The Impact of Sexual Misconduct on Scientific Production and Gender Diversity

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This version: May 26, 2025

Abstract

Sexual misconduct at work remains a persistent challenge in contemporary organizations. Although a growing body of important work has documented the profound impact on survivors, fundamental questions about the broader organizational implications remain unexplored. This project investigates the potential effects of sexual misconduct in academia. Specifically, I ask: How do sexual misconduct incidents in university departments shape scientific production, collaboration patterns, and gender diversity? I draw on a novel database comprising over 1,000 documented cases of workplace sexual misconduct across multiple universities and disciplines and employ a coarse exact matching approach paired with a staggered difference-in-difference design. I collect information from 359 research-focused departments that experienced at least one sexual misconduct incident and around 5,000 control departments at research-focused universities.

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Thank you.

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1 Mechanism and Framing

+/-5 years treat	On Men Faculty			On Women Faculty		
	Misconduct	**News Reports**	**Removal**	**Misconduct**	**News Reports**	**Removal**
Productivity / Publications	→ or ↑ A4, B4	↓ B3, B4	↓ B2,B4	↓ B1, B4, A2?	↓ B3	→ or ↑ B2
Novelty / References	↑ B1	→	↓	→ B1 or ↓ B2	→	→
Impact / Citations	↑ A4, B1, B4	↓ A4, B1, B4	↓ A4, B1, B4 ?	↓ B1, B4	→ or ↑ B5	→
Direction of Science	→ ?	→ ?	→ ?	→ ?	→ ?	→ ?
Quality / Impact Factor	↑ B5	↑ B5	↓ B5	↑ B5 ?	?	?

→: No Effect, ↓: Decrease, ↑: Increase

Panel A: Moderator (condition):

1. **Type of spillover effect:** Total, peer, or indirect spillover.
2. **Relevance of victim to department:** Peer/grad student vs. undergraduate student or employee
3. **Severity:** One-time versus serial, sexualized comment versus assault.
4. **Seniority of the accused faculty:** Resources, power, network.
5. **Physical Proximity:** Departments where physical presence is essential versus not.

Panel B: Mediator (how and why):

1. **Selection into Dept.:** There is a type of academic who joins (doesn't join) such an department.
2. **Collaborator selection:** Women less likely to work with the accused faculty.
3. **Attention:** Crisis management and emotional processing of department members. Distortion of within-department collaborations.
4. **Collaborator Network:** The collaborator network decreases for the department members (first the accused faculty, then the network of the accused faculty)
5. **Extra Support** Due to loyalty or a form of affirmative action

Scientific Production as a Social Process

The production of new knowledge is conceptualized as a recombination of existing knowledge Mokyr (2004).

Scientific production is increasingly a collective effort. Adams et al. (2005) and Wuchty, Jones and Uzzi (2007) observe an increase in team size since the 1990s.

Scientific production as a social process. - PI structure as a power hierarchy - interpersonal interactions important

The role of Power - the social dynamics are strongly linked to hierarchy and power.

Sexual misconduct as stigma, especially in domain of science and education

The occurrence of sexual misconduct in a university department will likely have direct effects on the victim. It will also have indirect effects on department members or potential department members.

I argue that sexual misconduct is a stigmatized event

Own Reflection

It's curious that this stigma here is independent of the person and of the company (in fact both would be highly "pure" or something alike...in pursuit of knowledge). But its the activity that makes the event stigmatized. For example, this is not a tobacco company. And To return to Sharla's comment, maybe this is morally more offputting (?)

Literature Review on Stigma (and some work on scandal

Hudson, B. 2008. "Against All Odds: A Consideration of Core-Stigmatized Organizations." Academy of Management Review 33 (1): 252–66. https://doi.org/10.5465/AMR.2008.27752775.

Hudson (2008) Distinguishes between core stigma and event stigma. Core stigma is when something about the firm is stigmatized. Examples she provides are pornography producers, tobacco companies, or tattoo parlors. Event stigma, on the other hand, are stigmatized events that happen to or at a firm. She describes them as "discrete, anomalous, episodic event" such as bankruptcy (McKinley, Ponemon, & Schick, 1996; Neu & Wright, 1992; Sutton & Callahan, 1987); industrial accidents, such as the Exxon Valdez oil tanker spill in Alaska (Hoff man, 1999; Hoffman & Ocasio, 2001; Lacey, 2003);These are essentially scandals.

Lull, James, and Stephen Hinerman, eds. 1997. Media Scandals: Morality and Desire in the Popular Culture Marketplace. New York: Columbia University Press. https://archive.org/details/r

Lull and Hinerman (1997) "Scandals are surprising and adverse events that re- veal illegitimate or deviant information about an actor." Taken from McDonnell, Odziemkowska and Pontikes

(2021)

Keplinger, Ksenia, Stefanie K. Johnson, Jessica F. Kirk, and Liza Y. Barnes. 2019. "Women at Work: Changes in Sexual Harassment between September 2016 and September 2018." PloS One 14 (7): e0218313. https://doi.org/10.1371/journal.pone.0218313. Keplinger et al. (2019) "Although many people experience sexual harassment in the workplace, many never report it (Fitzgerald, Swan and Fischer, 1995). Explanations for the lack or reporting relate to threats to self-esteem and risk of secondary victimization—women fear facing doubts, scrutiny, and blame for the harassment they experience (Fitzgerald, Swan and Fischer, 1995; Foster and Fullagar, 2018). These fears are captured by stigma theory, which suggests that individuals will avoid sharing a stigma because of self-blame, shame, and fear of negative judgments from others (Goffman, 1963, 1959). Stigma theory say that in order to deal with shame, people need sympathetic others who share the same social stigma to feel 'human' and 'essentially' normal in spite of appearances and in spite of his [or her] own self-doubt" (Goffman, 1963) p. 31. Indeed, research on sexual assault shows that disclosing a societally stigmatized experience can affect self-esteem such that positive, validating responses are associated with higher self-esteem whereas negative, blaming, and doubting responses are associated with lower self-esteem Filipas and Ullman (2001)." This is a survey experiment. → This paper also talks about potential backlash of increased reporting and the #MeToo movement. The movment may have brought to light that it is ok to harass women since others are doing that too.

McDonnell, Mary-Hunter, Kate Odziemkowska, and Elizabeth Pontikes. 2021. "Bad Company: Shifts in Social Activists' Tactics and Resources After Industry Crises." Organization Science 32 (4): 1033–55. https://doi.org/10.1287/orsc.2020.1410. McDonnell, Odziemkowska and Pontikes (2021)'s finding: "Although SMOs that historically collaborated with the compromised industry expe- rience stigma by association in the form of lowered contributions, those that historically contentiously targeted the compromised industry experience in- creased public support after the scandal." "Scandals are more likely to transmit stigma across an industry in cases in which the offending actor has higher status (Hoffman and Ocasio 2001,Adut2005), the offense is more severe (Barnett and King 2008), and the event garners more publicity (Hoffman and Ocasio 2001,Adut2005)." "Industry scandals are more conducive to spillover stigma than firm-specific scandals as they lead to increased contestation of an organizational form rather than a specific firm (Yue et al. 2013)." "" event stigma" (Hudson 2008) that can spread across populations through processes of stigma by association (Lange et al. 2011). Stigma by association occurs through two distinct pathways. First, stigma can flow through informal cognitive associations or " categorical dele- gitimization," wherein individuals take negative in- formation about one category member as indicative of a deficiency in the entire group (Greve et al. 2010,p. 89). Through this mechanism, one actor'sstigmatiz- ing action can contaminate an entire group of similar peers (Jensen 2006, Jonsson et al. 2009,Vergne2012). For example, following the Enron scandal that im- plicated Arthur Anderson's Houston office, clients severed ties broadly from all of Arthur Anderson 's other offices, hoping to avoid reputational damage (Jensen 2006). Second, formal, structural relation- ships provide pathways through which stigma by association can flow. Here, stigma passes through observable ties to a scandalized actor (Barnett and King 2008,McDonnellandWerner2016). For exam- ple, Janney and Gove (2017) show that companies with board linkages to firms implicated in stock op- tions backdating experienced significantly negative stock price returns." "The question of whether stigma transfers through cross-sector alliances, such as between corporations and their SMO collaborators, remains open. [...] But research on stigma by association suggests that negative spillovers may operate more indiscrimin- ately than these executives acknowledge. Pontikes et al. (2010) find adverse employment outcomes when actors had previously worked on a movie project alongside others who were blacklisted as Commu- nists during Hollywood's " Red Scare" even when the blacklisted coworker had a very dissimilar role, such as the screenplay writer. Effects are even found in lab- oratory studies: a person is devalued simply by co- incidental connections to a stigmatized alter, such as sitting next to a person in a doctor's waiting room (Hebl and Mannix 2003) or appearing together in a photograph by happenstance (Penny and Haddock 2007,Pryoretal.2012). Taken together, this research suggests that categorical distinction is not enough to prevent stigma spillovers. We, therefore, expect that SMOs that have previously collaboratively engaged with an industry suffer spillover stigma and re- duced public support when that industry experiences ascandal."

Kang, Sonia K., Katherine A. DeCelles, András Tilcsik, and Sora Jun. 2016. "Whitened Résumés: Race and Self-Presentation in the Labor Market." Administrative Science Quarterly 61 (3): 469–502. https://doi.org/10.1177/0001839216639577. Great discussion about Goffman's argument about individual and racial stigma.

Azoulay, Pierre, Alessandro Bonatti, and Joshua L. Krieger. 2017. "The Career Effects of Scandal: Evidence from Scientific Retractions." Research Policy 46 (9): 1552–69. https://doi.org/10.1016/j.respol.2017.07.003. "Finally, the citation penalty may represent more than just the market's response to an information shock. For instance, it may be part of an implicit incentive scheme that sees ordinary scientists recoil from the prior work of scientists embroiled in scandal, particularly if they have achieved great fame. That part of the punishment is carried out by giving less credit to the author's earlier work makes sense especially if some of the citations accruing to these scientists were "ceremonial" in nature. If principal investigators can control the likelihood of their team making a mistake or explicitly cheating, then this stigmatization [whether understood as a deterrent or as pure sociological mechanism à la Adut, 2005 (Adut, 2005)] could discourage scientific misconduct."

Literature Review on Scandels

"DP19298 Optimizing the Workplace: The Interplay between Working Environment, Corporate Outcomes and Employee Well-Being." n.d. CEPR. Accessed May 5, 2025. https://cepr.org/publicatio

Iaria, Alessandro, Carlo Schwarz, and Fabian Waldinger. n.d. "Gender Gaps in Academia: Global Evidence over the Twentieth Century." https://www.fabianwaldinger.com/$_{f}iles/ugd/0d0a02_{5}faf4$

Jin, Ginger Zhe, Benjamin Jones, Susan Feng Lu, and Brian Uzzi. 2013. "The Reverse Matthew Effect: Catastrophe and Consequence in Scientific Teams." w19489. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w19489.

Krauskopf, Erwin. 2021a. "The Shanghai Global Ranking of Academic Subjects: Room for Improvement." El Profesional de La Información, July. https://doi.org/10.3145/epi.2021.jul.08.

———. 2021b. “The Shanghai Global Ranking of Academic Subjects: Room for Improvement.” El Profesional de La Información, July. https://doi.org/10.3145/epi.2021.jul.08.

Lu, Susan Feng, Ginger Zhe Jin, Brian Uzzi, and Benjamin Jones. 2013. “The Retraction Penalty: Evidence from the Web of Science.” Scientific Reports 3 (1): 3146. https://doi.org/10.1038/srep03

“Sexual$_H arassment.Pdf.ȷn.d.GoogleDocs.AccessedMay$5, 2025.$https : //drive.google.com/file/d/1L$
$embed_f acebook.$

1.1 How does sexual misconduct shape department-level productivity, collaboration patterns, and gender diversity?

- **Most department members are not expected to be directly affected by sexual misconduct incidence because of its stigma and power balance.**
  - Sexual harassment is a stigmatized event that suppresses information sharing and reporting.
  - Power imbalance further adds to information sharing and reporting.
  - Conclusion: Creating barriers to information
- **These barriers to information may differ by gender**
  - Since women are more likely to be target of sexual misconduct (citations from intro), it could be that women are more likely to seek out information.
  - Since this is not public information, wisper network plays an important role. (Given the stigma attached to sexual misconduct, it likely takes some time to circulate. But overall, it will remain an open secret or at least some unconfirmed speculation.)
  - Wisper network explanation. Examples are information flow through close network or anonymous platform (RateMyProf).
  - Conclusion: Information flow informally and asymmetrically through wisper networks
- **Informal, rumor-like information may lead to inequality in information and motivated reasoning.**
  - Baseline is that nobody wants to associate themselves with a perpetrator (reputation) (citations)
  - Inequality in information
  - Motivated reasoning
  - gender difference in search costs

- Conclusion: Gender inequality in information distribution and motivated reasoning changes the barriers to collaboration with risky faculty.

- **Prior:**
  - Women Are less likely to collaborate with accused faculty after misconduct incident due to wisper-network. Due to the barriers to information flow, that may show up within 10 years rather than 5 years
  - due to uncertainty within department and potentially correlated climate...I expect that women have more outside-departmental collaborations compared to control department. ⇒ How do I think about the correlation of sexual harassment and work climate that may give rise to the harassment?

1.2 How does publicizing sexual misconduct shape department-level productivity, collaboration patterns, and gender diversity?

- **Media reporting as a scandal**
  -
  -
  -
- **The scandal is likely to affect the department's reputation.**
  - Retraction shows that it may impact trust and personal admiration of individuals (Azoulay, Bonatti and Krieger, 2017).
  - This is not scientific misconduct but instead inter-personal misconduct.
  - Reputational cost: retention, hiring stronger than the wisper network
- **Retention and hiring**
  - Overall, hiring will be more strongly characterized by self-selection, especially among women
  -
  -
- **Stained co-authors and students, especially men**
  - ceremonial citations (Azoulay bonatti, krieger 2017) –> test using all versus young papers
  - Co-authors repair work...more likely to co-author with women after the scandal?
  -

Sexual misconduct at the workplace is seen as a scandal. The literature on scandal would suggest that the regard for the accused faculty and anyone who associates themselves with that faculty are likely to decrease. - oranizational misconduct - scientific misconduct - plos one

We'd expect that the publicizing of sexual misconduct impacts citations of department members, but especially collaborators. This likely also has a significant effect on talent attraction. Decrease in women talent.

With regard to scientific production. This is expected to negatively impact productivity, possibly change direction of science due to shock in collaboration network.

I expect decreases in productivity because it is demoralizing and there might be a lot of coping and admin work going on.

1.3 How does the exit of a faculty accused of sexual misconduct shape department-level productivity, collaboration patterns, and gender diversity?

- **The exit of an accused faculty should increase feeling of psychological safety for women.**
  - procedural justice?
  - Safety
  -
- **The exit of an accused faculty should have a disruptive effect on collaborators.**
  -
  -
  -
- **Department should increase in gender representation**
  - Reputation
  - Repair work
  -
- **Resources**

- University resources would free up, but grant-based research would get lost
-
-

Exit will increase feeling of safety and institutional integrity by faculty.

The shorter time between misconduct and exit, the more the exit will increase feeling of safety and institutional integrity.

This should lead to change in direction of science, increase in productivity due to more resources and peace of mind.

Coping Mechanism

writes that "It was further noted that much of this behavior has resulted in female faculty avoidingthe workplace and opportunities to socialize with colleagues and in their leaving or“trying to leave” in disproportionate numbers;"

Excerpt: Some assistant and full professors (both male and female) report responding to this situation by working from home, dropping out of departmental life, and avoiding socializing with colleagues. Several faculty members’ reputations for bad behavior place a higher service work burden on colleagues. Women are leaving or trying to leave in disproportionate numbers.

The female graduate students report being anxious, demoralized, and depressed. Some female students report that they avoid working with some faculty members because of things they have heard about those faculty members. Some female students report avoiding working with faculty members because they directly witnessed or were subjected to this harassment and inappropriate sexualized professional behavior. There was and is a lack of support for students who lost their advisors or instructors due to sanctions. The female graduate students would like more women in the department but they cannot recommend this department as a good place to come.

In addition, male graduate students report being extremely worried about the climate of harassment. They are worried that they will be tainted by the national reputation of the department as being hostile to women. They are worried about

They do not know exactly who (among those who did not get a job yet) has a bad reputation, but they are worried about the department's lack of administrative support in the face of this climate of harassment. They do not want to have any reputation that might come with being advised by a harasser (a problem exacerbated by the lack of clarity about who the harassers are). And some are ignoring the environment because they are not sure what to do after they discover these problems.

Some faculty are angry about the incivility within the department and the lack of appropriate professional development. Students are being socialized into an unprofessional environment. Meanwhile, there is unprofessional behavior from the top, with administrators avoiding or ignoring problems instead of addressing them. After being a close-knit community, the department has been seriously damaged, and the recovery process needs to be handled rigorously and with clear guidance.

Finally, as we note, the department has a reputation in the international philosophical community for being extremely unfriendly to women. This has tarnished the department's ability to recruit top-level faculty and graduate students. [...] Also, it is clear that many faculty members are not sufficiently familiar with university policy, and state and federal law regarding sexual harassment and discrimination.

Scandal

Scandalizing could induce organizational response. From hong's paper: rior research shows that a scandal could trigger organizational responses that address the specific transgression and transgressor that provoke the scandal or closely related issues (Adut, 2005; Barnett and King, 2008; Galasso and Luo, 2021). those who worked with Harvey We- instein in the past were more affected (Luo and Zhang, 2022). This could be because scandals are more likely to damage the reputation of the associated parties (Pontikes et al., 2010) and/or because the association increases the saliency of these events and makes them pay more attention (Fiske and Taylor, 1991).

MY LITERATURE REVIEW: https://docs.google.com/spreadsheets/d/1lyUsS7XwXPpruVHGyznD
1022231519gid = 1022231519https : //docs.google.com/document/d/1BMNNoC0v6IRxNCYfOH−psr1rbGPYzlMAnxd3GVnAUN4/edit?tab = t.0

Introduction

Sexual misconduct in the workplace encompasses a spectrum of harmful behaviors including harassment, assault, and actions that devalue individuals based on their sex. These behaviors range from criminal offenses like stalking and rape to non-codified actions such as sexual jokes and unsolicited distribution of explicit materials (Cortina and Berdahl, 2008; Hersch, 2015; Graf, 2018; Canadian National Defence, 2021).

Sexual misconduct is widespread and has complex and lasting consequences for affected individuals. 59% of women and 27% of men report having personally experienced unwanted sexual advances or sexual harassment, either verbal or physical, in workplace or non-workplace settings (Graf, 2018). Psychologists and organizational behavior scholars have documented that sexual misconduct at the workplace reduces job satisfaction, increases turnover, and worsens psychological well-being, such as anxiety, stress disorder, or depression (Schneider, Swan and Fitzgerald, 1997; Cortina and Berdahl, 2008; Fitzgerald and Cortina, 2018). More recently, research has linked sexual harassment in the workplace to gender segregation and the gender wage gap (Folke and Rickne, 2022; Adams-Prassl et al., 2024; Collis and Van Effenterre, 2024).

Since sexual harassment is inherently a social process and correlated with other forms of hostility present at the workplace, it is possible that the impact of sexual misconduct is not contained within the victim-perpetrator diad. This may apply in particular to organizations where work is collaborative and inter-personal interactions and dynamics matter, such as academia which is the emperical setting of this study. Research is often thought of a solitary process. In reality, however, research has become increasingly collaborative since the 1990s (Adams et al., 2005; Wuchty, Jones and Uzzi, 2007). Since researchers are embedded in the university departments, this paper asks: *How do sexual misconduct incidents in university departments shape scientific production, collaboration patterns, and gender diversity?* Three points of time are investigated: the time of misconduct occurrence, the time of media reporting, and the time when a faculty accused of sexual misconduct leaves the department.

I leverage a dataset of all sexual misconduct that has been publicized between 1980 and 2024 in the United States and combine it with publication data from OpenAlex to construct department-compositions and obtain productivity measures.

This study employs a staggered difference-in-differences (DiD) design with Coarsened Exact Matching (CEM) as a preprocessing step to establish causal effects using observational data. The data contains temporal variation in the occurence of sexual misconduct incidents across academic departments in the United States. The treatment is not randomly assigned but rather determined by the documented occurrence of misconduct incidents in university departments. The treatment group consists of 359 university departments that experienced publicized sexual misconduct incidents between 1980 and 2024, while the control group comprises matched departments that did not experience such incidents during the same timeframe. There are a total of 5,076 control departments. I implement a CEM matching procedure where departments are matched on research discipline, state laws related to hostility and harassment, university type (public/private), and research intensity. This creates a quasi-experimental setting where I can compare outcomes before and after three key events: (1) misconduct occurrence, (2) media reporting, and (3) departure of faculty members facing sexual misconduct allegations. The unit of analysis is the university department-year.

Data analysis is currently underway but results are not ready to be shared yet. Descriptively, we can ask: what do treated departments look like? Among the subsample of treated departments, 34.8% of sexual misconduct cases took place in Arts & Humanities, 26.2% in Social and Behavioral Sciences, 9.2% in Physical, Chemistry, & Earth Sciences, and 8.6% in Agriculture, Biology, and Environmental Sciences. 72.6% are Public Universities.

The remainder of this draft describes the empirical approach taken in this project, the data used, and an analysis plan.

Introduction

Sexual misconduct at the workplace is widespread and has complex and lasting consequences for affected individuals. 59% of women and 27% of men report having personally experienced unwanted sexual advances or sexual harassment, either verbal or physical, in workplace or non-workplace settings (Graf, 2018). Psychologists and organizational behavior scholars have documented that sexual misconduct at the workplace reduces job satisfaction, increases turnover, and worsens psychological well-being, such as anxiety, stress disorder, or depression (Schneider, Swan and Fitzgerald, 1997; Cortina and Berdahl, 2008; Fitzgerald and Cortina, 2018).

More recently,

research has linked sexual harassment in the workplace to gender segregation and the gender wage gap (Folke and Rickne, 2022; Adams-Prassl et al., 2024; Collis and Van Effenterre, 2024).

Sexual misconduct at work remains widespread and has complex and long-lasting consequences for affected individuals.

While research documents severe harm to affected employees—including deteriorating psychological well-being manifested through anxiety, stress disorders, and depression (Schneider, Swan and Fitzgerald, 1997; Cortina and Berdahl, 2008; Fitzgerald and Cortina, 2018)—and its role in driving women from organizations Adams-Prassl et al. (2024); Batut, Coly and Schneider-Strawczynski (n.d.), a puzzling organizational response persists. Rather than addressing perpetrators, firms invest substantial resources in victim silencing through NDAs (Adams-Prassl et al., 2024; Barmes, 2023). This paper provides the first causal evidence that differential productivity impacts between misconduct *occurrence* and *disclosure* may explain this paradox.

To study the relationship between sexual misconduct and productivity, I turn to university departments. This setting offers three distinct advantages. First, academic publications constitute societally meaningful output with established productivity metrics. Second, the collaborative nature of contemporary research enables examination of interpersonal dynamics within knowledge production. Third, comprehensive documentation facilitates precise temporal identification of misconduct trajectories.

I build a panel dataset for over 5,000 university departments across nine disciplines between 1980 and 2024. To construct the treated departments, I leverage a dataset of all sexual misconduct cases at universities in the United States that has been publicized between 1980 and 2024. I use the universe of universities and randomly select nine departments per university as the comparison university departments. To study the relationship between sexual misconduct and productivity meaningfully, I restrict my sample to *research-focused* universities where the perpetrator was a *faculty*, resulting in 359 treated and 5,076 control university departments.

I hand-collect over 3,000 lawsuits, news-articles, or proprietary documents shared through online document libraries which allow me to establish a life cycle of a sexual misconduct case with three crucial points of time: the year when sexual misconduct starts to occur, the year when reporting starts to happen, and the year when the accused faculty leaves the department. I use these three points of time as three different "treatment" timings to establish the causal relationship of the (1) occurrence of sexual misconduct, (2) the public reporting of sexual misconduct, (3) the departure of the faculty facing sexual misconduct allegations. This rich information further allows me to capture contextual variation about each case that allows me to investigate how contextual factors shape productivity.

We have to assume that the publicized misconduct incidents are not random. To establish causality, I pair Coarsened Exact Matching (CEM) with a staggered difference-in-differences event study design. University departments are matched on five covariates: discrimination and harassment state laws, whether the university is public or private, discipline, research intensity of the university department, department size.

I provide causal evidence that *public reporting* of sexual misconduct incidents hurts university departments' overall productivity, but that the *occurrence* of sexual misconduct does not. The average number of publications per department member remains indistinguishable for departments where sexual misconduct took place when compared to the control departments. The public reporting of sexual misconduct reduces the average number of publications per department member by 0.1 (p-value < 0.05). It has twice the impact on men compared to women. One possible explanation for this gender difference could be that women leave the department. This is subject to further analysis. Next steps also include the examination of faculty who decide to co-author with the accused faculty and those who do not, looking at more outcome measures such as citations, journal impact factor, and direction of science. Lastly, I will take contextual factors into account, such as the role of the status of the targeted individual, speed of institutional processes, among others.

This paper contributes to three streams of research. To the best of my knowledge, it is the first study that provides causal evidence of the impact of sexual misconduct on broader organizational outcomes such as productivity. Second, this paper contributes to the literature on inequality in science and innovation.

Taken together, this paper is motivated by the puzzle that sexual misconduct hurts targeted individuals and contributes to gender inequality in the labor market and yet, organizations seem to spend substantial resources on cover-ups. The explanation for this paradox seems to be that the *occurrence* of sexual misconduct in a university department does not noticeably impact productivity while the *public reporting* of it does.

2 Empirical Design, Data, and Estimation

To study the impact of sexual misconduct incidents on organizational outcomes in academia, I construct a dataset that looks at the productivity outcomes of university departments.[1] The departments are listed in Table A. Treated departments have experienced a sexual misconduct case that became public.

[1] I define departments by following Clarivate's Core Collection containing 256 categories (https://mjl.clarivate.com/help-center and supplement these with SCImago categories when necessary (https://www.scimagojr.com/journalrank.php). Note, that for the purpose of this work, *departments* are defined as scholars who publish in a list of journals that corresponds to their department. Clarivate and SCImago call them categories.

2.1 Treated Research Departments

To construct the dataset of treated research departments, I leverage a dataset of all sexual misconduct incidents in academia that have been publicized. I use data from the Academic Sexual Misconduct Database (ASMD) Libarkin (2024) to define a list of academics who have been linked to an exposed sexual misconduct incident. The database accessed on November 19, 2024 contains 1,294 incidents[2]. These are incidents which became public either through a lawsuit or media reporting and include resolved and ongoing incidents. Note, that when I say *publicized*, then I mean the newspapers have reported about the start of the investigation or lawsuit, any updates, or the conclusion of such. The incidents involve faculty members, administrators, coaches, and other staff. These cases have concluded between 1980 and 2024 (see Figure 1). For the purpose of this study, I focus on *resolved incidents* at *research-focused* institutions committed by *faculty*, which reduces the sample to 359 incidents.[3]

To construct the outcome variables, I use the institution and department information, at which the respective incidents occurred and collect the publications, citation information, reference information, and abstracts for each institution x department pair. I collect publication data from OpenAlex. OpenAlex is an open-source database providing access to over 200 million publication records by combining databases such as Microsoft Academic Graph (MAG), Crossref, ORCID, Unpaywall, Pubmed, Pubmed Central, ISSN, and others (Priem, Piwowar and Orr, 2022).[4] OpenAlex prides itself on a superior linkage of information compared to alternative data providers such as Web of Science, Lens.org, or Dimensions.

I manually assign the department by examining each of the 359 incidents in the dataset. I assign the department based on four pieces of information: Libarkin's assignment of discipline,

[2]Note that the raw dataset contains two duplicates which I removed

[3]A university is considered research-focused if it has ever in its history been classified by Carnegie Classifications as one of these three categories: Research 1 - Very High Research Spending and Doctorate Production, Research 2 - High Research Spending and Doctorate Production, Research Colleges and University. I conducted a manual search and classification for the 57 universities without a Carnegie Classification. This removes 575 universities which are mostly technical colleges or U.S. Military/Navy Academies. Among the research-active universities, I remove ongoing cases (173) and cases for which both the individual and the discipline were unknown (83). Lastly, I remove all incidents which were committed by a coach, administrator, or unknown (126).

[4]More information can be found here: https://openalex.org/about

online news articles, an algorithm based on the faculty's publications (in cases where they could be linked to OpenAlex), and the department affiliation reported on their publications (in cases where they could be linked to OpenAlex).[5]

The list of departments consists of topic categories constructed by Clarivate and SJR where each topic category is linked to a corresponding journal list.[6]. There are a total of 527 distinct topic categories which are listed in Section A. My dataset consists of 142 unique topic categories.

The 359 incidents took place at 139 unique institutions, one institution is anonymous. All 139 institutions could be matched to OpenAlex.[7] Of the 359 incidents, I can link 347 accused and publicly exposed faculty to an OpenAlex profile. This contains four names and eight incidents where we have enough information to assign a department and university but not enough information to identify the accused individual.[8]

2.2 Identification Strategy and the Construction of Control Research Departments

Given my interest in the effect of a sexual misconduct incident on scientific production, my empirical strategy is focused on changes in published research output after the incident (A) occurred, (B) was reported on by the media, and (C) led to the departure of the faculty facing sexual misconduct allegations, respectively, relative to before the incident occured, was reported on by the media, or led to the departure of the faculty facing sexual misconduct

[5] I hired research assistants who have experience in the life sciences and assigned the individuals in the social sciences myself.

[6] The SJR topic category "Economics and Econometrics"'s corresponding journal list, for example, consists of 166 journals ranging from "American Economic Review" to "Economics of Energy and Environmental Policy" or "NBER Macroeconomics Annual book series"

[7] I employed an automatic matching by institution name. Each institution that did not return a 1:1 match was matched manually where I search for the correct match if no potential match has been returned by the search algorithm and remove false positives. Note that I also remove universities which are abroad. For example, Duke University (https://openalex.org/I170897317) has a partner university with Wuhan University. That partner university is called Duke Kunshan University and is located in China (https://openalex.org/I4210159968). I remove that university since it is not located in the US and most likely unaware of inter-personal dynamics at the department of interest.

[8] This means all 12 cases can be used to estimate the total effect but they cannot be used to estimate peer effects.

allegations, respectively.[9] To ensure that I estimate the causal effect of interest and not some other influence that is correlated with the passage of time, my specifications include time-fixed effects. However, there may still be time-related confounders such as policies or event-related trends. To mitigate this threat to identification, I implement a coarse exact matching approach described below.

To construct the control research departments, I use the universe of U.S. based research-focused universities over the 1980-2022 time period. To do that, I first construct a panel dataset of the IPEDS data between 1980 and 2023 and then construct a list of unique universities. IPEDS is a set of surveys conducted annually by the U.S. Department of Education's National Center for Education Statistics (NCES). Institutions that participate in a federal student aid program are required to respond according to the Higher Education Act of 1965. Note, that 2023 is the most recent data available.

I keep universities which have been categorized as research-active [10] according to the Carnegie Classification at least once in the history of Carnegie Classification. For that, I construct a panel dataset of the Carnegie Classifications between 1974 and 2023. I keep all university names which have ever been designated as a "Research University" during this time period. I then link the IPEDS database with the selection of research-active universities which results in a dataset of the universe of research-focused universities between 1980 and 2023. I then link these universities to OpenAlex. There are a total of 1152 research universities of which 582 could not be matched with OpenAlex. I inspected all 582 universities. I was unable to manually match them to OpenAlex. A closer look of a subsample shows that they are not research-intensive universities. This leaves us with 564 control universities.

To construct control research *departments*, I assign nine randomly selected departments, where I select a department for each of the nine disciplines defined by Clarivate's Core Collection. This will construct 5,076 total control departments, 564 control departments per discipline. Note, since this is the universe of research-active universities x discipline pairs, a

[9]Note that in approximately 65% of the reported cases, the accused faculty left the institution.

[10]Defined by Carnegie Classifications as one of these three categories: Research 1 - Very High Research Spending and Doctorate Production, Research 2 - High Research Spending and Doctorate Production, Research Colleges and University.

subset of these university x department pairs is, by definition, treated. Instead of removing them from the control set, I will account for that using a staggered treatment design. This will be discussed in Section 3.

2.3 Variable Construction

Outcome Variables

Publication Count I measure department x year productivity by counting the number of publications published every year by a given university department. The publication data will be assembled at the department x year x publication level and then aggregated at the department x year or department x year x subgroup (for example, women faculty) level. To capture the productivity of all department members equally, I will count within-department co-authored publications multiple times. For example, if two department members co-author together, their publication will count as two publications.

Citations For each publication, I count citations received annually from 2014 through 2024. In contrast to the publication count, I will count each publication's citations only once, regardless of how many co-authors are affiliated with the department. This measure captures how frequently scholars acknowledge or build upon their peers' scholarly contributions, which is a key indicator of research impact rather than simply measuring department-level productivity directly. To extend this coverage to years prior to 2014, I plan to use the Clarivate Web of Science data.

Journal Impact Factor To measure the quality of the work produced, I will use the database by Marx and Fuegi (2021), which covers journals from 1811 to 2019. To extend this coverage until 2024, I am currently working on constructing an impact factor measure that covers 1975 to 2024. For that, I plan to use the Clarivate Journal Impact Factor (JIF), which is derived from the Clarivate Citation Report and calculates the number of citations per publication a journal received in a given year for publications which were published the prior year. The JFI has been published every year since 1975 (Clarivate and Mangan, 2022) and made data from 1997 until 2023, including, available to me.

Direction of Science I measure the direction of science in the form of semantic similarity of the corpus of abstracts across years for every given department. I compute the semantic similarity between abstract corpora across consecutive years for each academic department. This temporal analysis employs large language model (LLM) embeddings, which represent state-of-the-art semantic representation capabilities in natural language processing. By measuring cosine similarities between year-specific embedding centroids, this approach captures subtle shifts in research focus, terminology, and conceptual frameworks that characterize the trajectory of scientific inquiry within disciplinary boundaries.

Gender I will infer the department members' *gender* based on their first and, if available, middle name using genderize.io. I will use a statistical probability cut-off point of 90% for either the first or middle names or 75% for first and middle names jointly.

Women representation I will count the number of publishing women faculty for any given university department and year.

Treatment Indicators I collect all publicly available materials on the set of publicly known sexual misconduct cases in the U.S. Academy (Libarkin, 2024). This includes news articles, lawsuit documents, proprietary documents posted on digital document libraries, and information shared in the Academic Sexual Misconduct Database. Based on this rich set of information, I code up the treatment indicators for *occurrence of a sexual misconduct*, *media reporting of a sexual misconduct incident*, and *departure of a faculty member facing sexual misconduct allegations* at the year level.

Heterogeneity in Treatment Effect

Spillover Effects by Gender I will investigate whether the impact of sexual misconduct is different for men and for women department members, where I will infer their *gender* based on their first name using genderize.io.

Spillover by Co-Authorship Status To understand the *spillover effects* on the department and the colleagues, I will calculate the outcome measure for the treatment group in three ways: (1) *Total Spillover Effect*, which is the outcome measure at the department level, (2) *Co-authors*, which looks at the scientific production of department members who co-authored with the accused faculty, and (3) *Non-Co-authors*, which looks at the scientific production of department members who don't collaborate with the accused faculty. This decomposition of the total effect allows me to disentangle the spillover effect the accused faculty had on department members who co-authored with them versus not.

Counterfactual for Accused Faculty To measure how the effect varies for co-authors and non-coauthors, I need to construct a counterfactual for the accused faculty in the control departments. I will do that by ranking faculty according to their productivity for each department x year. I will take the rank of the accused faculty from the treated department and select the faculty with the same rank in the control department as our counterfactual control faculty.

Covariates To assign a research discipline to each department, I use the nine primary disciplines based on Clarivate's Core Collection (https://mjl.clarivate.com/help-center): Agriculture, Biology & Environmental Sciences; Arts & Humanities; Business Collection; Clinical Medicine; Electronics & Telecommunication Collection; Engineering, Computing & Technology; Life Sciences; Physical, Chemical & Earth Sciences; Social And Behavioral Sciences.

To determine whether the university is a public or a private university, I use IPEDS' institutional datasets. I am able to match all 139 unique treated institutions with IPEDS data. The 564 control universities are part of the IPEDS dataset by design.

The research intensity at a given university is assigned using the Shanghai Ranking's *Global Ranking of Academic Subjects (GRAS)* which contains rankings of universities in 55 subjects across Natural Sciences, Engineering, Life Sciences, Medical Sciences, and Social Sciences (Shanghai Consultancy, 2024). The ranking is ideal for the purpose of this research because it ranks universities based on research output and quality, faculty quality, and research collaborations.[11]. In contrast, U.S. News Education Ranking focuses on research output *and* student experience, and the Carnegie Classifications are based on the number of doctoral degrees granted and the amount of research expenditure. I assign the GRAS at the university x subject level.

An institution's behavior is likely shaped by the laws under which it operates. To account for that, I construct a categorical variable at the state level that captures the extent to which state-level legal framework deviate from federal-law related to four categories: discrimination, workplace hostility, sexual harassment, and retaliation. To do so, I hand-collect the extent of legal deviations for each category.

Department size is determined by the number of publishing researchers in a given year.

3 Empirical Strategy

To estimate the causal effect of publicly exposed sexual misconduct incidents on academic department outcomes, I implement a staggered Difference-in-Differences (DiD) design. My approach incorporates Coarsened Exact Matching (CEM) as a preprocessing step to improve covariate balance before estimating treatment effects, allowing for causal inference under more credible assumptions. This section addresses empirical challenges, the matching design, and the regression specifications.

Departments experience the three "treatments" — misconduct, public exposure, and exiting of the accused faculty — at different points in time. The treatment effect is identified by

[11] More information about their methodology can be found here: `https://www.shanghairanking.com/methodology/arwu/2024`

comparing outcomes in treated departments before and after exposure, relative to matched control departments that have not yet been treated or will never be treated.

A department is classified as a valid control in a given treatment window if it did not experience a public sexual misconduct case within a symmetric 5-year window around the treatment year. I conduct robustness checks that tighten this requirement in two ways: (i) requiring that no other department in the same university was treated during the window, and (ii) restricting controls to departments in universities that are never treated.

The treatment in my setting is not randomly assigned. For a case to become public, it requires either involved parties that are willing to file a lawsuit or go public or local or national news media that is motivated and able to obtain evidence. This is more likely the case for sexual misconduct cases that are more severe or persistent and take place at public universities where freedom of information requests can be filed, for example. To account for potential differences in observed covariates, I use a multi-stage coarse exact matching approach.

This multi-stage coarse exact matching approach directly addresses several causal challenges. First, the CEM preprocessing helps mitigate bias by ensuring that treatment and control departments are balanced on key covariates that might drive treatment effect heterogeneity. Second, by preprocessing data through CEM before parametric analysis, I reduce model dependence and sensitivity to specification choices (Ho et al., 2007). The matching procedure creates more comparable treatment and control groups, addressing the fundamental concern that departments experiencing misconduct incidents may systematically differ from those that do not.

Additionally, the inclusion of university fixed effects (ψ_u) in all specifications provides additional protection against potential confounding from institution-level factors. By differencing out all time-invariant university characteristics, as well as any university-wide shocks that affect all university departments equally, this approach isolates the department-level impact of sexual misconduct incidents. This is particularly important given that universities may differ systematically in their reporting procedures, institutional cultures, and responses to misconduct cases. The university fixed effects ensure that our estimates reflect the causal impact of misconduct at the department level rather than capturing university-level heterogeneity.

My baseline model will be a simple difference-in-differnce estimator which I will bild out into a staggered Difference-in-Difference design (oftentimes called two-way fixed effects (TWFE)). Recent methodological developments allow me to address empirical challenges associated with staggered Difference-in-Difference design (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Baker, Larcker and Wang, 2022). Specifically, standard TWFE estimators can produce biased estimates in settings with heterogeneous treatment effects over time because they implicitly use already-treated units as controls for newly-treated units. This creates a weighted average of treatment effects where some effects receive negative weights, potentially leading to estimates with incorrect signs or magnitudes. I probe robustness to my results using the Sun and Abraham (2021) estimator which handles staggered Difference-in-Difference designs with treatment effect heterogeneity across cohorts and allows for matching weights.[12]

To account for uncertainty across all stages of analysis, I employ cluster-robust standard errors at the university x department level, addressing potential correlation in outcomes within departments over time.

3.1 Stage 1: Coarsened Exact Matching (CEM)

I employ a multi-stage approach that combines preprocessing through Coarsened Exact Matching (CEM) (Iacus, King and Porro, 2011, 2012) with subsequent regression-based analyses. This approach pairs departments that experienced sexual misconduct incidents with similar departments that did not experience such incidents based on pre-specified covariates. One of the key advantages of this approach is that it reduces model dependence by first addressing selection bias through matching before conducting parametric analysis (Ho et al., 2007). Note that for simplicity, I use *publication* as the outcome variable Y moving forward. But the analyses described below will also be conducted for the other outcomes of interest (citations, journal impact factor, and direction of science).

[12] I will also report the estimators from Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfœuille (2020) but since they don't allow for weights, they are not my preferred specification.

In the first stage, I implement CEM to create appropriate comparison groups by matching departments that experienced sexual misconduct incidents with similar departments that did not. The matching covariates are selected to address the fundamental challenge of selection bias in observational studies of sexual misconduct. To satisfy the conditional independence assumption necessary for causal inference, I identify and match on covariates that simultaneously predict both the likelihood of experiencing sexual misconduct incidents (treatment assignment) and departmental research productivity (outcome). This approach helps isolate the causal effect by creating balanced comparison groups that differ primarily in their treatment status rather than in other confounding characteristics.

Research Discipline. Research disciplines strongly influence the publication patterns (due to field-specific characteristics and norms). Thus, I stratify the matching process by research discipline. I use Clarivate's primary nine research categories defined in its Core Collection, where each of the 142 disciplines of the treated dataset is linked to one primary research discipline.

Legal Framework at the State Level. Institution's behavior is likely influenced by the law they are governed by. To account for that, I construct a categorical variable at the state level that captures deviation of state-level legal framework compared to federal-law related to discrimination, workplace hostility, sexual harassment, and retaliation. To do so, I hand-collect the legal deviations.

Research Intensity. The research intensity at a given university is assigned using the ShanghaiRanking's *Global Ranking of Academic Subjects (GRAS)* which contains rankings of universities in 55 subjects across Natural Sciences, Engineering, Life Sciences, Medical Sciences, and Social Sciences Shanghai Consultancy (2024).

This matching approach ensures that treatment and control departments share similar characteristics across dimensions that jointly determine both the probability of experiencing observed sexual misconduct incidents and departmental research productivity. By creating well-balanced comparison groups through CEM before applying regression analysis, I reduce model dependence and strengthen causal identification (Ho et al., 2007).

Stage 2: Staggered Difference-in-Difference Estimation

Analysis 1: Overall Treatment Effect Analysis Using the matched sample from Stage 1, I estimate the overall effect of sexual misconduct incidents on department productivity. I apply the following weighted regression model to the matched data:

$$Y_{iut} = \alpha_i + \lambda_t + \psi_u + \beta_1 Treat_i + \beta_2 Post_{it} + \tau(Treat_i \times Post_{it}) + \gamma DeptSize_{it} + \varepsilon_{iut} \quad (1)$$

where Y_{iut} is the number of publications for department i at university u at time t, α_i are department fixed effects, ψ_u are university fixed effects, λ_t are time fixed effects, $Treat_i$ is a binary indicator equal to 1 for departments that experience a misconduct incident (and 0 otherwise), $Post_{it}$ is a binary indicator equal to 1 for periods after department i experiences a misconduct incident (and 0 otherwise), τ is the coefficient of interest representing the causal effect of sexual misconduct exposure on departmental productivity, γ controls for department size, and ε_{iut} is the error term.

Standard errors are clustered at the university x department level, and control university x departments are weighted using the CEM stratum-specific weights:

$$w_i = \begin{cases} 1 & \text{if } i \text{ is treated} \\ \frac{m_T^s}{m_C^s} & \text{if } i \text{ is a control unit in stratum } s \end{cases} \quad (2)$$

where m_T^s is the number of treated units in stratum s and m_C^s is the number of control units in stratum s. The inclusion of university fixed effects ψ_u allows me to difference out any institution-level effects while identifying the department-level impact of sexual misconduct incidents. This approach controls for all time-invariant university characteristics that might confound the relationship between misconduct and departmental outcomes.

I will report the average treatment effect over the five post-treatment periods for which I will take the simple average of τ (Equation 3) with a standard error of the mean of the post-treatment coefficients. I will then continue with reporting the full event study in standard event-study plots.

$$\bar{\tau} = \frac{\sum_{t=1}^{5} \tau_{it}}{5} \tag{3}$$

Analysis 2: Heterogeneity Analysis by Gender and Co-Authorship Status Continuing with the matched sample, I investigate how the impact of misconduct incidents varies across different demographic groups within departments. I analyze:

1. **Gender**: Separate analyses for publications by women and men department members.
2. **Co-Authorship Status**: Separate analyses for department members who are co-authors of the accused faculty versus department members who are *not* co-authors of the accused faculty.

For each subgroup analysis, I estimate:

$$Y_{iut}^{g} = \alpha_i + \lambda_t + \psi_u + \beta_1 Treat_i + \beta_2 Post_{it} + \tau^g (Treat_i \times Post_{it}) + \gamma DeptSize_{it} + \varepsilon_{idt} \tag{4}$$

where Y_{iut}^{g} represents the productivity measure for subgroup g in department i at university u at time t, τ^g captures the causal effect of sexual misconduct exposure specific to subgroup g, and γ controls for department size.

I also employ interaction models to directly test for differential effects across gender and co-authorship status:

$$\begin{aligned} Y_{idt} = \alpha_i + \psi_u + \lambda_t + \beta_1 Treat_i + \beta_2 Post_{it} + \beta_3 Female_i \\ + \tau(Treat_i \times Post_{it}) + \phi(Treat_i \times Post_{it} \times Female_i) \\ + \gamma DeptSize_{it} + \varepsilon_{iut} \end{aligned} \tag{5}$$

3.2 Staggered Event Study Design

To test for pre-treatment trends and investigate the time-dynamic of the treatment effect, I estimate an event-study specification:

$$Y_{iut} = \alpha_i + \psi_u + \lambda_t + \sum_{k \neq -1} \beta_k \cdot \mathbb{1}(r_{it} = k) + \varepsilon_{iut} \tag{6}$$

where $r_{it} = t - T_i$ is time relative to the treatment year. The year prior to the treatment is the omitted category ($k = -1$). I plot the coefficients β_k to visually assess pre-trends and time-dynamic treatment effects.

4 Figures and Tables

Figures

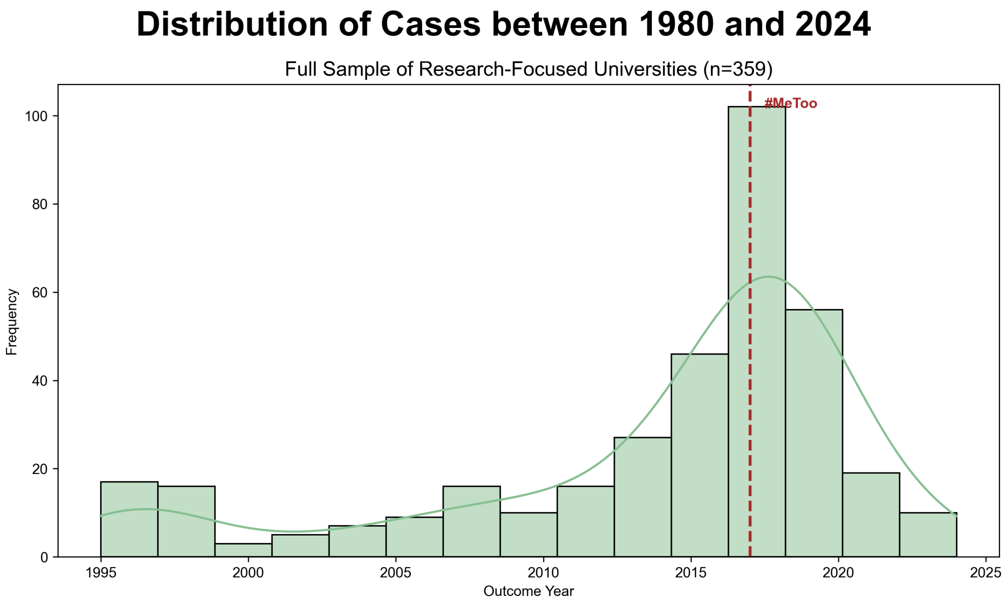

Figure 1: Distribution of Cases used for this Study

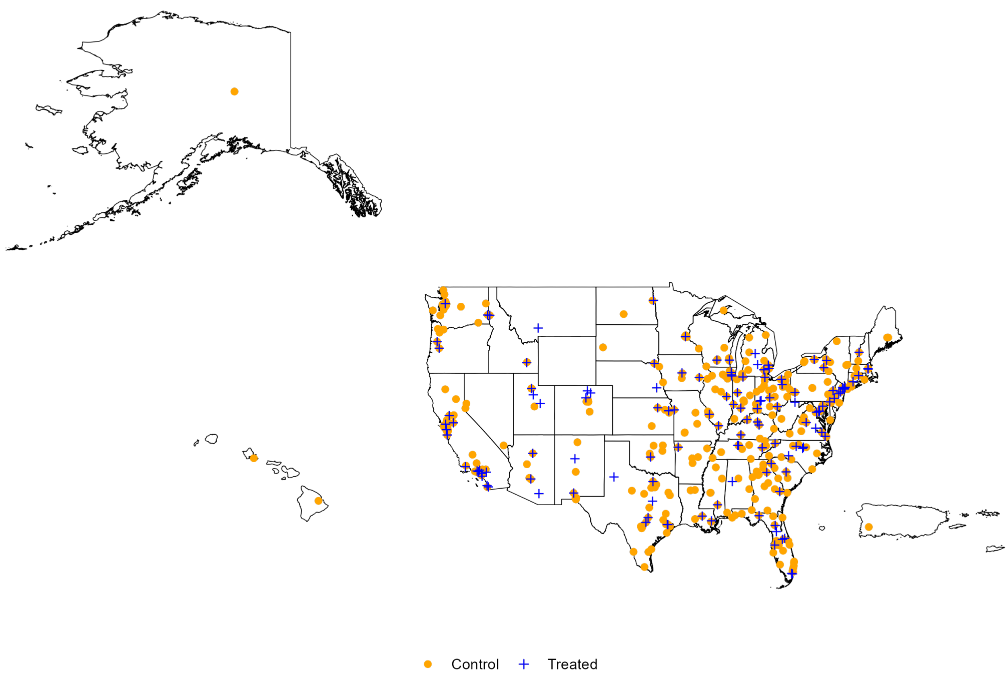

Figure 2: Treated and Control Universities - Treated and Control

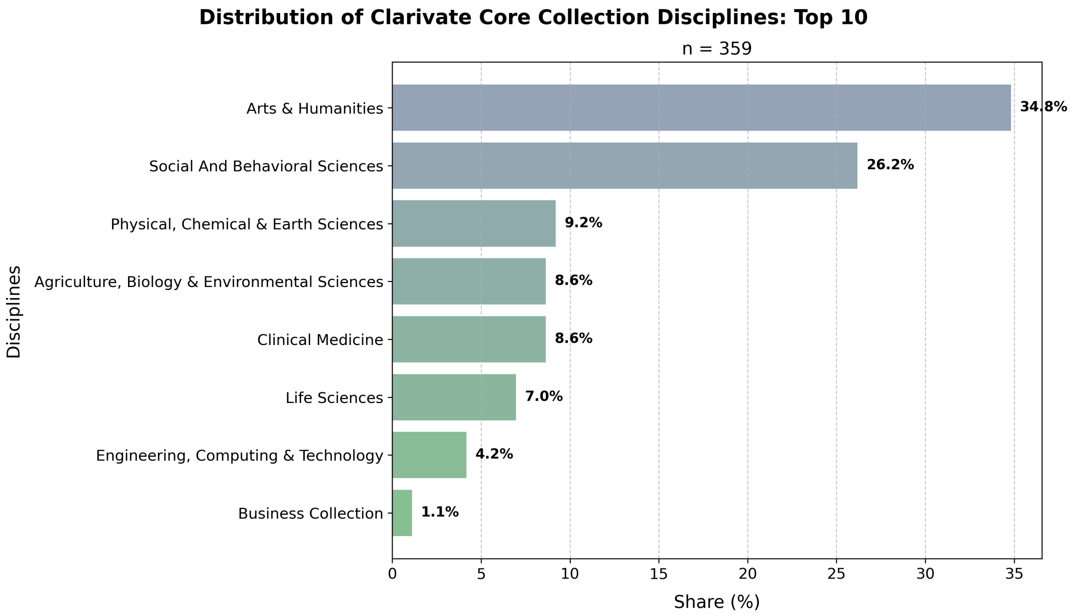

Figure 3: Treated and Control Universities - Treated and Control

Tables

Variable	Before Matching		After Matching	
	Control	**Treated**	**Control**	**Treated**
Publications	0.174 (0.97)	0.663 (2.95)	0.371 (1.28)	0.655 (2.96)
Sample Size (N)	30,105	169	23,725	168

Note: Values shown as Mean (SD). Control group statistics after matching use analytic weights. SMD = Standardized Mean Difference.

Table 1: Balance Statistics Before and After Matching at time period $t-1$

Variable	Before Matching	After Matching	Reduction (%)
Multivariate L1 distance	0.452	0.066	85.6
Univariate L1 distance			
Discipline	0.310	5.2e-14	100.0
Public Institution	0.172	1.1e-13	100.0
State Law for Hostility & Harassment	0.072	1.7e-13	100.0
Shanghai Ranking (GRAS)	0.131	.031	76.4
Standardized Mean Difference: 0.128			

Table 2: L1 Imbalance Before and After Matching at time period $t-1$

Variable	**Dispersion**	**Expected vs. Observed Count**
Publications	0.000	0.000
Publications Women	0.000	0.000
Publications Men	0.000	0.000

Note: The expected count of zeros under a Poisson distribution is calculated as: $n \times e^{-\lambda}$ where n is the total number of observations and λ is the sample mean. This formula is derived from the Poisson probability mass function $P(X = 0) = e^{-\lambda}$ multiplied by the sample size.

Table 3: Dispersion and Zero-Inflation Check

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(For Online Publication)

Appendix to

Misconduct in Academia

Manuela R. Collis

List of Appendices

A Clarivate Core Collection

I use nine primary departments which are based on Clarivate's Core Collection (`https://mjl.clarivate.com/help-center`): Agriculture, Biology & Environmental Sciences; Arts & Humanities; Business Collection; Clinical Medicine; Electronics & Telecommunication Collection; Engineering, Computing & Technology; Life Sciences; Physical, Chemical & Earth Sciences; Social And Behavioral Sciences. Below, I list for the research communities defined by Clarivate and SJR for each of the nine disciplines.

Disciplines and Communities

Agriculture, Biology & Environmental Sciences
- Agriculture/Agronomy
- Agricultural Chemistry
- Animal Sciences
- Aquatic Sciences
- Biology
- Biodiversity
- Biophysics
- Biotechnology
- Botany
- Conservation
- Developmental Biology
- Ecology/Environmental Sciences
- Entomology
- Evolutionary Biology
- Fisheries
- Food Science
- Forestry
- Horticulture
- Marine Biology
- Molecular Biology
- Mycology
- Paleontology
- Parasitology
- Plant Sciences
- Soil Science
- Veterinary Sciences
- Wildlife Management
- Zoology

Arts & Humanities
- Architecture
- Art
- Asian Studies
- Classical Studies
- Dance
- Film, Radio & TV
- Folklore
- History
- Humanities (General)
- Language & Linguistics
- Literary Criticism
- Literature
- Medieval Studies
- Music
- Philosophy
- Poetry
- Religion
- Renaissance Studies
- Theater

Business Collection
- Accounting
- Advertising
- Banking
- Business
- E-commerce
- Economics
- Finance
- Hospitality Industry
- Human Resources
- Insurance
- International Business
- Logistics
- Management
- Marketing
- Nonprofit Organizations
- Operations Research
- Real Estate

Clinical Medicine
- Allergy
- Anesthesiology
- Audiology
- Cardiology
- Critical Care
- Dentistry
- Dermatology
- Emergency Medicine
- Endocrinology
- Gastroenterology
- General Medicine
- Geriatrics
- Health Policy
- Hematology
- Immunology
- Infectious Diseases
- Medical Ethics
- Medical Informatics
- Medical Technology
- Neurology
- Nursing
- Nutrition
- Obstetrics & Gynecology
- Oncology
- Ophthalmology
- Orthopedics
- Pathology
- Pediatrics
- Pharmacology
- Physical Therapy
- Preventive Medicine
- Psychiatry
- Radiology
- Rheumatology
- Sports Medicine
- Surgery
- Toxicology
- Transplantation
- Tropical Medicine
- Urology

Electronics & Telecommunications Collection
- Artificial Intelligence
- Automation
- Computer Hardware
- Computer Science

- Control Systems
- Cybernetics
- Digital Signal Processing
- Electrical Engineering
- Electronics
- Embedded Systems
- Information Systems
- Machine Learning
- Mobile Communications
- Network Security
- Robotics
- Software Engineering
- Telecommunications

Engineering, Computing & Technology
- Acoustics
- Aerospace Engineering
- Architectural Engineering
- Automotive Engineering
- Biomedical Engineering
- Ceramics
- Chemical Engineering
- Civil Engineering
- Composite Materials
- Construction
- Energy & Fuels
- Environmental Engineering
- Fluid Dynamics
- Industrial Engineering
- Manufacturing
- Marine Engineering
- Materials Science
- Mechanical Engineering
- Metallurgy
- Mining Engineering
- Nanotechnology
- Nuclear Engineering
- Petroleum Engineering
- Polymers
- Remote Sensing
- Thermodynamics
- Transportation
- Water Resources

Life Sciences
- Biochemistry
- Biomedical Research
- Biometrics
- Cancer Research
- Cell Biology
- Computational Biology
- Genetics
- Genomics
- Immunobiology
- Limnology
- Microbiology
- Microscopy
- Molecular Biology
- Neuroscience
- Physiology
- Proteomics
- Stem Cell Research
- Structural Biology
- Systems Biology
- Tissue Engineering
- Toxinology
- Virology

Physical, Chemical & Earth Sciences
- Analytical Chemistry
- Applied Mathematics
- Astronomy & Astrophysics
- Atmospheric Science
- Atomic Physics
- Catalysis
- Chemistry
- Computational Physics
- Condensed Matter Physics
- Crystallography
- Electrochemistry
- Fluid Dynamics
- Geochemistry
- Geology
- Geophysics
- Inorganic Chemistry
- Mathematics
- Meteorology
- Mineralogy
- Nanotechnology
- Nuclear Physics
- Oceanography
- Optics
- Organic Chemistry
- Particle Physics
- Physical Chemistry
- Polymer Science
- Quantum Physics
- Seismology
- Spectroscopy
- Statistical Physics
- Thermodynamics

Social And Behavioral Sciences
- Anthropology
- Applied Linguistics
- Archaeology
- Area Studies
- Behavioral Sciences
- Child Development
- Clinical Psychology
- Cognitive Science
- Communication
- Criminology
- Cultural Studies
- Demography
- Developmental Psychology
- Economic Geography
- Education
- Educational Psychology
- Environmental Studies
- Ergonomics
- Ethics
- Ethnic Studies
- Experimental Psychology
- Family Studies
- Geography
- Gerontology
- Health Education
- Human Geography
- Industrial Psychology
- Information Science
- International Relations
- Law
- Library Science
- Political Science
- Psychoanalysis
- Psychology
- Public Administration
- Social Psychology
- Social Work
- Sociology
- Special Education
- Sports Science
- Substance Abuse
- Urban Studies
- Women's Studies