Title

Scholars on the Margins, or Marginalized Scholars? The (De)Valuation of Engaged Scholars as a case of Epistemic Exclusion

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Scholars on the Margins, or Marginalized Scholars?
The (De)Valuation of Engaged Scholars as a case of Epistemic Exclusion

By

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DISSERTATION

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Table of Contents

Abstract iii

Acknowledgements v

Chapter 1: Introduction and Literature Review 1

Chapter 2: Data and Methods 15

Chapter 3: Engaged Scholars – Race and Gender Disparities 57

Chapter 4: Engaged Scholarship and Metrics of Academic Productivity 91

Chapter 5: Conclusion 148

Appendix A: Text Classification 151

Appendix B: Models from Chapter 3 162

Appendix C: Models from Chapter 4 174

References 202

Abstract

In this dissertation, I explore several ways in which engaged scholarship may serve as a vehicle for epistemic exclusion, a process through which types of scholarship predominantly done by women and scholars of color are delegitimized and under-rewarded. I use faculty recruitment data from six disciplines across six academic years to (1) classify early career scholars who identify as engaged scholars; (2) explore the extent to which women and scholars of color are more likely to identify as engaged scholars; and (3) investigate race and gender disparities in the association between engaged scholarship and metrics of productivity commonly used in academic evaluations. These three aims comprise the three analytic chapters in this dissertation. My findings show that engaged scholarship is indeed primarily done by women and scholars of color—particularly female scholars of color. I also find that those who identify as engaged scholars are both advantaged and disadvantaged in different measures of scholarly productivity. However, scholars of color—again, particularly female scholars of color—tend not to have advantages when they otherwise exist for engaged scholars. This demographic is also the *most* disadvantaged when engaged scholars are disadvantaged, compared to other groups. These findings reiterate the importance of examining gender inequality in academia through an intersectional lens, as occupational devaluation occurs through both gendered and racialized processes simultaneously.

Ultimately, I argue that these findings indicate that epistemic exclusion, like the devaluation of feminized work in other occupations, does not equally apply to all scholars who pursue engaged scholarship. Although some evidence suggests that engaged scholars are cited less and publish in lower impact journals—both indicators that such work is devalued—these effects are disproportionately shouldered by scholars of color (especially female scholars of

color). In light of these findings, I propose that future research should examine the career consequences of this differential devaluation of scholars who engage in scholarship predominantly done by women and scholars of color, as epistemic exclusion stands as an important measure to understand women and scholars of colors' continued underrepresentation and marginalization as academic faculty. Additionally, I suggest that future work on this topic should examine processes of epistemic exclusion in the context of graduate training in order to better understand how and why scholars pursue certain types of scholarship.

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Chapter 1: Introduction and Literature Review

The devaluation of women's work is a key contributing factor to continued occupational gender segregation, and therefore to the gender gap in earnings and occupational prestige (Baron and Newman 1990; England 2017; Padavic and Reskin 2002). Although devaluation operates in multiple contexts through multiple mechanisms, Paula England succinctly describes the underlying status beliefs that perpetuate devaluation: "cultural ideas deprecate women, and thus by cognitive association, devalue work typically done by women" (England 2005). Scholars have used the devaluation framework to explore occupational inequality in multiple areas of work, including care work (England, Budig, and Folbre 2002), computing (Hicks 2017), and academia (Frehill, Abreu, and Zippel 2015; Misra et al. 2011).

Within academic disciplines, scholars have noted a similar phenomenon—for which they have coined the term epistemic exclusion—through which types of scholarship predominantly done by women and scholars of color (both groups traditionally underrepresented in academic faculty positions) are delegitimized and under-rewarded (Dotson 2014; Settles et al. 2020). Although academia is overall a white and male institution (Bird 2011; Mihăilă 2018; Ray 2019a; Romero 1997), certain disciplinary fields have become increasingly female-dominated (England et al. 2007; Leslie et al. 2015). Epistemic exclusion nevertheless suggests that within all fields, regardless of male/female representation, types of scholarship associated with women and scholars of color are consistently devalued. Epistemic exclusion therefore stands as an important measure to understand women and scholars of colors' continued underrepresentation and marginalization as academic faculty.

Some empirical work exists examining the experience of epistemic exclusion amongst faculty of color (Settles et al. 2020), and finds that faculty of color face epistemic exclusion through both formal (i.e., tenure and promotion practices, limited ability to publish in mainstream journals, differential access to grant funding, etc.) and informal channels. Little work exists, however, that identifies the types of scholarship predominantly done by scholars of color and how they may be a vehicle for further underrepresentation in academia. Disparate literature suggests that interdisciplinary work (Gonzales and Rincones 2012; Rhoten and Pfirman 2007), indigenous methodologies (Louis 2007), Critical Race Theory (Bernal and Villalpando 2002), and community engaged scholarship (Ellison and Eatman 2008; Settles et al. 2020; Vogelgesang, Denson, and Jayakumar 2010) are devalued types of scholarship more likely done by women and/or scholars of color. At the occupation- or discipline-level, researchers can look at occupation statistics to determine the relative representation of women and people of color in a job or field to determine the extent of gender or racial segregation. Empirically identifying types of scholarship within and across fields, however, is a much more difficult task. Likewise difficult is determining the effect of such scholarship on valuation.

In this dissertation, I examine one specific type of scholarship as a potential vehicle of epistemic exclusion: engaged scholarship. Engaged scholarship, also called publicly engaged scholarship or community engaged scholarship, refers to the reframing of academic work as an inseparable whole in which teaching, research and service inform and enrich each other with the goal of addressing societal needs (Colbeck and Wharton-Michael 2006; Kellogg Commission on the Future of State and Land-Grant Universities 2000). Among tenured and tenure-track faculty, research finds that engaged scholars are often more likely to be female and scholars of color, though no study to date has examined gender and race disparities intersectionally, nor do we know the extent of such disparities across fields or time (Antonio, Astin, and Cress 2000; O'Meara 2002; Vogelgesang et al. 2010). Through the case study of engaged scholarship, this dissertation addresses two primary research questions. First, are women and scholars of color more likely to identify as engaged scholars? Within this larger question, I also investigate the extent to which race and gender disparities in engaged scholarship vary across academic disciplines, and the extent to which such disparities exist when considering scholar's race and gender simultaneously. Second, to what extent are metrics commonly used to evaluate scholarly productivity associated with engaged scholarship, and are there race and gender disparities in the effect of engaged scholarship on such metrics?

My findings indicate that engaged scholarship is indeed primarily done by women and scholars of color—particularly female scholars of color. This finding holds true in nearly all science, technology, engineering, and math (STEM) and social science (SS) fields. I also find that those who identify as engaged scholars are both advantaged and disadvantaged in different measures of scholarly productivity. However, scholars of color—again, particularly female scholars of color—tend not to have advantages when they otherwise exist for engaged scholars. This demographic is also the *most* disadvantaged when engaged scholars are disadvantaged, compared to other groups. These findings reiterate the importance of examining gender inequality in academia through an intersectional lens (Alegria and Branch 2015), as occupational devaluation occurs through both gendered and racialized processes simultaneously (Branch 2011).

I argue that these findings together indicate that epistemic exclusion, like the devaluation of feminized work in other occupations, does not equally apply to all scholars who pursue engaged scholarship. Although some evidence suggests that engaged scholars are cited less and publish in lower impact journals—both indicators that such work is devalued—these effects are disproportionately shouldered by scholars of color (especially female scholars of color). In light of these findings, I propose that future research should examine the career consequences of this differential devaluation of scholars who engage in scholarship predominantly done by women and scholars of color, as epistemic exclusion stands as an important measure to understand women and scholars of colors' continued underrepresentation and marginalization as academic faculty. Additionally, I suggest that future work on this topic should examine processes of epistemic exclusion in the context of graduate training in order to better understand how and why scholars pursue certain types of scholarship.

In the remainder of this chapter I review the extant literature relevant to the two primary research questions investigated in this dissertation: occupational segregation, devaluation, epistemic exclusion, and engaged scholarship. I then provide an outline of the empirical dissertation chapters.

1.1 Literature Review

1.1.1 Occupational Segregation and the Devaluation of Work Done by Members of Non-Dominant Social Groups

Occupational segregation by gender is well established as an explanatory factor in the gender wage gap (Bielby and Baron 1986; Charles and Grusky 2004; Petersen and Morgan 1995; Reskin and Roos 1990). A growing body of literature has examined multiple causes of occupational segregation. Neoclassical economic theories explaining supply and demand focus primarily on individual-level processes, such as the accumulation of human capital and rational choices in finding jobs or hiring/promoting employees (Becker 1985; Polacheck 1981).

Sociologists expanded these theories to incorporate the influence of organizational and social structures on individual action, such as Reskin and Roos' (1990) classic work on queuing theory. Instead of aggregating individual preferences and decisions, queuing theory emphasizes the role of power and conflict between groups, examining the collective nature of occupational segregation (Reskin and Roos 1990). Researchers have also examined occupational race and gender segregation due to employer discrimination (Bertrand and Mullainathan 2004; Bielby and Baron 1986; Pager and Shepherd 2008; Reskin 1993), cultural and psychological constraints on career choices (Cech 2013b; Correll 2001, 2004), and the organization of many jobs that structurally favor male and white bodies, preferences, and social lives (Acker 1990; Ray 2019a).

As with other forms of segregation (e.g., geographic and/or residential segregation: Massey and Denton 1993), segregation according to such social categories as race and gender is rooted in social beliefs about who belongs where and deserves what. This way of thinking about social value along nominal social characteristics implies that the social *status* of such groups plays a key role. Expanding on Max Weber's classic statement about status inequality based on honor, respect, and esteem (Weber [1922] 1978), Cecilia Ridgeway argues that modern sociologists do not give enough credit to status as an independent mechanism by which social inequality is created and maintained (Ridgeway 2014). As a source of social inequality, status is more difficult to see than other types of inequality—such as material resources—as it is rooted in everyday interactions and estimations of worth (Ridgeway 2014). Furthermore, as a mechanism of persistence, status-based inequalities provide leverage on understanding societal inequality at micro- and macro-levels (Ridgeway 2014). Ridgeway posits that status operates at each of these levels separately, but plays such an important role in the persistence of inequality because these levels are interconnected and mutually reinforcing (2014).

Status-based inequalities are particularly salient for categorical inequalities—i.e., inequalities based on categories that don't have an inherent ranking, such as race and gender

(Ridgeway 1991). Race and gender are generally seen as essentialized in the body, yet sociologists have shown that both are socialized, interactional identities (e.g. Omi and Winant 2014; West and Fenstermaker 1995) that are constantly made and remade through social relations. Not coincidentally, status inequalities based on these categories are also primarily created and recreated through micro-level social interactions (Berger, Ridgeway, and Zelditch 2002; Ridgeway 1991; Ridgeway and Smith-Lovin 1999). By forming and reforming conceptions of race and gender alongside beliefs about social status hierarchies, categorical inequalities become embedded in the structures of race and gender formation themselves.

The devaluation framework explaining occupational segregation draws on this conception of status inequality, as the devaluation of work associated with women and people of color occurs because such groups are largely deemed as less competent compared to dominant social groups. The resulting devaluation reinforces status beliefs: such work often has less prestige and pay. Even controlling for level of education, skills, and experience, occupations predominantly held by women consistently pay less than male-dominated occupations (Cohen and Huffman 2003; Cotter et al. 1997; England 1992a). Furthermore, the devaluation of occupations is not static, but rather changes with demographic shifts in the labor market. These changes have been documented over time—both in lower pay for occupations as they shift to a higher representation of female workers (Levanon, England, and Allison 2009), and in higher occupational prestige of a profession as it shifts from predominantly female to predominantly male (Hicks 2017).

Additionally, research shows that devaluation is not a one-size-fits-all phenomenon. Although female-dominated occupations pay less overall, multiple studies find evidence that male and white workers within such occupations have distinct advantages over women and people of color (Alegria 2019; Budig 2002; Williams 1992; Wingfield 2009). Christine Williams (1992) observed a "glass escalator" effect in female-dominated professions, wherein male workers were promoted faster and more often than similarly skilled female workers. Adia Harvey Wingfield (2009) expanded this work with an intersectional approach, finding that the glass escalator effect specifically applied to *white* men in female-dominated professions; black men often experienced further marginalization in such jobs, especially if the occupation was seen as white women's work. Sharla Alegria (2019) also demonstrated the significance of an intersectional approach to work and valuation: in the male-dominated tech industry, she found that white women experienced a "glass step-stool" effect, in which they were often side-stepped out of more lucrative engineering positions into managerial roles, while women of color did not experience even that small advantage.

1.1.2 Devaluation in Academia and Epistemic Exclusion

Academia has long been recognized as a male and white institution, both demographically and culturally (Bazner, Vaid, and Stanley 2021; Bird 2011; Romero 1997; Zippel and Ferree 2019). Historically, women and minoritized race/ethnicity groups were explicitly excluded from higher education through institutional policies and quotas (Harper, Patton, and Wooden 2009; Parker 2015; Zambrana and MacDonald 2009). Yet the underlying organization of academia was also built on the implicit exclusion of these groups through processes that defined legitimate science and knowledge creation, in opposition to the topics and epistemologies established by women and people of color (Furner 2017; Go 2020; Lengermann and Niebrugge 2006; Morris 2017; Schiebinger 1991, 2004). Referring to this history, scholars have labeled this phenomenon as epistemic exclusion (Go 2020) or epistemic apartheid (Ray 2019b).

This history has led to modern academic gatekeeping that relies heavily on schemas of legitimacy aimed at validating the status quo (Posselt et al. 2020). In the modern sense, epistemic exclusion refers to the systematic devaluation of research topics, methodologies, and knowledge production of scholars whose research is typically outside the disciplinary norms of their field (Dotson 2014; Settles et al. 2020). These marginalized forms of scholarship are also most often done by scholars who embody equally marginalized identities, such as women and faculty of color (Settles et al. 2020). Settles et al. (2020) find that the devaluation inherent in epistemic exclusion manifests through marginalized scholars feeling that the type of work they do is often seen as "on the margins" in their discipline: their work is difficult to publish in central journals, cited less, and inhibits their ability to secure grant funding. These particular consequences of epistemic exclusion directly affect metrics of scholarly productivity that largely correlate to how merit and scholarly legitimacy are measured in academia (Posselt et al. 2020).

Although Settles et al. (2020) provide a rich understanding of how faculty of color experience epistemic exclusion, we know less about what specific types of scholarship may be vehicles for epistemic exclusion; the extent to which such types of scholarship disadvantage women and faculty of color across disciplines; and whether, like the racialized glass escalator, all scholars who pursue such types of scholarship are equally disadvantaged.

These questions drive the analysis contained in this dissertation. I address them by exploring a single type of scholarship—engaged scholarship—which extant literature suggests is devalued across fields *and* is more likely done by women and scholars of color.

1.1.3 Engaged Scholarship

Engaged scholarship broadly refers to scholarly practices aimed toward the democratization and co-community production of knowledge and contribution to the public good. The scope of engaged scholarship includes terms used to describe various engaged activities such as public scholarship, community engaged scholarship, translational research, and service learning.

The term “engaged scholarship” became popular through Ernest Boyer’s 1990 book “Scholarship Reconsidered,” in which he critiqued American higher education for losing focus on its original purpose: benefiting the public good. At the time, Boyer was the president of the Carnegie Foundation for the Advancement of Teaching, an organization that developed (and continues to maintain) the most prominent classification system in American higher education (Giles, Sandmann, and Saltmarsh 2010). Boyer proposed that the purpose of higher education in society was to use “the rich resources of the university to [address] our most pressing social, civic, and ethical problems” through teaching, research, and the application of scholarship to community needs (Boyer 1996:32). He identified four dimensions of scholarship that university faculty fulfill: discovery, integration, application, and teaching. Practiced together, these four realms of practice constitute what Boyer called engaged scholarship.

The scholarship of discovery refers to the pursuit of inquiry and investigation in search of new knowledge, i.e., basic research. Many institutions view basic research as synonymous with scholarship and as the primary basis for faculty evaluation (Baker 2001; Posselt et al. 2020). The scholarship of integration consists of making connections across disciplines and advancing knowledge through synthesis; it is often referred to as interdisciplinary, cross-disciplinary, or multi-disciplinary scholarship. The scholarship of application asks how knowledge can be applied to contemporary social issues in a dynamic process that generates and tests new theory and knowledge. Finally, the scholarship of teaching includes not only transmitting knowledge, but also transforming and extending it.

Current forms of engaged scholarship vary widely. Practitioners have integrated and expanded Boyer's original conceptualization to include: collaborating with community partners to design and disseminate research projects (Solem, Lee, and Schlemper 2009; Urrieta and Méndez Benavídez 2007); teaching or sharing knowledge beyond universities (Doberneck, Glass, and Schweitzer 2010); and orienting their research towards social justice or activism (Cech 2013a; Pratt-Clarke 2012; Urrieta and Méndez Benavídez 2007). A meta-analysis examining 20 years of engaged scholarship after Boyer's seminal book found that engaged scholarship broadly adheres to five principles of practice: high-quality scholarship, reciprocity[1], identified community needs, boundary-crossing, and democratization of knowledge (Beaulieu, Breton, and Brousselle 2018). Through these practices, engaged scholars do not limit the faculty role to knowledge production, but expand it to become actors of change who contribute to the common good as both scientists and citizens (Checkoway 2013).

At the institutional level, support for engaged scholarship has grown steadily in the past few decades. National higher education initiatives promoting engaged scholarship include Boyer's own Carnegie Foundation Community Engagement Classification; the Kellogg Commission on the Future of State and Land-Grant Universities Returning to our Roots Report; the Campus Compact for the Public Purpose of Higher Education; and the National Association of State Universities and Lang-Grant Colleges Council on Extension, Continuing Education, and Public Service. Each of these initiatives involve a wide range of U.S. colleges and universities

[1] Reciprocity refers to the co-production of scholarship with the public or community (however "community" is defined).

committing to support and advance engaged scholarship in higher education (Giles et al. 2010). Many individual universities also form their own offices and initiatives supporting engaged scholarship.

Despite the apparent widespread support for engaged scholarship, research shows that these initiatives have done little to change actual practices in academic gatekeeping—namely faculty tenure and promotion. Hutchinson (2011) calls this mismatch between institutional rhetoric and tenure/promotion practices the "rhetoric/application divide." In reviewing the literature on this divide, she found that while this divide has evidently lessened since the 1990s, faculty who practice engaged scholarship still "toil on the margins" (Hutchinson 2011:146).

Interestingly, Hutchinson compares the slow change in faculty evaluation of engaged scholarship to the progress of the women's movement as building a foundation to crack the metaphorical glass ceiling. Yet she and other researchers who have found that engaged scholars feel that their work is undervalued and under rewarded (Colbeck and Wharton-Michael 2006; Furco 2001; Holland 1999; Jaeger and Thornton 2006) have not yet asked if the rhetoric/application divide is in part driven by the *same* forces perpetuating gender (and other categorical forms of) inequality.

Most studies examining *who* practices engaged scholarship find that women and non-white scholars are more likely to be engaged scholars than their white and male counterparts. (Antonio, Astin, and Cress 2000; O'Meara 2002; Vogelgesang et al. 2010). Researchers have postulated that this is due to historically marginalized groups placing a higher value on social idealism and community engagement (Ellison and Eatman 2008; Ibarra 2006). Yet research also finds that scholars already marginalized in academia express worry about the sense of career risk in perusing engaged scholarship (Ellison and Eatman 2008). These risks pertain to balancing meaningful engaged work with being seen as less legitimate scholars, and fears of not making tenure by not having the "right" publications. No study to date, however, has framed the process as one of devaluation and delegitimization *because* engaged scholarship is primarily done by women and non-white scholars (traditionally underrepresented groups in academia).

In this dissertation, I explore the extent to which women and scholars of color across multiple disciplines identify as engaged scholars. I also address whether (and to what extent) these groups face disadvantages in getting their work published and cited in peer-reviewed journals—metrics of scholarly productivity commonly used in faculty evaluation. In framing the devaluation of engaged scholarship as a racialized and gendered phenomenon, I suggest that this is likely a case of status-based inequality: the work done by women and scholars of color is devalued and delegitimized *because* women and people of color are deemed less competent and worthy (Ridgeway 2014). Embedded social beliefs about group status influence academic interactions and processes, which in turn create a long-lasting and *durable* form of inequality (Ridgeway 2014; Tilly 1998).

1.2 Outline of the Dissertation

In this dissertation, I use data from multiple university campuses' faculty recruitments to identify early-career scholars applying to assistant-level faculty positions.[2] I (1) identify engaged scholars, (2) test whether women and scholars of color are more likely to identify as engaged scholars across six broad disciplines, and (3) investigate whether applicants who identify as engaged scholars are significantly different from non-engaged scholars based on several metrics

[2] Described in depth in Chapter Two.

of scholarly productivity. These three stages comprise the three analytic chapters of this dissertation, outlined below.

In Chapter Two, I document the methodological process used to identify engaged scholars using three faculty application documents: cover letters, teaching statements, and research statements. Using a computational grounded approach (Nelson 2017), I use multiple text analysis tools to code the application documents for descriptions of applicants' engaged scholarship activities and orientations. I then create several measures of engaged scholarship at the application level.

In Chapter Three, I use these measures to test for race and gender disparities in those who identify as engaged scholars. I find that women—and particularly women of color—are the most likely applicants to identify as engaged scholars in most disciplines, across all years of the data, and in all three application documents. I discuss these findings in relation to the literature on engaged scholars, and why intersectional analyses of engaged scholars are necessary to understand who pursues engaged scholarship and why they do so.

In the final analytic chapter, Chapter Four, I investigate the extent to which engaged scholars differ from non-engaged scholars in metrics of scholarly productivity commonly used in faculty hiring and promotion evaluation. My findings suggest that engaged scholars overall have more publications, but tend to publish their work in journals with lower impact factors and also have fewer citations than non-engaged scholars. Although these trends vary somewhat by field, my main finding is that when engaged scholars are associated with an advantage (i.e., number of publications), such advantage does not apply to scholars of color, particularly not to women of color. Similarly, when engaged scholars are disadvantaged (i.e., journal impact factors and citations), scholars of color are *more* disadvantaged compared to other groups. Together, these findings suggest that not only is engaged scholarship a likely vehicle for epistemic exclusion, but also that something similar to a racialized glass escalator effect occurs *among* engaged scholars.

Finally, in the conclusion, Chapter Five, I discuss these findings in total. I suggest future lines of research to build upon this dissertation, and also provide suggestions for how academics can better recognize, and therefore mitigate, the effects of epistemic exclusion.

Chapter 2: Data and Methods

In this chapter I shift focus from the theoretical background motivating this study to the empirical reality of addressing the research hypotheses stated in the previous chapter. This chapter includes (1) a description of the creation, components, and limitations of the primary data used in this dissertation; (2) a detailed account of the text classification process used to develop multiple measures of engaged scholarship; and (3) an overview of the research methods and variables used in subsequent chapters to address this dissertation's key research questions. I organize this overview of my data and research methods into four sections.

2.1 Data

The data for this study come from a multilevel administrative database called Evaluating Equity in Faculty Recruitment (EEFR). The EEFR dataset contains detailed information on each stage of the faculty recruitment process from multiple university campuses across six years.

Using administrative data for social science research presents several unique data considerations. Administrative data are the byproduct of an organizational or institutional process. Often, such data are derived from administrative systems for such purposes as transaction, delivery of service, or personnel management (Connelly et al. 2016; Elias 2014). While traditional forms of social science data are collected for the purpose of addressing specific research questions (i.e. surveys, experiments, observational studies, etc.), administrative data are repurposed data that were not produced with the intent of research (Connelly et al. 2016). Researchers must therefore fully understand the processes that generate administrative data in order to construct valid measurements of social processes recorded therein (Goerge and Lee 2002; Gomm 2008; Marsh and Elliot 2008).

The EEFR dataset is a compilation of information from the online recruitment management system used by a large, multi-campus state university system in the western United States I call University of the West (UWest). UWest comprises multiple institutions which vary widely in geographic location, undergraduate/graduate population size, and disciplinary focus. Each campus operates relatively independently, all are classified as R1 or R2 institutions, and each contains top-ranked programs in a variety of academic disciplines.

The recruitment management system is used by most academic departments at UWest campuses to post faculty job recruitments. It is also the portal through which all applicants submit their application materials. Thus, the core of the EEFR dataset includes structured data pertaining to the announcement and outcome of each recruitment, as well as unstructured text data from the documents applicants upload to the system (e.g. Curriculum Vitaes, cover letters, letters of recommendation, etc.). The EEFR dataset is also linked to several other data sources that provide national context to the UWest actors in the EEFR dataset including: information about the demographics of the hiring committee and hiring department(s); pool availability by field from the Survey of Earned Doctorates; program rankings of UWest departments and other U.S. institutions from the National Research Council; and citation indexes and journal impact factors from bibliometric databases. Together, these data sources create a detailed view of the actors and institutions involved in the faculty recruitment process.

The EEFR dataset is organized into four main levels: the recruitment, the department(s) advertising the recruitment, the faculty hiring committees convened for each recruitment, and the applications submitted to each recruitment. The dataset is continually expanding, with new waves of data added each fall from the previous academic year. For this study, I use recruitments in the EEFR dataset that occurred between the 2013-14 academic year and the 2018-19 academic year, inclusive. Although the EEFR dataset includes data from all disciplines and departments, I only use data from recruitments designated as science, technology, engineering, and math (STEM) and social science (SS) fields. This limitation is mainly due to data availability. At the time of writing, the EEFR database includes core variables—such as recruitment department, campus and year—from all disciplines, but the "constructed" data is only available for STEM and SS disciplines. These variables are key for this analysis and include: variables constructed from applicants' Curricula Vitae (CVs) such as publications and grant funding, variables linked to bibliometric databases concerning those publications, variables of institutional prestige linked to NRC program rankings, and variables measuring disciplinary applicant pool availability linked to the SED data. STEM and SS fields were the two broad disciplinary categories at the time of analysis that had been fully cleaned and systematized for inclusion in the dataset.

For this dissertation, I use the recruitment-level structured data and the application-level structured and unstructured data. In sections three and four of this chapter, I describe the specific variables from the structured data I used in each stage of the analysis. I also limit the data to assistant-level faculty recruitments. These recruitments have the largest applicant pools as they aim to hire early-stage scholars who have not yet achieved tenure.[3] Table 2.1 presents the number of recruitments included in this study by field and academic year. There is some variation between the academic years in the overall number of recruitments, but in general, the majority of recruitments were in either Social Sciences or Engineering (28.7% of all recruitments and 24.6% of recruitments respectively). Just under 20% of recruitments were in the Biological

[3] In examining engaged scholarship as a potential barrier to entry to tenure-track positions, I do not want to include applicants who may be far along in their academic career or have already achieved tenure at another institution.

Table 2.1: Recruitments by Field and Year

	Broad Field													
	Social Sci		*Ag/NatRes*		*Engineering*		*BioSci/Med*		*Math /CS*		*Physical Sci.*		***Total***	
	N	%	N	%	N	%	N	%	N	%	N	%	**N**	**%**
Academic year recruitment was initiated														
2013-14	53	*30.6*	12	*6.9*	38	*22.0*	34	*19.7*	12	*6.9*	24	*13.9*	**173**	***100.0***
2014-15	47	*27.5*	9	*5.3*	34	*19.9*	34	*19.9*	15	*8.8*	32	*18.7*	**171**	***100.0***
2015-16	60	*30.8*	6	*3.1*	43	*22.1*	33	*16.9*	17	*8.7*	36	*18.5*	**195**	***100.0***
2016-17	55	*29.6*	9	*4.8*	50	*26.9*	27	*14.5*	17	*9.1*	28	*15.1*	**186**	***100.0***
2017-18	55	*27.9*	8	*4.1*	53	*26.9*	38	*19.3*	21	*10.7*	22	*11.2*	**197**	***100.0***
2018-19	40	*25.5*	1	*0.6*	47	*29.9*	29	*18.5*	22	*14.0*	18	*11.5*	**157**	***100.0***
Total	**310**	***28.7***	**45**	***4.2***	**265**	***24.6***	**195**	***18.1***	**104**	***9.6***	**160**	***14.8***	**1,079**	***100.0***

Source: EEFR data from 2013-19, only including recruitments with more than10 applicants and which require a CV and Cover Letter.

Sciences, and the fewest were in Physical Sciences, Math/Computer Science, and Agriculture/Natural Resources with 14.8%, 9.6% and 4.2% of all recruitments, respectively.

I use three sources of unstructured text data at the application level—cover letters, research statements, and teaching statements[4]—all of which are commonly used in faculty applications. By including all three documents in my investigation of engaged scholarship, I aim to capture any mentions of engaged scholarship practices or orientations in the broad realms of scholarship identified in Earnest Boyer's conceptualization of engaged scholarship: discovery (research), teaching, and application, and integration[5] (Boyer 1990). Through a multi-stage computational text analysis, I use these documents to identify applicants who discuss engaged scholarship in their applications. I detail this process in depth in the following section of this chapter.

All personal identifiers were recoded into de-identified numerical and categorical variables in the structured EEFR dataset[6] in three steps. First, the unstructured text documents were parsed from PDF format to plain-text for analysis. Second, the Stanford Named Entity

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[4] The applications also include diversity statements. While these may also be sites for applicants to describe engaged scholarship, I do not include them in this analysis because they are not as commonly required across the years, campuses, and recruitments in the data. They are becoming more common in applications (either as required or optional documents), and future analyses of engaged scholarship in the EEFR data may benefit from using them.

[5] There are several limitations to using these documents to identify engaged scholars. Firstly, research shows that junior faculty and graduate students may be advised to avoid practicing engaged scholarship until they have more job security in the form of tenure (Ellison and Eatman 2008). Thus, faculty applicants may downplay or exclude mentions of their engaged scholarship practices or orientations in their written application materials. I recognize that any measure I produce may not represent *all* engaged scholars—rather, only those who have chosen to discuss engaged scholarship at the time of applying to a faculty position. Notwithstanding, this study ultimately investigates how engaged scholarship is evaluated in the hiring process. Classifying the same documents that hiring committees use for applicant evaluation is thus representative of their knowledge about a scholar's engaged activities. Secondly, as described in Chapter One, engaged scholarship covers a broad range of scholarly activities and orientations toward scholarship. In coding documents as engaged or not, I consider both the content of their scholarship and any statements they make regarding their orientation or motivation. In some regards, I aim to code the documents overly inclusively by counting any mentions—however brief—of engaged activities. I originally planned only to include documents that followed a "show don't tell" logic: explaining what they had already done that would count as engaged scholarship. Ultimately, however, I coded documents as engaged even when an applicant described plans for future engagement or only briefly mentioned engaged activities. Erring on the side of inclusivity, my analysis may include scholars who do not actually identify as engaged scholars, but hopefully covers all scholars who do.

[6] Protocols for data management and analysis have been approved by the UC Davis Institutional Review Board.

Recognizer (Finkel, Grenager, and Manning 2005) was used to replace all names, locations, and organizations in the text during the parsing process with the generic labels: EEFRPERSON, EEFRLOCATION, EEFRORGANIZATION. Finally, applicant names were removed from all text documents and replaced with EEFRAPP. These replacements were meant to protect the anonymity of actors in the EEFR dataset, and also served to remove any bias based on location, institutional affiliations, or names during human-based text analysis.

The EEFR dataset provides a unique context in which to identify engaged scholars, and likewise to test whether those scholars experience different hiring outcomes because of distinguishing academic achievements. Studies of engaged scholarship have typically utilized qualitative methods to study samples of faculty who already identify as engaged scholars (e.g. Baker 2001; Bloomgarden 2008; Doberneck, Glass, and Schweitzer 2010; O'Meara 2008). Such studies offer great depth in understanding the meaning of engaged scholarship and the variation in how it is practiced. Yet we do not yet understand the breadth of engaged scholarship practices across disciplines, nor do we know how it is practiced by those who have not yet gained entry to faculty positions. Similarly, studies of epistemic exclusion have provided insights into the experience of women and scholars of color, identifying the various mechanisms by which exclusion is achieved (Settles et al. 2020; Settles, Buchanan, and Dotson 2018). Yet these studies are likewise limited by their focus on current faculty and have not yet shown how epistemic exclusion may operate across disciplines or institutions.

The EEFR dataset allows for an examination of engaged scholarship across multiple disciplines, institutions, and years. I build on previous qualitative studies of engaged scholarship and epistemic exclusion by examining both concepts across the multiple levels of the EEFR dataset—allowing for comparisons across disciplines and examination of changes over time.

2.1.1 Limitations

While the EEFR dataset is rich in many aspects, it has limited power generalize about engaged scholarship beyond UWest and the faculty applicant pool. Faculty recruitments in this dataset thus do not cover the full range of faculty jobs available nationwide. Nevertheless, the UWest system is comparable to a wide range of colleges and universities in the rest of the country, as the multiple campuses vary by geographic setting, size, prestige, and disciplinary specialties.

Additionally, the EEFR dataset is selective in that it only includes scholars applying to faculty positions. If engaged scholarship is undervalued in the academy, graduate students interested in engagement may tend not to pursue faculty positions. Similarly, research on the academic pipeline has shown multiple points at which women and non-white scholars are likely disadvantaged *prior* to faculty applications, ultimately encouraging these scholars to pursue non-academic career trajectories (e.g. Blickenstaff 2005; Branch 2016; NRC 2010; Xie and Shauman 2003). Thus, a focus on faculty recruitment may overlook unobserved processes in academic gatekeeping that limit engaged scholarship within the pool of faculty applicants (Ward 2010). The results presented in subsequent chapters specifically address engaged scholars who persist through the academic pipeline to the point of applying for a faculty position—a point in the pipeline that is key to understanding further disparities in academic jobs.

2.2 Text Classification

In order to identify engaged scholars among applicants, I apply a computational grounded text analysis method (Nelson 2017) to classify language in faculty applications that describes engaged activities and orientations. The three-part method involves: (1) pattern detection using exploratory text analysis; (2) pattern refinement through a deep reading of the texts (guided by the exploratory analysis output); and (3) pattern confirmation using a supervised machine learning model (built using classifications discovered in the first two steps). Unlike many computational text analysis methods, this method does not aim to remove researcher subjectivity from the analysis (Nelson 2017). Instead, it focuses on scaling up sociological interpretive content analysis by combining quantitative and qualitative text analysis approaches (Grimmer and Stewart 2013; Nelson 2017; Nelson et al. 2018).

I describe the text classification process across the two phases through which I accessed the data: (1) a pilot study where I used a three-step computational grounded text analysis on data from recruitments in engineering and biological sciences; and (2) a modified computational grounded text analysis on data from recruitments in all STEM and SS fields. I describe both phases in depth to elucidate each decision that could influence the final measures of engaged scholarship. These decisions concern text pre-processing, exploratory model specifications, hand-coding protocols, and supervised machine learning model specification. Before describing the two phases of text analysis, the following section provides background information on the computational grounded method.

2.2.1 Computational Text Analysis

Recent innovations in computational text analysis and linguistics provide a wide variety of tools to social scientists for scaling up classic human-intensive content analysis. Cultural sociologists in particular have been at the forefront of exploring ways to measure meaning in large textual corpora (Bail 2014; DiMaggio, Nag, and Blei 2013; Goldenstein and Poschmann 2019; Lee and Martin 2015). Many techniques focus on ways to map meaning and topics inductively across entire corpora. Such approaches use unsupervised machine learning and natural language processing (NLP) techniques without imposing a priori coding schemes to the data.

For this study, however, the goal is not to identify all topics that faculty applicants discuss in their application materials. Instead, I aim specifically to identify faculty applications containing text associated with the practice of, and orientation toward, engaged scholarship. To that end, I impose a priori coding on the text using knowledge about engaged scholarship.

The classic sociological approach of hand-coded content analysis does not scale well to large text corpora due to human resource and time limitations. Especially in cases such as this one, where I expect engaged scholarship to appear infrequently in applications, hand-coding large random samples of data may not yield many examples of engaged scholarship. Supervised machine learning (SML) models can scale-up human hand-coding (Nelson et al. 2018; Rona-Tas et al. 2019) but require large amounts of pre-coded data for training.

To address issues of scale, coding reliability, and the limitations of any single method, the best approach for this research question is to combine multiple methods of text analysis. In her 2017 paper "Computational Grounded Theory: A Methodological Framework," Laura Nelson proposes such a method. Her three-stage approach—pattern detection, refinement, and confirmation—combines exploratory text analysis, guided hand-coding, and scaled-up supervised classification.

In the Pattern Detection stage, Nelson (2017) proposes several techniques for human-centered computational exploratory analysis. These techniques aim to identify latent patterns and word relationships within the corpus. In this study, I use both topic models and targeted keyword/phrase searches to identify paragraphs in the corpus which are likely to contain mentions of engaged scholarship.

Topic modeling has gained popularity—particularly in the social sciences—as an unsupervised method to automate text classification into latent "topics" with minimal human intervention. Common topic modeling algorithms, such as Latent Dirichlet Allocation (LDA) and Structural Topic Models (STM), assume that topics (word co-occurrences) cluster within corpus documents more frequently than expected by chance (DiMaggio et al. 2013). Topic models have been used by sociologists in a wide range of empirical research, such as cultural shifts over time in news articles (DiMaggio et al. 2013), job applicant dispositions toward diversity (Penner et al. 2019), and changes in academic topics within a single field over time (Bohr and Dunlap 2018).

Topic models, however, are extremely sensitive to user selection of hyperparameters such as the number of topics (Arun et al. 2010; Sbalchiero and Eder 2020). Such models have also been critiqued for their inaccuracy and potential underestimation of topic prevalence within a corpus (Nelson et al. 2018). Additionally, the assumption that unsupervised models remove researcher subjectivity discounts the myriad decisions in text cleaning and preparation, hyperparameter selection, and the highly subjective nature of topic interpretation (Lee and Martin 2015).

In the Pattern Refinement stage, Nelson (2017) proposes using the results of exploratory analysis to guide a deep reading of the text. I use this phase to read the documents identified as likely to contain engaged scholarship, and then create an inductive coding scheme of how engaged scholarship is discussed across applications. The third and final stage of the computational grounded approach is Pattern Confirmation. In this stage, (Nelson 2017) I focus on testing the generalizability and reliability of the coding scheme on the entire corpus. I utilize supervised machine learning and targeted hand-coding to train and test the reliability of the established coding scheme in identifying engaged paragraphs.

2.3 Phase One: Pilot Study

I first conducted a pilot study using data from EEFR recruitments that took place between 2013 and 2018 in two STEM fields: engineering and biological sciences. These two fields encompass a wider variety of departments and specific disciplines than other broad field categories, and are very likely to have interdisciplinary recruitments. The pilot data included all cover letters, research statements, and teaching statements from 426 faculty recruitments in engineering and biological sciences across the ten campuses between the academic years of 2013-14 and 2017-18. In all, the pilot data contained 165,043 documents from 56,689 applicants.

I began the exploratory analysis and hand-coding using entire application documents. I soon found that classifying an entire document as engaged (or not) missed too much nuance in the ways applicants discussed engaged scholarship. Additionally, a single document often contained topics beyond engaged scholarship, complicating interpretation of the model's output. Thus, I split each document into paragraphs and re-started the text analysis. This provided leverage on understanding the extent to which applicants with any engaged language discuss engaged scholarship throughout their application. With a paragraph-level analysis, I could also calculate the proportion of a document's paragraphs that include engaged language to get a quantitative measure of engagement rather than a simple yes/no. The following account of text pre-processing and the computational grounded text analysis begins once the documents were parsed to the paragraph level.

2.3.1 Pilot: Text Pre-Processing

The original documents from the EEFR database were stored in PDF format, read into Python as plain text, parsed to the paragraph level, and cleaned of identifying information using the Stanford Named Entity Recognizer (Finkel et al. 2005). The majority of paragraphs were parsed correctly, but approximately 10% of paragraphs were parsed incorrectly due to formatting variation and errors.[7] Of those incorrectly parsed paragraphs, the text was either less than a sentence, a combination of all application documents, or not in recognizable English words. In the pilot corpus I thus retained only paragraphs longer than 10 words, less than 1000 words, and those from documents with 10 or fewer paragraphs. This resulted in 1,017,804 paragraphs in the pilot corpus.

Before beginning the text analysis, I used the R package “tm” to create a “cleaned” version of the corpus, changing all letters to lower case and removing punctuation. I also created two additional versions of the corpus: one with words stemmed and one with words lemmatized. Both of these approaches aim to simplify the words in the entire corpus to root words, thus reducing complexity. In the stemmed corpus, common suffixes indicating verb tenses or plural nouns are cut off (i.e. “schools” becomes “school” and “seeing” becomes “see”, but “found” does not change to “find”). Lemmatization is a higher level of complexity reduction, in which a dictionary of common word forms identifies words in verb tenses of words and plural form to reduce them to their proper root word (i.e. “schools” become “school”, “seeing” becomes “see”, and “found” becomes “find”). I used the well-known TreeTagger dictionary for lemmatization, which uses a Part-of-Speech tagger (Schmid 1994).

[7] Based on human-validation of a sample of 300 parsed paragraphs.

Text pre-processing decisions, especially about word simplification, can greatly alter the interpretive results of a text analysis (Denny and Spirling 2018). I therefore maintained all three versions of the corpus—verbatim, stemmed, and lemmatized—to use as robustness tests while training the SML model in the third stage of analysis.

2.3.2 Pilot: Pattern Detection

In this exploratory phase of the computational grounded method, I aimed to find paragraphs with examples of engaged scholarship to guide the deep reading. I used the R package "stm" (Roberts, Stewart, and Tingley 2014) to train multiple structural topic models. Structural topic models build on the commonly used probabilistic topic models (such as LDA) by incorporating document metadata into the model. This approach allows the algorithm to account for document-level variables—known as covariates— that may contribute to topic clustering (Roberts et al. 2014). In the context of the EEFR applications, I included document type (research statement, teaching statement, and cover letter) and recruitment field (biological sciences and engineering) as covariates.

To estimate an appropriate number of latent topics in the corpus, I used the "stm" function "searchK." This function uses measures such as semantic coherence and residual analysis to estimate an appropriate number of latent topics in the corpus. Although topic models are commonly critiqued because specification of topic numbers is never concretely "right" (Grimmer and Stewart 2013), "searchK" provides a data-driven means to determine a range of appropriate topics. Within a range of 40 to 100 topics, the model performed most coherently at 80 topics (see Appendix A, Section 1 for "searchK" results and interpretation).

Using 80 topics, I ran three models using different document-level covariate specifications: (1) no covariates; (2) covariates for document type; and (3) covariates for document type and field. I compared the output of these models and found no significant differences between the topics. Among the 80 topics, I identified six that contained top words that might refer to different types of engaged scholarship. These six topics referred to research as problem-solving, ethics and citizenship, or social justice (see Table 2.2 for the top words in the six topics, and see Appendix A, Section 2 for the topic prevalence and top words for all topics).

Table 2.2: STM Topic Top Words Which May Indicate Engaged Scholarship Paragraphs

Topic Number	**Top Words**
2	find, none, act, cause, interested, little, help, possible, discover, independent, work, new
16	environmental, climate, research, state, project, study, policy, science, technology, political, politics, social
55	research, health, social, science, technology, study, medical, work, project, policy, medicine, public
65	philosophy, moral, ethic, our, philosophical, such, ethical, work, argue, science, theory, project
78	history, science, study, medium, culture, cultural, social, gender, historical, work, race, technology
80	woman, embryo, moral, technology, research, teaching, gender, religion, dissertation, art, course, sociology

A common problem for social scientists when interpreting topic models is that the top words are open to interpretation by individual researchers; they alone offer no means of pattern confirmation. The output of the topic model also includes a measure of estimated topic prevalence in each paragraph. I did not use this paragraph topic prevalence to measure engaged scholarship, but rather to identify paragraphs most likely to discuss engaged scholarship. From each of the six topics identified as potentially referring to engaged scholarship, I created a sample of paragraphs with a high likelihood of being about engaged scholarship.[8] With this sample of 2000 paragraphs, I moved to the Pattern Refinement phase of the computationally grounded approach.

2.3.3 Pilot: Pattern Refinement

The goal of this phase was to inductively identify references to engaged scholarship. I began with a deep reading of the texts guided by the six engaged scholarship STM topics in order to: (1) confirm that the six potentially engaged scholarship STM topics actually indicate engaged scholarship; (2) understand the context in which applicants discussed engaged scholarship; and (3) inductively code for the different types of engaged scholarship.

Toward the first aim, I developed an indicator variable identifying whether each paragraph mentioned any type of engaged scholarship. Toward the second aim, I noted whether there were significant differences in type of document, recruitment field, and specific recruitments among paragraphs coded as engaged. Finally, toward the third aim, I created a variable identifying the different "types" of engaged scholarship described in each paragraph coded as engaged. This inductive approach to types of engagement allowed me to combine categories from prior studies on engaged scholarship (i.e. non-academic collaboration, community partners, research for public good, etc.) with new, or more nuanced, categories that emerged from the applications.

After coding 1000 paragraphs I began to understand the broad categories of engaged scholarship in this sample (see Table 2.3). I realized, however, that among top-ranked[9] topic

[8] The number of paragraphs per engaged topic included in the sample varied by overall topic prevalence in the corpus. I used the "stm" theta score—an estimation of the proportion of a topic within a document (in this case, paragraph). I chose paragraphs with at least .01 prevalence of any of the six topics.
[9] Ranked by the predicted prevalence that a specific topic appears in a paragraph.

model-identified paragraphs I was not finding many paragraphs that actually referenced engaged scholarship practices. Instead, I began searching for keywords and phrases that are used commonly in the literature on engaged scholarship[10] to identify potentially engaged paragraphs. This subset of paragraphs resulted in many more engaged examples than the topic model-identified paragraphs. I added the resulting coded paragraphs to the sample. After coding an additional 1000 paragraphs, I identified a higher number of engaged paragraphs but did not find more engaged categories. Table 2.3 shows the collapsed types of engagement that emerged from the paragraphs into 5 broad categories: engaged learning, engaged research, outreach/communication, engaged/public orientation, and non-academic collaboration.

Of the 2000 paragraphs, 10% were coded as engaged.[11] Engaged scholarship would likely be less prevalent in the full pilot corpus, as this sample was created from the STM topics likely to denote engaged scholarship and a keyword search focused on engaged words and phrases. In the Pattern Confirmation phase, I aimed to verify the reliability of these coded paragraphs as representative of the full spectrum of engaged scholarship types. With a hand-coded content analysis of a simple random sample of 2,500 paragraphs, I would also be able to better estimate the prevalence of engaged scholarship in the full corpus.

[10] See Chapter One Section 1.1.3 of this dissertation for a review of this literature. Keywords and phrases (some stemmed to identify multiple forms of a given word) included: activist, advocacy, advocat, applied research, applied scholar, citizen scholar, citizenship, civic, cocurricular service, community engage, community needs, community partner, democratization of knowledge, engaged research, engaged scholar, engagement, experiential learning, integrative learning, legal advice, managed learning, marginalized, nontraditional, outreach, participatory action, participatory research, project based learn, prosocial, public concern, public engage, public good, public issue, public scholar, publicly , reciprocity, relational learning, service learning, social good, social impact, social justice, social values, technical assistance, transdisciplin, translational research, underserve

[11] Most of which were from the keyword-identified paragraphs.

Table 2.3: Engaged Types Identified in the Pilot Corpus

Broad Type	Sub-Types
Engaged Research	Community Engaged Research Participatory Action Research Publicly Engaged Research Translational Research
Engaged Learning	Citizen Students Experiential Learning Community Engaged Learning Service Learning
Outreach/Communication	Community Outreach Scientific Communication
Engaged Orientation	Policy Social Justice Public Good
Non-Academic Collaboration	Community Partnership Non-profit research partners

2.3.4 Pilot: Pattern Confirmation

Using the paragraphs coded in the guided reading and previous research on engaged scholarship, I trained two research assistants to identify engaged scholarship in the random sample. The training included provision and discussion of descriptions of engaged scholarship and several articles about engaged scholarship (see Appendix A, Section 3 for the training materials).

The research assistants coded several training sets of paragraphs that I had previously coded. Through several Zoom sessions we discussed engaged scholarship, the EEFR dataset, and coding instances where we all agreed or where paragraphs were coded differently. All data seen by the coders were de-identified for personal information and document- and recruitment-level information.

After coding the 2,500-paragraph sample, we had an inter-coder reliability of 80%. We found that the actual prevalence of engaged scholarship in the corpus was closer to 2% of paragraphs. At first glance, this seems like an exceedingly low percentage, but this refers to the *paragraphs* within applications. The percentage of *applicants* with at least one engaged paragraph may be much higher than 2%, as it is unlikely that even an engaged scholar has an entire application comprised of engaged paragraphs. Compared to non-engaged paragraphs, we did not have enough engaged paragraphs to begin training a machine learning algorithm, so I used a targeted keyword search to identify more paragraphs that were likely to be engaged and the coding team continued until 500 total engaged paragraphs were identified.[12]

With such a low occurrence of engaged scholarship, traditional human-powered content analysis of even this relatively large sample would yield little statistical power in identifying larger trends in the EEFR data concerning engaged scholarship. The total coded paragraphs covered 398 out of 426 recruitments, but only 2,786 out of 56,545 total applicants.

Research comparing several methods of computational text classification found that supervised machine learning (SML) performed better than unsupervised models at correctly identifying both range and prevalence of topics when compared to hand-coded data (Nelson et al. 2018). SML is often used to scale-up resource intensive hand-coding (Rona-Tas et al. 2019), but most models perform better with more (as opposed to less) hand-coded input data. This creates a paradox for researchers with limited hand-coding resources and large data sets. Especially for corpora where the category of interest is not common, training data may have heavy class imbalances between categories. With this in mind, I opted to use SML models to classify the

[12] In total, the 500 engaged paragraphs consisted of: 200 paragraphs coded as engaged from the topic model and first keyword search (out of 2,000 paragraphs), 50 from the simple random sample of 2,500 paragraphs, and an additional 250 paragraphs from the second keyword search.

paragraphs with a binary indicator—engaged or not. Although the hand-coding revealed multiple categories of engaged scholarship, for the purpose of this study I determined that dividing the training data into these multiple classifications would yield too few training paragraphs for most of the categories. In future research with potentially more resources for hand-coding, exploring the distribution of the different types of engaged scholarship across the EEFR applicants may be possible.

I used the R package "RTextTools" (Jurka et al. 2013) to train multiple SML classification models. For each model, I split the hand-coded paragraphs into training (75% of the paragraphs) and testing (25% of the paragraphs) sets with equal proportions of engaged paragraphs. The testing set would be used to evaluate how well each model performed in terms of correctly and completely identifying engaged scholarship. To find the best-performing model, I compared results across models with different specifications including: text pre-processing (normal, stemmed, and lemmatized), n-gram tokenization (including only single words, two-word phrases, and 3-word phrases), document-term matrix sparsity (reducing the words included in the final model by word frequency), and weighting by term-frequency-inverse-document-frequency, also known as tf-idf (see Appendix A, Section 4 for more details on model specifications and document-term matrix sparsity). Of these options, I concluded that the stemmed corpus with n-grams up to three and a document-term matrix sparsity of .998 performed the most reliably. When interpreting the classifier results, I used three widely used measures of fit: precision, recall, and F1 scores (Nelson et al. 2018). Precision measures the model's accuracy, while recall measures coverage, and F1 scores combine these measures. In the context of this study, the precision score indicates the proportion of paragraphs the model coded as engaged that were also coded as engaged by the hand-coders. Recall refers to the proportion of paragraphs that were hand-coded as engaged that the model correctly identified. The F1 score is the harmonic mean between precision and recall, and thus is often used as measure of overall model fit.

"RTextTools" includes options to train individual algorithms, or simultaneously train multiple algorithms to obtain ensemble agreement metrics. Ensemble agreement refers to whether multiple algorithms make the same prediction, and has been shown to have high accuracy compared to human coding (Collingwood and Wilkerson 2012). I used four algorithms that are common in text analysis: Support Vector Machines (SVM), Scaled Linear Discriminant Analysis (SLDA), Generalized Linear Model via penalized maximum likelihood (GLMNET), and Random Forests (RF). By training all four models on the same data, RTextTools allows the user to compare model performance through multiple measures of model fit.

As Table 2.4 shows, the best model had high precision (80%), but had relatively low recall (60%). This means that, while the model correctly classified paragraphs as engaged 80% of the time, it only identified 60% of the paragraphs in the full corpus that were engaged. For some applications of classified text, this recall level may be acceptable. For this study, the classified paragraphs will be used to identify engaged scholars. These scholars are likely uncommon among applicants, and also likely to occur amongst scholars who are underrepresented in applicant pools. If we are missing at least a third of those applicants, any future analysis based on this measure may be wildly inaccurate.

One potential remedy to maintain high precision and increase recall is to add more coded data to the training set—specifically to add more paragraphs that are coded as engaged. To achieve this without additional months of hand-coding or hiring more research assistants (which was not possible due to resource constraints), I used the classifier to identify engaged paragraphs

Table 2.4: SML Model 1 Measures of Fit

	Algorithm							
	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.94	.98	.95	.93	.92	.99	.93	.98
1	.83	.58	.58	.64	.91	.38	.76	.46

Note: The data for this model included all hand-coded paragraphs. The training set included 3,311 paragraphs and the testing set included 1,102 paragraphs. With the 500 engaged paragraphs total, each set had 11.3% engaged paragraphs.

Table 2.5: SML Model Ensemble Agreement for Hand-Coded Data

	Coverage	Accuracy
n ≥2	1.00	.92
n ≥3	.97	.92
n ≥4	.88	.95

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

that I would then use as additional training data. I ran the classifier trained on the hand-coded paragraphs on a random sample of 50,000 uncoded paragraphs.

Even without high recall, I selected paragraphs that had been coded as engaged by three or more algorithms (see Table 2.5) to have 90% precision. This resulted in 995 paragraphs coded as engaged, i.e., about 2%. As these paragraphs were not going to be used to determine engaged scholarship prevalence, but to provide more training data for engaged scholarship, I was not concerned with low recall. I was, however, concerned with the reliability of these paragraphs as actually discussing engaged scholarship. From these paragraphs, I hand-coded a random sample of 300 paragraphs and found that the 90% precision rating was accurate—i.e. only about 10% of paragraphs I hand-coded were not about engaged scholarship.

I added the additional 995 paragraphs to the training set and re-trained the SML models. This set of training data improved overall recall compared to the first model (see Table 2.6). Using this model, I ran the trained classifier on the full corpus of documents and accepted paragraphs as engaged if the estimated precision was above .80. I coded paragraphs as engaged if at least three algorithms coded a paragraph as engaged, or if any two of the SVM, RF, or GLMNET algorithms coded a paragraph as engaged.

Table 2.6: SML Model 2 Measures of Fit

	Algorithm							
	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.92	.95	.90	.91	.85	.96	.87	.95
1	.87	.80	.78	.75	.85	.58	.84	.65

Note: The data for this model included all hand-coded paragraphs and *the SML-coded paragraphs. The training set included 4,080 paragraphs and the testing set included 1,359 paragraphs. With the 1495 engaged paragraphs total, each set had 27.5% engaged paragraphs.*

Table 2.7: SML Model Ensemble Agreement for Hand-Coded Data

	Coverage	Accuracy
n ≥2	1.00	.87
n ≥3	.92	.92
n ≥4	.78	.95

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

2.3.5 Pilot: Engaged Scholarship Measurement

From the pilot corpus, this approach resulted in 16,926 out of 1,017,804 paragraphs (1.7%) being coded as engaged. I created the following application-level variables from the paragraph-level engaged indicator:

- any_engaged: a binary variable indicating if any paragraph in an application was coded as engaged
- prop_paras_engaged: the proportion of total paragraphs in an application coded as engaged

- cover_engaged, res_engaged, teach_engaged: binary variables indicating if any paragraph in an applicant's cover letter, research statement, or teaching statement was coded as engaged
- prop_cover_engaged, prop_res_engaged, prop_teach_engaged: the proportion of paragraphs in an applicant's cover letter, research statement, or teaching statement coded as engaged

At the applicant level, 18% of applicants have at least one paragraph coded as engaged. Between the three document types, 11.3% of applicants have at least one paragraph coded as engaged in their teaching statement, about 7% of applicants have at least one paragraph coded as engaged in their cover letter, and about 7% in their research statement.

2.3.6 Pilot: Conclusion

Using the pilot data, I developed a modified approach to the computational grounded method of text analysis. Although the three stages of the text analysis are conceptually distinct, in practice I iterated between the stages as I learned more about the data. For example, although I began the exploratory and hand-coding analyses at the document level, I soon realized that the paragraph level would be a better level of measurement. After starting the deep reading of the paragraphs, I found that the topic model output was not exactly indicative of engaged types, and revisited the Pattern Detection stage with a keyword and phrase search to add to the deep-reading sample. Finally, in the Pattern Confirmation stage, I found that a single SML classification did not yield enough accuracy based on the amount of hand-coded data I had created. I thus returned to hand-coding to validate the SML output and identify more engaged paragraphs for a second run on the SML classifier. In the following section, I describe how I applied the knowledge gained from the pilot study to modify the computational grounded method on the full EEFR STEM and SS sample.

2.4 Phase Two: Full Data

While the entirety of the EEFR dataset covers all academic recruitments, for this study I refer to the "full data" as all STEM and SS fields. As shown in Table 2.1 the data cover 1,079 recruitments, which include 138,738 applications.

2.4.1 Full Data: Text Pre-Processing

I applied the same pre-processing pipeline for the full data as I did with the pilot data. All documents were parsed from PDF to plain text using Python, parsed at the paragraph-level, and de-identified for names, locations, and organizations. I retained paragraphs that were longer than 10 words, shorter than 1000 words, and paragraphs from documents with 10 or fewer paragraphs. This filter reduced the corpus from 3,391,704 paragraphs to 2,763,878 paragraphs. Almost 40% of paragraphs were from research statements (see Table 2.8), while a little over a third of paragraphs were from cover letters and a little over a quarter of paragraphs were from teaching statements. Based on the results from the pilot data, I did not lemmatize the corpus, but did use stemming during the SML process.

Table 2.8: Paragraphs by Document Type in Full Corpus

	Paragraphs	
Document Type	No.	%
Cover Letter	887,128	*32.10*
Research Statement	1,104,602	*39.97*
Teaching Statement	772,148	*27.94*
Total	**2,763,878**	***100.00***

2.4.2 Full Data: Pattern Detection

Unlike the pilot study, I opted to only use an expanded keyword and phrase search to initially identify paragraphs likely to reflect engaged scholarship. Using the 14-categories of engaged scholarship discovered in the pilot study, I created a very broad list of keywords and phrases that might indicate applicants' engaged practices or orientations.[13] A search for these terms in the full corpus resulted in 302,452 paragraphs that included recruitments from all campuses, years, and fields. From these paragraphs, I took a random sample of 2,500 paragraphs for the next stage of Pattern Refinement.

2.4.3 Full Data: Pattern Refinement

Similar to the pattern refinement stage of the pilot study, I coded the 2,500 paragraphs identified from the keyword search as engaged (or not) and added qualitative notes on what type of engaged scholarship was evident. Overall, I found that the engaged scholarship categories identified in the pilot study were consistently present in the full data, but with a broader range of fields included I categorized the broad types slightly differently. For example, I found that "Community Engagement," whether through teaching/learning or research practices should be its own category. While "Policy" was a relatively small category, it was distinct from "Engaged Orientations" toward social justice and the public good. These had been included in the same category in the Pilot study, but are separate categories in the final typology. Table 2.9 presents

[13] Keywords and phrases: activist, advocacy, advocat, applied research, applied scholar, citizen scholar, citizenship, citizen student, citizen engage, civic engage, civic mission, civic duty, civic scholar, cocurricular service, community engage, community needs, community partner, community outreach, community science, community based, common good, democratization of knowledge, engaged orientation, engaged learning, engaged research, engaged scholar, engagement, experiential learning, integrative learning, legal advice, managed learning, marginalized, nontraditional, public outreach, outreach, participatory action, partner with, participatory research, project based learn, prosocial, policy, practitioner, public concern, public engage, public good, public issue, public scholar, publicly, real world , reciprocity, relational learning, scientific communication, service learning, social good, social impact, social justice, social values, stakeholder, transdisciplin, translational.

the broad types of engaged scholarship identified in the full corpus, descriptions of those types, and illustrative examples from the applications for each type.

2.4.4 Full Data: Pattern Confirmation

The main difference between this stage in the pilot study and this stage with the full data was a need for more hand-coded data to classify the full corpus. With all STEM and SS fields included there was more heterogeneity in overall language. I used the same SML model specification as in the pilot study in regard to n-gram, sparsity, and stemming (see Appendix A, Section 4). I split the corpus into a training group (75%) and testing group (25%) with equal ratios of engaged/not-engaged paragraphs. This model did not perform well in regard to either precision or recall[14] for engaged paragraphs,[15] so I hand-coded an additional 1,000 paragraphs and retrained the classifier. The goal during this phase was to increase the precision and recall in at least two of the training algorithms to similar levels as in the pilot study.

I used this trained classifier to code a random sample of 50,000 paragraphs from the full corpus. I then hand-coded an additional 500 paragraphs from the model output that were most likely to be engaged and 500 paragraphs that were most likely to not be engaged. I soon realized that adding more hand-coded training data to the classifier improved the performance metrics much more gradually than in the pilot study. I also noticed in hand-coding the "likely to be engaged" paragraphs identified by the classifier that the paragraphs from SS fields were being coded much more accurately than the STEM fields. For this reason, I split the corpus into STEM and SS fields and re-trained the SML classifier. This split considerably improved the SML

[14] See *Pilot Study: Pattern Confirmation* (section 2.3.4) for explanation of these performance metrics
[15] The performance metrics of this classifier and the subsequent classifiers trained in this section can be found in Appendix A, Section 4, Table A.1 and A.2.

Table 2.9: Engaged Types, Descriptions, and Illustrative Text examples from Full Corpus

Broad Type	Description	Example from Paragraphs: Modified text
Citizen Students	Orientation or goal of teaching is to create responsible "citizens" who think critically and contribute to democracy.	"My central objective in teaching is to give students the tools to become critical thinkers, analytical readers and writers, and engaged citizens." "Teaching must contribute to global citizenship by aiming to cultivate creative minds capable of skillful data-collection, critical analysis and unbiased implementation of diverse solutions." "Students learn to work with data and view old debates with fresh eyes. The integrity and strength of a democracy relies on informed citizens who think independently."
Community Engagement	Research and teaching/learning which involves the community (community can be defined broadly, from local to global). Often includes reciprocal relationship with community towards knowledge creation and dissemination. Includes community partnership, participatory methods, and service learning.	"My research always emerges from, and is translated back into, the struggles of [marginalized] individuals and communities." "This community service course paired students with local conservationists to develop sustainable education programs for residents of EEFRLOCATION." "Assignments required students to interact with scientists and community members, and to be accountable to the larger town of EEFRLOCATION when disseminating their work. In particular, students worked to communicate research findings that honored the range of life experiences of community members." "I believe in conducting research that produces immediate co-benefits for the participants in my projects. Therefore, I have to cultivate relationships within the community, develop research projects that address their immediate and emergent needs, quickly analyze data, summarize my results, and share them with my community partners and clients."
Outreach teaching	Teaching outside of the university – in K-12 classrooms, public events, or other audiences for the purpose of enriching	"Finally, I am dedicated to outreach related to the dissemination and accessibility of knowledge. I strongly believe that learning should have no barriers to entry, and in this spirit, I have ensured that all online courses I have developed are publicly accessible for free. I also taught a university-level high school course hosted by EEFRORGANIZATION."

	public knowledge and understanding of science.	"As part of a EEFRORGANIZATION grant, I visited elementary classrooms and gave talks [basic physics] using hands-on demonstrations. I have since given outreach talks on topics ranging from EEFRLOCATION operations, to delta formation, to rock classifications at a number of different schools."
Policy	Specific policy goal or outcome from research (i.e. not just policy "implications")	"Overall my research seeks to provide timely, policy-relevant estimates to local, state and national officials who are grappling with where and to what extent to target policies aimed at reducing the negative impacts environmental disamenities." "In this capacity, I found it rewarding to contribute to local, state and federal policy as a scientist."
Non-academic Collaboration	Beyond community partnerships, research collaboration with non-profit groups, government agencies, etc. (Does not include industry partnerships for profitable ends)	"My work involves collaborations and partnerships with clinicians, nurses, epidemiologists, statisticians, sociologists, nutritionists and policy experts." "My connections with conservation organizations, research institutes, and federal and state government agencies in the EEFRLOCATION, EEFRLOCATION, and the EEFRLOCATION could also provide new opportunities for student research and outreach projects." "I have engaged in successful collaborative research with a number of federal and local agencies, and I look forward to building fruitful working relationships with new partners and stakeholders at EEFRORGANIZATION."
Engaged Orientation	Orientation toward research and/or teaching and learning specifically to impact the public good or foster social change/justice.	"My research critically investigates the spatial and social relationships at the intersection of [my research topics] and social justice in urban geographies." "I am excited about making an impact in the field of [computer science] through building automated systems for better interpretation of data to aid better decision-making for social good." "My research agenda dovetails with my teaching pedagogy grounded in social justice." "With my work in developing [devices] for the treatment of diseases that strike people across the world, I aim to contribute to global health and wellbeing."

Scientific Communication	Knowledge dissemination beyond academia and/or the university.	“I actively use various forms of social media and news for scientific outreach, and I founded an online program for connecting research scientists with students in the classroom.” “I have become increasingly aware of the societal need to bridge the gap between the general public (particularly those in traditionally underrepresented groups) and the scientifically literate. In this regard, I have organized and performed experiments to groups of students and parents in EEFRLOCATION and EEFRLOCATION, inspiring young minds to pursue careers in the sciences. Further, I have served as a volunteer judge at [local] science fairs, giving expert feedback and encouraging deeper thinking to solve the problems at hand.”
Translational	Specific goals of applying research output toward a problem (often in a clinical setting).	“This work is fundamentally grounded in translational science, because both of these methods target mechanisms of treatment engagement and satisfaction in order to improve treatment outcomes in this vulnerable population.” “Given the prevalence of sequential data in healthcare, I aim at solving real-world and practical problems with high impact in this domain. To this end, I closely work with physicians to obtain feedback from clinical experts and increase the real-world impact of the solutions that I develop.”

Note: Quoted text are amalgamations and slightly altered excerpts from application documents. Some details (such as scientific discipline, research topics, and locations/organizations) were changed to protect applicants’ anonymity.

performance metrics[16] for both the SS paragraphs and the STEM paragraphs and I proceeded with this split for the rest of the training and hand-coding.

As mentioned previously, the larger corpus and inclusion of all fields (even when split by STEM/SS) required much more hand-coded training data. To more efficiently add engaged paragraphs to the training data, I used the SML classifier to train a random sample of paragraphs for each the SS and STEM corpora and then hand-coded the paragraphs most reliably identified as engaged or not-engaged. I repeated this process six additional times, each time adding the new hand-coded data to the SML training data. I saw consistent model improvement based on the performance metrics.

Table 2.10: SML Full Corpus Measures of Fit

	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.89	.93	.89	.90	.88	.93	.87	.94
1	.84	.77	.79	.77	.84	.73	.86	.71

Note: The data for this model included all hand-coded paragraphs and *the SML-coded paragraphs. The training set included 5,850 paragraphs and the testing set included 1,949 paragraphs. Each set had 32.7% engaged paragraphs.*

Table 2.11: SML Full Corpus Ensemble Agreement

	Coverage	Accuracy
n ≥2	1.00	.88
n ≥3	.94	.91
n ≥4	.81	.93

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

[16] These can all be found in Appendix A, Section 5, Tables A.3-6. I also split the STEM fields further into Engineering/Math and Statistics/Computer Science/Physical Sciences and Agriculture/Natural Resources/Biological Sciences to see if the heterogeneity between fields was still affecting the classifier. I found no significant differences between these splits and the all-STEM classifier and so proceeded with a single SS classifier and STEM classifier.

Ultimately, I classified the full corpus with combined hand- and SML-coded paragraphs from the STEM and SS corpora. The final SML model performance metrics are shown in Table 2.10 and 2.11. I accepted paragraphs as engaged if at least three of the algorithms coded the paragraphs as engaged or if two algorithms agreed between the SVM, RF, or GLMNET algorithms. This resulted in 60,909 paragraphs (2.3%) coded as engaged (see Table 2.12).

2.4.5 Full Data: Engaged Scholarship Measurement

I used the same variables as developed in the pilot study to measure engaged scholarship. Compared to the pilot study with 1.7% of paragraphs coded as engaged, the full data had 2.3% of paragraphs coded as engaged.

Table 2.12: SML-Coded Paragraphs by Document Type

	Not Engaged			*Engaged*			*Total*		
	No.	Col%	Row%	No.	Col%	Row%	No.	Col%	Row%
Cover	844,885	32.1	97.5	22,031	36.2	2.5	866,916	32.2	100.0
Research	1,053,728	40.0	98.1	20,804	34.2	1.9	1,074,532	39.9	100.0
Teaching	733,566	27.9	97.6	18,074	29.7	2.4	751,640	27.9	100.0
Total	2,632,179	100.0	97.7	60,909	100.0	2.3	2,693,088	100.0	100.0

Note: Total paragraphs are fewer than during classification because 70,790 paragraphs were dropped from 4,427 applications coded as "not complete" by the EEFR recruitment, and thus are not included in the following analysis.

2.5 Text Classification Summary

I use the engaged scholarship variables in the next two chapters to address the core research questions driving this study. While I had initially planned to follow the three-step computational grounded method, I found that the text classification process is more circuitous than linear. The three steps broadly go in order of exploring, reading, and classifying a text corpus. In practice, each step leads the researcher to a deeper understanding of their text corpus, which often has the effect of going back to a previous step to tweak the earlier process. For example, through the process of the pilot study, I found that the topic models were not as useful as targeted keyword and phrase searching for this corpus and research questions. Additionally, during the "full data" phase, I went back and forth much more between deep readings (to add more training data) and running the SML models. This targeted approach to hand-coding, especially once the paragraphs were divided into STEM and SS categories, led me to see patterns in language around engaged scholarship that I had not noticed in the pilot study.

In developing this system of text classification, I found that engaging with the text documents expanded the ways I define engaged scholarship in the context of this study. For example, SS paragraphs discussing engagement approached it more like the literature suggests—with a critical eye toward expanding the academy and "producers of knowledge" beyond academics through reciprocal relationships with communities. STEM field paragraphs much more often discussed outreach teaching, scientific communication, and involvement with the community as a one-way relationship where academics brought knowledge to the community. Additionally, these practices were often cited as being for the purpose of encouraging more people (and more "diverse" people) to pursue STEM careers. Finally, I noticed that SS paragraphs were more likely to cite social justice as a reason for democratizing knowledge or for their research/teaching orientations. STEM paragraphs with similar tones used phrases like "social good," "public good," or "equity" rather than "justice." Some of these themes are explored further in the next chapter, but these findings should be explored further in a full analysis of their own with more intensive and nuanced coding. It was difficult to strike a balance of depth and breadth in this study. These trade-offs are part of any research process, but are especially salient in text analysis of large corpora. The tools for computational text analysis are constantly improving, but I am yet to be convinced that they will ever operate independent of researchers trained to critically evaluate social data measuring social processes.

As with any text analysis, whether computer-assisted or otherwise, these measures of engaged scholarship have multiple limitations. Identifying engaged scholarship in the paragraphs revealed a wide range of scholarly activities and orientations toward scholarship. Trusting the SML algorithms to truly "understand" the concept of engaged scholarship from the hand-coded training set is a false goal. The reliability of any machine learning is only as good as the materials used to train the algorithm. My aim was thus to strike a compromise between total precision (only attainable through careful hand-coding) and recall (coverage of "true positives") in order to utilize the scale of the EEFR dataset. I aim to have identified *enough* true positive instances of engaged scholarship paragraphs to reveal relevant patterns amongst applicants regarding race and gender and the proclivity to discuss engaged scholarship in their application materials.

While the EEFR dataset is not publicly available for other researchers to fully reproduce this text analysis, my hope is that the details provided in this chapter provide enough transparency to allow readers to determine the validity of each decision and output interpretation.

2.6 Analytic Methods

Using the engaged scholarship measures developed in the text classification, the remainder of this dissertation comprises two analyses addressing the research aims presented in Chapter One. In Chapter Three, I investigate whether women and scholars of color more likely to identify as engaged scholars. Ostensibly, an applicant's written statements are their first opportunity to describe their scholarship to the faculty hiring committee. I use the multiple engaged scholarship measures developed in this chapter to explore whether there are significant race and gender differences in the use of engaged language across the three application document types and the recruitment year and field.

The measures of engaged scholarship I use in this analysis are based on language in applicants' written statements. Yet, temporally, before many hiring committees fully read such statements they often make preliminary decisions based on scholarly productivity and prestige metrics found in applicants' CVs (Rivera 2017). To assess whether these factors may be associated with engaged scholarship, in Chapter Four I ask: do engaged scholars differ significantly in metrics of academic success compared to other applicants? To address this question, I test whether the use of engaged language is associated with three indicators of scholarly productivity: number of publications, publication citations, and the average journal impact factor of applicants' publications.

Below, I describe the key analytic variables—engaged scholarship, race/ethnicity, and gender—used in all analyses. I also describe the recruitment-level control variables used across all analyses, as the representation of applicants by race/ethnicity, gender, and engaged scholarship may be associated with structural aspects of the EEFR dataset. The applicants included in this study were respondents to specific recruitments which varied in content by year, institution, and hiring department(s). Some of these structural factors may have influenced the demographic make-up of the applicant pool, including whether more or less engaged scholars applied. In subsequent chapters, I describe the additional variables used for each specific analysis.

2.6.1 Engaged Scholarship Variables

Based on the text classification process described earlier in this chapter, all analyses utilize multiple measures of engaged scholarship that broadly cover two dimensions of the use of engaged language: the frequency with which, and the application document in which, an applicant uses engaged language. The two measures refer to the use of *any* engaged language and the *amount* of engaged language used. The *any* measure is operationalized as a binary variable indicating whether each application document contained at least one paragraph coded as engaged from the SML classifier. The *amount* measure is operationalized as the proportion of paragraphs in each application document coded as containing any engaged language.

In Chapter Three, I use these measures to assess race and gender disparities in the use of engaged language. Using the frequency variables, I test whether such disparities amongst all applicants in the use of *any* engaged language are similar to disparities in the *amount* of engaged language used by those who use engaged language at least once. I also examine whether race and gender disparities in the use of engaged language vary by document type. As described in section 2.4, this dissertation does not include nuanced measures of the *types* of engaged scholarship practiced by applicants. The document-level differences, however, provide some leverage toward discerning what types of engagement an applicant uses. Broadly, engaged language in research and teaching statements likely discuss types of engaged scholarship associated with each respective area of scholarship, while engaged language in cover letters may refer to any realm of scholarship, as well as general scholarly orientations and motivations.

In Chapter Four, I assess whether either of the engaged scholarship dimensions (frequency and document type) is associated with differences in commonly used metrics of academic productivity. A large body of research has explored differences in such measures by race and gender (Dion, Sumner, and Mitchell 2018; Ginther, Kahn, and Schaffer 2016; Ledin et al. 2007; Lerchenmueller and Sorenson 2018; Maliniak, Powers, and Walter 2013; Smith et al. 2021; Weisshaar 2017; Witteman et al. 2019; Xie and Shauman 1998), and studies of epistemic exclusion suggest that women and scholars of color who practice marginalized forms of scholarship may be disadvantaged in processes that generate such metrics (Settles et al. 2020). As this dissertation aims to investigate engaged scholarship as a potential vehicle for epistemic exclusion, I assess the extent to which engaged scholars may differ on metrics commonly used to evaluate faculty applicants.

Table 2.13: Engaged Scholarship Language Across Application Documents

	Applicants with Any Engaged Paragraphs		*Proportion of Paragraphs with Engaged Language*	
	N	%	Mean	sd
Document Type				
Cover Letter	15,066	*10.86*	0.113	0.176
Research Statement	14,212	*10.24*	0.098	0.162
Teaching Statement	14,511	*10.49*	0.120	0.192
Among All Documents	31,740	*22.88*	0.112	0.106

Note: Applicants with Any Engaged Paragraphs calculated among all applicants; Proportion of Paragraphs with Engaged language calculated amongst applicants with at least one engaged paragraph (N=31,740).

Among all paragraphs coded using the SML model, 2.4% were coded as engaged (broken down by document type in Table 2.12). At the applicant level, I find that 22.88% of all applicants have at least one engaged paragraph in their full application (Table 2.13). Between documents, 10.86% of applicants use engaged language in their cover letter, 10.24% use engaged language in their research statement, and 10.49% use engaged language in their teaching statement.[17] Thus, while applicants are nearly equally likely to use engaged language between

[17] Note, these are not mutually exclusive, an applicant may have engaged language in more than one document.

the three documents, the overall number of applicants who use any engaged language (31,740 applicants) likely use engaged language in at least two documents. Finally, while applicants are similarly likely to use engaged language between the three document types, teaching statements contain the highest percentage of engaged paragraphs, while research statements contain the lowest.

2.6.2 Race/Ethnicity and Gender

The EEFR dataset includes a measure of race/ethnicity with seven categories, shown in Table 2.14.[18] In Chapter One, I refer to scholars of color as a single group to differentiate between the dominant racial group in American society (white) and those who are not in that

Table 2.14: Applicants by race/ethnicity

	N	*%*
Black or African American	3,148	*2.3*
American Indian/Alaskan Native	342	*0.3*
Declined to State	8,055	*5.9*
Hispanic/Latinx	9,458	*6.9*
Asian/Asian American/Pacific Islander	45,844	*33.3*
White	69,070	*50.2*
Multiple Ethnicities	62	*0.1*
Missing	1,533	*1.1*
Total	**137,512**	***100.0***

group. Researchers and theorists have shown that racial categories—either binary in relation to whiteness or separated into multiple categories—are deeply flawed and are neither mutually exclusive nor fixed in time or within a single individual (e.g. James 2008; Waters 1990; Zuberi 2001). Instead, racial categories are "created, inhabited, transformed and destroyed" through

[18] Based on faculty applicants' self-identified race/ethnicity at the time of application.

political and sociohistorical processes sociologists Michael Omi and Howard Winant call "racial formation" (Omi and Winant 2014:55). The interactional and shifting nature of racial categories makes measurement constantly imprecise, and some researchers chose to omit racial categories from analyses to avoid mis-classification or reification of racial ideologies (Bonilla-Silva 2006). However, while racial categories are socially constructed, the consequences of racial categorization are real, stable, and particularly important to understanding social structures of inequality (Bonilla-Silva 2006; Omi and Winant 2014).

Quantitative analyses using race as a categorical variable have been criticized for claiming to measure causal "effects" of race, which in turn reify the categories as essential (Stewart 2008; Zuberi 2001). Instead, I interpret racial categories as measuring *racial relations*, i.e., the effect of race as a relational process imbued with status and power implications for the behavior of individuals and organizations.

For the purpose of this study, I use a four-category race/ethnicity variable composed of: (1) Black/African American, Hispanic/Latinx, and Native American/Native Alaskan (BHN); (2) Asian, Asian American, and Pacific Islander (AAPI); (3) white; and (4) other/missing. BHN is a single category not because these race/ethnicity categories are homogenous, but because of sample size limitations and previous literature which suggests that these groups together face different barriers in academia than white or AAPI scholars (Astin 1982; Nelson, Brammer, and Rhodes 2010; Settles et al. 2020). BHN scholars together represent less than 10% of the total applicant pool in the analytic sample, while AAPI scholars (33.3%) and white scholars (50.3%) make up almost two-thirds of all applicants (Table 2.15).

The focus of this analysis concerns whether engaged scholarship is more likely to be done by marginalized scholars, and can thus be considered as a potential vehicle for epistemic

Table 2.15: Gender and Race of Applicants by Recruitment Field

	Social Sciences		Ag/ Natural Resources		Engineering		Biological Sciences		Math/ Computer Science		Physical Sciences		**Total**	
	N	%	N	%	N	%	N	%	N	%	N	%	**N**	**%**
Gender														
Female	18,877	*43.2*	1,197	*34.9*	6,679	*17.7*	7,147	*31.5*	2,813	*21.8*	3,670	*21.4*	**40,383**	***29.4***
Male	23,450	*53.7*	2,157	*62.8*	30,103	*79.8*	15,012	*66.3*	9,609	*74.6*	13,031	*76.1*	**93,362**	***67.9***
Other/Miss	1,380	*3.2*	80	*2.3*	934	*2.5*	495	*2.2*	457	*3.5*	421	*2.5*	**3,767**	***2.7***
Total	**43,707**	***100.0***	**3,434**	***100.0***	**37,716**	***100.0***	**22,654**	***100.0***	**12,879**	***100.0***	**17,122**	***100.0***	**137,512**	***100.0***
Race/Ethnicity														
BHN	6,845	*15.7*	388	*11.3*	2,129	*5.6*	2,258	*10.0*	686	*5.3*	1,193	*7.0*	**13,499**	***9.8***
AAPI	9,205	*21.1*	976	*28.4*	17,856	*47.3*	7,532	*33.2*	5,835	*45.3*	5,176	*30.2*	**46,580**	***33.9***
White	25,042	*57.3*	1,893	*55.1*	15,892	*42.1*	11,778	*52.0*	5,535	*43.0*	9,870	*57.6*	**70,010**	***50.9***
Other/Miss	2,615	*6.0*	177	*5.2*	1,839	*4.9*	1,086	*4.8*	823	*6.4*	883	*5.2*	**7,423**	***5.4***
Total	**43,707**	***100.0***	**3,434**	***100.0***	**37,716**	***100.0***	**22,654**	***100.0***	**12,879**	***100.0***	**17,122**	***100.0***	**137,512**	***100.0***

Note: Of the applicants coded as "Other/Missing" on the gender variable 1,533 applicants were coded as "Missing" and 2,234 were coded as "Gender: Decline to State." Of the applicants coded as "Other/Missing" on the Race/Ethnicity variable, 1533 applicants were coded as "Missing," 62 were coded as "Multiple Ethnicities," and 5,828 were coded as "Race/Ethnicity: Decline to State."

exclusion. Settles et al. (2020) found that AAPI scholars reported significantly fewer experiences of epistemic exclusion than BHN scholars, even though both groups are statistical minorities in the U.S. population and face discrimination based on racial ideologies. The authors attributed this qualitatively different experiences between BHN and AAPI scholars in part to the relative overrepresentation of AAPI scholars and relative underrepresentation of BHN in academia, as tokenism and marginalization experiences are tied to numerical representation and status (Settles et al. 2020). Therefore, due to the quantitative underrepresentation of BHN scholars in this sample and prior research suggesting that BHN scholars disparately experience epistemic exclusion compared to other groups, the following analysis examines BHN scholars as an aggregated category.[19]

The EEFR dataset variable measuring gender includes three categories: male, female and other/missing. Like race/ethnicity, gender is neither biological nor fixed, yet continues to serve as a primary frame through which social life is organized in micro-interactions and macro-structures of power and status (Ridgeway 2011). Many scholars have explored the numerous ways gender is "done," performed, achieved, and expressed (e.g. Butler 1988; Martin 2003; West and Zimmerman 1987), and in this analysis I rely on applicants' self-identification of gender when applying to a faculty position to measure this concept.

To operationalize race/ethnicity and gender, I combine the race/ethnicity and gender categories described above into a single categorical variable which identifies an applicant's self-identified race/ethnicity *and* gender. This variable, *racegender*, has seven categories: female

[19] It is important to note, as shown in Table 2.14, that the three groups included under the BHN label are not equally represented in the applicant pool. BHN scholars are primarily Hispanic/Latinx and Black/African American. While I believe it is important to include applicants who identify as Native American/Alaskan Native in this study, they make up a very small percentage of BHN scholars and may have discernable different epistemologies and experiences in the hiring process which I cannot statistically account for in this study due to the small number of applicants in that category.

BHN, female AAPI, female white, male BHN, male AAPI, male white, and gender and/or race missing/other. These intersections of race/ethnicity and gender are an attempt to illuminate the impacts of non-multiplicative hierarchies of status and power that vary by both race/ethnicity *and* gender.

To interpret the categorical differences between these groups, I use Leslie McCall's intersectional framework of "intercategorical complexity" to "provisionally adopt existing analytical categories to document relationship of inequality among social groups" (McCall 2005:1773). This means that I use existing categories of race/ethnicity and gender to examine the relationships between groups—not to establish these categories as definitive or permanent (Glenn 2009; McCall 2005). Again, any disparities identified in this analysis do not represent inherent group differences, but are representative of inequalities group members face in *relation* to other groups as an outcome of processes within the gendered and racialized institutions of academia.

2.6.3 Recruitment-level Control Variables

All applicants, and therefore application materials, exist in the EEFR dataset in response to year-, institution-, and department-specific faculty recruitment efforts. Each recruitment's requested candidate qualifications vary by these recruitment-specific variables and may impact whether applicants who follow certain epistemologies are more or less likely to apply. I include recruitment-level control variables in each step of the analysis to account for this variation. *Academic_year_id* controls for the recruitment year and *institution_id* controls for each campus. The substantive field of each recruitment is identified by the National Center for Education Statistics' (NCES) 2010 Classification of Instructional Programs (CIP) codes matched to the recruiting department(s) (NCES 2010). The CIP codes are a taxonomic coding scheme of academic programs that include detailed six-digit codes for specific programs which can be aggregated to a series of two-digit broad field codes (NCES 2010). From the two-digit CIP codes, the EEFR *field* variable distinguishes six broad fields: Social Sciences, Agricultural/Natural Resources, Physical Sciences, Biological/Medical Sciences, Math/Statistics/Computer Science, and Engineering.

Chapter 3: Engaged Scholars – Race and Gender Disparities

In the previous chapter, I detailed the development of multiple measurements of engaged scholarship language in faculty job applications. In this chapter, I use these measures to address the first research question presented in Chapter One: Are women and scholars of color more likely to identify as engaged scholars when applying to faculty positions?

Research has identified race, gender, and field disparities among current faculty in the practice of engaged scholarship (Abes 2002; Antonio 2002; Ellison and Eatman 2008; O'Meara 2008; Vogelgesang et al. 2010). It has yet to discover whether these disparities are reflected in the pool of applicants who apply to such positions. In this chapter, I present a detailed analysis of gender and race disparities in who among assistant-level faculty applicants identifies themselves as an engaged scholar in their application materials. Beyond expanding previous research on engaged scholars beyond current faculty, I also address limitations of previous research in several key ways: (1) unpacking race *or* gender disparities in engagement by framing disparities along dimensions of race *and* gender; (2) expanding our knowledge of race and gender disparities in the practice of engaged scholarship beyond scholars who are current faculty; (3) identifying variations in race and gender disparities in engagement across broad fields and over time; and (4) considering whether race and gender disparities in engagement are associated with different types of engaged scholarship practices.

The following analysis is largely descriptive of faculty applicants' use of engaged scholarship language in their cover letters, research statements, and teaching statements across six STEM and SS disciplines over six years of data. Understanding race and gender disparities in engaged scholarship across multiple levels of analysis (document, applicant, discipline, year, etc.) is necessary groundwork to guide future analyses exploring *why* such disparities exist.

3.1 Background

Previous research has established three distinct trends in the practice of engaged scholarship among current university faculty. First, female faculty and faculty of color are more likely to practice engaged scholarship (Antonio 2002; Ellison and Eatman 2008; O'Meara 2008; Vogelgesang et al. 2010). While none of these studies empirically establish *why* this pattern persists, they include numerous anecdotal assertions suggesting that personal values of social idealism and community improvement contribute to the phenomenon (Antonio et al. 2000; Ellison and Eatman 2008).

Second, between broad fields, engaged scholarship is most common in education, forestry/agriculture, and health sciences faculty; it is least common among faculty in engineering, the humanities, and math/statistics (Abes 2002; Vogelgesang et al. 2010). The forces behind these differences have not been widely evaluated past anecdotal connections between fields—such as education and health sciences—and community involvement (Antonio et al. 2000; Vogelgesang et al. 2010).

Third, while it is unclear whether the prevalence of engaged scholarship has increased over time, there is evidence that scholarly attention toward encouraging engaged scholarship has increased over the past 20 years (Beaulieu et al. 2018). There has been an increasing number of studies done examining engaged scholarship (Beaulieu et al. 2018), as well as an increasing number of national organizations, institutional efforts, and administrative confederations promoting the practice of engaged scholarship (Giles et al. 2010; Kellogg Commission on the Future of State and Land-Grant Universities 2000; Stanton 2008).

In this chapter, I build on this body of knowledge and make four key advancements on past research. First, our knowledge of race and gender disparities in engaged scholarship are limited to analyses of race and gender studied separately. While overall gender or racial disparities are informative, such an approach tends to overlook racial differences within gender—and, gendered differences within racial groups (McCall 2005)—often specifically overlooking those most marginalized in each category (Purdie-Vaughns and Eibach 2008). For example, although we know that female faculty and faculty of color are more likely to practice engaged scholarship, we do not know whether these trends are driven particularly by women of color, men of color, white women, etc. This analysis addresses this limitation by focusing on disparities in engaged scholarship along dimensions of race and gender simultaneously. I find that women of color—specifically Black, Native American/Native Alaskan and Hispanic/Latina women—are by far the most likely of all applicants to identify as engaged scholars. This group is also the most underrepresented group in the faculty applicant pool (see Table 3.2 in this chapter), which heightens the need to understand whether such scholars are further marginalized through their use of engaged scholarship language in their applications.

Second, engaged scholarship has so far only been studied among current university faculty. There is a large body of research explicating multiple processes that influence and filter scholars in or out of academic careers (e.g., Blickenstaff 2005; Branch 2016; NRC 2010; Turner, González, and Wood 2008; Xie and Shauman 2003). This research has identified persistent race and gender gaps across all levels of academia. Race and gender disparities in the practice of engaged scholarship may indicate that there is also an engaged scholarship gap across different levels of academia. This study does not account for this entire gap in our knowledge, but does contribute an examination of engaged scholarship among a previously unstudied subset of scholars: tenure-track faculty *applicants*. While this group is also highly selective—all have completed doctorate degrees and are seeking faculty positions—examining the prevalence of engaged scholarship among such applicants adds a dimension of understanding to the established trends in engaged scholarship among current faculty. This chapter examines whether these trends are representative among faculty applicants—or instead, whether engaged scholarship may act as a filter that *influences* faculty hiring outcomes. Overall, my findings are consistent with previous findings, in that women and scholars of color are more likely than men and white applicants to be engaged scholars. However, no previous study has reported the *size* of this gap, and my findings demonstrate that women of color are far more likely than any other group to identify as engaged scholars. White women and Asian/Asian American women's likelihood of being engaged is closer to that of men of color than to women of color.

Third, as outlined above, extant research has explored race, gender, and field disparities in the practice of engaged scholarship. It has not, however, addressed whether race and gender disparities vary across fields or over time. Such variations may be key to understanding whether engaged scholarship operates as a vehicle for epistemic exclusion: as we know from research on other occupations, there are disparate gendered and racialized consequences for individuals pursuing work in occupations that are typically feminized and devalued (England 2017; Williams 1992; Wingfield 2009). Additionally, academic disciplines have unevenly become more inclusive of women and scholars of color over time (Beutel and Nelson 2006; Nelson et al. 2010), which may indicate disparate trends in engaged scholarship over time as well. This analysis considers each of these influences in turn. I examine aggregate race and gender disparities in engaged scholarship; whether race and gender disparities in engaged scholarship vary significantly by field; and whether race and gender disparities in engaged scholarship vary across time. My findings show that while the use of engaged language increased in applications over the five years included in the analytic sample, the race and gender disparities in engagement stayed relatively stable over time.

Fourth, prior research has only examined race and gender disparities in specific engaged practices, such as only on community-based scholarship (e.g. O'Meara et al. 2011) or service-learning (e.g. Furco 2001). Yet we do not know the extent of race and gender differences in each type of engaged scholarship, and whether they are comparatively distinct. As discussed in Chapter Two, I use application document types as a proxy for discerning between engaged research and engaged teaching practices. While this proxy does not address the nuance in the aforementioned practices of engaged scholarship, it does broadly indicate whether an applicant mentions engaged scholarship in relation to their research (i.e., in their research statements) or in relation to teaching (i.e., in their teaching statement). Engaged language in the cover letter could relate to an aspect of an applicants' scholarly approach or practice. However, cover letters are typically applicants' first opportunity to introduce themselves to the hiring committee, and the use of engaged scholarship language in this document could be a strong indicator that an applicant broadly self-identifies as an engaged scholar. This analysis does not include a measure of engaged scholarship that differentiates between specific engaged practices, but with increased hand-coding resources such differences will be the subject of future work.

Together, these gaps in our knowledge about engaged scholars motivate the following research questions:

- Among faculty applicants, are there race and/or gender disparities in who identifies as an engaged scholar?
- Do the race and gender disparities vary by field, year, and/or the document type in which an applicant discusses engaged scholarship?

3.2 Data and Methods

The data used for this chapter come from the EEFR dataset described in section 2.1 of this dissertation. The dependent variables in this analysis—the use of engaged language—were developed using a computational grounded text analysis (Nelson 2017) detailed in sections 2.3-2.4 of Chapter 2. The key independent and recruitment-level control variables used in all models in this chapter are described in depth in section 2.6, and are reviewed briefly below.

3.2.1 Dimensions of Engaged Scholarship

To test for race and gender disparities in who identifies as an engaged scholar, I analyze two dimensions of engaged scholarship: the frequency with which an applicant uses engaged language, and the document type in which an applicant uses engaged language. I divide the analysis into two sets of models based on the two engaged language frequency variables: *any* and *amount.*[20] To assess the use of *any* engaged language, a binary variable for each document type (cover letter, research statement, and teaching statement) indicates whether the document contains at least one paragraph with engaged language. I assess the *amount* of engaged language with a variable measuring the proportion of paragraphs with engaged scholarship language in each document. Between the three document types, I consider race and gender differences across field to assess whether applicants are equally likely to use engaged language in each document, or if there are significant race and gender differences between the document types. Three binary variables control for whether each document type was submitted by an applicant. Table 3.1 presents the distribution of applicants across these dimensions of engaged scholarship. In total, 22.88% of applicants use engaged language in *at least one* of their application documents. I

[20] See Chapter Two for the development and operationalization of these variables.

broadly refer to these scholars as “engaged scholars.” Many applicants use engaged language in more than one document, as roughly 10% of all applicants use engaged language at least once in their cover letter, research statement, or teaching statement, respectively. Engaged scholars (N=31,740) have the highest proportion of engaged paragraphs in teaching statements where, on average, 12% of the documents’ paragraphs contain engaged language. Engaged scholars have the lowest proportion of engaged paragraph in research statements (9.8%, on average).

Table 3.1: Engaged Scholarship Language Across Application Documents

	Applicants with Any Engaged Paragraphs		*Proportion of Paragraphs with Engaged Language*	
	N	%	Mean	sd
Document Type				
Cover Letter	15,066	*10.86*	0.113	0.176
Research Statement	14,212	*10.24*	0.098	0.162
Teaching Statement	14,511	*10.49*	0.120	0.192
Among All Documents	31,740	*22.88*	0.112	0.106

Note: Applicants with Any Engaged Paragraphs calculated among all applicants; Proportion of Paragraphs with Engaged language calculated among applicants with at least one engaged paragraph (N=31,740). This information is also shown in Chapter Two, table 2.12.

3.2.2 Independent and Control Variables

This chapter focuses on race and gender disparities in the use of engaged language, and whether those disparities vary by application document, field, and/or year. Race and gender is measured using a seven-category variable with the following levels: female BHN, female white, female AAPI, male BHN, male white, male AAPI, and Other/missing.[21] Prior research has focused on *either* gender or race differences in who practices engaged scholarship. By using a single race/gender measure, I investigate disparities in the use of engaged scholarship on both

[21] Indicates gender and/or race/ethnicity categorized as other or missing.

dimensions simultaneously in order to explore differences between groups which may have distinctly different lived experiences and privileges within the academy (Jordan 2006; Turner 2002).

All models in this analysis control for the recruitment-level variables described in section 2.6: field, year, institution, and National Research Council (NRC) program rank of the hiring department. Field is measured by a six-category variable that includes: Agriculture/Natural Resources, Biological Sciences, Engineering, Math/Computer Science, Physical Sciences, and Social Sciences. The EEFR variable measuring NRC program rank for the hiring department is coded as a five-level ordinal variable: unranked, 1^{st}-50^{th} percentile, 50^{th}-75^{th} percentile, 75^{th}-90^{th} percentile, and 90^{th}-100^{th} percentile. Table 3.2 presents the race and gender distribution of applicants by these recruitment-level variables. The representation of different race and gender groups stays relatively stable over the years in the EEFR dataset, but vary more significantly by broad field category. The Social Sciences and Agriculture/Natural Resources have the highest representation of both BHN and female applicants, while Math/Computer Science and Engineering have the highest representation of AAPI applicants. The distribution of applicants coded as "Other" or missing race and/or gender classification is relatively equal across all fields and years of the data. Finally, female and BHN applicants are slightly overrepresented in recruitments for departments that are unranked by the NRC, or are in the bottom 50^{th} percentile of programs while white male applicants are slightly overrepresented in recruitments for positions in departments ranked in the top 75^{th} percentile.

I also include application-level controls that account for several measures of applicants' background characteristics. These include whether an applicant has a U.S.-based or international institutional affiliation at the time of application, the number of years since an applicant earned

Table 3.2: Race and Gender of Applicants by Recruitment Field, Year, and hiring department NRC Rank (percentile)

	Race/Ethnicity and Gender															
	Female BHN		Female AAPI		Female White		Male BHN		Male AAPI		Male White		Other/ Missing		**Total**	
	No.	*%*	No.	*%*	No.	*%*	No.	*%*	No.	*%*	No.	*%*	No.	*%*	**No.**	***%***
Broad Field																
Social Sci.	3,152	*7.2*	4,356	*10.0*	10,670	*24.4*	3,649	*8.3*	4,826	*11.0*	14,200	*32.5*	2,854	*6.5*	43,707	*100.0*
Ag/NatResources	134	*3.9*	349	*10.2*	678	*19.7*	253	*7.4*	626	*18.2*	1,209	*35.2*	185	*5.4*	3,434	*100.0*
Engineering	383	*1.0*	3,119	*8.3*	2,998	*7.9*	1,734	*4.6*	14,704	*39.0*	12,859	*34.1*	1,919	*5.1*	37,716	*100.0*
Biological Sci.	732	*3.2*	2,166	*9.6*	4,049	*17.9*	1,525	*6.7*	5,346	*23.6*	7,706	*34.0*	1,130	*5.0*	22,654	*100.0*
Math/CompSci.	147	*1.1*	1,434	*11.1*	1,151	*8.9*	526	*4.1*	4,393	*34.1*	4,367	*33.9*	861	*6.7*	12,879	*100.0*
Physical Sci.	269	*1.6*	1,084	*6.3*	2,227	*13.0*	920	*5.4*	4,082	*23.8*	7,629	*44.6*	911	*5.3*	17,122	*100.0*
Total	**4,817**	***3.5***	**12,508**	***9.1***	**21,773**	***15.8***	**8,607**	***6.3***	**33,977**	***24.7***	**47,970**	***34.9***	**7,860**	***5.7***	**137,512**	***100.0***
Dept. NRC rank (percentile)																
Unranked	1,468	*5.6*	2,565	*9.8*	4,637	*17.7*	1,821	*7.0*	5,955	*22.7*	8,059	*30.8*	1,688	*6.4*	26,193	*100.0*
1st-50th	863	*4.5*	1,878	*9.8*	3,167	*16.6*	1,461	*7.6*	4,344	*22.7*	6,426	*33.6*	996	*5.2*	19,135	*100.0*
50th-75th	1,010	*2.7*	3,566	*9.6*	5,024	*13.6*	2,146	*5.8*	10,937	*29.5*	12,352	*33.3*	2,025	*5.5*	37,060	*100.0*
75th-90th	600	*2.5*	2,004	*8.2*	4,111	*16.8*	1,379	*5.6*	5,202	*21.3*	9,776	*40.0*	1,360	*5.6*	24,432	*100.0*
90th-100th	876	*2.9*	2,495	*8.1*	4,834	*15.8*	1,800	*5.9*	7,539	*24.6*	11,357	*37.0*	1,791	*5.8*	30,692	*100.0*
Total	**4,817**	***3.5***	**12,508**	***9.1***	**21,773**	***15.8***	**8,607**	***6.3***	**33,977**	***24.7***	**47,970**	***34.9***	**7,860**	***5.7***	**137,512**	***100.0***
Academic year																
2013-14	804	*4.0*	1,758	*8.8*	3,176	*15.8*	1,148	*5.7*	5,064	*25.2*	7,083	*35.3*	1,032	*5.1*	20,065	*100.0*
2014-15	769	*3.2*	2,026	*8.4*	3,948	*16.5*	1,443	*6.0*	5,669	*23.6*	8,758	*36.5*	1,385	*5.8*	23,998	*100.0*
2015-16	766	*3.3*	2,094	*9.0*	3,600	*15.4*	1,375	*5.9*	5,949	*25.5*	8,308	*35.6*	1,221	*5.2*	23,313	*100.0*
2016-17	750	*3.2*	2,175	*9.1*	3,803	*16.0*	1,529	*6.4*	5,460	*22.9*	8,629	*36.3*	1,451	*6.1*	23,797	*100.0*
2017-18	879	*3.7*	2,123	*8.9*	3,670	*15.4*	1,682	*7.1*	6,130	*25.7*	7,930	*33.3*	1,406	*5.9*	23,820	*100.0*
2018-19	849	*3.8*	2,332	*10.4*	3,576	*15.9*	1,430	*6.4*	5,705	*25.3*	7,262	*32.2*	1,365	*6.1*	22,519	*100.0*
Total	**4,817**	***3.5***	**12,508**	***9.1***	**21,773**	***15.8***	**8,607**	***6.3***	**33,977**	***24.7***	**47,970**	***34.9***	**7,860**	***5.7***	**137,512**	***100.0***

Note: Other/Missing refers to race or gender not specified in the EEFR data.

their PhD, and applicants' current job category. The institution affiliation variable is a binary variable coded one if an applicant's current institutional affiliation is in the United States. Most applicants in the analytic sample (76%) were currently affiliated with institutions in the United States. The time since degree variable is an ordinal variable coded with five levels: 0, 1-2, 3-5, 6-10, and 11+ years. Finally, the EEFR variable for applicants' current job category is a categorical variable with nine categories: graduate student/PhD candidate, postdoctoral researcher or fellow (postdoc), assistant professor, associate/full professor, visiting professor, research/teaching fellow, researcher, lecturer, and other job. Table 3.3 presents the distribution of applicants across these variables by race and gender. Overall, BHN applicants are less likely to have postdoc positions compared to other applicants. These differences are likely driven by such groups representation in fields where postdocs are normative.

3.2.3 Analytic Strategy

I use logistic regression models to estimate applicants use of *any* engaged language and OLS regression models to estimate the *amount* of engaged language an applicant uses. I model the use of *any* engaged language among all faculty applicants in the analytic sample to test for race and gender disparities between those who use no engaged language, and those who used engaged language at least once in each document. I model the *amount* of engaged language used only among those applicants who use engaged language at least once to test for race and gender differences in whether some groups use *more* engaged language in each document.

The data for all analyses is structured at the document-within-application-level with clustered standard errors to correct for the non-independence of multiple observations of each applicant by document type, as well as applicants who may have applied to multiple

Table 3.3: Percent of Applicants by Current Job, Time Since Degree, and International Institution Affiliation, by Race and Gender

	Applicant Race/Gender							
	Female AHN	Female AAPI	Female White	Male AHN	Male AAPI	Male White	Other/ Missing	**Total**
	% Apps	% Apps	% Apps	% Apps	% Apps	% Apps	% Apps	**% Apps**
Current Job Title								
Postdoc	28.32	32.29	34.79	28.50	36.32	35.56	28.22	**34.21**
Assistant Professor	13.62	10.75	10.63	10.55	9.04	9.43	13.87	**10.12**
Associate Professor	4.65	3.65	3.38	5.96	5.07	4.82	6.88	**4.73**
Visiting Professor	6.62	4.88	5.89	5.53	4.63	5.27	6.54	**5.31**
Research/Teaching Fellow	3.01	3.05	3.69	3.29	3.45	3.82	4.35	**3.61**
Graduate Student/PhD Candidate	21.67	21.40	19.41	19.84	14.03	15.38	13.23	**16.61**
Researcher	7.56	13.88	9.84	11.77	17.72	13.68	12.43	**13.68**
Lecturer	8.32	4.90	7.56	7.24	3.51	5.53	6.87	**5.58**
Other	6.23	5.20	4.81	7.32	6.22	6.50	7.61	**6.15**
Years since PhD								
0	17.81	22.34	17.02	19.11	16.13	14.81	13.89	**16.49**
1-2	23.76	18.81	21.28	18.38	17.43	18.00	17.52	**18.65**
3-5	28.16	28.06	30.49	25.83	30.45	31.48	29.51	**30.18**
6-10	21.49	22.15	24.07	25.12	26.01	24.92	25.59	**24.73**
11+	8.78	8.64	7.14	11.56	9.97	10.79	13.49	**9.95**
Institution Affiliation								
Non-U.S. Institution	15.29	17.13	21.76	25.68	23.85	28.02	20.10	**23.94**
U.S. Institution	84.71	82.87	78.24	74.32	76.15	71.98	79.90	**76.06**
Sample Size (n)	**4,817**	**12,508**	**21,773**	**8,607**	**33,977**	**47,970**	**7,860**	**137,512**

recruitments[22] (i.e., multiple applications). I include two two-way interaction terms to test whether the use of engaged language by document type varies by recruitment field or year.[23]

I first estimate a base model for each measure of engaged language (*any* and *amount*) that addresses the first research question in this chapter: are there race and gender disparities in who identifies as an engaged scholar? These models estimate aggregate race and gender differences in engaged language in the presence of recruitment-level controls.

I then address this chapter's second research question: do the race and gender disparities in who identifies as an engaged scholar vary by field, year, and/or application document type? I test whether the aggregate race and gender disparities vary on these dimensions using a series of nested models that add the following two-way interaction terms: race and gender by field, race and gender by year, and race and gender by document type. I use model fit statistics and predicted probabilities to assess whether each additional interaction term provides evidence that the race and gender disparities in engaged language vary by field, year, or document type. Based on these assessments, I also test whether race and gender disparities in engaged language by document type vary by field or year with two three-way interaction terms: race and gender by field and document type, and race and gender by year and document type.

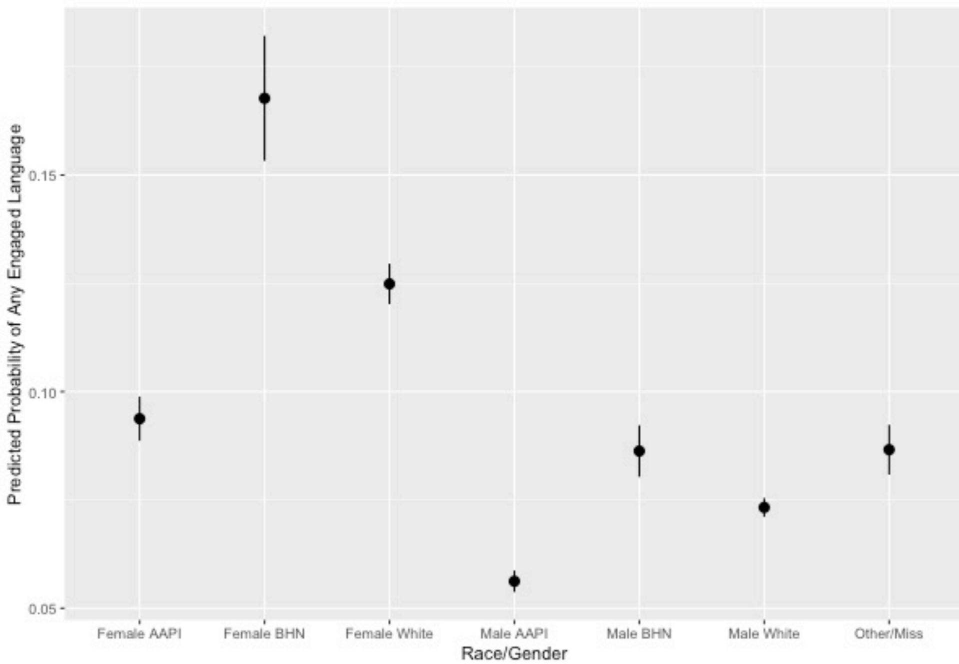
[22] Each application has three observations in the data—one for cover letter, teaching statement, and research statement. Within each document-observation there is a variable for whether the document has *any* engaged language and the *amount* of engaged language if *any*=1. The standard errors are clustered using an applicant id variable which identifies the three documents as a single application, and also accounts for applicants who applied to multiple recruitments (and thus have multiple applications in the EEFR data).
[23] I tested several base models with no interactions between control variables compared to models controlling for interactions between document type and field or year and found both interactions to significantly improve overall model fit. The coefficients and model fit statistics are shown in Appendix B, Table B.1 and 2.

3.3 Results

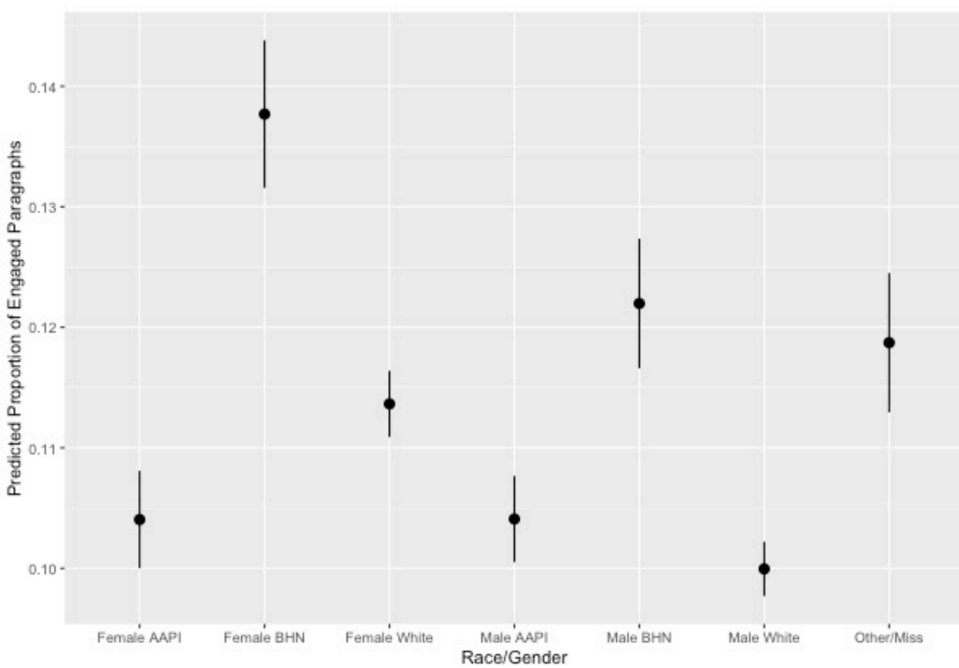
3.3.1 Race and gender disparities in who identifies as an engaged scholar

Figure 3.1 presents the race and gender disparities in the predicted probability that an applicant uses *any* engaged language in their application documents (Panel (a)), and the predicted proportion of paragraphs in an application document with engaged language among applicants with at least one engaged document (Panel (b)). These results address the first research question: Among faculty applicants, are there race and gender disparities in who identifies as an engaged scholar? Among all applicants, there are clear race and gender disparities in the probability that an applicant uses *any* engaged language—most notably that female BHN candidates' documents are far more likely than any other group's to have at least one engaged paragraph. Within race/ethnicity groups, female applicants' documents are overall more likely to have at least one engaged paragraph compared to males' documents. The only male applicants who are as likely to have any engaged paragraph as any female are male BHN candidates, who have a similar predicted probability of having any engaged paragraph as female AAPI candidates.

Together, these results indicate that both race *and* gender influence whether an applicant references engaged scholarship at least once in their application materials—in general female and BHN applicants' documents are more likely to have engaged language compared to male and white or AAPI applicants'. Yet, the marginal differences between all female applicants are much larger than the marginal differences between all male candidates, suggesting that there is more heterogeneity among female applicants' documents than male applicants' documents in regard to engagement. In fact, the difference between engaged language in documents submitted by female BHN applicants and female white and AAPI applicants is larger than the difference



(a)



(b)

Figure 3.1: Aggregate estimated race and gender disparities controlling for recruitment- and application-level variables, in the: (a) predicted probability among all applicants of having at least one engaged paragraph in their application; and (b) predicted proportion of paragraphs in an application with engaged language among applicants who have at least one engaged paragraph in their application. Estimates based on Model 1 in Appendix B, Table B.1 (*any* engaged language) and Table B.2 (*amount* of engaged language).

between female white and AAPI applicants and male BHN applicants. While both race *and* gender impact engagement, future research should particularly assess why female BHN scholars are so much more likely than all other groups to identify as engaged scholars in their application materials.

Among applicants who have at least one engaged paragraph, female BHN application documents also use the *most* engaged language. On average, 13.8% of paragraphs in each document of a female BHN's application packet contain engaged language. Among documents with at least one engaged paragraph, race is more influential than gender on the amount of engaged language used. As shown in Panel (b) of Figure 3.1, both female and male BHN application documents have a higher proportion of engaged paragraphs per document (13.8% and 12.2% respectively) than any other group.[24] BHN application documents have a higher proportion of engaged paragraphs compared to white women's documents (11.4%), as well as a higher proportion of engaged paragraphs compared to white men and all AAPI applicants' documents (all below 10.5% and not significantly different from each other).

In sum, application documents submitted by female BHN applicants are the most likely to have *any* engaged language, and to include the *most* engaged language, suggesting that female BHN applicants are the most likely group to identify as engaged scholars. White women and male BHN applicants are overall the second most likely groups to present themselves as engaged scholars. Although white women are more likely than male BHN applicants to use *any* engaged language, male BHN candidates use *more* engaged language than white women. These findings may indicate a qualitative difference in the depth of engagement with this epistemological

[24] Except for applicants with either gender or race/ethnicity coded as "Other/Missing." This group does not have a statistically significantly different predicted proportion of engaged paragraphs per document compared to Male BHN applicants. While there may be a substantive reason for this, I do not have enough information on the Other/Missing group to understand their relationship to engaged scholarship.

approach between race and gender groups, but could also be driven by race and gender differences in the use of engaged language in different application documents, differences by field in the use of engaged language, or changes in the applicant pool over time. Ostensibly, cover letters describe an applicant's overall scholarly approach and experience, while research and teaching statements focus specifically on those areas of scholarship respectively. Candidates may vary in their deployment of engaged language across these documents, and such variation may grant insight into why we see race and gender differences in the use of *any* and the *amount* of engaged language. Additionally, the aggregate race and gender disparities in engagement presented in this section may vary significantly by field and recruitment year—both of which may indicate structural variation in the EEFR data that needs to be controlled for,[25] or substantive race and gender differences in engagement due to field-specific normative practices. Each of these sources of variation is addressed in turn in the following section.

3.3.2 Race and Gender Differences in Engagement by Year, Field, and Document Type

As described in section 3.1.3, I test for variation in the race and gender differences in engaged language by field, year, and/or document type using a series of nested models in which I alternately add interaction terms to address each additional dimension of variation. Using overall model fit statistics[26] and marginal differences in predicted probabilities, I find that race and gender differences in engaged scholarship do vary significantly by field and document type, but the disparities have not changed over time.

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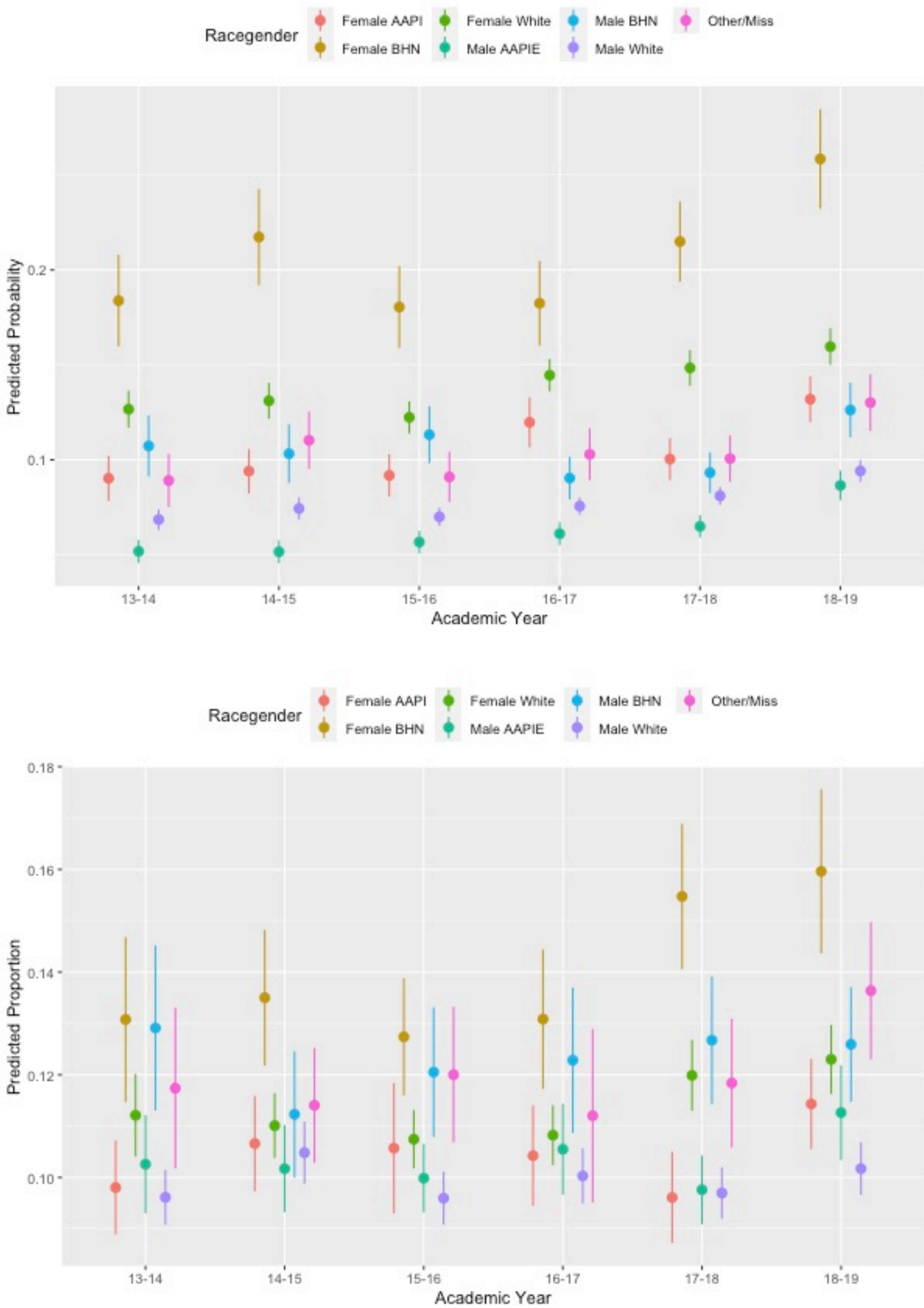
[25] Although the models in this section control for field, year, and institution of recruitment, individual recruitments within those categories may be more likely to have female or BHN (or engaged scholar) applicants due to the specialty area of the recruitment or language in the recruitment ad targeted at such groups. Thus, interaction effects between race and gender and the recruitment-level variables show us not only whether race and gender disparities in engaged scholarship vary by field, but also whether there is race and gender variation in recruitments that needs to be accounted for.
[26] I use AIC and BIC model fit statistics, shown in the coefficient tables in Appendix C.



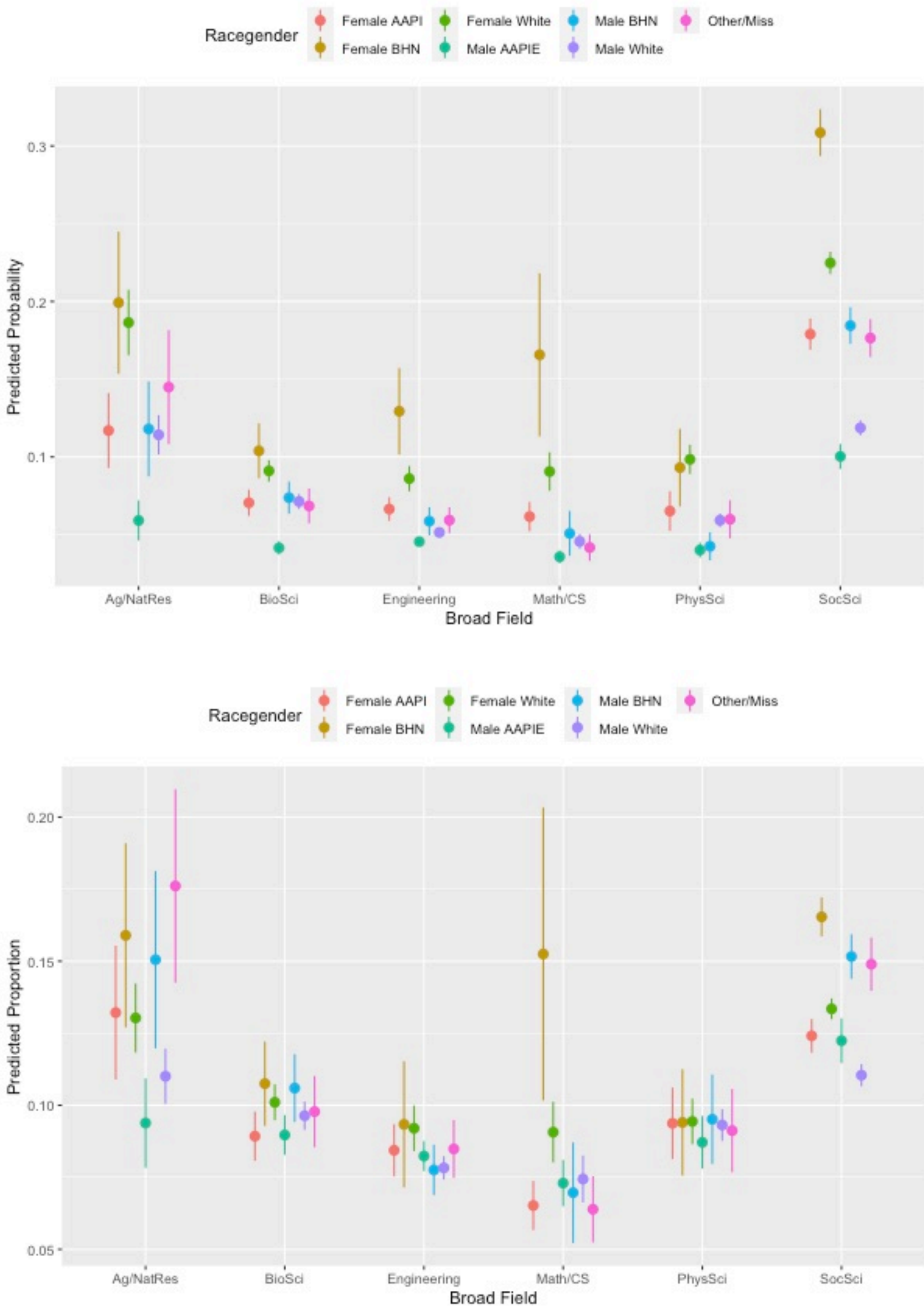
(a)

(b)

Figure 3.2: Estimated race and gender disparities across recruitment year, controlling for recruitment- and application-level variables, in the: (a) predicted probability among all applicants of having at least one engaged paragraph in their application; and (b) predicted proportion of paragraphs in an application with engaged language among applicants who have at least one engaged paragraph in their application. Estimates based on Model 8 in Appendix B, Table B.1 (*any* engaged language) and Table B.2 (*amount* of engaged language).

Figure 3.2 presents the predicted probability that an application document has *any* engaged language by race and gender across the six years of data (Panel (a)) and documents' predicted proportion of engaged paragraphs by race and gender across years (Panel (b)). There is slight variation in the race and gender disparities in the use of *any* engaged language across years, but overall, the race and gender disparities shown in Panel (a) of Figure 3.1 are stable across time. There is slightly more variation in the race and gender disparities in the *amount* of engaged language across years, though these differences were also not significantly different overall from the differences shown in Panel (b) of Figure 3.1. Overall, the use of *any* engaged language, and the *amount* of engaged language was relatively stable across the first four years of the data and increased slightly in the last two years. This suggests that while more applicants overall identified as engaged scholars in their application materials in the later years of the data, the race and gender differences in who identified as an engaged scholar did not change over time.

The predicted probabilities of *any* engaged language by race and gender across the six broad recruitment fields are shown in Panel (a) of Figure 3.3, and the predicted proportion of engaged paragraphs by race and gender across field are shown in Panel (b) of Figure 3.3. The results for the use of *any* engaged language show that among all application documents, the race and gender disparities are most similar to the aggregate group disparities in Engineering, Math/Computer Science, and the Social Sciences. In these fields, female BHN application documents are far more likely to include engaged language at least once, followed by white women. In Engineering and Math/Computer science, male BHN applications are not significantly more likely to use any engaged language compared to other male candidates'



(a)

(b)

Figure 3.3: Estimated race and gender disparities across recruitment field, controlling for recruitment- and application-level variables, in the: (a) predicted probability among all applicants of having at least one engaged paragraph in their application; and (b) predicted proportion of paragraphs in an application with engaged language among applicants who have at least one engaged paragraph in their application. Estimates based on Model 8 in Appendix B, Table B.1 (*any* engaged language) and Table B.2 (*amount* of engaged language).

applications, while in the Social Sciences they are far more likely to do so. In that vein, Engineering and Math/CS have the lowest gender parity and the lowest representation of faculty of color among applicants (see Table 3.2).

In Agriculture/Natural Resources, Biological Sciences, and the Physical Sciences, female white and BHN applicants are generally more likely to have any engaged language in their applications compared to other groups, but are not significantly different from each other. Both Agriculture/Natural Resources and Biological Sciences have above 30% female applicants and above 10% BHN applicants—both of which are higher than the overall average representation of female and BHN applicants respectively (see Table 2.14). In Agriculture/Natural Resources and Biological Sciences, female AAPI, and male white, and male BHN applicant's documents are all similarly likely to have *any* engaged language, while male AAPI applicant's documents are significantly less likely to have engaged language compared to all groups. In the Physical Sciences, there appears to be a larger gender gap, where documents submitted by female applicants are more likely to have engaged language compared to male applicants' documents.

These trends are quite different when considering the *amount* of engaged language used in documents submitted by applicants with at least one engaged paragraph in any document. The aggregate race and gender disparities show that female BHN applicants' documents have significantly more engaged language , followed by male BHN candidates' (shown in Panel (b) of Figure 3.1). This suggests that even though female scholars are more likely than male scholars to use *any* engaged language, among engaged scholars BHN scholars use more of their application document space to describe engaged scholarship activities and orientations. This *amount* difference means that those reading the application documents (i.e., faculty hiring committees) may perceive engaged scholarship as a type of scholarship predominantly done by BHN applicants.

When broken down by field, however, we see that this trend is most strongly driven by female BHN applicants in Agriculture/Natural Resources, Math/Computer Science and the Social Sciences, and by male BHN candidates in Agriculture/Natural Resources and the Social Sciences. Although Math/Computer Science application documents overall have the lowest predicted proportion of engaged paragraphs in their applications, documents submitted by female BHN applicants in this field have one of the highest predicted proportions of engaged paragraphs out of any field. In Biological Science, Physical Science, and Engineering, there do not appear to be any significant race and gender differences among any groups in the amount of engaged language used in an entire application.

Though this varies by field, I find that female BHN candidates are the most likely to present themselves as engaged scholars in their applications. This pattern is most apparent in Math/Computer Science and the Social Sciences, even though these two fields are polar opposites in their respective representation of female BHN applicants. 7.2% of applicants in the Social Sciences are BHN women, the highest out of any field, while Math/Computer Science has one of the lowest applicant percentages of BHN women at 1.1% of applicants (see Table 3.2). Although not as apparent in the amount of engaged language used, fields with lower levels of gender parity tend to have more significant overall gender gaps in the use of *any* engaged language.[27]

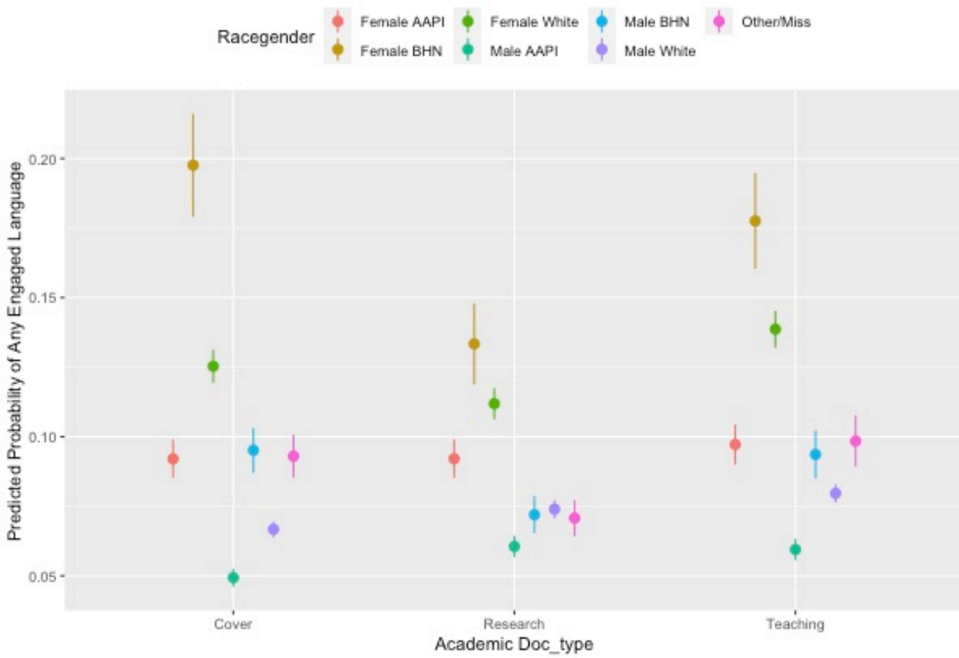
Beyond categorizing fields by levels of gender parity or representation of BHN scholars (though overall, these are all very low for STEM fields except the Social Sciences and to a lesser

[27] I explore this trend further in the next section.

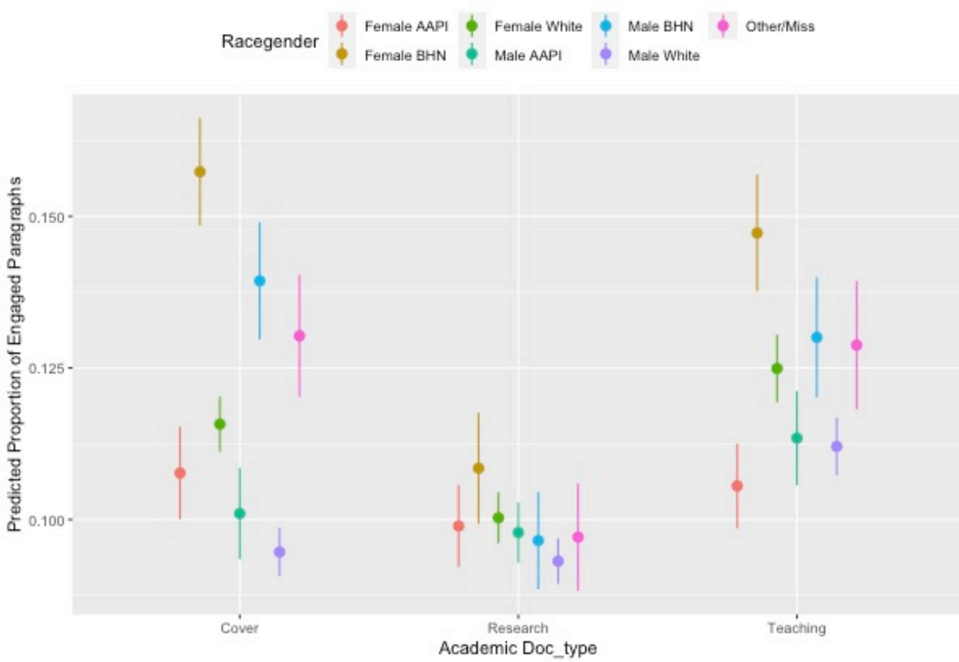
extent Agriculture/Nat Resources), I also consider whether these patterns in race and gender disparities in engagement might be driven by variation in the use of engaged language across document types. The predicted probabilities of *any* engaged language by race and gender across the three document types (controlling for whether an applicant submitted that document in their application) are shown in Panel (a) of Figure 3.4. The predicted proportion of engaged paragraphs by race and gender across documents are shown in Panel (b) of Figure 3.4.

Overall, the use of any engaged language in research statements is less common than the use of any engaged language in cover letters and teaching statements—though these trends clearly vary by applicant race and gender. Across all documents, female BHN applicants have the highest predicted probability of using any engaged language, followed by white women. In cover letters and teaching statements, female AAPI and male BHN applicants are similarly likely to use engaged language, followed by white men and AAPI men respectively. However, in research statements, there is a very clear gender gap, where all female applicants are more likely than all male applicants to use engaged language.

Figure 3.5 shows the predicted probabilities of *any* engaged language by document type across STEM field. The fields in which female BHN applicants are more likely than any other group to use engaged language (Social Sciences, Engineering, and Math/Computer Science) are also the fields where research statements are the most likely (or at least equally likely to teaching statements) to contain any engaged language by document type. The exception is Agriculture/Natural Resources, where all three document types are equally likely to contain engaged language and white women are equally likely to use engaged language compared to female BHN applicants.



(a)



(b)

Figure 3.4: Estimated race and gender disparities across document type, controlling for recruitment- and application-level variables, in the: (a) predicted probability among all applicants of having at least one engaged paragraph in their application; and (b) predicted proportion of paragraphs in an application with engaged language among applicants who have at least one engaged paragraph in their application. Estimates based on Model 8 in Appendix B, Table B.1 (*any* engaged language) and Table B.2 (*amount* of engaged language).

In the *amount* of engaged language used by document type (Panel (b) of Figure 3.4), female BHN applicants again have the highest predicted proportion of engaged paragraphs in each document type. In cover letters, female BHN and male BHN candidates have the highest predicted proportion of engaged language compared to any other group. As Figure 3.5 shows, the fields where cover letters have an equal or higher predicted proportion of engaged paragraphs

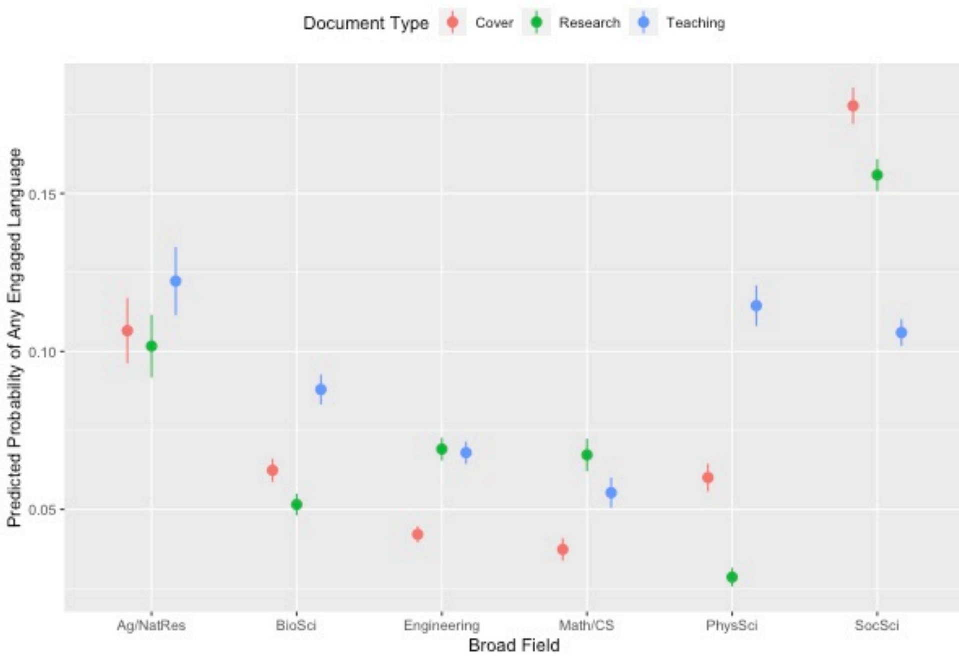


Figure 3.5: Estimated differences in engaged language in each document type across recruitment field, controlling for recruitment- and application-level variables, in the predicted probability among all applicants of having at least one engaged paragraph in their application. Estimates based on Model 8 in Appendix B, Table B.1 (*any* engaged language) and Table B.2 (*amount* of engaged language).

compared to other documents (Agriculture/Natural Resources and Social Sciences) are also the fields where female BHN and male BHN candidates have the highest predicted proportion of engaged paragraphs (see Panel (b) of Figure 3.3). These two fields also have the greatest gender parity and representation of BHN scholars among applicants, and are the most likely fields to have applicants who identify as engaged scholars.

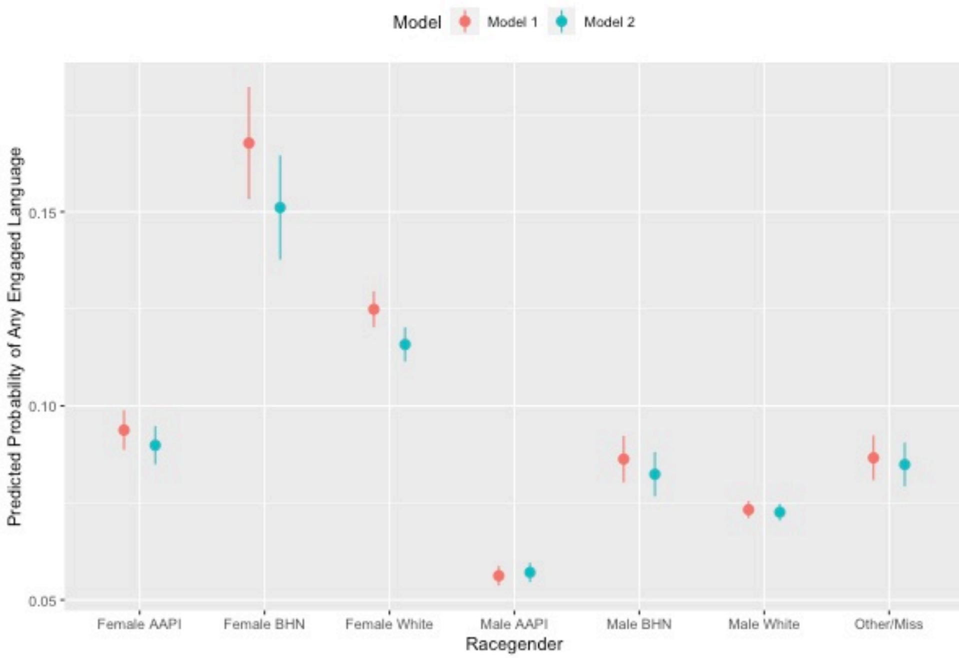
Although female BHN applicants have a significantly higher predicted proportion of engaged paragraphs in their teaching statements compared to all other groups, the fields where teaching statements have a significantly higher predicted proportion of engaged paragraphs compared to all other document types (Biological Sciences, Engineering, and Physical Sciences), have little to no race and gender disparities in the amount of engaged language.

3.3.3 Race and Gender Field Representation and Engaged Scholarship

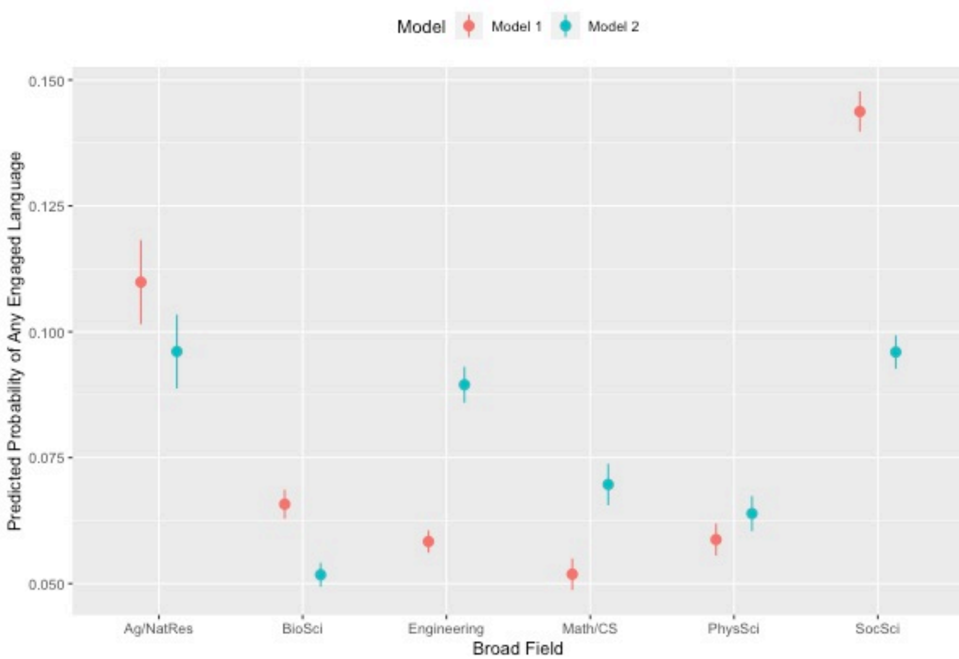
As noted in the previous section, fields with the most gender and race parity in the applicant pool have the smallest race and gender gap in who identifies as an engaged scholar. In this section, I test whether controlling for the relative representation of women and scholars of color in a field explains the field-level gender and race disparities in engaged scholarship. I use two EEFR variables[28] that measure the representation of women and the representation of BHN scholars in the availability pool of each recruitment specialty area. The availability pool refers to the estimated availability of scholars who earned PhDs at U.S. institutions within disciplinary fields that match each recruitment before each recruitment was initiated.

Figure 3.6 shows the changes in predicted probabilities of an application document having *any* engaged across race and gender (Panel (a)) and broad field (Panel (b). Controlling for the representation of women and BHN scholars in a field's availability pool (Model 2) had a bigger effect on overall field differences than overall race and gender differences. Female and BHN applicants' predicted probability of using *any* engaged language in their application documents decreased slightly, while male AAPI and male white applicants' predicted probabilities remained relatively constant. The predicted probability of a document containing

[28] The pool availability data was creating using data from the Survey of Earned Doctorates conducted by the National Science foundation and other federal agencies.



(a)



(b)

Figure 3.6: Estimated predicted probability that an applicant uses *any* engaged language across (a) race and gender, and (b) broad field for two models: Model 1 (interaction model discussed in section 3.3.2) and Model 2 (interaction model with control variables for the representation of women and BHN scholars in recruitment specialty areas availability pool). Estimates based on Model 1 and 2 in Appendix B, Table B.3.

any engaged language decreased significantly in the three fields with the highest representation of women and BHN scholars: Agriculture/Natural Resources, Biological Sciences, and Social

Sciences. The opposite occurred for the fields with the lowest representation of women and BHN scholars: Engineering, Math/Computer Science, and Physical Sciences. Controlling for female and BHN representation in recruitment specialty areas lessened field differences overall. Figure 3.7 shows the race and gender disparities in the use of *any* engaged scholarship language across the six broad fields when controlling for the representation of women and BHN scholars in the availabilities pool. While the overall field differences are smaller, the same pattern of race and gender disparities that were evident in the base model (Panel (a) of Figure 3.3) did not change

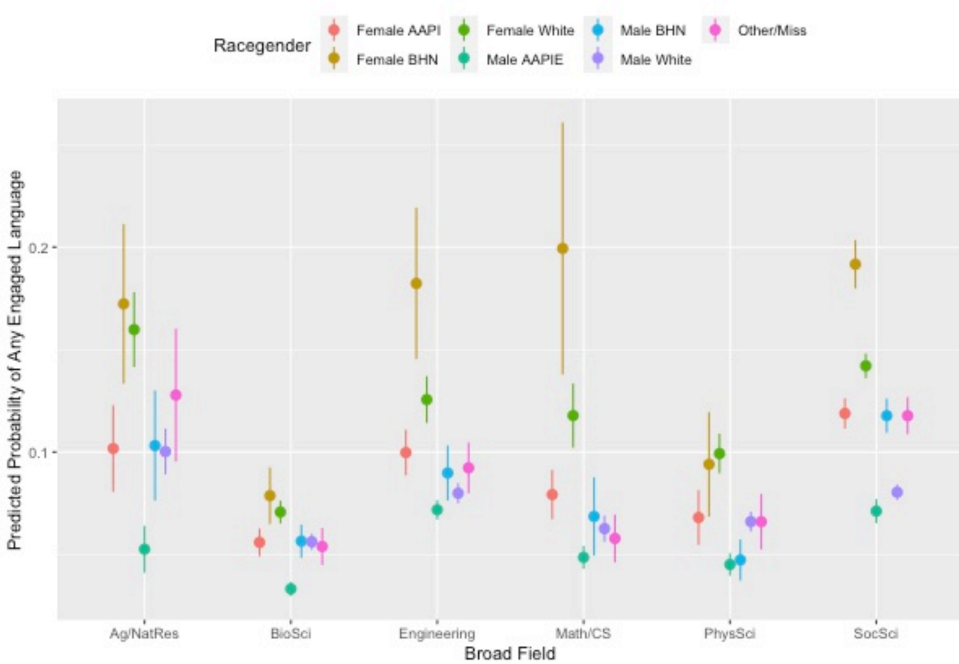


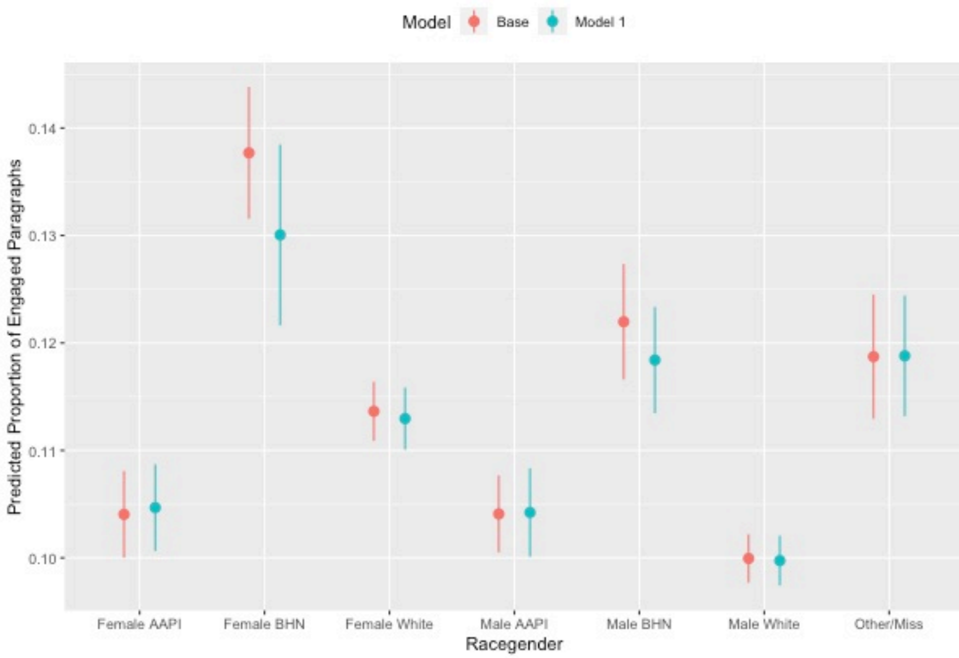
Figure 3.7: Estimated predicted probability of applicants' use of *any* engaged language by race and gender across recruitment field, controlling for recruitment specialty area availability pool representation of women and BHN scholars. Estimates based on Model 2 in Appendix B, Table B.3.

significantly. This suggests that field disparities in applicants' use of *any* engaged language are mostly explained by the representation of women and BHN scholars in the availability pool. However, overall and within fields, the relative representation of women and BHN scholars does not affect race and gender disparities in applicants' use of *any* engaged language.

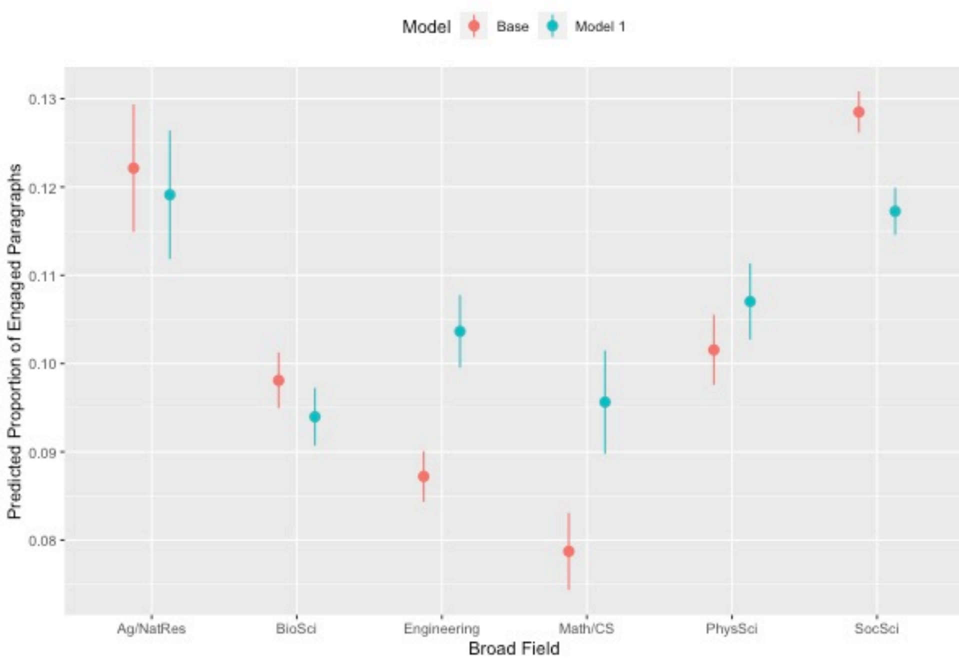
A similar, though smaller, effect can be seen in the *amount* of engaged language used in application documents: controlling for the representation of women and BHN scholars in the availability pool explains most of the variation in field differences, but does not significantly affect race and gender disparities. Figure 3.8 shows the changes in the predicted proportion of engaged paragraphs in application documents across race and gender (Panel (a)) and field (Panel (b)) after controlling for the representation of women and BHN scholars in a recruitment field.

The results show that BHN applicants have a slightly lower proportion of engaged paragraphs in their application documents when controlling for the representation of women and BHN scholars in the availability pool and all other groups' estimates are relatively stable. Despite the changes for BHN scholars, however, the overall pattern of race and gender disparities does not change: BHN scholars still have the highest proportion of engaged paragraphs in their applications compared to all other groups. However, as shown in Panel (b), controlling for female and BHN representation in recruitment availability pools significantly decreases overall field differences.

In sum, these findings suggest that fields with more gender and racial parity *overall* have more engaged scholars than fields with less gender and racial parity. However, the representation of women and BHN scholars in a field has little to no effect on gender and race disparities in who identifies as an engaged scholar. This bolsters the main finding in this chapter: female and BHN applicants, and particularly female BHN applicants, are the most likely to identify as engaged scholars.



(a)



(b)

Figure 3.6: Estimated predicted proportion of engaged paragraphs in an application across (a) race and gender, and (b) broad field for two models: Model 1 (interaction model discussed in section 3.3.2) and Model 2 (interaction model with control variables for the representation of women and BHN scholars in recruitment specialty areas availability pool). Estimates based on Model 1 and 2 in Appendix B, Table B.4.

3.4 Discussion

Together, these analyses provide insight into the race and gender disparities on multiple dimensions of engaged scholarship. The findings presented in this chapter are largely descriptive and take a landscape view of engaged scholars across the six broad STEM fields included in the analyses. While there are likely significant race and gender differences in engagement *within* these broad fields,[29] this analysis focuses on significant race and gender disparities *between* fields.

To the two research questions presented in this chapter, I find very clear evidence for several patterns: (1) in aggregate, female BHN applicants are more likely to align themselves with engaged scholarship practices and orientations than any other group, while male AAPI applicants are the least likely to do so; (2) the first pattern is consistent across years, fields, and each type of document; (3) although the aggregate race and gender disparities do not vary by year, they do vary across fields in a manner that seems related to both engaged language in documents across fields and the representation of women and BHN scholars across fields. Below, I elaborate on each of these main findings.

First, while documents submitted by female BHN applicants are consistently more likely to contain engaged language, I also find evidence that overall, female applicants are more likely to identify as engaged scholars. This trend is largely driven by female BHN and female white applicants. Among male applicants, documents submitted by male BHN candidates are the most likely to contain engaged language. This trend provides some support that identifying as a marginalized racial or ethnic group increases one's likelihood of engagement for both men and women.

[29] For example, the specific disciplines included within the Social Sciences broad field categorization vary widely in their representation of female and BHN faculty.

Previous research has focused on either race *or* gender disparities in who identifies as an engaged scholar. While this analysis supports findings that women and scholars of color are more likely to identify as engaged scholars, I unambiguously find that, at the intersection of race and gender, women of color are the most likely among faculty applicants to identify as engaged scholars. Feminist theorists have long noted that focusing on race or gender in isolation consistently overlooks the experiences of women of color by generally describing social experiences of white women or men of color (Collins 2002; Crenshaw 2019; Lorde 2012; Thomas, Dovidio, and West 2014). Caroline Turner describes women of color in academia as "hidden within studies that look at the experiences of women faculty and within studies that examine the lives of faculty of color" (2002:76). Such oversights miss the often unique experiences of women of color, which are both significantly different from those of other female scholars and from the experiences of men of color (Turner 2002). The findings in this chapter suggest that women of color in academia are more likely to pursue engaged scholarship despite evidence that such a pursuit leads them to continuously "toil on the margins" (Hutchinson 2011:146).

Research on engaged scholars finds that early-career faculty report feeling a sense of professional risk in engaged scholarship; they perceive such scholarship as generally not rewarded or highly valued (Ellison and Eatman 2008). Yet, female BHN faculty applicants—already the most underrepresented group in academia—are the most likely to identify as engaged scholars despite such risks. They persist in advancing epistemologies of social justice, the public good, and the democratization of science.

Across academic disciplines, there is a robust literature in which women of color reflect on this duality: multiple marginalities within academia, as well as a commitment to social justice and scholar activism within and beyond the academy (Few 2007; Pratt-Clarke 2012; Rodriguez 2006; Turner 2002; Urrieta and Méndez Benavídez 2007). Such narratives demonstrate solidarity among women of color in academia, measuring a successful academic career by its change upon the world and the academy. Although the findings in this chapter cannot speak to the motivations of female BHN applicants to pursue engaged scholarship, they do align with such narratives identifying the group of scholars most underrepresented among applicants as also the most likely to practice engaged scholarship.

In contrast to previous studies examining race or gender differences in engaged scholarship, my examining groups by race and gender also illuminates which applicants were least likely to identify themselves as engaged scholars. Across all fields and application documents, male AAPI scholars were consistently the group least likely to use engaged language. Similarly, among female candidates, female AAPI applicants were consistently the group least likely to use engaged language. This finding aligns with Settles et al.'s (2020) finding that, among scholars of color, AAPI faculty are the least likely to report facing epistemic exclusion. Settles et al. (2020) did not specify whether this was because AAPI faculty do not engage in similar types of scholarship as other scholars of color, or because AAPI faculty do not face the same consequences of devaluation when engaging in such scholarship. The findings from this analysis suggest that, in regard to engaged scholarship, the former may be the case. Finally, I find that in fields where teaching statements are the most likely document to contain engaged language, white women are as likely as female BHN candidates to use engaged language, even though female BHN candidates are more likely to use engaged language across all document types. In fields where cover letters or research statements are the most likely documents to contain engaged language, female BHN applicants are significantly more likely than all other groups to identify as engaged scholars. Additionally, in fields with more gender parity in the applicant pool, more applicants overall identify as engaged scholars, but the race and gender disparities are relatively unchanged.

These findings suggest that, while female BHN scholars are most likely to be engaged scholars across all fields and application documents, there are field-specific processes that influence other groups in the practice of engaged scholarship. Additionally, more detailed categories of engaged practices could explain the variation in race and gender disparities across fields. For instance, what are the references to engaged scholarship in cover letters that create such a stark difference between BHN scholars and all other groups (see Figure 3.4)? Similarly, is there more variation in the use of engaged language in research statements that is not measurable with the variable used in this analysis? These questions are both a limitation of the present study and a clear starting point for future work.

3.5 Conclusion

On their own, the findings presented in this chapter suggest that studies on engaged scholars miss several key trends in race and gender disparities in engagement by only looking at race or gender alone. Future analyses should explore whether these intersectional results hold true for other groups of scholars (e.g., faculty or graduate students), and should aim to add a qualitative understanding of what motivations may drive female BHN scholars toward engaged scholarship more than other groups.

Regarding epistemic exclusion, the findings in this chapter provide strong evidence that engaged scholarship is most often practiced by women and BHN scholars—specifically by female BHN scholars. A key aspect of the epistemic exclusion theory is that epistemologies more often practiced by already marginalized groups in academia (i.e., women and scholars of color) tend to be devalued and under-rewarded (Dotson 2014; Settles et al. 2020). The devaluation, like the devaluation of work typically done by women in other occupations (England 2017; Reskin 1988), is inherently tied to *who* is seen as typically doing that type of scholarship. Future research querying evaluation of engaged scholars should investigate race and gender disparities in the experience of devaluation of engaged scholarship—that is, how the race and gender disparities identified in this chapter relate to race and gender disparities in whether such scholars perceive their work as devalued.

As discussed in Chapter One, scholarly evaluation is a complex process not easily measured or quantified. Metrics of scholarly merit commonly used in evaluation, e.g., number of publications, however, are more readily measurable, and several of these are the focus of the next chapter. In the next chapter I explore the relationship between engaged scholars and several metrics commonly used to validate scholarly value.

Chapter 4: Engaged Scholarship and Metrics of Academic Productivity

To explain the persistent underrepresentation of women and scholars of color as faculty in academia, numerous studies have examined race and gender disparities in scholarly productivity and their roles in tenure and promotion evaluation (e.g. Cole and Zuckerman 1984; Ginther et al. 2011; Ledin et al. 2007; Long 1992; Smith and Garrett-Scott 2021; Weisshaar 2017; Xie and Shauman 1998). Such studies predominately focused on the gender gap in productivity measures—often peer-reviewed publications, citations, and for some fields, grant-funding—finding that women tend to have lower productivity output than men, although the gap has decreased over time (Dion et al. 2018; Ginther et al. 2011; Lerchenmueller and Sorenson 2018; Maliniak et al. 2013; Xie and Shauman 1998). Fewer studies have examined race/ethnicity disparities in such metrics, yet from the available studies that have, we know that the gap is wider and has been less variable over time and across academic fields (Antonio 2002; Ginther et al. 2016; Ledin et al. 2007; Smith and Garrett-Scott 2021).

Scholars have examined many possible explanations for these disparities. Their findings show that unequal access to institutional resources and structural positions within academia explain much of the gap (Weisshaar 2017; Xie and Shauman 1998). More recent work suggests that differences in scholarly practices may be both undertheorized and largely excluded from examinations of productivity disparities (Grant and Ward 1991; Leahey 2006; Maliniak et al. 2013; Posselt et al. 2020; Weisshaar 2017).

Specifically, many studies posit that women and scholars of color may pursue types of scholarship that are less likely to be published, published in central journals, and cited broadly (Gonzales and Rincones 2012; Grant and Ward 1991; Leahey 2006; Maliniak et al. 2013; Settles et al. 2020; Weisshaar 2017). Data to measure these differences and a motivating theoretical framework, however, have been limited by two factors. First, previous measures of scholarship type are developed based on research topics of already published work (Grant and Ward 1991; Maliniak et al. 2013). Using these measures to then assess likelihood of publication and citation is biased by endogeneity of the dependent variable. Second, studies examining whether “types of scholarship” more likely pursued by women and scholars of color are published, cited, or funded less do not address *why* such topics may face these disadvantages (e.g. Maliniak et al. 2013). Such ungrounded theoretical frameworks leave us with no means of understanding why types of research pursued by women and scholars of color are disadvantaged, beyond assuming that these differences are simply gender- or race-based preferences.[30]

In this chapter, I address the first limitation using a unique data set of faculty applications that includes measures of a scholarship type more frequently done by women and scholars of color: engaged scholarship (see Chapter Two of this dissertation for information on the process of developing engaged scholarship measures, and Chapter Three for an analysis of race and gender disparities in who identifies as an engaged scholar). I address the second limitation by positioning the question of scholarship valuation within theories of racialized and gendered labor, including theories of epistemic exclusion (Dotson 2014; Settles et al. 2020), the racialized glass escalator (Alegria 2019; Budig 2002; Williams 1992; Wingfield 2009), and gendered and racialized organizations (Acker 1990; Ray 2019a). In so doing, I test not only whether engaged scholarship accounts for a significant part of the race and gender gap in metrics of scholarly productivity, but also whether there are differential returns in productivity or prestige in doing

[30] Such assumptions about women’s “preferences” for lower status work or types of work has been shown by many sociologists to be much more than an individual phenomenon. For example, Shelley Correll (2001, 2004) has demonstrated through used experimental methods and quantitative studies that that gendered cultural beliefs constrain individual career aspirations and “preferences.” Additionally, Paula England has examined multiple perspectives on the devaluation of work done by women, regardless of choice (England 1992b, 2017; England, Budig, and Folbre 2002).

such scholarship among different race and gender groups. Put differently: do women and scholars of color identifying as engaged scholars experience further disadvantage in accumulating metrics of productivity compared to non-engaged scholars?

4.1 Background

4.1.1 Academia as a Gendered and Racialized Organization

In her influential article "Hierarchies, Jobs, Bodies: A Theory of Gendered Organizations," Joan Acker (1990) described the ways that unequal gender and sexuality hierarchies are embedded in the logic that organizes most occupations. She posited that assumptions of "gender-neutrality" in the logic of organizations obscures the myriad ways in which male bodies, preferences, and personal lives are the basis of an "ideal worker," and thus continuously disadvantage or exclude those who do not fit this ideal (Acker 1990). Scholars have applied similar theories to race (Acker 2006; Ray 2019a), exploring how organizational formation is often directly based on racial hierarchies and social processes driving racial formation. The core of these organizational inequality regimes (Acker 2006) is a widespread social belief in status hierarchies and the gendered, racialized bodies to which these hierarchies apply (Ridgeway 1991, 2014). Organizational hierarchies and practices serve to obscure these larger status inequalities; status assumptions about competency or fitness for certain work thereby become institutionalized and are assumed to be gender- and race-neutral (Ray 2019a; Ridgeway 2014; Tomaskovic-Devey and Avent-Holt 2018).

Gendered and racialized organizations are not limited to occupations that are numerically dominated by any particular group—i.e., predominantly male or white occupations. Research shows that male advantage persists in both male- and female-dominant professions (Alegria

2019; Budig 2002; Williams 1992), though the form of advantage may vary by specific organizational values. For example, Williams (1992) describes a "glass escalator" effect in female-dominated professions where men are typically promoted or placed in managerial roles at higher rates than similarly qualified and experienced female workers. Such positions are not universally advantageous, however. Alegria (2019) found that, while women were more likely to be promoted to managerial roles in male-dominated technology firms, such positions disadvantaged women out of more lucrative opportunities in the long run. In both cases, men continued to occupy structurally advantaged positions, re-affirming gendered status beliefs about who belongs in such roles.

Scholars have also shown that an intersectional approach to these gendered advantages is crucial (Alegria 2019; Wingfield 2009). Adia Harvey Wingfield (2009) found that the "glass escalator" phenomenon in female-dominated fields is a particular advantage experienced by white men. Within a single occupation, Sharla Alegria (2019) found that certain workers were tracked into differential roles even when starting in the same position. The study followed software engineers in a large technology firm and Alegria (2019) found that white women were given a "step-stool" advantage and tracked out of engineer positions into managerial roles. In some industries, such tracking might seem like a gendered advantage, but in the tech-firm, Alegria noted that in the long term, managerial positions were not as lucrative as engineering positions, as mid-level managers were later excluded from c-level promotions. Furthermore, this small advantage for white women did not apply to women of color—who were more likely to remain in engineering positions, but who then faced discrimination and tokenism (Kanter 1977) which often led to leaving the company or transitioning out of tech-work. Alegria's findings suggest that the racialized glass escalator effect may not only apply to entire occupations which are female dominated, but that within occupations, specific tasks or types of work are viewed as feminine or masculine. Thus, workers may be evaluated differentially based on their race and gender identity and the type of work in which they are engaging within the same job position, such as a faculty position in academia.

Multiple scholars have explored the myriad ways in which academic institutions are both gendered (Bird 2011; Mihăilă 2018; Zippel and Ferree 2019) and racialized (Bazner et al. 2021; Ray 2019b; Romero 1997) organizations that systematically favor male and white bodies, work styles, personal lives, and approaches to knowledge creation. Historically, women and minoritized racial groups were explicitly excluded from higher education through institutional policies and quotas (Harper et al. 2009; Parker 2015; Zambrana and MacDonald 2009). Yet the underlying organization of academia was also built on implicit exclusion of these groups through processes that defined legitimate science and knowledge creation in opposition to the topics and epistemologies established by women and people of color (Furner 2017; Go 2020; Lengermann and Niebrugge 2006; Morris 2017; Schiebinger 1991, 2004). In the historical sense, scholars have labeled this phenomenon as epistemic exclusion (Go 2020) or epistemic apartheid (Ray 2019b).

Despite more recent increases in the academic representation of women and people of color, research finds that epistemic exclusion continues to operate in ways that subtly disadvantage such scholars. In the modern sense, epistemic exclusion refers to the systematic devaluation of research topics, methodologies, and knowledge production of scholars whose research is typically outside the disciplinary norms of their field (Dotson 2014; Settles et al. 2020). These marginalized forms of scholarship are also most often done by scholars who embody equally marginalized identities, such as women and faculty of color (Settles et al. 2020).

Settles et al. (2020) find that the devaluation inherent in epistemic exclusion manifests through marginalized scholars feeling that the type of work they do is often seen as “on the margins” in their discipline: their work is difficult to publish in central journals, cited less, and inhibits their ability to secure grant funding. These particular consequences of epistemic exclusion directly affect metrics of scholarly productivity that largely correlate to how merit and scholarly legitimacy are often measured in academia (Posselt et al. 2020).

4.1.2 Metrics of productivity

Scholarly merit and legitimacy are often discussed in terms of research output and impact, and measured through a scholar’s peer-reviewed publications, citations, conference presentations, and ability to secure grant funding (Basu 2006; van den Brink and Benschop 2012; Posselt et al. 2020). As Posselt et al. (2020) contend, however, the veil of meritocracy serves to legitimize stratification: citation counts and the peer-review process perpetuate a “cycle of homogenization and stratification of knowledge and capital” (2020: 37). Despite the well-documented inequities produced by reliance on these measures of productivity in academic evaluation (Baker 2001; Bell and Chong 2010; Bernal and Villalpando 2002; Gonzales and Rincones 2012; Posselt et al. 2020), such measures remain consequential forms of academic capital, which scholars must pursue to attain and maintain faculty positions (Apple 1999; van den Brink and Benschop 2012; Gonzales and Rincones 2012; Leahey 2006; Slaughter and Leslie 1997).

Decades of research confirm persistent race and gender gaps in several of these measures—particularly publications, and citations, (Cole and Zuckerman 1984; Dion et al. 2018; Leahey 2006; Lerchenmueller and Sorenson 2018; Long 1992; Maliniak et al. 2013; Weisshaar

2017; Xie and Shauman 1998). Prevailing explanations focus on the unequal distribution of institutional resources and structural positions (Weisshaar 2017; Xie and Shauman 1998) of women and historically marginalized racial groups. Yet few studies have considered whether the current historical and gendered and racialized organization of academia prioritizes and rewards certain types of research in the production of these metrics.

As previously discussed, Settles et al. (2020) found that scholars of color who engaged in types of research more commonly done by scholars of color perceived that their work was marginalized and not taken seriously by colleagues and mainstream publishing outlets. Other research has shown that female scholars are more likely to engage in interdisciplinary work (Rhoten and Pfirman 2007) and that such work is less likely to be published in high-impact journals or be cited in the short term (Gonzales and Rincones 2012; Kniffin and Hanks 2017). Finally, multiple studies have demonstrated that research topics and methodologies more likely to be pursued by women and scholars of color—specifically research that examines gender or minority populations—are less likely to be published in top-tier journals (Diaz and Bergman 2013; Grant and Ward 1991; Stanley 2007).

Together, these findings suggest that scholars who have historically been marginalized or outright excluded from higher education (i.e., women and historically marginalized racial groups) often pursue types of research that are less likely to be published, published in top-tier journals, and cited broadly. No study to date, however, has examined whether phenomena in other gendered and racialized organizations—like the (racialized) glass escalator—occur within types of academic work that are female- and minority-dominated. That is: while forms of scholarship more often done by women and minorities are devalued overall in academia, do female and scholars of color who do such work see comparatively differential returns in publications and citations?

Such an inquiry is at the core of this chapter. Building on findings presented in Chapter Three of this dissertation, where I found that women and scholars of color were more likely to identify as engaged scholars, I turn now to investigate the role of engaged scholarship in faculty applicants' metrics of scholarly productivity. I do this for three metrics of productivity—number of publications, average impact factor of journal for journal publications, and number of citations—in three stages. First, I investigate whether gender and race disparities exist in metrics of scholarly productivity among faculty applicants across six broad STEM fields. I then explore whether engaged scholarship explains part of those disparities, and finally, whether the effect of engaged scholarship on metrics of productivity vary by race and gender.

4.2 Data and Methods

The data used in this analysis come from the EEFR dataset described in section 2.1 of this dissertation. The dependent variables in this analysis—metrics of scholarly productivity—were developed using information from EEFR applicants' Curricula Vitae (CVs) and bibliometric data compiled from Scopus, the online abstract and citation database of peer-reviewed literature provided by Elsevier. The key independent and control variables in all models in this chapter are described in depth within section 2.6 and are reviewed briefly below.

4.2.1 Metrics of Scholarly Productivity

Most analyses examining scholarly productivity focus on a single metric: either number of publications (e.g. Cole and Zuckerman 1984; Grant and Ward 1991; Leahey 2006; Padilla-

Gonzalez et al. 2011; Teodorescu n.d.; Xie and Shauman 1998), or citation networks (Dion et al. 2018; Maliniak et al. 2013; Smith and Garrett-Scott 2021). Such analyses together form a wealth of knowledge about gender and racial gaps in measures of productivity, yet are unable to assess whether women and scholars of color face the same barriers in accruing different forms of academic capital. The main goal of my analysis is to understand the association between engaged scholarship and metrics of productivity, which may be differentially related to applicants' accumulation of publications, publication impact, and citations.

This chapter analyzes metrics of scholarly productivity among applicants to assistant-level faculty recruitments. Although applicants vary considerably in background qualifications, applicants to these recruitments are generally early-career scholars who have not attained tenure at another institution (see Table 4.2). Most previous studies of scholarly metrics of productivity analyze samples of tenured or tenure-track faculty, and therefore either adjust outcome measures to account for differences in the length of a scholar's career or use short-term measures of productivity (e.g. Weisshaar 2017; Xie and Shauman 1998). The limited career exposure of the scholars in this analysis serves to limit the heterogeneity in these metrics of scholarly productivity (Lerchenmueller and Sorenson 2018). I use statistical controls for applicants' previous job category and time since degree (discussed in section 4.2.4 below) to account for variation in exposure.

The EEFR variables for publication counts, journal impact factors, and publication citation counts were constructed through a multi-step process. First, publication information from applicants' CVs was extracted using text-scraping tools in Python. The titles and publication outlets were then used to search the Scopus database for journal impact factors (for journal publications) and citation counts. The variable for publication counts includes all types of publications, such as journal articles, books, conference papers, and chapters from edited volumes.[31] Research suggests that the normative type and number of publications vary by field (Allison 1980; Hammarfelt and de Rijcke 2015; Wood 2016), and all analyses in this chapter include statistical control variables for field of recruitment. As shown in Table 4.1,[32] the mean number of applicant publications is 16.35 publications. This varies considerably by race and gender, as female BHN applicants have the fewest publications (10.19), while Male AAPI applicants have the most (19.96).

The EEFR variable measuring journal impact factor includes all applicants with at least one journal article publication. Journal impact factor refers to the mean number of citations per article in a publication over a two year period (Mingers and Leydesdorff 2015). The EEFR dataset includes a variable for journal impact factor that converts the impact factors into field-specific percentiles.[33] The analyses in this chapter use applicants' average journal impact factor percentile to compare impact factors between and within fields. Female BHN applicants tend to have the lowest average journal impact factor (74th percentile), while female AAPI applicants, on average, publish in journals with the highest impact factors (76th percentile) (see table 4.1). These differences are smaller than the differences in publication and citation counts and could be

[31] Among applicants in the analytic sample, the publication count variable was missing 1.76% of applicants. I tested whether the missingness was associated with any key variables in this analysis, and found that in several fields, BHN scholars were more likely to have missing publication data. Full results from the logistic regression model examining missingness are available in Appendix C, Section 1. Although I cannot account for these patterns of missingness in the data, and potential bias in this measure should be considered when interpreting results.
[32] See Appendix C Section 2 for histogram graphs showing the distribution of each outcome variable.
[33] Among applicants in the analytic sample, the journal impact factor variable was missing for 26.1% of applicants. I tested whether the missingness was associated with any key variables in this analysis and found that there were no race/gender groups more likely to be missing impact factor information, but that applicants with engaged language in their research statement were slightly less likely to have missing data than applicants with no engaged language in their research statement. Full results from the logistic regression model examining missingness are available in Appendix C, Section 1. I cannot account for these patterns of missingness in the data, and potential bias in this measure should be considered when interpreting results.

reflective of data availability, or could be truly representative of relatively small race and gender disparities in journal impact factors.

Table 4.1: Descriptive Statistics for Metrics of Productivity Variables

	Publications		Average Impact Factor (Percentile)		Citations	
Applicant Race/Gender	Mean	*sd*	Mean	*sd*	Mean	*sd*
Female BHN	10.19	*16.34*	74.56	*18.23*	14.04	*28.05*
Female AAPI	13.36	*16.17*	76.56	*17.34*	21.81	*30.05*
Female White	12.77	*16.11*	75.26	*17.49*	18.65	*27.93*
Male BHN	13.42	*19.41*	74.43	*18.66*	18.74	*31.11*
Male AAPI	19.96	*24.88*	75.30	*17.83*	23.33	*32.81*
Male White	17.17	*22.22*	75.50	*17.93*	20.81	*29.67*
Other/Missing	17.22	*25.33*	75.30	*17.43*	18.62	*26.89*
Total	**16.35**	***21.64***	**75.42**	***17.81***	**20.79**	***30.27***
N	135,008		84,536		98,491	

Journal impact factors as a measure of publication quality have faced recent criticism, as they tend to reify academic prestige hierarchies and reproduce inequalities (Bell and Chong 2010; Gruber 2014; Seglen 1997), yet are consistently used in consequential academic gatekeeping processes such as hiring and promotion evaluation (McKiernan et al. 2019). Much less research attention has been given to race and gender gaps in journal impact factors compared to publication counts and citation counts. The studies that do consider disparities in journal impact factors have primarily focused on gender gaps, and broadly find little to no significant differences (Beaudry and Larivière 2016; Mauleón and Bordons 2006; Tower, Plummer, and Ridgewell 2007). Several studies examining women's representation in academia have used journal impact factors, or whether scholars publish in "top-tier" journals, as multivariate control variables (Leahey 2006; Weisshaar 2017) and report inconclusive univariate differences.

The EEFR variable measuring citations[34] includes all applicants with at least one publication. Most studies evaluating the gender and race citation gap measure citation networks within a single discipline (e.g. Dion et al. 2018; Maliniak et al. 2013), and do not use citation counts to evaluate differences between individual scholars. These studies demonstrate that citations exhibit gender homophily—i.e. men tend to cite other men and women tend to cite other women—and that men are also more likely than women to self-cite (King et al. 2017; Maliniak et al. 2013).

I do not account for either of these trends in this analysis, but suggest that future research examine whether such practices are consistent among those who identify as engaged scholars and those who do not. Additionally, whether a scholar with a high citation count has a small number of well-cited publications or a large number of less well-cited publications is not an element I aim to capture in this analysis, as I cannot assess which metric is more influential on hiring decisions across the fields included in this analysis. I instead use a scholar's total count of citations while controlling for total number of publications. As shown in Table 4.1, applicants had a mean number of 20.79 citations—though, like the other metrics of productivity, this varies by race and gender.

4.2.2 Engaged Scholarship Variables

I measure engaged scholarship using the variables developed in Chapter Two to capture two dimensions of applicants' use of engaged scholarship language in their application

[34] The variable measuring citations has a relatively high amount of missingness (17.31%)—more than the missingness for publications. I tested whether the missingness was associated with any key variables and found that applicants in Biological Sciences were more likely to have missing citation data, but there were no significant race and gender differences in missing citation data. Full results from the logistic regression model examining missingness are available in Appendix C, Section 1. I cannot account for these patterns of missingness in the data, and potential bias in this measure should be considered when interpreting results.

documents: the frequency with which they use engaged language, and the document type in which they use engaged language. As described in section 3.2.1 of Chapter Three, the engaged scholarship variables capture the use of *any* engaged language—a binary variable—and the *amount* of engaged language (measured as a proportion of paragraphs with engaged language) for each document type. All models also include three binary variables to account for whether each document type was submitted by an applicant. As publications and citations are metrics of scholarly output that are particularly representative of the scholarship of discovery (i.e. basic research) (Boyer 1990), the models analyzing disparities in these two metrics include engaged scholarship measures for cover letters and research statements. These two documents are where applicants likely discuss practices and orientations most associated with the scholarship of discovery. In comparing the two documents, engaged language in research statements is more likely to imply that the applicant engages in some type of engaged research—either topically or methodologically (see Table 2.8 in section 2.4.3 in Chapter Two for examples of such types of engaged research). Engaged language in cover letters could also refer to engaged research practices, but could also imply that the applicant uses engaged teaching practices or grounds their research in an "engaged orientation" (also see Table 2.8 in section 2.4.3 in Chapter for examples of other types of engagement). Substantively, I expect that engaged research practices (i.e., those discussed in research statements) will have more of a direct effect on metrics of productivity. However, I include cover letters as a secondary source of engaged scholarship practice and orientation.

4.2.3 Race and Gender Variable

Most previous analyses of metrics of scholarly productivity focus on the gender gap; fewer identify racial gaps in these measures. Analyses that include both race and gender find important distinctions along these intersections, specifically that the productivity gap is largest for women of color compared to other groups (Ginther et al. 2016). The findings in Chapter Two showed that women of color were the most likely of all applicants to identify as engaged scholars, and in this chapter I seek to examine the role of engaged scholarship on metrics of productivity. Thus, like the previous chapter, the analyses in this chapter examine race *and* gender disparities in metrics of scholarly productivity, measured by a seven-category variable with the following levels: female BHN, female white, female AAPI, male BHN, male white, male AAPI, and Other/missing.[35]

4.2.4 Recruitment-Level Control Variables

All models in this analysis control for the recruitment-level variables described in section 2.6 of Chapter Two: field, proportion of female and BHN PhDs, year, institution, and prestige of the hiring department. Field is measured by a six-category variable that distinguishes: Agriculture/Natural Resources, Biological Sciences, Engineering, Math/Computer Science, Physical Sciences, and Social Sciences. Hiring department prestige is based on field-specific rankings developed by the National Research Council (NRC) and the EEFR variable measuring prestige is coded as a categorical variable by ranking percentiles: unranked, 1^{st}-50^{th}, 50^{th}-75^{th}, 75^{th}-90^{th}, and 90^{th}-100^{th}. Table 3.2 in Chapter Three presents the race and gender distribution of applicants by these recruitment-level variables.

[35] Indicates gender and/or race/ethnicity categorized as other or missing. This variable is discussed further in section 2.6 of Chapter Two of this dissertation.

Prior research has typically analyzed differences in metrics of productivity within a single field, or between two or three fields (e.g. Grant and Ward 1991; Leahey 2006; Weisshaar 2017). I do not intend in this analysis to compare the relative number of publications, impact factors, or citations between fields, but rather to compare the gender and race gaps in these metrics within fields. Thus, all models include an interaction term between the race and gender variable and the field variable to allow for such comparison.

As discussed in section 2.1 of Chapter Two, the EEFR dataset is not a representative sample of faculty recruitments across fields or years, or the number of recruitments in each field vary by year. To account for this, I include an interaction term between the variables measuring recruitment year and field, as well as an interaction term between the variables measuring recruitment year and race and gender to account for unobserved variation in types of recruitments across years that may have indirectly targeted women and minority scholars.

4.2.5 Applicant-Level Control Variables

All models in this analysis also include variables controlling for several measures of applicants' background characteristics. Prior research finds that male faculty typically have more available institutional resources and better structural positions, and that these factors account for much of the gender gap in productivity (Weisshaar 2017; Xie and Shauman 1998). However, most prior studies also focus on scholars who are already tenured or tenure-track faculty. The present study mostly examines scholars who have not previously held tenure-track positions (see Table 4.2).

To account for potential differences in prior positions, I control for an applicants' current job, which is coded as a categorical variable. It includes: graduate student/PhD candidate, postdoctoral researcher or fellow (postdoc), assistant professor, associate/full professor, visiting professor, research/teaching fellow, researcher, lecturer, and other job. As shown in Table 4.2, most applicants in the sample are either postdocs or graduate students (34.21% and 16.6% respectively), though this varies by race and gender. Overall, BHN applicants are less likely to have postdoc positions compared to other applicants. These differences are likely driven by such groups representation in fields where postdocs are normative, and the multivariate models control for such variation. These differences likely represent field norms about career tracks and may influence productivity gaps within and between fields. At the time of assistant-level faculty recruitments, fields where applicants have fewer years of exposure or are more likely graduate students (such as the Social Sciences) are likely to have lower average publications and citations.

The accumulation of scholarly metrics of productivity generally increases with more time in the field. I control for the time since an applicant earned their PhD with a categorical variable with coded with five levels: 0, 1-2, 3-5, 6-10, and 11+ years.[36] The majority of applicants in the sample are either 3-5 years or 6-10 years past their PhD (see Table 4.2)—though, like current job categories, this varies by race and gender, often driven by field differences.

Research has established that institutional prestige plays a key role in faculty hiring (Clauset, Arbesman, and Larremore 2015; Headworth and Freese 2016) and the accumulation of metrics of productivity (Allison 1980; Headworth and Freese 2016; Long 1992; Weisshaar 2017). Although the EEFR dataset does not include a direct measure for applicants' access to

[36] I measure exposure as categorical instead of continuous because preliminary analyses showed that the relationship between the three measures of productivity was non-linear. The categorical variable allows for the metrics of productivity to vary across these time categories. The 1-2 year category aims to capture applicants who may have had a short-term research/teaching postdoctoral position, postdoctoral fellowship, or other short-term job; the 3-5 year category aims to capture applicants who may have had a longer postdoc, junior faculty position (pre-tenure), or other more established first job after PhD; the 6-10 year category aims to capture applicants who may have made tenure or been denied tenure in a faculty position, or had a very established job; and the 11+ year category aims to capture applicants who have likely taken significant time away from academia.

Table 4.2: Percent of Applicants by Current Job, Exposure, and International Institution Affiliation, Applicant's Average Referrer Rank, and with at least one grant/fellowship, by Race/Gender

	Applicant Race/Gender							
	Female BHN	Female AAPI	Female White	Male BHN	Male AAPI	Male White	Other/ Missing	**Total**
	% Apps	% Apps	% Apps	% Apps	% Apps	% Apps	% Apps	**% Apps**
Current Job Title								
Postdoc	28.32	32.29	34.79	28.50	36.32	35.56	28.22	**34.21**
Assistant Professor	13.62	10.75	10.63	10.55	9.04	9.43	13.87	**10.12**
Associate Professor	4.65	3.65	3.38	5.96	5.07	4.82	6.88	**4.73**
Visiting Professor	6.62	4.88	5.89	5.53	4.63	5.27	6.54	**5.31**
Research/Teaching Fellow	3.01	3.05	3.69	3.29	3.45	3.82	4.35	**3.61**
Graduate Student/PhD Candidate	21.67	21.40	19.41	19.84	14.03	15.38	13.23	**16.61**
Researcher	7.56	13.88	9.84	11.77	17.72	13.68	12.43	**13.68**
Lecturer	8.32	4.90	7.56	7.24	3.51	5.53	6.87	**5.58**
Other	6.23	5.20	4.81	7.32	6.22	6.50	7.61	**6.15**
Exposure (years since PhD)								
0	17.81	22.34	17.02	19.11	16.13	14.81	13.89	**16.49**
1-2	23.76	18.81	21.28	18.38	17.43	18.00	17.52	**18.65**
3-5	28.16	28.06	30.49	25.83	30.45	31.48	29.51	**30.18**
6-10	21.49	22.15	24.07	25.12	26.01	24.92	25.59	**24.73**
11+	8.78	8.64	7.14	11.56	9.97	10.79	13.49	**9.95**
Institution Affiliation								
Non-U.S. Institution	15.29	17.13	21.76	25.68	23.85	28.02	20.10	**23.94**
U.S. Institution	84.71	82.87	78.24	74.32	76.15	71.98	79.90	**76.06**
Referrer's Average Rank Percentile	71.5	74.3	72.5	72.9	74.5	74.2	73.7	**73.8**
(mean and standard deviation)	(21.3)	(19.8)	(20.7)	(21.4)	(20.1)	(20.4)	(20.8)	**(20.5)**
Has at least one grant/fellowship	21.47	15.48	22.16	15.94	13.20	16.00	20.47	**16.68**
Sample Size (n)	**4,817**	**12,508**	**21,773**	**8,607**	**33,977**	**47,970**	**7,860**	**137,512**

institutional resources or prestige, it does include the NRC program rankings for each applicant's letter of reference writers. Often, letter writers are an applicant's graduate advisor, dissertation committee members, or postdoc Principal Investigator (PI). While the institutional affiliation of each letter writer is not necessarily the same affiliation for the applicant, it is likely that the applicant was associated with their referrer's institutions or similarly ranked institutions (if the referrer changed positions). To account for an applicant's average institutional prestige and resources, I create a variable using the average rank (by percentile) of all of an applicant's referrers. The mean and standard deviation for this variable is shown in Table 4.2 for each field, with an overall average of referrers ranked in the 74th percentile.

In fields such as the life sciences where research is often dependent on soft-money, applicants' history of grant funding may also affect their level of productivity (Lerchenmueller and Sorenson 2018). I control for this with a dichotomous variable that indicates whether an applicant listed at least one grant or fellowship on their CV. The EEFR grant-funding variable does not include information on the amount of funding—which may be a significant factor in affecting scholar productivity—but less than 20% of all applicants reported *any* grant funding, so the dichotomous variable may still account for the general effect of funding.

Finally, the international gender gap in metrics of productivity varies widely and is largely due to different factors (Padilla-Gonzalez et al. 2011; Teodorescu 2000).[37] All applicants in the EEFR dataset are trying to attain a faculty position at a U.S. institution, yet about a quarter of applicants' current institutional affiliations are outside the U.S. (see Table 4.2). Additionally, literature on the key independent variable in this analysis—engaged scholarship—largely focuses on the context of higher education in the U.S. This literature was used as the basis for the

[37] No available research has compared the racial gap in metrics of productivity across countries.

development of the variables measuring engaged scholarship (see Chapter Two), and thus may be biased toward recognizing engaged scholarship in applications from U.S.-based scholars. To account for potential differences in applicants' backgrounds across international institutions and bias toward engaged scholarship in U.S.-based applicants, I include a dichotomous control variable indicating whether an applicant is currently associated with an institution in the U.S.

4.2.6 Analytic Strategy

The goal of this chapter is to assess the association between engaged scholarship and gender and racial gaps in scholarly productivity among faculty applicants. Extant research suggests that engaged scholars struggle to publish their work in mainstream journals, thus their work is less visible and less widely cited (Settles et al. 2020). I analyze each dependent variable—publications, average impact factors, and citations, and—separately, but begin with the same modeling strategy so that I can directly compare the effect of engaged scholarship on each metric, thus addressing this gap in existing literature.

I begin with a "base" model (Model 1) examining race and gender disparities in each dependent variable, controlling for recruitment- and applicant-level variables (arrow 1 in Diagram 4.1). In the models for average impact factors and citations I control for applicants' number of publications, and these models are estimated only for applicants who have at least one publication. In the model for citations, I control for applicants' average journal impact factor. In Model 2, I add the engaged scholarship variables (*any* and *amount*) to test whether engaged scholarship mediates the relationship between race and gender and each metric of productivity (the arrows labeled "2" in Diagram 4.1). I assess the effect of engaged scholarship through comparing model fit statistics and changes in the predicted values of the dependent variables across race and gender groups. Finally, in Model 3, I add interaction terms between the engaged scholarship variables and race and gender to test for a moderating effect of engaged scholarship on the race and gender disparities in each dependent variable—i.e., does the effect of engaged scholarship on metrics of productivity vary across the race and gender groups (arrow 3 in Diagram 4.1)?[38]

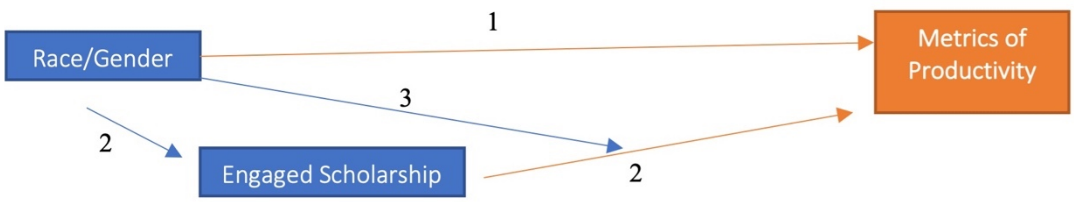


Diagram 4.1

The publication count and citation count variables are operationalized as count variables and I use Poisson regression models for each.[39] The variable measuring average journal impact factor percentile is a continuous variable that ranges from 0-100, and I use OLS regression models to assess the relationship between race/gender and engaged scholarship on this outcome.

[38] I also ran the same three models for each dependent variable using fixed effects models which controlled for detailed field-specialties at the recruitment level. These models decreased some of the field-differences in the productivity metrics but had little influence on race and gender disparities (overall and within fields) or on the effect of engaged scholarship on metrics of productivity.

[39] It is a common practice for researchers to use negative binomial models instead of Poisson models when there is overdispersion on the outcome variable (the standard deviation is greater than the mean, as is the case for all three outcome variables). However, recent econometrics research shows (Wooldridge 2010) that this is unnecessary when using robust standard errors because Poisson models still provide robust estimation for effects on the mean. All models in this chapter have robust standard errors, as I cluster the standard errors by applicant id to account for applicants who submit applications to multiple recruitments. This robustness to overdispersion also holds for data that is zero-inflated—which the citation and grant variables are—and multiple sources suggest that zero-inflated models are unnecessary (Allison 2012; Wooldridge 2010). However, for readers unconvinced by these arguments against negative binomial and zero-inflated models, I include both of these models with the same variables used in the “full” model of this analysis in Appendix C, Section 2. Based on the coefficients in these models, I find that the general relationships (significance and sign) of the key variables are the same as the results presented in the Poisson models in this chapter.

4.2.7 Limitations

Beyond the limitations discussed in Chapter Two and Three concerning the EEFR dataset and the measures of engaged scholarship, the analysis presented in this chapter has several additional limitations. First, the data used in this analysis are unable to measure a causal relationship between engaged scholarship and metrics of productivity. Early career scholars who are applying for tenure-track faculty positions are already a selective population (as discussed in section 2.1.1) in which processes like epistemic exclusion may have already excluded female scholars, scholars of color, and/or engaged scholars. Additionally, the measures of engaged scholarship used in this analysis are based on applicants' descriptions of themselves and their work found in their application documents. Temporally, applicants often write these documents describing their scholarship and accomplishments *about* the measures of productivity used in this chapter as outcome variables. I cannot account for whether an applicant identified as an engaged scholar *before* publishing the scholarship measured in this chapter, or at some time later on. Although it is likely that if a scholar describes themselves as an engaged scholar in their application materials, their previously published scholarship would contain some type of engaged work. I cannot account for the temporal order of when a scholar used engaged scholarship in relation to the outcome measures used in this chapter. Thus, I discuss the relationship between engaged scholarship and metrics of productivity as associations, not as causations.

4.3 Results

4.3.1 Race and Gender Disparities in Publications

Figure 4.1 presents the aggregate predicted number of publications for applicants in each field. These field differences are likely driven by disciplinary norms about publishing concerning typical publication type and length or collaboration versus solo authorship. Applicants in Social Science fields typically have the fewest at 11.1 publications, while applicants in Engineering fields average 17.9 publications. Figure 4.2 presents the race and gender disparities in number of publications in each broad field, controlling for recruitment- and application-level variables. Overall, female BHN applicants have the lowest predicted number of publications; male AAPI applicants have the highest, often followed closely by white male applicants. The relative differences between other groups vary across fields. In Agriculture/Natural Resources, Math/CS, and the Physical Sciences, female AAPI and female white applicants have very similar publication rates, while in the Social and Biological Sciences white women have significantly more publications than female AAPI applicants. In most fields, male BHN applicants have

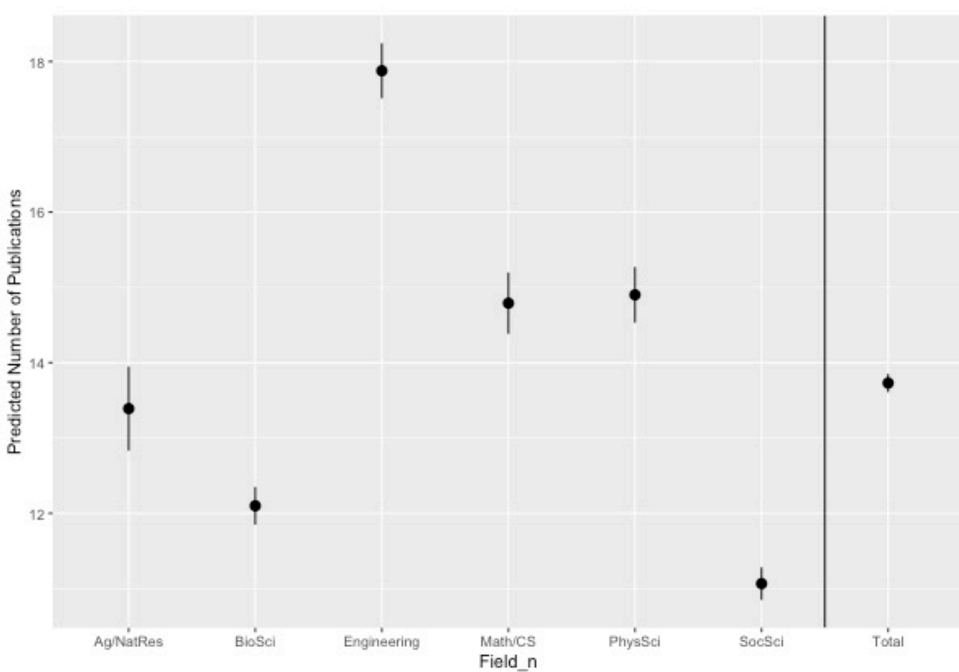


Figure 4.1: Aggregate estimated number of publications by field, controlling for recruitment- and application-level variables. Estimates based on Model 1 in Appendix C, Section 3, Table A (D.3.A).

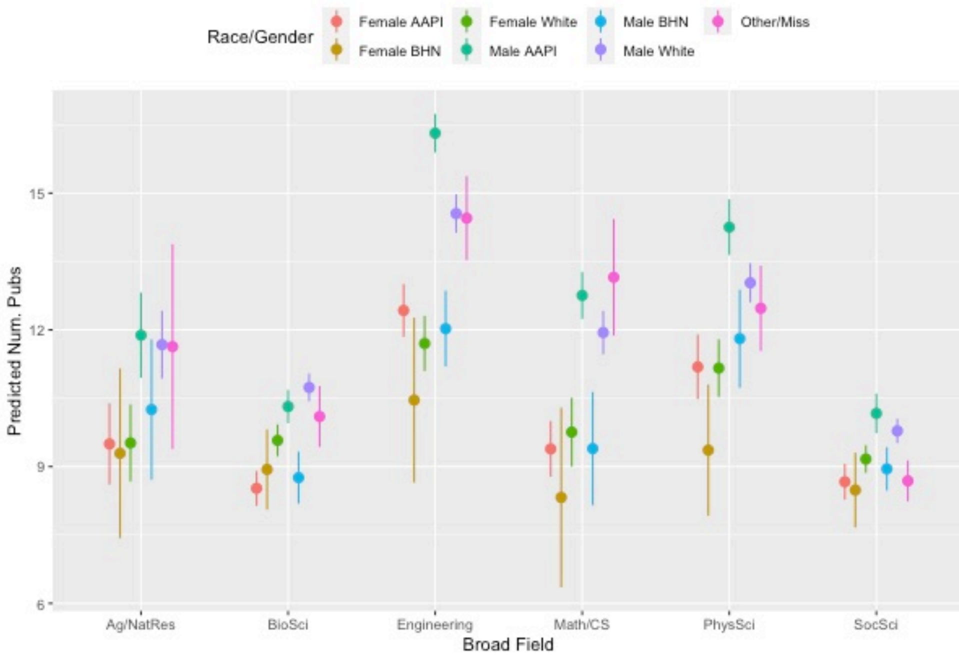


Figure 4.2: Estimated race and gender disparities in number of publications across fields controlling for recruitment- and application-level variables. Estimates based on Model 1 in Appendix C, Section 3, Table A (D.3.A).

similar publication rates to female AAPI and female white applicants, although they have slightly more than any female applicants in the Physical Sciences and Agriculture/Natural Resources.

The overall race and gender gap is smallest in the Biological Sciences and Social Sciences; the largest is in Math/CS, Engineering, and the Physical Sciences. Most prior research has focused on the gender gap in publication rates among current faculty (e.g. Grant and Ward 1991; Leahey 2006; Weisshaar 2017), while very few studies have examined racial differences in faculty publications (Antonio 2002). The results presented in this section suggest that such analysis may miss important race *and* gender group differences—specifically, female BHN scholars applying to faculty jobs across all fields tend to have the fewest publications, while white male and male AAPI have the most. Multiple studies suggest that productivity gaps are due to differential access to institutional resources, and for junior scholars the effect of quality mentorship may be particularly influential on early career publications. Although the controls for average referrer rank and previous job category account for some of these processes, the results suggest that women of color in particular may have the least access to institutional resources and mentorship, while male AAPI and male white scholars have the most. Additionally, other factors not accounted for in this study (such as family commitments, amount of grant-funding for research activities, and quality of mentorship as an early career scholar) may be account for the observed race and gender disparities.

4.3.2 The Effect of Engaged Scholarship on Race and Gender Disparities in Publications

To address whether engaged scholarship explains any of the race and gender disparities in publications, I add the engaged scholarship variables measuring *any* and *amount* of engaged scholarship language in research statements and cover letters to the model estimating publication counts. Using AIC and BIC model fit statistics, I find that including the engaged scholarship variables improves the overall model fit in (see Appendix C, Section 3, Table A for model coefficients and model fit statistics). While the overall model fit improvement suggests that engaged scholarship explains a significant part of the variance in publication count differences, I find that controlling for engaged scholarship has little effect on the race and gender disparities. Figure 4.3 presents the predicted publication counts by race and gender between the base model and the model controlling for engaged scholarship. Figure 4.3 also includes the predicted publication counts by race and gender from the model with engaged scholarship interaction terms between race/gender and engaged scholarship and field and engaged scholarship. The results show that controlling for engaged scholarship, all female applicants have slightly fewer predicted publications and male AAPI and male white applicants have slightly more predicted

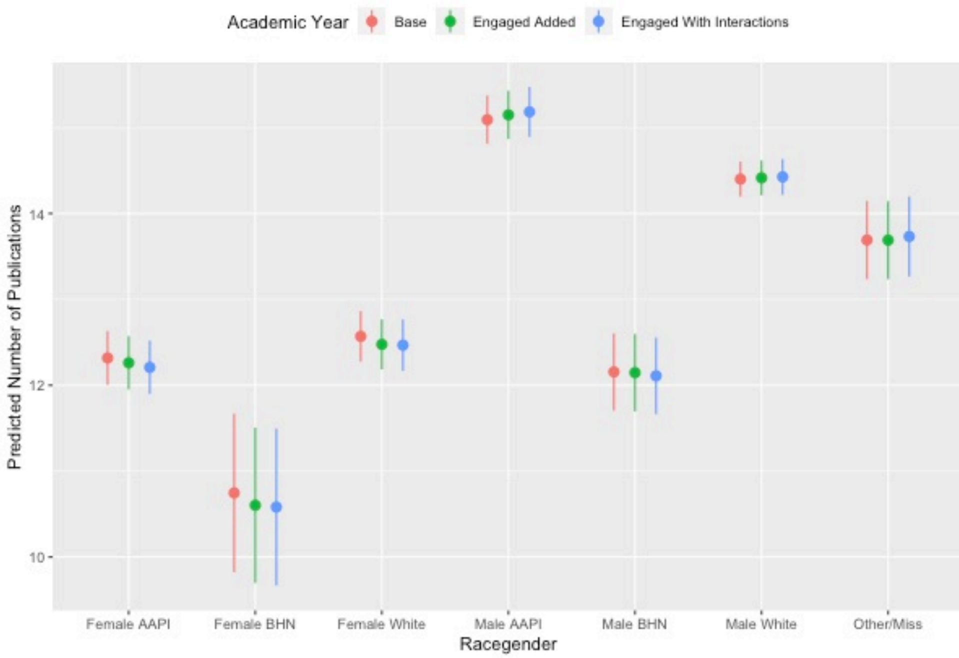


Figure 4.3: Estimated race and gender disparities in number of publications for three models: (1) Base model (controlling for recruitment- and application-level variables); (2) Engaged Added model (base model with added control variables for engaged scholarship); and (3) Engaged with Interactions model (Engaged Added model with added interaction terms between race/gender and engaged variables and between field and engaged variables. Estimates based on Model 1, 2, and 3 in Appendix C, Section 3, Table A (D.3.A).

publications. These effects are quite small, however, and do not provide strong evidence that engaged scholarship significantly contributes to explaining race and gender differences in publishing productivity.

Although engaged scholarship does not significantly account for the overall race and gender gaps, it does impact overall publication rates as suggested by the improved model fit statistics between Model 1 and 2. Figure 4.4 shows the average marginal effects of any engaged scholarship language on publication count (across all fields and race/gender groups) and Figure 4.5 shows the average marginal effects of *any* engaged scholarship language by race and gender. Average marginal effects are useful for the *any* engaged language variables, as they measure the expected change in predicted publication count if an applicant uses any engaged language in their application versus applicants who use no engaged language. The solid black line at zero in

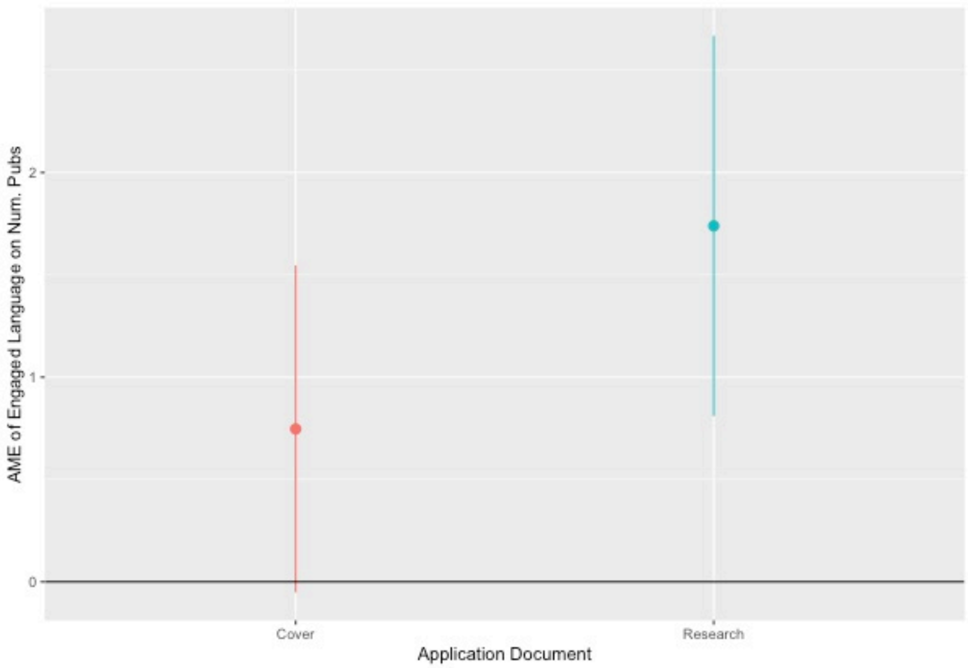


Figure 4.4: Estimated average marginal effects of engaged scholarship variables on number of publications, controlling for recruitment- and application-level variables. Estimates based on Model 2 in Appendix C, Section 3, Table A (D.2.A).

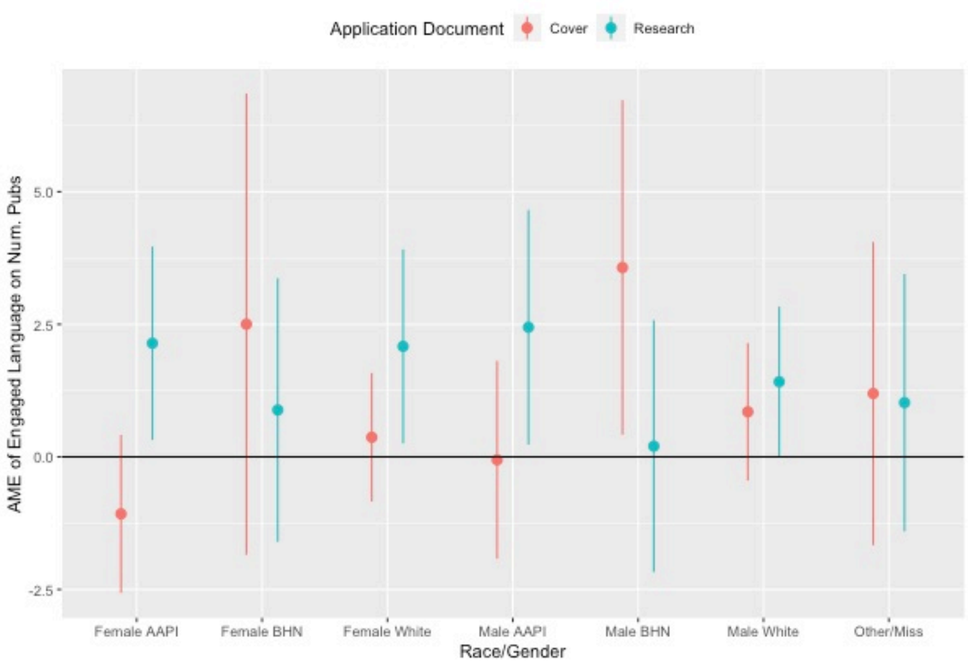


Figure 4.5: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in number of publications, controlling for recruitment- and application-level variables. Estimates based on Model 3 in Appendix C, Section 3, Table A (D.3.A).

Figure 4.4 represents no change in predicted publication count between scholars who use *any* engaged language and those who use no engaged language. Average marginal effects above zero mean that applicants who use engaged language at least once have a higher predicted publication count than applicants who use no engaged language; while average marginal effects below zero mean that applicants who use engaged language at least once have lower predicted publication counts than applicants who use no engaged language.

The results show that the use of *any* engaged language does appear to be associated with some applicants' average number of publications. In Model 2 (not including an interaction between engaged scholarship and race/gender), we see that applicants who use *any* engaged language have, on average, more publications than applicants who use no engaged language. In Figure 4.5, we see that all applicants except BHN applicants who use *any* engaged language in their research statements have significantly more publications than similar applicants who use no engaged language. This effect is largest for male AAPI applicants who use engaged language in their research statement, who have 2.44 more publications than male AAPI applicants with no engaged language. This effect is similar for female white and AAPI applicants who identify as engaged scholar in their research statements, who have 2.08 and 2.14, respectively, more publications than similar non-engaged applicants. No such publication advantage exists for either female or male BHN applicants who use any engaged language in their research statements. However, male BHN applicants who use engaged language in their cover letters have an average of 3.57 more publications than male BHN applicants who do not use any engaged language in their cover letters.

These results together show that although female BHN scholars are the most likely of any applicant—and male BHN scholars are the most likely of any male scholar—to use engaged language in their applications, the use of engaged scholarship language is not significantly associated with their average number of publications. Conversely, AAPI and white engaged scholars tend to have *more* publications than similar non-engaged scholars, even though these are also groups who are already more advantaged regarding research output.

When disaggregated by recruitment field, we see that the effect of engaged scholarship on race and gender disparities in publishing varies significantly. Figure 4.6 presents the average marginal effects of the use of *any* engaged language on publications by race and gender across fields. In Agriculture/Natural Resources and Engineering, applicants who use engaged language

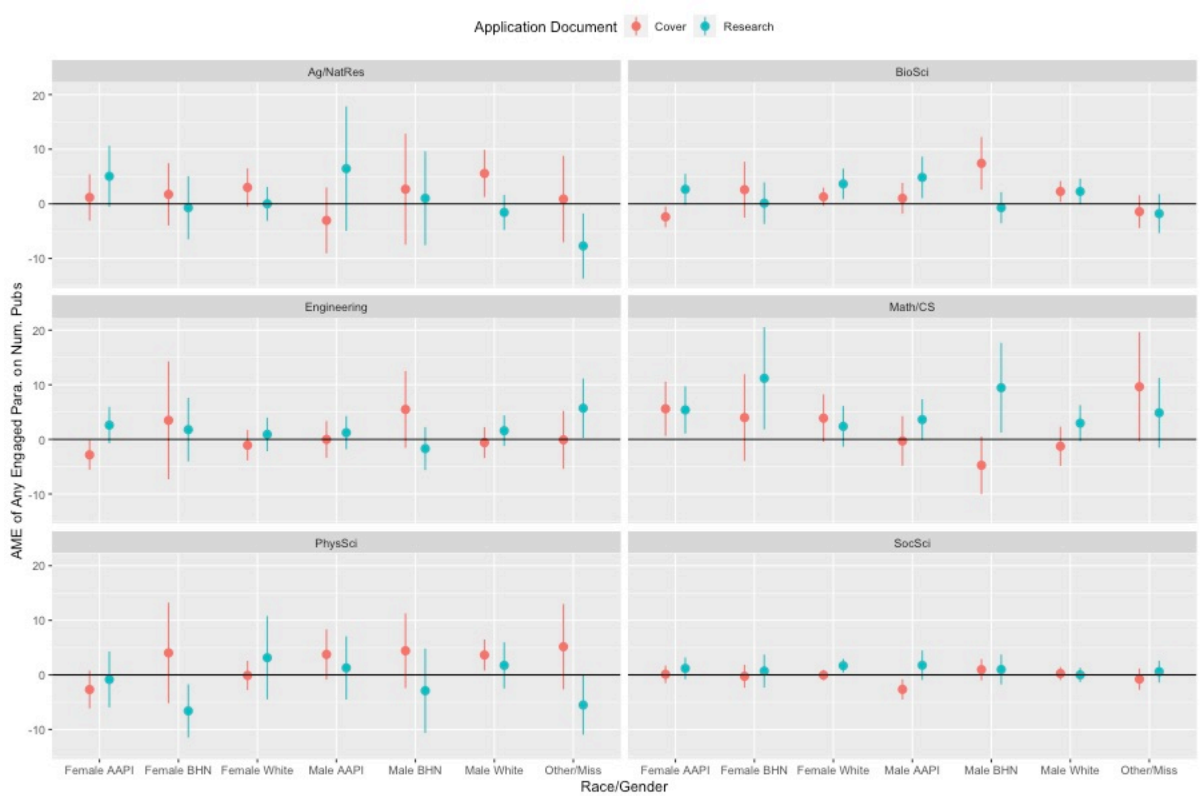
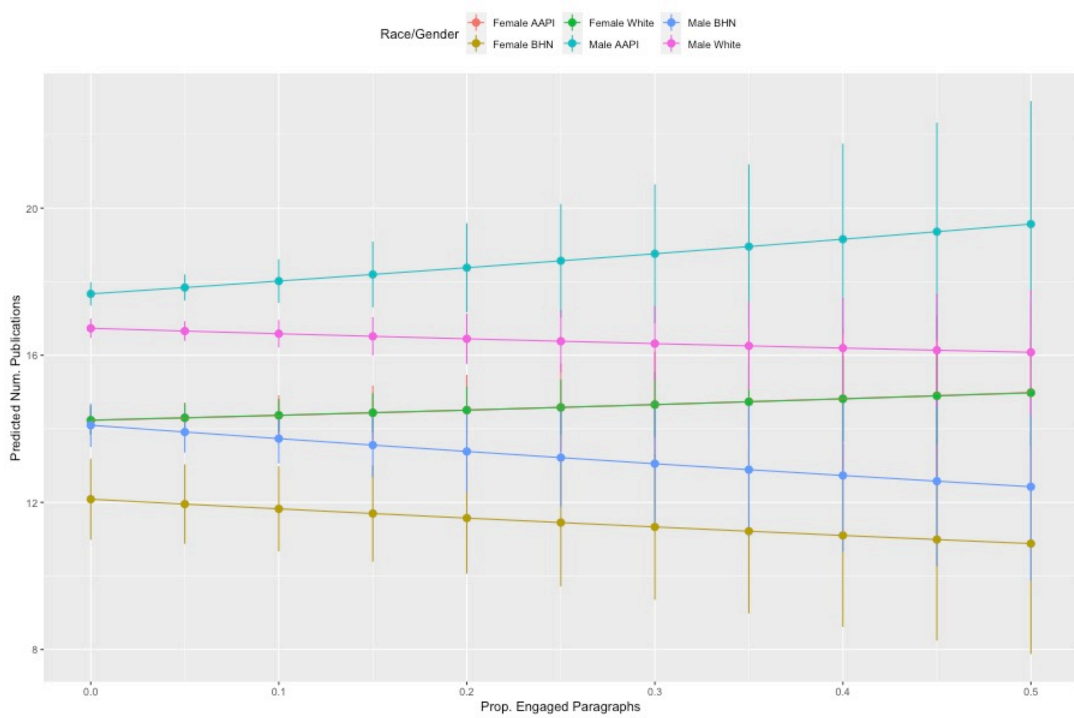


Figure 4.6: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in number of publications across fields, controlling for recruitment- and application-level variables. Estimates based on Model 3 in Appendix C, Section 3, Table A (D.3.A).

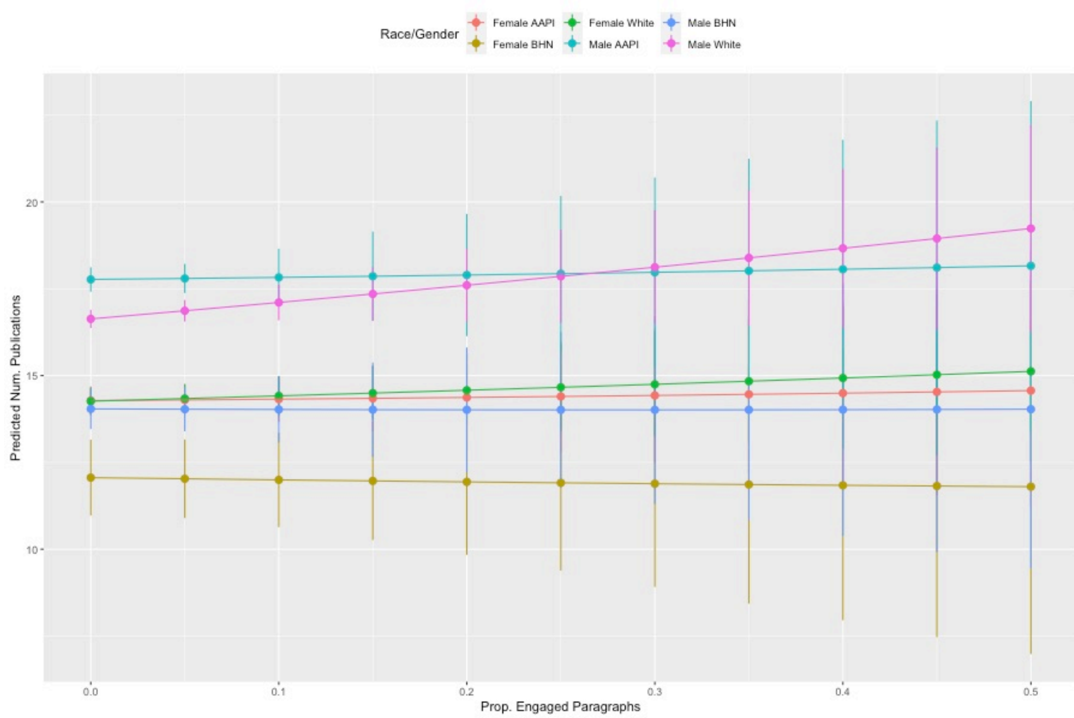
in their research statements do not have significantly different publication rates than non-engaged scholars. In Math/CS, however, applicants who use engaged language in their research statements have more publications than non-engaged applicants; this difference is significant for female AAPI, female BHN, male AAPI, and male BHN scholars. In the Biological Sciences, male and female BHN scholars who use engaged language in their research statements have the same predicted number of publications as similar non-engaged scholars, but all other scholars who use engaged language in their research statement have more publications than similar non-engaged scholars. Finally, Physical Sciences is the only field in which some engaged scholars have fewer predicted publications compared to non-engaged scholars—but only for BHN applicants.

White male scholars who use engaged language in their cover letters have significantly more publications than non-engaged scholars in Agriculture/Natural Resources, Biological Sciences, and Physical Sciences. Male BHN and female AAPI scholars who use engaged language in their cover letters see a similar advantage in publications in Biological Sciences and Math/CS respectively. Notably, although female BHN use engaged language in their cover letters at a much higher rate than any group across all fields, they see no such advantage in publications from identifying as an engaged scholar.

The *amount* of engaged language an applicant uses shows a similar. Figure 4.7 presents the change in predicted publication counts by race and gender as the proportion of engaged paragraphs an applicant uses in their cover letter (panel a) and research statements (panel b) increases. The higher the proportion of engaged paragraphs male white, female BHN, and male BHN applicants use in their cover letters, the fewer publications they are predicted to have, though the magnitude of change is highest for male BHN applicants. The opposite is true for



(a)



(b)

Figure 4.7: Estimated predicted publications by race and gender across increasing proportion of engaged paragraphs in applicants' (a) cover letters and (b) research statements, controlling for recruitment- and application-level variables. Estimates based on Model 3 in Appendix C, Section 3, Table A (D.3.A).

female white, female AAPI, and male AAPI candidates, whose publication count increases as the proportion of engaged paragraphs in their cover letter increases[40]. In research statements (panel b), female BHN and male BHN applicants with higher proportions of engaged paragraphs have the same predicted publication count as BHN applicants who use no engaged language. For all other race and gender groups, having a higher proportion of paragraphs in their research statement is associated with *more* publications. This effect is small for female AAPI, female white, and male AAPI applicants, but is much larger for white male applicants.

In all, these results show no consistent pattern in the effect of engaged scholarship on race and gender disparities in publications across fields. However, when the use of engaged scholarship language *is* associated with differences in publications, it does not benefit the group most likely to identify as engaged scholars—female BHN applicants. This finding is similar to findings from other studies, where men in female-dominated occupations are advantaged differentially compared to women (i.e. Williams' "glass escalator" effect (1992)), and these advantages do not benefit men of color (i.e. the "racialized glass escalator" effect (Wingfield 2009)). I extend these theories by suggesting that in a type of work predominantly done by women of color, women of color gain the *least* advantage when such an advantage exists.

4.3.3 Race and Gender Disparities in Journal Impact Factors

Figure 4.8 presents the aggregate average journal impact factor percentile for applicants in each field, controlling for number of journal articles, and recruitment- and application-level

[40] Female AAPI and female white applicants have nearly identical publication counts across all proportion of engaged paragraphs in the cover letter, and the estimates for female AAPI applicants are occluded by the estimates for female white applicants.

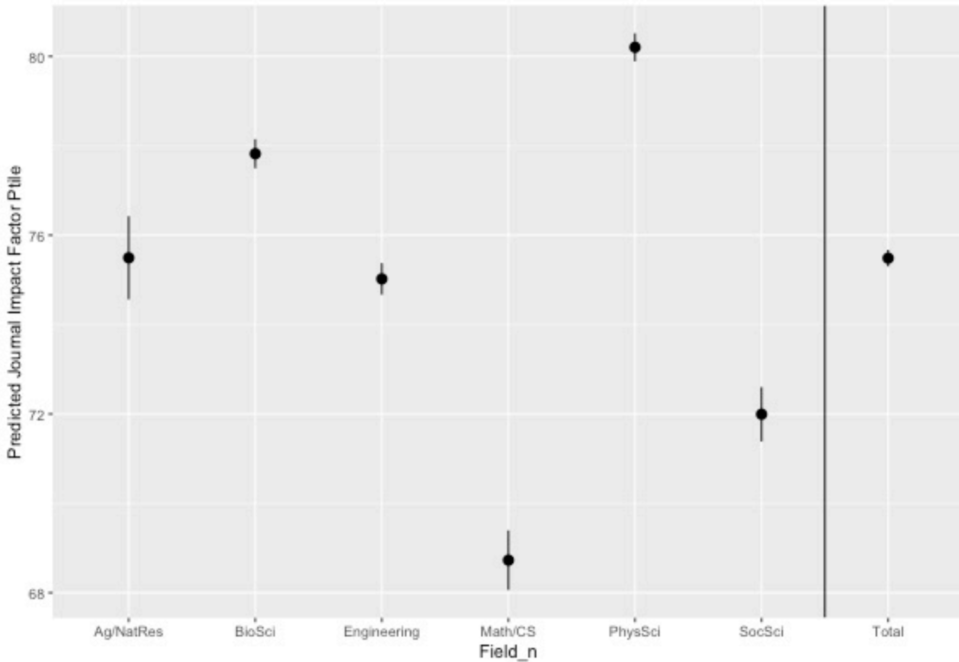


Figure 4.8: Aggregate estimated average journal impact factor (percentile) by field, controlling for recruitment- and application-level variables and number of journal publications. Estimates based on Model 1 in Appendix C, Section 3, Table B (D.3.B).

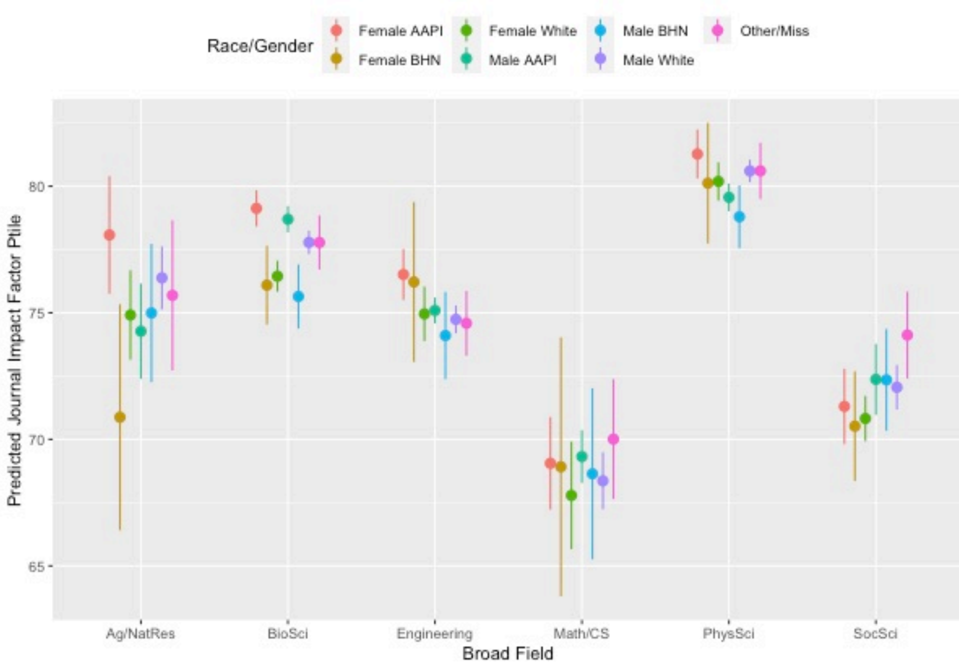


Figure 4.9 Estimated race and gender disparities average journal impact factor (percentile) across fields controlling for recruitment- and application-level variables. Estimates based on Model 1 in Appendix C, Section 3, Table B (D.3.B).

variables. Overall, applicants in Math/Computer Science and the Social Sciences have the lowest average impact factor percentile (68.73 and 71.99, respectively) while applicants in the Physical Sciences have the highest (80.20). Figure 4.9 presents the race and gender disparities in applicants' average journal impact factor percentile in each broad field. Unlike the race and gender disparities in publication counts, no clear race and gender pattern exists across fields in impact factors. In Agriculture/Natural Resources, female BHN applicants have the lowest average impact factors compared to other groups, while female AAPI applicants have the highest. In the Social Sciences, female BHN applicants also have the lowest average impact factors, but female applicants in general have lower average impact factors compared to all male candidates. Applicants in the Physical Sciences have an almost opposite trend, where female applicants and white male applicants publish in journals with higher average impact factors compared to male BHN and male AAPI applicants. In two fields—Biological Sciences and Engineering—male BHN applicants publish in journals with the lowest average impact factors and female AAPI applicants publish in journals with the highest average impact factors. The race and gender gap is largest in Agriculture/Natural Resources, followed by Biological Sciences, and smallest in Math/Computer Science.

Overall, no consistent pattern of race and gender disparities in journal impact factor emerges across fields. This is consistent with the (relatively limited) available literature on differences in impact factors. Such previous studies have mainly examined a single field (e.g. Medicine (Beaudry and Larivière 2016); Ecology (Cameron, White, and Gray 2016); or Materials Science (Mauleón and Bordons 2006)), and find no evidence for gender disparities in impact factors.[41] While these findings do not suggest a *consistent* pattern in race and gender

[41] No available research on race/ethnicity disparities in impact factors.

differences across fields, we do see several fields with notable disparities. In Agriculture and Natural Resources, we clearly see that female BHN applicants have the lowest average impact factor compared to all other groups; in the Biological Sciences BHN applicants have lower average impact factors compared to all other groups; and there is a relatively clear gender gap in the Social Sciences where all female applicants have lower average impact factors compared to all male applicants.

4.3.4 The Effect of Engaged Scholarship on Average Journal Impact Factors

Although the race and gender disparities in journal impact factors had no distinct pattern across fields, I still test whether the engaged scholarship variables mitigate the disparities that do exist. Using AIC and BIC model fit statistics, I find that including the engaged scholarship variables improves the overall model fit in estimating applicants' average journal impact factors (see Appendix C, Section 3, Table B for model coefficients and model fit statistics). While the overall model fit improvement suggests that engaged scholarship explains a significant part of the variance in impact factors, I find that controlling for engaged scholarship has little effect on the race and gender disparities. Figure 4.10 presents applicants' predicted average journal impact factor percentiles by race and gender between the base model and the model controlling for engaged scholarship. Figure 4.10 also includes predicted journal impact factors by race and gender from the model with engaged scholarship interaction terms between race/gender and engaged scholarship and field and engaged scholarship.[42] The results show that controlling for

[42] The model fit statistics did *not* improve between Model 2 and Model 3, suggesting that while the effect of engaged scholarship is significant on impact factors (Model 1 to Model 2), the added interaction effect between race and gender and engaged scholarship variables is not significant, and the effect of engaged scholarship on impact factor does not vary by race and gender groups.

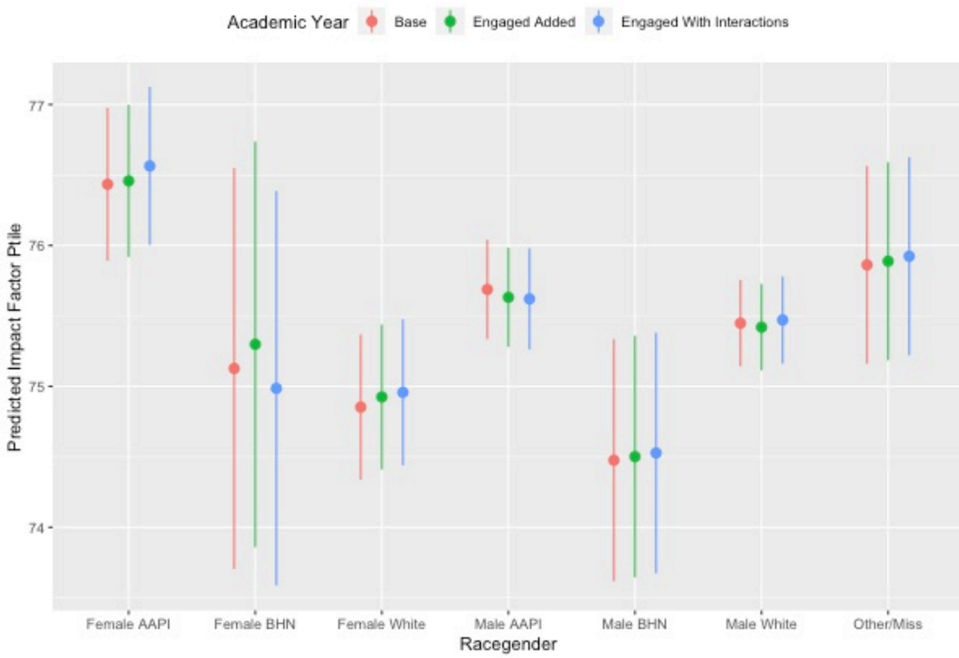


Figure 4.10: Estimated race and gender disparities in average journal impact factor (percentile) for three models: (1) Base model (controlling for recruitment- and application-level variables and number of journal publications); (2) Engaged Added model (base model with added control variables for engaged scholarship); and (3) Engaged with Interactions model (Engaged Added model with added interaction terms between race/gender and engaged variables and between field and engaged variables. Estimates based on Model 1, 2, and 3 in Appendix C, Section 3, Table B (D.3.B).

engaged scholarship, all female applicants have slightly fewer predicted publications and male AAPI applicants have slightly more predicted publications. These effects are all relatively small, however, and do not provide strong evidence that engaged scholarship significantly contributes to explaining race and gender differences in average journal impact factors.

Figure 4.11 shows the average marginal effects of *any* engaged scholarship language on average impact factors by race and gender. The figure shows that, in regard to the use of *any* engaged language, engaged scholars do not publish in journals with significantly different average impact factors compared to non-engaged scholars. Figure 4.12 shows the same effects disaggregated by field. The aggregate effects of *any* engaged language on impact factors by race and gender (i.e., no effect) are true in most fields, with three exceptions. First, male and female

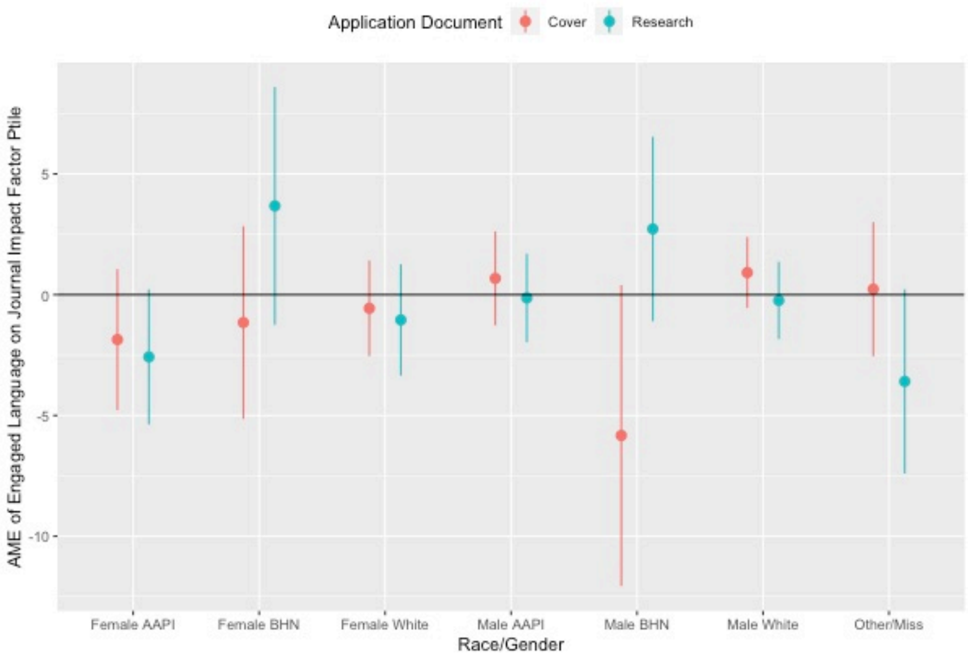


Figure 4.11: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in average journal impact factor (percentile), controlling for recruitment- and application-level variables and number of journal publications. Estimates based on Model 3 in Appendix C, Section 3, Table B (D.3.B).

BHN applicants in Biological Sciences who use engaged language in their cover letters publish, on average, in journals with significantly lower average impact factors than BHN applicants who use no engaged language. Second, female BHN applicants in Math/Computer Science who use engaged language in their research statement publish in journals with higher average impact factors than female BHN applicants who use no engaged language. Third, female AAPI applicants in Engineering who use engaged language in their research statements, on average, publish in journals with lower impact factors than non-engaged female AAPI applicants.

Although the use of *any* engaged language seems to have little to no association with applicants' average journal impact factors, the *amount* of engaged language used is associated with significant differences in impact factors. Figure 4.13 presents the aggregate association

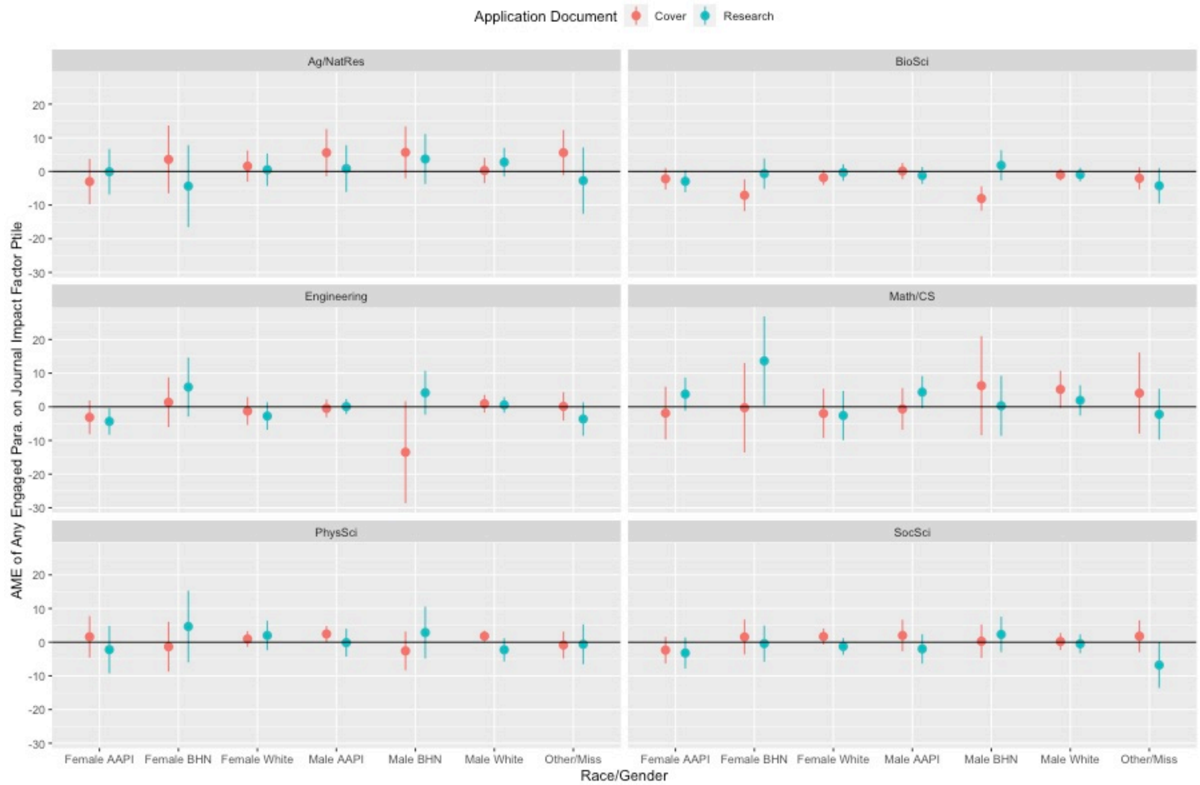
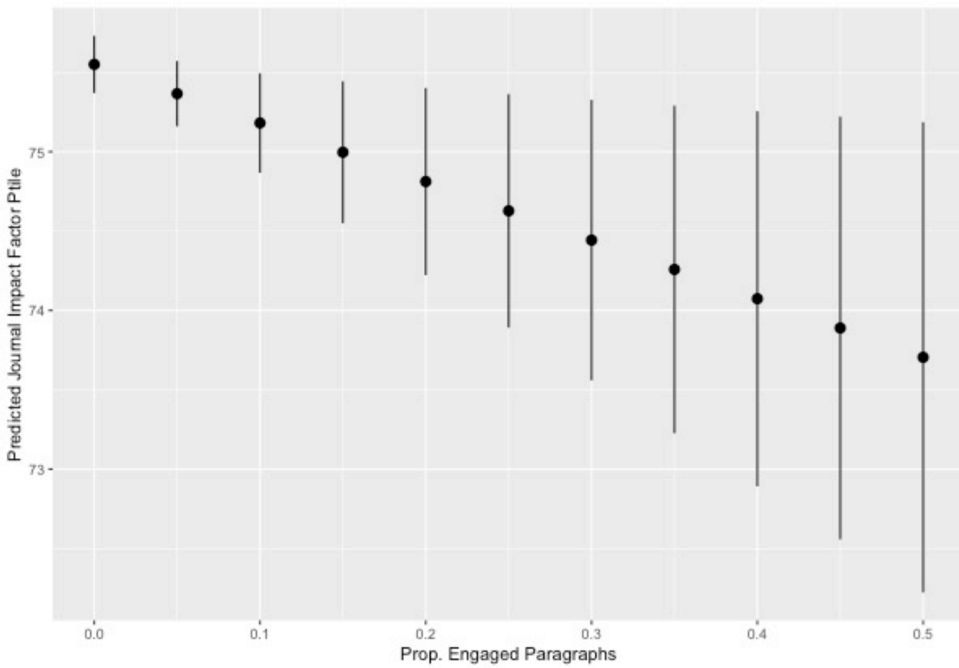
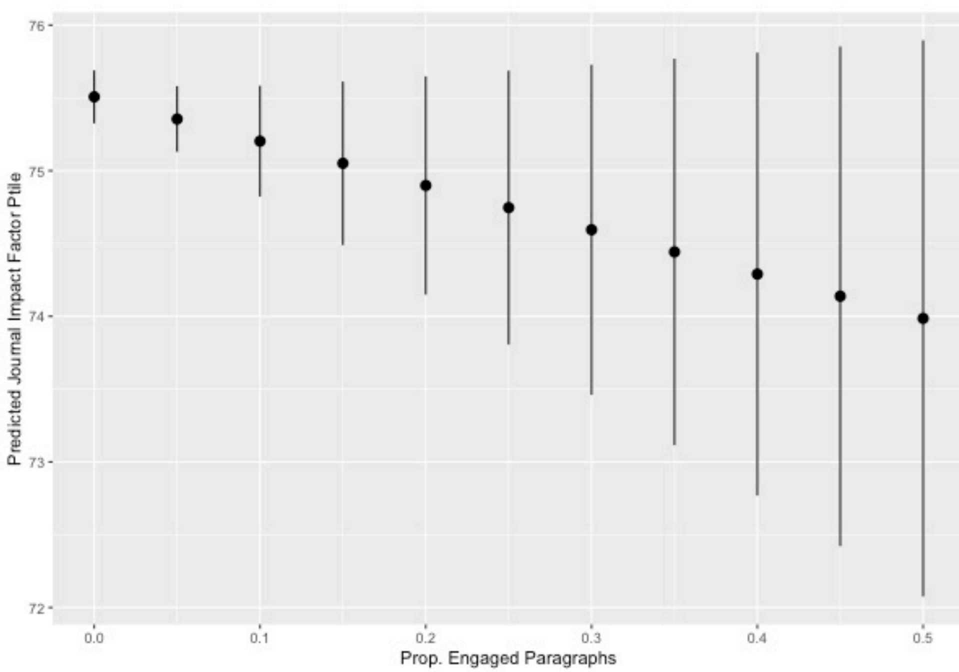


Figure 4.12: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in average journal impact factor (percentile), controlling for recruitment- and application-level variables and number of journal publications. Estimates based on Model 3 in Appendix C, Section 3, Table B (D.3.B).

between the proportion of engaged language used in cover letters and research statements (panel a and b, respectively) on applicants' average impact factors. The figure shows the predicted impact factor percentile for applicants with increasing proportions of engaged paragraphs in each document type. Applicants with higher proportions of engaged paragraphs in both research statements and cover letters have lower average journal impact factors than applicants who use less engaged language. Based on model fit statistics (shown in Appendix C, Section 3, Table B (D.3.B)) and an examination of predicted impact factors across race and gender groups, I did not find that these engaged scholarship effects varied significantly across race and gender groups.



(a)



(b)

Figure 4.13: Estimated average journal impact factor (percentile) for applicants with different proportions of engaged paragraphs (between 0 and .5) in their (a) cover letter and (b) research statement. Estimates based on Model 3 in Appendix C, Section 3, Table B (D.3.B).

This relationship broadly fits an epistemic exclusion framework, in which a scholarship type most frequently done by women and scholars of color (engaged scholarship) is less likely to be published in high impact journals. The magnitude of the association, however, is relatively small, as the difference between scholars with no engaged paragraphs and 50% engaged paragraphs is less than two percentiles of journal impact factor. Although the negative association appears consistent as engaged scholarship increases, it is unlikely that a scholar who publishes, on average, in journals two percentage points lower than other scholars will be evaluated substantially differently. As discussed in section 4.2.1, the small differences in journal impact factors by race and gender could be due to data collection issues (i.e., a high amount of missingness).

Despite this, the findings in the previous section suggest that engaged scholars do not necessarily have fewer publications than non-engaged scholars, and some engaged non-BHN scholars have *more* publications than similar non-engaged scholars. Yet this publication count advantage for (some) engaged scholars does not mean those publications are in higher impact journals.[43] While the results from the publication analysis showed that non-BHN engaged scholars have a publication count advantage—suggesting some sort of differential advantage that did not apply to scholars most likely to identify as engaged scholars—the results for impact factors suggest that all applicants who identify more strongly with engaged research practices and orientations publish in journals with lower average impact factors. This analysis cannot account for the mechanism driving this trend, as engaged scholars might submit articles to high-prestige journals at equal rates as non-engaged scholars and face more rejection, or they might

[43] This could be related, as the publication process in higher impact journals may take more time than the publication process for lower impact journals. Scholars may consciously make publication trade-offs between quantity of articles and journal impact factors. The statistical models support this, as the variable for applicants' total number of journal publications is negative and statistically significant.

focus on submitting articles to journals or publication outlets that focus on engaged scholarship and are not considered "central" to a field. Regardless of which process is occurring, the outcome is the same—engaged scholars publish the same number of articles as, or sometimes more articles than, non-engaged scholars, but do so in slightly lower-impact journals.

Scholars in many fields broadly critique the use of journal impact factors as a measure of scholarship value (Bell and Chong 2010; Gruber 2014; Seglen 1997), yet faculty hiring and promotion committees continue to rely on such measures in evaluating scholars (McKiernan et al. 2019). The results in this analysis do not portend that research by engaged scholars is less impactful, but that the journals engaged scholars publish in, on average, have lower impact factors than the journals non-engaged scholars publish in. This distinction is important, because regardless of *why* this phenomenon occurs, the use of impact factors in faculty hiring and promotion decisions means that engaged scholars' work may be seen as having slightly less impact on a field, and therefore less scholarly value, than non-engaged work. Unlike scholarly productivity as measured by publication counts, this association between engaged scholarship and lower journal impact factors does not vary significantly by race or gender, suggesting that *overall,* engaged scholarship may be evaluated as less impactful than non-engaged scholarship. This finding fits more in a devaluation framework, where work associated with women and people of color is valued and compensated less than work associated with men and white people (England 1992b; Huffman and Cohen 2004; Reskin 1988). This effect has a greater impact on women and scholars of color, as they are more likely to identify as engaged scholars, but overall work by engaged scholars is published in journals with slightly lower impact factors regardless of the race or gender of the scholar.

4.3.5 *Race and Gender Disparities in Citations*

Although related to journal impact factors, the number of citations a scholar accrues across their publications is another way of measuring their "impact" on the field. Figure 4.14 presents the aggregate predicted number of citations for applicants in each field. These field differences are likely driven by disciplinary publishing and citation norms not observed in this dataset. Applicants in the Biological Sciences have, on average, the highest number of citations (20.76 citations), while applicants in Math/CS and the Social Sciences have the lowest (12.91 citations and 12.73 citations respectively), and applicants in Agriculture/Natural Resources, Engineering, and Physical Science recruitments fall in between. I do not seek to explain field differences in

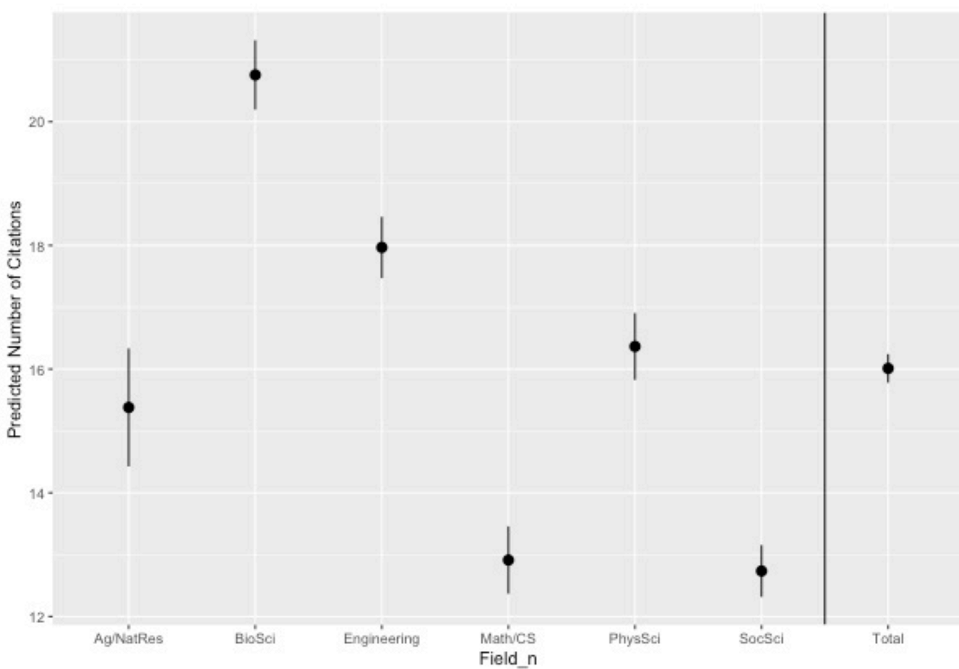


Figure 4.14: Aggregate estimated number of citations by field, controlling for recruitment- and application-level variables and number of publications. Estimates based on Model 1 in Appendix C, Section 3, Table C (D.3.C).

this chapter, but instead use these differences as a baseline to assess differences in the race and gender citation gap in each field.

Figure 4.15 presents the race and gender citation disparities in each broad field. Similar to the race and gender publication disparities, female BHN scholars typically have the fewest citations compared to other groups. The two exceptions are in Agriculture/Natural Resources, where female BHN applicants have the highest citation count of any applicant group, and Math/CS, where female BHN applicants have similar citation counts to other female

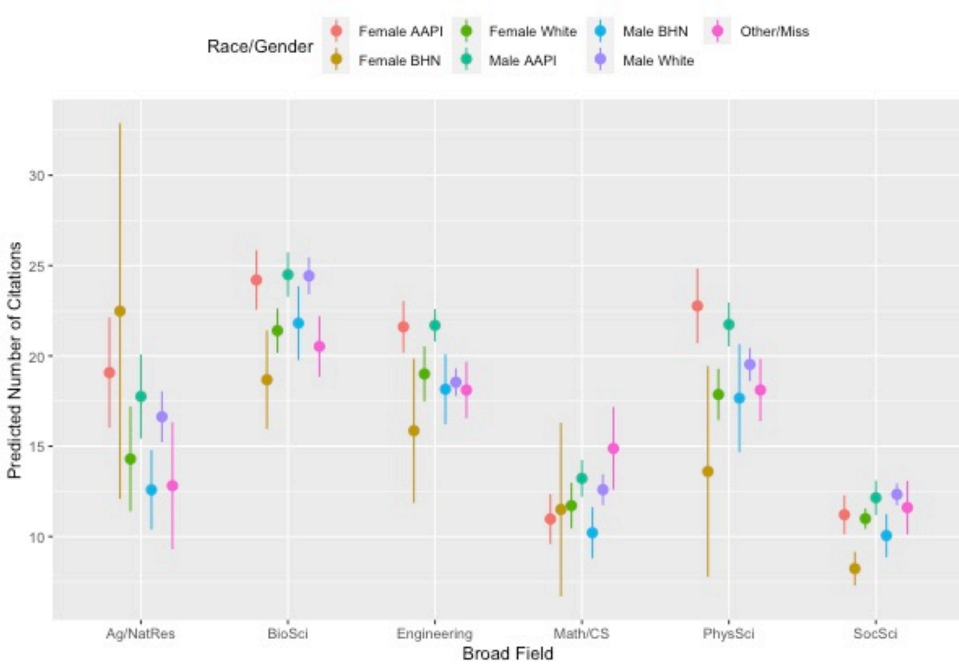


Figure 4.15: Estimated race and gender disparities in number of citations across fields controlling for recruitment- and application-level variables and publication count. Estimates based on Model 1 in Appendix C, Section 3, Table B (D.3.C).

applicants—all of whom have a higher average citation count than male BHN applicants. In the other four fields—Biological Sciences, Engineering, Physical Sciences, and Social Sciences—female BHN scholars have the fewest citation counts compared to other scholars. Across all fields, male BHN scholars either have the fewest or second fewest (when female BHN have the fewest) citations. This racial gap is starkest in the Social Sciences, where female and BHN scholars have fewer citations than nearly all other groups. In Biological Sciences, Engineering, and Physical Sciences, male and female AAPI applicants have the highest number of citations compared to all groups (except for white men in Biological Sciences). In the other four fields—Biological Sciences, Engineering, Physical Sciences, and Social Sciences—female BHN scholars have the fewest citation counts compared to other scholars. Across all fields, male BHN scholars either have the fewest or second fewest (when female BHN have the fewest) citations. This racial gap is starkest in the Social Sciences, where female and BHN scholars have fewer citations than nearly all other groups. In Biological Sciences, Engineering, and Physical Sciences, male and female AAPI applicants have the highest number of citations compared to all groups (except for white men in Biological Sciences).

Like publications, extant research on disparities in citations have predominantly focused on the gender gap (e.g. Dion et al. 2018; Maliniak et al. 2013) and much less on racial disparities (Smith and Garrett-Scott 2021). The results presented here do not provide evidence for any clear gender gaps, but do demonstrate the need for more research on why BHN scholars tend to have fewer citations than AAPI or white scholars, and specifically why female BHN scholars often have the fewest citations (Smith et al. 2021).

4.3.6 The Effect of Engaged Scholarship on Race and Gender Disparities in Citations

I now measure the extent to which engaged scholarship explains these race and gender disparities in citations. I find that the AIC and BIC model fit statistics both improve after adding engaged scholarship variables to the model as a control, and improve further when adding interactions between engaged scholarship variables and race/gender (see Appendix C, Section 3,

Table C for model coefficients and model fit statistics). However, similar to publication counts and impact factors, I find that controlling for engaged scholarship has little effect on race and gender disparities in citation count. Figure 4.16 presents the predicted probabilities for number of citations by race and gender between the three models: (1) the base model controlling for recruitment- and application-level variables; (2) the base model with controls for engaged scholarship; and (3) the base model with control for engaged scholarship and interactions between race/gender and engaged scholarship variables and between field and engaged scholarship variables. The estimates do not change significantly for most groups, but increase slightly for female BHN applicants and decrease slightly for male AAPI applicants.

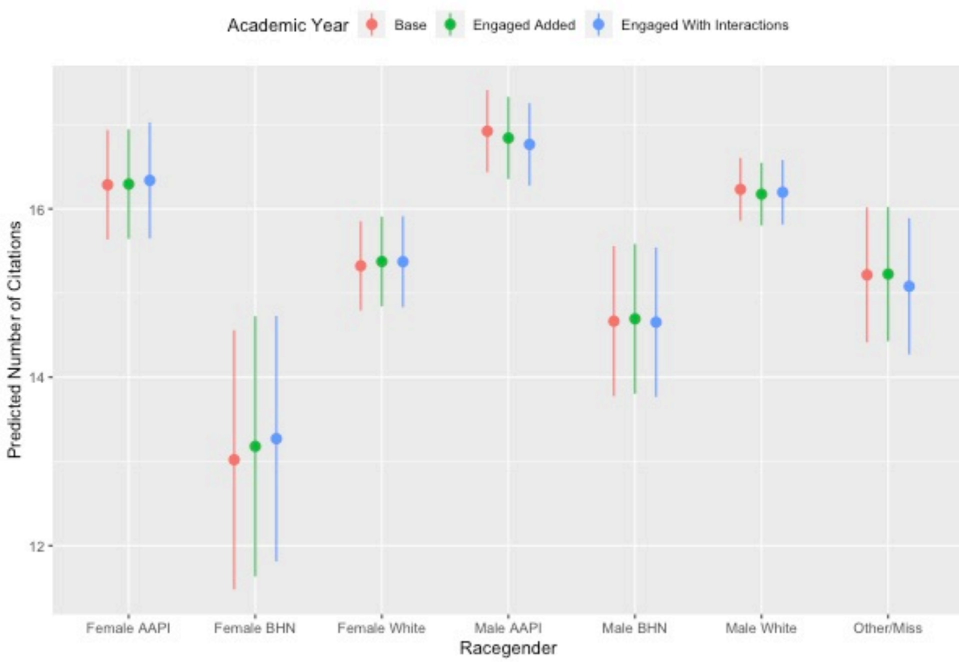


Figure 4.16: Estimated race and gender disparities in number of citations for three models: (1) Base model (controlling for recruitment- and application-level variables); (2) Engaged Added model (base model with added control variables for engaged scholarship); and (3) Engaged with Interactions model (Engaged Added model with added interaction terms between race/gender and engaged variables and between field and engaged variables. Estimates based on Model 1, 2, and 3 in Appendix C, Section 3, Table C (D.3.C).

Substantively, this finding suggests that while the engaged variables do help explain the variance in citation counts between applicants, engaged scholarship does not explain a significant amount of the race and gender disparities noted in the previous section. However, the model improvement from the race/gender and scholarship variable interaction terms suggests that the effect of engaged scholarship may vary across race and gender groups.

Figure 4.17 presents the average marginal effects of the use of *any* engaged scholarship language on aggregate race and gender differences in citations. The results show that for most applicants, engaged scholars do not have significantly different citation counts compared to non-engaged scholars. However, female BHN applicants who use *any* engaged language in their research statements have fewer citations than female BHN non-engaged scholars. There is a similar, though smaller in magnitude, effect for female white applicants who use engaged

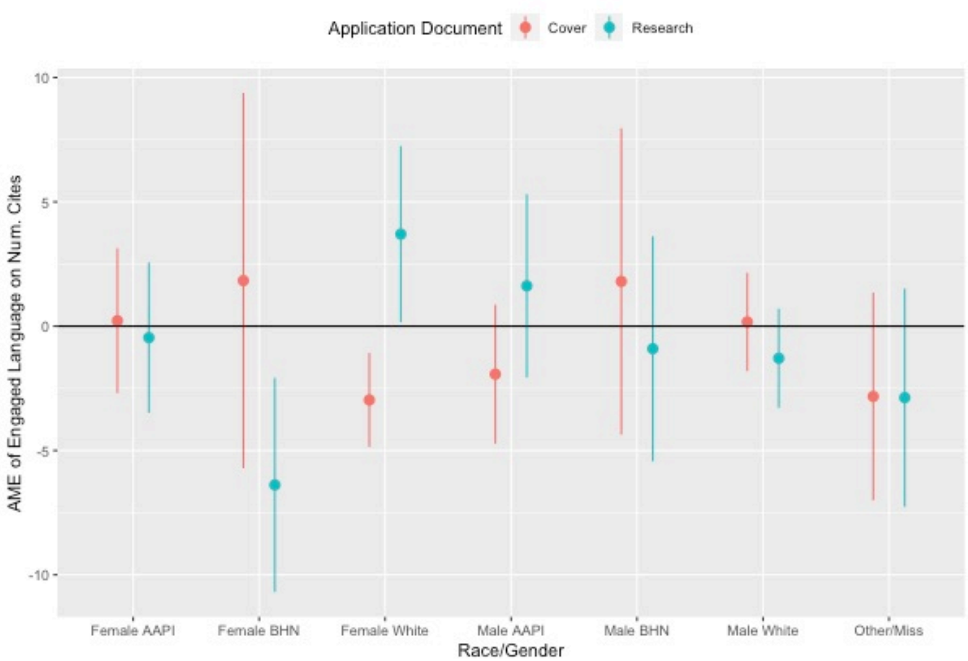


Figure 4.17: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in number of citations, controlling for recruitment- and application-level variables and publication count. Estimates based on Model 3 in Appendix C, Section 3, Table C (D.3.C).

language in their cover letter. Additionally, female white applicants who use engaged language in their research statements have, on average, more citations than female white scholars who do not use engaged language. Based on these results, engaged scholars overall do not have significantly different citation counts compared to non-engaged scholars *except* for an engaged research citation advantage for female white applicants and disadvantage for female BHN scholars.

When these effects are disaggregated across fields as shown in Figure 4.18, we see that in four fields—Agriculture/Natural Resources, Biological Sciences, Engineering, and Math/CS—

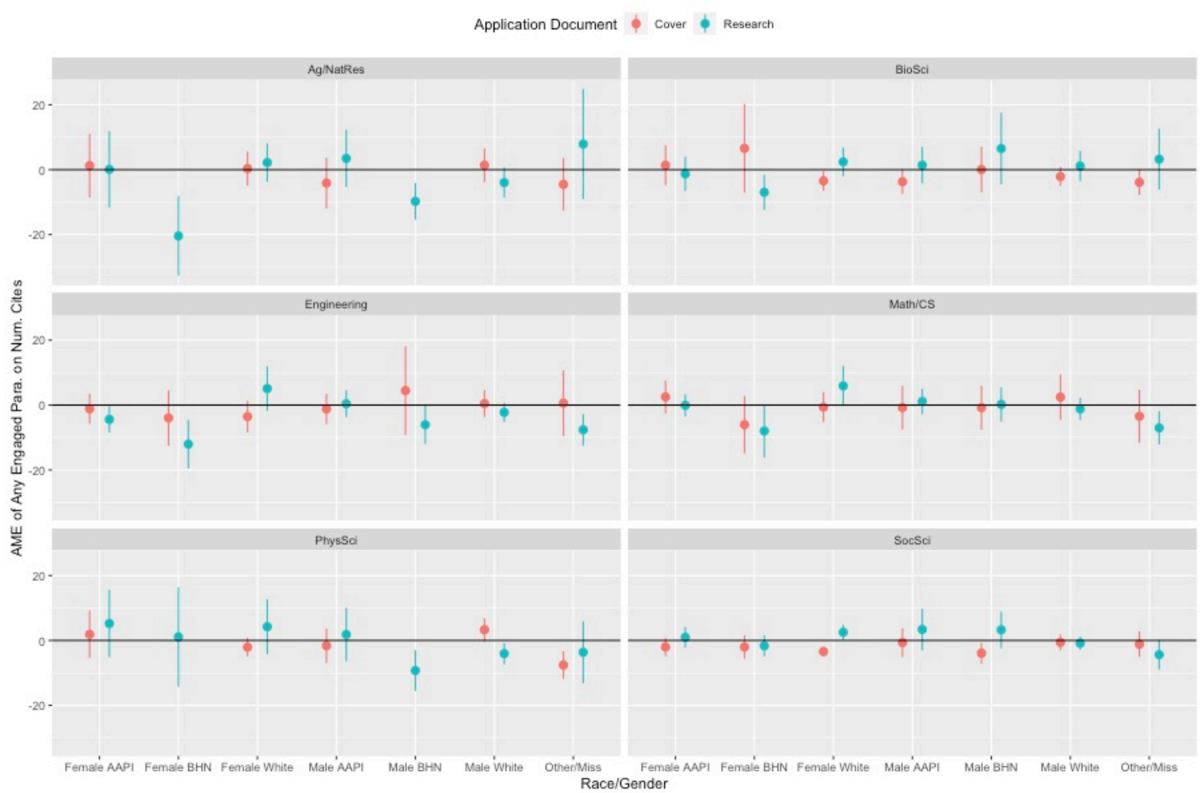
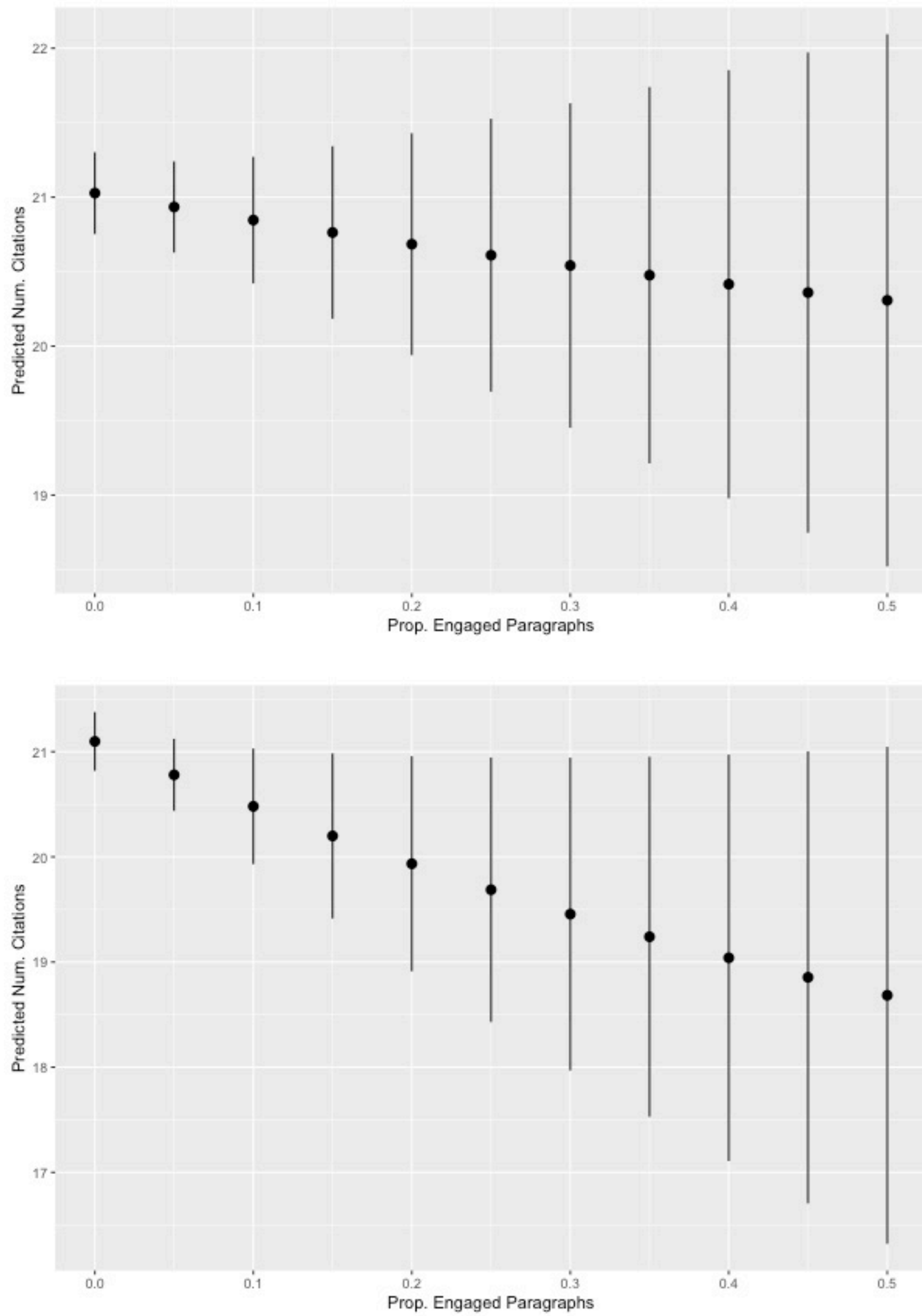


Figure 4.18: Estimated average marginal effects of engaged scholarship variables on race and gender disparities in number of publications across fields, controlling for recruitment- and application-level variables and publication count. Estimates based on Model 3 in Appendix C, Section 3, Table C (D.3.C). *Note: the estimated average marginal effects of engaged language in the cover letter for male and female BHN scholars in Agriculture/Natural Resources and Physical Sciences are omitted form this graph because the variance was so large it made the scale of the graphs difficult to interpret all other AMEs. None of the omitted effects were significantly different from zero.*

female BHN scholars who used *any* engaged language in their research statement have, on average, fewer citations. Similarly, male BHN applicants in Agriculture/Natural Resources, Engineering, and Physical Science fields who used engaged language in their research statements or cover letters had fewer citations. Except for female AAPI applicants in Engineering and male white applicants in Physical Sciences, BHN applicants who used *any* engaged language in their research statement were the only group who had fewer citations than similar applicants who did not use engaged language. Female white applicants who used engaged language in their cover letters had significantly fewer citations in Biological Sciences and Social Sciences recruitments compared to female white applicants who used no engaged language in their cover letters. However, female white applicants in Math/CS and the Social Science who used engaged language in their research statements have more citations than do similar non-engaged scholars. When examined across fields, it is readily apparent that BHN scholars—particularly female BHN scholars—see the most disadvantage in citation counts when they identify as engaged scholars. On the contrary, female white scholars are the only group who have a citation advantage when using engaged language in their research statements.

This conclusion is reflected somewhat differently in the association between the *amount* of engaged language scholars use and citation counts. Figure 4.19 shows the predicted citation counts for applicants with varying proportions of engaged language in their cover letters (panel a) and research statements (panel b). The results show that the more an applicant uses engaged language in their application materials, the fewer citations they are likely to have. This effect is stronger for research statements than cover letters.

This effect, however, is not equivalent across race and gender groups, as shown in Figure 4.20. Male BHN applicants with a higher proportion of engaged paragraphs in their cover letters



(b)

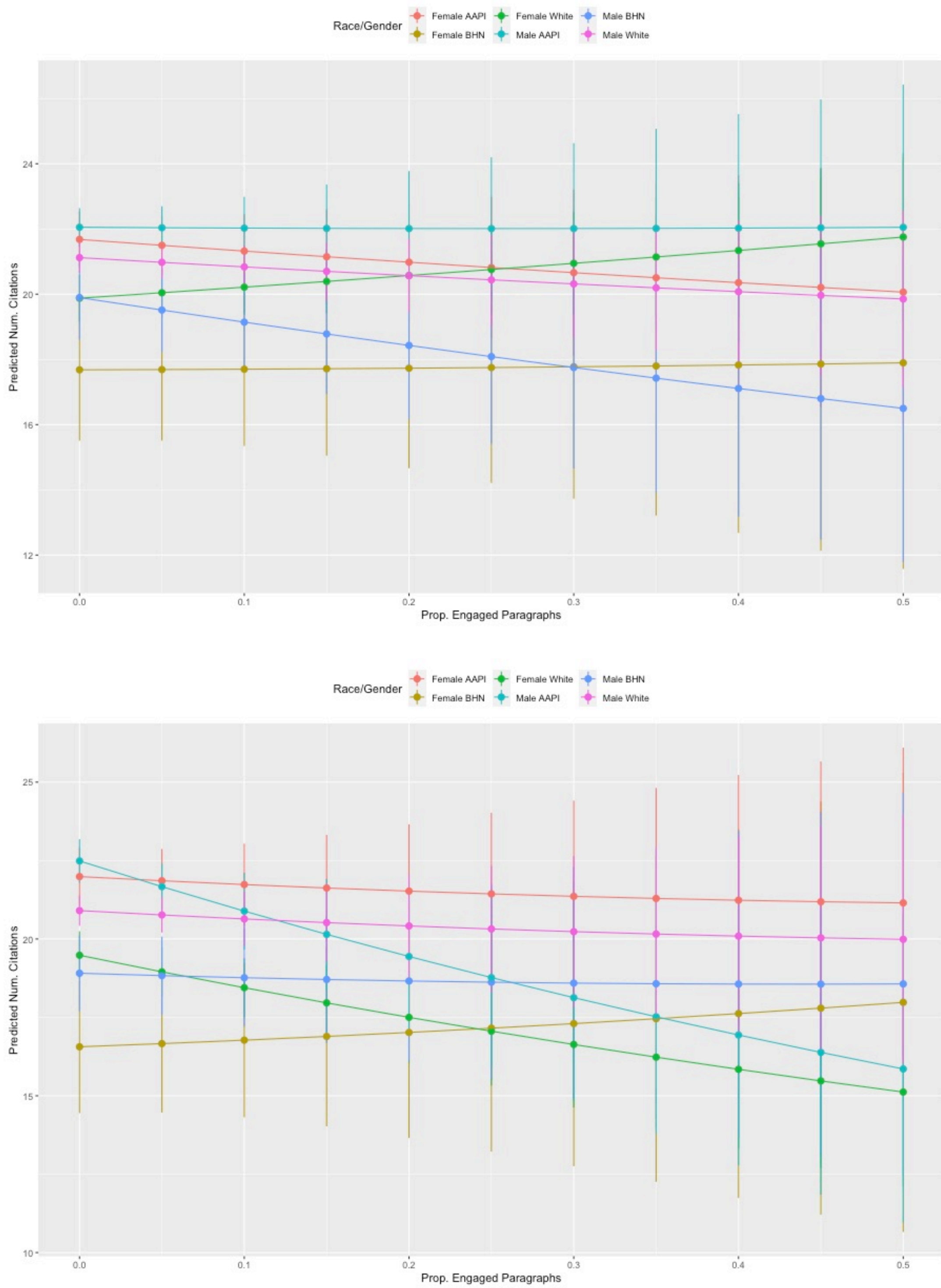
Figure 4.19: Estimated citation counts for applicants with different proportions of engaged paragraphs (between 0 and .5) in their (a) cover letter and (b) research statement. Estimates based on Model 3 in Appendix C, Section 3, Table C (D.3.C).

(Figure 4.20, panel a) tend to have fewer citations than applicants with fewer engaged paragraphs, while the opposite is true for white women. There is little to no association between the proportion of engaged paragraphs in female BHN applicants' cover letters and their predicted citation count. In research statements, however (panel b), female BHN applicants with a higher proportion of engaged paragraphs in their research statements tend to have more citations than female BHN applicants with less engaged paragraphs. All other groups have little to no association between the proportion of engaged paragraphs in their research statement and their predicted citation counts, except male AAPI and female white applicants, who have a negative association between the amount of engaged language they use in their research statement and citation counts.

Overall, the relationship between the *amount* of engaged language an applicant uses in their research and cover letters and their citation count is similar to the relationship between the *amount* of engaged language and impact factors—negative. However, the variations by race and gender groups show a more convoluted picture, as no consistent pattern emerges between the two document types.

In conclusion, applicants' use of *any* engaged paragraphs is associated with fewer average citations. This is most apparent for female BHN scholars who use engaged language in their research statements, and for female white applicants who use engaged scholarship language in their cover letters. These patterns are reversed, however, when considering the proportion of engaged paragraphs in engaged scholars' applications—female BHN scholars who use more engaged language in their research statements and female white scholars who use more engaged language in their cover letters have slightly higher predicted citation counts compared to similar engaged scholars who use less engaged language.

Although the relationship between the *amount* of engaged language an applicant uses and their number of citations is not consistent between cover letters and research statements, the use



(a)

(b)

Figure 4.20: Estimated citation counts for applicants with different proportions of engaged paragraphs (between 0 and .5) in their (a) cover letter and (b) research statement, by race and gender. Estimates based on Model 3 in Appendix C, Section 3, Table C (D.3.C).

of *any* engaged language does seem to have a more discernable effect on citations.[44] Female BHN applicants who use *any* engaged language in their research statement had fewer citations than similar non-engaged scholars in four fields, and male BHN applicants who use *any* engaged language in their research statements had fewer citation in three fields. Both of these groups already have the lowest citation counts and are the most underrepresented groups in most fields. This means that BHN scholars may face differential devaluation of their engaged work vis-à-vis citations compared to white and AAPI engaged scholars. As mentioned in the section analyzing publications, this could be due to phenomena like the racialized glass escalator—although in the case of publications there was differential advantages, while in the case of citations we see differential *dis*advantages for already marginalized groups. While female and BHN scholars are generally underrepresented in faculty positions, engaged scholarship is predominantly practiced by women and people of color, and specifically women of color. Within this female- and BHN-dominated subsect of academics, however, white and AAPI scholars experience a publication advantage that BHN scholars do not, and BHN scholars experience an additional citation disadvantage that white and AAPI scholars do not.

4.4 Discussion

4.4.1 Race and Gender Disparities in Metrics of Productivity

The three metrics of scholarly productivity analyzed in this chapter—publication count, average journal impact factor, and citation count—are interconnected processes. Over an academic career they contribute to the cumulation of advantage. Broadly, the process of

[44] Importantly, there are admittedly few significant associations between engaged scholarship and applicants' number of citations across race and gender groups, fields, and application documents. The results presented in this section may overstate the association between engaged scholarship and race/gender disparities in citation counts.

cumulative advantage for "eminent" scientists was first identified by Robert Merton in what he termed the "Matthew Effect" (Merton 1968). More recent scholarship has expanded this principle to explain why race and gender disparities in academia are so persistent (e.g. Dion, Sumner, and Mitchell 2018; Headworth and Freese 2016; King et al. 2017).

The present study focuses on these metrics of productivity among early career scholars. Results suggest notable race and gender disparities among such scholars, though the disparities vary somewhat by measure of productivity and field of study. Scholars from historically marginalized racial groups (BHN scholars) have the fewest publications and citations across most fields; AAPI and male white scholars tend to have the most. Disparities in average journal impact factor are less consistent across fields, and overall group differences are also smaller than overall differences in publication and citation counts.

These findings align with some extant research, though they diverge in several important ways. For all metrics there exists much more (and sometimes only) extant research examining gender gaps in scholarly productivity. Much less is known about race/ethnicity differences in these metrics. Previous studies have consistently found that men tend to have higher publication counts than female scholars, though this gap has decreased over time (Cole and Zuckerman 1984; Long 1992; Maliniak et al. 2013; Weisshaar 2017; Xie and Shauman 1998). Yet the findings in this chapter suggest that the more persistent gap is driven by both race *and* gender.

I find that BHN scholars in general, and especially female BHN scholars, have the fewest publications across STEM and SS disciplines. These findings seem to translate to fewer overall citations for BHN scholars, even when controlling for number of publications. However, neither of these disparities is reflected consistently when looking at the average impact factor of journals within which BHN scholars publish. In some fields (like the Social Sciences), we see more of a gender gap in average impact factors: all female applicants have lower average impact factors than all male applicants. In other fields (like the Biological Sciences), we see more of a race gap: BHN scholars have the lowest average impact factors and AAPI scholars have the highest average impact factors.

Most extant analyses of impact factor differences have focused on the gender gap, finding little evidence that such a gap exists in any of the fields studied—Medicine (Beaudry and Larivière 2016); Ecology (Cameron, White, and Gray 2016); or Materials Science (Mauleón and Bordons 2006). Results from this chapter show that some fields *do* have significant overall gender gaps. More research is needed on specific fields to investigate what drives certain fields to have more of a race gap, other fields to have more of a gender gap, and yet others to have relative gender and racial parity.

The findings presented in this chapter suggest that while BHN scholars have fewer total publications in most fields, these applicants do not differ as significantly regarding the prestige of the journals they publish in. Yet, even controlling for journal impact factor and number of publications, BHN scholars consistently have fewer citations than other groups. As citation networks are particularly sensitive to cumulative advantage effects (Dion et al. 2018; Maliniak et al. 2013), this racial citation gap for early career scholars could compound more quickly than the disparities in publications. Racial disparities in citations are already significantly understudied compared to gender gaps; future research should examine the rate at which the disparities noted in this study for early career scholars change over the course of an academic career.

4.4.2 *The Effect of Engaged Scholarship on Metrics of Productivity*

The race and gender disparities in the metrics of productivity examined in this chapter set the backdrop for the chapter's central questions: 1) does engaged scholarship account for any of the race and gender disparities in productivity; and 2) does the association between engaged scholarship and productivity vary across race and gender groups? For publication count, average journal impact factor, and citation count, I find that engaged scholarship does significantly explain part of the variance in each metric but does not significantly affect overall race and gender disparities. This finding does not suggest that scholarship types more commonly done by women and scholars of color do not explain the race and gender gap—only that this particular type of scholarship (engaged scholarship) does not do so on its own. Future work could identify multiple discipline-specific forms of scholarship which are predominantly done by women and scholars of color, and further examine the overall effect of scholarship types.

Notwithstanding, I do find evidence that engaged scholarship is associated with applicants' publications, average impact factors, and citations; and that the associations vary by race and gender groups for publications and citations. Engaged scholars overall tend to have more publications compared to non-engaged scholars, but this does not hold true for BHN applicants. Male and female BHN applicants already tend to have fewer publications compared to other applicants in most fields; in fields where engaged scholars have more publications than non-engaged scholars, BHN scholars are the only group who not have more publications.

This finding is even more consequential, as BHN scholars (and particularly female BHN scholars) are the most likely of any applicant to identify as an engaged scholar. The effect of differential advantages for men in female-dominated occupations has been termed the "glass escalator" (Williams 1992) (though only for *white* men—see: Wingfield 2009). While literature suggests that scholarship types more frequently done by women and minorities may face devaluation (i.e., epistemic exclusion: Settles et al. 2020), the effect of engaged scholarship on publications suggests that such devaluation is *only* experienced by scholars of color. This conclusion is supported further when we look at the relationship between engaged scholarship and citations. While work done by engaged scholars is cited less overall than work by non-engaged scholars, BHN engaged scholars have the fewest citations compared to other groups. In publications we see differential advantage, and in citations we see differential *dis*advantage—both of which are variations of a similar phenomenon of the racialized glass escalator (Wingfield 2009).

Journal impact factors are the only metric in the current study that do not adhere to this pattern of differential valuation. Engaged scholars in all race and gender groups have lower average impact factors compared to non-engaged scholars. This relationship is most consistent with the theory of epistemic exclusion (Dotson 2014; Settles et al. 2018), in that type of scholarship predominantly pursued by women and scholars of color tend to *generally* be devalued in academia. In the case of engaged scholarship, female BHN scholars are the most likely group to identify as engaged scholars, and so the overall devaluation of engaged work vis-à-vis high-impact journal publication disproportionately effects women of color. However, all applicants who identify as engaged scholars face this disadvantage.

4.5 Conclusion

In sum, this chapter makes several important contributions to knowledge about race and gender disparities in metrics of productivity, as well as the effect of engaged scholarship on such metrics. Most likely done by women and BHN scholars, engaged scholarship does appear to serve as a vehicle for epistemic exclusion. However, in certain cases where engaged scholars have an advantage (i.e., publications), BHN scholars are the only group not to see such an advantage. Furthermore, in the case of citations, BHN scholars are *more* disadvantaged compared to other groups.

Together these findings suggest that scholarship types may be an important aspect in understanding gender and race disparities in academia. This chapter specifically speaks to gender and race disparities in early career scholars. Yet extant research suggests that such differences are likely to grow, as academic disparities accumulate throughout one's career (Branch 2016; Long, Allison, and McGinnis 1993; Xie and Shauman 2003). For academic institutions wishing to curb gender and (particularly) race inequities, rethinking the role of scholarship type may be key to reconsidering scientific value and impact.[45]

These findings are nevertheless limited by several important factors. First, the measure of engaged scholarship would likely lend more precise results if it were able to identify *types* of engaged scholarship. For example, the practices of community-engaged research, policy-related research, and social justice-based scholarship may vary by race and gender groups, and may be valued differentially across fields. Such nuance is missing from this analysis, though the main results do have important implications for engaged work writ large.

Second, the outcome variables in this chapter for average journal impact factor and citation counts had relatively high proportions of missingness due to data collection (26.1% and 17.3%, respectively). This study aimed to take a landscape-level view of engaged scholarship across six broad STEM and SS fields, but the reliability of the resources for measuring these

[45] In fact, a recent article explored nearly 40 years of academic publications and citation networks and found that women and minority scholar produced more innovative early-career scholarship, but were still cited less and seen as less impactful in the short-term (Hofstra et al. 2020). This pattern led to more of these scholars leaving academia in both the short- and long-term.

outcome variables is not consistent across disciplines (Harzing and Alakangas 2016). While the results presented in this chapter provide relative field-level comparisons, future work digging deeper into devaluation processes would likely benefit from focusing on a narrower range of fields with more a more qualitative approach to measuring impact and productivity.

Third, while differential devaluation of engaged scholars by race (i.e., a racialized glass escalator effect) may drive the racial disparities noted in publication and citation counts, this finding could also be due to a selection effect. The data set used in this dissertation cannot account for a causal relationship between engaged scholarship and metrics of productivity (as discussed in section 4.2.7), and so I also cannot measure whether those who select into using engaged scholarship by race and gender do so in a way that is correlated with publication metrics.

Addressing these limitations in future work may lend more nuanced understanding of the mechanisms of devaluation that operate differentially across race and gender groups and across academic disciplines. For example, future work should examine different types of engaged scholarship, and ideally investigate processes affecting early career scholars' productivity prior to applying for faculty positions (such as graduate school or postdoctoral scholars). Nonetheless, the results presented in this chapter provide evidence that engaged scholarship is likely a vehicle for epistemic exclusion, and that the devaluation of scholarship types predominantly done by women and scholars of color disproportionately disadvantages BHN scholars compared to other groups.

Chapter 5: Conclusion

In this dissertation, I examined several ways in which engaged scholarship may be a vehicle for epistemic exclusion. In Chapter Two, I presented a detailed account of the multi-step classification process used to identify engaged scholars through faculty application documents. Across six broad science, technology, math, and engineering (STEM) and social science (SS) fields, I found that 22.9% of faculty applicants used engaged scholarship language in at least one of their application documents, and roughly 10% of each document type (cover letter, research statement, and teaching statement) included at least one engaged paragraph.

In Chapter Three, I explored the extent to which women and scholars of color are more likely to identify as engaged scholars. I also tested whether the representation of women and Black/African American, Hispanic/Latinx, and Native American/Alaskan (BHN) scholars in a field's pool of available PhDs explained the race and gender disparities. I found that overall, all female applicants are significantly more likely to identify as engaged scholars compared to all male applicants. Within genders, BHN applicants were more likely than other groups to identify as engaged scholars, and overall, female BHN applicants were by far the most likely group to identify as engaged scholars. I also found that the relative representation of women and BHN scholars in a recruitment field's availability pool did not significantly alter the race and gender disparities in engagement, but did explain most of the field-level differences in engagement. Fields with a higher proportion of women and BHN scholars in the availability pool overall had more engaged scholars, but within all fields female BHN scholars were consistently the most likely to identify as engaged. While previous research has found that women and scholars of color are the most likely groups to identify as engaged scholars, no prior study has examined engagement at the intersection of race and gender.

In Chapter Four, I investigated whether engaged scholars had significantly different metrics of scholarly productivity than non-engaged scholars. Publication count, citation count, and journal impact factor are common metrics used to evaluate scholars' productivity and contribution to their respective field in critical academic gatekeeping processes such as hiring and promotion. I found that overall, engaged scholars tended to have more publications, but lower average journal impact factors and fewer citation than non-engaged scholars, controlling for recruitment-level factors and multiple applicant-level background characteristics. These findings suggest that while early-career engaged scholars may be more productive, processes such as epistemic exclusion may limit their access to high-prestige journals. I also tested whether there were race and gender disparities in engaged scholar's metrics of scholarly productivity. I found that the positive association between engaged scholarship and publication count did not apply to BHN applicants. Additionally, controlling for publication count and average impact factor, I found that BHN engaged scholars had even fewer citations than white and AAPI engaged scholars.

In sum, the results presented in Chapter Three and Four make several contributions to our understanding of engaged scholarship as a vehicle for epistemic exclusion. First, engaged scholarship is indeed more likely to be pursued by women and scholars of color—groups which are underrepresented in most academic disciplines. However, no previous research has examined engaged scholarship using both gender *and* race, and my finding that female BHN are the most likely of any group to identify as an engaged scholarship has consequences for both research on engaged scholarship, as well as academia's evaluation of engaged scholarship. Across academic disciplines, there is a robust literature in which women of color reflect on the duality of multiple marginalities within academia, and a commitment to social justice and scholar activism within and beyond the academy. As Settles et al. (2020) suggested, it is difficult to disentangle the devaluation of research done by people of color from other race-based prejudices, but as a predominantly white institution, it seems unlikely that the devaluation of engaged scholarship and the fact that women of color are the most likely to do such work are not intrinsically connected.

Furthermore, the findings presented in Chapter Four suggest that not only is engaged scholarship devalued overall (potentially because it is predominately undertaken by women and BHN scholars), but that there is *differential* devaluation of engaged scholars by race. I suggest that the effects of epistemic exclusion to no apply wholesale to any particular type of scholarship, but that types of scholarship predominantly done by women and BHN scholars are devalued the most when BHN scholars pursue them. My findings indicate that epistemic exclusion may not apply to all scholars who pursue types of scholarship more often done by women and scholars of color. Instead, epistemic exclusion—similar to the racialized glass escalator effect identified in other feminized occupations—is a specific mechanism within feminized and minoritized types of scholarship that further marginalizes scholars of color.

Together the findings presented in this dissertation suggest that scholarship types may be an important aspect in understanding gender and race disparities in academia, specifically to gender and race disparities in early career scholars. Extant research suggests that such differences are likely to grow, as academic disparities accumulate throughout one's career (Branch 2016; Long et al. 1993; Xie and Shauman 2003). For academic institutions wishing to curb gender and (particularly) race inequities, rethinking the role of scholarship type may be key to reconsidering scientific value and impact.

Appendix A: Text Classification

A.1 SearchK

Topic models run using a user-specified number of topics—a fact which can greatly alter the model output and subsequent interpretation of topics. Generally, a model with more topics will have more overlapping topics, and may pick up on topics that are not very prevalent in the corpus. A model with fewer topics will have more distinct topics, but may lump nuanced topics together in a single topic. Although there is no "right" number of topics for any corpus (Grimmer and Stewart 2013), the STM package includes a "searchK" function which performs several automated tests to help researchers identify a balance of nuance and parsimony in their topic model (Roberts et al. 2014). I ran the searchK function on the pilot corpus, testing the performance of the topic model between 40 and 100 topics at intervals of 10.

The results are shown in Figure A.1. The aim is to identify a number of topics where semantic coherence is high and residuals are low. Between these two measures, it appears that between 60 and 80 topics was appropriate. Since I assumed engaged scholarship might be a relatively rare topic in the pilot corpus, I opted for the higher end of this range and ran the STM with 80 topics.

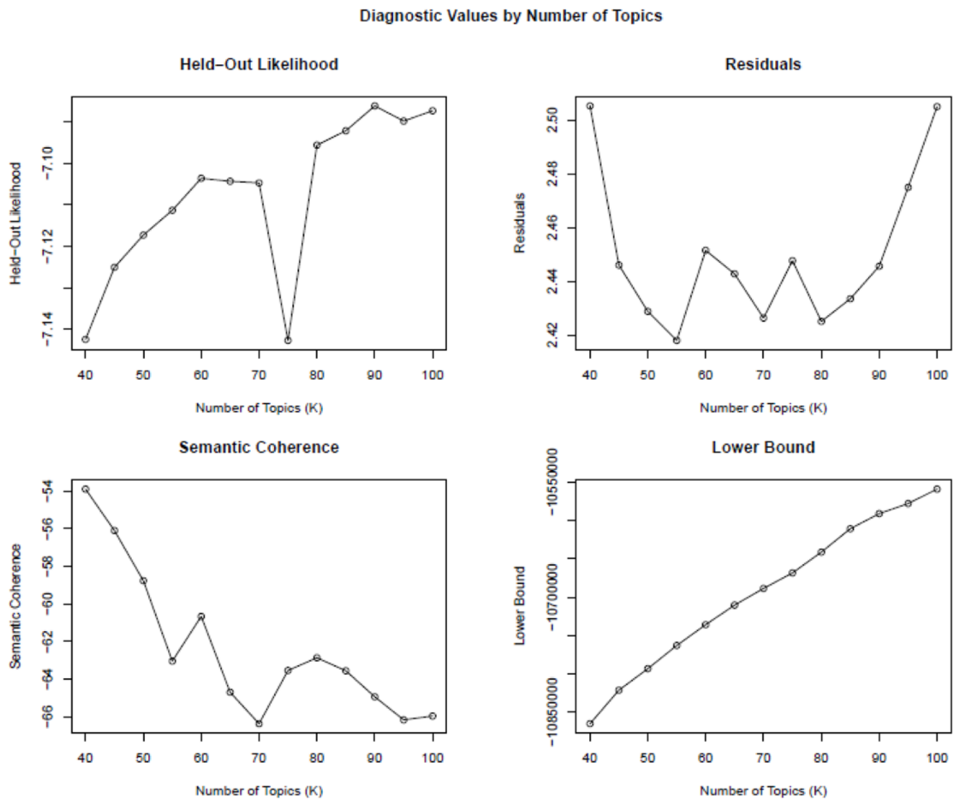


Figure A.1: Results of the searchK STM function, testing the performance of the topic model between 40 and 100 topics at intervals of 10.

A.2 STM Topic Top Words and Topic Prevalence

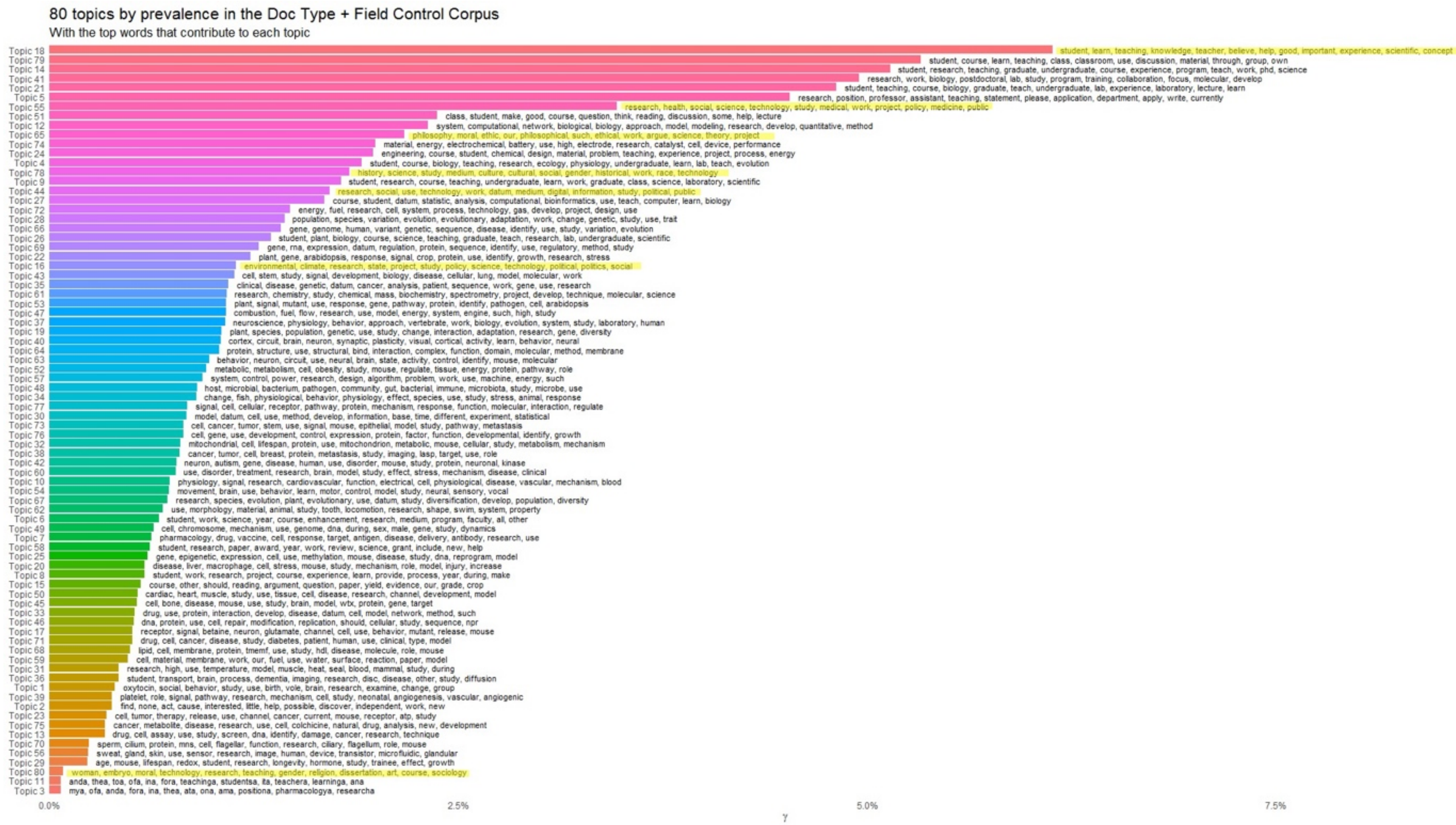


Figure A.2: STM topic top words and topic prevalence. The six topics identified as most likely to refer to paragraphs with engaged language are highlighted.

A.3 Hand-Coding Training for Research Assistants

In addition to multiple meeting over Zoom with the two research assistants, I also provided the following synopsis of engaged scholarship:

"Previous research has examined the different ways academic researchers describe engaged scholarship. However, these studies have only examined the scholarship of researchers who are *already* tenured faculty, and who have *self-identified* as engaged scholars. This project seeks to analyze a corpus (text data-base) of individuals *seeking* to become faculty – and most of whom are *not* engaged scholars. The task is to develop a systematized way of *identifying* engaged scholars through coding paragraphs from their faculty applications as describing activities or motivations aligned with engaged scholarship or not.

The key task then, identifying engaged scholars, necessitates an understanding of what engaged scholarship means. There are a ton of online resources to help understanding engaged scholarship (just googling "what is engaged scholarship" provides quite a few helpful links – many university campuses have offices or centers for engaged scholarship, and each has their own set of definitions). I would recommend reading some of those descriptions for an overview, but I've also provided a few scholarly articles (a few of which are mentioned below in this document) I'd like you to read through. In each PDF I've highlighted the most relevant portions.

Historically, the term "engaged scholarship" became popular with a book published in 1990 by Ernest Boyer titled "Scholarship Reconsidered" in which he critiqued American higher education as being too focused on prestige-mongering within the academy and not focused on higher education's original purpose: benefiting the public good. Boyer stated that universities purpose in society was to use "the rich resources of the university to [address] our most pressing social, civic, and ethical problems" through teaching and research (Boyer 1990). Boyer identified four dimensions of scholarship that university faculty fulfil: discovery, integration, application and teaching—and suggested that engaged scholarship incorporate all four realms. The scholarship of discovery refers to the pursuit of inquiry and investigation in search of new knowledge (this is what most faculty see as the main, and often only, goal of academic research). The scholarship of integration consists of making connections across disciplines and advancing knowledge through synthesis (now it is often referred to as "interdisciplinary," "cross-disciplinary," or "multi-disciplinary" research where research across multiple fields and/or researchers is utilized). The scholarship of application asks how knowledge can be applied to the social issues of the times in a dynamic process that generates and tests new theory and knowledge. The scholarship of teaching includes not only transmitting knowledge, but also transforming and extending it.

The scholarly articles I've included in the email often reference Boyer and the four realms of scholarship he identified. Yet they also update the concept of "engaged scholarship" as it has evolved in practice in the decades since "Scholarship Reconsidered" was published. Below are summaries from the findings of two articles that hand-coded (similar to the task you'll be undertaking) documents from faculty who already describe themselves as engaged scholars. Both articles were attempting to create a typology of the different ways engaged scholarship is done today. After reading through these brief descriptions, please also read the attached scholarly articles (again, the relevant portions are highlighted). I've also attached an Excel document with some examples of paragraphs from the data this project uses that I've already coded. The spread sheet includes the paragraph's text, a column where a "1" indicates that the paragraph discussed engaged scholarship or a "0" if it did not, and an additional column where I've written a few notes on what “type” of engaged scholarship (or keywords) was present in the paragraph if it was coded a “1”.

Please write down any questions as you go through the attached articles and example paragraph coding – we’ll use our Zoom time on Friday to discuss.

O’Meara (2008) used hand-coding and rich description to analyze 68 personal essays from faculty members across the U.S. who had been nominated for a nationally recognized award for community-engaged scholarship. Her sample was composed of faculty who self-identify and are publicly recognized as engaged scholars, and she was primarily coding for scholar’s motivations to pursue engaged scholarship. Examining the language the scholars in her sample used is useful for identifying how scholars may talk about their work across disciplines and institutions. Using examples O’Meara provides from her samples’ self-descriptions, I identified the following categories with specific phrases that engaged scholars in her sample used to describe their work:

Civic and social: civic engagement, civic educator, moral and civic responsibility, serving society, socially just/social justice, transformative, passion for justice and democracy, democratic practices, public-making.

Community: reciprocally informing the community, community engagement, transformation of community life, commitment to community, community based.

Scale/space: real-world settings, larger environment and society, public scholar, urban mission.

Impact and collaboration: impact on people, co-producers, interdisciplinary collaborations

Similarly, Doberneck, Glass and Schweitzer (2010) used hand coded interpretive content analysis on over 150 faculty tenure and promotion written statements at a single university to uncover a typology of activities faculty describe under the umbrella of engaged scholarship. The resulting typology had four broad sections that covered both research and teaching practices:

Publicly engaged research and creative activities: collaboration with community partners (broadly defined) in any stage of the research process such as defining research questions, research design, data acquisition, data analysis/interpretation, disseminating the results.

Publicly engaged instruction: sharing knowledge with various audiences through formal or informal arrangements - both within universities to nontraditional audiences or outside of universities and in collaboration with community partners.

Publicly engaged service: the use of university expertise to address specific issues identified by individuals, organizations, or communities where the research questions of the faculty member are not the primary impetus for the project.

Publicly engaged commercialized activities: projects where university-generated knowledge is translated into practical or commercial applications for the economic benefit of individuals, organizations, or communities."

The "attached articles" mentioned in the synopsis included: Beaulieu, Breton, and Brousselle 2018; Doberneck, Glass, and Schweitzer 2010; Vogelgesang, Denson, and Jayakumar 2010. Representative examples of engaged paragraphs can be found in Chapter Two, Table 2.8.

A.4 SML Model Specifications

I tested multiple SML model specification combinations in order to find a model which most reliably identified engaged scholarship paragraphs in the pilot corpus. As shown in Figure

A.3, I organized the different models tested in a tree-diagram to represent the different variations tested. At the top level is the text pre-processing version of the corpus: original, stemmed, and lemmatized.[46] As discussed in Jurka et al. (2013), the RTextTools package allows users to remove sparse terms and specify the number of n-grams allowed as tokens (see Jurka et al. 2013 for an explanation of these specifications and their effect on the model). I used the SVM model to test these multiple model specifications, and determined model fit using the F1 statistic (for both paragraphs identified as engaged and not-engaged). I found overall that the .8 and .9 sparsity models did not perform well (F1 scores below .6 for identifying engaged paragraphs).

I also found that the lemmatized corpus had the lowest F1 model scores—all below .64 for identifying engaged paragraphs (the original and stemmed corpora both consistently had F1 scores over .67). Ultimately, the stemmed model with a sparsity of .998 had the highest F1 score for identifying engaged paragraphs: .69.

[46] See Chapter Two, Section 2.3.1 for a discussion of lemmatization versus stemming.

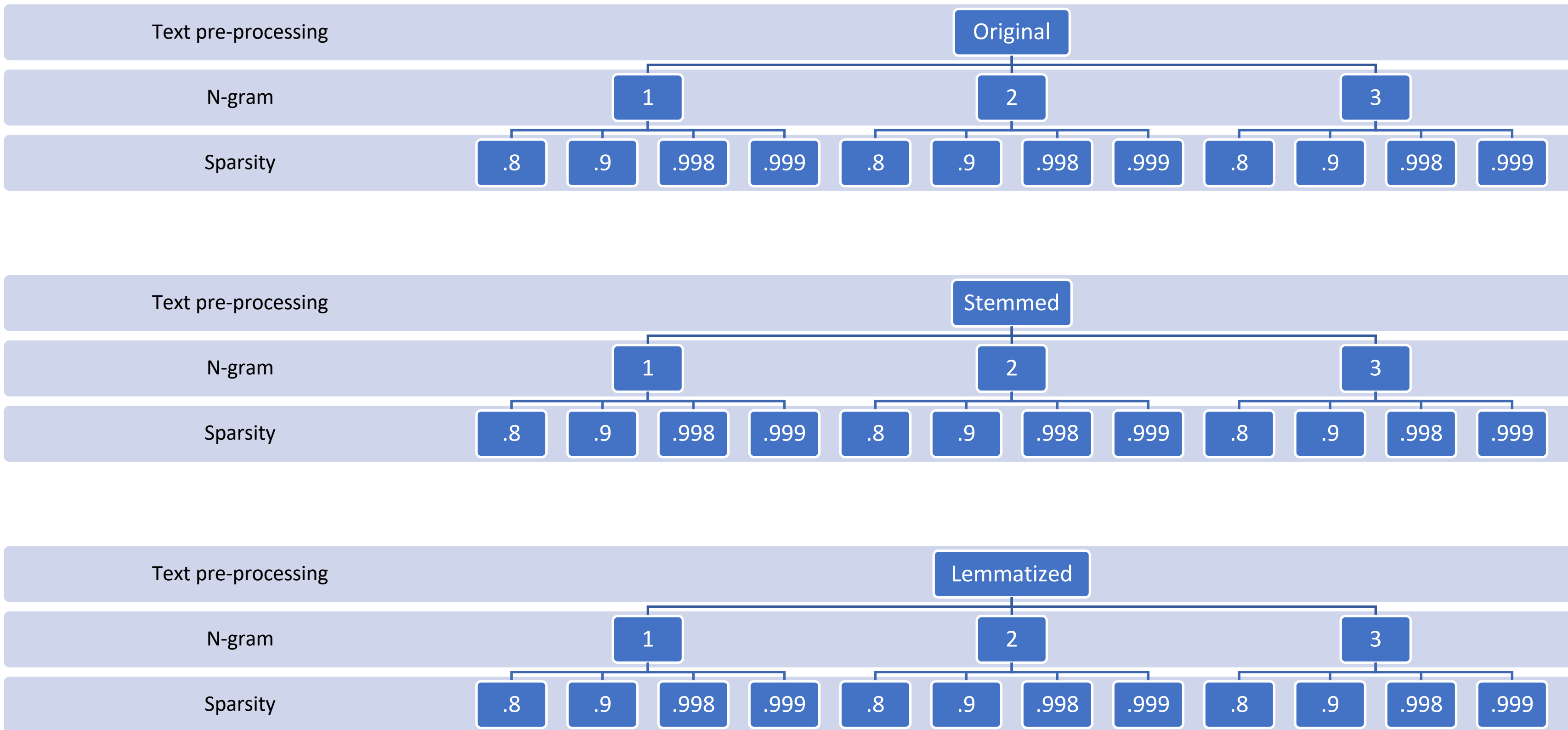


Figure A.3: Conceptual diagram of models tested for SML model performance identifying engaged versus not-engaged paragraphs.

A.5 Full Corpus SML Models Measures of Fit

Table A.1: SML Full Corpus Measures of Fit – First Model

	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.80	.93	.82	.85	.79	.96	.81	.93
1	.71	.45	.60	.55	.80	.38	.74	.46

Note: The data for this model included all hand-coded paragraphs and *the SML-coded paragraphs. The training set included 1,874 paragraphs and the testing set included 626 paragraphs. Each set had 13.2% engaged paragraphs.*

Table A.2: SML Full Corpus Ensemble Agreement – First Model

	Coverage	Accuracy
n ≥2	1.00	.80
n ≥3	.93	.82
n ≥4	.75	.86

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

Table A.3: SML Full Corpus Measures of Fit – STEM Paragraphs Only

	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.90	.92	.89	.85	.87	.95	.89	.92
1	.74	.71	.63	.71	.82	.60	.76	.68

Note: The data for this model included all hand-coded paragraphs and *the SML-coded paragraphs. The training set included 1,645 paragraphs and the testing set included 549 paragraphs. Each set had 33.7% engaged paragraphs.*

Table A.4: SML Full Corpus Ensemble Agreement – STEM Paragraphs Only

	Coverage	Accuracy
n ≥2	1.00	.87
n ≥3	.94	.89
n ≥4	.77	.93

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

Table A.5: SML Full Corpus Measures of Fit – SS Paragraphs nly

	SVM		*SLDA*		*RF*		*GLMNET*	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Engaged								
0	.83	.95	.75	.54	.79	.99	.81	.94
1	.81	.55	.34	.56	.92	.40	.76	.49

Note: The data for this model included all hand-coded paragraphs and *the SML-coded paragraphs. The training set included 1,255 paragraphs and the testing set included 419 paragraphs. Each set had 29.7% engaged paragraphs.*

Table A.6: SML Full Corpus Ensemble Agreement – SS Paragraphs Only

	Coverage	Accuracy
n ≥2	1.00	.82
n ≥3	.94	.84
n ≥4	.50	.86

Note: n refers to the number of algorithms that agree on either a coded 0 or 1. Coverage is the proportion of the corpus coded with that many algorithms in agreement. Accuracy is the proportion of correctly coded paragraphs within the set of paragraphs with that many algorithms in agreement.

Appendix B: Models from Chapter 3

Table B.1: Estimated Coefficients from Logit Models of Any Engaged Language in Application Documents

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Recruitment-Level Variables										
Broad Field										
Social Sci.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Ag/NatRes	-0.324***	-0.582***	-0.320***	-0.325***	-0.588***	-0.846***	-0.588***	-0.862***	-1.100***	-0.867***
	(-8.05)	(-3.95)	(-7.94)	(-8.06)	(-3.92)	(-5.57)	(-3.92)	(-5.66)	(-5.28)	(-5.66)
Engineering	-1.011***	-1.108***	-1.015***	-1.013***	-1.122***	-1.695***	-1.123***	-1.693***	-1.857***	-1.700***
	(-41.14)	(-8.52)	(-41.26)	(-41.16)	(-8.50)	(-12.87)	(-8.50)	(-12.85)	(-9.80)	(-12.85)
Biological Sci.	-0.913***	-1.318***	-0.913***	-0.915***	-1.335***	-1.637***	-1.336***	-1.655***	-1.830***	-1.669***
	(-33.06)	(-12.90)	(-33.08)	(-33.08)	(-12.91)	(-15.44)	(-12.91)	(-15.58)	(-12.18)	(-15.71)
Math/CS	-1.156***	-0.815***	-1.157***	-1.158***	-0.824***	-1.395***	-0.822***	-1.400***	-1.342***	-1.402***
	(-33.66)	(-4.16)	(-33.67)	(-33.68)	(-4.14)	(-6.98)	(-4.13)	(-6.99)	(-5.50)	(-7.01)
Physical Sci.	-0.864***	-1.307***	-0.866***	-0.866***	-1.325***	-1.686***	-1.326***	-1.697***	-1.807***	-1.695***
	(-29.25)	(-8.79)	(-29.33)	(-29.26)	(-8.82)	(-10.74)	(-8.82)	(-10.79)	(-7.87)	(-10.71)
Academic Year										
2013-14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2014-15	0.069*	0.071*	0.192	0.069*	0.071*	0.072*	0.182***	0.201***	0.200***	0.357*
	(2.15)	(2.21)	(1.74)	(2.15)	(2.21)	(2.21)	(4.32)	(4.69)	(4.68)	(2.39)
2015-16	0.053	0.055	0.072	0.053	0.055	0.056	-0.129**	-0.127**	-0.129**	0.013
	(1.69)	(1.75)	(0.64)	(1.69)	(1.75)	(1.76)	(-3.00)	(-2.90)	(-2.96)	(0.09)
2016-17	0.079**	0.085**	0.011	0.079**	0.085**	0.086**	0.043	0.020	0.020	-0.029
	(2.60)	(2.80)	(0.09)	(2.60)	(2.79)	(2.79)	(1.05)	(0.48)	(0.49)	(-0.19)
2017-18	0.179***	0.183***	0.251*	0.179***	0.183***	0.184***	0.049	0.049	0.045	0.131
	(5.96)	(6.08)	(2.43)	(5.95)	(6.08)	(6.08)	(1.22)	(1.18)	(1.10)	(0.94)
2018-19	0.369***	0.369***	0.437***	0.370***	0.370***	0.372***	0.252***	0.280***	0.276***	0.159
	(12.25)	(12.25)	(4.02)	(12.26)	(12.25)	(12.25)	(6.17)	(6.67)	(6.59)	(1.08)
Recruitment Department NRC Rank (Percentile)										

Unranked	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1st-50th	-0.584***	-0.580***	-0.585***	-0.586***	-0.581***	-0.586***	-0.582***	-0.587***	-0.588***	-0.587***
	(-22.81)	(-22.58)	(-22.84)	(-22.82)	(-22.59)	(-22.61)	(-22.59)	(-22.63)	(-22.64)	(-22.62)
50th-75th	-0.458***	-0.444***	-0.453***	-0.460***	-0.445***	-0.449***	-0.445***	-0.448***	-0.448***	-0.442***
	(-21.12)	(-20.42)	(-20.85)	(-21.13)	(-20.42)	(-20.44)	(-20.40)	(-20.37)	(-20.38)	(-20.11)
75th-90th	-0.688***	-0.670***	-0.684***	-0.690***	-0.672***	-0.678***	-0.672***	-0.678***	-0.678***	-0.673***
	(-26.76)	(-26.02)	(-26.57)	(-26.78)	(-26.03)	(-26.01)	(-26.01)	(-25.98)	(-25.98)	(-25.77)
90th-100th	-0.339***	-0.324***	-0.335***	-0.340***	-0.325***	-0.329***	-0.325***	-0.328***	-0.329***	-0.323***
	(-15.07)	(-14.38)	(-14.86)	(-15.08)	(-14.39)	(-14.42)	(-14.38)	(-14.38)	(-14.39)	(-14.15)
Applicant-Level Variables										
Race/Gender										
Female BHN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Female AAPI	-0.706***	-0.713***	-0.704***	-1.041***	-1.057***	-0.942***	-1.054***	-0.939***	-0.955***	-0.994***
	(-17.38)	(-14.89)	(-6.34)	(-19.05)	(-16.40)	(-15.08)	(-16.42)	(-15.10)	(-14.39)	(-6.38)
Female White	-0.388***	-0.436***	-0.330***	-0.616***	-0.673***	-0.625***	-0.677***	-0.628***	-0.707***	-0.636***
	(-11.29)	(-11.07)	(-3.54)	(-13.46)	(-12.81)	(-12.07)	(-12.94)	(-12.18)	(-12.97)	(-5.01)
Male BHN	-0.719***	-0.671***	-0.556***	-0.881***	-0.839***	-0.779***	-0.835***	-0.774***	-0.758***	-0.388*
	(-16.70)	(-13.15)	(-4.77)	(-15.51)	(-12.41)	(-11.88)	(-12.39)	(-11.83)	(-11.12)	(-2.47)
Male AAPI	-1.238***	-1.381***	-1.274***	-1.856***	-2.008***	-1.727***	-2.006***	-1.724***	-1.710***	-1.738***
	(-31.48)	(-24.52)	(-12.16)	(-34.06)	(-27.96)	(-24.94)	(-27.97)	(-24.93)	(-22.54)	(-11.40)
Male White	-0.999***	-1.199***	-0.944***	-1.440***	-1.650***	-1.502***	-1.653***	-1.502***	-1.554***	-1.479***
	(-28.96)	(-29.18)	(-10.12)	(-31.10)	(-30.33)	(-28.22)	(-30.49)	(-28.31)	(-27.57)	(-11.61)
Other/Miss	-0.764***	-0.733***	-0.752***	-0.981***	-0.957***	-0.857***	-0.959***	-0.858***	-0.830***	-0.862***
	(-17.32)	(-13.75)	(-6.24)	(-17.07)	(-13.73)	(-12.71)	(-13.81)	(-12.79)	(-11.71)	(-5.35)
Institutional Affiliation										
Non-U.S. Institution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
U.S. Institution	0.500***	0.492***	0.499***	0.501***	0.493***	0.496***	0.493***	0.496***	0.497***	0.495***
	(20.57)	(20.21)	(20.52)	(20.58)	(20.21)	(20.22)	(20.21)	(20.22)	(20.22)	(20.17)
Time Since Degree (Years)										
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1-2	0.355***	0.353***	0.355***	0.355***	0.354***	0.356***	0.354***	0.357***	0.357***	0.357***
	(10.91)	(10.81)	(10.92)	(10.91)	(10.81)	(10.81)	(10.82)	(10.81)	(10.82)	(10.81)
3-5	0.331***	0.329***	0.330***	0.332***	0.330***	0.332***	0.330***	0.332***	0.332***	0.331***
	(10.42)	(10.31)	(10.39)	(10.42)	(10.30)	(10.30)	(10.31)	(10.30)	(10.29)	(10.26)
6-10	0.170***	0.171***	0.170***	0.170***	0.172***	0.173***	0.172***	0.173***	0.173***	0.172***

	(4.93)	(4.96)	(4.92)	(4.93)	(4.96)	(4.95)	(4.96)	(4.95)	(4.94)	(4.92)
11+	0.165***	0.163***	0.165***	0.165***	0.163***	0.164***	0.164***	0.164***	0.164***	0.163***
	(3.85)	(3.80)	(3.86)	(3.85)	(3.80)	(3.79)	(3.80)	(3.79)	(3.79)	(3.77)
Current Job Category										
Postdoc	0.047	0.046	0.049	0.047	0.047	0.047	0.047	0.047	0.047	0.048
	(1.46)	(1.43)	(1.51)	(1.46)	(1.43)	(1.43)	(1.43)	(1.42)	(1.42)	(1.46)
Asst. Prof.	0.283***	0.281***	0.284***	0.284***	0.282***	0.284***	0.282***	0.284***	0.284***	0.284***
	(8.03)	(7.95)	(8.06)	(8.03)	(7.95)	(7.95)	(7.95)	(7.95)	(7.95)	(7.96)
Assoc./Full Prof.	0.356***	0.351***	0.356***	0.357***	0.352***	0.354***	0.352***	0.355***	0.355***	0.356***
	(7.63)	(7.52)	(7.64)	(7.63)	(7.51)	(7.51)	(7.51)	(7.51)	(7.51)	(7.53)
Visiting Prof.	0.144***	0.143***	0.145***	0.144***	0.143***	0.144***	0.143***	0.144***	0.144***	0.146***
	(3.47)	(3.44)	(3.51)	(3.47)	(3.44)	(3.44)	(3.44)	(3.44)	(3.43)	(3.48)
Research/Teaching	0.166***	0.164***	0.167***	0.166***	0.164***	0.165***	0.164***	0.165***	0.165***	0.167***
Fellow	(3.50)	(3.45)	(3.54)	(3.50)	(3.45)	(3.45)	(3.45)	(3.45)	(3.45)	(3.48)
Grad. Student/PhD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cand.	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Researcher	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(-0.26)	(-0.27)	(-0.26)	(-0.26)	(-0.27)	(-0.27)	(-0.28)	(-0.28)	(-0.28)	(-0.28)
Lecturer	0.188***	0.191***	0.190***	0.188***	0.191***	0.193***	0.191***	0.193***	0.193***	0.194***
	(5.08)	(5.14)	(5.13)	(5.08)	(5.14)	(5.13)	(5.14)	(5.14)	(5.14)	(5.17)
Other Job	0.016	0.013	0.018	0.016	0.013	0.013	0.013	0.013	0.013	0.015
	(0.38)	(0.30)	(0.43)	(0.38)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.35)
Avg. Referrer NRC	-0.376***	-0.379***	-0.376***	-0.376***	-0.380***	-0.383***	-0.381***	-0.384***	-0.384***	-0.384***
Rank (Percentile)	(-8.90)	(-8.97)	(-8.89)	(-8.89)	(-8.97)	(-8.98)	(-8.98)	(-8.98)	(-8.98)	(-8.97)
Document Type										
Cover Letter	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Research Statement	-0.067***	-0.067***	-0.067***	-0.564***	-0.574***	-0.635***	-0.645***	-0.701***	-0.787***	-0.818***
	(-4.63)	(-4.63)	(-4.63)	(-11.14)	(-11.10)	(-12.11)	(-10.32)	(-11.05)	(-11.75)	(-5.87)
Teaching Statement	-0.039**	-0.039**	-0.039**	-0.578***	-0.588***	-0.862***	-0.713***	-0.985***	-1.011***	-0.952***
	(-2.64)	(-2.64)	(-2.64)	(-11.65)	(-11.54)	(-17.19)	(-11.47)	(-15.86)	(-15.05)	(-7.04)
Submitted Document										
Cover Letter	0.300***	0.305***	0.302***	0.300***	0.305***	0.307***	0.306***	0.308***	0.308***	0.310***
	(3.94)	(3.96)	(3.98)	(3.94)	(3.95)	(3.95)	(3.95)	(3.95)	(3.95)	(3.98)
Research Statement	0.589***	0.597***	0.595***	0.590***	0.599***	0.605***	0.600***	0.608***	0.609***	0.615***
	(23.53)	(23.69)	(23.66)	(23.53)	(23.70)	(23.74)	(23.73)	(23.84)	(23.84)	(23.95)
Teaching Statement	0.619***	0.617***	0.619***	0.621***	0.619***	0.623***	0.620***	0.625***	0.626***	0.626***
	(25.80)	(25.53)	(25.72)	(25.82)	(25.55)	(25.61)	(25.56)	(25.68)	(25.68)	(25.60)
Constant	-2.223***	-2.162***	-2.268***	-1.894***	-1.825***	-1.732***	-1.762***	-1.673***	-1.638***	-1.710***
	(-22.34)	(-21.30)	(-18.27)	(-18.38)	(-17.20)	(-16.27)	(-16.39)	(-15.49)	(-15.06)	(-11.64)
Observations	404037	404037	404037	404037	404037	404037	404037	404037	404037	404037

AIC	248292.807	247896.115	248218.340	247771.816	247370.795	244771.469	247161.612	244599.235	244564.210	244517.989
BIC	248827.361	248757.946	249080.171	248437.281	248363.538	245873.304	248263.447	245810.163	246429.694	246710.751

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is the base model with all control variables; Model 2-5 add race/gender interactions (Model 2 adds race/gender and Field interaction to base, Model 3 adds race/gender and Year interaction to base, Model 4 adds race/gender and document type interaction to base, Model 5 adds race/gender and field interaction and race/gender and Document Type interaction); Model 6 adds field and document type interaction to Model 5; Model 7 adds year and document type interaction to Model 5; Model 8 adds field and document type interaction and year and document type interaction to Model 5; Model 9 adds three-way interaction between field, document type, and race/gender to Model 8; Model 10 adds three-way interaction between year, document type, and race/gender to Model 8.

Table B.2: Estimated Coefficients from OLS Regression Models of Proportion of Engaged Language in Application Documents (for Applicants with at Least One Engaged Paragraph in Any Document)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Recruitment-Level Variables										
Broad Field										
Social Sci.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Ag/NatRes	-0.006	-0.012	-0.006	-0.006	-0.006	-0.033***	-0.006	-0.034***	-0.055	-0.033***
	(-1.55)	(-0.63)	(-1.54)	(-1.55)	(-1.55)	(-5.75)	(-1.55)	(-5.83)	(-1.78)	(-5.76)
Engineering	-0.041***	-0.066***	-0.041***	-0.041***	-0.041***	-0.070***	-0.041***	-0.069***	-0.130***	-0.069***
	(-20.63)	(-5.67)	(-20.50)	(-20.63)	(-20.63)	(-19.43)	(-20.62)	(-19.45)	(-9.52)	(-19.60)
Biological Sci.	-0.030***	-0.054***	-0.030***	-0.030***	-0.030***	-0.067***	-0.030***	-0.067***	-0.109***	-0.066***
	(-14.23)	(-6.46)	(-14.13)	(-14.23)	(-14.23)	(-20.30)	(-14.23)	(-20.29)	(-7.97)	(-19.98)
Math/CS	-0.050***	-0.013	-0.050***	-0.050***	-0.050***	-0.085***	-0.050***	-0.084***	-0.068*	-0.084***
	(-19.19)	(-0.49)	(-19.16)	(-19.19)	(-19.19)	(-20.42)	(-19.19)	(-20.12)	(-2.50)	(-19.91)
Physical Sci.	-0.027***	-0.062***	-0.027***	-0.027***	-0.027***	-0.062***	-0.027***	-0.061***	-0.132***	-0.061***
	(-11.16)	(-6.14)	(-11.33)	(-11.16)	(-11.16)	(-15.57)	(-11.16)	(-15.31)	(-10.88)	(-15.22)
Academic Year										

2013-14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2014-15	0.001	0.002	0.002	0.001	0.001	0.001	0.010*	0.012**	0.012**	-0.001
	(0.56)	(0.69)	(0.22)	(0.56)	(0.56)	(0.56)	(2.39)	(2.71)	(2.90)	(-0.04)
2015-16	0.001	0.001	-0.001	0.001	0.001	0.001	-0.017***	-0.015***	-0.014***	-0.016
	(0.24)	(0.36)	(-0.12)	(0.24)	(0.24)	(0.24)	(-4.03)	(-3.57)	(-3.44)	(-0.94)
2016-17	0.001	0.002	0.002	0.001	0.001	0.001	-0.001	-0.002	-0.000	-0.006
	(0.32)	(0.63)	(0.21)	(0.32)	(0.32)	(0.32)	(-0.20)	(-0.44)	(-0.07)	(-0.34)
2017-18	0.004	0.004	0.024*	0.004	0.004	0.004	-0.002	-0.002	-0.002	0.012
	(1.43)	(1.55)	(2.19)	(1.43)	(1.43)	(1.43)	(-0.57)	(-0.58)	(-0.47)	(0.70)
2018-19	0.012***	0.012***	0.027*	0.012***	0.012***	0.012***	0.005	0.006	0.007	-0.013
	(4.45)	(4.54)	(2.32)	(4.45)	(4.45)	(4.45)	(1.01)	(1.40)	(1.55)	(-0.78)
Recruitment Department NRC Rank (Percentile)										
Unranked	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1st-50th	-0.008***	-0.007**	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007**	-0.008***
	(-3.31)	(-3.15)	(-3.31)	(-3.31)	(-3.31)	(-3.31)	(-3.31)	(-3.31)	(-3.14)	(-3.31)
50th-75th	-0.015***	-0.014***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.014***	-0.015***
	(-7.76)	(-7.32)	(-7.85)	(-7.75)	(-7.75)	(-7.75)	(-7.75)	(-7.75)	(-7.31)	(-7.84)
75th-90th	-0.025***	-0.023***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.023***	-0.025***
	(-11.43)	(-10.93)	(-11.41)	(-11.43)	(-11.43)	(-11.43)	(-11.43)	(-11.43)	(-10.93)	(-11.40)
90th-100th	-0.018***	-0.017***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.017***	-0.018***
	(-8.55)	(-8.14)	(-8.54)	(-8.55)	(-8.55)	(-8.55)	(-8.55)	(-8.55)	(-8.13)	(-8.53)
Applicant-Level Variables										
Race/Gender										
Female BHN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Female AAPI	-0.034***	-0.038***	-0.030**	-0.059***	-0.059***	-0.050***	-0.059***	-0.050***	-0.063***	-0.067***
	(-8.95)	(-8.42)	(-3.19)	(-9.94)	(-9.94)	(-8.48)	(-9.91)	(-8.45)	(-8.77)	(-4.16)
Female White	-0.024***	-0.028***	-0.016	-0.047***	-0.047***	-0.041***	-0.047***	-0.042***	-0.055***	-0.049***
	(-7.08)	(-7.25)	(-1.79)	(-9.19)	(-9.19)	(-8.24)	(-9.23)	(-8.27)	(-9.09)	(-3.41)
Male BHN	-0.016***	-0.012*	-0.000	-0.025***	-0.025***	-0.019**	-0.024***	-0.018**	-0.011	0.017
	(-3.85)	(-2.31)	(-0.03)	(-3.69)	(-3.69)	(-2.84)	(-3.61)	(-2.77)	(-1.32)	(0.82)
Male AAPI	-0.034***	-0.039***	-0.024*	-0.074***	-0.074***	-0.057***	-0.074***	-0.056***	-0.063***	-0.059***
	(-9.04)	(-7.53)	(-2.52)	(-12.35)	(-12.35)	(-9.47)	(-12.27)	(-9.39)	(-7.23)	(-3.85)
Male White	-0.038***	-0.050***	-0.030***	-0.076***	-0.076***	-0.063***	-0.076***	-0.063***	-0.085***	-0.071***
	(-11.21)	(-12.48)	(-3.51)	(-15.20)	(-15.20)	(-12.65)	(-15.17)	(-12.63)	(-13.84)	(-5.10)
Other/Miss	-0.019***	-0.015**	-0.012	-0.035***	-0.035***	-0.027***	-0.035***	-0.027***	-0.020*	-0.029
	(-4.44)	(-2.60)	(-1.06)	(-5.06)	(-5.06)	(-3.95)	(-5.13)	(-4.03)	(-2.26)	(-1.56)

Institutional Affiliation										
Non-U.S. Institution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
U.S. Institution	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(4.25)	(4.11)	(4.22)	(4.25)	(4.25)	(4.25)	(4.25)	(4.25)	(4.11)	(4.22)
Time Since Degree (Years)										
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1-2	0.009**	0.008**	0.009***	0.009**	0.009**	0.009**	0.009**	0.009**	0.008**	0.009***
	(3.26)	(3.20)	(3.33)	(3.26)	(3.26)	(3.26)	(3.26)	(3.26)	(3.20)	(3.33)
3-5	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(3.60)	(3.56)	(3.64)	(3.60)	(3.60)	(3.60)	(3.60)	(3.60)	(3.56)	(3.64)
6-10	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*
	(2.29)	(2.28)	(2.26)	(2.29)	(2.29)	(2.29)	(2.29)	(2.29)	(2.28)	(2.26)
11+	0.010**	0.010**	0.009**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.009**
	(2.65)	(2.70)	(2.61)	(2.65)	(2.65)	(2.65)	(2.65)	(2.65)	(2.70)	(2.61)
Current Job Category										
Postdoc	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.72)	(0.79)	(0.69)	(0.72)	(0.72)	(0.72)	(0.72)	(0.72)	(0.79)	(0.69)
Asst. Prof.	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**
	(2.68)	(2.61)	(2.70)	(2.68)	(2.68)	(2.68)	(2.68)	(2.68)	(2.61)	(2.70)
Assoc./Full Prof.	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*
	(2.14)	(2.08)	(2.20)	(2.14)	(2.14)	(2.14)	(2.14)	(2.14)	(2.08)	(2.20)
Visiting Prof.	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**
	(2.69)	(2.65)	(2.67)	(2.69)	(2.69)	(2.69)	(2.69)	(2.69)	(2.65)	(2.66)
Research/Teaching	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Fellow	(1.47)	(1.51)	(1.41)	(1.47)	(1.47)	(1.47)	(1.47)	(1.47)	(1.51)	(1.41)
Grad. Student/PhD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cand.	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Researcher	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(1.36)	(1.38)	(1.34)	(1.36)	(1.36)	(1.36)	(1.36)	(1.36)	(1.38)	(1.34)
Lecturer	0.011**	0.011***	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**	0.011***	0.011**
	(3.26)	(3.40)	(3.25)	(3.26)	(3.26)	(3.26)	(3.26)	(3.26)	(3.39)	(3.25)
Other Job	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.27)	(0.24)	(0.23)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.24)	(0.23)
Avg. Referrer NRC	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**
Rank (Percentile)	(-2.87)	(-2.98)	(-2.82)	(-2.87)	(-2.87)	(-2.87)	(-2.87)	(-2.87)	(-2.98)	(-2.82)
Document Type										
Cover Letter	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Research Statement	-0.014***	-0.014***	-0.014***	-0.048***	-0.048***	-0.047***	-0.051***	-0.049***	-0.059***	-0.077***

	(-8.86)	(-8.86)	(-8.86)	(-8.33)	(-8.33)	(-8.10)	(-7.41)	(-7.16)	(-7.79)	(-5.42)
Teaching Statement	0.008***	0.008***	0.008***	-0.040***	-0.040***	-0.064***	-0.049***	-0.071***	-0.077***	-0.076***
	(3.91)	(3.91)	(3.91)	(-6.30)	(-6.30)	(-10.27)	(-6.14)	(-9.12)	(-9.25)	(-4.36)
Submitted Document										
Cover Letter	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	(1.41)	(1.41)	(1.40)	(1.41)	(1.41)	(1.41)	(1.41)	(1.41)	(1.41)	(1.40)
Research Statement	0.027***	0.028***	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***	0.028***	0.027***
	(12.63)	(12.90)	(12.26)	(12.63)	(12.63)	(12.63)	(12.63)	(12.62)	(12.89)	(12.25)
Teaching Statement	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***
	(18.36)	(18.33)	(18.28)	(18.36)	(18.36)	(18.36)	(18.36)	(18.36)	(18.32)	(18.27)
Constant	0.093***	0.096***	0.086***	0.120***	0.120***	0.127***	0.124***	0.131***	0.139***	0.135***
	(10.89)	(11.00)	(7.71)	(13.09)	(13.09)	(13.96)	(13.10)	(13.86)	(14.22)	(8.98)
Observations	92436	92436	92436	92436	92436	92436	92436	92436	92436	92436
AIC	-61110.736	-61202.246	-61116.000	-61384.900	-61384.900	-63641.751	-61505.430	-63717.982	-63833.167	-63740.216
BIC	-60648.457	-60456.938	-60370.693	-60809.409	-60809.409	-62971.918	-60835.597	-62953.806	-62219.906	-62126.956

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is the base model with all control variables; Model 2-5 add race/gender interactions (Model 2 adds race/gender and Field interaction to base, Model 3 adds race/gender and Year interaction to base, Model 4 adds race/gender and document type interaction to base, Model 5 adds race/gender and field interaction and race/gender and Document Type interaction); Model 6 adds field and document type interaction to Model 5; Model 7 adds year and document type interaction to Model 5; Model 8 adds field and document type interaction and year and document type interaction to Model 5; Model 9 adds three-way interaction between field, document type, and race/gender to Model 8; Model 10 adds three-way interaction between year, document type, and race/gender to Model 8.

Table B.3: Estimated Coefficients from Logit Models of Any Engaged Language in Application Documents, Adding Applicant Availability Pool Variables and Interactions

	Model 1	Model 2
Recruitment-Level Variables		
Broad Field		
Social Sci.	0.000	0.000
	(.)	(.)
Ag/NatRes	-0.862***	-0.418**
	(-5.66)	(-2.86)
Engineering	-1.693***	-0.665***
	(-12.85)	(-4.96)
Biological Sci.	-1.655***	-1.331***
	(-15.58)	(-12.53)
Math/CS	-1.400***	-0.552**
	(-6.99)	(-2.71)
Physical Sci.	-1.697***	-1.056***
	(-10.79)	(-6.61)
Academic Year		
2013-14	0.000	0.000
	(.)	(.)
2014-15	0.201***	0.230***
	(4.69)	(5.28)
2015-16	-0.127**	-0.115**
	(-2.90)	(-2.58)
2016-17	0.020	0.087*
	(0.48)	(2.09)
2017-18	0.049	0.032
	(1.18)	(0.78)
2018-19	0.280***	0.292***
	(6.67)	(6.93)
Recruitment Department NRC Rank (Percentile)		
Unranked	0.000	0.000
	(.)	(.)
1st-50th	-0.587***	-0.528***
	(-22.63)	(-20.43)
50th-75th	-0.448***	-0.389***
	(-20.37)	(-17.73)
75th-90th	-0.678***	-0.489***
	(-25.98)	(-18.50)
90th-100th	-0.328***	-0.312***
	(-14.38)	(-13.62)
Applicant-Level Variables		
Race/Gender		
Female BHN	0.000	0.000
	(.)	(.)
Female AAPI	-0.939***	-0.791***
	(-15.10)	(-12.68)
Female White	-0.628***	-0.559***
	(-12.18)	(-10.74)

Male BHN	-0.774***	-0.671***
	(-11.83)	(-10.35)
Male AAPI	-1.724***	-1.471***
	(-24.93)	(-21.30)
Male White	-1.502***	-1.306***
	(-28.31)	(-24.46)
Other/Miss	-0.858***	-0.703***
	(-12.79)	(-10.41)
Institutional Affiliation		
Non-U.S. Institution	0.000	0.000
	(.)	(.)
U.S. Institution	0.496***	0.435***
	(20.22)	(17.66)
Time Since Degree (Years)		
0	0.000	0.000
	(.)	(.)
1-2	0.357***	0.246***
	(10.81)	(7.55)
3-5	0.332***	0.203***
	(10.30)	(6.36)
6-10	0.173***	0.033
	(4.95)	(0.96)
11+	0.164***	0.004
	(3.79)	(0.09)
Current Job Category		
Postdoc	0.047	-0.024
	(1.42)	(-0.72)
Asst. Prof.	0.284***	0.255***
	(7.95)	(7.23)
Assoc./Full Prof.	0.355***	0.316***
	(7.51)	(6.73)
Visiting Prof.	0.144***	0.107**
	(3.44)	(2.58)
Research/Teaching Fellow	0.165***	0.122*
	(3.45)	(2.57)
Grad. Student/PhD Cand.	0.000	0.000
	(.)	(.)
Researcher	-0.010	-0.046
	(-0.28)	(-1.22)
Lecturer	0.193***	0.126***
	(5.14)	(3.41)
Other Job	0.013	-0.026
	(0.30)	(-0.62)
Avg. Referrer NRC Rank (Percentile)	-0.384***	-0.318***
	(-8.98)	(-7.46)
Document Type		
Cover Letter	0.000	0.000
	(.)	(.)
Research Statement	-0.701***	-0.723***
	(-11.05)	(-11.16)
Teaching Statement	-0.985***	-1.003***
	(-15.86)	(-15.87)
Submitted Document		
Cover Letter	0.308***	0.352***
	(3.95)	(4.50)
Research Statement	0.608***	0.697***
	(23.84)	(25.87)

Teaching Statement	0.625***	0.439***
	(25.68)	(17.94)
Availability Pool Variables		
Prop. Female		2.551***
		(33.15)
Prop. BHN		2.302***
		(15.91)
Constant	-1.673***	-3.402***
	(-15.49)	(-29.42)
Observations	404037	404037
AIC	244599.235	241289.898
BIC	245810.163	242522.645

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is Model 8 from Table B.1; Model 2 adds the availability pool variables measuring the proportion of females and BHN PhDs in the recruitment field

Table B.4: Estimated Coefficients from OLS Regression Models of Proportion of Engaged Language in Application Documents for Applicants with At Least one Engaged Paragraph in Any Document, Adding Applicant Availability Pool Variables and Interactions

	Model 1	Model 2
Recruitment-Level Variables		
Broad Field		
Social Sci.	0.000	0.000
	(.)	(.)
Ag/NatRes	-0.034***	-0.029
	(-5.83)	(-1.45)
Engineering	-0.069***	-0.062***
	(-19.45)	(-5.12)
Biological Sci.	-0.067***	-0.081***
	(-20.29)	(-9.11)
Math/CS	-0.084***	-0.022
	(-20.12)	(-0.83)
Physical Sci.	-0.061***	-0.076***
	(-15.31)	(-7.19)
Academic Year		
2013-14	0.000	0.000
	(.)	(.)
2014-15	0.012**	0.013**
	(2.71)	(3.03)
2015-16	-0.015***	-0.015***
	(-3.57)	(-3.65)
2016-17	-0.002	0.000
	(-0.44)	(0.03)
2017-18	-0.002	-0.003
	(-0.58)	(-0.70)

2018-19	0.006	0.006
	(1.40)	(1.41)
Recruitment Department NRC Rank (Percentile)		
Unranked	0.000	0.000
	(.)	(.)
1st-50th	-0.008***	-0.009***
	(-3.31)	(-3.75)
50th-75th	-0.015***	-0.014***
	(-7.75)	(-7.66)
75th-90th	-0.025***	-0.019***
	(-11.43)	(-8.95)
90th-100th	-0.018***	-0.017***
	(-8.55)	(-8.54)
Applicant-Level Variables		
Race/Gender		
Female BHN	0.000	0.000
	(.)	(.)
Female AAPI	-0.050***	-0.051***
	(-8.45)	(-7.85)
Female White	-0.042***	-0.043***
	(-8.27)	(-7.75)
Male BHN	-0.018**	-0.013
	(-2.77)	(-1.74)
Male AAPI	-0.056***	-0.056***
	(-9.39)	(-7.94)
Male White	-0.063***	-0.069***
	(-12.63)	(-12.38)
Other/Miss	-0.027***	-0.019*
	(-4.03)	(-2.36)
Institutional Affiliation		
Non-U.S. Institution	0.000	0.000
	(.)	(.)
U.S. Institution	0.008***	0.006***
	(4.25)	(3.38)
Time Since Degree (Years)		
0	0.000	0.000
	(.)	(.)
1-2	0.009**	0.006*
	(3.26)	(2.39)
3-5	0.009***	0.007**
	(3.60)	(2.60)
6-10	0.006*	0.004
	(2.29)	(1.33)
11+	0.010**	0.007
	(2.65)	(1.87)
Current Job Category		
Postdoc	0.002	0.001
	(0.72)	(0.35)
Asst. Prof.	0.008**	0.008*
	(2.68)	(2.53)
Assoc./Full Prof.	0.009*	0.008*
	(2.14)	(1.97)

Visiting Prof.	0.010**	0.009*
	(2.69)	(2.42)
Research/Teaching Fellow	0.006	0.006
	(1.47)	(1.38)
Grad. Student/PhD Cand.	0.000	0.000
	(.)	(.)
Researcher	0.004	0.004
	(1.36)	(1.32)
Lecturer	0.011**	0.010**
	(3.26)	(3.00)
Other Job	0.001	0.000
	(0.27)	(0.07)
Avg. Referrer NRC Rank (Percentile	-0.011**	-0.009*
	(-2.87)	(-2.47)
Document Type		
Cover Letter	0.000	0.000
	(.)	(.)
Research Statement	-0.049***	-0.049***
	(-7.16)	(-7.15)
Teaching Statement	-0.071***	-0.071***
	(-9.12)	(-9.12)
Submitted Document		
Cover Letter	0.009	0.011
	(1.41)	(1.60)
Research Statement	0.027***	0.032***
	(12.62)	(14.74)
Teaching Statement	0.036***	0.031***
	(18.36)	(15.64)
Availability Pool Variables		
Prop. Female		0.074***
		(11.41)
Prop. BHN		0.072***
		(4.79)
Constant	0.131***	0.080***
	(13.86)	(7.84)
Observations	92436	92436
AIC	-63717.982	-64059.099
BIC	-62953.806	-62993.026

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is Model 8 from Table B.2; Model 2 adds the availability pool variables measuring the proportion of females and BHN PhDs in the recruitment field

Appendix C: Models from Chapter 4

C.1 Outcome Variables

The outcome variables in Chapter 4 for average journal impact factor and citation counts had relatively high proportions of missingness due to data collection (26.1% and 17.3%, respectively). Among applicants in the analytic sample, the publication count variable was missing 1.76% of applicants. The missingness for each variable resulted not from issues with the EEFR dataset, but with errors parsing publication data from applicants' CVs and then matching the CV publication data to bibliometric data in Scopus. I created a dummy variable for each outcome that indicated whether an applicant was missing data for that outcome and used binary logistic regression models on this "missing" outcome variable to test if any of the key independent or control variables in the analysis were associated with missing outcome variables. Table C.1 presents the model coefficients for each of these models (one for each missing-outcome binary variable, where 0 indicates non-missing data and 1 indicates missing data). Based on these results, I find that BHN scholars were more likely to have missing publication data than male white and AAPI applicants, but none of the engaged variables were associated with missing publication data. BHN applicants were more likely to be missing journal impact information compared to other groups, and applicants in the Social Sciences were more likely to have missing data compared to applicants in other fields. Finally, AAPI applicants were slightly less likely than other groups to have missing citation data, and applicants with engaged paragraphs in their research statements were slightly less likely to have missing citation data compared to applicants with no engaged language.

Table C.1: Estimated Coefficients from Binary Logistic Regression Models of Missing Data for Outcome Variables: Publications, Impact Factor, Citations

	Missing Publications	Missing Impact Factor	Missing Citations
Recruitment-Level Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	-0.282	-1.271***	0.875**
	(-0.39)	(-4.96)	(2.93)
Engineering	-0.723	-1.607***	-0.544*
	(-1.70)	(-7.30)	(-2.03)
Biological Sci.	0.761*	-2.713***	0.621***
	(2.27)	(-10.15)	(3.33)
Math/CS	0.224	-1.020***	0.438
	(0.38)	(-3.61)	(1.50)
Physical Sci.	-1.412*	-3.632***	-0.017
	(-2.03)	(-7.64)	(-0.05)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	0.004	0.037	0.423*
	(0.01)	(0.17)	(2.37)
2015-16	0.141	-0.226	0.398*
	(0.43)	(-1.16)	(2.33)
2016-17	-0.202	-0.111	0.106
	(-0.53)	(-0.55)	(0.59)
2017-18	0.538	0.108	0.122
	(1.63)	(0.55)	(0.73)
2018-19	0.685*	0.326	0.484**
	(2.13)	(1.73)	(2.85)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	0.287***	-0.291***	0.195***
	(3.47)	(-8.39)	(5.83)
50th-75th	-0.142	-0.300***	-0.124***
	(-1.93)	(-10.27)	(-4.06)
75th-90th	-0.409***	-0.129***	-0.060
	(-4.59)	(-3.62)	(-1.80)
90th-100th	-0.462***	-0.146***	-0.341***
	(-5.31)	(-4.52)	(-10.38)

Applicant-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	-0.536	-0.608**	-0.340*
	(-1.49)	(-3.28)	(-2.12)
Female White	-0.577	-0.520**	-0.269
	(-1.84)	(-3.17)	(-1.87)
Male BHN	-0.055	-0.340	-0.032
	(-0.16)	(-1.72)	(-0.19)
Male AAPI	-0.928*	-0.735***	-0.358*
	(-2.44)	(-4.23)	(-2.39)
Male White	-0.649*	-0.614***	-0.227
	(-2.14)	(-3.83)	(-1.64)
Other/Miss	-0.535	-0.409*	-0.028
	(-1.39)	(-2.05)	(-0.17)
Time Since Degree			
0	0.000	0.000	0.000
	(.)	(.)	(.)
1-2	-0.212*	0.149**	-0.160***
	(-2.32)	(3.22)	(-3.92)
3-5	-0.533***	-0.484***	-0.474***
	(-5.77)	(-11.14)	(-12.05)
6-10	-0.961***	-1.020***	-0.686***
	(-8.61)	(-21.69)	(-15.86)
11+	-1.094***	-1.380***	-0.685***
	(-7.91)	(-22.37)	(-12.84)
Current Job Category			
Postdoc	-0.661***	-1.018***	-0.813***
	(-6.16)	(-22.36)	(-19.17)
Asst. Prof.	-0.385**	-0.236***	-0.329***
	(-2.96)	(-4.75)	(-6.86)
Assoc./Full Prof.	0.216	-0.477***	0.077
	(1.41)	(-7.24)	(1.29)
Visiting Prof.	-0.122	-0.300***	-0.209***
	(-0.89)	(-5.08)	(-3.89)
Research/Teaching	-0.075	-0.549***	-0.318***
Fellow	(-0.57)	(-8.27)	(-5.01)
Grad. Student/PhD	0.000	0.000	0.000
Cand.	(.)	(.)	(.)
Researcher	-0.209	-0.608***	-0.482***
	(-1.82)	(-11.92)	(-10.65)
Lecturer	0.202*	-0.020	0.063
	(2.02)	(-0.39)	(1.38)

Other Job	-0.057	-0.228^{***}	0.042
	(-0.45)	(-4.01)	(0.83)
Institutional Affiliation			
Non-U.S. Institution	0.000	0.000	0.000
	(.)	(.)	(.)
U.S. Institution	-0.197^{**}	-0.035	-0.269^{***}
	(-3.06)	(-1.15)	(-9.99)
Engaged Scholarship Variables			
Any Engaged Language in Document			
Cover Letter	-0.172	0.089	-0.019
	(-1.49)	(1.95)	(-0.42)
Teaching Statement	-0.008	-0.129^{*}	0.009
	(-0.05)	(-2.33)	(0.17)
Research Statement	-0.052	-0.007	-0.243^{***}
	(-0.36)	(-0.14)	(-4.72)
Proportion of Engaged Paragraphs in Document			
Cover Letter	0.295	-0.095	-0.166
	(0.90)	(-0.65)	(-1.13)
Research Statement	-0.422	0.348^{*}	0.310
	(-1.00)	(2.30)	(1.93)
Teaching Statement	-0.187	0.158	-0.009
	(-0.51)	(1.00)	(-0.06)
Submitted Document			
Cover Letter	-0.516^{*}	-0.302^{**}	-0.196^{*}
	(-2.56)	(-2.90)	(-2.00)
Research Statement	-0.308^{***}	-0.187^{***}	-0.177^{***}
	(-4.16)	(-5.93)	(-6.18)
Teaching Statement	-0.231^{**}	-0.456^{***}	-0.207^{***}
	(-3.12)	(-14.70)	(-7.11)
Constant	-1.918^{***}	2.783^{***}	0.259
	(-5.52)	(14.63)	(1.53)
Observations	134679	112109	119431
AIC	22148.682	89774.997	93551.382
BIC	23482.930	91093.927	94878.980

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the non-missing values of these three outcome variables, the distribution of applicants' number of publications and number of citations are both right skewed with a high zero-count for both variables. The distribution of applicants' average journal impact factors is slightly left skewed. Figures C.1-3 present the distributions of each variable.

Figure C.1: Frequency Distribution of Applicants' Publication Count.

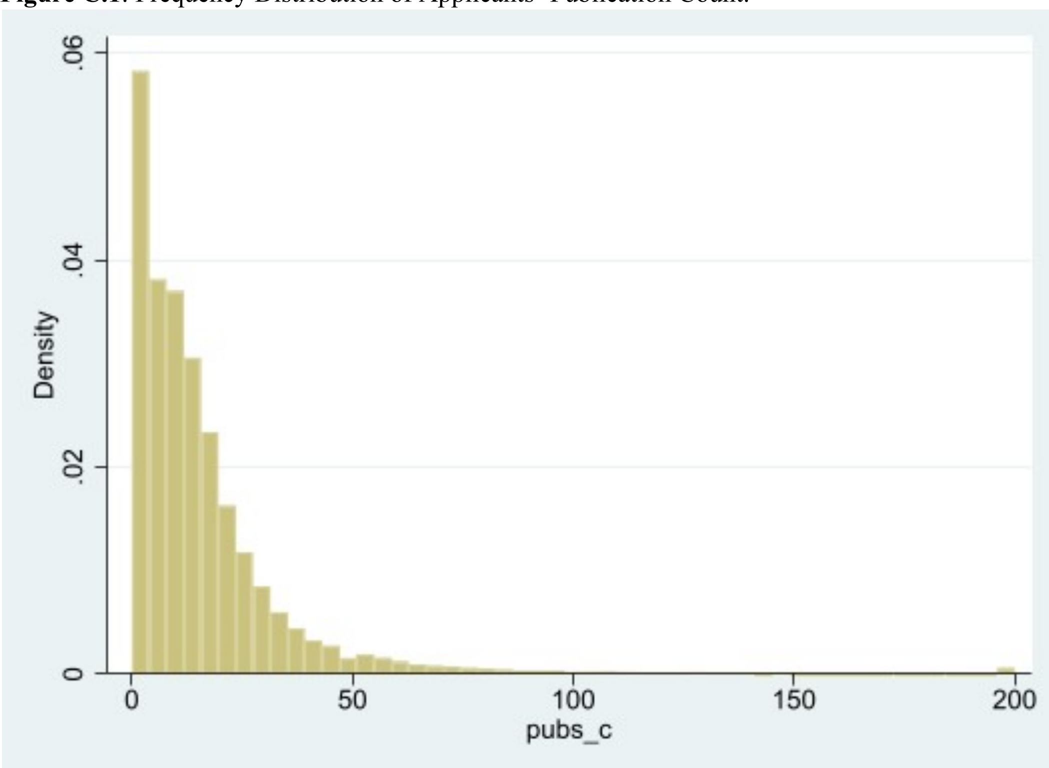


Figure C.2: Frequency Distribution of Applicants' Average Journal Impact Factor

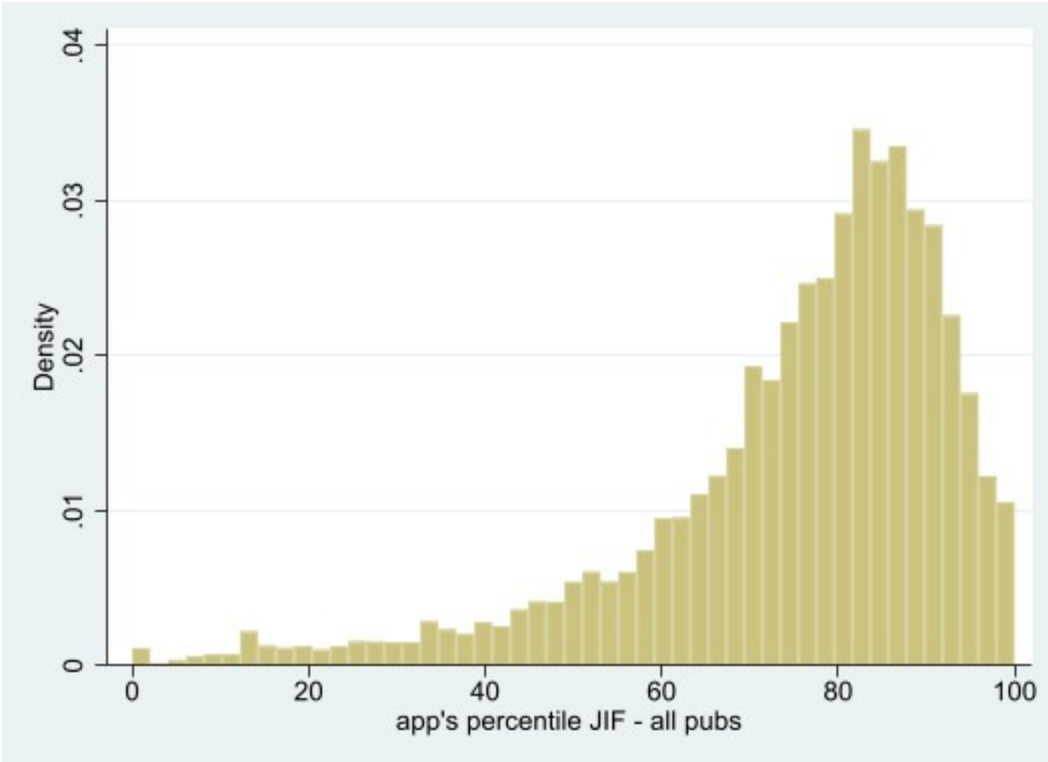
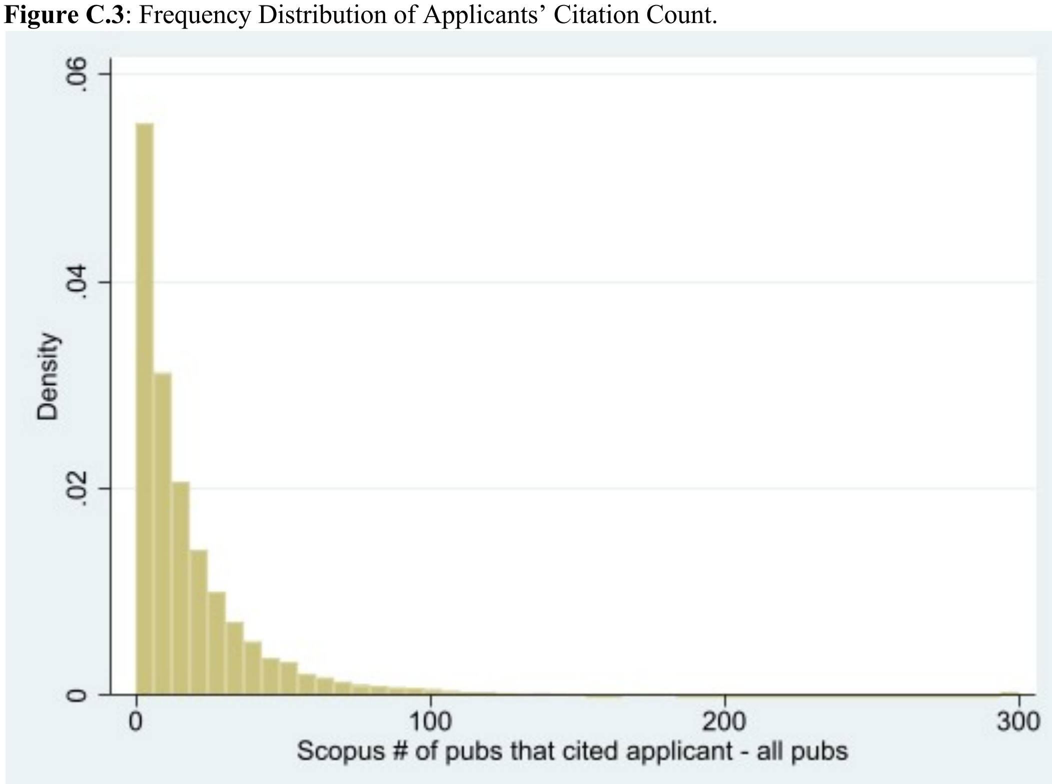


Figure C.3: Frequency Distribution of Applicants' Citation Count.



C.2 Negative Binomial and Zero-Inflated Models

In Chapter Four, Section 4.2.6, Footnote 10, I discuss why I use Poisson regression models to estimate applicants' publication and citation counts. I also ran negative binomial models and zero-inflated Poisson models with the same variables as the Poisson models presented in Chapter 4. Table C.2 presents a comparison of the coefficients estimating applicants' publication counts from the base Poisson model used in Chapter 4, the same variables modeled using a negative binomial model, and the same variables models using a zero-inflated Poisson model. Overall, the key independent variables in each model have the same significance and coefficient sign.

Table C.2: Estimated Coefficients from Poisson, Negative Binomial, and Zero-Inflated Poisson Models of Publication Count

	Poisson	Negative Binomial	Zero-Inflated Poisson
Recruitment-Field Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	0.088	0.242*	0.157
	(0.75)	(2.04)	(1.47)
Engineering	0.351***	0.403***	0.470***
	(3.43)	(3.96)	(4.99)
Biological Sci.	0.155*	0.189**	0.170*
	(2.11)	(2.75)	(2.45)
Math/CS	0.245	0.260	0.193
	(1.63)	(1.65)	(1.32)
Physical Sci.	0.175	0.227*	0.312**
	(1.53)	(2.25)	(3.14)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	-0.038	-0.002	0.008
	(-0.34)	(-0.02)	(0.07)

2015-16	0.110	0.100	0.106
	(0.76)	(1.01)	(0.75)
2016-17	0.097	0.228*	0.177
	(0.84)	(2.24)	(1.56)
2017-18	0.173	0.218*	0.354**
	(1.53)	(2.28)	(3.22)
2018-19	0.220	0.182	0.385***
	(1.88)	(1.88)	(3.37)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	-0.101***	-0.071***	-0.094***
	(-7.62)	(-5.84)	(-7.62)
50th-75th	-0.032**	-0.019	-0.019
	(-2.71)	(-1.76)	(-1.72)
75th-90th	0.020	0.049***	0.024*
	(1.46)	(4.14)	(1.98)
90th-100th	0.030*	0.018	0.035**
	(2.33)	(1.52)	(2.97)
Availability Pool			
Proportion Female	-0.018	0.035	-0.003
	(-0.43)	(0.89)	(-0.08)
Proportion BHN	-1.536***	-1.513***	-1.630***
	(-13.82)	(-16.68)	(-15.61)
Applicant-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	0.141	0.211*	0.193
	(1.33)	(2.48)	(1.84)
Female White	0.148	0.196*	0.204*
	(1.43)	(2.43)	(1.99)
Male BHN	0.087	0.209*	0.150
	(0.78)	(2.25)	(1.37)
Male AAPI	0.237*	0.275***	0.304**
	(2.27)	(3.34)	(2.95)
Male White	0.212*	0.262***	0.282**
	(2.08)	(3.31)	(2.79)
Other/Miss	0.066	0.181	0.105
	(0.58)	(1.96)	(0.95)
Time Since Degree (Years)			

0	0.000	0.000	0.000
	(.)	(.)	(.)
1-2	0.001	-0.033	-0.021
	(0.04)	(-1.82)	(-1.19)
3-5	0.184***	0.138***	0.177***
	(10.88)	(8.09)	(11.14)
6-10	0.383***	0.330***	0.382***
	(21.20)	(18.23)	(22.45)
11+	0.746***	0.721***	0.750***
	(32.32)	(31.70)	(34.60)
Current Job Category			
Postdoc	0.175***	0.177***	0.164***
	(9.95)	(9.91)	(9.80)
Asst. Prof.	0.506***	0.507***	0.526***
	(23.97)	(24.47)	(26.29)
Assoc./Full Prof.	0.884***	0.860***	0.920***
	(34.31)	(33.00)	(38.12)
Visiting Prof.	0.331***	0.278***	0.330***
	(13.58)	(12.08)	(14.38)
Research/Teaching Fellow	0.279***	0.244***	0.298***
	(10.76)	(9.76)	(12.41)
Grad. Student/PhD Cand.	0.000	0.000	0.000
	(.)	(.)	(.)
Researcher	0.238***	0.230***	0.229***
	(13.08)	(12.38)	(13.27)
Lecturer	0.146***	0.086***	0.148***
	(5.45)	(3.76)	(5.80)
Other Job	0.292***	0.248***	0.304***
	(12.46)	(10.83)	(13.70)
Institutional Affiliation			
Non-U.S. Institution	0.000	0.000	0.000
	(.)	(.)	(.)
U.S. Institution	-0.115***	-0.141***	-0.130***
	(-10.43)	(-14.10)	(-12.76)
Avg. Referrer NRC Rank (Percentile)	0.028	0.056**	0.025
	(1.28)	(2.75)	(1.28)
Coauthor Count	0.028***	0.059***	-0.006***
	(15.05)	(28.28)	(-4.80)
Any Grant	0.173***	0.156***	0.068***
	(14.79)	(15.42)	(6.17)
Constant	1.890***	1.775***	2.031***
	(17.69)	(21.29)	(19.25)
/			
lnalpha		-0.048***	
		(-6.19)	

Inflated Model	
Recruitment-Level Variables	
Broad Field	
Social Sci.	0.000 (.)
Ag/NatRes	0.245 (0.80)
Engineering	0.089 (0.39)
Biological Sci.	-0.299 (-1.49)
Math/CS	-0.678 (-1.89)
Physical Sci.	0.187 (0.75)
Academic Year	
2013-14	0.000 (.)
2014-15	0.262 (1.12)
2015-16	-0.212 (-0.86)
2016-17	0.195 (0.87)
2017-18	0.243 (1.14)
2018-19	0.165 (0.75)
Recruitment Department NRC Rank (Percentile)	
Unranked	0.000 (.)
1st-50th	0.025 (0.67)
50th-75th	-0.010 (-0.31)
75th-90th	-0.037 (-1.01)
90th-100th	-0.005 (-0.15)
Availability Pool Variables	

Prop. Female	-0.606***
	(-5.30)
Prop. BHN	-0.021
	(-0.08)
Applicant-Level Variables	
Race/Gender	
Female BHN	0.000
	(.)
Female AAPI	0.215
	(0.96)
Female White	0.184
	(0.96)
Male BHN	0.243
	(1.09)
Male AAPI	0.184
	(0.92)
Male White	0.320
	(1.73)
Other/Miss	0.094
	(0.43)
Time Since Degree (Years)	
0	0.000
	(.)
1-2	-0.109*
	(-2.21)
3-5	-0.089
	(-1.90)
6-10	-0.135**
	(-2.73)
11+	0.048
	(0.81)
Current Job Category	
Postdoc	-0.230***
	(-4.69)
Asst. Prof.	0.292***
	(5.40)
Assoc./Full Prof.	0.421***
	(6.42)
Visiting Prof.	0.047
	(0.72)
Research/Teaching Fellow	0.039
	(0.56)
Grad. Student/PhD Cand.	0.000
	(.)

Researcher			-0.180***
			(-3.43)
Lecturer			-0.008
			(-0.15)
Other Job			0.129*
			(2.26)
Insitutional Affiliation			
Non-U.S. Institution			0.000
			(.)
U.S. Institution			-0.137***
			(-4.60)
Avg. Referrer NRC Rank (Percentile)			-0.049
			(-0.76)
Any Grant			-1.206***
			(-25.31)
Constant			-1.499***
			(-7.51)
Observations	132300	132300	132300
AIC	2262630.874	971526.971	1828904.571
BIC	2263952.906	972858.796	1831529.049

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All models also controlled for interactions between race/gender and field, race/gender and year, and field and year.

Table C.3 presents a comparison of the coefficients estimating applicants' citation counts from the base Poisson model used in Chapter 4, the same variables modeled using a negative binomial model, and the same variables models using a zero-inflated Poisson model. Overall, the key independent variables in each model have the same significance and coefficient sign.

Table C.3: Estimated Coefficients from Poisson, Negative Binomial, and Zero-Inflated Poisson Models of Citation Count

	Poisson	Negative Binomial	Zero-Inflated Poisson
Recruitment-Level Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	0.880^{***}	0.784^{***}	0.865^{***}
	(3.70)	(3.73)	(3.67)
Engineering	0.277	0.216	0.269
	(1.80)	(1.64)	(1.87)
Biological Sci.	0.480^{***}	0.546^{***}	0.418^{***}
	(5.15)	(5.86)	(4.51)
Math/CS	0.114	0.014	0.047
	(0.50)	(0.08)	(0.21)
Physical Sci.	0.107	0.239	0.080
	(0.48)	(1.42)	(0.36)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	-0.225	-0.236	-0.153
	(-1.36)	(-1.36)	(-0.95)
2015-16	-0.528^{***}	-0.565^{***}	-0.462^{***}
	(-4.08)	(-5.06)	(-3.61)
2016-17	-0.363^{*}	-0.300^{*}	-0.314
	(-2.23)	(-2.28)	(-1.94)
2017-18	-0.292^{*}	-0.338^{***}	-0.303^{*}
	(-2.04)	(-3.42)	(-2.14)
2018-19	-0.538^{***}	-0.597^{***}	-0.499^{***}
	(-4.01)	(-5.80)	(-3.75)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	-0.003	0.013	-0.011
	(-0.18)	(0.71)	(-0.63)
50th-75th	0.055^{***}	0.080^{***}	0.045^{**}
	(3.41)	(4.73)	(2.81)
75th-90th	0.070^{***}	0.156^{***}	0.049^{**}
	(3.75)	(7.54)	(2.68)
90th-100th	0.082^{***}	0.109^{***}	0.064^{***}
	(4.84)	(5.82)	(3.81)

Availability Pool			
Prop. Female	1.130***	1.048***	0.984***
	(19.79)	(16.04)	(17.44)
Prop. BHN	-2.644***	-2.734***	-2.311***
	(-15.79)	(-14.73)	(-13.89)
Applicant-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	0.361**	0.298**	0.352**
	(3.21)	(2.96)	(3.17)
Female White	0.346***	0.378***	0.309**
	(3.43)	(4.45)	(3.10)
Male BHN	0.206	0.126	0.249
	(1.56)	(1.14)	(1.93)
Male AAPI	0.302**	0.170	0.297**
	(2.86)	(1.77)	(2.84)
Male White	0.405***	0.405***	0.380***
	(3.97)	(3.87)	(3.76)
Other/Miss	0.274	0.250	0.290*
	(1.84)	(1.71)	(1.98)
Time Since Degree (Years)			
0	0.000	0.000	0.000
	(.)	(.)	(.)
1-2	-0.020	-0.034	-0.045
	(-0.57)	(-0.95)	(-1.31)
3-5	0.184***	0.153***	0.150***
	(5.80)	(4.74)	(4.75)
6-10	0.410***	0.405***	0.371***
	(12.74)	(12.33)	(11.59)
11+	0.652***	0.610***	0.614***
	(17.38)	(16.45)	(16.44)
Current Job Category			
Postdoc	0.214***	0.167***	0.174***
	(6.95)	(5.39)	(5.71)
Asst. Prof.	-0.018	-0.025	-0.056
	(-0.55)	(-0.75)	(-1.71)
Assoc./Full Prof.	-0.064	-0.091*	-0.088*
	(-1.59)	(-2.33)	(-2.18)
Visiting Prof.	-0.022	-0.107**	-0.042
	(-0.55)	(-2.77)	(-1.08)
Research/Teaching Fellow	0.184***	0.137***	0.151***
	(4.26)	(3.31)	(3.52)

Grad. Student/PhD Cand.	0.000	0.000	0.000
	(.)	(.)	(.)
Researcher	0.076*	0.024	0.037
	(2.41)	(0.75)	(1.19)
Lecturer	-0.074	-0.131*	-0.077
	(-1.73)	(-2.57)	(-1.81)
Other Job	0.104**	0.052	0.075*
	(2.82)	(1.40)	(2.06)
Institutional Affiliation			
Non-U.S. Institution	0.000	0.000	0.000
	(.)	(.)	(.)
U.S. Institution	0.150***	0.152***	0.144***
	(9.39)	(10.44)	(9.03)
Avg. Referrer NRC Rank (Percentile)	0.751***	0.766***	0.742***
	(21.80)	(23.01)	(21.59)
Coauthor Count	0.039***	0.082***	0.037***
	(17.84)	(38.04)	(17.59)
Total Publications	0.001***	0.002***	0.001**
	(4.24)	(5.95)	(2.95)
Avg. Journal Impact Factor	0.021***	0.014***	0.021***
	(28.90)	(25.04)	(28.51)
Constant	-0.178	0.259*	0.015
	(-1.52)	(2.51)	(0.12)
/			
lnalpha		-0.209***	
		(-17.47)	
Inflated Model			
Recruitment-Level Variables			
Broad Field			
Social Sci.			0.000
			(.)
Ag/NatRes			-0.026
			(-0.06)
Engineering			0.141
			(0.29)
Biological Sci.			-1.925**
			(-3.15)
Math/CS			-0.962
			(-1.73)
Physical Sci.			0.050
			(0.09)
Academic Year			

2013-14	0.000
	(.)
2014-15	0.239
	(0.72)
2015-16	0.421
	(1.33)
2016-17	0.685*
	(2.21)
2017-18	0.547
	(1.93)
2018-19	1.118***
	(4.08)
Recruitment Department NRC Rank (Percentile)	
Unranked	0.000
	(.)
1st-50th	-0.096
	(-1.51)
50th-75th	-0.196***
	(-3.49)
75th-90th	-0.348***
	(-5.31)
90th-100th	-0.405***
	(-6.91)
Availability Pool	
Prop. Female	-1.867***
	(-9.54)
Prop. BHN	2.195***
	(5.38)
Applicant-Level Variables	
Race/Gender	
Female BHN	0.000
	(.)
Female AAPI	-0.038
	(-0.12)
Female White	-0.594*
	(-2.28)
Male BHN	0.030
	(0.09)
Male AAPI	0.086
	(0.30)
Male White	-0.242
	(-1.00)

Other/Miss	0.154
	(0.48)
Time Since Degree (Years)	
0	0.000
	(.)
1-2	-0.105
	(-1.51)
3-5	-0.417***
	(-6.11)
6-10	-0.674***
	(-8.15)
11+	-0.465***
	(-4.31)
Current Job Category	
Postdoc	-0.567***
	(-7.23)
Asst. Prof.	-0.487***
	(-5.50)
Assoc./Full Prof.	-0.137
	(-1.05)
Visiting Prof.	0.008
	(0.09)
Research/Teaching Fellow	-0.290*
	(-2.54)
Grad. Student/PhD Cand.	0.000
	(.)
Researcher	-0.374***
	(-4.16)
Lecturer	0.081
	(1.02)
Other Job	-0.114
	(-1.19)
Institutional Affiliation	
Non-U.S. Institution	0.000
	(.)
U.S. Institution	-0.237***
	(-3.97)
Avg. Referrer NRC Rank (Percentile)	-0.522***
	(-4.49)
Coauthor Count	-0.681***
	(-19.62)
Total Publications	-0.058***
	(-15.51)

Avg. Journal Impact Factor			-0.004*
			(-2.35)
Constant			1.178***
			(3.87)
Observations	94672	94672	94672
AIC	1954778.931	720210.047	1879847.902
BIC	1956065.243	721505.817	1882420.525

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All models also controlled for interactions between race/gender and field, race/gender and year, and field and year.

C.3 Model Coefficients for Poisson Models

Table C.4: Estimated Coefficients from Poisson Regression Models of Applicants Total Number of Publications

	Model 1	Model 2	Model 3
Recruitment-Level Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	0.088	0.073	0.037
	(0.75)	(0.62)	(0.31)
Engineering	0.351***	0.332**	0.286**
	(3.43)	(3.23)	(2.62)
Biological Sci.	0.155*	0.153*	0.068
	(2.11)	(2.09)	(0.85)
Math/CS	0.245	0.225	0.139
	(1.63)	(1.53)	(1.00)
Physical Sci.	0.175	0.197	0.115
	(1.53)	(1.71)	(0.96)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	-0.038	-0.038	-0.042
	(-0.34)	(-0.34)	(-0.37)
2015-16	0.110	0.098	0.088
	(0.76)	(0.68)	(0.60)
2016-17	0.097	0.071	0.069

	(0.84)	(0.61)	(0.59)
2017-18	0.173	0.135	0.110
	(1.53)	(1.20)	(0.96)
2018-19	0.220	0.161	0.131
	(1.88)	(1.38)	(1.16)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	-0.101***	-0.101***	-0.100***
	(-7.62)	(-7.66)	(-7.49)
50th-75th	-0.032**	-0.029*	-0.031**
	(-2.71)	(-2.46)	(-2.59)
75th-90th	0.020	0.014	0.013
	(1.46)	(1.04)	(0.94)
90th-100th	0.030*	0.029*	0.030*
	(2.33)	(2.26)	(2.32)
Availability Pool Variables			
Prop. Female	-0.018	-0.074	-0.058
	(-0.43)	(-1.71)	(-1.34)
Prop. BHN	-1.536***	-1.529***	-1.508***
	(-13.82)	(-13.52)	(-13.33)
Applicant-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	0.141	0.144	0.115
	(1.33)	(1.35)	(1.01)
Female White	0.148	0.144	0.096
	(1.43)	(1.38)	(0.86)
Male BHN	0.087	0.096	0.044
	(0.78)	(0.85)	(0.37)
Male AAPI	0.237*	0.258*	0.206
	(2.27)	(2.46)	(1.83)
Male White	0.212*	0.227*	0.177
	(2.08)	(2.21)	(1.61)
Other/Miss	0.066	0.078	0.041
	(0.58)	(0.69)	(0.34)
Time Since Degree (Years)			
0	0.000	0.000	0.000
	(.)	(.)	(.)

1-2	0.001	-0.003	-0.001
	(0.04)	(-0.15)	(-0.07)
3-5	0.184***	0.181***	0.182***
	(10.88)	(10.72)	(10.79)
6-10	0.383***	0.383***	0.386***
	(21.20)	(21.23)	(21.36)
11+	0.746***	0.748***	0.751***
	(32.32)	(32.50)	(32.61)
Current Job Category			
Postdoc	0.175***	0.174***	0.177***
	(9.95)	(9.92)	(10.09)
Asst. Prof.	0.506***	0.502***	0.505***
	(23.97)	(23.82)	(23.96)
Assoc./Full Prof.	0.884***	0.880***	0.882***
	(34.31)	(34.18)	(34.26)
Visiting Prof.	0.331***	0.327***	0.331***
	(13.58)	(13.44)	(13.59)
Research/Teaching Fellow	0.279***	0.277***	0.281***
	(10.76)	(10.69)	(10.83)
Grad. Student/PhD Cand.	0.000	0.000	0.000
	(.)	(.)	(.)
Researcher	0.238***	0.235***	0.238***
	(13.08)	(12.94)	(13.04)
Lecturer	0.146***	0.141***	0.145***
	(5.45)	(5.27)	(5.40)
Other Job	0.292***	0.290***	0.291***
	(12.46)	(12.41)	(12.46)
Institutional Affiliation			
Non-U.S. Institution	0.000	0.000	0.000
	(.)	(.)	(.)
U.S. Institution	-0.115***	-0.118***	-0.117***
	(-10.43)	(-10.67)	(-10.69)
Avg. Referrer NRC Rank (Percentile)	0.028	0.034	0.036
	(1.28)	(1.57)	(1.65)
Coauthor Count	0.028***	0.028***	0.028***
	(15.05)	(15.09)	(15.13)
Any Grant	0.173***	0.167***	0.166***
	(14.79)	(14.44)	(14.43)
Engaged Scholarship Variables			
Any Engaged Language in			

Document			
Cover Letter		0.033	0.006
		(1.51)	(0.05)
Research Statement		0.117***	-0.030
		(5.08)	(-0.28)
Proportion of Engaged Paragraphs in Document			
Cover Letter		0.049	-0.085
		(0.60)	(-0.27)
Research Statement		0.007	-0.237
		(0.09)	(-0.63)
Submitted Document			
Cover Letter		0.052	0.054
		(1.06)	(1.09)
Research Statement		0.084***	0.092***
		(6.49)	(6.99)
Constant	1.890***	1.784***	1.838***
	(17.69)	(15.32)	(14.93)
Observations	132300	132300	132300
AIC	2262630.874	2257904.976	2254846.828
BIC	2263952.906	2259285.765	2256854.357

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is the base model described in Chapter 4 with all control variables; Model 2 adds the engaged scholarship variables; Model 3 adds an interaction term between the engaged scholarship variables and race/gender.

Table C.5: Estimated Coefficients from Poisson Regression Models of Applicants Total Number of Citations

	Model 1	Model 2	Model 3
Recruitment-Level Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	3.152	2.643	2.019

	(1.21)	(1.01)	(0.76)
Engineering	4.929*	4.401*	4.061
	(2.35)	(2.09)	(1.88)
Biological Sci.	5.991***	5.291***	5.338***
	(4.03)	(3.57)	(3.41)
Math/CS	-0.441	-0.917	-2.203
	(-0.15)	(-0.30)	(-0.75)
Physical Sci.	10.614***	10.097***	9.833***
	(5.99)	(5.70)	(5.29)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	1.703	1.944	1.814
	(0.73)	(0.84)	(0.76)
2015-16	-3.425	-3.330	-3.710
	(-1.43)	(-1.40)	(-1.56)
2016-17	0.742	0.895	0.725
	(0.35)	(0.43)	(0.35)
2017-18	0.431	0.452	0.504
	(0.21)	(0.22)	(0.25)
2018-19	-1.521	-1.164	-1.505
	(-0.75)	(-0.57)	(-0.74)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	0.291	0.208	0.285
	(1.12)	(0.80)	(1.09)
50th-75th	0.746***	0.688**	0.723**
	(3.32)	(3.06)	(3.22)
75th-90th	-1.394***	-1.543***	-1.502***
	(-5.48)	(-6.06)	(-5.89)
90th-100th	0.079	0.016	0.068
	(0.33)	(0.07)	(0.28)
Availability Pool			
Prop. Female	10.999***	11.205***	11.214***
	(12.99)	(13.35)	(13.37)
Prop. BHN	-5.496*	-3.849	-3.579
	(-2.12)	(-1.49)	(-1.38)
Application-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	-0.075	-0.384	0.338

	(-0.04)	(-0.18)	(0.16)
Female White	0.683	0.414	0.408
	(0.35)	(0.21)	(0.20)
Male BHN	2.409	2.247	2.001
	(1.07)	(1.00)	(0.85)
Male AAPI	1.790	1.265	1.224
	(0.89)	(0.63)	(0.59)
Male White	1.320	0.827	0.645
	(0.69)	(0.43)	(0.33)
Other/Miss	2.617	2.368	2.322
	(1.18)	(1.07)	(1.02)
Time Since Degree (Years)			
0	0.000	0.000	0.000
	(.)	(.)	(.)
1-2	-0.506	-0.486	-0.466
	(-0.80)	(-0.77)	(-0.74)
3-5	2.511^{***}	2.524^{***}	2.545^{***}
	(4.17)	(4.19)	(4.23)
6-10	3.194^{***}	3.162^{***}	3.178^{***}
	(5.27)	(5.23)	(5.25)
11+	2.484^{***}	2.454^{***}	2.475^{***}
	(3.88)	(3.83)	(3.86)
Current Job Category			
Postdoc	3.324^{***}	3.295^{***}	3.297^{***}
	(5.64)	(5.59)	(5.60)
Asst. Prof.	-1.289^{*}	-1.237	-1.235
	(-2.04)	(-1.96)	(-1.95)
Assoc./Full Prof.	-3.903^{***}	-3.816^{***}	-3.825^{***}
	(-5.54)	(-5.42)	(-5.43)
Visiting Prof.	-1.240	-1.215	-1.205
	(-1.82)	(-1.78)	(-1.77)
Research/Teaching	1.961^{**}	1.965^{**}	1.963^{**}
Fellow	(2.90)	(2.90)	(2.90)
Grad. Student/PhD	0.000	0.000	0.000
Cand.	(.)	(.)	(.)
Researcher	1.091	1.089	1.072
	(1.79)	(1.79)	(1.76)
Lecturer	-0.294	-0.239	-0.255
	(-0.41)	(-0.34)	(-0.36)
Other Job	-1.603^{*}	-1.603^{*}	-1.598^{*}
	(-2.36)	(-2.36)	(-2.36)
Institutional Affiliation			
Non-U.S.	0.000	0.000	0.000
Institution	(.)	(.)	(.)

U.S. Institution	3.082***	3.118***	3.112***
	(15.20)	(15.38)	(15.39)
Avg. Referrer NRC Rank (Percentile)	8.762***	8.686***	8.665***
	(20.38)	(20.17)	(20.16)
Journal Publications	0.023***	0.024***	0.024***
	(4.85)	(4.94)	(5.02)
Coauthor Count	0.598***	0.596***	0.595***
	(21.37)	(21.34)	(21.32)
Engaged Scholarship Variables			
Any Engaged Paragraphs in Document			
Cover Letter		-0.157	-2.143
		(-0.36)	(-0.95)
Research Statement		-0.422	0.389
		(-0.93)	(0.15)
Proportion of Engaged Paragraphs in Document			
Cover Letter		-4.210**	-1.083
		(-2.99)	(-0.16)
Research Statement		-3.340	-3.922
		(-1.94)	(-0.43)
Submitted Document			
Cover Letter		0.726	0.714
		(0.71)	(0.70)
Research Statement		0.657*	0.731**
		(2.44)	(2.70)
Constant	53.419***	52.744***	52.809***
	(25.85)	(23.06)	(22.55)
Observations	82687	82687	82687
AIC	698846.396	698759.213	698718.736
BIC	700095.654	700064.408	700620.591

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is the base model described in Chapter 4 with all control variables; Model 2 adds the engaged scholarship variables; Model 3 adds an interaction term between the engaged scholarship variables and race/gender.

Table C.6: Estimated Coefficients from Poisson Regression Models of Applicants Total Number of Citations

	Model 1	Model 2	Model 3
Recruitment-Level Variables			
Broad Field			
Social Sci.	0.000	0.000	0.000
	(.)	(.)	(.)
Ag/NatRes	0.880***	0.832***	0.837***
	(3.70)	(3.48)	(3.50)
Engineering	0.277	0.239	0.247
	(1.80)	(1.57)	(1.63)
Biological Sci.	0.480***	0.432***	0.433***
	(5.15)	(4.64)	(4.30)
Math/CS	0.114	0.082	0.055
	(0.50)	(0.36)	(0.24)
Physical Sci.	0.107	0.090	0.025
	(0.48)	(0.40)	(0.11)
Academic Year			
2013-14	0.000	0.000	0.000
	(.)	(.)	(.)
2014-15	-0.225	-0.216	-0.216
	(-1.36)	(-1.31)	(-1.30)
2015-16	-0.528***	-0.527***	-0.461***
	(-4.08)	(-4.08)	(-3.51)
2016-17	-0.363*	-0.362*	-0.340*
	(-2.23)	(-2.22)	(-2.21)
2017-18	-0.292*	-0.296*	-0.248
	(-2.04)	(-2.07)	(-1.71)
2018-19	-0.538***	-0.533***	-0.514***
	(-4.01)	(-4.00)	(-3.74)
Recruitment Department NRC Rank (Percentile)			
Unranked	0.000	0.000	0.000
	(.)	(.)	(.)
1st-50th	-0.003	-0.007	-0.005
	(-0.18)	(-0.38)	(-0.30)
50th-75th	0.055***	0.052**	0.053***
	(3.41)	(3.24)	(3.33)
75th-90th	0.070***	0.058**	0.061**
	(3.75)	(3.07)	(3.23)
90th-100th	0.082***	0.078***	0.079***
	(4.84)	(4.64)	(4.68)

Availability Pool			
Prop. Female	1.130***	1.139***	1.136***
	(19.79)	(19.96)	(19.91)
Prop. BHN	-2.644***	-2.543***	-2.512***
	(-15.79)	(-15.25)	(-15.00)
Application-Level Variables			
Race/Gender			
Female BHN	0.000	0.000	0.000
	(.)	(.)	(.)
Female AAPI	0.361**	0.340**	0.334**
	(3.21)	(3.02)	(2.62)
Female White	0.346***	0.326**	0.326**
	(3.43)	(3.22)	(2.80)
Male BHN	0.206	0.195	0.187
	(1.56)	(1.48)	(1.28)
Male AAPI	0.302**	0.271*	0.269*
	(2.86)	(2.56)	(2.26)
Male White	0.405***	0.373***	0.368**
	(3.97)	(3.66)	(3.17)
Other/Miss	0.274	0.255	0.282
	(1.84)	(1.71)	(1.75)
Time Since Degree (Year)			
0	0.000	0.000	0.000
	(.)	(.)	(.)
1-2	-0.020	-0.018	-0.019
	(-0.57)	(-0.53)	(-0.55)
3-5	0.184***	0.185***	0.185***
	(5.80)	(5.82)	(5.83)
6-10	0.410***	0.408***	0.407***
	(12.74)	(12.66)	(12.65)
11+	0.652***	0.650***	0.650***
	(17.38)	(17.32)	(17.33)
Current Job Category			
Postdoc	0.214***	0.211***	0.212***
	(6.95)	(6.84)	(6.88)
Asst. Prof.	-0.018	-0.015	-0.012
	(-0.55)	(-0.45)	(-0.37)
Assoc./Full Prof.	-0.064	-0.059	-0.059
	(-1.59)	(-1.45)	(-1.44)
Visiting Prof.	-0.022	-0.021	-0.018
	(-0.55)	(-0.52)	(-0.46)
Research/Teaching Fellow	0.184***	0.183***	0.182***
	(4.26)	(4.22)	(4.23)

Grad. Student/PhD Cand.	0.000	0.000	0.000
	(.)	(.)	(.)
Researcher	0.076^{*}	0.074^{*}	0.075^{*}
	(2.41)	(2.35)	(2.38)
Lecturer	-0.074	-0.071	-0.070
	(-1.73)	(-1.66)	(-1.65)
Other Job	0.104^{**}	0.104^{**}	0.105^{**}
	(2.82)	(2.82)	(2.85)
Institutional Affiliation			
Non-U.S. Institution	0.000	0.000	0.000
	(.)	(.)	(.)
U.S. Institution	0.150^{***}	0.152^{***}	0.152^{***}
	(9.39)	(9.49)	(9.48)
Avg. Referrer NRC Rank (Percentile)	0.751^{***}	0.747^{***}	0.745^{***}
	(21.80)	(21.68)	(21.64)
Coauthor Count	0.039^{***}	0.039^{***}	0.039^{***}
	(17.84)	(17.74)	(17.81)
Total Publications	0.001^{***}	0.001^{***}	0.001^{***}
	(4.24)	(4.36)	(4.31)
Avg. Journal Impact Factor	0.021^{***}	0.021^{***}	0.021^{***}
	(28.90)	(28.79)	(28.79)
Engaged Scholarship Variables			
Any Engaged Language in Document			
Cover Letter		-0.072^{**}	0.118
		(-2.72)	(0.59)
Research Statement		-0.013	-0.387^{**}
		(-0.48)	(-2.67)
Proportion of Engaged Paragraphs in Document			
Cover Letter		-0.016	0.070
		(-0.22)	(0.18)
Research Statement		-0.216^{*}	0.172
		(-2.22)	(0.39)
Submitted Document			
Cover Letter		0.167^{***}	0.169^{***}
		(3.66)	(3.70)

Research Statement		0.072^{***}	0.078^{***}
		(3.83)	(4.05)
Constant	-0.178	-0.356^{**}	-0.368^{**}
	(-1.52)	(-2.81)	(-2.66)
Observations	94672	94672	94672
AIC	1954778.931	1952474.884	1948241.982
BIC	1956065.243	1953817.944	1950190.365

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 is the base model described in Chapter 4 with all control variables; Model 2 adds the engaged scholarship variables; Model 3 adds an interaction term between the engaged scholarship variables and race/gender.

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