Mentorship and the Gender Gap in Academia*

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Abstract

This paper examines how the absence of female professors affects graduates from top-50 U.S. economics Ph.D. programs. We leverage quasi-random variation in sabbatical timing and detailed data on advisor relationships and career outcomes. When a female professor goes on leave, third-year female Ph.D. students become 19 percent less likely to secure academic placements and publish 31 percent fewer early-career papers. Remarkably, male students in the same cohort experience corresponding gains, fully offsetting the losses of their female peers. We parse publication effects from placement outcomes. Treated women continue to publish less even after accounting for placement, while men's publication gains appear entirely driven by improved placement. Gender homophily in mentorship – female students are 51 percent more likely than male students to have female advisors – helps explain these patterns, along with zero-sum dynamics in the junior job market. Adding one senior female professor to each top-50 department would close one-third of the assistant professor gender gap at top-25 schools.

Keywords: gender gap, economics, homophily, mentorship, network

JEL Codes: A14, I23, J16, J24, J71

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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 less likely to connect with each other, and less likely to form meaningful professional relationships than with others of the same gender. 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. If mentorship is gendered, then increasing female faculty presence should improve the early-career outcomes of female Ph.D. students.

Studying mentorship is challenging. In our context, students select into Ph.D. programs — and choose advisors — based on institutional prestige, field interests, faculty expertise, gender, among other factors. Consequently, female students in departments with more female professors may inherently differ from those in departments with fewer, in ways that also affect their post-Ph.D. outcomes. We address this concern by leveraging quasi-random variation from female professors' sabbatical leaves. These leaves offer three 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 are underrepresented among tenured faculty (Davies et al., 2022; Ginther and Kahn, 2004), each leave induces a meaningful decline in available female faculty. Third, the timing of sabbaticals is 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 sabbatical leaves of top-50 faculty. We match each of these 3,750 faculty members with 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 — about 13,000 in total

[1] Existing studies highlight discrimination (Bertrand, 2020; Kahn and Ginther, 2017), household constraints (Kleven et al., 2019; Le Barbanchon et al., 2021), gender differences in preferences and behavior (Buser et al., 2014; Charness and Gneezy, 2012; Shurchkov and Eckel, 2018), and social norms (Cortes and Pan, 2019) as contributing factors.

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

— during the same period, along with their dissertations (which name academic advisors) from ProQuest and JEL; their publications and co-author networks; 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 departments where a female professor goes on sabbatical publish less in their early careers (defined as the first five years after graduation) than unaffected female cohorts: their probability of publishing declines by 15 percent (relative to a mean of 0.53), and their total publication count falls by 31 percent (relative to a mean of 1.65). These students are also less likely to secure academic placements, with declines similar in magnitude to the drop in publication rates. Second, the temporary absence of a female professor does not just disadvantage women, it benefits men: male students in the same cohort are more likely to publish, produce more papers, and secure academic placements. Third, and perhaps most surprising, this shift in opportunity from female to male students reveals a zero-sum dynamic: the gains for male students directly offset the losses for female students.

We argue that gender homophily in academic professional and social networks drives these effects. To support this interpretation, we first present evidence of gender homophily in advisor-advisee relationships: even after controlling for department-year-field fixed effects, female students are 51 percent more likely than male students to have a female advisor, with an average probability of 7 percent for male students.[3] Second, we show that sabbatical leaves break advisor-advisee matches and disproportionately affect female students in their third year. These students are less likely to match with a female advisor and they form weaker relationships with their advisor, proxied by advisor-student coauthorship and the frequency of advisor mentions in dissertation acknowledgments.[4]

Together, these patterns point to gender homophily in advisor-advisee relationships as driver behind our result, consistent with a setting where mentorship shapes promotion through both human capital transmission and preferential treatment (Athey et al., 2000). We further support this interpretation by analyzing the quality of students' publications and the ranking of their job placements. Third-year female students experience a sizeable decrease in top-five and "deep-impact" journal publications (Angrist et al., 2020) (61 percent and 37 percent decrease relative to an average of 0.15 and 0.70, respectively), while male students show a small, statistically insignificant increase (17 and 6 percent relative to an average of 0.24 and 0.98, respectively). Again, we find close to no aggregate effect due to the gender composition. Placement patterns closely track the publication results for women. The share

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

[4]We rule out alternative explanations, mediated by the field of study or professor quality.

of affected women placed at top-25 institutions falls by 50 percent. These findings suggest that the absence of female professors hinders the development and placement of affected female students due to mentor-driven losses in human capital and broader misallocation — effectively ranking them down in the academic job market.

One central question remains: what explains the gains for men? We argue that men benefit indirectly from women's losses in a competitive job market: they improve their relative standing without a direct impact on their productivity. Consistent with this view, the share of affected men placed at top-25 institutions remains flat; they take positions at lower-ranked academic institutions. Their placement, rather than increased productivity, explains the publication gains: their publication record matches the average at their placement institutions. Crucially, this pattern points to a segmented job market structured around Ph.D. programs, where placement depends less on absolute productivity and more on relative standing within a department. The results are consistent with departmental sorting mechanisms that filter students into different tiers of the academic job market based on internal rankings — or with hiring institutions relying on implicit quotas or preferences tied to department prestige and referral norms.

This segmented structure amplifies the gendered effect of the lack of senior female professor, by not only harming female graduates, but by benefiting their male peers. Overall, these patterns underscore how a temporary, one-year absence of a female professor — orthogonal to students' ex ante ability — can shift the course of their professional lives: determining whether they enter academia, where they are placed, and how successful they become.

How does it all matter? Our results have equity implications. The lack of female representation at senior levels of academia (e.g., among associate and full professors) contributes to the "leaky pipeline" of female academics, leading to an asymmetry in female representation at each successive stage of the academic career ladder.[5] Indeed, a simulation based on our estimates 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 — raising their average gender ratio from 0.21 to 0.32. These schools have the lowest female representation in our sample. This approach would also directly address the gender gap among senior professors, all while resulting in minimal losses in academic productivity among assistant professors, a common concern in diversity hiring. Furthermore, 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

[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. This result is extended in Canaan and Mouganie (2023).

Ph.D. students to professors is more likely to occur at top schools rather than at lower-ranked schools.

The primary contribution of this study lies in exploiting a novel quasi-experimental design to isolate the causal effects of female mentorship on women's professional trajectories. Women are underrepresented in senior positions in many industries, occupations, and fields — including economics, engineering, and computer science (Bertrand, 2018; Blau and Kahn, 2017; Cheryan et al., 2017; Cortes and Pan, 2019). While prior research has documented many challenges facing female economists, including biases in hiring and promotion (Ceci et al., 2014; Ginther and Kahn, 2004; Sarsons et al., 2021), publication and citation disparities (Alexander et al., 2021; Card et al., 2020; Hengel, 2022; Koffi, 2021; Lassen and Ivandić, 2024; Paredes et al., 2020; Wu, 2018), and biased teaching evaluations (Boring, 2017; Mengel et al., 2019), it has largely focused on individuals who have already succeeded in entering the academic profession. We shift the lens upstream — examining Ph.D. students — and identify how increasing female representation at the top shapes the trajectories of those earlier in the pipeline and diversifies the leaders of the next generation. Taking advantage of the quasi-random timing of female professors' sabbatical leaves, combined with a novel dataset on job placements, professional networks, and publication output, we document that the absence of female faculty during graduate training significantly reduces female students' early-career publications and academic placements. Gender homophily has been documented in many aspects of professional life — including job search networks (Beaman, 2013; Torres and Huffman, 2002; Zeltzer, 2020; Zhu, 2018) and academic collaboration (Davies et al., 2022; Ductor and Prummer, 2024; Garcia-Jimeno and Parsa, 2024). We find that gender homophily in mentorship plays a central role in perpetuating these gender gaps in academic economics, with effects concentrated among third-year students — when students typically transition to independent research. In doing so, our findings pinpoint a specific location in the "leaky pipeline," the stoppage of which could substantially increase female representation in faculty positions.[6] The prior studies closest to this one are Blau et al. (2010) and Ginther et al. (2020)'s analysis of the CeMENT mentorship program, which connects young female faculty members with senior mentors and finds similar positive effects on the young faculty's publication records. Our study shifts focus not only further upstream, but to all female students — not just those with access to AEA mentorship programs — during their formative PhD years, through a universal relationship in the production of professors and their professional life.

[6] Hilmer and Hilmer (2007) provide observational evidence that women with male advisors out-perform those with female advisors; we show that this finding is the result of differential selection, not heterophilic treatment effect.

We also contribute by extending the analysis to male students. Female setbacks produce male advances — relative gains translate into better placements and publication outcomes for men, even as overall productivity remains unchanged — reinforcing gender disparities in career trajectories. These findings reveal a zero-sum dynamic and add to evidence of equity-efficiency tradeoffs in employment. We find that the additional value of female faculty to female students is large enough to fully offset the costs to male students, mirroring other educational settings in which equity targets are, if anything, efficiency-enhancing (Black et al., 2023; Bleemer, 2022).

2 Data description

To explore the role of female professors on sabbatical leave on the early career outcomes of Ph.D. students, we construct 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 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 identifying a list of top U.S. economics departments and the full roster of faculty members in these departments. For each department, we then collect the faculty members' sabbatical leave information along with the yearly list of Ph.D. graduates and their advisors. Finally, we match the professors and Ph.D. students to their respective academic publications. For detailed information on the data collection process, please refer to Appendix B.

[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.

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 that were ranked in the top 50 in each of the three years, which resulted in a total of 47 departments. For each department, we then scraped the list of all faculty members and their positions, focusing on 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 33 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 (CVs).

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. Our results are robust to including these leaves and alternative CV coding choices (see Appendix C). The CV collection added 783 additional leave events to our sample (36 percent of the total leaves).

To sum up, we define a professor on leave as one listed as on leave or visiting in any of these sources. Between 1994 and 2019, we identify 2,179 faculty leave events, 1,505 of which

[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.

[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).

(76 percent) involve associate or full professors.

It is important to note that despite a systematic data collection effort, our dataset likely undercounts the total number of faculty sabbaticals. This reflects the nature of the available information: we only observe leaves publicly documented in CVs, course catalogs, and department websites. As a result, we may be missing a non-random subset of sabbaticals — especially those taken on campus — that are both harder to detect and less likely to disrupt advising. In contrast, our measure and these sources tend to capture off-campus sabbaticals — the subset most likely to reduce the faculty-student interaction our research design exploits. In settings like ours, if anything, the undercounting typically results in attenuation bias, though the small share of sabbatical years diluting the "control" years bounds this bias to be small (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). See Appendix B for a detailed description and coverage evaluation of our dataset. For a sensitivity analysis on the definition of sabbatical leaves, ensuring the robustness of our main results, we refer you to Appendix Subsection C.2.

Ph.D. student-level data: We compiled data on Ph.D. students for each department for the years 1990 to 2022 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.[12]

ProQuest dissertation database is a repository of dissertations, serving as the official archive for the US Library of Congress. Proquest metadata 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

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

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 neighboring 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 neighboring school within the same university. For instance, a Ph.D. student from Harvard Kennedy School with an advisor in the economics department could be mis-assigned to the economics department. We refer you to Appendix Subsection C.4 for robustness checks against alternative criteria.

Finally, a natural concern is that faculty absence could affect Ph.D. completion — a prerequisite for inclusion in our sample, since both ProQuest and JEL report only students who file dissertations — rather than just placement or publication outcomes. In practice, faculty sabbaticals do not affect the number graduates or the gender composition of graduates (Appendix Figure A1). We revisit this point later in the analysis.

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 us to get citation data for a large sample of papers (2,033,825 combining both).[14] We also linked all the publication records of every 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 datasets pertaining to Ph.D. students and faculty members. 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. We assigned a gender to all students

[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

and professors using the Genderize.io database. For our estimation sample, we manually verified the predicted gender, covering the gender of 97.2 percent of the students (i.e., 205 students or 2.8 percent of the students with an unidentified gender) and 100 percent of the professors. See Appendix Subsection B.4 for an evaluation of the gender prediction variable.

Figure 1 shows the evolution of the share of female Ph.D. students and faculty members over time for 12711 students and 3,749 unique faculty members for whom we collected information. The share of women among full professors rose from 5 percent in 1994 to 13 percent in 2019, while the share of female associate professors grew from 5 percent in 1995 to 20 percent in 2019. Among assistant professors, the share of women fluctuated, increasing from 22 percent in 1995 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, consistent with previous findings (Auriol et al., 2022; Ductor et al., 2023; Kleemans and Thornton, 2023; Lundberg and Stearns, 2019). Ductor et al. (2023). 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).

We finally collected job placement data for the Ph.D. students in our estimation sample from sources such as LinkedIn profiles, CVs, and departmental records for up to three years post-graduation. See Appendix Subsection B.2 for details.

2.2 Final sample and descriptive statistics

We focus on 8867 students who earned their Ph.D. between 1998 and 2014, alongside 3,749 unique faculty members present in these 46 departments.[15] 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. We set 2014 as the final year because the publication dataset extends through 2019, and our analysis focuses on early-career outcomes — defined as the first five years post-Ph.D. — which align with the typical tenure-track evaluation period.

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

[15] Our sample of graduates closely matches counts we calculated using data from the Integrated Postsecondary Education Data System (IPEDS), which reports degree completions from all U.S. postsecondary institutions. Based on IPEDS, 9,256 students earned Economics Ph.D.s from these 46 departments between 1998 and 2014, compared to 8,867 in our sample—representing 96 percent of the IPEDS count.

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 1.70, while for associate professors, the median is also 1 but with a lower mean of 0.89, see Table 1. These statistics indicate a predominantly male professional environment.

The characteristics of 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 roughly the same average number of top-five publications as males and higher citations per paper per year. These results contrast with Ductor et al. (2023), which shows that women have 40 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.[16] 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.[17]

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 percent). 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 contrasts 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 and female Ph.D. students have about the same number of unique co-authors, while female Ph.D. students have more unique female co-authors. Regarding job placement,

[16] 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 defined as the most frequently used JEL code in their publications from the past 10 years.

[17] One possible explanation for this difference is that our leave variable could include maternity leaves. However, given our focus on senior (associate and full) professors and age-related biological constraints, parental leaves may not represent a significant share of the female sabbatical leaves in our sample. Supporting this view, 131 of the 204 female leave spells in our data involve verified visiting institutions (through CVs or faculty records), making them unlikely to be parental leaves. Among the remaining 73 leave spells, only 23 involve professors within 15 years of graduation, suggesting these individuals were likely over 40. Thus, parental leave likely does not account for a substantial portion of female sabbatical leaves in our sample.

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 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.[18] 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,[19] a female professor's temporary absence is likely to meaningfully reduce the number of female faculty members in a given year.

Figure 2 illustrates this decline by plotting the departmental presence of female professors (full and associate) around each of the 203 female professor leave spells — representing 9.3 percent of all leaves — in the top 50 departments from 1994 to 2019.[20] The figure reports

[18]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).

[19]Remember from Subsection 2.2, the mean number of female professors is 1.70, with a median of 1.

[20]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. 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.

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 effects. Given that a department might have female 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 $s \in \{-4, \ldots, -1\}$ 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 a 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 a 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 A2, 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. Figure 3 illustrates this by plotting the estimated yearly coefficients from a regression similar to Equation 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, third-year students develop and build their research agendas. We argue that this year constitutes a critical phase for students' later academic careers. During this period, students not only develop their research direction but also 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).[21] Figure C1 illustrates this trend, showing the evolution of completion times for a

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

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 Subsection 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 4. 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.

Note that this data limitation raises a potential empirical concern: our treatment is defined only for students who complete the Ph.D., an outcome that faculty absence might itself influence. While we cannot fully rule out selection effects, recall from Section 2 that the number of graduates is unaffected by sabbaticals, and the gender composition of graduates remains unchanged following both all sabbaticals and female faculty sabbaticals (Appendix Figure A1, Figure 3).

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, as discussed earlier, 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 5, 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 and academic placement of third-year female Ph.D. students. Figure 5a shows that third-year students — those graduating two years after the faculty leave — are 7.7 percentage points less likely to publish within five years, a 15 percent drop from the sample mean of 0.53 (significant at the 5 percent level). The number of publications also drops by 0.51 (Figure 5b), a 31 percent decline relative to the sample mean of 1.65, significant at the 1 percent level. We find no statistically significant effects for female students in other cohorts, including those graduating before the leave (the pre-treatment period). Given the importance of early-career publications for academic survival, we should find a lower share of female economists in academic positions. Figure 5c confirms this: third-year students are 9.6 percentage points less likely to secure an academic position–defined as a postdoctoral or assistant professor role within one year of graduation–mirroring the publication effect (–0.096 vs. –0.077).[22] As with publications, we observe no statistically significant effects for other cohorts. The concentration of the effect among third-year students supports our interpretation: the absence of a female professor does not affect all students equally, but disproportionately harms those in the critical early phase of their research development.

Result 2: Evidence from male students — third-year male Ph.D. students gain from the absence of female professor. Using publication and placement variables for the male Ph.D. students, we provide evidence of apparent gains for the male students. Starting with the probability of publishing at least one paper, we find an increase of 7.0 percentage points for male third-year students (significant at the 1 percent level), corresponding to 13 percent of the sample mean of 0.56 (Figure 5a). Publication counts rise by 0.22 papers (11 percent of the sample mean of 2.12), and the probability of academic placement increases by

[22] The results are similar when defining academic placement as holding an assistant professor position within three years post-Ph.D.

3.7 percentage points (Figure 5b; Figure 5c), both statistically significant at the 10 percent level. Similar to the findings for female students, we observe no significant impact on other student cohorts, including those graduating before the sabbatical leave.

Result 3: Zero-sum game. The contrasting results for male and female students — where female Ph.D. students lose from the absence of a female professor, while the male Ph.D. students gain — suggest a zero-sum dynamic among affected cohorts. Figure 6 supports this interpretation by presenting estimates from Equation 2 using a pooled sample of male and female Ph.D. students. The coefficients are close to zero and statistically insignificant for all cohorts.

3.2 Robustness checks

We first engage with the recent event study literature in econometrics (Roth et al., 2022), which highlights how treatment effect heterogeneity and variation in treatment timing can bias estimates of the average treatment effect.[23] We show that these concerns do not drive our results. We also show the robustness of our results to a range of alternative specifications, treatment definitions, and sample restrictions.

Multiple leave events and variation in treatment timing. Our setting deviates from the standard staggered treatment adoption framework. Departments can experience multiple treatment events, and treatment does not persist. While we do not expect dynamic effects in the usual sense — as each post-treatment year reflects different Ph.D. cohorts — leaves can affect all five cohorts present during a professor's absence. Furthermore, our event study regressions involve extensive overlap: many department-year observations have multiple treatment indicators switched on, reflecting leaves by different professors at different times (see also Sandler and Sandler, 2014). Control groups may also be partially treated, having been exposed to a leave just before or after. Standard methods developed for settings with staggered treatment adoption — where treatment begins at different times but persists indefinitely — do not directly apply.[24]

To address concerns about repeated leaves and time-varying treatment effects, we begin

[23]Recent work shows that standard two-way fixed effects models — with group and time fixed effects — can produce misleading estimates. These models often compare early- and late-treated units and may apply non-intuitive weights, including negative weights on observations that serve as both treated and controls (Goodman-Bacon, 2021).

[24]See, e.g., Callaway and Sant'Anna (2021) and Sun and Abraham (2021).

by estimating each lead and lag separately using the following specification:

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

which we run separately for $s \in \{-5, \ldots, 5\}$. This regression estimates the effect of a female professor's sabbatical leave s years before or after a student's graduation year, using all other years as the reference category. We restrict the sample to match that of our baseline regressions.[25]

The estimates closely match our baseline results, including no effect on students who graduated before the leave (see Figure 7 and Table 4 Panel B). Despite the different control group, the effects remain concentrated among third-year students. This robustness check alleviates concerns about treatment effect heterogeneity and dynamic effects often highlighted in the event study literature.

To further address concerns about repeated leave events, we estimate a stacked difference-in-differences specification with stricter sample restrictions than our baseline. These restrictions ensure a cleaner control group by isolating untreated cohorts more effectively. By stacking all treatment events, this approach reduces the risk of negative weighting that can arise in standard two-way fixed effects models (Cengiz et al., 2019). The resulting estimates closely align with our main results (see Appendix 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 -0.41 to -0.75 across the 16 alternative estimates presented in Appendix C (compared to -0.51 using our main

[25]Because this specification estimates each lead and lag separately, it avoids the missing values introduced by including all indicators at once. As a result, it yields about 20 percent more observations than the baseline. To ensure comparability, we report estimates in Figure 7 using the same restricted sample as the main regressions. Results using the full sample — including the additional 20 percent of observations — are nearly identical.

definition), and all coefficients are statistically different from zero at the 5 percent level.[26]

4 Gendered professional relationships

We have shown that the absence of female faculty leads to declines in publication and academic placement outcomes for female Ph.D. students, alongside apparent gains for male students, with negligible aggregate effects for the affected cohorts. We argue that two forces drive these ripple effects: professional relationships matter for career outcomes, and they tend to be gendered. These relationships play a key role in human capital formation, information exchange, and professional advancement.[27] These dynamics stand out in academia — especially during the Ph.D. years — which function as a hybrid between an educational setting and a workplace, akin to an apprenticeship. An advisor can offer valuable guidance, share research ideas, or connect their advisees with influential colleagues, all of which can significantly shape a student's career trajectory.[28]

While professionals benefit from having a mentor, a (strong) relationship cannot be forced, and we show that these relationships tend to be gendered. Gendered affinity, differences in communication styles, or interpersonal dynamics — including the potential for sexual tension — can 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 a result, the absence of a female professor can disadvantage female Ph.D. students relative to their male peers. Although these dynamics may be especially pronounced in academia, they also appear in other professional settings and may contribute to broader gender disparities in career outcomes.[29]

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.

Gendered relationships. In line with previous research demonstrating homophily in various contexts, such as friendship formation (Currarini et al., 2009; McPherson et al., 2001b),

[26] 10 of the 16 estimates are significant also at the 1 percent level.

[27] See Cingano and Rosolia (2012); Schmutte (2014); Zimmerman (2019) for evidence on how networks shape job market outcomes.

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

[29] Cullen and Perez-Truglia (2021) show that male employees benefit more from informal ties with male managers.

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 8 plots three series: (1) the share of female students with a female advisor, (2) the share of male students with a female advisor, and (3) a benchmark share under random matching.[30] Between 1994 and 2019, female students consistently matched with female advisors more often than male students did, with average match rates of 12.5 and 7.5 percent, respectively. The share for female students closely tracked the benchmark throughout the period, except for a brief dip between 2010 and 2015.

The regression estimates in Table 5 closely align with the visual pattern in Figure 8. We regress a dummy variable equal to one if a student has a female advisor on an indicator for whether the student is female, incrementally adding fixed effects: year (Column 1), department (Columns 2–3), field (Column 4), and department-by-year-by-field interactions in the fully saturated specification. We define fields using dissertation JEL codes.[31] Standard errors are clustered at the department–year level. In Columns 1 and 2, female students are 5 percentage points more likely than male students to have a female advisor. Controlling for field fixed effects narrows the gap to 4.7 percentage points. In the most saturated specification — controlling for department, cohort, and field — the estimate falls to 3.6 percentage points. All estimates are statistically significant at the 1 percent level. This final gap represents 51 percent of the male mean (0.07). These results suggest that differences in department and field composition explain only a small share of the gender gap. Advisor–advisee homophily in our setting aligns with findings from other academic and professional contexts.[32]

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, in Figure 9, we estimate the following

[30] We compute the benchmark as the share of women among associate and full professors at each department-year, weighted by the number of students in that department-year.

[31] JEL codes are missing for approximately 20 percent of the sample. Column 3 replicates the department–year specification on the restricted sample for comparability.

[32] For example, Gallen and Wasserman (2023) document gender homophily in student–alumni mentoring networks.

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.

Figure 9 shows that professors advise 0.12 fewer students two years after taking leave — a 24 percent drop relative to the sample mean of 0.49 graduating students per year. We observe a similar drop in the number of students graduating three years after the leave.

We next provide evidence that the affected female students end up in a "weaker" relationship with their advisor. Measuring the strength of a tie in practice is challenging and depends on the context. Following the definition in Granovetter (1973), the strength of a tie is determined by four main factors: time, emotional intensity, intimacy and reciprocal services. We use co-authorship between students and their advisors as a proxy for relationship strength. Using a specification similar to Equation 2, Column 2 of Table 6 shows that female students (Panel A) publish 38 percent fewer papers with their advisors, relative to a mean of 0.186 (statistically significant at the 5 percent level). Male students (Panel B) show a smaller, statistically insignificant increase. Note from Column 1 of Table 6 that co-authorship with advisor does not drive our main findings.

Forty-five percent of graduates in our sample do not publish any papers during their early careers (see Table 3). As an alternative proxy for advisor–advisee tie strength — observable for all students — we count how often a student mentions their advisor in the dissertation acknowledgments.[33] Column 3 of Table 6 reports estimates of Equation 2 using these acknowledgment measures as outcomes. For female third-year students, we observe a decline in advisor mentions at the beginning of the dissertation, corresponding to 9.5 percent

[33] We searched each dissertation for the advisor's last name and counted every mention that appeared within the first 10,000 characters. This cutoff helps distinguish acknowledgments from citations. To define it, we divided the text into 1,000-character bins and calculated how often the advisor's name appeared near the word "acknowledgment" versus near a year (a proxy for citation). As expected, the advisor's name most frequently appears near "acknowledgment" early in the document, while references near a year dominate later. This pattern reverses around the 10,000-character mark, as shown in Figure A3.

of the sample mean of 2.333 (statistically significant at the 5 percent level). In contrast, we detect no such effect for affected male students, and we find no impact on the number of times students cite their advisor (Column 4).[34] Notably, female students, on average, cite their advisor less often than male students (8.5 times versus 10.0 times).

Sabbatical leaves influence advisor matching for female students: Fewer female advisors and advisors with more Ph.D. students. What types of advisors do the affected female students match with? Using the main specification in Equation 2, we examine several advisor characteristics: gender, the number of other Ph.D. students they advise, the number of other female Ph.D. students, total publication output, and average citations per paper. Table 7 reports the results for third-year students.

Three patterns emerge. First, Column 1 shows that affected female students are 8 percentage points less likely to match with a female advisor — a 66 percent drop relative to the sample mean. Second, Column 4 shows that they match with advisors who supervise more Ph.D. students overall. Third, Columns 6–9 show no evidence that they match with lower-quality advisors, suggesting that advisor quality does not explain our main results. In contrast, we find no meaningful effects for male students.

Discarding alternative explanations. While our findings point to the gendered nature of mentorship and professional networks as key drivers of career outcomes for young economists, we explore and discard two alternative explanations.[35]

First, could our findings reflect the concentration of female professors in fields where female students also tend to specialize — so their absence disproportionately affects women? We know from Table 2 and Table 3 that both female students and professors are more likely to work in Labor/Public and that they are less likely to work in Macro/Finance compared to their male counterparts. To test this mechanism, we run seven regressions — one per field — where the treatment variable equals one if at least one professor in that field was on leave in a given year, regardless of the professor's gender (see Appendix Subsection E.1 for details). We find no systematic evidence supporting a field-mediated explanation. Specifically, we find no evidence that the number of students graduating in a given field changes when a professor in that field goes on sabbatical, nor do we observe early-career effects (Appendix Figure E2 and E3). This aligns with our expectations, given the gender-specific nature

[34] We proxy a student citing their advisor by any mention after the 10,000$^{\text{th}}$ character in the dissertations.

[35] Also rooted in gender homophily, if students begin forming mentorship relationships prior to their third year — with female students often investing in ties with female professors early on — a one-year mentorship gap early in their research life could lead to a similar decline. While this explanation also depends on gender homophily, we discard this specific explanation in Appendix Subsection E.2.

of the treatment effect: female students lose, while male students gain. Although female students tend to specialize in labor/public economics, male students still dominate both these fields and economics as a whole. In our sample, women account for only 35 percent of labor/public students. Combined with the gendered nature of the main effects, this suggests the results do not reflect a field-driven mechanism that operates independently of student gender. We further rule out more gendered field-based explanations by estimating the same seven regressions separately for male and female students. Appendix Figure E4 and E5 plot these results, estimating in one regression the field sabbatical and female sabbatical effects to assess potential confounding. We continue to find no systematic field effects. Most importantly, the female sabbatical effects in each of the regressions are similar to the benchmark female sabbatical effect suggesting that our female sabbatical effects does not confound any of these field sabbatical effects. This complements an earlier result: affected female students continue to cite their advisors at the same rate (Table 6). This suggests the disruption stems not from topic mismatch with the advisor, but from weaker or less effective mentorship — likely due to the absence of a better-matched advisor.

The second explanation considers whether male professors take leave at times when female professors do not. Hence, male students may benefit from the presence of male professors, rather than from the absence of female faculty. To test this, we first estimate the baseline regression from Equation 2, substituting male professors on sabbatical leave for female professors (Table A1). Next, we estimate the baseline model while controlling for male sabbaticals, including the same number of leads and lags as in the female-leave specification (Table A2). We use two measures of male professor leave: (1) a binary indicator for whether any male professor is on leave in a given department-year, and (2) a count of male professors on leave. The second measure accounts for the fact that 60 percent of department-year observations in our sample include at least one male sabbatical. The results show no effect of male professor leave on early-career outcomes for either female or male students (Table A1). Controlling for male sabbaticals also leaves the estimated effects of female professor leave essentially unchanged (Table A2). These findings indicate that our results are not driven by gender-specific leave timing.[36]

5 Publication and placement quality

The previous section showed that the temporary absence of female professors disrupts advisor-advisee relationships for third-year female students, while leaving their male counterparts

[36] We also test whether high-productivity professors drive the results and find no evidence of this (see Table A3).

unaffected. Why, then, do male students' early-career outcomes appear to benefit?

We argue that men gain as a byproduct of women's losses in a competitive academic job market. Mentor-driven losses in human capital and broader misallocations push female students down the placement ladder, allowing male students to improve their relative standing without becoming more productive. In line with this explanation, we first show that affected female students publish fewer papers in top-five and high-impact journals and are disproportionately absent from top-ranked academic institutions. Affected male students, by contrast, do not publish more in high-quality outlets. They enter academia from lower-ranked institutions, and their publication output closely matches others placed at the same institutions.

Placement and publication quality effects for female students. We begin by showing that the absence of female professors leads affected female students to place at lower-ranked institutions and produce less research of high quality. We classify student placements into three tiers using the *RePEc* U.S. Department Rankings as of 2015: Group 1 includes top-25 economics departments, Group 2 includes all other academic departments, and Group 3 consists of non-academic placements. Table 9 presents the marginal effects from a multinomial regression using Group 3 as the base category.[37] Affected female students are 3.7 percentage points less likely to place in a top-25 department — 50 percent decline relative to their 7.4 percent base rate — accounting for 43 percent of the overall drop in female Ph.D. students entering academia.

To proxy for research quality, we use three measures: the number of top-five journal publications, the number of "deep impact" publications (Angrist et al., 2020), and average citations per paper per year.[38] Panel B (Column 1) of Table 8 shows that affected female students publish 61 percent fewer top-five papers relative to a mean of 0.152. Panel C shows a 37 percent decline in deep impact publications (mean = 0.70). These declines mirror the downward shift in placement.

Male students: Gains in relative position. In contrast to the affected female students, the affected cohort of male students has an estimated coefficient close to zero in the same top-25 departments, indicating that they do not replace their female counterparts. Instead they enter academia from lower ranked schools: positions outside of the top-25 departments

[37] We define all covariates as in our main regression (Equation 2). Appendix D provides the full specification. Table D1 reports results using an alternative ranking based on average citations per paper among assistant professors.

[38] Top-five journals include the *AER*, *QJE*, *Econometrica*, *JPE*, and *ReStud*. Deep impact journals follow the classification in Angrist et al. (2020).

fully account for their increase in academia. Column 2 of Table 8 shows a 17 percent increase in top-five publications and a 6 percent increase in deep impact publications, neither statistically significant.[39] Their citation counts remain flat.

While the affected cohort of male students do not become better quality researcher, we still need to explain their increased publication count. We document that their academic placement fully accounts for the increase in publication count for the male cohort. To do this, we re-estimate the regressions using the deviation between a student's publication record and the average for others placed at the same institution (by gender).[40] Column 4 of Table 8 shows that affected female students publish less than others placed in the same institutions, although the gap disappears for top-five and deep impact publications. Column 5 shows that male students perform similarly to their peers across all metrics, except for a modest, statistically significant decline in citations.[41]

Together, these results suggest that men benefit not from increased productivity but indirectly from their academic position. This points to a segmented job market: students' relative position within their own departments matters, rather than their standing in a global pool. Many U.S. Ph.D. programs informally rank students and concentrate placement support — strong letters, endorsements, and faculty advocacy — on those at the top.[42] Hiring institutions may also impose implicit quotas on the number of candidates they recruit from each program, further reinforcing institutional prestige and internal rankings. Prior research shows that a small number of elite programs produce the vast majority of tenure-track faculty in the U.S., and that faculty hiring follows steep prestige hierarchies (Clauset et al., 2015).

Implications and discussion. Regardless of the primary mechanism, our findings underscore that the absence of a female professor significantly alters the career trajectories of affected Ph.D. students. The losses for women numerically offset 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 highest-ranked departments. From the perspective of

[39]Despite the sizable losses for women, we detect no aggregate change in publication quality (Column 3), reflecting that women make up only 30 percent of the cohort.

[40]We pool institutions with no other sample students into composite groups: central banks, public sector, research institutes, teaching institutions, private sector, and unknown placements. See full details in the table note to Table 8.

[41]Note that when running the main regression for graduates placed academia in Table A4, we still find a positive coefficient for male and a negative one for female. This suggests that the effect doesn't simply come from those staying in academia; but their actual placement ranking matters to explain the rise in publication for men.

[42]As Tyler Cowen notes in his blog post in 2002, top departments explicitly rank their students, and peer institutions often rely on those rankings in hiring: https://marginalrevolution.com/marginalrevolution/2022/01/how-the-job-market-works-at-top-schools.html

home institutions, this "replacement" does not maintain equal placement quality. Beyond the home institutions, our findings carry implications for the top-25 departments, which employ the lowest share of female assistant professors in our sample, 21.9 compared to 26.2 percent in the bottom-25. To illustrate the potential impact of senior female hires, consider a simple counterfactual: if each of the top-50 departments hired one additional senior female professor (holding other factors constant), our estimates imply a 50 percent increase in the share of women among assistant professors in top-25 schools — from 21.4 to 32.0 percent over the 2015–2019 period. This calculation draws on the gender composition of our Ph.D. sample and the coefficients in Table 9, assuming an assistant professor remains in the role for six years.[43]

Of course, real-world dynamics are more complex. Hiring a senior female professor may influence not only student placement but also the broader composition of faculty and student bodies through channels not captured by our model—such as selection effects, peer dynamics, or equilibrium responses in male hiring. Additionally, our calculation abstracts from longer-run dynamics. As newly hired female assistant professors progress toward tenure and begin advising their own students, the effects could compound across cohorts. A back-of-the-envelope projection using our observed tenure conversion rate (approximately 40 percent) suggests this channel alone could add 0.1 female professors per year to the tenured ranks at top-25 departments after six years. If these hires had occurred at the start of our sample period (1998), the cumulative effect by 2015-–2019 would raise the simulated female share of assistant professors from 32.0 to 38.0 percent, as these women progress to tenure and begin mentoring students.[44] 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. This approach could achieve roughly one-third of the progress needed to reach gender parity among assistant professors, while simultaneously improving gender balance at the senior level. Importantly, these gains would come without measurable losses in research productivity — addressing a common concern about potential trade-offs in diversity-focused hiring.

[43] We calculate an average of 154 graduating female Ph.D. students per year. Multiplying by the estimated marginal effect of 0.039 yields approximately six additional women entering top departments annually. Over six years, this results in 36 additional female assistant professors. Adding these to the observed counts of 49 female and 181 male assistant professors over 2015-–2019 yields a simulated female share of 32 percent.

[44] We assume that 40.5 percent of the 6 extra assistant professors per year end up as a tenured professor in a top-25 school after 6 years, which gives 0.097 extra female professors per departments per year after 6 years. For the period 2015–2019 this would have compounded to an 1.36 extra tenured female professors per department and an 25.9 extra assistant professors in the top-25 schools overall. Adding this to the number of assistant professors as mentioned above, gives the female share of 38.0 percent.

6 Conclusion

This study provides causal evidence that female professors play a pivotal role in advancing the careers of female Ph.D. students. Leveraging quasi-random sabbatical timing, we show that their temporary absence disrupts advisor-advisee relationships, weakens professional ties, and significantly reduces affected female students' early-career publications and chances of academic placement—especially at top-ranked institutions. These effects arise from gender homophily in mentorship: female students are more likely to match with female advisors and to form stronger professional bonds when female faculty are present. In their absence, women are effectively "ranked down" in the academic job market.

Strikingly, male students in the same cohort experience corresponding gains, revealing a zero-sum dynamic in which one group's losses improve another's relative standing. Yet the net educational value of female faculty remains positive: their contributions to female students fully offset any losses to men. These results challenge the assumption that gender equity in hiring trades off against overall efficiency.

While our analysis focuses on academia, these dynamics extend to other professions where advancement depends on mentorship and access to informal networks. In such settings, the underrepresentation of women at senior levels compounds inequality further down the pipeline. By isolating a specific link between senior female presence and junior female success, we show that mentorship structures can entrench — or interrupt — gender gaps in elite career paths.

Our findings also raise questions about which women succeed in a profession still dominated by men at the top. In the presence of gender homophily, if decision-makers — such as those responsible for hiring, promotion, and resource allocation — are predominantly men, this not only creates a bias toward promoting and supporting male academics, but also increases the likelihood of success of female Ph.D. students who form relationships with men. These women 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.

Hiring more female associate and full professors offers a scalable lever: it not only narrows the gender gap among assistant professors but also reshapes who succeeds in the profession. Over time, this shift could reinforce itself, as today's junior scholars become tomorrow's mentors.

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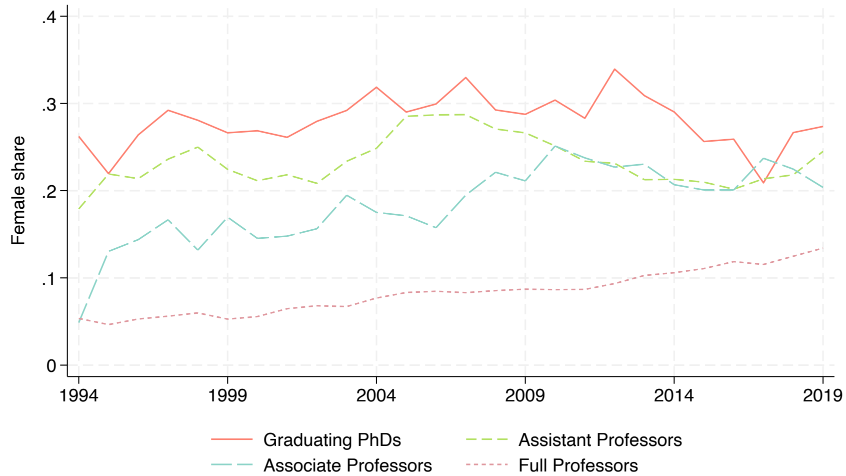
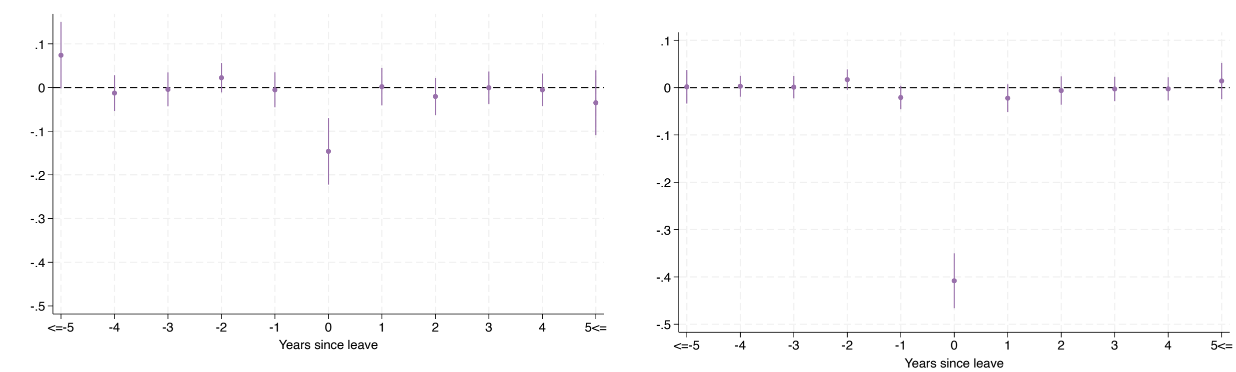
Figure 1: Female shares of Ph.D. students and faculty members



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

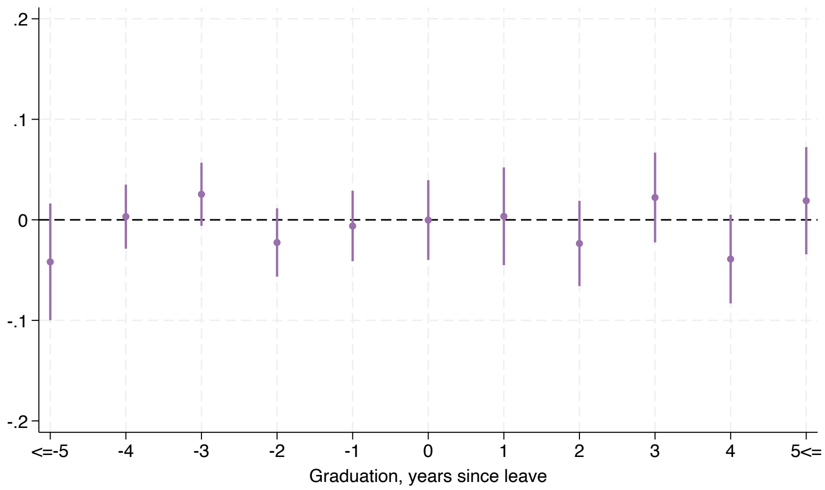


(a) Probability of at least one female professor present

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

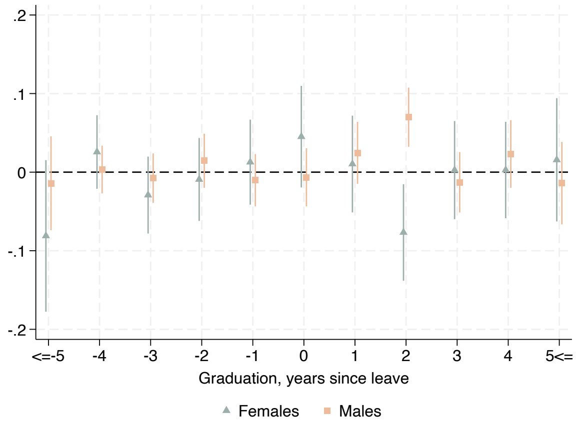


Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation 1. The outcome variable is an indicator variable denoting female Ph.D. students.

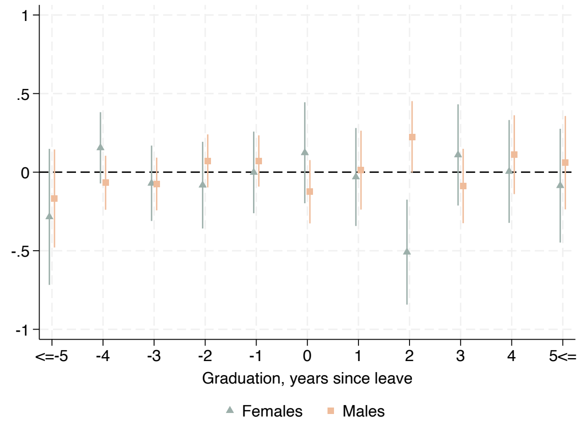
Figure 4: Timing of leave and classification of Ph.D. students

	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^*

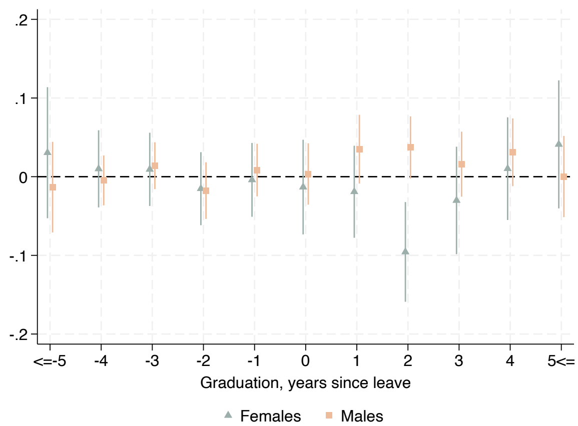
Figure 5: Female professors on sabbatical leaves and students' early-career outcomes



(a) Probability of publication



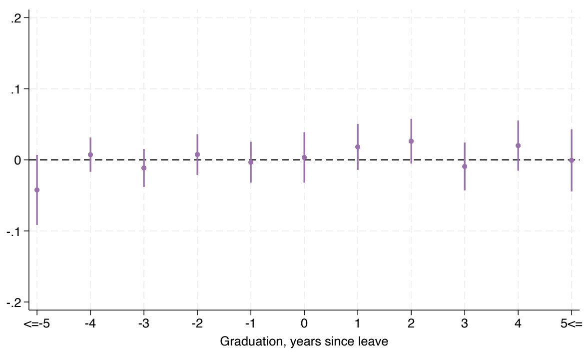
(b) Number of publications



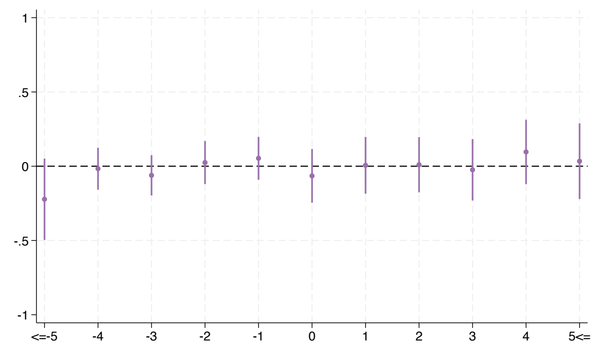
(c) Probability of staying in academia

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.

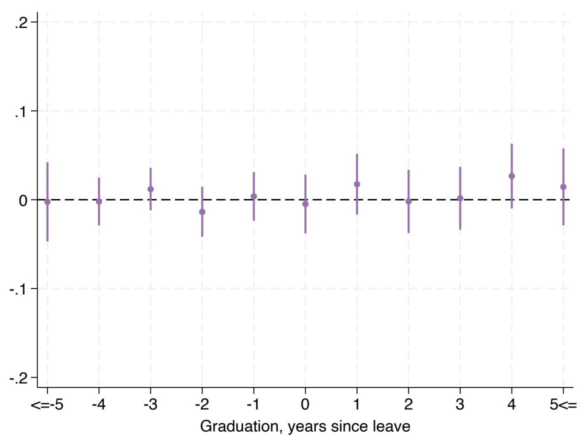
Figure 6: Zero-sum: Female professors on sabbatical and early-career outcomes, pooled sample



(a) Probability of publication



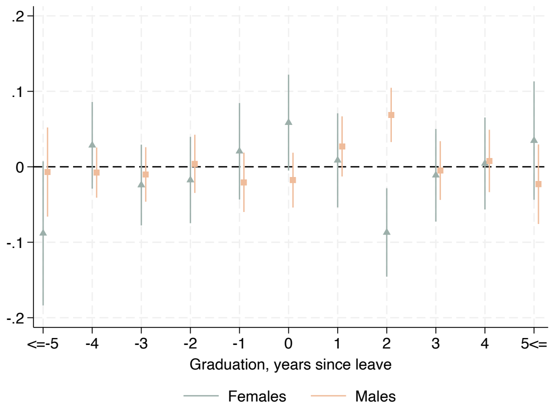
(b) Number of publications



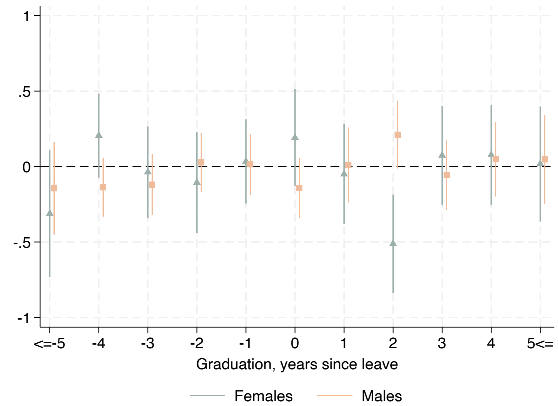
(c) Probability of staying in academia

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.

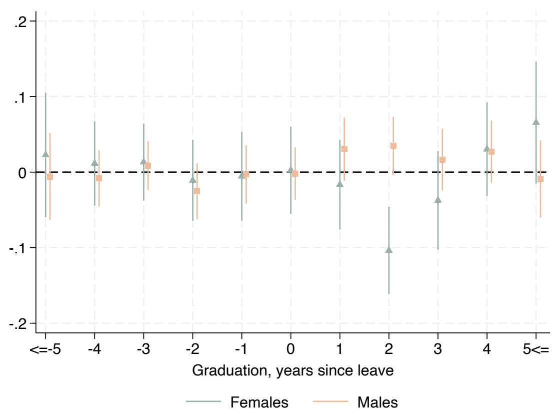
Figure 7: Robustness: Female professors on sabbatical leaves and students' early-career outcomes, leads and lags estimated in separate regressions



(a) Probability of publication



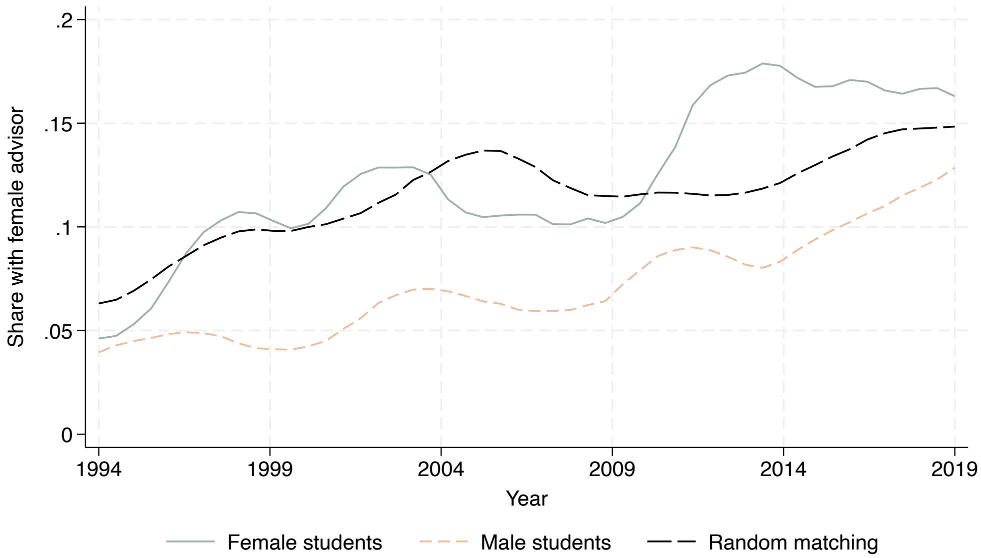
(b) Number of publications



(c) Probability of staying in academia

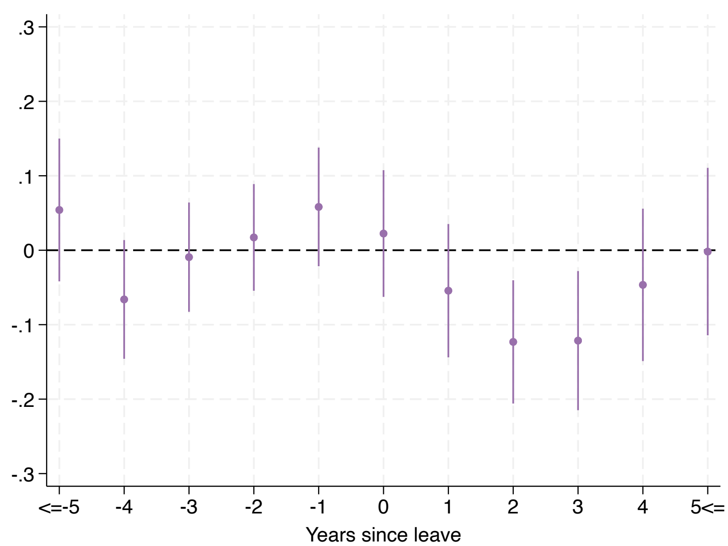
Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators corresponding to those in Equation 3, where each of the time indicators are estimated through separate regressions. The outcome variables are the same as in Figure 5. Standard errors are clustered at the department-year level.

Figure 8: 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 labeled "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 9: 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	Median	SD	Mean	Median	SD	Mean	Median	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Number of faculty and graduating Ph.D. students									
Graduating Ph.D. students	12.25	11	0.23	3.17	3	0.08	9.08	8	0.18
Faculty	32.54	31	0.39	4.44	4	0.07	28.04	27	0.35
Full professors	19.99	19	0.30	1.70	1	0.05	18.29	17	0.28
Associate professors	4.63	4	0.09	0.89	1	0.03	3.75	4	0.08
Assistant professors	7.91	8	0.12	1.85	2	0.04	6.00	6	0.10
Observations	1046			1046			1046		
Panel B: Share of faculty with a graduating Ph.D. student									
Full professors	0.36	0	0.0033	0.35	0	0.0113	0.36	0	0.0035
	(n=20911)			(n=1781)			(n=19130)		
Associate professors	0.23	0	0.0060	0.20	0	0.0131	0.24	0	0.0068
	(n=4847)			(n=929)			(n=3918)		
Assistant professors	0.09	0	0.0031	0.05	0	0.0051	0.10	0	0.0037
	(n=8276)			(n=1933)			(n=6279)		

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	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sabbatical leaves						
Sabbatical leave	0.06	0.0015	0.08	0.0051	0.06	0.0016
Observations	24791		2671		22120	
Panel B: Mentoring						
Advisees	0.40	0.0050	0.32	0.0125	0.41	0.0054
Female advisees	0.10	0.0023	0.12	0.0075	0.10	0.0024
Male advisees	0.30	0.0040	0.20	0.0093	0.31	0.0044
Observations	24791		2671		22120	
Panel C: Productivity (previous 10 years)						
Publications	14.20	0.0862	11.87	0.2035	14.49	0.0933
Top-five publications	2.18	0.0221	2.13	0.0587	2.19	0.0237
"Deep impact" publications	7.62	0.0539	7.12	0.1332	7.68	0.0583
Average citations per paper and year	6.80	0.0703	7.83	0.1801	6.68	0.0757
Observations	24791		2671		22120	
Panel D: Networks (previous 10 years)						
Unique co-authors	9.53	0.0673	8.23	0.2001	9.68	0.0713
Unique female co-authors	1.61	0.0167	2.08	0.0670	1.55	0.0169
Unique male co-authors	7.84	0.0544	6.08	0.1445	8.06	0.0583
Observations	24791		2671		22120	
Panel E: Main research field (shares)						
Micro	0.13	0.0021	0.11	0.0059	0.13	0.0023
Macro/Finance	0.25	0.0027	0.21	0.0079	0.25	0.0029
Labor/Public	0.21	0.0026	0.37	0.0093	0.19	0.0027
IO	0.06	0.0015	0.04	0.0036	0.06	0.0017
Environmental	0.04	0.0013	0.04	0.0039	0.04	0.0014
Development/History	0.07	0.0016	0.09	0.0055	0.06	0.0016
Other	0.16	0.0023	0.14	0.0068	0.16	0.0025
Observations	24791		2671		22120	

Note: The unit of observation is professor-year. Panel A shows the fraction of professors on sabbatical leave. Panel B shows the average number of graduating advisees per year and by gender. Panel C 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 D shows the average number of unique co-authors over the previous 10 year by gender, and finally, Panel E shows the share of professors by their main research field. The sample is restricted to associate and full professors.

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

	Total		**Females**		**Males**	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (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	6987		2070		4917	
Panel B: Productivity (5 years post Ph.D.)						
Any publication	0.55	0.0060	0.53	0.0110	0.56	0.0071
Publications	1.98	0.0329	1.65	0.0519	2.12	0.0412
Top-five publications	0.21	0.0089	0.15	0.0129	0.24	0.0114
"Deep impact" publications	0.90	0.0199	0.70	0.0309	0.98	0.0250
Average citations per paper and year	3.73	0.1253	3.65	0.2717	3.77	0.1366
Publications with advisor	0.22	0.0085	0.18	0.0127	0.24	0.0109
Observations	6987		2070		4917	
Panel C: Networks (conditional on publication)						
Unique co-authors	3.14	0.0586	2.97	0.1001	3.21	0.0716
Unique female co-authors	0.60	0.0193	0.73	0.0350	0.54	0.0230
Unique male co-authors	2.52	0.0464	2.21	0.0788	2.65	0.0567
Observations	3842		1098		2744	
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	6987		2070		4917	
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	0.0106	0.31	0.0074
Labor/Public	0.21	0.0055	0.29	0.0113	0.18	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	0.0027
History/Development	0.09	0.0038	0.10	0.0076	0.08	0.0044
Other	0.16	0.0049	0.14	0.0085	0.17	0.0059
Observations	5572		1634		3938	

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 had at least one publication five years 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 5). Finally, Panel E shows the share of students in different research fields, defined in terms of the JEL codes of the dissertations. All panels are based on the main estimation sample (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**			**All Ph.D. students**		
	HasPub. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)	HasPub. (7)	#Pubs. (8)	Academia (9)
Panel A: Baseline estimates:									
FemSabbat, $t-2$	-0.077**	-0.509***	-0.096***	0.070***	0.224*	0.037*	0.026	0.010	-0.002
	(0.031)	(0.170)	(0.032)	(0.019)	(0.116)	(0.020)	(0.016)	(0.095)	(0.018)
Observations	2070	2070	2070	4917	4917	4917	6987	6987	6987
R^2	0.054	0.060	0.084	0.032	0.041	0.047	0.027	0.033	0.046
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518	0.550	1.978	0.511
Panel B: Leads and lags separately:									
FemSabbat, $t-2$	-0.087***	-0.512***	-0.104***	0.069***	0.212*	0.035*	0.021	-0.005	-0.006
	(0.030)	(0.166)	(0.029)	(0.018)	(0.115)	(0.019)	(0.015)	(0.091)	(0.017)
Observations	2070	2070	2070	4917	4917	4917	6987	6987	6987
R^2	0.050	0.057	0.082	0.032	0.040	0.045	0.026	0.032	0.045
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518	0.550	1.978	0.511

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 5 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 7 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: 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	12421	12421	9935	9935	9935
R^2	0.018	0.133	0.146	0.169	0.381
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 6: Publications with the advisor and mentions of the advisor in the dissertation texts

	Publications		Mentions of advisor	
	Without advisor	With advisor	"Acknow."	"Cites"
	(1)	(2)	(3)	(4)
Panel A: Female students				
FemSabbat, $t-2$	-0.442***	-0.066**	-0.212**	-0.278
	(0.162)	(0.031)	(0.106)	(1.090)
Observations	2070	2070	1814	1814
Mean dep.var.	1.467	0.182	2.332	8.541
Panel B: Male students				
FemSabbat, $t-2$	0.174*	0.051	-0.079	0.131
	(0.103)	(0.035)	(0.086)	(0.750)
Observations	4917	4917	4327	4327
Mean dep.var.	1.881	0.236	2.335	9.983

Note: Column 1 uses publications without the advisors as outcome, while Column 2 uses publications co-authored with the advisor as outcome. The outcomes in Columns 3-4 are constructed by searching for mentions of the advisor name within the dissertations, before and after the 10,000th character, respectively. Standard errors clustered on department-year are shown in the parentheses. ***p<0.01, **p<0.05, *p<0.10.

Table 7: 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	“Deep impact”	Citations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Female Ph.D. students									
FemSabbat, $t-2$	-0.080***	0.000	0.996	0.394**	0.116	0.264	-0.459	-0.125	-0.458
	(0.024)	(0.029)	(0.723)	(0.189)	(0.113)	(1.289)	(0.338)	(0.786)	(0.763)
Observations	2070	2070	1753	2070	2070	1821	1821	1821	1821
Mean dep.var.	0.121	0.698	25.178	2.998	1.234	20.998	3.935	11.032	10.206
Panel B: Male Ph.D. students									
FemSabbat, $t-2$	-0.000	-0.027	-0.422	0.006	-0.021	-1.051	0.307	0.033	0.103
	(0.012)	(0.026)	(0.584)	(0.156)	(0.058)	(0.900)	(0.215)	(0.496)	(0.637)
Observations	4917	4917	4128	4917	4917	4314	4314	4314	4314
Mean dep.var.	0.065	0.689	24.522	2.898	0.690	20.485	4.143	10.98	10.936

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, Columns 7 and 8 the number of top-five and “Deep impact” publications the advisor had over the last 10 years, and Column 9 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.

Table 8: The effects of sabbatical leaves on measures of publication quality

	Students' own outcomes			**Deviation from placement average**	
	Females (1)	Males (2)	All (3)	Females (4)	Males (5)
Panel A: Publications					
FemSabbat, $t-2$	-0.509***	0.224*	0.010	-0.370**	0.043
	(0.170)	(0.116)	(0.095)	(0.175)	(0.118)
Observations	2070	4917	6987	2070	4917
Mean dep.var.	1.648	2.117	1.978	0	0
Panel B: Top-five publications					
FemSabbat, $t-2$	-0.093**	0.041	0.002	-0.061	0.022
	(0.043)	(0.033)	(0.026)	(0.041)	(0.032)
Observations	2070	4917	6987	2070	4917
Mean dep.var.	0.152	0.237	0.212	0	0
Panel C: "Deep impact" publications					
FemSabbat, $t-2$	-0.255***	0.063	-0.027	-0.111	0.003
	(0.093)	(0.072)	(0.058)	(0.090)	(0.065)
Observations	2070	4917	6987	2070	4917
Mean dep.var.	0.696	0.981	0.897	0	0
Panel D: Average citations					
FemSabbat, $t-2$	0.074	-0.379	-0.252	0.795	-0.673*
	(0.772)	(0.356)	(0.325)	(0.686)	(0.403)
Observations	2070	4917	6987	2070	4917
Mean dep.var.	3.653	3.765	3.732	0	0

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, Panel C for the sum of "Deep impact" publications (see Angrist et al., 2020), while Panel D 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. The estimates in Columns 4-5 use the deviation from the placement average as outcome, calculated as students' own outcome minus the average of the outcome of other students placed in the same institution. Standard errors clustered on department-year are shown in the parentheses. ***p<0.01, **p<0.05, *p<0.10.

Table 9: The effects of sabbatical leaves on job placement, marginal effects from multinomial regression on placement categories

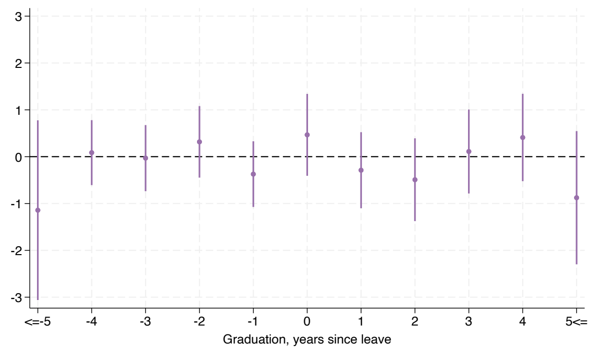
	Female Ph.D. students			**Male Ph.D. students**		
	Top-25 Economics department (1)	Other departments (2)	Out of academia (3)	Top-25 Economics department (4)	Other departments (5)	Out of academia (6)
FemSabbat, $t-2$	-0.037**	-0.049	0.086***	0.001	0.041**	-0.042*
	(0.016)	(0.032)	(0.033)	(0.013)	(0.019)	(0.021)
Observations	2070	2070	2070	4917	4917	4917
Share in category	0.074	0.420	0.507	0.083	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 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.

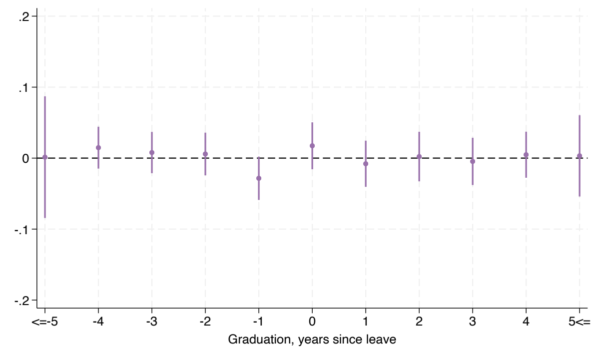
Online appendix

A Extra figures and tables

Figure A1: Number and female share of graduating Ph.D. students and faculty sabbaticals



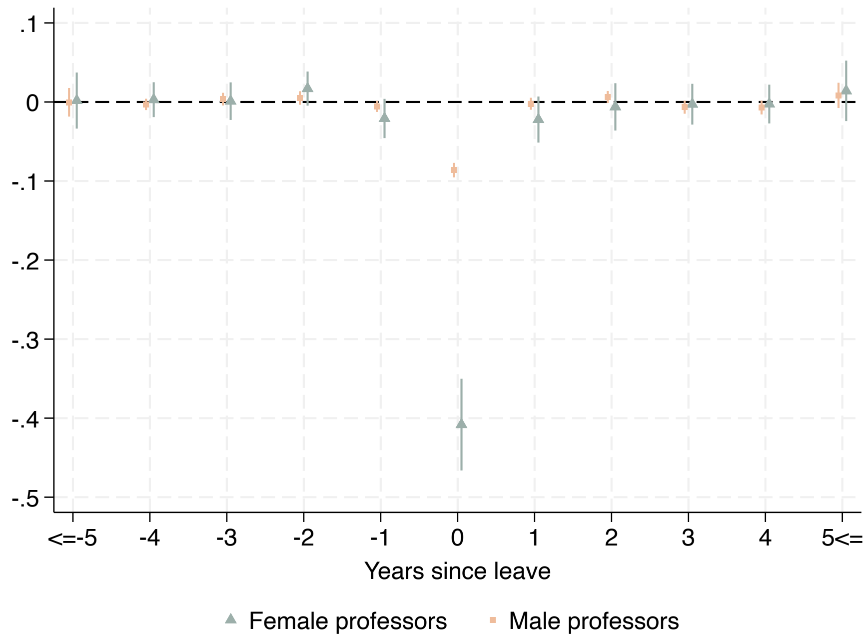
(a) Number of graduating Ph.D. students



(b) Female share of graduating Ph.D. students

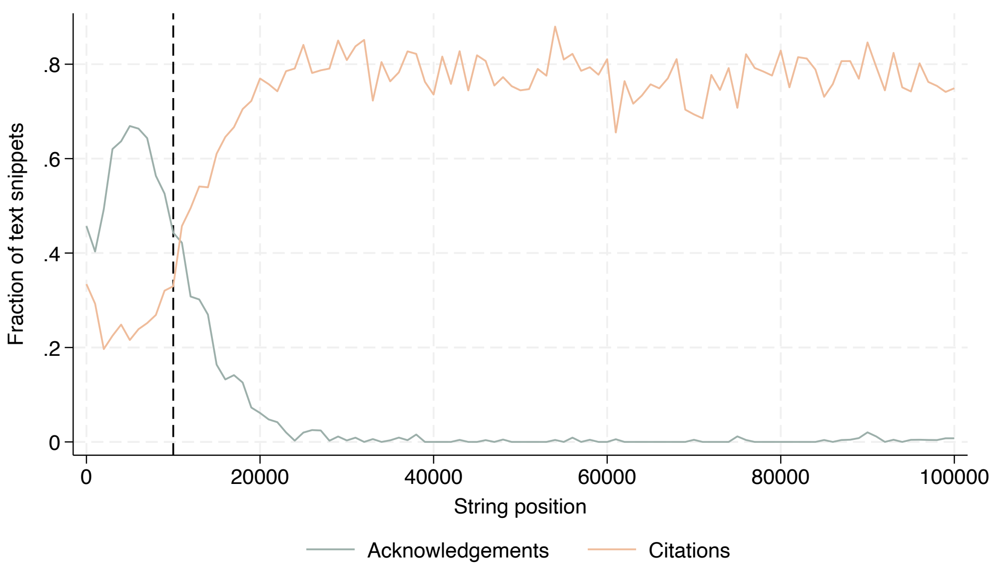
Note: The outcome in Figure a) is the number of graduates by department and year, while the outcome in Figure b) is the female share of graduates. Both figures show coefficients and 95% confidence intervals for year-since-faculty leave indicators.

Figure A2: 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 A3: Mentions of the advisor name within the dissertations and how often it appears together with the word "acknowledgement" and a year



Note: The figure is based on keywords within Ph.D. dissertations. We first extract all mentions of the advisor names within the dissertations, with the text around the advisor name. The vertical axes display the share of mentions that appear together with the keyword "acknowledgement" (in green) and a year (in orange). We calculate the shares by each 1,000 character bin of the dissertations, as shown by the horizontal axes.

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 men on leave:						
MaleSabbat, $t-2$	-0.032	-0.125	0.002	-0.003	0.026	0.010
	(0.027)	(0.117)	(0.027)	(0.017)	(0.092)	(0.017)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.531	1.649	0.493	0.558	2.117	0.518
Panel B: Sum of male professors on leave:						
MaleSabbat, $t-2$	0.002	0.055	0.002	0.005	-0.003	0.011**
	(0.010)	(0.048)	(0.009)	(0.006)	(0.027)	(0.005)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.531	1.649	0.493	0.558	2.117	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: Controlling for male professors on leave (binary):						
FemSabbat, $t-2$	-0.069**	-0.491***	-0.095***	0.073***	0.220*	0.040**
	(0.032)	(0.167)	(0.032)	(0.019)	(0.116)	(0.020)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.531	1.649	0.493	0.558	2.117	0.518
Panel B: Controlling for male professors on leave (sum):						
FemSabbat, $t-2$	-0.070**	-0.544***	-0.106***	0.060***	0.200	0.031
	(0.032)	(0.171)	(0.032)	(0.020)	(0.123)	(0.020)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.531	1.649	0.493	0.558	2.117	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.

Table A3: The effects of top 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: Star professors, publications:						
StarSabbat, $t-2$	0.029	0.010	-0.003	0.003	0.023	0.029*
	(0.027)	(0.126)	(0.025)	(0.016)	(0.096)	(0.017)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518
Panel B: Star professors, top-five publications:						
StarSabbat, $t-2$	0.029	0.181	0.012	0.014	0.076	0.027*
	(0.028)	(0.140)	(0.027)	(0.018)	(0.103)	(0.016)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518
Panel C: Star professors, "Deep impact" publications:						
StarSabbat, $t-2$	0.013	0.044	0.009	-0.022	-0.005	0.021
	(0.026)	(0.123)	(0.024)	(0.017)	(0.090)	(0.016)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518
Panel D: Star professors, citations:						
StarSabbat, $t-2$	0.045	0.176	0.006	0.033*	0.129	0.042***
	(0.029)	(0.133)	(0.026)	(0.017)	(0.095)	(0.015)
Observations	2070	2070	2070	4917	4917	4917
Mean dep.var.	0.530	1.648	0.493	0.558	2.117	0.518

Note: Star professors are defined as the top five professors over the last 10 years within each department. Panel A is based on total publications, Panel B is based on top-five publications, Panel C is based on "Deep impact" publications, while Panel D is based on average citation per paper.
***p<0.01, **p<0.05, *p<0.10.

Table A4: The effects of sabbatical leaves on early-career outcomes of third-year students, conditional on academia

	#Pubs	#Top-5 pubs	#Deep impact pubs	Citations
	(1)	(2)	(3)	(4)
Panel A: Female Ph.D. students				
FemSabbat, $t-2$	-0.290	-0.131*	-0.255*	0.885
	(0.250)	(0.077)	(0.151)	(1.540)
Observations	1021	1021	1021	1021
Mean dep.var.	2.468	0.270	1.160	5.422
Panel B: Male Ph.D. students				
FemSabbat, $t-2$	0.107	0.033	-0.081	-1.436***
	(0.182)	(0.059)	(0.123)	(0.546)
Observations	2548	2548	2548	2548
Mean dep.var.	3.025	0.414	1.552	5.490

Note: The table presents estimates from the specification in Equation 2, using a sample restricted to Ph.D. students ending up in academia. Column 1 displays estimates for overall publications in the early career, Column 2 for top-five publications, Column 3 for "Deep impact" publications (see Angrist et al., 2020), while Column 4 displays 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). 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.[45] 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

[45] 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 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: EconLit 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

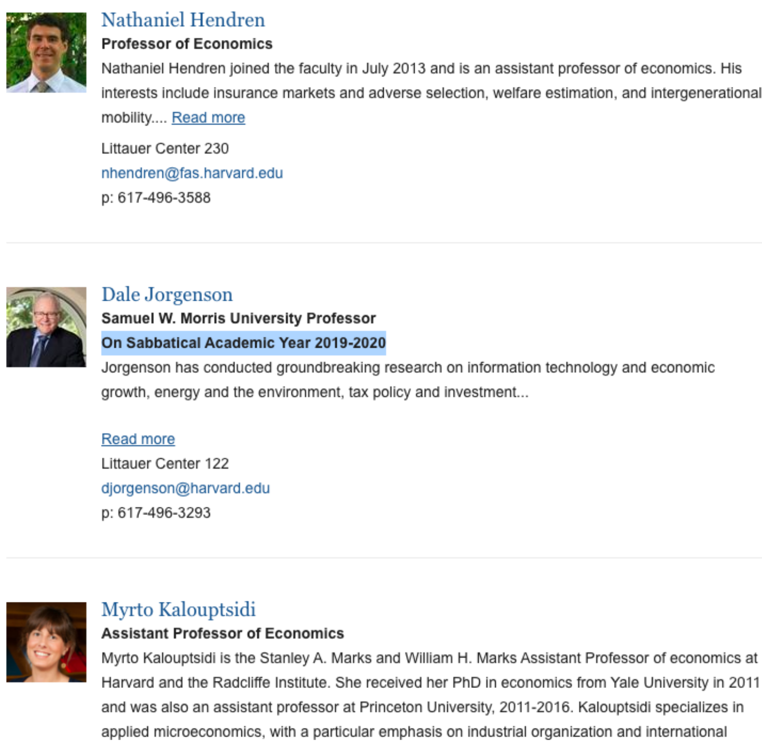
AN HISTORICAL EDITION OF FAS COURSES OF INSTRUCTION

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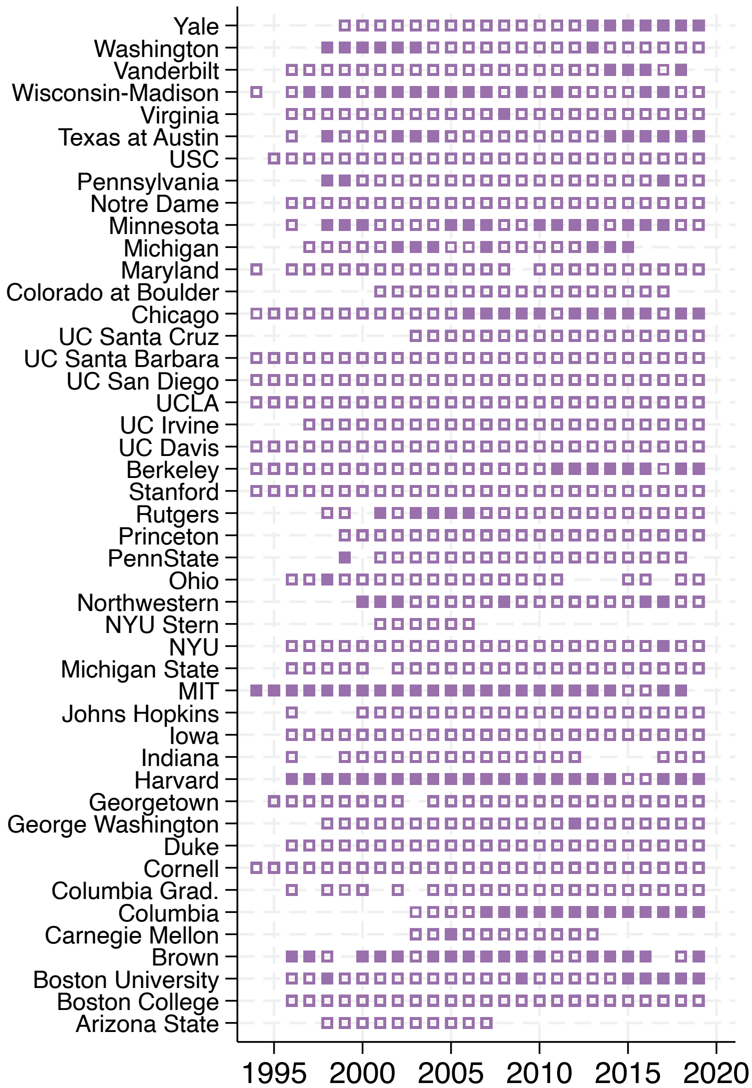
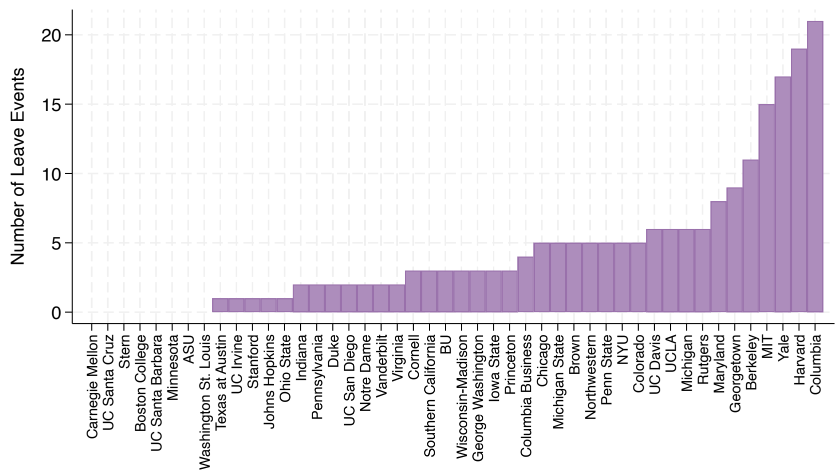
Note: The figure displays a screenshot from the website of the Department of Economics at Harvard University as of October 31, 2019. The website is available here.

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



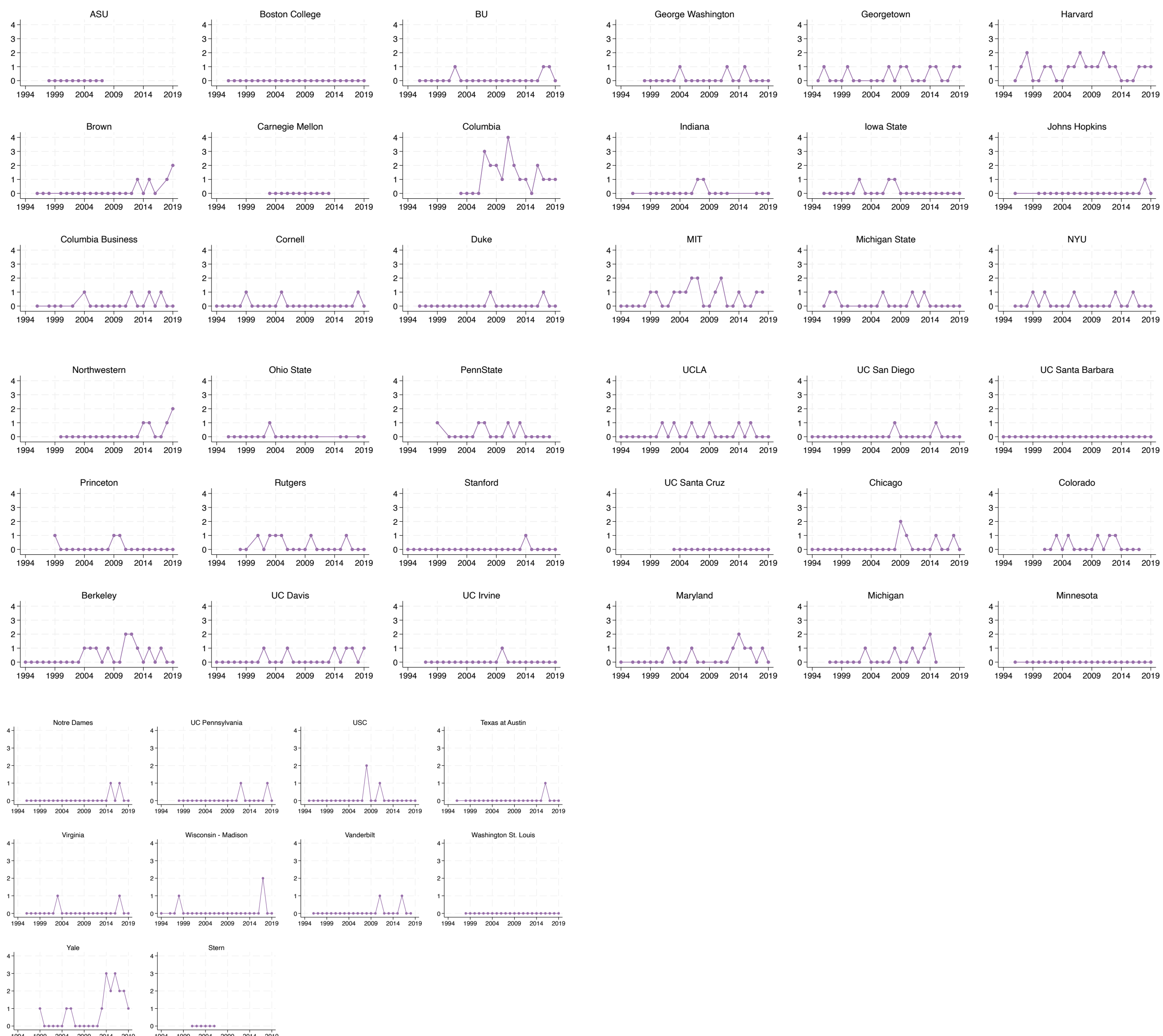
Note: The squares indicate for which department-years we have information on faculty members and their rank. The filled squares show for which of this department-year observation we have information on sabbatical leaves from the department-level data sources.

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	0.9727	0.9251	0.8438	0.7742	0.6216
Mean gender probability	1.0000	0.9837	0.9348	0.8783	0.8218	0.7010
Observations	4138	1061	227	192	124	436

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. 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% 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 less significant) 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 1.25 (the average treatment intensity). If we scale the coefficients with this number, we derive an estimate of -0.076 for the probability of publishing a paper versus the baseline of -0.077, an estimate of -0.414 versus the baseline of -0.509 for the sum of publications and an estimate of -0.068 versus the baseline of -0.096 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 in the same way).

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 0.39. If we scale the coefficients with this number, as above, we obtain magnitudes that are slightly smaller than our main estimates. Still, most estimates 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 final 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.[46] In Figure C1a, we plot the average and median Ph.D. duration by year of graduation.[47] 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 2011, 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.[48] Estimates are presented in Table C5. Overall, the estimated effects on third-year female students are very similar to our baseline estimates, while those for males are somewhat weaker.

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

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

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

[48] 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.

each department, separately for female and male students. We then impose these median durations on all students.[49] 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 no longer statistically significant at conventional levels. The other key coefficients are significant at the 5% level.

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.[50] 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 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

[49]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.

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

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.[51]

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. In Panel B, we add a quadratic time trend. These specifications 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 C, we show estimates from a specification where we interact each department fixed effect with dummy variables denoting five year periods.[52] This rather demanding specification gives estimates that are similar, but somewhat greater in magnitude compared 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 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

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

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

different subsets of the data. With the exception of the probability of staying in academia and the sum of publications 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, $t-2$	-0.065	-0.549**	-0.062	0.112***	0.349**	0.049*
	(0.044)	(0.214)	(0.042)	(0.030)	(0.142)	(0.029)
Observations	9432	9432	9432	21776	21776	21776
Mean dep.var.	0.530	1.535	0.489	0.538	1.978	0.503

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, $t-2$	-0.092***	-0.582***	-0.123***	0.043**	0.072	0.042*
	(0.032)	(0.165)	(0.032)	(0.021)	(0.126)	(0.023)
Observations	2070	2070	2070	4917	4917	4917

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, $t-2$	-0.061**	-0.331**	-0.055**	0.053***	0.164*	0.038**
	(0.025)	(0.152)	(0.028)	(0.015)	(0.089)	(0.015)
Observations	2070	2070	2070	4917	4917	4917
Panel B: Share of female professor on leave						
FemSabbat, $t-2$	-0.147**	-0.763**	-0.124*	0.108***	0.323	0.092**
	(0.064)	(0.352)	(0.071)	(0.041)	(0.252)	(0.037)
Observations	1696	1696	1696	3951	3951	3951
Panel C: Share of female professor on leave including zeros						
FemSabbat, $t-2$	-0.149**	-0.790**	-0.161**	0.112***	0.270	0.076**
	(0.058)	(0.326)	(0.065)	(0.041)	(0.248)	(0.034)
Observations	2070	2070	2070	4917	4917	4917

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, $t-2$	-0.068**	-0.460***	-0.067**	0.072***	0.250**	0.039*
	(0.031)	(0.167)	(0.032)	(0.019)	(0.114)	(0.020)
Observations	2070	2070	2070	4917	4917	4917
Panel B: Excluding semester-long leaves						
FemSabbat, $t-2$	-0.081**	-0.473***	-0.098***	0.042**	0.105	0.034*
	(0.035)	(0.159)	(0.031)	(0.020)	(0.122)	(0.021)
Observations	2070	2070	2070	4917	4917	4917
Panel C: Excluding leaves followed by quit						
FemSabbat, $t-2$	-0.080**	-0.499***	-0.093***	0.064***	0.194*	0.031
	(0.032)	(0.164)	(0.032)	(0.019)	(0.116)	(0.020)
Observations	2070	2070	2070	4917	4917	4917
Panel D: Excluding leaves by professors without tenure						
FemSabbat, $t-2$	-0.092***	-0.540***	-0.094***	0.057***	0.201	0.041**
	(0.033)	(0.183)	(0.034)	(0.019)	(0.122)	(0.021)
Observations	2070	2070	2070	4917	4917	4917

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, $t-2$	-0.080**	-0.538***	-0.125***	0.055***	0.155	0.043**
	(0.031)	(0.167)	(0.030)	(0.021)	(0.119)	(0.021)
Observations	2064	2064	2064	4887	4887	4887
Panel B: Median duration by gender-department						
FemSabbat, $t-2$	-0.052	-0.411**	-0.070**	0.035*	0.061	0.041**
	(0.033)	(0.179)	(0.035)	(0.021)	(0.130)	(0.021)
Observations	2026	2026	2026	4786	4786	4786

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. (1)	#Pubs. (2)	Academia (3)	HasPub. (4)	#Pubs. (5)	Academia (6)
Panel A: On JEL list + no restriction on advisor						
FemSabbat, $t-2$	-0.073**	-0.438**	-0.121***	0.055***	0.213*	0.024
	(0.034)	(0.191)	(0.035)	(0.020)	(0.120)	(0.023)
Observations	1954	1954	1634	4609	4609	3938
Mean dep.var.	0.541	1.764	0.514	0.552	2.152	0.528
Panel B: On JEL list + advisor in department						
FemSabbat, $t-2$	-0.089**	-0.571***	-0.121***	0.055***	0.194	0.024
	(0.035)	(0.200)	(0.035)	(0.020)	(0.130)	(0.023)
Observations	1634	1634	1634	3938	3938	3938
Mean dep.var.	0.558	1.771	0.514	0.572	2.216	0.528

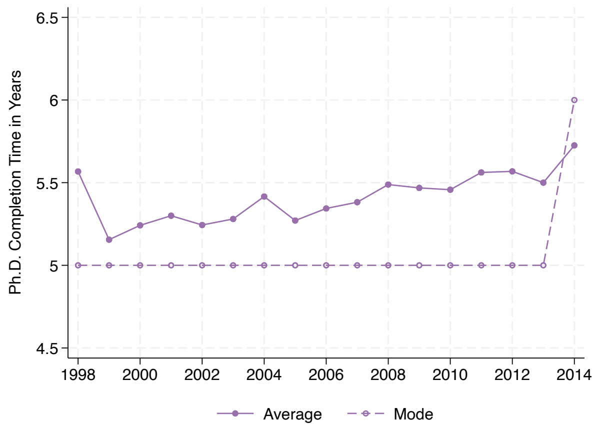
Note: The table present results on early career outcomes under alternative sample restriction. In Panel A, we restrict the sample to students appear on the JEL dissertation list (and put no restrictions on their advisors). In Panel B, we restrict the sample to the JEL list but also impose the baseline 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

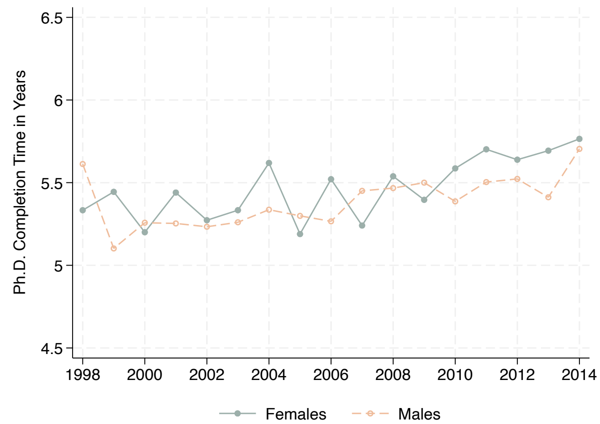
	Female Ph.D. students			Male Ph.D. students		
	HasPub.	#Pubs.	Academia	HasPub.	#Pubs.	Academia
	(1)	(2)	(3)	(5)	(6)	(7)
Panel A: Linear time trend						
FemSabbat, $t-2$	-0.065*	-0.550***	-0.099***	0.077***	0.322**	0.034
	(0.037)	(0.185)	(0.031)	(0.022)	(0.125)	(0.022)
Observations	2070	2070	2070	4917	4917	4917
Panel B: Quadratic time trend						
FemSabbat, $t-2$	-0.099**	-0.716***	-0.074*	0.093***	0.276*	0.009
	(0.042)	(0.218)	(0.039)	(0.025)	(0.142)	(0.024)
Observations	2070	2070	2070	4917	4917	4917
Panel C: Five years-department fixed effects						
FemSabbat, $t-2$	-0.095**	-0.749***	-0.064*	0.114***	0.346**	0.046*
	(0.038)	(0.188)	(0.038)	(0.023)	(0.139)	(0.026)
Observations	2070	2070	2070	4917	4917	4917

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; in Panel B we include a quadratic department time trend; and in Panel C, 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



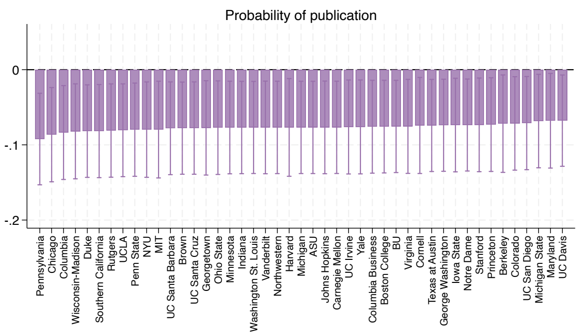
(a) Average and median



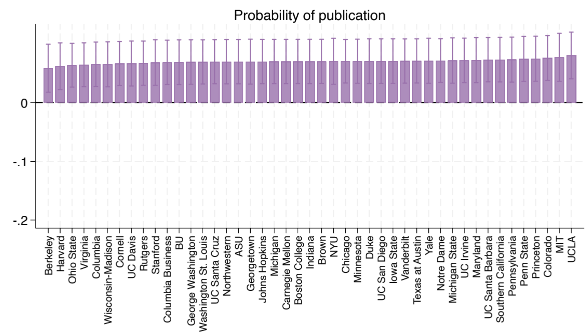
(b) Average by gender

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.

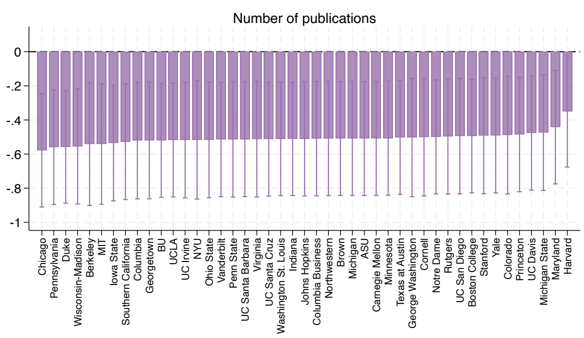
Figure C2: Robustness: Leave out departments one-by-one



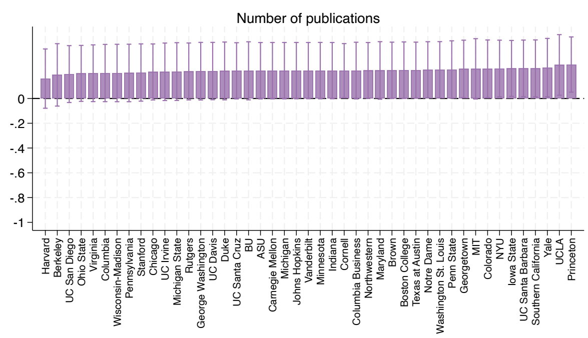
(a) Females



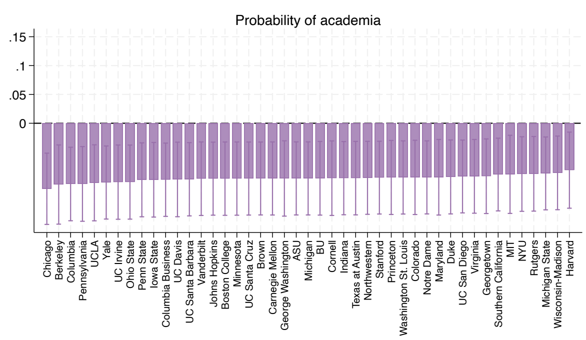
(b) Males



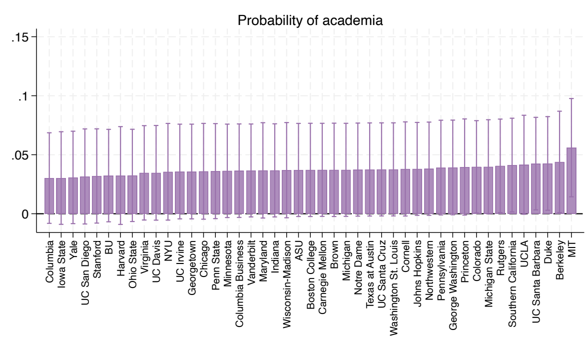
(c) Females



(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 placement quality and alternative ranking

In this section we present additional details on the analysis of Section 5 of the main paper.

In Table 9, 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 departments in the *RePEc* US Economics department ranking as of 2015; 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 when we define the top group based on the 25 economics departments with the highest average citation count per paper of their assistant professors. The group consists of the following schools: Northwestern, Chicago Booth, Harvard Kennedy School, Harvard Business School, Columbia Business School, LSE, Harvard, MIT, Dartmouth, Columbia, UC Berkeley, MIT Sloan, Washington St. Louis, Princeton, Stanford Graduate School of Business, UPenn, Haas School of Business, Wharton School of Business, Boston University, UCLA, Arizona State University, Yale School of Management, University of Chicago, University of British Columbia, and University of Houston. As before, we define Group 2 as other departments, and Group 3 as out of academia. Estimates are shown in Table D1. As can be seen, we find very similar estimates as in our main specification, presented in Table 9.

Table D1: The effects of sabbatical leaves on job placement, marginal effects from multinomial regression on placement categories, alternative ranking based on citations

	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, $t-2$	-0.036**	-0.049	0.085**	-0.010	0.043**	-0.034
	(0.017)	(0.034)	(0.034)	(0.012)	(0.020)	(0.020)
Observations	2070	2070	2070	4917	4917	4917
Share in category	0.069	0.425	0.507	0.081	0.437	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.

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. Consistent with the findings of Lundberg and Stearns (2019), in Figure E1 gender differences in field representation remained relatively stable over our sample period.[53] So an 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. But gender difference in field representation are not large enough and even in labor/public economics, where female representation is relatively higher, male students still outnumber female students. In our data, women account for just 35 percent of labor/public students. This imbalance, combined with the gendered nature of the treatment effect — female students lose, male students gain — rules out a field-based mechanism that operates independently of the student gender.

In what follows we explore any potential field effect, by creating a dummy variable equal to one if a professor in field f was on leave in a given department d and year t for each of the seven fields in our sample. We then run one regression for each field, first discarding any aggregate field level effect in the number of students graduating in a field and early career outcomes. We further discard any gendered field interaction effect by running the regressions for the pool of male and female students separately.

We first investigate whether sabbatical leaves affect the number of students graduating within each field:

$$\#FieldStudents^{f}_{d,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \phi_s FieldSabbat^{f}_{d,t-s} + \varepsilon_{d,t}, \tag{E.1}$$

where $\#FieldStudents^{f}_{d,t}$ denotes the number of students graduating in field f in each department d and year t. We run these regressions at the department-year level, separately for each of the seven fields. Figure E2 reports the estimated coefficients. Only one of the 77 coefficients — Macroeconomics in year 0 — is negative and statistically significant at the 5 percent level, consistent with no systematic changes in the number of students graduating in a field where a professor goes on leave. We also show in Figure E3 no systematic department level early career effect associated to a professor on leave in a specific field.

We then run the seven different field regressions on early career outcome for the pool of male and female students separately, with a regression that has both $FieldSabbat$ and

[53] 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 based on the most frequently used JEL code in their publications over the past 10 years.

$FemSabbat$, dealing with the potential correlation of $FieldSabbat$ and $FemSabbat$ from uneven gender composition across field:

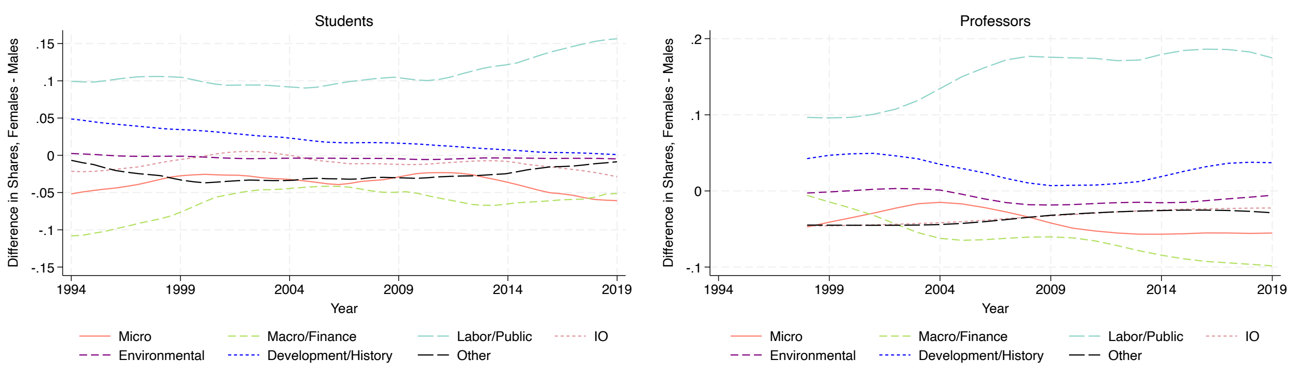
$$y_{id,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \phi_s FieldSabbat^{f}_{id,t-s} + \sum_{s=-5}^{s=5} \gamma_s FemSabbat_{id,t-s} + \varepsilon_{id,t}. \tag{E.2}$$

We cluster standard errors at the level of department-year.

Figure E4 and E5 report the results for third-year students only (due to space constraints). We find no statistically significant effects for female students, except in macroeconomics, where the probability of publication increases. For male students, we find a negative and statistically significant effect in microeconomics for the probability of publication and the number of publications, and a negative effect on the number of publications combined with a positive effect on the probability of academia when a professor in the category "Other" goes on leave. Crucially, for both male and female students, the estimated effects of female sabbaticals across the seven field regressions closely align with the benchmark estimate (long-dash horizontal line). This pattern suggests that our main result is not confounded by field-level sabbatical effects.[54]

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

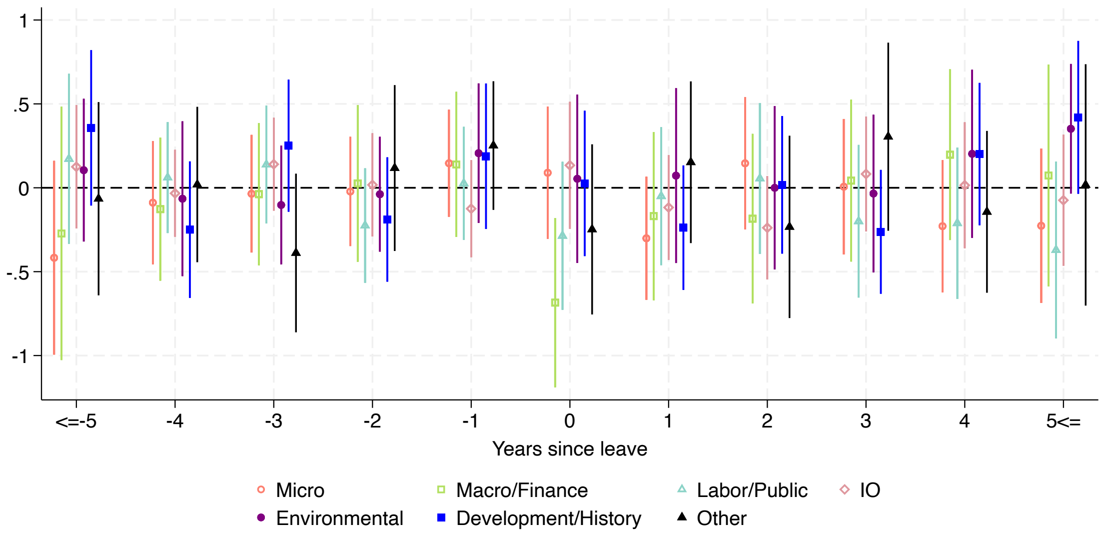
Figure E1: Gender differences in research fields: students and advisors



Note: The figure is based on the sample of students and professors 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 professors in different fields. The right figure starts in 1998, as we have comparable JEL codes in the publication data from 1991 and onwards only.

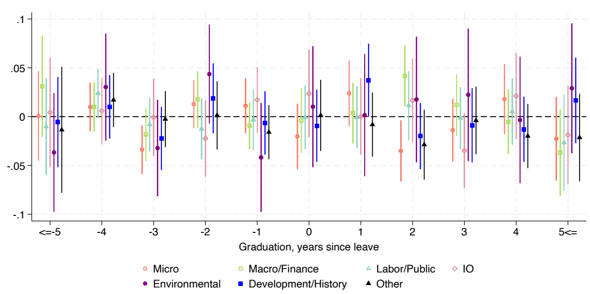
[54] Estimates from regressions excluding the female sabbatical variable are similar to those shown in Figure E4 and E5.

Figure E2: Number of students and sabbatical leaves by professors in different research fields

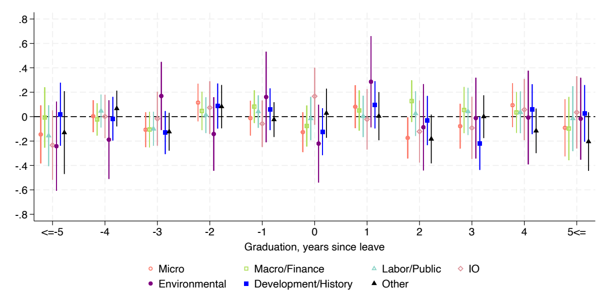


Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation E.1, estimated separately for each research fields. The outcome variable is the number of students graduating in each field. The regression is estimated at the level of department-year.

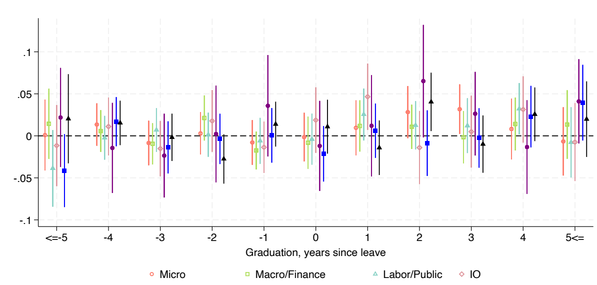
Figure E3: Early career outcomes and sabbatical leaves by professors in different research fields



(a) Probability of publication



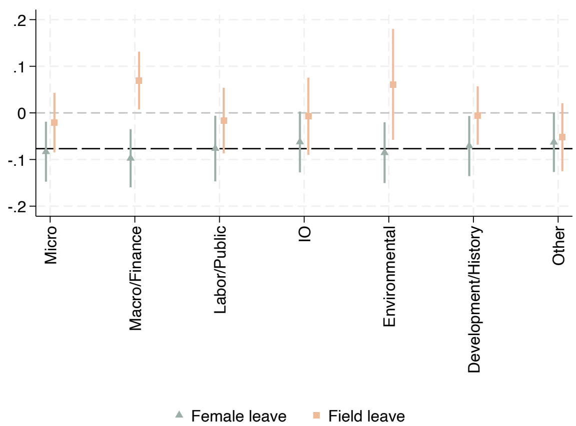
(b) Number of publications



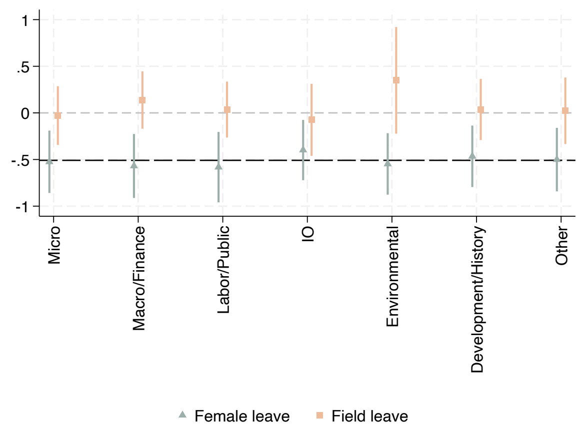
(c) Probability of staying in academia

Note: The figure shows coefficients and 95% confidence intervals for year-since-leave indicators denoting whether a professor in a given field went on sabbatical. The regressions are estimated separately for each research field, and on a pooled sample of male and female Ph.D. students. Standard errors are clustered at level of department-year.

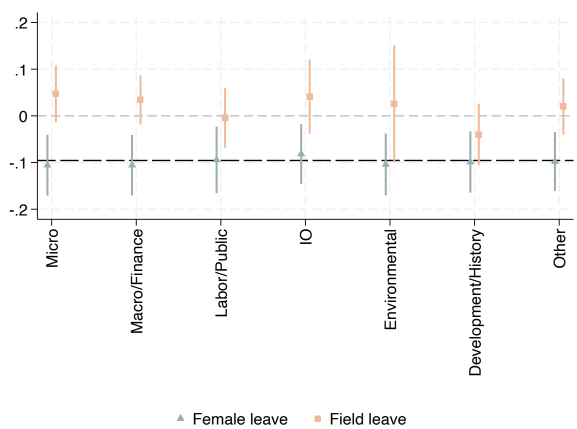
Figure E4: Early career outcomes and sabbatical leaves by professors in different research fields, female students



(a) Probability of publication



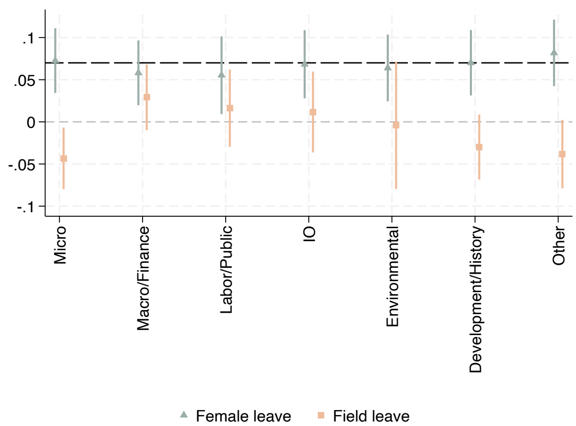
(b) Number of publications



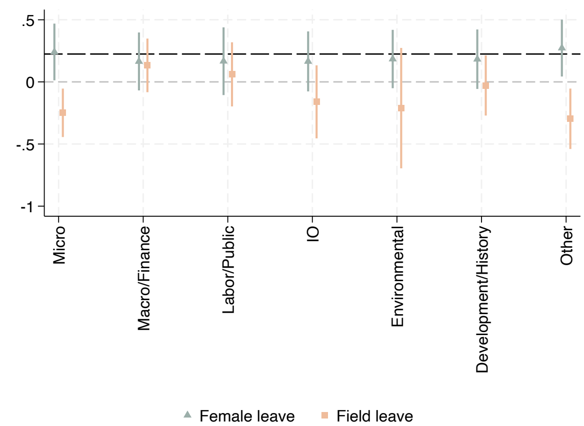
(c) Probability of staying in academia

Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation E.2, where we estimate jointly the effects of female professors on leave and professors in different fields on leave. The regressions are estimated separately for each research fields. The figure only presents estimates for third year students. For comparison, the long-dash horizontal lines show the baseline estimates from our main female sabbatical specification. Standard errors are clustered at level of department-year.

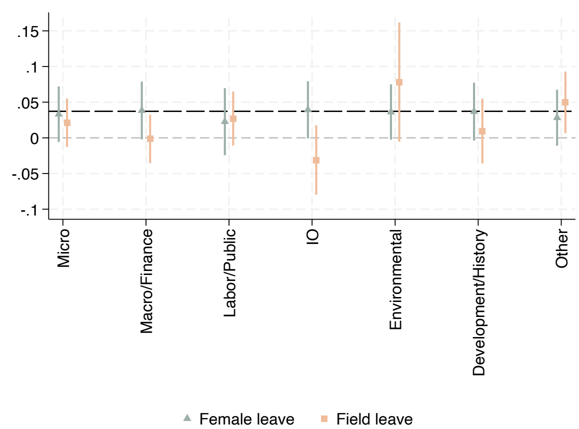
Figure E5: Early career outcomes and sabbatical leaves by professors in different research fields, male students



(a) Probability of publication



(b) Number of publications



(c) Probability of staying in academia

Note: The figure shows coefficients and 95% confidence intervals for the year-since-leave indicators corresponding to those in Equation E.2, where we estimate jointly the effects of female professors on leave and professors in different fields on leave. The regressions are estimated separately for each research fields. The figure only presents estimates for third year students. For comparison, the long-dash horizontal lines show the baseline estimates from our main female sabbatical specification. 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 five advisees during the previous five years. Approximately 20% of the professor-year observations satisfies this criteria. Figure E6 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 25%. Figure E7 shows the density distribution of this object, separately for female and male professors. 357 advisors are defined as female concentrated by this definition (out of which 14% are females), while 308 advisors are defined as male concentrated (out of which 3% are females).

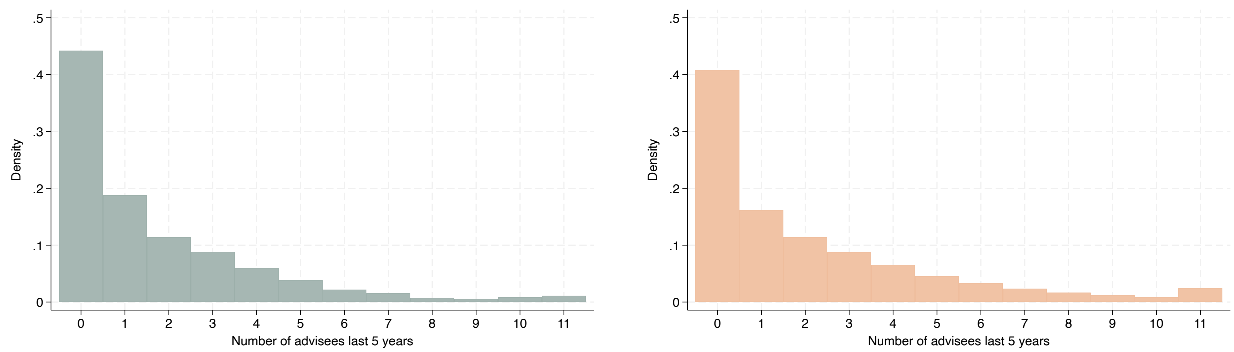
We then conduct separate analyses on the impact of sabbatical leaves taken by these two groups, using a specification similar to Equation 2:

$$y_{id,t} = \alpha_d + \delta_t + \sum_{s=-5}^{s=5} \gamma_s Sabbat^g_{id,t-s} + \varepsilon_{id,t}, \tag{E.3}$$

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 E8 and Figure E9 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 systematic 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.

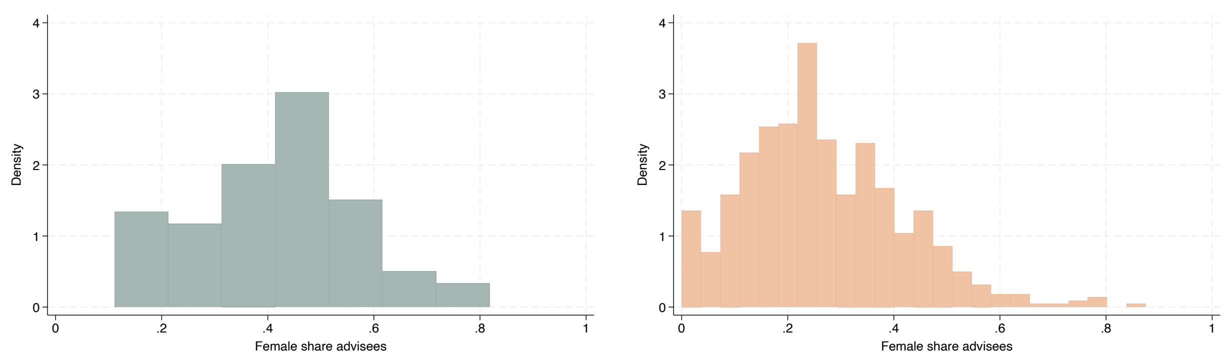
Figure E6: The number of advisees last 5 years, density distribution



(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.

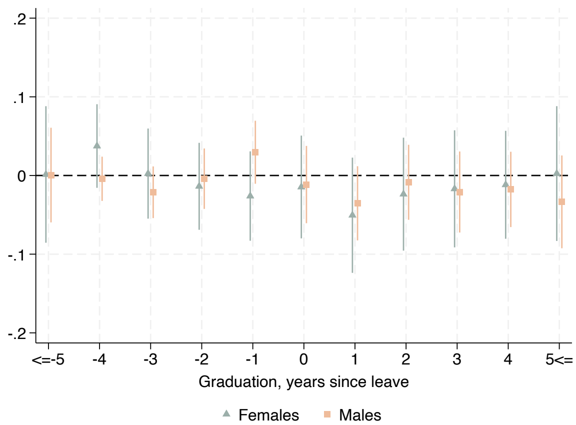
Figure E7: Share of female advisees, density distribution



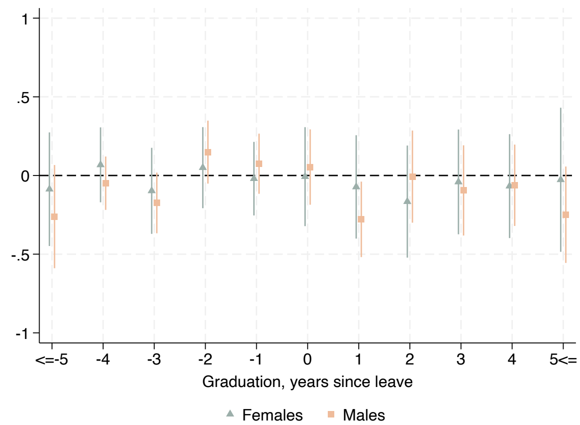
(a) Female professors (associate and full) **(b)** Male professors (associate and full)

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.

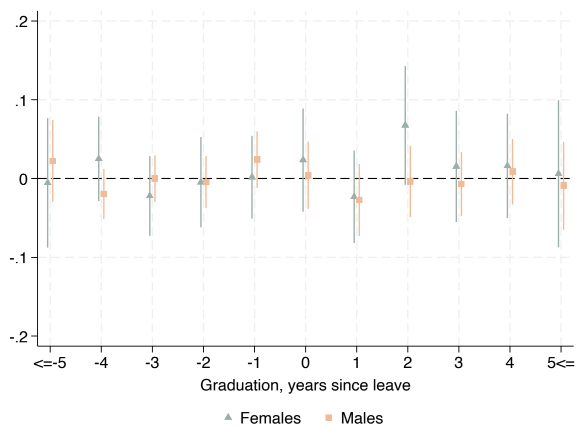
Figure E8: Early-career outcomes and sabbatical leaves by female concentrated advisors



(a) Probability of publication



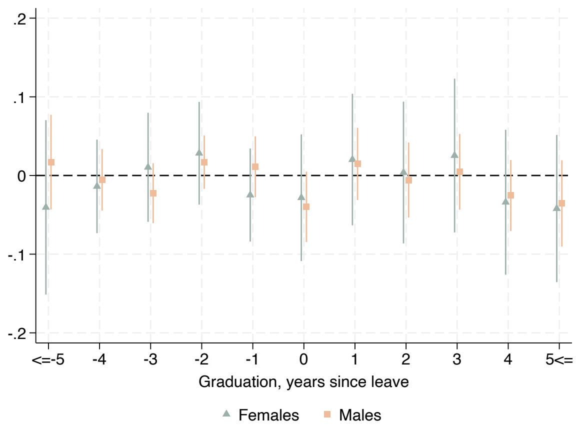
(b) Number of publications



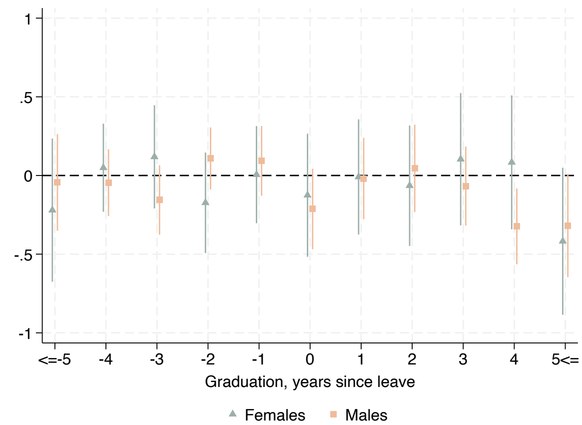
(c) Probability of staying in academia

Note: The figures show coefficients and 95% confidence intervals for the graduation year-since-leave indicators from Equation E.3. The treatment indicators in the regression capture whether a "female concentrated" advisor went on sabbatical leave. Standard errors are clustered at department-year.

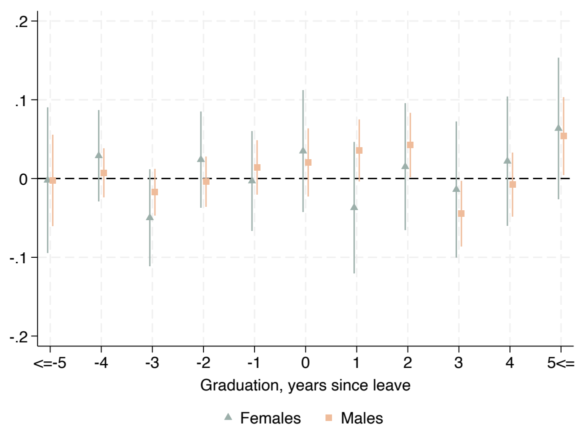
Figure E9: Early-career outcomes and sabbatical leaves by male concentrated advisors



(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.3. The treatment indicators in the regression capture whether a "male concentrated" advisor went on sabbatical leave. Standard errors are clustered at department-year.