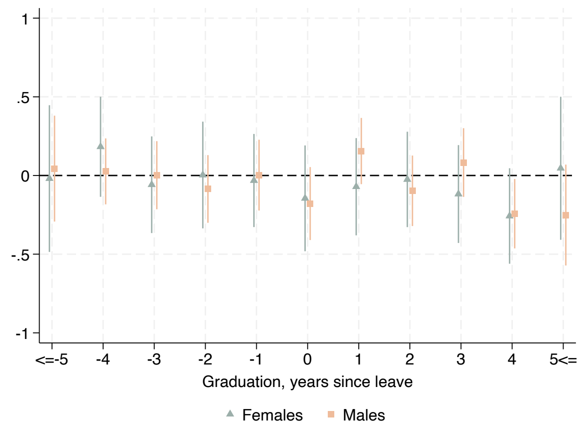
(c) Probability of staying in academia

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators from Equation E.2. The treatment indicators in the regression capture whether a "female concentrated" advisor went on sabbatical leave. Standard errors are clustered at department-year.

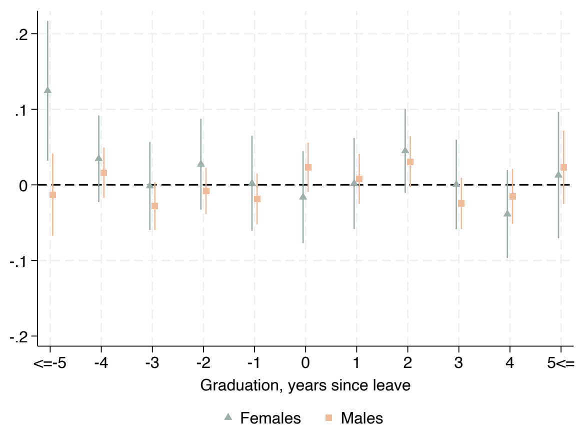
Figure E6: Early-career outcomes and sabbatical leaves by male concentrated advisors



(a) Probability of publication



(b) Number of publications



(c) Probability of staying in academia

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators from Equation E.2. The treatment indicators in the regression capture whether a "male concentrated" advisor went on sabbatical leave. Standard errors are clustered at department-year.