





Discussion Paper Series – CRC TR 224

Discussion Paper No. 677 Project A 04

Consequences of Affirmative Action: The Impact of Hiring a Female Professor

Maximilian Mähr¹

April 2025 (First version: March 2025)

¹University of Mannheim, email: maximilian.maehr@uni-mannheim.de

Support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 is gratefully acknowledged.

Consequences of Affirmative Action: The Impact of Hiring a Female Professor*

Maximilian Mähr[†]

April 2025

Abstract

This paper studies how appointing a female professor through affirmative action affects hiring decisions and gender attitudes of faculty. For identification I use the introduction of a nationwide affirmative action policy in Germany that provides subsidies to departments appointing women to permanent full professorships. Using administrative data on all academic personnel employed at German public universities, I find that exposure to a female professor increases the share of female Ph.D. students but leaves hiring of women among full professors, assistant professors, and postdoctoral researchers unaffected. The rise in female Ph.D. enrollment is driven by individuals who completed their undergraduate studies in the same department. Additional findings show that after a woman joins the department, young male faculty members increase their collaboration with female colleagues. Further, I document that research productivity and direction are unaffected by the presence of an additional woman. Finally, I estimate that approximately two-thirds of subsidized female appointments would have occurred without the program.

JEL Codes: I23, J16, J24, J71, J78

Keywords: Affirmative Action, Gender Diversity, Women in Academia

^{*}I am grateful to Antonio Ciccone, Ulf Zölitz, and Giuseppe Sorrenti for their continued and invaluable support and guidance in this project. In addition, I thank Jens Oehlen, David Müller, Felix Köhler, Felix Rusche, Fabian Waldinger, Michèle Tertilt, Philipp Ager, and Camille Urvoy for helpful comments and encouragement. I thank audiences at the University of Mannheim, University of Munich and Stockholm University for comments. Support by the German Research Foundation (DFG) through CRC TR 224 (project A04) is gratefully acknowledged. The author declares no relevant or material financial interests that relate to the research described in this paper. All errors are my own.

 $^{^{\}dagger} University \ of \ Mannheim, \ email: \ maximilian.maehr@uni-mannheim.de$

1 Introduction

Despite an increase in the share of women pursuing academic careers, women currently hold only one in four professorships (European Commission, 2021). In response, policies meant to strengthen the presence of women among professors are becoming increasingly common. These policies include quotas for female recruitment (NRW, 2014; Wallon, Bendiscioli and Garfinkel, 2015), female quotas in funding schemes (National Health & Medical Research Council, 2022), and mandated female representation on academic evaluation panels (Swiss National Science Foundation, 2021).

However, diversity policies are controversial. Proponents argue that intervening in the labor market's matchmaking process is necessary to overcome institutional norms that impede women's advancement to leadership positions (Mengel, Sauermann and Zölitz, 2019; Card et al., 2020; Dupas et al., 2021; Kleemans and Thornton, 2021; Sarsons et al., 2021; Janys, 2024). Exposure to women can break down negative perceptions by allowing them to demonstrate their capabilities (Dahl, Kotsadam and Rooth, 2021) and create an environment that supports the advancement of other women through role model effects (Jensen and Oster, 2009; Porter and Serra, 2020). Opponents argue that in absence of highly qualified women, diversity policies may undermine merit-based hiring and deepen the quality gap between male and female candidates. This may reinforce negative stereotypes by displacing competent men with less qualified women and possibly lead to resistance from within targeted organizations (Whelan and Wood, 2012; Besley et al., 2017).

Hence, some studies support diversity policies among professors. Others do not. Surprisingly, we lack empirical evidence on how deliberately increasing the representation of women among professors impacts universities.

In this paper, I provide such evidence by analyzing an affirmative action policy introduced by the German Ministry of Education, the *Professorinnenprogramm*. The program subsidizes the first-time appointment of women to permanent full professorships, offering up to 825,000 Euros per position over five years. Since its inception in 2008, the program has supported the appointment of 845 women, 12% of all female professorship appointments in Germany.

For identification, I exploit the program's subsidy allocation process. Universities that pass an initial application process become eligible for up to three subsidies. Eligible universities then allocate these subsidies across their departments. To address endogeneity in subsidy allocation, I exploit the program's requirement that subsidized appointments must be permanent appointments, which requires permanent financing by the university once the five-year subsidy has expired. This requirement increases the likelihood that subsidized appointments are assigned to departments with a high probability of full professor retirements during or following the subsidy period. Retirement probabilities satisfy the exclusion restriction, as they are determined by historical hiring patterns and are very difficult to adjust given the regulation of retirement in German public universities. Institutional constraints further reinforce this argument: departments cannot independently create new permanent positions – these require negotiations with the federal states and are typically only justified in response to increased teaching demands – nor

can they demand or incentivize early retirement. I strengthen this design by also considering retirement probabilities of departments in ineligible universities – those rejected in the initial application stage. This additional cross-sectional variation helps disentangle retirement-driven trends from program effects, allowing identification under considerably weaker assumptions.

I find that my instrument for subsidy uptake is a strong predictor of female hiring. At eligible universities, a 10 percentage-point higher probability of experiencing at least one retirement within the next five years is associated with a 4.7 percentage-point higher probability of appointing a female professor compared to ineligible universities, beyond their pre-existing hiring differences. I validate my identification strategy through multiple robustness checks. Retirement probabilities do not predict female hiring outside subsidy periods or at ineligible universities. Additionally, the observed correlation clearly stands out from a distribution of placebo estimates generated by randomly reassigning university eligibility and departmental retirement probabilities.

Following the appointment of a female professor, the subsequent hiring of full professors remains unchanged. My findings suggest that affirmative action neither facilitates nor impedes the advancement of other women to full professorships.

Among junior researchers, trickle-down effects are limited: there is no statistically significant change in female hiring at the assistant professor or postdoctoral level. However, at the Ph.D. level, the number of women increases by 19%, rising to 29% for doctoral students who completed undergraduate studies in the same department. I provide evidence that this effect is likely to be driven by increased interaction between female students and newly appointed female professors. This mechanism aligns with existing research identifying role models as crucial factors for the advancement of female academics (Porter and Serra, 2020; Blau et al., 2010; Ginther et al., 2020).

Next, I examine how exposure to a female professor influences collaboration patterns. Existing research suggests that exposure to underrepresented groups can reduce stereotypes and increase future engagement with those groups (Carrell, Hoekstra and West, 2015). I hypothesize that if negative stereotypes exist, shifts in gender attitudes might be reflected in the share of female co-authors. Overall, I find no significant increase in female co-authorship. However, when disaggregating effects by gender, I observe a modest rise in male faculty co-authoring with women, particularly two to three years after a female professor joins the department. This effect is primarily driven by junior male faculty – defined as tenured professors with below-median experience – who exhibit a 24% increase in female co-authorship. Further analysis suggests that this pattern emerges mainly from new mixed-gender collaborations originating within the peer network of newly appointed female professors. Taken together, these results indicate that gender attitudes are malleable through increased exposure to women.

I also assess whether the presence of an additional female professor affects a department's research productivity. Neither the quantity nor quality of publications – measured through journal rankings and citations – shows a noticeable shift. Additionally, I investigate whether existing department members engage with new research areas following the arrival of a female professor. Prior studies suggest that women often prioritize different research topics (Dolado,

Felgueroso and Almunia, 2012; Chari and Goldsmith-Pinkham, 2017), potentially influencing their colleagues' research trajectories. My analysis of department-specific topic profiles reveals no significant thematic shifts.

Finally, I quantify the program's effectiveness in generating female professorships that would not have occurred in the absence of subsidies. To do so, I compare changes in female hiring across fields with high and low shares of subsidized appointments, relative to the pre-funding period. The analysis rests on stronger identifying assumptions than the previous analysis — most notably, that in the absence of the program, trends in female hiring would have evolved in parallel across fields, conditional on field-specific linear time trends. My estimates suggest that roughly two-thirds of subsidized female hires would have been made in the absence of the program, implying that departments strategically use subsidies to hire women they would have recruited anyway. Based on my estimates, it takes approximately 2.9 subsidized appointments—costing approximately 2.2 million Euros—to generate one additional female professor who would not have been hired without the program.

My study adds to a line of research on how diversity in leadership roles impacts the advancement of women. Most existing studies focus on corporate settings and elections. For example, gender quotas in local governments in India yield mixed results regarding increased women's political participation (Chattopadhyay and Duflo, 2004; Bhavnani, 2017). Beaman et al. (2009) find that female representation reduced gender disparities in aspirations and education through role model effects. However, women running for re-election do not result in increased entry of new women candidates (Bhalotra, Clots-Figueras and Iyer, 2018). Conversely, De Paola, Scoppa and Lombardo (2010) document that a short-term gender quota in local government in Italy boosted women's political participation. In Norway, gender quotas on corporate boards had limited impact beyond immediate changes in board composition (Bertrand et al., 2019). In academia, several studies suggest that female role models can influence the career choices of female students. Porter and Serra (2020) show that exposure to a successful female alumna increases the likelihood of female students choosing an economics major by 89%. Carrell, Page and West (2010) find that top female students at the US Air Force Academy are 26 percentage points more likely to complete a STEM major when taught by female instructors. Bagues et al. (2023), in their analysis of Spain, investigate the appointment of female professors and its impact on future hiring and Ph.D. enrollment. Their identification strategy relies on random assignment of full professorship applicants to peer evaluators. Unlike my findings, they report no effect on the share of female Ph.D. students, though they do not specifically focus on students who completed their undergraduate studies in the same department, where I find the most significant increase. In addition, their analysis includes the hiring of tenured associate professors, whereas my study focuses exclusively on full professorships. This distinction may be important, as newly appointed full professors in Germany typically have greater autonomy and resources, including the capacity to recruit and fund Ph.D. candidates. In contrast, newly hired professors in many Spanish universities often lack comparable institutional support or funding, which may limit their ability to supervise or employ Ph.D. students.

A related set of studies evaluates how diversity affects performance. Ahern and Dittmar (2012), Matsa and Miller (2013), and Nygaard (2011) evaluate the effect of Norway's board composition quota on firm performance and governance, finding no definitive results. Kim and Starks (2016) demonstrate that gender diversity on U.S. corporate boards can enhance firm valuation, driven by the contributions of female directors. In Italy, Flabbi et al. (2019) show that female corporate leadership positively impacts the upper end of the female wage distribution while negatively affecting the lower end, with overall firm performance benefiting from a higher proportion of female workers. Hoogendoorn, Oosterbeek and Van Praag (2013) analyze the impact of gender diversity on business team performance in a field experiment, finding that mixed-gender teams outperform male-dominated teams in terms of profit and sales. I extend the existing literature by not only assessing changes in hiring but also analyzing the broader effects of these appointments on research output and collaboration patterns. Achieving gender parity might lead to more balanced policy recommendations and a broader range of research questions, as women tend to have different policy priorities compared to men. For instance, surveys among economists indicate that women are generally more supportive of government intervention and environmental regulation, whereas men are more inclined to prioritize economic growth and are less concerned about inequality (Chari and Goldsmith-Pinkham, 2017; May, McGarvey and Kucera, 2018). I contribute to this literature by showing that the appointment of a female professor does not lead to a thematic shift in the department's overall research agenda, nor is there a clear tendency to focus more on female-related topics. I am unaware of other studies that causally identify the effect of diversity on the direction of academic research.

Further, my study contributes to a body of research that evaluates policies aimed at increasing the representation of women among full professors. Appendix Figure B.1 indicates that among currently evaluated policies, mentoring programs stand out as the sole measure efficiently increasing the proportion of female full professors. Blau et al. (2010) and Ginther et al. (2020) demonstrate in a randomized control trial that junior female economists in the U.S., when mentored by a senior woman, achieve significantly higher tenure rates (+77%), toptier publications (+175.6%), and grants (+294.8%). However, the current share of senior female professors is too low to support the large-scale implementation of mentoring programs. In addition, mentoring programs are costly as they burden already stretched senior female researchers (Vernos, 2013; Guarino and Borden, 2017) and their efficiency is likely to decrease in the number of participating junior women. Other policies have proved inefficient in increasing the share of women among professors. Bagues, Sylos-Labini and Zinovyeva (2017) evaluate the random assignment of academics to hiring committees in Italy and Spain, finding that the presence of a female evaluator can reduce female candidates' chances of success by around 5.3%

¹ Another concern with mentoring is the potential for self-image bias among advisors (Lewicki, 1983). Mentors will likely advise young researchers to become like them and adopt their research characteristics. In the process, young researchers give up some of their characteristics. While this may improve female participation, it shifts the research characteristic distribution toward the mentor, leading to the under-representation of valuable research characteristics in the limit; assuming that all research characteristics are equally valuable in the research process (Siniscalchi and Veronesi, 2020).

² Carnes et al. (2015) and Devine et al. (2017) document a significant rise in female hires following a gender bias workshop at the University of Wisconsin-Madison. However, they cannot rule out that their effects are driven by unobserved field- or university-specific factors as the intervention only took place at a single university.

in Italy and 3.3% in Spain. Deschamps (2018) documents a similar effect in sign and magnitude when evaluating gender quotas in academic hiring committees in France. Antecol, Bedard and Stearns (2018) show that 'tenure clock stopping policies' do not significantly affect tenure rates and can even disadvantage female candidates when also men are eligible. Notably, no prior research evaluates the efficiency of affirmative action policies in academia, despite theoretical work highlighting their efficacy (Siniscalchi and Veronesi, 2020). This paper addresses this gap. I show that two-thirds of subsidized female appointments – an implicit affirmative action policy – would have occurred in absence of the program, suggesting that departments often strategically utilize subsidies to hire women they would have hired anyway. This implies that the cost of an additional female professorship is 2.1 million Euros; roughly three times the cost of a subsidized appointment.

The rest of the paper is organized as follows. The next section outlines the institutional setting. Section 3 describes the data. Section 4 outlines the empirical framework, results of which are discussed in Section 5. Section 6 concludes.

2 Background

In 2023, approximately 2.9 million students were enrolled in institutions of higher education in Germany. Of these, 50% attended public universities, 37.5% were enrolled at universities of applied sciences, and 8.2% at private universities. The remaining 4.3% studied at specialized institutions such as universities of public administration, art and music colleges, teacher training colleges, and theological colleges (CHE Hochschuldaten, 2024). While all types of institutions of higher education can apply for funds from the *Professorinnenprogramm*, this analysis focuses exclusively on Germany's 83 public universities, as listed in Appendix Table A.1. Other institutions, such as teacher training colleges and universities of applied sciences, are excluded, as they primarily offer practice-oriented, career-focused education.

Public universities are autonomous entities under state oversight, with most state constitutions granting them the right to self-administer within the framework of the respective State Higher Education Act (*Landeshochschulgesetz*). This autonomy leads to substantial variation in legal rules and regulations across institutions. The following overview outlines the most common practices.

2.1 German University System

More than two-thirds of the financial resources for universities in Germany are provided by the states, while the federal government contributes 20% (HRK, 2024). Each federal state allocates funding to its universities based on factors such as student enrollment and research performance. University budgets are typically set annually or biennially through negotiations between universities and the federal ministries of research. For example, BW-MF (2022) lists the specific budgets for universities in Baden-Wuerttemberg for the year 2022.

German universities typically organize themselves into specialized departments, each focused on a specific academic field, such as economics. Related fields are grouped into faculties; for instance, economics is usually part of the social sciences faculty. The Federal Statistical Office of Germany recognizes 33 distinct academic fields and eight faculties, as outlined in Appendix Table A.2. On average, each university encompasses sixteen fields, resulting in a total of 1,342 unique departments. Within departments, academic leadership is often divided among chairs, which are organizational units led by professors.

Full Professors While some German universities have introduced tenure-track systems, they are not yet widely adopted. Consequently, most German universities do not follow the U.S. model of categorizing professors into assistant, associate, and full ranks. Instead, the primary distinction is between full professors and assistant professors.³ Full professors are permanent civil servants, while assistant professors hold temporary positions that may be either tenure-track or non-tenure-track positions. As permanent civil servants, full professors enjoy job security, with dismissal only possible in cases of severe misconduct.⁴ The statutory retirement age is gradually rising, starting at 65 for individuals born before 1946 and reaching 67 for those born after 1964. Professors have the option of early retirement from the age of 63 associated with a pension reduction of 3.6% per year. Upon request, they can extend retirement to their 70th birthday (§14 in BMJ (2024)).⁵ Salary and pension payments are complemented by costs supporting the professor in fulfilling their duties, like academic support staff and research equipment.

To manage and forecast these costs, professors (as well as other civil servant positions) are assigned designated positions in the federal states' budget, so called 'Planstellen'. While departments are autonomous in the appointment of individuals to a professorship the creation and renewal of 'Planstellen' can only be authorized in accordance with the federal state. Usually, the creation of new full professorships is tied to predictable long-term increases in teaching demand resulting from higher student demand or the accreditation of new study programs.

³ Additionally, there are special cases such as endowed professorships (funded by third-party sources like companies), joint professorships (co-funded with non-university research institutions), honorary professors (part-time university lecturers), and guest professors, which I exclude from the analysis.

 $^{^4}$ The termination of the civil servant status is regulated in §31 BBG, §22 BeamtStG, and §§32 – 36 BBG, §23 BeamtStG.

⁵ In particular, retirement can be extended to the age of 68 if there are no conflicting institutional reasons, while postponement until the age of 70 requires a compelling institutional interest.

Appendix Figure B.2 displays an excerpt from the 2019 budget of the state of Baden-Wuerttemberg, detailing the employment plan for the University of Mannheim.

⁷ To predict changes in teaching demand, administrators compare future teaching demand with contemporaneous teaching resources. The stock of teaching resources can be calculated by weighting the department personnel by their position-specific teaching obligations. Teaching obligations differ by positions and state and are normally measured in teaching units. Usually, a teaching unit roughly translates to 15 lectures a 45 minutes per semester (this excludes pre- and post-lecture preparation). For example in the state of North Rhine-Westphalia full professors are assigned nine teaching units per semester, while assistant professors are assigned five teaching units per semester (NRW, 2009). Future teaching demand is calculated by multiplying the anticipated student body by the average course-specific teaching load. Usually, students are expected to participate in 20 lectures a 45 minutes per week. Short-term deviations can be addressed by hiring lectures on a temporary basis. For instance, in 2013, a significant increase in temporary lecture positions occurred following a school reform, which saw the completion of two secondary school classes, effectively doubling the count of first-year university students.

Appointing Full Professors A full professorship is filled through a formalized appointment procedure.⁸ First, the position is publicly advertised, often internationally.⁹ Then, the department selects an appointment committee, which oversees the entire appointment process and is tasked with finding and recruiting the most suitable candidates for the position. The committee consists of department members but can sometimes also include external members. After the application deadline, a hearing is conducted, inviting the most promising candidates. The hearing typically includes a public seminar and interviews with department members. After the hearing, the committee selects the most suitable candidates and requests external, independent evaluations. Following this, the appointment committee ranks and nominates up to three top candidates. After an offer is made, negotiations over the offer occur in a meeting with the dean and the rectorate, covering details like additional compensation and research budgets. Following the negotiation, the university extends a written offer to the candidate. If declined, subsequent candidates are considered until the position is filled or a new advertisement is required.

Assistant Professors Although tenure-track assistant professorships were introduced in 2002, two-thirds of assistant professorships remain non-tenure track. Non-tenure track positions are typically six-year temporary civil service roles. After this period, candidates undergo an evaluation and, if positively assessed, may receive a two-year extension. While candidates are free to apply for permanent positions – such as full professorships – at other institutions at any time¹⁰, they cannot formally request an internal evaluation for a permanent role at their current institution.

In contrast, tenure-track assistant professorships are designed to transition into permanent positions following a successful final evaluation. A key distinction is that candidates in tenure-track roles are entitled to request an internal evaluation for a permanent appointment. Like non-tenure track positions, tenure-track roles are temporary civil service appointments within the W1 salary bracket.

The hiring process for assistant professorships mostly mirrors that of full professors.

Other Researchers The remaining academic personnel within a department includes postdoctoral researchers, doctoral candidates, and research assistants, who are primarily engaged in

⁸ To formally qualify as a university professor, candidates must show "additional scientific qualifications" beyond their PhD. In Germany, this is often done through a habilitation, an academic exam that demonstrates competence in both research and teaching. Alternatively, candidates can fulfill this requirement through an assistant professorship or by proving "equivalent achievements". What counts as equivalent varies by field and is not standardized. It might include work similar to a habilitation thesis or a set of published articles (cumulative habilitation).

⁹ Although a public and, in most cases, international advertisement for a vacant professorship is generally legally required, there are circumstances where this requirement can be waived entirely or the appointment process significantly simplified. The specific state higher education laws outline varying conditions for such cases. For example, no advertisement is necessary if a temporary civil servant or employee position is to be converted into a permanent one or in the case of the availability of an exceptionally qualified individual whose recruitment is of special interest to the university. In some federal states, the Ministry of Science must also approve the advertisement of the professorship, while at some universities, this decision lies with the academic senate.

¹⁰ The situation is different, for those pursuing a habilitation, who typically remain at the same institution until the process is complete.

research activities. They are supported by lecturers and teaching assistants, whose roles are more focused on instruction.

In the German system, doctoral candidates are often hired directly by individual professors – typically through their chairs – rather than through centralized graduate schools, as is more common in the US or UK. This more personalized hiring process may help explain some of the effects observed on Ph.D. recruitment following professorial appointments.

2.2 Professorinnenprogramm

The *Professorinnenprogramm* is an affirmative action policy initiated by the German Ministry of Education to enhance the representation of women among full professors. The program provides a five-year subsidy of up to 825,000 Euros (165,000 Euros per year) to cover costs associated with the initial appointment of women to full professorships. These expenses include the professor's salary, as well as costs for support staff and research equipment. Universities that successfully complete an initial application procedure can receive subsidies for up to three positions.

Subsidies are contingent on two conditions. First, they are limited to women being appointed to a full professorship in Germany for the first time. Second, the subsidies are available only for permanent positions. This typically requires either the creation of a new budgeted permanent position in coordination with the federal state or the availability of an existing vacant permanent position. The program also supports 'early appointments' of female full professors – defined as appointments to positions that are not yet permanently budgeted – provided there is a guaranteed transition to a regular, budgeted professorship by the end of the subsidy period.

Initiated in 2008 with a budget of 150 million EUR (wave 1), the program was renewed in 2013 (wave 2), 2018 (wave 3), and 2023 (wave 4), each time with a higher budget or with subsequently increasing budgets (see Table 3). The budgets for each wave are distributed in two application calls, detailed in Table 1. Universities that receive positive evaluations in the first call of a wave cannot reapply in the second call of the same wave. My period of analysis covers the first three funding waves. I define each unique combination of funding wave and call as a funding period, sequentially labeled by $g \in G \equiv \{1, 2, 3, 4, 5, 6\}$, with $\tau \equiv \tau(g)$ mapping to the year the evaluation results for funding period g are announced.

Application Process The Professorinnenprogramm employs a structured procedure for allocating subsidies.¹¹ All institutions of higher education are eligible to apply. Participation requires submitting an application to the German Federal Ministry of Education. The application consists of a fifteen-page document detailing statistics and plans related to the gender equality concept. The document comes in two parts. The first part describes the current representation of women at different qualification levels, including statistics on the share of women across departments and ranks over time. The second part outlines existing and planned measures aimed at (1) increasing the proportion of women in top academic positions, (2) promoting career

¹¹ A formal description of the application process is provided in Bundesanzeiger (2018). Appendix Figure B.3 provides a chronological sequence of the application process.

Table 1: Application Timeline by Funding Period

Wave	Call	g	Announcement	Application Deadline	Application Results	Appointment Deadline
1	1	1	10/03/2008	16/06/2008	03/09/2008	31/12/2009
1	2	2	10/03/2008	02/03/2009	04/06/2009	31/12/2010
2	1	3	06/12/2012	28/03/2013	11/07/2013	31/12/2014
2	2	4	06/12/2012	28/03/2014	03/07/2014	31/12/2015
3	1	5	10/11/2017	29/05/2018	08/11/2018	31/12/2019
3	2	6	10/11/2017	29/05/2019	05/11/2019	31/12/2020

Note: The table displays how each distinct combination of funding wave and call corresponds to a funding period, denoted sequentially by $g \in G \equiv \{1, 2, 3, 4, 5, 6\}$. The last two columns indicate the respective deadlines and announcement dates associated with each funding period.

and professional development for young female scientists, and (3) encouraging female student enrollment in underrepresented fields. Universities that received funding in previous calls of the program must provide evidence of successful implementation of their prior equality concept. Importantly, the first-stage application does not specify the positions to be financed, which will only be addressed in the second stage. On average, 82% of universities applied in each of the last three program waves.

Following submission, a twelve-member review panel evaluates all applications. The German Ministry of Education, in consultation with state education ministries, selects the panel members based on disciplinary diversity, representation from major German science organizations, and international expertise. If an application is approved, the ministry commits to funding the initial appointment of up to three female full professors, provided the budget allows.¹² For example, university B may be deemed eligible, while university A is not (Figure 1c).

The selection criteria are opaque and not publicly disclosed nor does the ministry publicly disclose evaluation details or rankings. To gain insight into the selection process, I conduct a text analysis of publicly available application documents. However, because not all universities publish their applications, the analysis may be subject to selection bias. The analysis reveals that neither linguistic characteristics nor specific topics within the documents predict eligibility status. A detailed breakdown of this analysis is provided in Appendix Section C.A.

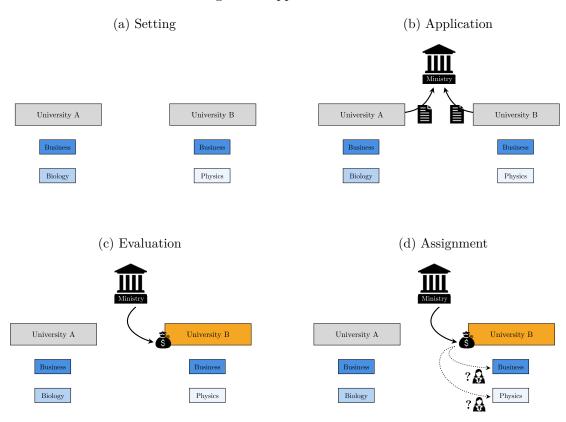
In the second stage, universities that receive a positive evaluation allocate subsidies to departments (Figure 1d). The assignment process is entirely within universities and not publicly documented. The only constraint is that the department must submit a funding plan outlining how the position will be permanently financed once the subsidy period has ended.

Once a department is selected to receive funding, it advertises the position with a note indicating that it is supported by the *Professorinnenprogramm*. While the announcement does not explicitly state that the position is to be filled by a woman, the reference to the program – whose purpose is widely understood – implicitly signals this intention. An example job posting is shown in Appendix Figure B.4. This is followed by the job market process and the formal appointment

¹² In the third program wave, the ten universities with the highest-ranked applications could receive funding for a fourth appointment.

procedure for full professors. Upon the successful appointment of a woman, the university submits a subsidy request to the ministry, specifying the required annual funding and duration. Requests are processed in chronological order until the program's budget is fully allocated.

Figure 1: Application Process



Note: The figure provides a schematic overview of the *Professorinnenprogramm*'s application process. The example assumes two universities, A and B, each with two departments (Figure 1a). Universities submit a 15-page equality concept to the German Ministry of Education, detailing current female representation and outlining measures to improve gender equality in academic positions (Figure 1b). In the example, both universities submit an application to the ministry. A review panel evaluates the submissions. Successful universities can utilize funding for up to three female full professorships (Figure 1c). In the example, university B is deemed eligible, while university A is not. Then, universities internally allocate subsidies to departments (Figure 1d).

Descriptives By 2024, the *Professorinnenprogramm* had subsidized 845 female professorships, with 63% originating from public universities. In the sample, I observed 429 subsidized female professorships at public universities. Panel A of Table 2 shows that in each wave, approximately 60 out of 83 public universities were eligible for subsidies. Figure B.5c displays the university-specific eligibility status across waves and calls. Panel B of Table 2 reveals that each university appointed an average of 2.3 to 2.6 subsidized female professors per university, with annual subsidies ranging from 133,000 Euros in the first wave to 155,000 Euros in the third wave over an average duration of 4.7 years. The reason not every university maximizes the number of subsidized positions is due to the program being oversubscribed. For example, consider the first call of the first wave. Panel A of Table 3 shows that if each eligible university were to utilize all three possible subsidized appointments, this would result in 222 appointments. However,

as calculated in Panel C of Table 3 given an available budget of 105 million Euros, only a maximum of 140 appointments are feasible. Consequently, by design, not all universities are able to subsidize three positions.

Table 2: Appointment Characteristics by Wave and University Type

	Pul	olic Univers	ities	Otl	her Universi	ties
	Wave I	Wave II	Wave III	Wave I	Wave II	Wave III
Panel A: University Characteris	tics					
Succesful Universities	54	59	57	58	64	70
Total Appointments	141	137	151	133	127	146
Appointments per University	2.52 (0.69)	2.32 (0.71)	2.60 (0.88)	2.38 (0.95)	1.98 (0.85)	2.13 (0.88)
Panel B: Appointment Characte	eristics					
Share Regular Appointments	0.67 (0.47)	0.76 (0.43)	0.79 (0.41)	0.53 (0.50)	0.61 (0.49)	0.75 (0.43)
Subsidy per Year (1,000 EURs)	133.80 (23.58)	136.67 (19.39)	$155.52 \\ (20.14)$	101.38 (34.24)	109.09 (30.52)	119.66 (34.03)
Subsidy Period (years)	4.70 (0.72)	4.69 (0.73)	4.88 (0.45)	4.46 (1.09)	4.45 (1.05)	4.91 (0.45)
Job Search (months)	10.86 (5.68)	13.39 (5.96)	11.60 (5.70)	$9.48 \ (5.72)$	12.87 (5.71)	11.17 (5.92)
Age at Appointment	42.24 (4.86)	42.27 (5.96)	43.13 (6.08)	· (.)	· (.)	· (.)
Subsidy Period / Work Life	0.07 (0.01)	0.07 (0.01)	0.07 (0.01)	· (.)	· (.)	· (.)

Note: The distinction between public and other universities is based on the list provided in Appendix Table A.1. All statistics are calculated using data obtained from the Federal Government's funding portal by searching the term '*Professorinnenprogramm*' (Bundesregierung, 2023).

The average age of subsidized appointments is 42 years, indicating that the subsidy covers about 7% of all professor-related expenses until retirement, assuming a retirement age of 67. Less than one-third of these appointments are 'early', meaning that a regular budgeted full professorship is not yet available. For these early appointments, a guaranteed transition to a regularly budgeted full professorship must be ensured by the end of the subsidy period.

Appendix Figure B.6 displays the distribution of subsidized appointments across faculties and years. About half of all appointments are in the social sciences and humanities, which already had a relatively high share of female professors before the program. One-third of the appointments are in the natural sciences and engineering, fields with low shares of female professors. Appendix Figure B.7 shows that more than half of call-specific budgets are exhausted within the first six months.

Table 3: Wave- and Call-specific Characteristics

	Wa	ve I	Wav	re II	Wav	e III	,	Wave IV	7
	Call 1	Call 2	Call 3						
Panel A: Instituional Framework									
Budget (Million EURs)	105	45	90	60	130	70	3	320 Tota	ıl
Max. Appointments per University	3	3	3	3	3+1	3+1	3+1	3+1	3+1
Max. Subsidy Duration (years)	5	5	5	5	5	5	5	5	5
Max. Yearly Subsidy (1,000 EURs)	150	150	150	150	165	165	165	165	165
Min. Appointments within Budget	140	60	120	80	158	85			
Panel B: Actual Appointments									
Succesful Universities	74	38	82	41	78	49			
Appointments	184	90	176	88	176	121			
Avg. Subsidy Duration (years)	4.5	4.8	4.6	4.6	4.9	4.9			
Avg. Yearly Subsidy (1,000 EURs)	121.6	110.9	125.2	119.8	140.2	134.6			
Panel C: World w/o Budget Cap									
Possible Appointments	222	114	246	123	234	147			
Max. Required Budget (Million EURs)	166	85	184	92	193	121			
Funding Gap (percent)	158	188	204	153	148	172			

Note: The last row in Panel A assumes that each subsidized appointment utilizes both the maximum funding period and the maximum funding amount. The calculations in Panel C consider a scenario without budget constraints, where each eligible university subsidizes three female professors, using the maximum funding period and maximum funding amount. All statistics are calculated using data obtained from the Federal Government's funding portal by searching the term '*Professorinnenprogramm*' (Bundesregierung, 2023), along with wave-specific legal regulations (Bundesministerium für Bildung und Forschung, 2008, 2012, 2018, 2022).

3 Data

The analysis is based on an annual panel of 1,342 departments from 2003 to 2023, compiled from three primary data sources. First, I utilize administrative records on all academic personnel employed at public German universities. These data serve two main purposes: constructing a departmental panel to track hiring patterns for both junior and senior researchers and estimating departmental retirement probabilities, which are essential for my identification strategy. Second, I incorporate publicly available data on the *Professorinnenprogramm*. Finally, I use data from *OpenAlex* to gather information on scholarly output, which allows for the measurement of both publication quality and research topics at the departmental level.

3.1 Measuring Hiring Dynamics

The empirical analysis is primarily based on the *Hochschulpersonalstatistik*, accessed through the Federal Statistical Office of Germany (Destatis, 2018). The repeated cross-sectional data contain anonymized information on all academic personnel employed at public and applied German universities from 2003 to 2023. The *Hochschulpersonalstatistik* provides a wide range of demographic and professional details for each professor including affiliation, department, pay grade, gender, nationality, year of Ph.D. completion, and whether the individual holds a position

such as dean or university president. The list of all included variables, along with averages by gender, is presented in Appendix Table A.3.

To prepare the data for the empirical analysis, I first create individual identifiers based on time-invariant characteristics to enable tracking of professors over time and across different universities. I aggregate the individual-level data into a panel of departments and years, which aligns with the level at which subsidies are assigned. Analogously, I construct department-level panels for post-docs, Ph.D. students, and research assistants, utilizing comparable information available for professors. These additional panels allow for the investigation of potential spillover effects to junior researchers.

3.2 Professorinnenprogramm

I corroborate the department rosters with application data on the *Professorinnenprogramm*, which can be retrieved through the Federal Government's funding portal using the search term "Professorinnenprogramm" (Bundesregierung, 2023). For each subsidized appointment, I collect the professor's name, institutional affiliation, associated department, type and date of appointment, yearly subsidy endowment, and funding duration. This information enables me to create variables for each department, indicating the start and end of the start-up funding periods.

3.3 Measuring Retirement Probabilities

To predict department-specific retirement probabilities, I use a a logistic Lasso estimator to identify the most influential predictors from a broad set of potentially relevant characteristics (Friedman, Hastie and Tibshirani, 2010). To prevent overfitting, the data is divided into an estimation sample and a prediction sample (Hansen, 2022). The penalized log-likelihood is estimated using only data from before the first funding period, i.e., for t < 2008:

$$\hat{\boldsymbol{\rho}} = \underset{\boldsymbol{\rho} \in \mathbb{R}^k}{\operatorname{arg max}} \sum_{l} \sum_{t < 2008} \left\{ \operatorname{Retire}_{lt}^{(5)} \cdot f(\boldsymbol{X}_{lt}) - g(f(\boldsymbol{X}_{lt})) \right\} - \lambda ||\boldsymbol{\rho}||_1$$
where $g(\xi) = \log \left(1 + \exp(\xi) \right)$. (LASSO)

Retire_{lt}⁽⁵⁾ is a binary variable set to one if professor l retires within five years of year t, i.e., Retire_{lt}⁽⁵⁾ $\equiv 1$ if Retire_{lt+\tau} = 1 for any $\tau \in \{0,1,...,4\}$. This modelling choice is intended to reflect the requirement that a permanent position must be guaranteed only at the end of the subsidy period, which spans a maximum of five years. The vector \mathbf{X}_{lt} includes individual characteristics of professor l that may predict retirement. In particular, the vector contains variable measuring gender, race, academic field, years since appointment as a full professor (modeled up to a cubic polynomial), state of employment, remuneration bracket, and the number of male colleagues. To account for potential non-linearity, the function $f(\cdot)$ also includes first-order interactions between all these variables. In total the model contains 214 potential predictors. The function $g(\cdot)$ implements the logistic Lasso, λ describes the penalization parameter. The value of

 λ is calibrated using ten-fold cross-validation, selecting the value minimizing the mean-squared prediction error (Chen and Lee, 2021).

After training the model on pre-2008 data, it is evaluated on the post-2008 data to forecast individual-level retirement probabilities.¹³ The probability of any retirement occurring in department i within the next five years from t is computed as the complement of observing no individual retirements:

$$\operatorname{Retire}_{it}^{(5)} \equiv 1 - \prod_{l \in \mathcal{L}} \left(1 - \widehat{\operatorname{Retire}}_{lt}^{(5)} \right) \quad \forall t \ge 2008.$$

The set \mathcal{L} represents all full professors employed in department i in year t, i.e., $\mathcal{L} \equiv \mathcal{L}(i,t) = \{l : l \in i \text{ in } t\}$.

In Section 5.1, I validate my findings using binary retirement indicators based on age thresholds, which produce estimates of comparable magnitude but lower statistical significance. In Appendix Section D.A, I show that this pattern arises because binary measures discard substantial variation in retirement timing – variation my continuous probability metric captures.

3.4 Measuring Research Output

To analyze potential changes in research pattern, I collect bibliographical information on all research produced at German public universities through *OpenAlex* (Priem, Piwowar and Orr, 2022). *OpenAlex* serves as a scholarly catalog encompassing the world's academic papers, researchers, journals, and institutions. It succeeded the Microsoft Academic Graph, which was discontinued in May 2021. *OpenAlex* regularly expands its database by aggregating and standardizing data from various sources, including ORCID, Pubmed, arXiv, and Crossref. For each paper, the data include the complete list of authors (including their affiliation at the time of publication), the journal of publication, the references cited by the paper, and the citations it has received. The analysis is limited to research output from researchers who have been affiliated with a public German university at some point, identified through *OpenAlex*'s institution identifier. Research output is measured by the quantity and quality of publications and the number of citations received. I assess the quality of publications using journal impact factors provided in Scopus (2023).

While the research data include institutional information, they lack details on the department and position of researchers. To match research output to the department rosters, I utilize complementary information from the *Hochschullehrerverzeichnis*, an annual directory listing German university professors along with their affiliations and descriptions of their disciplines

¹³ Due to the focus on forecasting, no inference is made on the model parameters, which eliminates the need for a double selection estimator (Belloni, Chernozhukov and Hansen, 2014).

(Hochschulverband, 2002–2022).¹⁴ The matching procedure is described in Appendix Section D.B.

4 Empirical Strategy

Identification Strategy To causally identify how affirmative action appointments affect departments, I implement an instrumented difference-in-differences design. My main argument is that the *Professorinnenprogramm*'s requirement to eventually convert subsidized appointments into permanent positions makes departments in eligible universities with high retirement probabilities during the funding period more likely beneficiaries of the program, compared to those with low retirement probabilities. Retirement probabilities are primarily determined by historical hiring decisions, making them predetermined and not subject to manipulation. Additionally, departments cannot create vacancies by dismissing tenured professors, as they hold lifetime civil service positions. Similarly, departments cannot accommodate subsidized appointments through the creation of new permanent positions, as these are contingent on negotiations with the federal state and typically limited to addressing increased teaching demand. These institutional constraints ensure that retirement probabilities serve as a plausible source of exogenous variation.

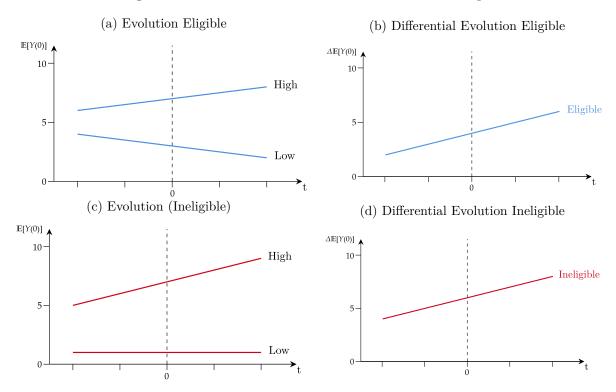
I extend the design by also considering retirement probabilities of departments in ineligible universities – those that did not pass the first-stage application process. Incorporating this additional cross-sectional variation allows identification under considerably weaker assumptions, as it allows for potential retirement-specific trends in potential outcomes.¹⁵

Figure 2 illustrates this logic. Figures 2a and 2c show the trajectories of some arbitrary potential outcome Y(0) in departments with high and low retirement probabilities across eligible and ineligible universities. When excluding ineligible universities, identification would require parallel trends in Figure 2a, which effectively rules out that departments with differing retirement probabilities follow different trends in potential outcomes. In contrast, including ineligible universities allows for a more flexible identification strategy, as it suffices to assume that the differential evolution of average untreated outcomes between high- and low-retirement departments in eligible and ineligible universities – illustrated in Figures 2b and 2d – move in parallel. This assumption seems more plausible.

¹⁴ Another approach would involve inferring the department identifier from the research output of a researcher. However, this method is complicated by the fact that the academic work of researchers does not always align with their department. For instance, an economist might be employed in a business department because the university lacks a dedicated economics department. Moreover, the position of the researcher cannot be identified at all from the *OpenAlex* data.

¹⁵ Retirement-specific trends may arise if retirement probabilities exhibit autocorrelation even after controlling for covariates. In such cases, departments with high retirement probabilities will, on average, be older, while those with low retirement probabilities will tend to be younger. Since the potential outcomes of older and younger departments are unlikely to evolve in the same way, this would violate the parallel trends assumption.

Figure 2: Exclusion Restriction – Parallel Trend Assumption



Note: The figure provides a schematic overview of the parallel trend assumption in the triple difference-in-differences framework described in Section 4. Figure 2a illustrates an exemplary average residualized potential outcome evolution for departments with high and low retirement probabilities within eligible universities. Figure 2b depicts the average differential evolution of potential outcomes between these departments. Analogously, Figures 2c and 2d show the average evolution of residualized potential outcomes and their differential evolution within ineligible universities. The triple difference estimator assumption requires that the differential evolution in Figures 2b and 2d follow a parallel trend. In a standard difference-in-differences setting – where the analysis is limited to departments in eligible universities – one would need to assume that the average potential outcomes for departments with high and low retirement probabilities in Figure 2a evolve in parallel, which would rule-out retirement-specific trends.

Empirical Model I formalize the triple-difference identification strategy using the following regression framework,

Female
$$\operatorname{Hiring}_{it} = \alpha_i + \alpha_{u(i)t} + \alpha_{f(i)t} + \phi_1 \operatorname{Retire}_{ig}^{(5)} \cdot \operatorname{Post}_{tg} + \psi_1 \operatorname{Retire}_{ig}^{(5)} \cdot \operatorname{Post}_{tg}^{1st} \cdot \operatorname{Eligible}_{u(i)g} + \psi_2 \operatorname{Retire}_{ig}^{(5)} \cdot \operatorname{Post}_{tg}^{2nd} \cdot \operatorname{Eligible}_{u(i)g} + \varepsilon_{it}$$

$$(IV1)$$

where I initially restrict the analysis to the initial funding period, g = 1, starting in $\tau(g) = 2008$. In Section 4, I extend the framework to include all funding periods, addressing issues related to staggered treatment adoption and multiple treatment assignments.

In Equation (IV1), Female Hiring_{it} equals one if department i appoints a female full professor in year t. Retire⁽⁵⁾_{ig} represents the probability that department i experiences any retirement in $t \in [\tau(g), \tau(g) + 5]$. Eligible_{u(i)g} indicates whether university u(i) is eligible for funding in period g.

Post_{tg} is equal to one in all post funding years, i.e., $t \ge \tau(g) = 2008.^{16}$ This period can be divided into two distinct phases. The first is the funding period, represented by the indicator Post_{tg}^{1st}, which covers the years when funding is available – typically two years.¹⁷ The second is the post-funding phase, indicated by Post_{tg}^{2nd}, encompassing all years after the funding has been exhausted. According to the instrument's logic, retirements in eligible universities should predict female hiring only during the funding phase, with no effect in the post-funding phase.

The parameter of interest, ψ_1 , captures the differential effect of retirement on female hiring between eligible and ineligible universities in the funding period. The coefficients ψ_2 – the effect of retirement at eligible universities after the funding period – and ϕ_1 – the effect of retirement at ineligible universities – can be seen as a placebo test for the identification strategy, as no effect is expected in either the post-funding period or in ineligible universities.¹⁸.

The specification extensively controls for possible unobserved factors affecting female hiring and the interacted instrument. In particular, α_i captures time-invariant department-specific factors like homophily preference of department i. Further, $\alpha_{u(i)t}$ captures time-varying university-specific factors at university u(i) in t. Partialling out these effects transforms absolute into relative retirement probabilities, which ensures that the instrument has no predictive power in universities with homogeneous retirement probability distributions.¹⁹ Lastly, $\alpha_{f(i)t}$ captures time-varying field-specific factors affecting all fields f(i) in t, such as a large birth cohort of economists retiring in t leading to a surge in the demand for female economists. All other unobserved factors enter the error term ε_{it} , which is clustered at the department-level (Abadie et al., 2023).

In a second step, I then use predicted female hiring from Equation (IV1) to estimate the following two-stage least squares regression,

$$Y_{it+h} = \alpha_i + \alpha_{u(i)t} + \alpha_{f(i)t} + \beta \overline{\text{Female Hiring}}_{it} + u_{it}$$
 (IV2)

where Y describes some outcome of department i in year t + h. For all other variables, the previous explanations apply.

Identifying Assumption Causal identification of β in Equation (IV2) relies on the assumption, that in the absence of the *Professorinnen programm*, the difference of the average outcome among departments with high and low retirement probabilities in eligible universities evolves in the same way as the difference of the average outcome among units with high and low retirement

¹⁶ Note that, $\tau(g)$ does not always align with the actual year of a subsidized appointment. While this might introduce some noise it guarantees the temporal alignment of pre- and post-treatment years within a funding period. Otherwise, when expanding the research design to incorporate all funding periods, I would observe multiple pre- and post-treatment years within each of the six funding periods. In the first funding period, I assume $\tau(g) = 2008$, even though some of subsidized appointments where made in 2009 or 2010. In the dynamic version of Equation (IV1), this will lead to a downward bias of the first two lead estimates, because the specification assumes some departments as treated although the appointment will only happen within the next two years.

 $^{^{\}rm 17}$ Appendix Figure B.7 illustrates the share of funds utilized over time for each funding period.

¹⁸ All other combinations of Retire_{ig}, Eligible_{u(i)g}, and Post_{tg} are omitted due to collinearity with the fixed effects included in the model.

¹⁹ Specifically, a department with a high likelihood of retirement should not be more likely to receive the subsidy if other departments at the same university have similarly high retirement probabilities.

probabilities in ineligible universities. This implies that, conditional on covariates, retirement probabilities in eligible universities are orthogonal to u it in Equation (IV2).

Staggered Adoption and Multiple Treatment In case of a single funding period, Specifications (IV1) and (IV2) allow one to causally identify the effect of hiring a female professor. The presence of multiple funding periods – six in total – necessitates to adjust the estimation procedure. While considering all funding periods allows us to leverage additional temporal variation, as departments receive treatment at different points in time, it also introduces issues of cross-lag contamination and multiple treatment assignments.

When employing a standard fixed-effects estimator with staggered treatment assignment, units that have already been treated serve as comparison units for units that have not yet been treated. This can introduce bias, when there is treatment effect heterogeneity (Roth et al., 2023). Additionally, departments may receive subsidies in multiple funding periods, resulting in several treatments. In such cases, fixed-effects estimators are not robust to heterogeneous effects and may be contaminated by the effects of other treatments (de Chaisemartin and D'Haultfœuille, 2023).

To address both issues, I implement a stacked regression design, following Cengiz et al. (2019) and Dube et al. (2023). This approach constructs a separate panel for each funding period g, including all first-time subsidy-receiving departments and clean non-subsidy-receiving departments. The stacked regression design aggregates estimates from these funding period-specific panels. Identification holds as long as the parallel trends assumption is valid in each panel.

The stacked panel is constructed as follows: (1) Consider each funding period as a separate event g beginning in year $\tau(g)$. (2) For each event g, fix departmental retirement probabilities and the university eligibility status in $\tau(g)$. (3) For each event g define an event window $T(g) \equiv [\underline{\tau}(g), \overline{\tau}(g)]$ where $\underline{\tau}(g) \equiv \max\{2005, \tau(g) - c\}$ and $\overline{\tau}(g) \equiv \min\{\tau(g) + c, 2023\}$. The event window is defined by the tuning parameter, c, which is set to c = 5. (4) For each funding period g define an exclusions set containing observations for which $t \notin T(g)$ and departments that previously received funding in some funding period g' for which $\tau(g') < \tau(g)$.

Under these restrictions, each event-specific panel only includes departments receiving subsidies for the first time and *clean* departments that have not received subsidies in any previous subsidy period. Stacking all datasets from different funding periods and interacting all fixed effects with event indicators, allows to consistently estimate treatment effects via standard fixed effects estimators, avoiding biases from multiple treatments or staggered adoption (Dube et al., 2023; Wing, Freedman and Hollingsworth, 2024). For inference, standard errors are clustered by department i and event g.

²⁰ Increasing c allows the evaluation of treatment effects over a larger time horizon but also increases the event-specific exclusion sets. In my setting opting for c=5 allows to balance both effects. In addition, the sample covers the periods from 2005 to 2023, by construction the same boundaries apply to each event-specific panel. Table 4 provides an overview of all event-specific panel endpoints.

Table 4: Panel Construction by Wave and Call

Wave	Call	g	$\tau(g)$	$\underline{ au}(g)$	$\overline{ au}(g)$
1	1	1	2008	2003	2014
1	2	2	2010	2005	2016
2	1	3	2013	2007	2019
2	2	4	2015	2009	2021
3	1	5	2018	2012	2023
3	2	6	2020	2014	2023

Note: The table displays how each distinct combination of funding wave and call corresponds to a funding period, denoted sequentially by $g \in G \equiv \{1, 2, 3, 4, 5, 6\}$. The last two columns define the endpoints of the event windows specific to each funding period, denoted as $T(g) \equiv [\underline{\tau}(g), \overline{\tau}(g)]$.

5 Results

I present four key results. First, I validate the identification strategy by showing that retirement probabilities are a strong predictor of female hiring in eligible universities. Second, I evaluate the impact of appointing an additional female professor on future hiring at both senior and junior levels. Third, I examine how the presence of a female professor influences collaboration patterns and research output within the department. Finally, I quantify the program's effectiveness by estimating the extent to which subsidized appointments result in the hiring of female professors who would not have been appointed otherwise.

5.1 Effects on Hiring

First Stage To establish a causal link between the appointment of female professors and departmental outcomes, I rely on the identification strategy outlined in section 4. I first demonstrate that retirement probabilities in eligible universities during the funding period are strong predictors of female hiring. Table 5 presents static estimates of Equation (IV1). The most rigorous specification, shown in Column (4), indicates that, among departments at eligible universities, a 10 percentage-point increase in the probability of experiencing any retirement²¹ in the funding period is associated with a 4.7 percentage-point higher likelihood of appointing a woman as a full professor compared to departments at ineligible universities, beyond their pre-existing hiring differences. This estimate is highly significant, with an F-statistic exceeding 24. In contrast, estimates for retirement probabilities in ineligible universities, as well as in eligible universities during the post-funding period, are close to zero, suggesting that hiring patterns remain unchanged relative to the pre-funding period.

Complementing these static estimates, Figure 3 presents dynamic event study results. The estimates suggest that departments with different levels of retirement are not on diverging outcome trajectories before the funding period. For departments in eligible universities, the pre-trend coefficients remain stable and close to zero. Once the funding period begins, there is a rapid and substantial increase in the share of appointed female professors in departments

²¹ Within five years of the funding period's start.

Table 5: First Stage Estimates

	Dependent Variable: Any Woman Getting Tenure						
	(1)	(2)	(3)	(4)			
Retire · Post	0.041 (0.082)	0.054 (0.085)	0.042 (0.082)	0.039 (0.079)			
Retire · Eligible · $Post^{1st}$	0.528*** (0.083)	0.441*** (0.084)	0.495*** (0.089)	0.471*** (0.096)			
Retire \cdot Eligible \cdot Post ^{2nd}	0.043 (0.086)	0.057 (0.089)	0.044 (0.086)	0.037 (0.097)			
Observations F-statistic	$147,591 \\ 40.47$	147,591 27.56	147,591 30.94	$147,\!591 \\ 24.07$			
Fixed Effects Department Field × Year University × Year	- -	√ -	√ √	√ √			

Note: The table presents regression results from estimating Equation (IV1) across multiple specifications. All regressions are estimated using a combined dataset constructed by stacking funding period-specific panels (as detailed in Section 4) and interacting all fixed effects with funding period indicators. The F-statistic reflects the test results for the null hypothesis that the coefficient ψ_1 equals zero. Robust standard errors, clustered by department and funding period, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

with high retirement probabilities in eligible universities, relative to comparable departments in ineligible universities and the pre-period. This effect diminishes after the funding period ends – after approximately two years 22 – with estimates reverting to pre-funding levels. This reversion suggests that subsidized appointments do not influence subsequent hiring of female full professors, indicating that the program neither promotes nor hinders the advancement of other women to full professorships.

Design Validity The dynamic effects of retirement probabilities in ineligible universities confirm the validity of the identification strategy. In the pre-period, all estimates are tightly clustered around zero, supporting the parallel trends assumption.²³

I conduct three additional exercises to validate my identification strategy. First, I re-estimate the first-stage equation by randomly reassigning eligibility status among universities and retirement probabilities among departments for each funding period. This exercise allows to compare the actual realization of eligibility status and retirement probabilities with hypothetical scenarios that did not realize. As shown in Figure 4, the actual correlation is a clear outlier within the nearly normal distribution of placebo estimates.

Second, Columns (1)–(3) of Table 6 demonstrate that my estimates are insensitive to how retirement probabilities are incorporated into the instrument in Equation (IV1). Column (1) replicates the main specification, where retirement probabilities are fixed at their initial value

²² For a detailed overview of the length of funding periods see Table 1. Note, that available funds can be exhausted before the end of the funding period. Appendix Figure B.7 shows the share of funds utilized over time for each funding period.

²³ While there is a slight increase in point estimates during the post-period, these remain statistically indistinguishable from zero. This marginal uptick may reflect universities making female appointments in anticipation of a favorable first-round evaluation, which ultimately does not materialize.

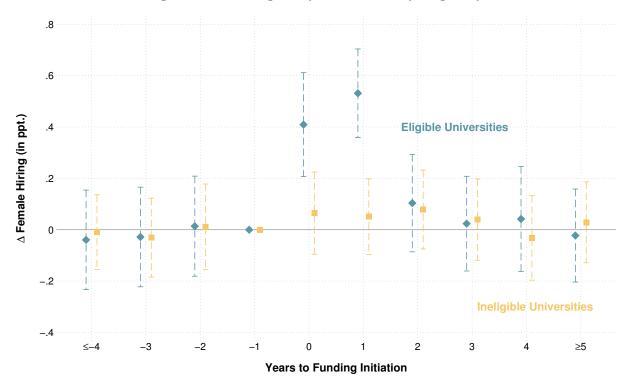


Figure 3: First Stage – Dynamic Effect by Eligibility

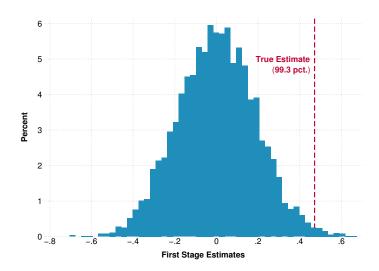
Note: The figure presents first-stage event study estimates based on the regression framework outlined in Equation (IV1). All post-indicators in Equation (IV1) are replaced by a set of indicators that represent the relative time in years from the start of the funding period, as shown on the horizontal axis. Standard errors are clustered by department and funding period. Bars represent 95% confidence intervals.

within each funding period, aligning with a standard DiD framework where temporal variation is only introduced through a pre-post comparison. Alternatively, retirement probabilities could be recalculated annually and used as a time-varying measure in the interaction term. Column (2) shows that this approach slightly reduces the instrument's statistical power but otherwise does not affect the results. Column (3) further controls for time-varying retirement probabilities as a covariate, yielding similar estimates.²⁴ Third, Columns (4)–(6) of Table 6 show that the first-stage correlation remains stable when measuring retirement with a binary indicator based on different age thresholds. Throughout, the instrument remains sufficiently strong, although estimates from the binary measure are smaller in magnitude²⁵ and less statistically significant than those from the continuous approach. This pattern reflects that the binary indicators discard variation in retirement timing that the continuous measure is able to capture, as discussed in Appendix Section D.A.

²⁴ A limitation of incorporating time-varying retirement probabilities, whether as an instrument or a control variable, relates to the issue of "bad controls". If retirement probabilities in the post-period are influenced by those in the funding period – which is mechanically true in the presence of autocorrelation – conditioning on them in any form can introduce meaningful bias (?).

²⁵ The reduction in magnitude is partly mechanical. Specifically, in a model with a constant, an indicator variable, and a dependent variable bounded between zero and one, the OLS estimator is given by $\hat{\beta}_1(x \in \{0, 1\}, y \in [0, 1]) = \bar{y}_1 - \bar{y}_0$, which is constrained within the interval [-1, 1]. Conversely, when the indicator variable is replaced with a continuous measure bounded between zero and one, it follows that $\hat{\beta}_1(x \in [0, 1], y \in [0, 1]) \in \mathbb{R}$.

Figure 4: First Stage Placebo Estimates



Note: The figure presents the distribution of 5,000 first-stage placebo estimates, which were obtained by randomly reassigning eligibility status among universities and retirement probabilities among departments within each funding period. These estimates represent the regression results for the parameter ψ_1 from Equation (IV1). This parameter captures the differential impact of retirement on female hiring between eligible and ineligible universities during the funding period. The vertical dashed line marks the actual first-stage estimate, which lies at the 99.3rd percentile of the placebo distribution. Standard errors are clustered by department and funding period.

Table 6: First Stage Estimates – Validity

		Dependent Variable: Any Woman Getting Tenure						
	Retire	ment Probabi	lities	Retiren	Retirement Age Threshold			
	Fixed	Varying	Varying	≥ 65	≥ 66	≥ 67		
	(1)	(2)	(3)	(4)	(5)	(6)		
Retire \cdot Post	0.039 (0.079)	0.052 (0.085)	0.055 (0.082)	0.038 (0.052)	0.032 (0.053)	0.031 (0.052)		
$Retire \cdot Eligible \cdot Post^{1st}$	0.471*** (0.096)	0.429*** (0.098)	0.428*** (0.093)	0.225*** (0.057)	0.207*** (0.057)	0.195*** (0.058)		
Retire \cdot Eligible \cdot Post ^{2nd}	0.037 (0.097)	$0.055 \\ (0.100)$	0.058 (0.097)	$0.040 \\ (0.055)$	0.034 (0.056)	0.033 (0.055)		
Observations F-statistic	$147,\!591 \\ 24.07$	147,591 19.16	$147,591 \\ 21.18$	$147,\!591 \\ 15.58$	147,591 13.19	$147,\!591 \\ 11.77$		
Fixed Effects		,	,					
Department Field \times Year	√	√	√	√	√	√		
University × Year	∨ ✓	∨ ✓	∨ ✓	∨ ✓	∨ ✓	∨ ✓		
Controls Retirement	-	-	\checkmark	-	-	-		

Note: The table presents regression results from estimating Equation (IV1) using different approaches to measure departmental retirement. Columns (1)–(3) employ a continuous retirement measure based on the logistic LASSO estimator described in Section 3.3. In Column (1), retirement probabilities are computed at the start of the funding period and remain fixed throughout the corresponding panel. Column (2) allows for time-varying retirement probabilities, recalculating them annually for the subsequent five years. Column (3) extends this specification by additionally controlling for time-varying retirement probabilities. Columns (4)–(6) replace retirement probabilities with a binary indicator based on the retirement age thresholds specified in the column headers. All regressions are estimated using a combined dataset constructed by stacking funding period-specific panels (as detailed in Section 4) and interacting all fixed effects with funding period indicators. The F-statistic tests the null hypothesis that the coefficient on the triple interaction term is equal to zero. Robust standard errors, clustered by department and funding period, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

Junior Faculty and Ph.D. Hiring Next, I evaluate potential trickle-down effects by analyzing changes in the hiring of women among assistant professors, post-docs, and Ph.D. students. Figure 5b shows that the number of female assistant professors remains unchanged following the appointment of a female full professor. Similarly, Figure 5c reveals a slight increase in the proportion of female post-docs three years post-funding, though this effect is statistically insignificant.

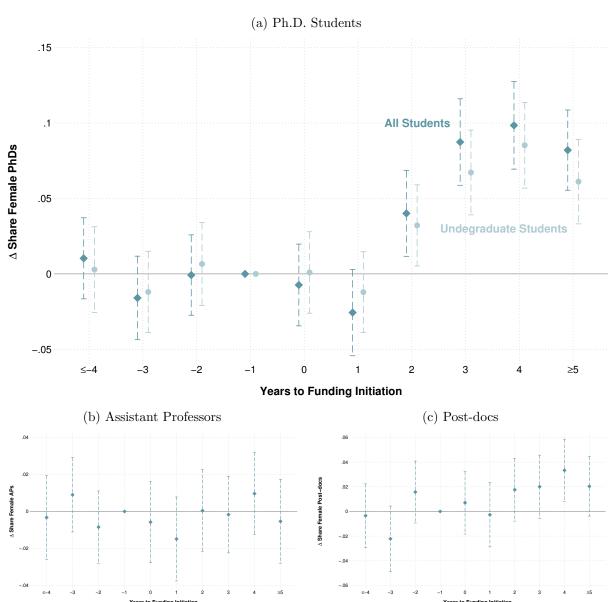
In contrast, Figure 5a highlights a significant increase in the hiring of female Ph.D. students. Again, the figure displays stable pre-trends. Three years after the funding period ends, there is a significant uptake in the hiring of female Ph.D. students. Relative to the pre-funding period and departments in ineligible universities, experiencing a certain retirement within the next five years is associated with a 4.6 percentage-point rise in female Ph.D. recruitment. This effect is almost entirely driven by women pursuing their Ph.D. at their home institution – defined as those who completed their undergraduate studies in the same department – with a rise of 3.9 percentage points.²⁶

Corresponding 2SLS estimates, combining the first stage and reduced form results, are displayed in Panel B of Table 7. Each subsidized female professor appointment leads to a 9.8 percentage-point increase (+19%) in the overall share of female Ph.D. students and a 8.3 percentage-point increase (+29%) among those studying at their home institution. I discuss robustness checks addressing weak-instrument concerns in Appendix Section C.B.

Mechanism The observed hiring shift could stem from shifts in preferences among students, professors, or both. For instance, female students may be more likely to pursue PhDs at their home institution after exposure to newly appointed female professors – a pattern consistent with existing evidence on how female role models influence career trajectories (Porter and Serra, 2020; Blau et al., 2010; Ginther et al., 2020). Alternatively, current professors might prioritize recruiting female PhD students in response to the appointment of a female full professor. However, this explanation is less compelling given the absence of significant effects on the hiring of female assistant professors and post-docs. The lack of impact on these groups – who are typically affiliated with other institutions and thus unable to interact with the subsidized professor – further supports the role model hypothesis. Overall, the evidence strongly suggests that role model effects drive these changes.

The *Hochschulpersonalstatistik* data allows one to infer the 'home institution' of Ph.D. students through a variable indicating the highest degree awarding institution. From this, I construct the share of female Ph.D. students pursuing their their doctoral studies at their 'home institution'.

Figure 5: Reduced Form – Effects on Junior Female Hiring



Note: Each figure presents reduced-form event study estimates based on the regression framework outlined in Section 4. The outcome variable in each figure is the share of appointed women within the group specified in the caption. The post-indicator is replaced by a set of indicators that represent the relative time in years from the start of the funding period, as shown on the horizontal axis. Standard errors are clustered by department and funding period. Bars represent 95% confidence intervals.

Table 7: Change in Hiring Patterns

	Junior F	aculty	Ph.D. St	udents
	Ass. Professor	Post-Doc	Overall	Home
	(1)	(2)	(3)	(4)
Panel A: Reduced For	rm			
Retire · Post	0.017	0.009	0.004	-0.013
	(0.014)	(0.012)	(0.012)	(0.016)
Retire · Eligible · Post	0.016	-0.003	0.046***	0.039***
_	(0.013)	(0.011)	(0.014)	(0.014)
Observations	147,591	147,591	147,591	147,591
Panel B: 2SLS				
Female Hiring	0.034	-0.006	0.098***	0.083***
	(0.121)	(0.109)	(0.028)	(0.029)
Observations	147,591	147,591	147,591	147,591
F-statistic	24.07	24.07	24.07	24.07
Panel C: OLS				
Female Hiring	0.124**	0.190**	0.401***	0.359***
	(0.049)	(0.082)	(0.108)	(0.083)
Observations	147,591	147,591	147,591	147,591
Fixed Effects				
Department	\checkmark	\checkmark	\checkmark	\checkmark
$Field \times Year$	\checkmark	\checkmark	\checkmark	\checkmark
University \times Year	\checkmark	\checkmark	\checkmark	\checkmark

Note: The table presents regression results from estimating Equation (IV1) across multiple specifications. All regressions are estimated using a combined dataset constructed by stacking funding period-specific panels (as detailed in Section 4) and interacting all fixed effects with funding period indicators. Robust standard errors, clustered by department and funding period, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

5.2Effects on Collaboration Patterns

Existing research suggests that exposure to underrepresented groups can reduce stereotypes and increase future engagement with those groups (Carrell, Hoekstra and West, 2015). I hypothesize that if negative gender stereotypes exist, changes in gender attitudes may manifest in coauthorship patterns. Specifically, I examine whether exposure to a female professor increases the share of female co-authors. My data allows for dynamic tracking of co-authorship networks over time, enabling a detailed analysis of these patterns.

Reduced Form To track changes in collaboration patterns, I use the share of female co-authors as outcome variable²⁷ in my empirical design. Figure 6a displays how the average share of female co-authors among all department members changes after a woman joins the department. The event study reveals no significant overall increase in female co-authorship.

However, disaggregating these effects by gender in Figure 6b shows that while women's coauthorship patterns remain unchanged, men exhibit a slight increase in female co-authorship after being exposed to an additional female professor. This shift emerges two to three years post-exposure, likely reflecting the time required for author matching and publication lags.

Figure 6c breaks down these results by seniority, showing that the effect is most pronounced among junior men – defined as those with below-median experience. This aligns with evidence from outside academia suggesting that stereotype malleability declines with age (Gonsalkorale, Sherman and Klauer, 2009; Siyanova-Chanturia et al., 2015). The estimates indicate that a 10 percentage-point increase in retirement probabilities among departments in eligible universities – relative to departments in ineligible universities and the pre-funding period – raises the likelihood of junior men co-authoring with women by 2.9 percentage-points (average of Columns (4) and (5) in Panel A of Table 6c). The corresponding 2SLS estimates in Panel B of Table 8 indicate that hiring a female professor results in a 6.3 percentage-point (average of Columns (4) and (5) in Panel B of Table 6c) increase in female co-authorships among junior men, representing a 24% rise relative to the pre-funding period average.

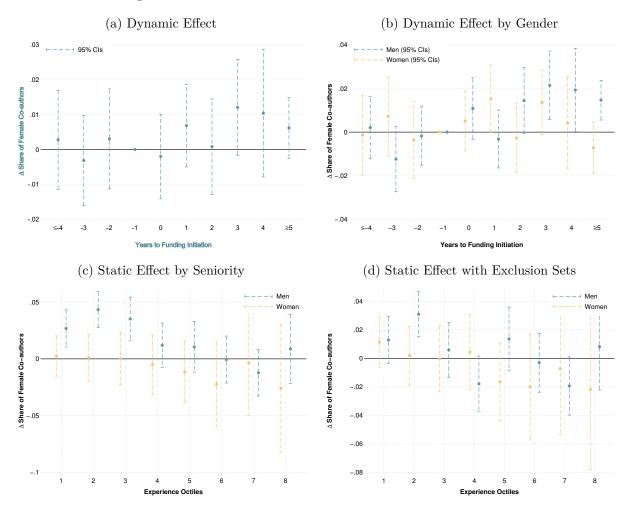
Accounting for Peer Network Instead of reflecting shifts in gender attitudes, the increase in female co-authors could result from faculty members gaining access to the peer networks of subsidized appointments, which are predominantly female (64%). To disentangle these channels, I model the potential peer networks of each affirmative action appointment and calculate co-author shares excluding these networks. Specifically, for all academic work published by professors in some department i, I exclude authors connected to the subsidized appointment joining department i.²⁸ I narrow the pool of co-authors along four dimensions.

First, I exclude the subsidized appointment itself. Second, I exclude former and future coauthors of subsidized appointments, as well as co-authors of these co-authors. Extending the

²⁷ To avoid the possibility that results are driven by changes in department composition following a subsidized appointment, I fix the department composition in each funding period-specific dataset in $\tau(g)$.

28 In departments without a subsidized appointment, the share of female co-authors remains unchanged.

Figure 6: Reduced Form – Effects on Collaboration Patterns



Note: The figure presents reduced-form event study estimates based on the regression framework outlined in Section 4, using the share of female co-authors as outcome variable. The post-indicator is replaced by a set of indicators that represent the relative time in years from the start of the funding period, as shown on the horizontal axis. Figures 6c and 6d restrict the sample by tenure length octiles, as indicated on the horizontal axis. In Figure 6d, the share of female co-authors is measured excluding the peer network of the subsidized appointment, as detailed in Section 5.2. Standard errors are clustered by department and funding period. Bars represent 95% confidence intervals.

peer network to include future co-authors might overstate the current network. However, future co-authors could already be part of the women's network today, even if no co-authorship exists yet. Third, I exclude authors who at some point have shared the same affiliation as the subsidized appointment, those employed in the same department during the same year. Fourth, I exclude authors working in the same specialized field as the subsidized appointment. I identify these authors using related works listed in the publication data.²⁹

Figure 6d shows that applying these exclusion sets substantially attenuates the previous estimates. This suggests that the primary effect is driven by access to the peer networks associated with subsidized appointments. This increase may partly reflect a mechanical effect: when a professor

²⁹ Related works are identified algorithmically by comparing the titles and abstracts of papers. Specifically, the OpenAlex algorithm identifies papers that share common concepts with a given paper. Each work in OpenAlex is linked to several concepts sourced from a repository of approximately 65,000 concepts from Wikidata. For technical details on how concepts are assigned to papers, refer to OpenAlex's technical documentation available at OpenAlex's technical documentation.

Table 8: Change in Collaboration Patterns

	All	Women	Men	Me	Men by Seniority (Quartiles)			
		,,,,,,,,,,,		Q1	Q2	Q3	Q4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: Reduced Fo	rm							
Retire · Post	-0.007	-0.001	-0.009	0.009	0.006	-0.002	-0.008	
	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.06)	
Retire \cdot Eligible \cdot Post	0.010	0.005	0.013	0.035***	0.024***	0.005	-0.002	
	(0.008)	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)	(0.008)	
Observations	$147,\!591$	147,591	$147,\!591$	147,591	$147,\!591$	$147,\!591$	$147,\!591$	
Panel B: 2SLS								
Female Hiring	0.019	0.011	0.028	0.074***	0.051**	0.011	-0.004	
	(0.025)	(0.023)	(0.025)	(0.027)	(0.024)	(0.023)	(0.026)	
Observations	147,591	147,591	147,591	147,591	147,591	147,591	147,591	
F-statistic	24.07	24.07	24.07	24.07	24.07	24.07	24.07	
Panel C: OLS								
Female Hiring	0.081**	0.094***	0.075*	0.081*	0.079*	0.077*	0.063	
	(0.040)	(0.034)	(0.044)	(0.049)	(0.041)	(0.045)	(0.044)	
Observations	$147,\!591$	147,591	$147,\!591$	147,591	147,591	147,591	147,591	
Fixed Effects								
Department	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
$Field \times Year$	\checkmark	\checkmark	\checkmark	✓	\checkmark	\checkmark	\checkmark	
University × Year	✓	✓	✓	✓	✓	✓	✓	

Note: The table presents regression results from estimating Equation (IV1) across multiple specifications. All regressions are estimated using a combined dataset constructed by stacking funding period-specific panels (as detailed in Section 4) and interacting all fixed effects with funding period indicators. Robust standard errors, clustered by department and funding period, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

joins a department, it naturally encourages greater collaboration between their existing co-author network and the current members of the department.

However, even after accounting for peer networks, I still observe a statistically significant increase in the share of female collaborators among junior men compared to departments with low retirement probabilities. This residual effect might provide evidence that gender attitudes are malleable through increased exposure to women, particularly among younger male scholars.

5.3 Effects on Quality and Direction of Research

Diversity may affect the performance of existing department members. A range of studies examines how diversity impacts performance outside the academic context. For instance, Ahern and Dittmar (2012), Matsa and Miller (2013), and Nygaard (2011) examine the effects of Norway's board composition quota on firm performance and governance, yielding mixed results. Kim and Starks (2016) and that gender diversity on U.S. corporate boards enhances firm valuation, primarily due to the contributions of female directors. In Italy, Flabbi et al. (2019) show that female corporate leadership improves overall firm performance, positively affecting the upper

end of the female wage distribution while negatively impacting the lower end. Hoogendoorn, Oosterbeek and Van Praag (2013) conduct a field experiment on business teams, revealing that mixed-gender teams outperform male-dominated teams in both profit and sales.

Publication Quality To test whether diversity affects scholarly output, I analyze whether a subsidized appointment influences the quality of publications by department members. Figures 7a and 7b show that the addition of a female professor has no impact on average publication quality of the department, as measured by either journal impact factor or citations.

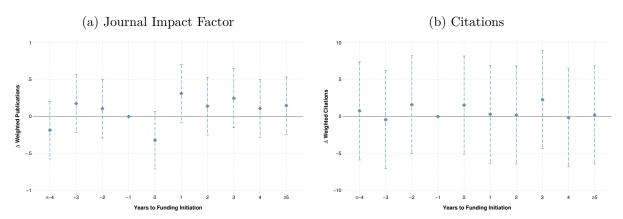


Figure 7: Reduced Form – Effects on Research Output

Note: Each figure presents reduced-form event study estimates based on the regression framework outlined in Section 4, using the research metric specified in the caption as outcome variable. The post-indicator is replaced by a set of indicators that represent the relative time in years from the start of the funding period, as shown on the horizontal axis. Robust standard errors, clustered by department and funding period, are reported in parentheses. Bars represent 95% confidence intervals.

Direction of Research Increasing gender diversity might also broaden the range of research questions pursued, as women often prioritize different policy areas compared to men (Dolado, Felgueroso and Almunia, 2012; Beneito et al., 2021). For example, surveys among economists indicate that women are generally more supportive of government intervention and environmental regulation, whereas men prioritize economic growth and are less concerned about inequality (Chari and Goldsmith-Pinkham, 2017; May, McGarvey and Kucera, 2018).

To test this hypothesis, I evaluate whether the research direction of departments shifts following the appointment of a female professor. I measure research direction using topic distributions constructed through a two-step procedure. First, I compute year-specific topic distributions for each department, capturing the extent to which researchers work on specific topics. In particular, for each department i in year t, I compute year-specific topic distributions by applying a topic model to all abstracts of papers published by researchers in the department. 30 A detailed description of the topic distribution construction is provided in Appendix Section D.C. Next, I track how these distributions evolve over time by calculating the Mahalanobis distance relative to the pre-funding period. This scalar measure serves as the outcome variable in the empirical framework outlined in Section 4.

³⁰ Again, to avoid that the results are driven by changes in the department composition following a subsidized appointment, I fix the department composition in each funding period-specific panel in $\tau(g)$.

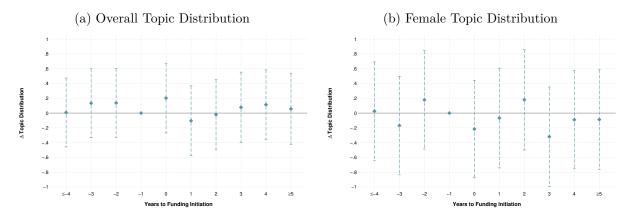
Table 9: Change in Publications

]	Publication Outcome	es	Research	Direction
	Total	Impact Factor	Citations	All Topics	Female Topics
	(1)	(2)	(3)	(4)	(6)
Panel A: Reduced For	m				
Retire · Post	0.105 (0.215)	0.098 (0.173)	0.443 (2.062)	-0.032 (0.212)	0.054 (0.246)
Retire \cdot Eligible \cdot Post	-0.313 (0.266)	0.106 (3.382)	0.732 (0.199)	0.054 (0.241)	-0.099 (0.342)
Observations	147,591	147,591	147,591	147,591	147,591
Panel B: 2SLS					
Female Hiring	-0.665 (0.521)	0.225 (0.194)	1.554 (2.930)	0.115 (0.412)	0.210 (0.617)
Observations F-statistic	$147,\!591 \\ 24.07$	$147,591 \\ 24.07$	$147,591 \\ 24.07$	$147,591 \\ 24.07$	$147,591 \\ 24.07$
Panel C: OLS					
Female Hiring	-0.014 (0.009)	-0.012 (0.008)	-0.010 (0.008)	0.184*** (0.064)	0.281** (0.091)
Observations	147,591	147,591	147,591	147,591	147,591
Fixed Effects					
Department	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
$\begin{aligned} & \text{Field} \times \text{Year} \\ & \text{University} \times \text{Year} \end{aligned}$	√ ✓	√ √	√ √	√ √	√ ✓

Note: The table presents regression results from estimating Equation (IV1) across multiple specifications. All regressions are estimated using a combined dataset constructed by stacking funding period-specific panels (as detailed in Section 4) and interacting all fixed effects with funding period indicators. Robust standard errors, clustered by department and funding period, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

Figure 8a shows that topic distributions remain stable for up to six years after the appointment of a female professor, suggesting no significant shifts in research direction. To further investigate whether researchers are more likely to work on topics traditionally associated with female scholars, I analogously train topic models exclusively on papers authored by women. As evident from Figure 8b, the topic distributions again remain stable across the entire event window, indicating no detectable shift toward "female themes".

Figure 8: Reduced Form – Effects on Direction of Research



Note: The figure presents reduced-form event study estimates based on the regression framework outlined in Section 4, using the change in topic distributions within departments relative to the pre-funding period as outcome variable. The post-indicator is replaced by a set of indicators that represent the relative time in years from the start of the funding period, as shown on the horizontal axis. Robust standard errors, clustered by department and funding period, are reported in parentheses. Bars represent 95% confidence intervals.

5.4 Policy Impact

For policymakers, a key question is the extent to which subsidized appointments contribute to the hiring of female professors who otherwise would not have been appointed. To address this question, it is essential to model the number of female full professors that would have been hired in the absence of the program. To construct this counterfactual, I outline a theoretical framework in Appendix Section C.C. Based on this theoretical framework, I implement a regression framework where I evaluate whether fields with a high share of subsidized hires experience greater increases in female hiring compared to fields with a low share of subsidized hires, relative to the pre-funding period. Drawing on these theoretical derivations and considering all funding periods g, I implement the following regression specification:

$$\Delta f_{jg} = \alpha_j + \alpha_g + \alpha_j \cdot g + \pi f_{jg}^{AA} + \varepsilon_{jg}, \tag{POLICY}$$

where Δf_{jg} represents the change in the share of female hires in field j between the pre- and post-period years corresponding to g and f_{jg}^{AA} denotes the share of affirmative action hires – both directly observable in the data. The specification controls for time-invariant, field-specific factors, α_j , as well as for time-varying effects common to all fields, α_g . Additionally, field-specific time trends, $\alpha_j \cdot g$, allow for temporal variation in α_j over time.

Identification in this framework may fail for several reasons. First, it depends on the theoretical assumptions outlined in Appendix Section C.C, which may not hold in practice – for example, the assumption that candidate pools are always sufficient to fill available positions. Second, the fixed effects in Equation (POLICY) must accurately capture the field-specific baseline change in female hiring, i.e., α_j in Appendix Section C.C. Identification may break down if these baseline trends evolve non-linearly, which is not an unreasonable possibility. A further limitation is that the regression does not account for cross-hiring, where fields recruit candidates from neighboring

disciplines. Consequently, estimates from Equation (POLICY) – particularly their magnitudes – should be interpreted with caution.

The parameter of interest, π , captures the average effective conversion rate of affirmative action-funded hires into additional female hires.³¹ Analogous to the discussion in the theoretical framework, if affirmative action-funded hires merely replace female hires that would have occurred regardless of the policy, the share of female hires should remain unaffected by affirmative action hires, implying $\pi = 0$, conditional on fixed effects. Analogously, if every affirmative action hire displaces an otherwise male hire, the female hiring share should increase proportionately with the share of affirmative action hires, leading to $\pi = 1$, conditional on fixed effects.

The results in Panel A of Table 10 indicate that each affirmative action appointment leads to approximately $\hat{\pi} \approx 0.34$ additional female hires. This suggests that in about two-thirds of cases, departments use the subsidies to appoint women they would have hired anyway. At this rate, roughly 2.9 affirmative action appointments – costing approximately 2.2 million Euros – are needed to generate one additional female hire that would not have been recruited without the program.

The binscatter in Figure 9 visualizes this relationship by plotting the residualized shares against each other. The mean across the dots corresponds with the estimate shown in Column (4) of Panel A in Table 10. Moreover, the figure suggests that the marginal effectiveness of affirmative action-funded hires decreases as the share of affirmative action hires grows, $\frac{\partial \pi}{\partial f_{j1}^{AA}} < 0$. This reflects a scenario where initial affirmative action hires successfully add new female hires, but beyond a certain point, additional affirmative action hires mostly replace women who would have been hired anyway.

Addressing Potential Cross-Hiring Effects One limitation of the design is that it does not capture the possibility of cross-hiring – that is, fields may recruit candidates from neighboring disciplines. Although the direction of any bias introduced by cross-hiring is unclear a priori, I address this issue by re-estimating Equation (POLICY) at the faculty level. Under the assumption that cross-hirings occur only among closely related fields (e.g., between economics and business, but not between economics and engineering), this approach effectively rules-out cross-hiring effects across observations.

Estimates from this exercise are presented in Panel B of Table 10. Notably, the sign and magnitude of the estimated effect remain similar to those obtained in the field-level regression, suggesting that each AA appointment translates to approximately $\hat{\pi} \approx 0.31$ additional female professors. However, the results are no longer statistically significant, likely due to the reduced variation and sample size resulting from aggregating fields into faculties.

³¹ Relating to the theoretical framework π represents the effective conversion rate in field j during period g, that is, $\pi = \frac{1}{N_G} \frac{1}{N_J} \sum_{g \in G} \sum_{j \in J} \bar{\pi}_{jg}$.

Table 10: Policy Effect Estimates

	De	pendent Variable:	Δ Share Female Hiri	ng
_	(1)	(2)	(3)	(4)
Panel A: Sample of Fields	3			
Share AA Hiring	0.476***	0.374**	0.346*	0.343*
	(0.121)	(0.165)	(0.185)	(0.187)
Observations	198	198	198	198
Number of Clusters	33	33	33	33
Panel B: Sample of Facult	ties			
Share AA Hiring	0.366*	0.329*	0.295	0.314
	(0.189)	(0.193)	(0.212)	(0.201)
Observations	48	48	48	48
Number of Clusters	8	8	8	8
Fixed Effects				
Funding Period	-	\checkmark	\checkmark	\checkmark
Unit	-	-	\checkmark	\checkmark
Unit-specific Trends	-	-	-	\checkmark

Note: This table presents regression regression estimates of the impact of AA-funded hires on the change in the share of female hires (Δf_{jg}) using the specification in Equation (POLICY). The regressions in Panel A are estimated on panel data across academic fields and funding periods. The regressions in Panel B are estimated on panel data across academic faculties and funding periods. All regressions include uni-specific fixed effects (α_j), common time effects (α_g), and unit-specific linear trends ($\alpha_j \cdot g$). Robust standard errors, clustered by field or faculty, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

15 pp

10 pp

5 pp

0 pp

Mean: 6.2%

Substitute Women

5 pp

0 %

5 %

10 %

15 %

Share AA Hiring

Figure 9: Policy Effect Estimates – Visual

Note: This figure displays a binscatter plot constructed from the residualized values of the dependent variable (Δf_{jg}) and the share of AA-funded hires, f_{jg}^{AA} . To generate the plot, both variables are first residualized with respect to the covariates in Equation (POLICY); the residuals are then binned into equally spaced intervals, with the mean value of the dependent variable computed for each bin. The red cross marks the overall mean share of AA hires across all funding periods, while the two grey arrows indicate the two extreme cases for π .

6 Conclusion

This paper studies the impact of hiring a female professor. I address the endogeneity in hiring decisions by leveraging the introduction of the *Professorinnenprogramm*, an affirmative action policy by the German Ministry of Education. The program provides a five-year subsidy of up to 825,000 Euros (165,000 Euros annually) to cover the costs associated with the initial appointment of women to permanent full professorships. Since its inception in 2008, the program has facilitated the appointment of 845 women as full professors, accounting for 12% of all female appointments to full professorships, with a total expenditure of 820 million Euros. For identification, I employ an instrumental variable design using administrative data on all academic personnel employed at public German universities from 2002 to 2023. I utilize the program's requirement that subsidized appointments must eventually be converted into permanent positions, which makes departments with high retirement probabilities during the subsidy period marginally more likely to appoint a woman as a full professor.

My analysis suggests three lessons about the impact of appointing a female professor. First, exposure to a female professor increases the share of female PhD students by 18%. This effect is primarily driven by students who completed their undergraduate studies in the same department, suggesting that female professors act as role models and mentors for aspiring female academics. Notably, I do not observe changes in the hiring patterns for senior academic positions. Second, exposure to a female professor increases the number of female co-authors among junior men, mainly through collaboration with the newly hired woman's peer network. Third, I document that research output and research direction remain unaffected by the presence of an additional female professor.

When considering affirmative action policies, policymakers must weigh these benefits against the estimated costs of 2.2 million Euros per additional female professor.

References

- Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When Should You Adjust Standard Errors for Clustering?" *Quarterly Journal of Economics*, 138(1): 1–35.
- Ahern, Kenneth R, and Amy K Dittmar. 2012. "The Changing of the Boards: The Impact on Firm Valuation of Mandated Female Board Representation." Quarterly Journal of Economics, 127(1): 137–197.
- Anderson, Theodore W, and Herman Rubin. 1949. "Estimation of the Parameters of a single Equation in a Complete System of Stochastic Equations." *Annals of Mathematical Statistics*, 20(1): 46–63.
- **Angrist**, **Joshua**, and **Michal Kolesár**. 2021. "One Instrument to Rule Them All: The Bias and Coverage of Just-ID IV." *NBER Working Paper*, 29417.
- Antecol, Heather, Kelly Bedard, and Jenna Stearns. 2018. "Equal but Inequitable: Who Benefits from Gender-neutral Tenure Clock Stopping Policies?" *American Economic Review*, 108(9): 2420–41.
- Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva. 2017. "Does the Gender Composition of Scientific Committees Matter?" American Economic Review, 107(4): 1207–38.
- Bagues, Manuel, Milan Makany, Giulia Vattuone, and Natalia Zinovyeva. 2023. "Women in Top Academic Positions: Is there a Trickle-down Effect?" Unpublished.
- Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, and Petia Topalova. 2009. "Powerful Women: Does Exposure Reduce Bias?" Quarterly Journal of Economics, 124(4): 1497–1540.
- Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "High-dimensional Methods and Inference on Structural and Treatment Effects." *Journal of Economic Perspectives*, 28(2): 29–50.
- Beneito, Pilar, José E Boscá, Javier Ferri, and Manu García. 2021. "Gender Imbalance across Subfields in Economics: When Does it Start?" *Journal of Human Capital*, 15(3): 469–511.
- Bertrand, Marianne, Sandra E Black, Sissel Jensen, and Adriana Lleras-Muney. 2019. "Breaking the Glass Ceiling? The Effect of Board Quotas on Female Labour Market Outcomes in Norway." *Review of Economic Studies*, 86(1): 191–239.
- Besley, Timothy, Olle Folke, Torsten Persson, and Johanna Rickne. 2017. "Gender Quotas and the Crisis of the Mediocre Man: Theory and Evidence from Sweden." *American Economic Review*, 107(8): 2204–2242.

- Bhalotra, Sonia, Irma Clots-Figueras, and Lakshmi Iyer. 2018. "Pathbreakers? Women's Electoral Success and Future Political Participation." *The Economic Journal*, 128(613): 1844–1878.
- **Bhavnani**, Rikhil R. 2017. "Do the Effects of Temporary Ethnic Group Quotas Persist? Evidence from India." *American Economic Journal: Applied Economics*, 9(3): 105–123.
- Blau, Francine D, Janet M Currie, Rachel TA Croson, and Donna K Ginther. 2010. "Can Mentoring Help Female Assistant Professors? Interim Results from a Randomized Trial." *American Economic Review*, 100(2): 348–52.
- BMJ, Bundesministerium der Justiz. 2024. "Gesetz über die Versorgung der Beamten und Richter des Bundes (Beamtenversorgungsgesetz BeamtVG)." URL: https://www.gesetze-im-internet.de/beamtvg/BJNR024850976.html, Accessed: 2024-06-03.
- Bound, John, David A Jaeger, and Regina M Baker. 1995. "Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable Is Weak." *Journal of the American Statistical Association*, 90(430): 443–450.
- Bundesanzeiger, Bundesministerium für Bildung und Forschung. 2018. "Richtliniezur Umsetzung des Professorinnenprogramms des Bundes und der Länder." URL: https://www.bundesanzeiger.de/pub/de/amtliche-veroeffentlichung?2, Accessed: 2022-06-24.
- Bundesministerium für Bildung und Forschung. 2008. "Bekanntmachung des Bundesministeriums für Bildung und Forschung von Richtlinien zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen." URL: https://www.gwk-bonn.de/presseaktuelles/presse-archiv, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2012. "Bekanntmachung des Bundesministeriums für Bildung und Forschung von Richtlinien zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm II." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2012/12/797_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2018. "Bekanntmachung Richtlinie zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm III. Bundesanzeiger vom 21.02.2018." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2018/02/1600_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2022. "Bekanntmachung Richtlinie zur Umsetzung des Professorinnenprogramms des Bundes und der

- Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm 2030." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2023/02/2023-02-02-Bekanntmachung-Professorinnenprogramm.html#searchFacets, Accessed: 2024-09-19.
- Bundesregierung, Die. 2023. "Förderkatalog." URL: https://foerderportal.bund.de/foekat/jsp/SucheAction.do?actionMode=searchmask, Accessed: 2023-10-24.
- **BW-MF, Baden-Württemberg Ministerium der Finanzen.** 2022. "Staatshaushaltsplan für 2022 Einzelplan 14 Ministerium für Wissenschaft, Forschung und Kunst." Accessed: 2024-06-03.
- Card, David, Stefano DellaVigna, Patricia Funk, and Nagore Iriberri. 2020. "Are Referees and Editors in Economics Gender Neutral?" Quarterly Journal of Economics, 135(1): 269–327.
- Carnes, Molly, Patricia G Devine, Linda Baier Manwell, Angela Byars-Winston, Eve Fine, Cecilia E Ford, Patrick Forscher, Carol Isaac, Anna Kaatz, Wairimu Magua, et al. 2015. "Effect of an Intervention to Break the Gender Bias Habit for Faculty at One Institution: A Cluster Randomized, Controlled Trial." Academic medicine: journal of the Association of American Medical Colleges, 90(2): 221.
- Carrell, Scott E, Marianne E Page, and James E West. 2010. "Sex and Science: How Professor Gender Perpetuates the Gender Gap." Quarterly Journal of Economics, 125(3): 1101–1144.
- Carrell, Scott E, Mark Hoekstra, and James E West. 2015. "The Impact of Intergroup Contact on Racial Attitudes and Revealed Preferences." NBER Working Paper, , (20940).
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-wage Jobs." *Quarterly Journal of Economics*, 134(3): 1405–1454.
- Chari, Anusha, and Paul Goldsmith-Pinkham. 2017. "Gender Representation in Economics Across Topics and Time: Evidence from the NBER Summer Institute." NBER Working Paper, , (w23953).
- Chattopadhyay, Raghabendra, and Esther Duflo. 2004. "Women as Policy Makers: Evidence from a Randomized Policy Experiment in India." *Econometrica*, 72(5): 1409–1443.
- CHE Hochschuldaten. 2024. "Studierende in Deutschland." URL: https://hochschuldaten.che.de/deutschland/studierende-in-deutschland/#: ~: text=Die%20meisten%20Studierenden%20(58%2C2,FH)%20eingeschrieben., Accessed: 2024-06-03.
- Chen, Le-Yu, and Sokbae Lee. 2021. "Binary Classification with Covariate Selection Through ℓ_0 -penalised Empirical Risk Minimisation." *Econometrics Journal*, 24(1): 103–120.

- **Dahl, Gordon B, Andreas Kotsadam, and Dan-Olof Rooth.** 2021. "Does Integration Change Gender Attitudes? The Effect of Randomly Assigning Women to Traditionally Male Teams." *Quarterly Journal of Economics*, 136(2): 987–1030.
- de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2023. "Two-way Fixed Effects and Differences-in-Differences Estimators with Several Treatments." *Journal of Econometrics*, 236(2): 105480.
- De Paola, Maria, Vincenzo Scoppa, and Rosetta Lombardo. 2010. "Can Gender Quotas Break Down Negative Stereotypes? Evidence from Changes in Electoral Rules." *Journal of Public Economics*, 94(5-6): 344–353.
- **Deschamps, Pierre.** 2018. "Gender Quotas in Hiring Committees: A Boon or a Bane for Women?" Sciences Po LIEPP Working Paper, 82.
- Destatis, Federal Statistical Office of Germany. 2018. "Hochschulpersonalstatistik." Administrative data. Information on how to request the data can be found at https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Hochschulen/Methoden/Erlaeuterungen/hochschulen.html.
- Devine, Patricia G, Patrick S Forscher, William TL Cox, Anna Kaatz, Jennifer Sheridan, and Molly Carnes. 2017. "A Gender Bias Habit-breaking Intervention Led to Increased Hiring of Female Faculty in STEMM Departments." *Journal of Experimental Social Psychology*, 73: 211–215.
- **Dolado, Juan J, Florentino Felgueroso, and Miguel Almunia.** 2012. "Are Men and Women-economists Eevenly Distributed across Research Fields? Some New Empirical Evidence." *SERIEs*, 3: 367–393.
- Dube, Arindrajit, Daniele Girardi, Oscar Jorda, and Alan M Taylor. 2023. "A Local Projections Approach to Difference-in-Differences Event Studies." *American Economic Review*.
- Dupas, Pascaline, Alicia Modestino, Muriel Niederle, Justin Wolfers, et al. 2021. "Gender and the Dynamics of Economics Seminars." *NBER Working Paper*, , (28494).
- Eberhard Karls Universität Tübingen. 2019. "Professur (W3) für Kunstgeschichte." URL: https://uni-tuebingen.de/fakultaeten/philosophische-fakultaet/fakultaet/ausschreibungenstellenangebote/professuren/w3/, Accessed: 2024-09-19.
- European Commission, Directorate General for Research. 2021. "Gender in Research and Innovation: Statistics and Indicators." URL: https://op.europa.eu/en/web/eu-law-and-publications/publication-detail/-/publication/67d5a207-4da1-11ec-91ac-01aa75ed71a1, Accessed: 2022-05-26.
- Flabbi, Luca, Mario Macis, Andrea Moro, and Fabiano Schivardi. 2019. "Do Female Executives Make a Difference? The Impact of Female Leadership on Gender Gaps and Firm Performance." *Economic Journal*, 129(622): 2390–2423.

- Friedman, Jerome, Trevor Hastie, and Rob Tibshirani. 2010. "Regularization Paths for Generalized Linear Models via Coordinate Descent." *Journal of Statistical Software*, 33(1): 1.
- Gemeinsame Wissenschaftskonferenz. 2013–2022. "Presse-Archiv." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2008/03/327_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Ginther, Donna K, Janet M Currie, Francine D Blau, and Rachel TA Croson. 2020. "Can Mentoring Help Female Assistant Professors in Economics? An Evaluation by Randomized Trial." Vol. 110, 205–09.
- Gonsalkorale, Karen, Jeffrey W Sherman, and Karl Christoph Klauer. 2009. "Aging and Prejudice: Diminished Regulation of Automatic Race Bias Among Older Adults." *Journal of Experimental Social Psychology*, 45(2): 410–414.
- **Grootendorst, Maarten.** 2022. "BERTopic: Neural Topic Modeling With a Class-based TF-IDF Procedure." arXiv Pre-print, 2203.05794.
- Guarino, Cassandra M, and Victor MH Borden. 2017. "Faculty Service Loads and Gender: Are Women Taking Care of the Academic Family?" Research in Higher Education, 58(6): 672–694.
- Hansen, Bruce. 2022. Econometrics. Princeton University Press.
- Hochschulverband, Deutscher, ed. 2002–2022. Hochschullehrer Verzeichnis Universitäten Deutschland. De Gruyter Saur.
- Hoogendoorn, Sander, Hessel Oosterbeek, and Mirjam Van Praag. 2013. "The Impact of Gender Diversity on the Performance of Business Teams: Evidence from a Field Experiment." *Management Science*, 59(7): 1514–1528.
- HRK, Hochschulrektorenkonferenz. 2024. "Hochschulfinanzierung." URL: https://www.hrk.de/themen/hochschulsystem/hochschulfinanzierung/, Accessed: 2024-06-03.
- **Janys, Lena.** 2024. "Testing the Presence of Implicit Hiring Quotas with Application to German Universities." Review of Economics and Statistics, 106(3): 627–637.
- **Jensen, Robert, and Emily Oster.** 2009. "The Power of TV: Cable Relevision and Women's Status in India." *Quarterly Journal of Economics*, 124(3): 1057–1094.
- Kim, Daehyun, and Laura T Starks. 2016. "Gender Diversity on Corporate Boards: Do Women Contribute Unique Skills?" *American Economic Review*, 106(5): 267–71.
- Kleemans, Marieke, and Rebecca L Thornton. 2021. "Who Belongs? The Determinants of Selective Membership into the National Bureau of Economic Research." Vol. 111, 117–22.
- Lee, David S, Justin McCrary, Marcelo J Moreira, and Jack Porter. 2022. "Valid t-ratio Inference for IV." American Economic Review, 112(10): 3260–90.

- **Lewicki, Pawel.** 1983. "Self-image Bias in Person Perception." *Journal of personality and social psychology*, 45(2): 384.
- Matsa, David A, and Amalia R Miller. 2013. "A Female Style in Corporate Leadership? Evidence from Quotas." American Economic Journal: Applied Economics, 5(3): 136–169.
- May, Ann Mari, Mary G McGarvey, and David Kucera. 2018. "Gender and European Economic Policy: A Survey of the Views of European Economists on Contemporary Economic Policy." *Kyklos*, 71(1): 162–183.
- Mengel, Friederike, Jan Sauermann, and Ulf Zölitz. 2019. "Gender Bias in Teaching Evaluations." *Journal of the European Economic Association*, 17(2): 535–566.
- Mimno, David, Hanna Wallach, Edmund Talley, Miriam Leenders, and Andrew McCallum. 2011. "Optimizing Semantic Coherence in Topic Models." 262–272.
- Ministerium für Wissenschaft, Forschung und Kunst Baden-Württemberg. 2020. "Stellenplan für Beamtinnen und Beamte im Landesbetrieb Universität Mannheim." URL: https://www.statistik-bw.de/shp/2020-21/pages/Epl14/ST/epl14_1420_st.pdf, Accessed: 2024-09-19.
- National Health & Medical Research Council. 2022. "Working towards gender equity in Investigator Grants." URL: https://www.nhmrc.gov.au/about-us/news-centre/working-towards-gender-equity-investigator-grants, Accessed: 2024-06-19.
- NRW, Gesetz über die Hochschulen des Landes Nordrhein-Westfalen. 2014. "§37a Gewährleistung der Chancengerechtigkeit von Frauen und Männern bei der Berufung von Professorinnen und Professoren." URL: https://recht.nrw.de/lmi/owa/br_bes_detail?sg=0&menu=0&bes_id=28364&anw_nr=2&aufgehoben=N&det_id=643733, Accessed: 2024-06-24.
- **Nygaard, Knut.** 2011. "Forced Board Changes: Evidence from Norway." *NHH Deptartment of Economics Discussion Paper*, , (5).
- OpenAI. 2024. "ChatGPT-4: Conversational AI powered by OpenAI." Accessed: 2024-06-27.
- **Porter, Catherine, and Danila Serra.** 2020. "Gender Differences in the Choice of Major: The Importance of Female Role Models." *American Economic Journal: Applied Economics*, 12(3): 226–54.
- Priem, Jason, Heather Piwowar, and Richard Orr. 2022. "OpenAlex: A Fully-open Index of Scholarly Works, Authors, Venues, Institutions, and Concepts." arXiv Pre-print, 2205.01833.

- Reimers, Nils, and Iryna Gurevych. 2019. "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks." Association for Computational Linguistics.
- Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature." *Journal of Econometrics*, 235(2): 2218–2244.
- Sarsons, Heather, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. 2021. "Gender Differences in Recognition for Group Work." *Journal of Political Economy*, 129(1): 101–147.
- Scopus, Elsevier. 2023. "CiteScore 2023." URL: https://www.scopus.com/sources, Accessed: 2024-06-24.
- Siniscalchi, Marciano, and Pietro Veronesi. 2020. "Self-image Bias and Lost Talent." NBER Working Paper, 28308.
- Siyanova-Chanturia, Anna, Paul Warren, Francesca Pesciarelli, and Cristina Cacciari. 2015. "Gender Stereotypes Across the Ages: On-line Processing in School-age Children, Young and Older Adults." Frontiers in Psychology, 6: 1388.
- Staiger, Douglas, and James H Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica*, 557–586.
- Swiss National Science Foundation. 2021. "Quoten für mehr Gleichstellung in der Forschung." URL: https://www.snf.ch/de/kjCKYzJgvuNWbsf2/news/news-210205-quoten-fuer-mehr-gleichstellung-in-der-forschung, Accessed: 2024-06-19.
- Vernos, Isabelle. 2013. "Quotas Are Questionable." Nature, 495(7439): 39–39.
- Wallon, Gerlind, Sandra Bendiscioli, and Michele S Garfinkel. 2015. "Exploring Quotas in Academia." *URL: www. embo. org/documents/science_policy/exploring_quotas.* pdf, Accessed: 2024-06-24.
- Whelan, Jennifer, and Robert Wood. 2012. "Targets and Quotas for Women in Leadership: A Global Review of Policy, Practice and Psychological Research." Gender Equality Project, Centre for Ethical Leadership, Melbourne Business School.
- Wing, Coady, Seth M Freedman, and Alex Hollingsworth. 2024. "Stacked Difference-in-Differences." NBER Working Paper, , (32054).

A Additional Tables

Table A.1: Public Universities by State

No.	State	University	No.	State	University
1	BB	Brandenburg University of Technology	43	NI	Osnabrück University
2	$^{\mathrm{BB}}$	European University Viadrina Frankfurt	44	NI	Technical University of Braunschweig
3	$^{\mathrm{BB}}$	Film University Babelsberg	45	NI	University of Göttingen
4	$^{\mathrm{BB}}$	University of Potsdam	46	NI	University of Hildesheim
5	BE	Free University of Berlin	47	NI	University of Lüneburg
6	$_{ m BE}$	Humboldt University of Berlin	48	NI	University of Oldenburgurg
7	BE	Technical University of Berlin	49	NI	University of Vechta
8	$_{\mathrm{BW}}$	Heidelberg University	50	NI	University of Veterinary Medicine
9	$_{\mathrm{BW}}$	Karlsruhe Institute of Technology	51	NW	Bielefeld University
10	$_{\mathrm{BW}}$	University of Freiburg	52	NW	German Sport University Cologne
11	$_{\mathrm{BW}}$	University of Hohenheim	53	NW	Ruhr University Bochum
12	$_{\mathrm{BW}}$	University of Konstanz	54	NW	RWTH Aachen University
13	$_{\mathrm{BW}}$	University of Mannheim	55	NW	Technical University of Dortmund
14	$_{\mathrm{BW}}$	University of Stuttgart	56	NW	University of Bonn
15	$_{\mathrm{BW}}$	University of Tübingen	57	NW	University of Cologne
16	BY	Bundeswehr University Munich	58	NW	University of Duisburg-Essen
17	BY	Catholic University of Eichstätt-Ingolstadt	59	NW	University of Dusseldorf
18	BY	Technical University of Munich	60	NW	University of Hagen
19	BY	University of Augsburg	61	NW	University of Münster
20	$_{ m BY}$	University of Bamberg	62	NW	University of Paderborn
21	BY	University of Bayreuth	63	NW	University of Siegen
22	$_{ m BY}$	University of Erlangen-Nuremberg	64	NW	University of Wuppertal
23	BY	University of Munich	65	RP	University of Administrative Sciences
24	$_{ m BY}$	University of Passau	66	RP	University of Kaiserslautern
25	BY	University of Regensburg	67	RP	University of Koblenz and Landau
26	BY	University of Ulm	68	RP	University of Mainz
27	BY	University of Würzburg	69	RP	University of Trier
28	$^{\mathrm{HB}}$	University of Bremen	70	$_{\mathrm{SH}}$	Kiel University
29	$_{ m HE}$	Goethe University Frankfurt	71	$_{ m SH}$	University of Flensburg
30	$_{ m HE}$	Technical University of Darmstadt	72	$_{\mathrm{SH}}$	University of Lübeck
31	$_{ m HE}$	University of Giessen	73	SL	Saarland University
32	$_{ m HE}$	University of Kassel	74	SN	Chemnitz University of Technology
33	$_{ m HE}$	University of Marburg	75	SN	Dresden University of Technology
34	$_{\mathrm{HH}}$	HafenCity University Hamburg	76	SN	Freiberg University of Mining
35	$_{\mathrm{HH}}$	Hamburg University of Technology	77	SN	Leipzig University
36	$_{\mathrm{HH}}$	Helmut Schmidt University	78	ST	University Halle-Wittenberg
37	$_{\mathrm{HH}}$	University of Hamburg	79	ST	University Magdeburg
38	MV	University of Greifswaldd	80	TH	Bauhaus University Weimar
39	MV	University of Rostock	81	TH	Ilmenau University of Technology
40	NI	Clausthal University of Technology	82	TH	University of Erfurt
41	NI	Hannover Medical School	83	TH	University of Jena
42	NI	Leibniz University Hannover			

Note: The table presents a list of all public universities along with their corresponding states included in the analysis, as listed in the 'Hochschulpersonalstatistik' (Destatis, 2018).

Table A.2: Subsidy Characteristics by Faculty and Field

				Subsidized Hirings		Subsidy Characteristics		
No.	Faculty	Field	Share	Total	Duration	Amount	Regular	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
1	Humanities	Media Studies	5.57	24	4.68	351	0.71	
2	Humanities	Language Studies	5.10	22	4.84	336	0.91	
3	Humanities	German Studies	5.10	22	4.63	299	0.73	
4	Humanities	History	3.71	16	4.52	300	0.81	
5	Humanities	Philosophy	2.32	10	4.26	298	0.60	
6	Humanities	Theology	1.39	6	4.74	324	0.83	
7	Sports Sciences	Sport	1.62	7	4.63	353	0.57	
8	Social Sciences	Educational Sciences	8.58	37	4.81	344	0.89	
9	Social Sciences	Business	6.73	29	4.65	346	0.90	
10	Social Sciences	Sociology	5.80	25	4.29	301	0.72	
11	Social Sciences	Legal Sciences	4.18	18	4.80	367	0.83	
12	Social Sciences	Psychology	3.94	17	4.49	335	0.76	
13	Social Sciences	Political Sciences	3.25	14	4.51	310	0.71	
14	Social Sciences	Economics	2.09	9	4.92	394	0.78	
15	Natural Sciences	Biology	5.80	25	4.72	356	0.76	
16	Natural Sciences	Chemistry	5.34	23	4.76	347	0.78	
17	Natural Sciences	Mathematics	3.71	16	4.90	367	0.69	
18	Natural Sciences	Physics	2.32	10	4.92	381	0.60	
19	Natural Sciences	Geography	2.09	9	4.31	338	0.56	
20	Life Sciences	Medicine	3.94	17	4.81	333	0.41	
21	Life Sciences	Dentistry	0.46	2	4.92	375	0.50	
22	Agricultural Sciences	Biotechnology	1.62	7	4.92	389	1.00	
23	Agricultural Sciences	Forestry	0.93	4	4.44	313	0.75	
24	Agricultural Sciences	Veterinary Medicine	0.23	1	2.00	171	0.00	
25	Agricultural Sciences	Nutrital Sciences	0.00	0	-	-	-	
26	Engineering	Architecture	3.25	14	4.88	362	0.79	
27	Engineering	Computer Science	3.02	13	4.35	342	0.23	
28	Engineering	Mechanical Engineering	1.39	6	4.92	379	1.00	
29	Engineering	Electrical Engineering	1.39	6	4.92	369	0.33	
30	Engineering	Civil Engineering	1.16	5	4.82	345	0.40	
31	Engineering	Mining	0.23	1	4.92	375	1.00	
32	Art Sciences	Visual Arts	2.09	9	4.68	311	0.89	
33	Art Sciences	Musicology	1.62	7	4.35	307	0.86	

Note: The table presents a list of all fields and their corresponding faculties included in the analysis, as listed in the 'Hochschulpersonalstatistik' (Destatis, 2018). Columns (4) and (5) provide the share and number of subsidized appointments by field, while columns (6) to (8) detail the subsidy duration, amount, and type by field.

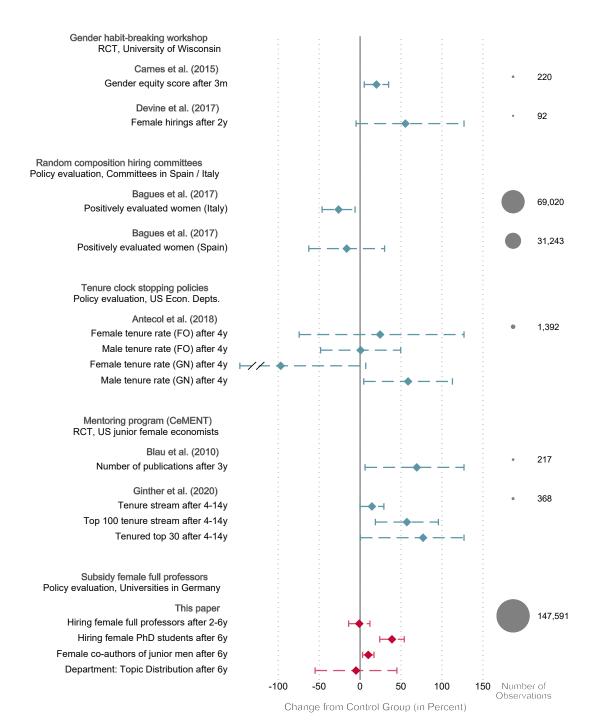
Table A.3: Full Professor Characteristics by Gender

		Men			Women		Difference
	Mean	SD	N	Mean	SD	N	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Field							
Humanities	0.170	0.376	183, 244	0.314	0.464	45, 314	0.145***
Sports	0.012	0.107	183,244	0.001	0.098	45,314	-0.002***
Social Sciences	0.238	0.426	183,244	0.302	0.459	45,314	0.063***
Natural Sciences	0.297	0.457	183,244	0.185	0.388	45,314	-0.112***
Health Sciences	0.024	0.154	183,244	0.049	0.216	45,314	0.025***
Agricultural Sciences	0.028	0.164	183,244	0.028	0.164	45,314	0.000
Engineering	0.200	0.400	183,244	0.083	0.276	45,314	-0.118***
Arts	0.024	0.154	183,244	0.049	0.216	45,314	0.025***
Panel B: Compensation							
C4	0.315	0.465	183,244	0.152	0.359	45,314	-0.143***
C3	0.169	0.374	183,244	0.164	0.370	45,314	0.008***
W3	0.326	0.469	183,244	0.349	0.477	45,314	-0.001
W2	0.152	0.359	183,244	0.273	0.445	45,314	0.111***
Full-time	0.981	0.137	183,244	0.967	0.179	45,314	-0.014***
Panel C: Financing Source							
Regular Budget	0.876	0.330	183, 244	0.818	0.385	45, 314	-0.053***
DFG Funds	0.006	0.075	183,244	0.009	0.095	45,314	0.003***
EU Funds	0.002	0.046	183,244	0.005	0.069	45,314	0.002***
Excellence Initiative	0.006	0.078	183,244	0.010	0.099	45,314	0.003***
Panel D: Leadership Position	ns						
Rector	0.000	0.015	42, 289	0.000	0.121	13,066	0.000
Prorector	0.003	0.058	42,289	0.006	0.121	13,066	0.003***
President	0.000	0.005	42,289	0.000	0.121	13,066	0.000
Vice-President	0.004	0.067	42,289	0.008	0.121	13,066	0.004***
Chancellor	0.000	0.000	42,289	0.000	0.000	13,066	0.000
Panel E: Pre-Tenure Position	n						
Ass. Prof. w/o TT	0.035	0.184	36, 229	0.062	0.241	10,376	0.027***
Ass. Prof. with TT	0.012	0.108	36,229	0.024	0.154	10,376	0.012***
W2 w/o TT	0.034	0.180	36,229	0.046	0.209	10,376	0.012***
W2 with TT	0.008	0.087	36,229	0.011	0.103	10,376	0.003***
Habilitation	0.602	0.490	36,229	0.541	0.498	10,376	-00.060***
Habilitation (equivalent)	0.207	0.405	36,229	0.202	0.402	10,376	0.003***
Panel F: Individual Characte	eristics						
Age	51.825	8.190	183, 244	49.163	7.806	45, 314	-2.678***
Age Tenure	40.775	5.010	114, 156	41.231	5.089	25,074	0.595***
Age Highest Degree	37.564	3.969	26,451	38.902	4.471	7,201	1.339***
German	0.925	0.264	183,244	0.911	0.285	45,314	-0.013***
PhD Highest Degree	0.338	0.473	41,391	0.400	0.490	12,690	0.061***
Habilitation Highest Degree	0.639	0.480	41,391	0.567	0.495	12,690	-0.071***

Note: The table shows descriptive statistics for the sample of full professors from 2008–2022. The difference reported in column (7) is the coefficient obtained by regressing an indicator for women on the respective variable controlling for year fixed effects. *** p < 0.01, ** p < 0.05, * p < 0.1.

B Additional Figures

Figure B.1: Literature Overview



Note: Effect and sample sizes for the evaluation of the gender-habit breaking workshop correspond to Table 3 in Carnes et al. (2015) and Table 1 in Devine et al. (2017). Effect and sample sizes for the random allocation of hiring committees in Italy and Spain are taken from Table 1 in Bagues, Sylos-Labini and Zinovyeva (2017). Effect and sample sizes for the evaluation of tenure clock stopping policies are taken from Table 2 in Antecol, Bedard and Stearns (2018). Effect and sample sizes for the evaluation of the CeMENT mentoring program are retrieved from Table 2 in Blau et al. (2010) and Table 3 in Ginther et al. (2020). Treatment effects across studies are made comparable by considering the main specification of each paper and computing the percent increase from the pre-treatment control-group mean.

Figure B.2: Employment Plan University of Mannheim

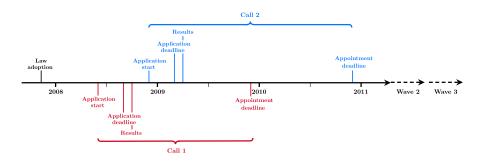
Ministerium für Wissenschaft, Forschung und Kunst 1420 Universität Mannheim

Tit. FKZ Bes.Gr.		Stellenzah l			
Entg Gr	Bezeichnung	2019	2020	2021	
	3 3 3				
682 01 133	Stellenplan für Beamtinnen und Beamte im Landesbetrieb Universität Mannheim				
	Vgl. Vermerke bei Kap. 1402 Tit. 422 01 und 428 01. Die in der Stellenübersicht im Wirtschaftsplan für Arbeitnehmerinnen und Arbeitnehmer aufgeführten Stellen dürfen, soweit es dienstlich notwendig ist, bzgl. Dienstarten und Wertigkeit anderweitig bis Entg.Gr. 14 TV-L besetzt werden. Voraussetzung ist Kostenneutralität und Einhaltung des Stellensolls.				
	a) Planstellen für Beamtinnen und Beamte im Landesbetrieb				
W 3	Rektor/Präsident	1,0	1,0	1,0	
W 3	Kanzler	1,0	1,0	1,0	
W 3	Universitätsprofessor	140,0	152,0	151,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2021 4)	* 0,0	* 1,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.08.2043 6)	* 0,0	* 1,0	* 1,0	
	kw nach Ablauf der Förderung, spätestens ab 01.02.2037 5)	* 0,0	* 1,0	* 1,0	
	kw nach Ablauf der Förderung, spätestens ab 01.08.2032 1)	* 0,0	* 1,0	* 1,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2020 5)	* 1,0	* 0,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2022 1)	* 1,0	* 0,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2022 2)	* 3,0	* 3,0	* 3,0	
W 2	Universitätsprofessor	3,0	3,0	3,0	
W 1	Professor als Juniorprofessor	57,5	61,5	56,5	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2021 9)	* 2,0	* 2,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2021 7)	* 0,0	* 1,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.09.2020 8)	* 0,0	* 1,0	* 0,0	
	kw nach Ablauf der Förderung, spätestens ab 01.01.2025 11)	* 0,0	* 2,0	* 2,0	
	kw nach Ablauf der Förderung, spätestens ab 01.03.2020 10)	* 1,0	* 1,0	* 0,0	
A 16	Leitender Regierungsdirektor	0,0	1,0	1,0	
A 16	Leitender Akademischer Direktor	1,0	1,0	1,0	
A 16	Leitender Bibliotheksdirektor	1,0	1,0	1,0	
A 15	Regierungsdirektor	5,0	5,0	5,0	
A 15	Akademischer Direktor	7,0	7,0	7,0	
A 15	Bibliotheksdirektor	3,0	3,0	3,0	
A 14	Oberregierungsrat	2,0	1,0	1,0	
A 14	Akademischer Oberrat	41,5	41,5	41,5	
A 14	Oberbibliotheksrat	5,0	5,0	5,0	
A 13	Regierungsrat	7,0	7,0	7,0	
A 13	Akademischer Rat 3)	60,5	60,5	60,5	
A 13	Bibliotheksrat	3,0	3,0	3,0	
A 13	Oberamtsrat (Bi)	3,0	3,0	3,0	

-970-

Note: The figure displays an excerpt from the 2019 budget of the state of Baden-Wuerttemberg, listing the Employment Plan for the University of Mannheim (Ministerium für Wissenschaft, Forschung und Kunst Baden-Württemberg, 2020).

Figure B.3: Application Timeline



Note: The figure exemplary presents the timeline of application steps for the first two funding periods, as outlined in Gemeinsame Wissenschaftskonferenz (2013–2022). Each funding period includes an application phase, followed by a funding phase during which successfully evaluated universities can use subsidies to appoint up to three women to full professor positions.

Figure B.4: Job Advertisement Example – University of Tübingen



Philosophische Fakultät

Professur (W3) für Kunstgeschichte

Am Kunsthistorischen Institut der Universität Tübingen ist zum 01.10.2019 eine

Professur (W3) für Kunstgeschichte

zu besetzen.

Die Stelleninhaberin/Der Stelleninhaber soll das Fach in Forschung und Lehre in großer Breite vertreten. Erwartet wird ein ausgewiesener Forschungsschwerpunkt im Bereich der Kunst des Mittelalters; einschlägige Kompetenzen in der Architekturgeschichte sind erwünscht, aber nicht Voraussetzung. Neben der Beteiligung an allen kunsthistorischen Studiengängen werden die Fähigkeit und Bereitschaft zur interdisziplinären Zusammenarbeit und insbesondere zur Mitwirkung in interdisziplinären Forschungsverbünden der Fakultät erwartet.

Einstellungsvoraussetzungen sind die Habilitation oder gleichwertige wissenschaftliche Leistungen, international beachtete Publikationen sowie nachgewiesene didaktische Eignung.

Diese Professur wird im Rahmen des Professorinnenprogramms III des Bundes und der Länder ausgeschrieben. Eine Besetzung der Stelle erfolgt vorbehaltlich der Zuweisung der im Professorinnenprogramm III beantragten Mittel.

The professorship is being advertised as part of the Professorinnenprogramm III of the German federal and state governments. The position will be filled subject to the allocation of the funds requested through the Professorinnenprogramm III.

Qualifizierte internationale Wissenschaftlerinnen und Wissenschaftler sind ausdrücklich aufgefordert, sich zu bewerben.

Schwerbehinderte werden bei gleicher Eignung bevorzugt berücksichtigt.

Bewerbungen mit den üblichen Unterlagen (Lebenslauf, Zeugnisse, Schriftenverzeichnis, Verzeichnis der abgehaltenen Lehrveranstaltungen) sowie den selbst verfassten Monographien und bis zu 5 Aufsätzen sind möglichst in elektronischer Form bis zum 15.03.2019 zu richten an bewerbung@philosophie.uni-tuebingen.de (Postanschrift: Dekan der Philosophischen Fakultät, Keplerstr. 2, 72074 Tübingen). Rückfragen können direkt an den Dekan gerichtet werden (Prof. Dr. Jürgen Leonhardt, juergen.leonhardt@uni-tuebingen.de).

Professur (W3) für Kunstgeschichte

Am Kunsthistorischen Institut der Universität Tübingen ist zum 01.10.2019 eine **Note:** The figure displays a job advertisement from the Art History department at the University of Tübingen (Eberhard Karls Universitäts Tübingen K2012) sintended to be funded through the *Professorinnenprogramm*.

zu besetzen.

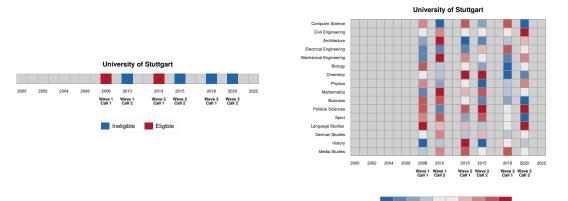
Die Stelleninhaberin/Der Stelleninhaber soll das Fach in Forschung und Lehre in großer Breite vertreten. Erwartet wird ein ausgewiesener Forschungsschwerpunkt im Bereich der Kunst des Mittelalters; einschlägige Kompetenzen in der Architekturgeschichte sind erwünscht, aber nicht Voraussetzung. Neben der Beteiligung an allen kunsthistorischen Studiengängen werden die Fähigkeit und Bereitschaft zur interdisziplinären Zusammenarbeit und insbesondere zur Mitwirkung in interdisziplinären Forschungsverbünden der Fakultät erwartet.

Figure B.5: Identifying Variation

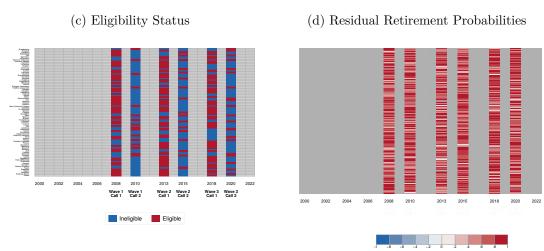
Panel A: University of Stuttgart

(a) Eligibility Status

(b) Residual Retirement Probabilities

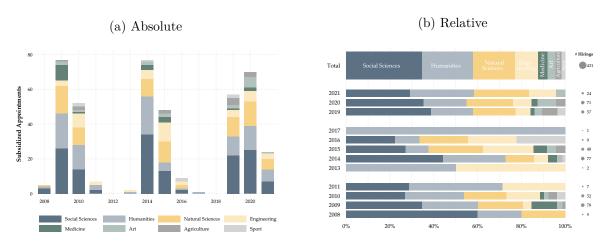


Panel B: All Universities



Note: Panel A of the figure illustrates the identifying variation for the University of Stuttgart. Figure B.5a displays the eligibility status of the University of Stuttgart across funding periods. Figure B.5b depicts residualized variation in department retirement probabilities for the University of Stuttgart across funding periods. Panel B of the figure illustrates the identifying variation across all universities. Figure B.5c displays the eligibility status of universities across funding periods. Figure B.5d depicts residualized variation in department retirement probabilities across funding periods, with each row representing a department within a university.

Figure B.6: Affirmative Action Appointments by Faculty and Year



Note: The figure shows the number of affirmative action appointments by year and faculty across public universities, as detailed in Appendix Table A.1. In total, the sample includes 431 subsidized appointments of women to full professor positions. Figure B.6a presents the absolute number of subsidized appointments, while Figure B.6b displays these numbers as a proportion of the total number of subsidized appointments per year.

1st Call 1st Call 2nd Call 2nd Call .8 Distributed Subsidies (in %) .6 .2 0 2010 2012 2014 2016 2020 2022 2008 2018

Figure B.7: Distributed Funds by Funding Period and Year

Note: The figure illustrates the share of funds utilized over time for each funding period. The share is calculated by summing the subsidies granted to all types of universities over time, as recorded in the Federal Government's funding portal (Bundesregierung, 2023), and dividing this total by the budget resources allocated for each funding period, as detailed in Table 3.

C Additional Analyses

C.A Text Analysis

To explore this possibility, I conduct a text analysis on all available application documents, which I gather by systemically searching all university webpages for *Professorinnen programm* application documents. In total I collect 247 documents: 143 covering eligible universities, 103 covering ineligible ones.

The analysis proceeds in two steps. First, I evaluate semantic similarity of application documents from positively and negatively evaluated universities. In particular, I evaluate whether the tone of application documents differs between the two cases or if they use different language to support their application. I measure semantic similarity through three measures. Subjectivity measures the degree to which a piece of text expresses personal opinions, feelings, or judgments, rather than factual information. It ranges from 0 to 1, where 0 indicates an objective, factual statement and 1 indicates a highly subjective, opinionated statement. Polarity is a measure of the sentiment expressed in a piece of text. It ranges from -1 to 1, where negative values indicate negative sentiment and positive values indicate positive sentiment. Lastly, I provide a measure of language similarity. To this end, I represent each application document as a word embedding. An embedding is a vector representation of a text body in continuous space. Application documents with similar embeddings are also likely to use similar language. To test for differences in embeddings between application documents of eligible and ineligible universities, I first retrieve the word embedding of each article using a pre-trained language model³². Next, I extract the first principal component across all application document embeddings. I standardize all three measures to mean zero and standard deviation one, such that a one unit increase corresponds to a one standard deviation increase of the respective measure.

To test for statistical differences along these measures I estimate the following regression equation

$$Y_{uq} = \alpha_u + \alpha_q + \beta \text{Eligible}_{uq} + \varepsilon_{uq} \tag{1}$$

where Y_{ug} indicates some text metric of application document submitted by university u in funding period g. Eligible_{ug} is an indicator equaling one if university u is positively evaluated in funding period g. Through α_u and α_g I account for unobserved university-specific and time-specific effects.

The estimates shown in Columns (1)–(3) of Table C.1 indicate that the application document do not differ along either dimension. Across all three measures I document a small and statistically insignificant effect indicating that application documents from eligible and ineligible universities use similar semantics and language.

Next, moving beyond semantics, I aim to analyze if the themes of application documents differs by eligibility status. In a first step, I display the most frequently used words in the application

³² In particular, I use the 'paraphrase-multilingual-MiniLM-L12-v2' language model, which paraphrases multilingual sentences and paragraphs as a 384 dimensional dense vector space.

Table C.1: Text Analysis of Application Documents

	Semantics			Topic Di	Topic Distribution		
	1st Principal Component	Subjectivity	Polarity	1st Principal Component	2nd Principal Component		
	(1)	(2)	(3)	(4)	(5)		
Eligible University	-0.027 (0.056)	0.067 (0.084)	0.024 (0.278)	0.031 (0.637)	-0.252 (0.206)		
Observations	134	134	134	134	134		
Fixed Effects University Funding Period	√ ✓	√ √	√ √	√ √	√ √		

Note: This table shows estimates from regressing various text-based metrics on an indicator of university eligibility. The sample includes all publicly available application documents of the Professorinnenprogramm. Columns (1)–(3) consider semantic metrics as described in Section C.A. Columns (4)–(5) consider the first two principal components of the topic model trained on the application documents. All specifications include university and funding period fixed effects. *** p < 0.01, ** p < 0.05, * p < 0.1.

documents in Appendix Figure C.1. The size of each word is proportional to its relative frequency within the application documents. Unsurprisingly, the application documents most frequently mention 'women'. To analyze the content structure in more detail, I proceed by training a topic model on the application documents. A topic model is a statistical model designed to discover abstract topics within a collection of documents or texts. It is employed in natural language processing and machine learning to identify the underlying themes or topics prevalent in a set of documents. The goal is to automatically extract meaningful patterns and associations among words for categorizing and understanding the content of text documents. Intuitively, a topic model algorithm computes a word embedding for each article and then clusters articles close in vector space.

Figure C.1: Application Documents – Wordcloud



Note: The figure displays wordclouds depicting the most frequently used words in the application documents discussed in Appendix Section C.A. All application documents have been translated into English, and common stopwords have been excluded. The size of each word is proportional to its relative frequency within the documents.

I train a topic model³³ on all available application documents. After training, I extract a topic distribution for each application document along the identified topics. To compare the topic distribution of application documents by eligibility status, I extract the first two principal components of the topic distribution and use them as outcome variables in Equation (1).

C.B Weak Instrument Considerations

It is well known that t-ratio tests over-reject when instruments are weak (Bound, Jaeger and Baker, 1995; Staiger and Stock, 1997). The discussion on dealing with potentially weak instruments revolves around two parameters: the first-stage F-statistic and the endogeneity coefficient ρ , measuring the correlation between structural and first-stage residuals. Within this framework, a high degree of endogeneity calls for a strong instrument, i.e., a high first-stage F-statistics. In contrast, 'low' endogeneity is reconcilable with a low first-stage F-statistic. In particular, conventional (unadjusted) IV standard errors sufficiently account for weak instruments unless endogeneity is 'extraordinarily high', defined as $|\rho| > .565$ (Angrist and Kolesár, 2021). However, because it might be challenging to bound ρ a priori, numerous frequentist methods exist to adjust standard errors and confidence intervals for potential inference distortions (Anderson and Rubin, 1949; Lee et al., 2022).

I address potential weak instrument concerns twofold. First, I report 95-percent confidence intervals $[\hat{\rho}_L, \hat{\rho}_U]$ of the endogeneity parameter ρ . Appendix Tables C.2 and C.3 show that my specification exhibits moderate to high levels of endogeneity, exceeding the threshold of $|\rho| > .565$ when considering my main specification. The high degree of endogeneity might be not surprising given that the hiring of professors is a highly endogenous process. At the same time, the high degree of endogeneity justifies my instrumental variable approach and offers an explanation for the stark difference between OLS and 2SLS estimates observed in Tables 7 and 8.

Complementing the bounding exercise on ρ , Appendix Tables C.2 and C.3 reports p-values of the Anderson-Rubin F-test (Anderson and Rubin, 1949) as well as tF-adjusted standard errors (Lee et al., 2022). The procedure by Anderson-Rubin yields confidence intervals with undistorted coverage for any pair of values ρ and F. On the other hand, tF-adjusted standard errors assume a worst-case endogeneity scenario, i.e., $|\rho|=1$, and accordingly adjust the conventional 2SLS standard errors by an adjustment factor based on the first-stage F-statistic and the considered significance level.³⁴ Under both procedures, my results stay significant at the 1-percent level even when considering a worst-case endogeneity scenario of $|\rho|=1$ as assumed when computing tF-adjusted standard errors.

³³ I use the 'BERTopic' Python module with default settings.

Both procedures yield correct coverage under arbitrarily weak instruments; however, the expected length of the Anderson-Rubin confidence interval is infinite, while the corresponding tF interval is finite (Lee et al., 2022).

Table C.2: Change in Hiring Patterns – Weak IV

	Junior F	aculty	Ph.D. St	tudents
	Ass. Professor	Post-Doc	Overall	Home
	(1)	(2)	(3)	(4)
Panel A: 2SLS Estim	ate			
Female Hiring	0.034 (0.121)	-0.006 (0.109)	0.098*** (0.028)	0.083*** (0.029)
Observations	147,591	147,591	147,591	147,591
Panel B: Weak IV C	onsiderations			
Endogeneity Parame $\max\{ \hat{ ho}_L , \hat{ ho}_U \}$	ter ρ 0.589	0.612	0.472	0.491
Anderson-Rubin Infe	erence 0.831	0.764	0.032	0.021
tF-adjusted Standard	l Errors			
5-percent Significance 1-percent Significance	(0.146) (0.161)	(0.142) (0.178)	(0.034) (0.041)	(0.033) (0.041)
Fixed Effects				
Department	\checkmark	\checkmark	\checkmark	\checkmark
$\mathrm{Field}\times\mathrm{Year}$	\checkmark	\checkmark	\checkmark	\checkmark
University \times Year	\checkmark	\checkmark	\checkmark	\checkmark

Note: Panel A displays 2SLS estimates based on Equation (IV2). Panel B reports three measures to discover and account for the presence of weak instruments. First, I report a bound on the endogeneity parameter ρ by following Online Appendix Section A.8.3 of Lee et al. (2022). In particular, I use 95-percent tF confidence intervals endpoints $[\hat{\beta}_L, \hat{\beta}_U]$ to compute the endpoints $\rho(\hat{\beta}_L)$ and $\rho(\hat{\beta}_U)$. Second, I report p-values of the Anderson-Rubin F-test of endogenous regressors (Anderson and Rubin, 1949). Third, I construct tF-adjusted standard errors for 5-percent and 1-percent significance levels using first-stage F-statistics and critical values provided in Lee et al. (2022). Robust standard errors, clustered by department and event, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, *** p < 0.05, ** p < 0.1.

Table C.3: Change in Collaboration Patterns – Weak IV

	All	Women	Men	Me	Men by Seniority (Quartiles)			
	1111	***************************************	111011	Q1	Q2	Q3	Q4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: 2SLS Estin	nate							
Female Hiring	0.019 (0.025)	0.011 (0.023)	0.028 (0.025)	0.074*** (0.027)	0.051** (0.024)	0.011 (0.023)	-0.004 (0.026)	
Observations	$147,\!591$	$147,\!591$	$147,\!591$	$147,\!591$	$147,\!591$	$147,\!591$	147,591	
Panel B: Weak IV C	onsiderati	ons						
Endogeneity Parame $\max\{ \hat{ ho}_L , \hat{ ho}_U \}$	eter ρ 0.464	0.764	0.452	0.552	0.489	0.452	0.689	
Anderson-Rubin Infe	erence 0.214	0.343	0.151	0.051	0.073	0.907	0.858	
tF-adjusted Standard	d Errors							
5-percent Significance 1-percent Significance	(0.034) (0.045)	(0.032) (0.041)	(0.035) (0.044)	(0.038) (0.048)	(0.033) (0.045)	(0.033) (0.045)	(0.036) (0.047)	
Fixed Effects								
Department	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
$Field \times Year$	\checkmark	\checkmark	\checkmark	✓	\checkmark	\checkmark	\checkmark	
University \times Year	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	

Note: Panel A displays 2SLS estimates based on Equation (IV2). Panel B reports three measures to discover and account for the presence of weak instruments. First, I report a bound on the endogeneity parameter ρ by following Online Appendix Section A.8.3 of Lee et al. (2022). In particular, I use 95-percent tF confidence intervals endpoints $[\hat{\beta}_L, \hat{\beta}_U]$ to compute the endpoints $\rho(\hat{\beta}_L)$ and $\rho(\hat{\beta}_U)$. Second, I report p-values of the Anderson-Rubin F-test of endogenous regressors (Anderson and Rubin, 1949). Third, I construct tF-adjusted standard errors for 5-percent and 1-percent significance levels using first-stage F-statistics and critical values provided in Lee et al. (2022). Robust standard errors, clustered by department and event, are reported in parentheses. Significance levels are indicated as follows: *** p < 0.01, *** p < 0.05, * p < 0.1.

C.C Quantifying the Impact of Affirmative Action

Model Framework Consider a model of academic fields $j \in J$ observed over two time periods, $t \in \{0, 1\}$. In the initial period (t = 0), each field has T_{j0} available positions and hires F_{j0} women. Over time, the total number of positions evolves according to a field-specific factor γ_j , so that in period t = 1 the total number of positions in field j is

$$T_{j1} = (1 + \gamma_j)T_{j0}.$$

Similarly, the model accounts for field-specific female hiring trends, captured by γ_i^F , such that

$$F_{j1} = (1 + \gamma_j^F) F_{j0}.$$

Modelling Affirmative Action In period t=1, an affirmative action (AA) initiative is introduced. This policy provides subsidies for female hires but does not increase the total number of available positions, so that T_{j1} remains unchanged. Let F_{j1}^{AA} denote the number of AA-funded female hires in field j. AA hires constitute only a fraction of the female hires that would have occurred in the absence of the policy, $F_{j1}^{AA} < (1 + \gamma_j^F)F_{j0}$. The total number and share of female hires in period t=1 can thus be written as

$$F_{j1} = (1 + \gamma_j^F)F_{j0} + \pi F_{j1}^{AA},$$

and

$$f_{j1} = \frac{1 + \gamma_j^F}{1 + \gamma_j} f_{j0} + \pi f_{j1}^{AA}.$$

Here $\pi \in [0, 1]$ captures the degree to which AA-funded hires substitute for other hires. Two extreme cases illustrate this interpretation. If $\pi = 0$, each AA hire fully replaces a woman who would have been hired anyway, so the total number of female hires remains unchanged. If $\pi = 1$, each AA hire displaces an otherwise male hire.

Candidate Pool Constraint Thus far, the models assume that there is an unlimited candidate pool in each field. However, in practice the number of suitable candidates is likely to be constrained – for instance, due to quality thresholds. To account for this, each field is assumed to have a time-variant pool of suitable candidates, with C_{jt}^F and C_{jt}^M denoting the numbers of available and suitable female and male candidates at time t, respectively. These pools are always sufficient to fill the available positions, i.e.,

$$C_{jt}^F \ge F_{jt}$$
 and $C_{jt}^M \ge M_{jt} \quad \forall j, t.$

In period t = 1, the maximum possible additional female hires attributable to AA are constrained by the number of available female candidates. Specifically, AA hires cannot exceed

$$\bar{F}_{j1}^{AA} = C_{j1}^F - (1 + \gamma_j^F) F_{j0}.$$

If $\pi F_{j1}^{AA} > \bar{F}_{j1}^{AA}$, all AA hires exceeding \bar{F}_{j1}^{AA} must substitute for women who would have been hired anyway. To reflect this constraint, I define the effective conversion rate $\bar{\pi}_j$ as

$$\bar{\pi}_j \equiv \pi \, \frac{\bar{F}_{j1}^{AA}}{F_{j1}^{AA}}.$$

which scales π by the proportion of AA hires that do not exceed the constraint.

Correspondingly, the change in the share of female hires from period t = 0 to t = 1 is given by

$$\Delta f_j = f_{j1} - f_{j0} = \underbrace{\left[\frac{1 + \gamma_j^F}{1 + \gamma_j} - 1\right] f_{j0}}_{\equiv \alpha_j} + \bar{\pi}_j f_{j1}^{AA}.$$

The first term, α_j , represents the baseline change in the female hiring share driven by the differential growth rates of female versus overall hires. The second term, $\bar{\pi}_j f_{j1}^{AA}$, captures the additional increase in female hires attributable to AA-funded positions.

D Additional Data

D.A Alternative Retirement Measures

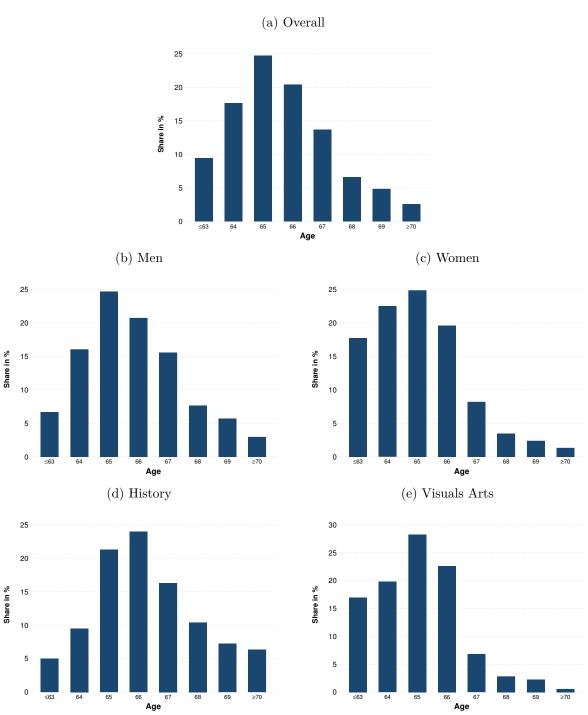
In Section 5.1, I show that my findings remain robust when using alternative retirement measures. Specifically, I construct binary indicators based on whether any department member reaches a certain age threshold, such as the statutory retirement age. While these binary measures yield estimates of similar size as the continuous measure, they are less statistically significant. I attribute this to two factors. First, my continuous approach accounts for cases where multiple professors in a department are nearing retirement by aggregating individual retirement probabilities. A binary model, on the other hand, cannot differentiate between departments with several impending retirements and those with only one. Second, a binary measure discards variation in retirement timing that the continuous measure is able to capture.

In particular, a binary approach would be reasonable if all professors retired precisely at the statutory retirement age. However, in Germany, professors have considerable flexibility in deciding when to retire. As shown in Appendix Figure D.1a, most professors retire at the age of 65, around 25%.³⁵ Besides, retirement ages vary widely, with the distribution being notably right-skewed: only around 25% of professors retire before 65, while around 50% retire after. Therefore, for example, a binary indicator with a cutoff at 65 would misclassify about 25% of retirement decisions as false negatives.

Retirement timing also varies across other dimensions. Appendix Figures D.1b and D.1c indicate that women retire substantially earlier than men. Similarly, Appendix Figures D.1d and D.1e reveal substantial differences across academic disciplines: historians tend to postpone retirement as long as possible, while art professors often retire early. A binary retirement indicator fails to account for these nuances, imposing an overly simplistic model on the data-generating process. In contrast, the continuous measure captures this variation, leading to higher statistical power in subsequent analyses. Therefore, the main analysis is based on this measure.

³⁵ The statutory retirement age has gradually increased, starting at 65 for individuals born before 1946 and reaching 67 for those born after 1964. Most professors retiring between 2000 and 2010 were still subject to the 65 or 66 statutory retirement age.

Figure D.1: Retirement Probability Distributions



Note: The figure illustrates the retirement probability distributions of full professors across various subgroups. Figure D.1a displays the overall share. Figures D.1b and D.1c break down this data by gender, while Figures D.1d and D.1e distinguishes history and arts department. All figures are based on the population of professors who retired between 2000 and 2010 and were employed at public German universities. The data is sourced from the Hochschulpersonal statistik, as detailed in Section 3.1.

D.B Matching Research Output

The 'Hochschullehrerverzeichnis' is an annual directory that lists all German university professors along with their affiliations and descriptions of their disciplines (Hochschulverband, 2002–2022). Appendix Figure D.2 shows an exemplary excerpt of the first entry of the 2008 HLV, which comprises 750 pages of similar layout. I first digitized all the directories covering the years 2002–2022 using optical character recognition. The first entry shown in Appendix Figure D.2 provides an overview of the typical structure of each entry:

Aach, Til; Dr.-Ing., Prof. RWTH Aachen; Signalverarbeitung u. Prozeβrechentechnik, Bildverarbeitung, med. Bildverarbeitung, Mustererkennung; di: RWTH, Fak. f. Elektrotechnik u. Informationstechnik, Lst. für Bildverarbeitung, Sommerfeldstraβe, 52056 Aachen, T: (0241) 8027860, F: 8022200, til.aach@lfb.rwth-aachen.de; www.isip.uniluebeck.de

This entry lists the name (Aach, Til), title (Dr.-Ing.), position (Prof.), institution (RWTH Aachen), academic discipline (Signalverarbeitung u. Prozeßrechentechnik, Bildverarbeitung, Mustererkennung), and contact information (di: RWTH, Fak. f. Elektrotechnik u. Informationstechnik, Lst. für Bildverarbeitung, Sommerfeldstraße, [...]).

The objective is to extract the position, department, and institution from each entry. To achieve this, I utilize classification algorithms trained using 1,000 randomly selected and manually classified entries. For each algorithm, I manually define a set of categories to choose from. For institutions, the potential targets include all public universities in Germany as listed in Appendix Tables A.1, while the set of potential departments corresponds to those listed in the HPS as listed in Appendix Table A.2. If an university does not have a specific department – for example, if a university lacks an art history department – the set of potential departments is limited to those that are actually present at that university (as identified through the HPS). The position categories include full professor, assistant professor, and other professor. In the latter category I classify emeritus and honorary professors. If the algorithm assigns multiple positions, the highest one is assigned. For instance, in the example provided, the algorithms correctly infer the position (full professor), department (computer science), and institution (RWTH Aachen).

In total, I classify entries for 1.2 million individuals, averaging approximately 60,000 entries per year. Next, I match these entries over time by identifying individuals with the same name, department, and university. If a direct match is not found, I narrow the criteria to just name and department to account for potential changes in affiliation. Throughout, I retain only individuals with unique matches. In the next step, I combine this panel with research output data obtained from OpenAlex. For each professor identified in the 'Hochschullehrerverzeichnis', I search for researchers with the same name and affiliation in the OpenAlex data. In cases of multiple matches, I manually verify and assign matches by comparing publication records. By aggregating

the resulting panel by department and year, I can track departmental research output and collaboration patterns over time.

Figure D.2: Exemplary Excerpt from the 'Hochschullehrerverzeichnis'

Note: The figure provides an exemplary excerpt from the *Hochschullehrerverzeichnis* in 2008 (Hochschulverband, 2002–2022). Each entry lists the professor's name, university, and field of specialization. The pages from each volume are digitized using optical character recognition. The entries are matched over time by identifying individuals with the same name, department, and university. If a direct match cannot be found, the criteria are narrowed to name and department to account for potential changes in affiliation. For further details, refer to Appendix Section D.B.

D.C Measuring Changes in Research Direction

To measure changes in research direction, I first construct department-specific topic distributions using a topic model – an unsupervised machine learning technique designed to uncover latent themes in textual data. This approach allows each text to be represented by a distribution of topics, providing a more nuanced and detailed representation compared to binary classifications. I utilize the BERTopic algorithm, as developed by Grootendorst (2022). Appendix Figure D.3 provides an overview of the steps involved in this analysis.

I begin by collecting all abstracts of papers published by professors working at Germany's public universities during the sample period. For each academic discipline, I train a separate topic model to identify and describe the topics within this field. For each field f, I randomly select 10,000 papers authored by researchers in field f and published between 2000 and 2022. To ensure equal representation of abstracts across years, I stratify the randomization process by year. The topic model is then trained on the entire set of abstracts from all years to ensure a consistent and time-invariant set of topics for each field. Notably, results from models trained on different datasets, such as annual subsets, are inherently not comparable, as explained below.

The topic model algorithm involves two key steps. First, it represents each abstract as a dense vector in continuous space, known as an embedding. For this purpose, I utilize the pre-trained multilingual language model 'paraphrase-multilingual-MiniLM-L12-v2' (Reimers and Gurevych, 2019). This sentence-transformer maps text to a 384-dimensional dense vector space, while supporting over 50 languages and considering the context in which words appear within sentences. Second, the topic model algorithm clusters embeddings that are sufficiently close to each other while being distinctly separated from other groups of embeddings. Each cluster represents a distinct topic. The number of topics, or clusters, is determined by setting hyperparameters that define what constitutes sufficiently close and sufficiently far distances between embeddings. For technical details, I refer the interested reader to Grootendorst (2022). To objectively select these hyperparameters, I perform cross-validation to find the set that maximizes the topic model's coherence score, a metric used to assess the quality and interpretability of the topics generated by the model (Mimno et al., 2011). This process results in a representative topic distribution for each field, denoted as $\mathbf{X}(f)$, and a covariance matrix $\mathbb{V}_{\mathbf{X}(f)}$, which describes the correlation of topics within a field. For instance, papers covering labor economics are more likely to touch on thematic areas from public economics rather than from monetary economics. I will utilize this substitutability information when calculating how topic distributions change over time. Lastly, I assign labels to each topic. This step is purely for human understanding and does not influence how the model assigns topics. Initially, I identify a collection of keywords and documents that most accurately depict each topic using a term frequency-inverse document frequency (TF-IDF) approach, which highlights their significance. These selected keywords and documents are then fed into OpenAI's ChatGPT-4 (OpenAI, 2024), which I ask to generate a concise description of the topic in three words.

Once the topic model is trained, I can use it to predict the topic distribution of previously unseen abstracts. The model converts each provided abstract into an embedding and assesses its

alignment within the clusters of identified topics from the training phase. This process enables us to predict the topic distribution across all academic work published during the sample period. To ensure each professor's equal weighting in computing departmental topic distributions, I first average the paper-specific topic distributions by author and year, resulting in annual topic profiles for each professor. Subsequently, these individual profiles are averaged by department and year to produce departmental topic distributions.

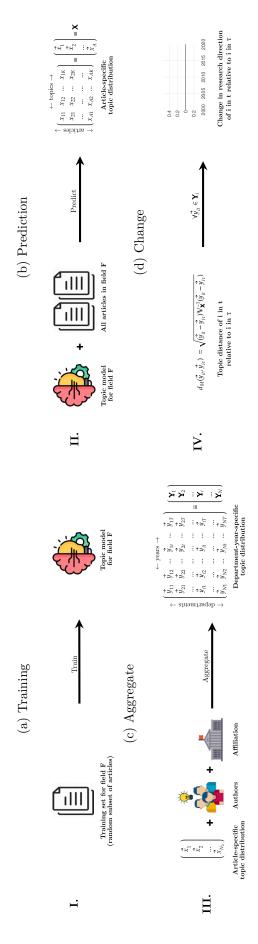
Next, I analyze whether these average topic distributions differ between departments that appoint a female professor and those that do not. I measure changes in topic distributions within departments across year via the Mahalanobis distance:

$$d_M \equiv d_M(\vec{y}_{it}, \vec{y}_{i\tau}) = \sqrt{(\vec{y}_{it} - \vec{y}_{i\tau}) \mathbb{V}_{\mathbf{X}}^{-1} (\vec{y}_{it} - \vec{y}_{i\tau})}$$

Here, the vectors \vec{y}_{it} and $\vec{y}_{i\tau}$, represent the topic distribution of department i in year t and the pre-funding period $\tau \equiv \tau(g)$, respectively. The Mahalanobis distance assumes that these vectors are drawn from some distribution \mathbf{X} on \mathbb{R}^K with covariance matrix $\mathbb{V}_{\mathbf{X}}$, which I replace by the sample analogs obtained from the field-specific topic models.

A unit increase in d_M indicates that department *i*'s topic distribution in year *t* deviates by one standard deviation from its distribution in τ . The measure is zero if the topic distribution remains constant over time and diverges quadratically to infinity as the distance between topic distribution increases. Unlike other measures, the Mahalanobis distance allows to account for different degrees of substitutability between topics by weighting the distance using the inverse of the covariance matrix, $\mathbb{V}_{\mathbf{X}}^{-1}$. For instance, shifts from labor economics to public economics are weighted less compared to shifts from labor economics to monetary economics in the distance calculation. I use d_M as the outcome measure in the regression framework described in Section 4.

Figure D.3: Constructing Field-Specific Topic Distribution



per field are used to train separate topic models for each academic discipline, ensuring consistent topic identification across years (Appendix Figure D.3a). The trained models are then applied to predict the topic distribution of unseen abstracts (Appendix Figure D.3b). To calculate departmental topic distributions, the topic profiles for each professor are averaged by year, then Note: The figure schematically describes the construction of field-specific topic distributions as described in Appendix Section D.C. First, abstracts from a stratified sample of 10,000 papers further aggregated at the department level (Appendix Figure D.3c). Finally, changes in departmental topic distributions relative to the pre-funding period are measured using the Mahalanobis distance (Appendix Figure D.3d).

References

- Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When Should You Adjust Standard Errors for Clustering?" Quarterly Journal of Economics, 138(1): 1–35.
- Ahern, Kenneth R, and Amy K Dittmar. 2012. "The Changing of the Boards: The Impact on Firm Valuation of Mandated Female Board Representation." Quarterly Journal of Economics, 127(1): 137–197.
- Anderson, Theodore W, and Herman Rubin. 1949. "Estimation of the Parameters of a single Equation in a Complete System of Stochastic Equations." *Annals of Mathematical Statistics*, 20(1): 46–63.
- **Angrist**, **Joshua**, and **Michal Kolesár**. 2021. "One Instrument to Rule Them All: The Bias and Coverage of Just-ID IV." *NBER Working Paper*, 29417.
- Antecol, Heather, Kelly Bedard, and Jenna Stearns. 2018. "Equal but Inequitable: Who Benefits from Gender-neutral Tenure Clock Stopping Policies?" *American Economic Review*, 108(9): 2420–41.
- Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva. 2017. "Does the Gender Composition of Scientific Committees Matter?" American Economic Review, 107(4): 1207–38.
- Bagues, Manuel, Milan Makany, Giulia Vattuone, and Natalia Zinovyeva. 2023. "Women in Top Academic Positions: Is there a Trickle-down Effect?" Unpublished.
- Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, and Petia Topalova. 2009. "Powerful Women: Does Exposure Reduce Bias?" Quarterly Journal of Economics, 124(4): 1497–1540.
- Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "High-dimensional Methods and Inference on Structural and Treatment Effects." *Journal of Economic Perspectives*, 28(2): 29–50.
- Beneito, Pilar, José E Boscá, Javier Ferri, and Manu García. 2021. "Gender Imbalance across Subfields in Economics: When Does it Start?" *Journal of Human Capital*, 15(3): 469–511.
- Bertrand, Marianne, Sandra E Black, Sissel Jensen, and Adriana Lleras-Muney. 2019. "Breaking the Glass Ceiling? The Effect of Board Quotas on Female Labour Market Outcomes in Norway." *Review of Economic Studies*, 86(1): 191–239.
- Besley, Timothy, Olle Folke, Torsten Persson, and Johanna Rickne. 2017. "Gender Quotas and the Crisis of the Mediocre Man: Theory and Evidence from Sweden." *American Economic Review*, 107(8): 2204–2242.

- Bhalotra, Sonia, Irma Clots-Figueras, and Lakshmi Iyer. 2018. "Pathbreakers? Women's Electoral Success and Future Political Participation." *The Economic Journal*, 128(613): 1844–1878.
- **Bhavnani**, Rikhil R. 2017. "Do the Effects of Temporary Ethnic Group Quotas Persist? Evidence from India." *American Economic Journal: Applied Economics*, 9(3): 105–123.
- Blau, Francine D, Janet M Currie, Rachel TA Croson, and Donna K Ginther. 2010. "Can Mentoring Help Female Assistant Professors? Interim Results from a Randomized Trial." *American Economic Review*, 100(2): 348–52.
- BMJ, Bundesministerium der Justiz. 2024. "Gesetz über die Versorgung der Beamten und Richter des Bundes (Beamtenversorgungsgesetz BeamtVG)." URL: https://www.gesetze-im-internet.de/beamtvg/BJNR024850976.html, Accessed: 2024-06-03.
- Bound, John, David A Jaeger, and Regina M Baker. 1995. "Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable Is Weak." *Journal of the American Statistical Association*, 90(430): 443–450.
- Bundesanzeiger, Bundesministerium für Bildung und Forschung. 2018. "Richtliniezur Umsetzung des Professorinnenprogramms des Bundes und der Länder." URL: https://www.bundesanzeiger.de/pub/de/amtliche-veroeffentlichung?2, Accessed: 2022-06-24.
- Bundesministerium für Bildung und Forschung. 2008. "Bekanntmachung des Bundesministeriums für Bildung und Forschung von Richtlinien zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen." URL: https://www.gwk-bonn.de/presseaktuelles/presse-archiv, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2012. "Bekanntmachung des Bundesministeriums für Bildung und Forschung von Richtlinien zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm II." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2012/12/797_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2018. "Bekanntmachung Richtlinie zur Umsetzung des Professorinnenprogramms des Bundes und der Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm III. Bundesanzeiger vom 21.02.2018." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2018/02/1600_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Bundesministerium für Bildung und Forschung. 2022. "Bekanntmachung Richtlinie zur Umsetzung des Professorinnenprogramms des Bundes und der

- Länder zur Förderung der Gleichstellung von Frauen und Männern in Wissenschaft und Forschung an deutschen Hochschulen Professorinnenprogramm 2030." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2023/02/2023-02-02-Bekanntmachung-Professorinnenprogramm.html#searchFacets, Accessed: 2024-09-19.
- Bundesregierung, Die. 2023. "Förderkatalog." URL: https://foerderportal.bund.de/foekat/jsp/SucheAction.do?actionMode=searchmask, Accessed: 2023-10-24.
- **BW-MF, Baden-Württemberg Ministerium der Finanzen.** 2022. "Staatshaushaltsplan für 2022 Einzelplan 14 Ministerium für Wissenschaft, Forschung und Kunst." Accessed: 2024-06-03.
- Card, David, Stefano DellaVigna, Patricia Funk, and Nagore Iriberri. 2020. "Are Referees and Editors in Economics Gender Neutral?" Quarterly Journal of Economics, 135(1): 269–327.
- Carnes, Molly, Patricia G Devine, Linda Baier Manwell, Angela Byars-Winston, Eve Fine, Cecilia E Ford, Patrick Forscher, Carol Isaac, Anna Kaatz, Wairimu Magua, et al. 2015. "Effect of an Intervention to Break the Gender Bias Habit for Faculty at One Institution: A Cluster Randomized, Controlled Trial." Academic medicine: journal of the Association of American Medical Colleges, 90(2): 221.
- Carrell, Scott E, Marianne E Page, and James E West. 2010. "Sex and Science: How Professor Gender Perpetuates the Gender Gap." Quarterly Journal of Economics, 125(3): 1101–1144.
- Carrell, Scott E, Mark Hoekstra, and James E West. 2015. "The Impact of Intergroup Contact on Racial Attitudes and Revealed Preferences." NBER Working Paper, , (20940).
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-wage Jobs." Quarterly Journal of Economics, 134(3): 1405–1454.
- Chari, Anusha, and Paul Goldsmith-Pinkham. 2017. "Gender Representation in Economics Across Topics and Time: Evidence from the NBER Summer Institute." NBER Working Paper, , (w23953).
- Chattopadhyay, Raghabendra, and Esther Duflo. 2004. "Women as Policy Makers: Evidence from a Randomized Policy Experiment in India." *Econometrica*, 72(5): 1409–1443.
- CHE Hochschuldaten. 2024. "Studierende in Deutschland." URL: https://hochschuldaten.che.de/deutschland/studierende-in-deutschland/#: ~: text=Die%20meisten%20Studierenden%20(58%2C2,FH)%20eingeschrieben., Accessed: 2024-06-03.
- Chen, Le-Yu, and Sokbae Lee. 2021. "Binary Classification with Covariate Selection Through ℓ_0 -penalised Empirical Risk Minimisation." *Econometrics Journal*, 24(1): 103–120.

- **Dahl, Gordon B, Andreas Kotsadam, and Dan-Olof Rooth.** 2021. "Does Integration Change Gender Attitudes? The Effect of Randomly Assigning Women to Traditionally Male Teams." *Quarterly Journal of Economics*, 136(2): 987–1030.
- de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2023. "Two-way Fixed Effects and Differences-in-Differences Estimators with Several Treatments." *Journal of Econometrics*, 236(2): 105480.
- De Paola, Maria, Vincenzo Scoppa, and Rosetta Lombardo. 2010. "Can Gender Quotas Break Down Negative Stereotypes? Evidence from Changes in Electoral Rules." *Journal of Public Economics*, 94(5-6): 344–353.
- **Deschamps, Pierre.** 2018. "Gender Quotas in Hiring Committees: A Boon or a Bane for Women?" Sciences Po LIEPP Working Paper, 82.
- Destatis, Federal Statistical Office of Germany. 2018. "Hochschulpersonalstatistik." Administrative data. Information on how to request the data can be found at https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Hochschulen/Methoden/Erlaeuterungen/hochschulen.html.
- Devine, Patricia G, Patrick S Forscher, William TL Cox, Anna Kaatz, Jennifer Sheridan, and Molly Carnes. 2017. "A Gender Bias Habit-breaking Intervention Led to Increased Hiring of Female Faculty in STEMM Departments." *Journal of Experimental Social Psychology*, 73: 211–215.
- **Dolado, Juan J, Florentino Felgueroso, and Miguel Almunia.** 2012. "Are Men and Women-economists Eevenly Distributed across Research Fields? Some New Empirical Evidence." *SERIEs*, 3: 367–393.
- Dube, Arindrajit, Daniele Girardi, Oscar Jorda, and Alan M Taylor. 2023. "A Local Projections Approach to Difference-in-Differences Event Studies." *American Economic Review*.
- Dupas, Pascaline, Alicia Modestino, Muriel Niederle, Justin Wolfers, et al. 2021. "Gender and the Dynamics of Economics Seminars." *NBER Working Paper*, , (28494).
- Eberhard Karls Universität Tübingen. 2019. "Professur (W3) für Kunstgeschichte." URL: https://uni-tuebingen.de/fakultaeten/philosophische-fakultaet/fakultaet/ausschreibungenstellenangebote/professuren/w3/, Accessed: 2024-09-19.
- European Commission, Directorate General for Research. 2021. "Gender in Research and Innovation: Statistics and Indicators." URL: https://op.europa.eu/en/web/eu-law-and-publications/publication-detail/-/publication/67d5a207-4da1-11ec-91ac-01aa75ed71a1, Accessed: 2022-05-26.
- Flabbi, Luca, Mario Macis, Andrea Moro, and Fabiano Schivardi. 2019. "Do Female Executives Make a Difference? The Impact of Female Leadership on Gender Gaps and Firm Performance." *Economic Journal*, 129(622): 2390–2423.

- Friedman, Jerome, Trevor Hastie, and Rob Tibshirani. 2010. "Regularization Paths for Generalized Linear Models via Coordinate Descent." *Journal of Statistical Software*, 33(1): 1.
- Gemeinsame Wissenschaftskonferenz. 2013–2022. "Presse-Archiv." URL: https://www.bmbf.de/bmbf/shareddocs/bekanntmachungen/de/2008/03/327_bekanntmachung.html#searchFacets, Accessed: 2024-09-19.
- Ginther, Donna K, Janet M Currie, Francine D Blau, and Rachel TA Croson. 2020. "Can Mentoring Help Female Assistant Professors in Economics? An Evaluation by Randomized Trial." Vol. 110, 205–09.
- Gonsalkorale, Karen, Jeffrey W Sherman, and Karl Christoph Klauer. 2009. "Aging and Prejudice: Diminished Regulation of Automatic Race Bias Among Older Adults." *Journal of Experimental Social Psychology*, 45(2): 410–414.
- **Grootendorst, Maarten.** 2022. "BERTopic: Neural Topic Modeling With a Class-based TF-IDF Procedure." arXiv Pre-print, 2203.05794.
- Guarino, Cassandra M, and Victor MH Borden. 2017. "Faculty Service Loads and Gender: Are Women Taking Care of the Academic Family?" Research in Higher Education, 58(6): 672–694.
- Hansen, Bruce. 2022. Econometrics. Princeton University Press.
- Hochschulverband, Deutscher, ed. 2002–2022. Hochschullehrer Verzeichnis Universitäten Deutschland. De Gruyter Saur.
- Hoogendoorn, Sander, Hessel Oosterbeek, and Mirjam Van Praag. 2013. "The Impact of Gender Diversity on the Performance of Business Teams: Evidence from a Field Experiment." *Management Science*, 59(7): 1514–1528.
- HRK, Hochschulrektorenkonferenz. 2024. "Hochschulfinanzierung." URL: https://www.hrk.de/themen/hochschulsystem/hochschulfinanzierung/, Accessed: 2024-06-03.
- **Janys, Lena.** 2024. "Testing the Presence of Implicit Hiring Quotas with Application to German Universities." Review of Economics and Statistics, 106(3): 627–637.
- **Jensen, Robert, and Emily Oster.** 2009. "The Power of TV: Cable Relevision and Women's Status in India." *Quarterly Journal of Economics*, 124(3): 1057–1094.
- Kim, Daehyun, and Laura T Starks. 2016. "Gender Diversity on Corporate Boards: Do Women Contribute Unique Skills?" *American Economic Review*, 106(5): 267–71.
- Kleemans, Marieke, and Rebecca L Thornton. 2021. "Who Belongs? The Determinants of Selective Membership into the National Bureau of Economic Research." Vol. 111, 117–22.
- Lee, David S, Justin McCrary, Marcelo J Moreira, and Jack Porter. 2022. "Valid t-ratio Inference for IV." American Economic Review, 112(10): 3260–90.

- **Lewicki, Pawel.** 1983. "Self-image Bias in Person Perception." *Journal of personality and social psychology*, 45(2): 384.
- Matsa, David A, and Amalia R Miller. 2013. "A Female Style in Corporate Leadership? Evidence from Quotas." American Economic Journal: Applied Economics, 5(3): 136–169.
- May, Ann Mari, Mary G McGarvey, and David Kucera. 2018. "Gender and European Economic Policy: A Survey of the Views of European Economists on Contemporary Economic Policy." *Kyklos*, 71(1): 162–183.
- Mengel, Friederike, Jan Sauermann, and Ulf Zölitz. 2019. "Gender Bias in Teaching Evaluations." *Journal of the European Economic Association*, 17(2): 535–566.
- Mimno, David, Hanna Wallach, Edmund Talley, Miriam Leenders, and Andrew McCallum. 2011. "Optimizing Semantic Coherence in Topic Models." 262–272.
- Ministerium für Wissenschaft, Forschung und Kunst Baden-Württemberg. 2020. "Stellenplan für Beamtinnen und Beamte im Landesbetrieb Universität Mannheim." URL: https://www.statistik-bw.de/shp/2020-21/pages/Epl14/ST/epl14_1420_st.pdf, Accessed: 2024-09-19.
- National Health & Medical Research Council. 2022. "Working towards gender equity in Investigator Grants." URL: https://www.nhmrc.gov.au/about-us/news-centre/working-towards-gender-equity-investigator-grants, Accessed: 2024-06-19.
- NRW, Gesetz über die Hochschulen des Landes Nordrhein-Westfalen. 2014. "§37a Gewährleistung der Chancengerechtigkeit von Frauen und Männern bei der Berufung von Professorinnen und Professoren." URL: https://recht.nrw.de/lmi/owa/br_bes_detail?sg=0&menu=0&bes_id=28364&anw_nr=2&aufgehoben=N&det_id=643733, Accessed: 2024-06-24.
- **Nygaard, Knut.** 2011. "Forced Board Changes: Evidence from Norway." *NHH Deptartment of Economics Discussion Paper*, , (5).
- OpenAI. 2024. "ChatGPT-4: Conversational AI powered by OpenAI." Accessed: 2024-06-27.
- **Porter, Catherine, and Danila Serra.** 2020. "Gender Differences in the Choice of Major: The Importance of Female Role Models." *American Economic Journal: Applied Economics*, 12(3): 226–54.
- Priem, Jason, Heather Piwowar, and Richard Orr. 2022. "OpenAlex: A Fully-open Index of Scholarly Works, Authors, Venues, Institutions, and Concepts." arXiv Pre-print, 2205.01833.

- Reimers, Nils, and Iryna Gurevych. 2019. "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks." Association for Computational Linguistics.
- Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature." *Journal of Econometrics*, 235(2): 2218–2244.
- Sarsons, Heather, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. 2021. "Gender Differences in Recognition for Group Work." *Journal of Political Economy*, 129(1): 101–147.
- Scopus, Elsevier. 2023. "CiteScore 2023." URL: https://www.scopus.com/sources, Accessed: 2024-06-24.
- Siniscalchi, Marciano, and Pietro Veronesi. 2020. "Self-image Bias and Lost Talent." NBER Working Paper, 28308.
- Siyanova-Chanturia, Anna, Paul Warren, Francesca Pesciarelli, and Cristina Cacciari. 2015. "Gender Stereotypes Across the Ages: On-line Processing in School-age Children, Young and Older Adults." Frontiers in Psychology, 6: 1388.
- Staiger, Douglas, and James H Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica*, 557–586.
- Swiss National Science Foundation. 2021. "Quoten für mehr Gleichstellung in der Forschung." URL: https://www.snf.ch/de/kjCKYzJgvuNWbsf2/news/news-210205-quoten-fuer-mehr-gleichstellung-in-der-forschung, Accessed: 2024-06-19.
- Vernos, Isabelle. 2013. "Quotas Are Questionable." Nature, 495(7439): 39–39.
- Wallon, Gerlind, Sandra Bendiscioli, and Michele S Garfinkel. 2015. "Exploring Quotas in Academia." *URL: www. embo. org/documents/science_policy/exploring_quotas.* pdf, Accessed: 2024-06-24.
- Whelan, Jennifer, and Robert Wood. 2012. "Targets and Quotas for Women in Leadership: A Global Review of Policy, Practice and Psychological Research." Gender Equality Project, Centre for Ethical Leadership, Melbourne Business School.
- Wing, Coady, Seth M Freedman, and Alex Hollingsworth. 2024. "Stacked Difference-in-Differences." NBER Working Paper, , (32054).