Accumulated Gender Discrimination in the Legal Field: Evidence from American Lawyers

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Submitted in Partial Fulfillment
of the
Prerequisite for Honors
in Economics
under the advisement of Professor Kyung Park

April 2022

Abstract

This paper explores potential explanations for the gap in performance between male and female associates in the legal field using the After the JD (AJD) dataset. I extend on the traditional Blinder-Oaxaca decomposition by considering a "second-stage decomposition" that accounts for discrimination at multiple stages, specifically from hiring to work assignment and from work assignment to performance assessment. My findings show that the vast majority of the gender gap in billed hours and number of clients remains unexplained by task assignment, mentorship, and pre-work characteristics, suggesting that traditionally important traits and activities have less impact than expected on the performance differential. However, I find that parental education, equity partner aspirations, and marital status are able to explain around half the gap in performance assessment, indicating the importance of social capital and determination in improving one's performance. Given the significance of performance in determining the salary and partnership opportunities of associates, this paper is important in addressing how we can close gender gaps in career outcomes in the context of a law firm.

Acknowledgements

There are no words to express my gratitude for my major and thesis advisor, Professor Kyung Park. His support for me over the past few years has positively impacted me in countless ways, and working with him on this thesis has been one of the highlights of my college experience. Thank you for helping me grow, both as an economist and as an individual.

I would like to extend my gratitude to all my friends in the Economics Research Seminar: Anushka Kelshikar, Melissa Carleton, Tiffany Chu, and Zahra Thabet. Through laughter and tears, we have finally made it. I am also incredibly grateful for everything Professor Akila Weerapana has done in his capacity as the instructor of the Economics Research Seminar, for assisting me through the entire process and pushing me to produce my best work possible.

To my previous professors who have been vital in cultivating my love for economics and statistics: Professor Casey Rothschild, Professor Cassandra Pattanayak, Professor Kartini Shastry, Professor Olga Shurchkov, and Professor Wendy Wang, thank you for always being kind and patient with me and for providing me with the necessary guidance to even consider writing a thesis in the first place.

Of course, this list would not be complete without a word of appreciation for my loved ones. Jason, you are my rock. Andy, you inspire me every day. And to my parents, thank you for being the best role models I could have asked for and for teaching me almost everything I know.

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1 Introduction

A few weeks ago, Judge Ketanji Brown Jackson was confirmed as a Supreme Court Justice. She is one of only five women, and the first African-American woman, to have served as a Justice at the highest level of the judiciary branch in the United States. In contrast, there have been 108 White Male Justices of the Supreme Court. Despite women making up half of the college-educated workforce, gender gaps in career outcomes, especially among high-skilled workers, still exist. In particular, even though Justice Jackson's case is a rarefied example of progress, significant gender disparities still exist in the legal field.

Many theories, complete with empirical evidence, have been put forth to explain these disparities; for instance, some papers highlight the significance of the child penalty or workplace flexibility in affecting female career outcomes (examples include: Budig and England (2001), Weeden (2005)). However, there are fewer papers that discuss the effect of accumulated discrimination on women in the workplace. In particular, researchers have failed to uncover how discrimination at each stage of a firm, from hiring to eventual promotion, can compound and affect outcomes at subsequent stages. This is crucial, as an isolated examination of discrimination at a particular stage may lead to incorrect conclusions about whether there are valid explanations for the differential and result in inaccurate policy recommendations. For instance, one may find that differences in promotion for female lawyers are due to differences in the number of clients they bring into the firm but fail to uncover why clients may be more likely to go with a male lawyer in the first place. Another example could be that women earn less than men because they go into particular sub-fields of law without asking what led to those decisions at an earlier career stage.

In my paper, I will focus on the gender gap in task assignment and performance, using a dataset that follows a large group of young lawyers over their career. Gender differences in the legal field are pronounced at each stage of a lawyer's career, from initial hiring to workplace environment to career outcomes. In particular, there are significant differences in performance between male and female lawyers, which becomes closely linked with differences in promotion outcomes (Dinovitzer

et al. (2009), Ziewacz (1996), Azmat et al. (2020)). A number of explanations have been forwarded as to why these differences may arise, ranging from differences in long-term career aspirations to differences in supervisors' treatment of female associates. My work will focus specifically on whether accumulated differences in work delegation and mentorship can explain the performance differential.

Performance is important as it is often linked directly with salary, promotion, and hiring decisions, particularly in highly skilled professions (Lazear and Shaw (2007), Lemieux et al. (2009)). The earnings gap between male and female lawyers has continued to persist over time at both associate and partnership levels. Being promoted to partner not only increases the income of lawyers, but also allows them to make more executive decisions within the law firm and gain more social connections outside of the workplace. Female executives may be more likely to enact policies to counter sexism and may be less likely to act in discriminatory ways when making hiring and promotion decisions. Having more connections also allows them to act as valuable mentors to more women entering highly skilled jobs. While the gender gap in promotion rates is large, accounting for performance assessment causes the promotion gap to no longer be significant, which points to the importance in understanding what factors contribute to the gaps in female performance (Azmat et al. (2020)).

The dataset I use covers a wide array of characteristics of each lawyer and documents assignment and performance information that are often not publicly observable. I will use two measures of performance: annual billed hours and number of new clients brought into the firm. Heinz et al. (2005) and Cotterman (2004) find that these measures are significant determinants of compensation and partnership. Lawyers are often paid based on the number of billable hours they accumulate annually. In addition, being able to bring in clients that provide a large sum of revenue for the firm is a marker of success for both associates and partners, so this information is often heavily used when making partnership decisions.

I start by exploring how the gap in task assignment and mentorship can be explained by

differences in pre-work characteristics, and then move onto analyzing the performance differential. In my paper, task assignment includes work assigned by superiors, such as drafting transactional documents, while mentorship includes social interactions with supervisors, such as engaging in recreational activity with partners. Pre-work characteristics, which I will also refer to as "on-the-CV characteristics", include academic records, extracurricular activity participation, and other characteristics job applicants are likely to list on their resumes. Similar to the motivation behind Bertrand and Mullainathan (2004)'s paper, I am interested in understanding how much of the difference in task assignment and mentorship is truly due to differences in qualifications versus differences in treatment due to arbitrary characteristics (in this case, gender). I hypothesize that differences in pre-work characteristics should be able to explain a sizable portion of the gap in task assignment. This aligns with existing information about law firms, as firms heavily emphasis the importance of associates' academic background and work experience.

Additionally, I hypothesize that a large portion of the differences in performance are attributable to differences to task assignment and pre-work characteristics. Mentorship and task allocation are both extremely important in the context of a law firm. Complex tasks allow associates to gain important skills necessary to transition into more executive roles, while at the same time allowing them to demonstrate their competence across a wide range of abilities (Chanen (2006), Jenkins (2001)). On the other hand, mentorship is important for transmitting knowledge and providing visibility and sponsorship, thereby increasing opportunities for promotion (Thomas et al. (1998), Thomas (2001)). Partner mentors can also provide emotional support, technical help, and other forms of advice and guidance for associates, especially if they are feeling unfairly treated in the workplace (Wilkins and Gulati (1996)).

I first assess which pre-work characteristics are important in determining task assignment. Then I use a Blinder-Oaxaca decomposition to uncover how much of the gap in task assignment can be explained by these observable characteristics. The results I obtain contradict my hypothesis: I find that the majority of the difference in task assignment cannot be attributed to differences in

initial worker qualifications upon arrival at the firm. Nevertheless, I cannot fully attribute the remainder of the gap to discrimination; there are other possible factors that could be affecting task assignment, such as differences in the "personalities" or motivation levels of associates.

Next, I turn to the performance gap. I first run a simple Blinder-Oaxaca decomposition to decompose the gender gap in performance into the difference in task assignment and the difference in returns to tasks. This first-stage decomposition shows that differences in task assignment can explain almost none of the gap in performance for both billed hours and number of clients. Since this decomposition can be integrated with the previous analysis that decomposed the differences in tasks into differences in pre-work characteristics and differences in the returns to pre-work characteristics, I then use a secondary Blinder-Oaxaca decomposition to break down the gender difference in performance assessment into three sections: one part attributable to the difference in pre-work characteristics, another due to differences in the returns of pre-work characteristics on tasks, and a third due to the differences in the returns of tasks on performance. This allows me to understand not only how much of the difference in performance assessment is due to task assignment, but also how much of the difference is due to earlier differences in worker qualifications.

Again, the results I find contradict my initial hypothesis: almost none of the gap can be explained by differences in pre-work characteristics or returns to pre-work characteristics. While nearly the entire performance differential is due to differences in the returns to tasks on performance, the difference in intercepts between the two groups is driving almost all of the difference. Significant differences in intercepts mean that the predictors used in the model cannot explain the difference in performance; this indicates either that there are other non-task related factors causing the performance gap or, if the model includes all possible drivers of performance, that there is discrimination against the group of workers, in this case female law-firm associates, with lower intercept values.

Given the significance of the intercept, I then attempt to find other characteristics that can explain a larger share of the difference in performance assessment by running Blinder-Oaxaca

decompositions with additional variables that I refer to as "off-the-CV characteristics." These refer to traits that associates hold that are not explicitly stated on resumes or cover letters, but may have an effect on career outcomes. Over time, it is possible that partners or clients are able to gain access to this information from repeated contact and deeper connections. I test a variety of factors, including the number of children, aspirational goals, sexual orientation, marital status, and other similar characteristics. Since tasks and "on-the-CV characteristics" do not seem to be able to explain the gap, it is possible that these factors may have an effect. Interestingly, I find that the education status of associates' parents and associates' aspirations to become equity partner can explain around half of the gender gap in billed hours, while the education status of associates' fathers and associates' marital status can also explain around half of the gender gap in the number of clients. These results are unexpected, but they seem to indicate there are other non-work related reasons as to why the gaps in performance may exist.

The results from this paper are important for a variety of reasons. First and foremost, despite a comprehensive dataset that allows me to take into account almost every aspect of an associate's resume, more than 70% of the gap in task assignment is left unexplained. This indicates there may be external and unobserved factors at play causing men to receive better assignments than women. Additionally, none of the gaps in performance can be attributed to differences in task assignment. This leads to two disheartening conclusions. First, improving the qualifications of female lawyers before entering the law firm so that they match the qualifications of male lawyers will not result in male and female lawyers receiving equal tasks; men will still get better tasks. Second, even if there was a mechanism by which women are given better tasks than they are currently receiving, there is no evidence that the performance gap (and hence the promotion gap) will improve.

While differences in "on-the-CV characteristics" do not seem to be able to explain differences in performance, decomposing the performance gap with respect to "off-the-CV characteristics" gives more promising results, suggesting avenues for future exploration. Specifically, differences in aspirations and parents' education levels seem to explain a larger portion of the performance gap,

especially with regards to billed hours. Differences in parental education levels often have to do with one's socioeconomic status and childhood opportunities, while aspirational differences may exist for numerous reasons. Female associates may be discouraged from becoming equity partners early on in the employment process due to instances of discrimination; on the other hand, they may not want to become partner because it is a substantial time commitment that takes away from time with their family and children. It is necessary to do further research in order to understand what truly drives these differences.

2 Literature Review

2.1 Accumulated Discrimination

Most of the literature tends to characterize discrimination as a singular episode with an independent cause, rather than viewing it as a process that gradually changes and potentially accumulates over time. However, recent papers have adopted a more holistic conception of discrimination across domains such as labor markets, justice systems, and educational institutions. Skaggs and Bridges (2013) provide evidence of how disparate treatment at one stage of the employment process influences outcomes and opportunities at other stages, resulting in discrepancies in employment opportunities, salary levels, and promotion probabilities between races and genders. Tomaskovic-Devey et al. (2005) show that wage advantages for white men accumulate over their career trajectories; they suggest that initial differences in education and cognitive skill are not the largest factors behind the wage gap; rather, the gap continues to widen significantly due to choices and decisions made by employers and coworkers.

As the number of stages in which external factors may influence workers' opportunities increases, chances of disparate treatment accumulate and compound. Korver-Glenn (2018) highlights how this could happen in the housing market, wherein at each of the five steps (establishing and maintaining relationships, marketing a house for sale, evaluating mortgage loan applications, assessing home value, and closing the transaction), there is the potential for exclusion or recycling of gender stereotypes. In the area of hiring, Pager et al. (2009) finds compounding inequality across three stages of hiring: initial point of contact, assessment of qualifications, and eventual job placement. At each stage, there is the possibility of either exclusion or inclusion with less desirable outcomes (e.g. female workers receiving lower-paying jobs than their male counterparts when they did receive job offers). Jones et al. (2017) have also used a cyclical model of discrimination, in which changes to one's occupational role or relationships with other workers in an organization can result in the accumulation or reduction of discrimination over time. All the papers described above are

sociology papers that theorize on the effects of accumulated discrimination; none of them include empirical work. To my knowledge, the only paper in the field of economics that discusses the effect of accumulated discrimination (or "systemic discrimination," as they refer to it), is Bohren et al. (2022), which illustrates the effect of discrimination over various stages through the use of two experiments. Thus, my paper will be the first to consider the effects of accumulated discrimination in a particular field through a natural experiment.

Accumulated discrimination can lead even prima facie neutral policies to unintentionally contribute towards discrimination. For instance, deciding college admissions based purely on standardized testing scores without taking into account race or class information may still result in racial minorities or socioeconomically disadvantaged individuals being discriminated against. These people may not have had access to the same support when taking standardized exams due to differences in geography, family background, and academic resources, resulting in equally intelligent and motivated students who differ only by their race and class having vastly different rates of acceptance. Understanding how different systems and how different stages within a system interact with each other is important for identifying all the channels through which disparities may exist between groups.

In my paper, I consider the accumulation of gender discrimination that could occur at two primary stages: from hiring to work assignment and from work assignment to performance assessment. Discrimination in work assignment can be defined as the disproportionate allocation of specific tasks to a select group of employees; in our case, it may look like assigning more desirable or challenging tasks to male compared to female associates (Chan and Anteby (2016)). Only recently have economists turned their attention to work and task assignments within firms; previously, attention was focused on group-level differences in other economic outcomes, such as wages and occupations.

2.2 Disparities in Task Assignment

There exists literature on task assignment in non-legal fields. Chan and Anteby (2016) find that female airport security-screening workers were assigned less valuable tasks than their male counterparts even after controlling for individual and firm specific characteristics; they argue this task segregation contributes to within-job inequality in job satisfaction. Female teachers are often assigned more teaching-related work, while male teachers are assigned more managerial work that allow them to demonstrate skills necessary for promotion opportunities (Williams (1992)). Female leaders, compared to their male counterparts, are also more likely to be given undervalued and time-consuming activities such as photocopying (Williams and Dempsey (2014)). Even controlling for ambition, self evaluations, and socio-demographic variables, women in middle job levels are still assigned fewer challenging experiences in their careers compared to male workers in similar positions (De Pater et al. (2010)). Female managers often report comparable amounts of work compared to their male counterparts; however, they also report significantly less challenging types of work, especially with regards to their early developmental experiences (King et al. (2012)).

Differences in preferences cannot explain this gap, as men and women are equally likely to express their interest for more difficult experiences. De Pater et al. (2010) suggest supervisors assign more challenging and rewarding tasks to same-sex subordinates; given the male-dominated nature of most white-collar workplaces, this indicates the existence of a task differential of the basis of gender that will continue to perpetuate, given the importance of tasks in determining promotion decisions.

Other papers have also examined the effect of pre-market characteristics on on-the-job training. Knoke and Ishio (1998) find that young female employee's rate of entry into company training programs at the start of their job is significantly lower than the rate of entry for young male workers, and controlling for various socioeconomic, occupational, and human capital variables further widens the gap substantially. This indicates that differences in worker qualifications cannot explain the gender gap in job training. Grönlund (2012) also finds a considerable training gap between men and

women working in the same occupation, which cannot be explained by human capital investments, motherhood, or part-time work. Barron et al. (1993) reports that while initial training intensity is the same for both female and male workers entering firms, the duration of training for male workers is twice as long as female workers; they additionally find lower market value for women's prior labor market experiences when deciding the position and type of training to provide for new workers. While on-the-job training is not necessarily the same as task assignments, they share similar characteristics. For instance, supervisors are often the ones who dictate who receives what types of on-the-job training or assignments. Both are also able to increase a worker's human capital by allowing them to understand how to do certain types of work and gain specialized skills for the job.

2.3 Disparities in Performance

Moving onto the relationship between work assignment and performance assessment, there do not seem to be many data-driven papers that attempt to uncover the relationship between these variables. Ilgen and Youtz (1984) theorize about the relationship between mentorship and performance and predict that minority employees may receive fewer opportunities to form connections with mentors and enhance their skills, which may depress their ability, motivation, and overall job performance. Many researchers have acknowledged the importance of the quality of work experience on career development and performance outcomes (Benschop and Doorewaard (1998), Tolich and Briar (1999)). Berlew and Hall (1966) suggest that employees who are given more difficult task assignments early on in their careers were also more successful after several years compared to those provided easier assignments. Thus, being assigned better tasks can result in workers being able to learn complex skills, demonstrate their ability, and increase their client base through increased exposure to high-end assignments, all of which contribute to better performance outcomes and promotion opportunities.

There has also been extensive work done on gender differences in performance evaluations.

Employers often rate male employees as significantly more able, likable, and worthy, even when their qualifications, output, and behavior are identical (Heilman (2001), Quadlin (2018), Ridgeway (2011)). In academia, Weisshaar (2017) demonstrates that there are gendered differences in the tenure evaluation process, as organizational and productivity differences cannot explain a large portion of the tenure gender gap; Hospido and Sanz (2021) also find that women are disadvantaged in the process of research evaluation, as all-female-authored papers are less likely to be accepted than all-male-authored papers for economic conferences, even after controlling for factors such as experience, affiliations, and referee fixed effects.

While quantitative performance measures, such as hours worked or number of clients, may be less susceptible to gender bias compared to performance evaluations, there still exists the possibility that supervisors have some decision-making power over whether to include hours as "billed hours", as well as whether employees are experienced enough to handle a certain number of clients. Additionally, exposure to a similar number of cases may still result in female associates retaining fewer clients compared to their male counterparts, potentially due to beliefs held by clients themselves. Therefore, gender biases held by both supervisors and clients, which often influence performance evaluation reports, may also be influencing seemingly objective metrics of performance.

2.4 Gender Gaps in Law Firms

Discrimination is a facet of prejudice that female and minority associates commonly face when they enter a law firm. Gender and racial minorities are frequently seen as incompetent and assumed to be less able or dependable compared to their white or male counterparts (Rhode (2011)). While white men enjoy a "presumption of competence," women have to do more work to attain similar outcomes. Therefore, women are often assigned worse cases in law firms and have lower rates of partnership compared to men (Azmat et al. (2020)).

The wage gap is a common topic that has been explored with regards to gender differences in outcomes in the legal field. Wood et al. (1993) reported large differences in wages for lawyers 14

years after graduating from law school. Controlling for work history, childcare, academic performance, and job-specific characteristics still leaves around one-third of the earnings gap unexplained. Other papers exploring the wage gap of lawyers find similar results. Dinovitzer et al. (2009) show that human capital only explains 15% of the difference in earnings for young lawyers, while different opportunity paths in the form of networking opportunities and time spent on specific areas of law can only account for 25%. The wage differential indicates differences in performance are also likely to exist, and these differences may not be able to be explained fully by differences in endowments or opportunities.

Some popular explanations as to why gender gaps in career outcomes for lawyers exist include differences in task assignment and mentorship, differences in family responsibilities and time flexibility, differential treatment by clients, and differences in cultural capital. In this paper, I will be exploring the first explanation: how differences in task distribution and mentorship affect the gender gap in performance metrics. Korzec (2000) points out that female junior associates often do not receive important projects that allow them to exhibit their intelligence and potential; likewise, Ziewacz (1996) finds that female associates are often assigned worse tasks due to differing perceptions held by partners in firms. Even controlling for performance, education, and ability, as well as individual and firm characteristics, there is still a considerable unexplained gap between female and male lawyers with regards to missing out desirable assignments and experiencing demeaning comments from superiors (Chowdhury (2016)). This becomes a "self-fulfilling prophecy," when men are given more opportunities to demonstrate their competence in the workplace and gain valuable skills, this causes partners to believe that they are also more suited for promotion opportunities (Sterling and Reichman (2012)). Korzec (2000) and Ziewacz (1996) both anecdotally document reasons why female and male partners may be reluctant to mentor female associates for a variety of reasons. For instance, female partners often have less executive power within firms, so they believe that their mentorship will provide female associates with less opportunities; on the other hand, male partners may not want to mentor female associates out of misguided beliefs regarding their

dedication and availability. In general, the literature seems to indicate that differences in work assignment and mentorship opportunities exist and may play a role in causing the performance and promotion differential.

A wide range of literature also documents how aspirational differences and childcare duties can be used to explain a portion of the gender gap in performance. Azmat et al. (2020) find that 60% of male associates report having high career aspirations to become partners, but only 32% of women report similar aspirations. Aspiration is linked to performance, because individuals with high aspirations often put in more time and effort, which may include working longer hours and being less likely to switch firms early on in their career. They may also be more likely to seek out opportunities for career advancement and are less likely to turn down promotion offers if they do arise (Azmat et al. (2020)). The presence of young children can also explain part of the difference in performance; women with children are often burdened with more childcare duties compared to their spouses and may not be able to work overtime or pick up extra assignments outside of their typical schedules (Azmat and Ferrer (2017)). However, it is important to distinguish between real aspirational differences and perceived aspirational differences; many women who may want to become partners or may not wish to have children may be painted by the same brush, causing them to be seen as less competent or available. This would fall under the category of statistical discrimination in the law firm, as opposed to differences in individual career and familial preferences.

A third explanation for the gender gap in partnership may be due to client-side discrimination and differences in client bases. Hughes (2017) finds that women are not more likely than men to want to leave large law firms; rather, they provide evidence to suggest the existence of implicit bias makes it difficult for women to network with a clientele base that is predominantly male. Ziewacz (1996) notes that women are often assigned more pro bono work, which may cause them to take up cases that result in lower pay and less potential client networks, even if they are able to successfully complete their assignments. In general, client generation and retention are crucial in the evaluation of associate and partner-level performance, which means any discrimination that

may exist against female lawyers from clients will have a detrimental effect on the billed hours and number of clients that female associates are able to generate. Women are often rated lower than men on many qualities related to leadership, such as assertiveness and competitiveness, which may cause people, especially male clients, to be hesitant to work with female lawyers (Rhode (2011)).

The exclusionary nature of the law firm may also play a part in pushing female associates to work fewer hours in the firm or off the promotion track entirely early on in their careers. Through 219 interviews with lawyers across fifteen years, Garth and Sterling (2018) identify certain characteristics that are important for career progression. Cultural capital, e.g. playing golf or fitting into elite country clubs, is notably important in determining one's ability to be on the promotion track. Cultural capital, formally defined as "external wealth converted into an integral part of the person...[that] cannot be transmitted instantaneously (unlike money, property rights...),“ remains a crucial component of fitting in and succeeding in the corporate law firm (Bourdieu (2011)). Many female lawyers do not have direct access to the necessary cultural capital or personal connections. In other words, "fitting in" is a luxury often only granted to male lawyers, that often comes through both familial and professional networks that have been granted to them by their inclusion within historically male-dominated social and educational institutions. White women commonly experience exclusion from "old boys" networks, with 60% of women reporting being left out of formal and informal networking events, as compared to only 4% of white men (Rhode (2011)). Female associates often lose out on opportunities due to their lack of cultural and social capital, which may have adverse effects on their ability to retain or find new high-paying clients (Ziewacz (1996)). This exclusion may cause women to abandon their partner aspirations, indicating early discrimination may be a potential factor behind the aspirational differences in career outcomes discussed previously.

All in all, there are yet to be any papers that attempt to uncover the importance of pre-work characteristics in explaining the gender gap in performance. While Azmat and Ferrer (2017) do compare female and male averages across four out of the sixteen task and mentorship-related ques-

tions, they do not consider the relationship between female and male associates' backgrounds on these tasks, nor do they consider the relationship between task assignment and performance. My paper will focus on decomposing the explanation behind the gap in performance in considerable more detail than previous investigations. Specifically, I will be utilizing Blinder-Oaxaca decompositions at multiple stages of associates' careers to understand how differences in inputs and returns at each stage affect the eventual performance outcomes of female versus male lawyers. Thus, my paper will also be the first to decompose the gap in performance assessment between men and women into differences in task assignment, pre-work characteristics, and the returns to each of these.

3 The Life of a Law Associate

It is important to understand the various stages of a law firm - from being hired to being assigned legal tasks as an associate to making partner - from a young lawyer's perspective. While there is limited information on how tasks are delegated within a law firm, there is ample research on the qualifications that matter for lawyers during the hiring process. For this paper, I will assume that many of the qualifications deemed important by a hiring committee are also viewed as important for task delegation. I argue this assumption is reasonable, because partners often have access to resumes of each incoming associate class, even if said partners did not directly take part in the hiring process. The legal field places a higher priority on pre-work characteristics than most professions, which suggests most of these characteristics are publicly available for partners to view. For instance, many firms even allow potential clients to see the academic record of each lawyer at their firm. Moreover, it is likely that even in firms without a formal process of sharing information on associates, partners often informally exchange information on newly hired lawyers.

Woodson (1996) describes the importance placed on academic achievement, in particular in the form of class rank as opposed to grade point average. Additionally, many firms, especially those with a focus on litigation, are interested in moot court experience, as well as other extracurricular activities, such as student government, that allow applicants to demonstrate leadership. Many lawyers also state that they view applicants who worked through law school or engaged in heavy family responsibilities to be particularly impressive, given this often indicates maturity and strong time management skills. Given the importance of maturity, work experience before entering the firm is also seen favorably by most hiring committees. Campbell and Tomkins (1992) similarly stress the importance of law school grades in determining one's chance of being hired by a law firm. However, they find that participation in law review is not a statistically significant factor in either the decision to interview a candidate or the decision to hire an applicant.

In general, there seems to be a strong emphasis on academic excellence, along with activities outside of the classroom that demonstrate leadership and dedication. If a student has a resume

with many of the aforementioned qualifications, they are then invited to participate in an interview, where partners get a chance to see the "personality" of applicants. The term "personality" is vague, but it is mentioned frequently in discussions with lawyers with regards to hiring decisions. Overall, it seems to encompass enthusiasm, motivation, and other characteristics specific to each law firm. While there is no measure of "personality" in the dataset I will be working with, I posit that a combination of the observable attributes, such as leadership positions in extracurricular activities or external organizations, are likely correlated with personality measures such as being hardworking or motivated.

Young lawyers are typically hired as junior associates; those with exemplary records in the first few years of work are then promoted to the rank of senior associate after 3-5 years. While a smaller portion of young lawyers may be hired as contract or staff attorneys, these individuals will not be covered in my paper. Each firm has their own hierarchy in terms of how associates eventually become promoted to partner. In some firms, senior associates must first be promoted to counsel, of-counsel, or special counsel before they are eligible to be considered for partnership decisions. However in most firms, being an counsel, of-counsel, or special counsel is an all-encompassing term for lawyers who are not associates or partners; these positions are typically filled by lawyers who wish to have a more stable position, may not want to take on as many hours as is required of partners, or have political or other ambitions. Thus, in the majority of law firms, senior associates can be directly promoted to partner, while counsel positions are typically delegated to associates who are unfit to make partner. It typically takes up to 9 years for junior associates to make partner. For law firms with an intermediary counsel position, it takes on average 6-7 years to be promoted to counsel, of-counsel, or special counsel, and then up to 3 years to become partner.

Most firms also distinguish between non-equity partners and equity partners. Non-equity partners have partial voting rights and fixed salaries that are not based on partnership distributions; in some firms, non-equity partners are also known as "prospective partners" because they may be promoted to equity partner in 2-3 years pending strong performance. On the other hand, eq-

uity partners own a percentage of the firm's earnings and have full voting rights on all important firm decisions. In most firms, becoming an equity partner, which accounts for around 57% of all partners, is the highest position one may achieve.

In general, lawyers report that promotion decisions often focus on associates' or counsels' ability to bring in business for the firm (Alexander and Nagel (2004)). The ability to bring in business is intrinsically tied to the number of clients lawyers are able to bring into the firm, the revenue the firm is able to gain off each client, as well as the amount of work that lawyers put into their cases. This stresses the importance of the two performance metrics I will be using in this paper: hours billed and number of clients brought in. Billable hours, a term I will use interchangeably with billed hours, are often used by lawyers to document the number of hours they spend working on a case, which can include drafting documents, conducting background research, meeting with clients, as well as all other time actively spent on the case. Billed hours have a direct impact on the revenue of firms, as clients are charged based on the number of billed hours spent on their cases multiplied by the hourly rate for the lawyer who billed the hour. There are often requirements for the minimum number of billed hours required for associates, and billable hours are also used by firms to determine bonus compensation. Since billed hours do not include training and observing, conversing with coworkers, working on pro bono cases, serving on a bar committee, writing articles for bar journals, interviewing applicants, and other work that cannot be specifically assigned to any clients or cases, the number of hours a lawyer works is often very different from the number of hours they are able to bill (Campbell and Charlesworth (2012)).

Additionally, firms are not only concerned with the quantity of work done by associates, but also the quality of work done; as a result, partners frequently monitor the quality of billed hours that associates log in for work and may discount hours if they feel the work done was insufficient or inadequate. Partners have an incentive to strictly scrutinize the work of their subordinates, given the potential reputational and legal harms that may accrue on the partners or entire firm (Phillips (2001)). This reduces the concern that the number of hours billed is only a reflection of the amount

of time spent on work, as opposed to the condition of the completed work. Associates also have a self-serving incentive to produce high-quality work, given the reputational damage of shoddy work is likely to cause them to lose clients and discourage partners from assigning them onto more cases.

Second, the number of clients that a lawyer is able to bring in is also a major determinant of their success. This heavy prioritization on the number of new clients a lawyer is able to attract to the firm makes it a useful addition to billed hours in studying the performance assessment of associates. Weil (2010) shows that most law firms, especially those larger in size, use formal origination credit scoring systems in order to reward lawyers who bring in a large number of new clients. The number of new clients a lawyer is able to attract is a reflection of their reputation and personal connections. Previous clients serve as a crucial channel for new introductions; leaving a good impression through a previous case increases the possibility of associates being introduced to new clients through past clientele. This performance metric is also important for promotion decisions, as being able to network effectively and attract a larger clientele base is a crucial skill that partners need to master in order to be successful. As Rose (2011) states, the likelihood of becoming a law firm partner depends on associates' historical productivity levels, ability to sustain high productivity after promotion, and ability to support themselves as partners. The latter two are strongly tied with the ability of lawyers to attract clients, while the first can be directly measured through billable hours.

Lastly, being able to attract more clients or bill more hours is often dependent on senior partners assigning important work to associates or being willing to use their client connections to help associates gain more clients. This suggests the importance of task assignment and mentorship in boosting associates' performance within a law firm.

4 Data

4.1 After the JD Survey and Sample Construction

I will be using the "After the JD" (AJD) dataset, a national longitudinal survey that follows the lives of an approximate 10 percent sample of American lawyers who entered the bar in 2000. The AJD study was commissioned through the American Bar Foundation to understand the career development of young lawyers in the early twenty-first century. The sample includes the four largest legal markets (Chicago, New York, Los Angeles, and Washington, DC), five medium-sized markets (Atlanta, Boston, Houston, Minneapolis, and San Francisco), as well as nine smaller markets. The first Wave was launched in 2002, after responding lawyers had been in practice for around two to three years. The second wave and third wave, which only surveyed respondents from Wave 1, came out in 2007 and 2012 respectively. The first wave contains 4,538 valid responses from all located members who met the survey criteria, which represents a response rate of 71%. Of those who responded, 633 respondents (14%) are minority lawyers.

Lehmann (2011) finds that the sex and racial makeup of respondents are comparable to those of young lawyers from the 2000 Census, indicating the survey's results may be fairly representative of the broader population of young lawyers. This allows me to generalize my results to the broader domain of all lawyers who received their JD in 2002 and potentially the years after, given the structure of law firms have not changed greatly in the past two decades. The second wave has a response rate of 50.6%. At this stage, lawyers who entered their first job in 2000-2001 would have been at their firms for around seven years. This time period can be seen as the "mid-career stage" of a lawyer's career trajectory; associates are in a variety of positions at this stage. Some have already been promoted to partner while others remain in their previous position; some have switched to other firms or different industries, while many have continued at the firm they entered directly from law school. Finally, the third wave, with a 53% response rate of respondents from the two previous waves, documents the late career stage of a law firm associate. Those who have not

yet been made partner are unlikely to make partner after this point. Overall, around 2,500 lawyers had responses across all three waves.

There are a few reasons this dataset is advantageous for my research question; first, it is the only national longitudinal study of lawyers in the United States, which allows me to follow the careers of these individuals over time to study how they change and develop. Additionally, the AJD uses a two-stage sampling approach by first selecting a wide array of geographic areas based on location and population size and then choosing individuals who passed the bar in 2000 and met the requirements of the study to participate in the questionnaire. Crucially, the AJD survey also includes a rich range of answers from respondents about their current employment and educational background. There are detailed responses on their current positions, firm sizes, task assignments, billed hours, and clientele makeup. Moreover, respondents were asked about their undergraduate grades and majors, law school grades and activities, and other relevant details about their academic life prior to entry into the workforce. Not only does the AJD data include academic and professional information, it also asks respondents about their personal and familial background, including their marital status, number and age of their children, parental education level, and other detailed information. All the analysis done in this paper is based on data from this dataset.

For my paper, I limit my sample size to lawyers who responded to all three Waves of the AJD survey, indicated their position as "Associate" in the first wave, and work in firms with more than 100 lawyers. Smaller firms may differ from larger firms in significant ways; the associates at these firms may be granted more assignments not due to their ability but rather due to the smaller size of the workplace. Therefore, their inclusion in the data may affect my results, as task assignment is then not due to one's qualifications or characteristics, but rather due to the nature of the firm. Thus, I chose 100 as the cutoff because previous papers state that middle- to large- sized law firms typically employ at least 100 lawyers (Dinovitzer et al. (2009)).

4.2 Descriptive Statistics

Table 1 provides the descriptive statistics of the respondents in the selected sample. Across men and women, the average annual billed hours in Wave 2 is around 1866 hours, with men billing more than 2000 hours on average while women billed less than 1700 hours, a difference that is significant at a 1% level. We see a similar trend in Wave 3, where the average annual billed hours is around 1655, with male associates billing around 150 more hours per year than female associates.

In terms of the number of clients associates brought into the firm, there are also stark differences between genders for this performance metric. In Wave 2, the number of clients brought in averages 6, with men bringing in closer to 7 clients and women bringing in less than 3 clients. This difference is also significant at the 1% level. By Wave 3, the number of clients that this cohort is bringing in essentially triples, with an average of approximately 17 clients. However, men are still bringing in around 4 more clients than women, though this difference is no longer statistically significant.

As for desirable task assignment, the principal component score for men has a positive average of 0.051, while women have a negative average of -0.052, which indicates women are being assigned less desirable tasks than men or are less likely to be assigned desirable tasks.

Turning to pre-work characteristics, there seem to be few significant differences between male and female associates. Across both groups, the average year associates attained their Bachelor's Degree around 1994, while around 40% of them attended law school directly after their undergraduate studies. Compared to their female counterparts, male associates ranked slightly higher in their law school classes and attended slightly more prestigious law schools, although the difference is not statistically significant. There are only two differences between the cohorts that are significant, both of which relate to extracurricular activities in law school: women on average were more likely to have participated as a member in their schools' moot courts and pro-bono law organizations. All other pre-work characteristics appear generally uniform across the board.

Table 1: Descriptive Statistics of the AJD Sample

Attribute	**All**	**Males**	**Females**	**M≠F**
Performance				
Yearly Billed Hours (Wave 2)	1866.086	2017.575	1684.300	***
Yearly Billed Hours (Wave 3)	1654.949	1727.758	1570.598	**
No. of Clients Brought In (Wave 2)	5.818	6.831	2.850	***
No. of Clients Brought In (Wave 3)	17.034	19.165	13.377	
Task Assignment				
Desirable Task Index	0.000	0.051	-0.052	**
Pre-Work Characteristics				
Undergrad Graduation Year	1994.159	1994.162	1994.156	
Direct to Law School (1 = Yes, 0 = No)	0.391	0.387	0.394	
Law Class Rank	2.130	2.072	2.188	
Law School Rank	2.677	2.599	2.757	
College Alumni Association (Member)	0.275	0.257	0.294	
College Alumni Association (Leadership)	0.023	0.023	0.023	
Moot Court (Member)	0.248	0.212	0.284	*
Moot Court (Leadership)	0.095	0.095	0.096	
Pro Bono Law (Member)	0.311	0.252	0.372	***
Pro Bono Law (Leadership)	0.068	0.054	0.083	
Student Government (Member)	0.068	0.050	0.087	
Student Government (Leadership)	0.082	0.077	0.087	
Charity Organization (Member)	0.293	0.297	0.289	
Charity Organization (Active Participant/Leadership)	0.150	0.167	0.133	
Charity Organization (Former Participant/Leadership)	0.025	0.023	0.028	
Part-time Law Student (1 = Yes, 0 = No)	0.064	0.063	0.064	

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Desirable Task Index refers to the principal component scores I derived from the list of all tasks and mentorship activities associates report engaging in; a detailed explanation of this can be found in Section 5.3. Law class ranks: 1 = Top 10%, 2 = 11-25%, 3 = 26-50%, 4 = 51-75%, 5 = 76-100%. Law school ranks: 1 = Top 10, 2 = Top 11 to 20, 3 = Top 21 to 100, 4 = Tier 4, 5 = Tier 5, 6 = Tier 6. T-tests of mean differences assume unequal variances. * = significant at 10%, **= significant at 5%, ***= significant at 1%.

5 Data Cleaning and Analysis

This section is structured as follows. First, I discuss the multivariate imputation technique I used to impute missing variables in my dataset. Afterwards, I will discuss how I use Group Lasso regression to select the task assignments I will be using in my decomposition. Lastly, I will explain how I used Principal Component Analysis (PCA) to create my outcome variable, a measure of desirable task allocation.

5.1 Missing Values

To handle any missing values in my dataset, I use multivariate imputation; specifically, I implemented the Multivariate Imputation via Chained Equations (MICE) package in R. Essentially, the MICE package imputes missing data through an iterative process of predictive models, where in each iteration, missing variables in the dataset are imputed using other known variables. Using multiple imputations, as opposed to a single imputation, allows me to reduce uncertainty in imputation.

The MICE package assumes that variables are missing at random and imputes on a variable-by-variable basis, allowing users to specify an imputation model per variable. More specifically, the chained equation process utilized by the MICE package can be broken down into a few steps. First, a simple imputation (e.g. imputing the mean) is performed on every missing value in the dataset to be thought of as "placeholders." Then, the placeholder imputations for one variable (Variable X_1) are set to missing. The known values in X_1 are regressed on all other variables in the imputation model with the same assumptions as other linear or logistic regression models outside of imputation. The predicted values from this regression are slotted in place of the "placeholders" to be used in the imputation models for the other predictors with any missing values. This process is repeated for every variable that has missing data; a "cycle" refers to a full iteration through every variable in the dataset that has missing values. For my data, I kept the number of cycles at 5, which is the default number of cycles set by the MICE package.

Once 5 cycles have been completed, the entire imputation process described above is repeated to generate multiple datasets with imputations, where the observed data is the same across each dataset; in total, I generated 5 imputed datasets, the default number of imputed sets provided by the package. All analysis was then conducted on the multiply imputed data, with regression results found from pooling the estimates across each dataset to reach one final estimate. Since the accuracy of the imputation depends on the information density and linear dependence among predictors, my imputation process is likely to produce accurate values, given the large quantity of survey questions and strong correlation between many variables (e.g. law school GPA and law school class rank).

For continuous variables, the imputation model was selected as Bayesian linear regression (ignoring model error). For binary categorical variables, the model was chosen as logistic regression. For categorical variables with more than 2 levels, Bayesian polytomous regression was used. Lastly, for ordinal categorical variables with more than 2 levels, I used a proportional odds imputation model. I only imputed variables with less than 20% of their total observations missing; otherwise, I chose to not include the variable in my analysis.

5.2 Pre-Work Characteristics

In order to select the pre-work characteristics for my regression, I use Group Lasso regression to reduce the number of predictors and allow for a more parsimonious model. Since there are over a hundred different predictors in the full model, there were likely issues of multicollinearity, which meant it was necessary to find a way to parse through and select a smaller number of variables. Group Lasso regression was utilized as opposed to Lasso regression due to the large number of categorical variables with more than two levels in our data. The Lasso solution would change depending on how my dummy variables are encoded; the Group Lasso circumvents this problem by defining each categorical variable as a singular group. For the Group Lasso, the estimator is as follows:

$$\hat{\boldsymbol{\beta}}_\lambda = \arg\min_{\boldsymbol{\beta}} \left(\|Y - X\boldsymbol{\beta}\|_2^2 + \lambda \sum_{g=1}^{G} \left\| \boldsymbol{\beta}_{\mathcal{I}_g} \right\|_2 \right) \tag{1}$$

where $\mathcal{I}_g$ is the index set belonging to the gth group of variables, where g is between 1 to G, with G being the total number of groups defined (Yuan and Lin (2006)). The 2 in both the superscript and subscript of $\|Y - X\boldsymbol{\beta}\|$ also indicates that I am using the squared L2 norm. Thus, the Group Lasso regression allows me to find the pre-work characteristics that are the most predictive of task allocation by shrinking the coefficients of other unimportant characteristics down to zero.

The full model includes a variety of characteristics related to academic achievement (e.g., law school class rank, undergraduate grade point average, declared undergraduate majors, etc.) and extracurricular participation (e.g., law review membership or leadership, race organization participation, etc.). A full list of all the variables used can be found in Table A1 in the Appendix. The characteristics to use for the full model were decided based on whether the variable would likely be one included on application materials when applying for law firms. For instance, variables related to educational debt, marital status, parental characteristics, and other variables deemed unlikely to be presented on a cover letter or CV were not included in the full model. Additionally, I removed gender organization participation and leadership as an attribute from the full model, given concerns that it would serve as a proxy for gender and distort the regression results, since more gender minorities are likely to participate in gender organizations compared to their male counterparts.

The Group Lasso regression found 10 pre-work characteristics to be non-zero. As seen in Table 2, these variables include two variables related to associates' JD grade and school rankings: a categorical variable that indicated whether one was in the top 10%, 11-25%, 26-50%, 51-75%, or 76-100% of one's law school class and another variable indicating whether one attended a Tier 1, 2, 3, 4, 5, or 6 law school based on rankings from US News. They also include four variables related to the extracurricular activities associates engaged in during law school: college alumni association, moot court, pro bono law organizations, as well as student government. These categorical variables were coded to indicate whether one did not participate, participated as a general member, or

participated as an executive board member. Another variable included in this set is participation in charity organizations during or after law school; this is coded to indicate whether one is or is not a member as well as whether one is a currently active or formerly active participant/officer. Finally, there are three variables related to one's undergraduate and JD experience: a categorical variable indicating the year one attended undergraduate school (split into five-year intervals), a binary variable indicating whether one attended law school directly from undergraduate studies, and another binary variable indicating whether one was a part-time student in law school.

The selection of pre-work characteristics here is particularly interesting, as many characteristics typically thought of as being important for determining the competence and ability of associates, such as participation or leadership in general law reviews or participation in clerkships were not chosen by the Group Lasso regression. However, variables such as law school class rank and law school rank were chosen, which aligns with Woodson (1996) and Campbell and Tomkins (1992)'s research regarding the importance of academic achievement for lawyers. Moreover, as seen in Table 2, the results of the OLS regression indicate that moot court leadership and charity organization participation are the two most significant pre-work characteristics in predicting task assignment, which supports the work done by Woodson (1996). These two activities are likely to signal to employers that one is mature, responsible, and passionate about inequality, which are all traits law firms view favorably. Notably, the male and female coefficients (Table 2, Columns 2 and 3) are generally different, in particular for law school rank and college alumni association participation. This seems to indicate that supervisors are prioritizing different attributes when determining task assignment for men and women.

Table 2: Desirable Task Assignment from Selected Pre-Work Characteristics (OLS Results)

	(1)	(2)	(3)	(4)
Predictor	**All**	**Males**	**Females**	**Difference in βs**
Intercept	-0.929**	-0.909	-0.946*	-0.037
	(0.394)	(0.660)	(0.531)	
Year of Undergrad				
1976-1980	0.860*	1.389*	0.348	-1.041
	(0.518)	(0.753)	(0.757)	
1981-1985	0.166	0.388	0.236	-0.152
	(0.357)	(0.468)	(0.621)	
1986-1990	0.044	0.091	-0.123	-0.214
	(0.214)	(0.293)	(0.331)	
1991-1995	0.132	0.242	0.041	-0.201
	(0.142)	(0.204)	(0.210)	
Direct to Law School	0.242*	0.212	0.222	0.010
	(0.142)	(0.206)	(0.207)	
Law School Class Rank				
Top 10%	0.467	0.633	0.432	-0.201
	(0.303)	(0.507)	(0.392)	
11-25%	0.526*	0.808	0.333	-0.475
	(0.302)	(0.504)	(0.392)	
26-50%	0.419	0.525	0.399	-0.126
	(0.303)	(0.508)	(0.391)	
51-75%	0.646*	0.687	0.717*	0.030
	(0.334)	(0.567)	(0.428)	
Law School Rank				
Tier 1	0.013	-0.220	0.128	0.348
	(0.228)	(0.397)	(0.314)	
Tier 2	0.080	0.104	-0.014	-0.118
	(0.220)	(0.394)	(0.293)	
Tier 3	0.067	-0.040	0.062	-0.118
	(0.226)	(0.403)	(0.297)	
Tier 4	0.214	0.180	0.124	-0.056
	(0.242)	(0.420)	(0.331)	
Tier 5	0.383	-0.084	0.890	0.974
	(0.252)	(0.420)	(0.360)	
College Alumni Association				
Member	0.065	-0.095	0.233	0.328
	(0.109)	(0.160)	(0.159)	
Leadership	0.015	-0.153	0.171	0.324
	(0.328)	(0.498)	(0.472)	
Moot Court				

Table 2 – continued from previous page

Predictor	(1) All	(2) Males	(3) Females	(4) Difference in βs
Member	0.041	-0.112	0.084	0.196
	(0.112)	(0.169)	(0.162)	
Leadership	0.515***	0.711***	0.336	-0.375
	(0.165)	(0.234)	(0.245)	
Pro Bono Law				
Member	-0.047	-0.083	0.023	0.106
	(0.106)	(0.160)	(0.150)	
Leadership	0.047	0.035	0.134	0.099
	(0.198)	(0.314)	(0.266)	
Student Government				
Member	-0.288	-0.564*	-0.042	0.522
	(0.191)	(0.312)	(0.249)	
Leadership	0.181	0.417	0.039	-0.378
	(0.182)	(0.267)	(0.260)	
Charity Organization				
Member	0.136	0.190	0.057	-0.378
	(0.110)	(0.155)	(0.162)	
Active Participant/Leadership	0.509***	0.410**	0.471**	0.061
	(0.144)	(0.198)	(0.227)	
Former Participant/Leadership	0.183	0.164	0.242	0.078
	(0.307)	(0.455)	(0.432)	
Part-time Law	0.268	0.091	0.573*	0.482
	(0.210)	(0.308)	(0.313)	
N	440	222	218	
R^2	0.111	0.180	0.157	

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. Column 2 refers to the coefficients of each predictor found by running a sample with only self-identified males, while Column 3 refers to the coefficients of each predictor found by running a sample with only self-identified females. Column 4 is the female coefficient subtracted by the male coefficient. * = significant at 10%, **= significant at 5%, ***= significant at 1%.

5.3 Task Assignment

I use Principal Component Analysis in order to construct a variable for task assignment. Principal Component Analysis is a technique used to reduce the dimensionality of large datasets and solve problems associated with multicollinearity by creating new unitless variables known as principal components (PCs) from a linear combination of the original variables (which I will refer to as "predictors" in this section) in the dataset. It is often used to preserve information while simultaneously decreasing the number of predictors necessary for regression analysis.

Each principal component is a linear combination of all the standardized predictors; one can think of it as multiplying each standardized predictor by a different "weight." The order of the principal components also matters; the first PC is able to explain the largest percentage of the variation in the predictors, the second PC explains the second largest percentage, and so on. These weights are found in the following way: the first PC is chosen to minimize the distance between the original data and their projection onto the PC; this also allows us to maximize the variance of the new projected points, which minimizes the squared error. The second PC is chosen in a similar manner with an additional constraint added: it must be uncorrelated with any previously defined PC. These conditions are then used for the selection of all subsequent PCs. In total, the number of the principal components that are generated is equivalent to the total number of original predictors; however, one may choose to use less than the total number of principal components.

I use the first principal component as my outcome variable for the first-stage Blinder-Oaxaca decomposition and as my predictor variable for the second-stage decomposition. Of the sixteen different task and mentorship activities, a high degree of multicollinearity exists due to the fact that associates who were assigned a particular "good" task were also assigned other "good" tasks, while those who were assigned some "bad" task were likely assigned other "bad" tasks. Therefore, it would be difficult to interpret the coefficients on each task variable if they had all been used in the regression analysis without transforming them into PCs. Overall, I chose to use only the first principal component, as it seemed to load promotion-track or "desirable" tasks such as "appearing

in court as first/second chair" with a higher positive weight, while less desirable tasks such as "doing routine research" received smaller or even negative weights, resulting in convenient interpretability for the purpose of my analysis. The component loadings for each of the 16 tasks are shown in Table 3.

This classification of desirable versus undesirable tasks aligns with previous literature that interviewed lawyers about whether they consider various tasks to be "good" or "bad" tasks (Lehmann (2011)). Each associate's principal component score is believed to reflect whether or not they were often assigned desirable tasks; the gap between female and male associates therefore reflects the difference in desirable task assignment based on gender. Overall, there is a -0.103 gap when subtracting the male mean from the female mean, indicating that female associates are on average being assigned less desirable tasks. This difference is statistically significant at a 5% level. Appendix Figure A1 additionally depicts the PC score distributions for male and female associates, showing a gap exists across the entire distribution, not just at the mean.

Table 3: Principal Component Means and Loadings

	Desirable Tasks
Male Mean	0.051
Female Mean	-0.052
F-M Gap in Means	-0.103
Tasks	**Component Loadings**
Traveling to meet clients, interview witness, court appearance	0.433
Appearing in court as first/second chair	0.394
Writing motions or taking dispositions	0.377
Formulating strategy with attorneys/clients	0.364
Responsible for keeping client updated	0.362
Assigning/supervising work of others	0.296
Handling the entire matter	0.286
Spend recreational time with partners	0.195
Join partners for breakfast/lunch	0.152
Spending 100+ hrs on discovered docs	0.102
Participate monthly in bar/civic association	0.069
Spend recreational time with associates	0.010
Write for publications, presentations, or seminars	0.001
Participate in office recruitment committee	-0.015
Drafting transactional documents	-0.043
Doing routine research	-0.062

Notes: Only the component loadings for the first principal component (refered to as "Desirable Tasks") found through principal component analysis is depicted. The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey.

6 Empirical Methodology

In this section, I will first give a brief explanation of the standard Blinder-Oaxaca decomposition model. Next, I will provide a more detailed explanation and graphical illustration of the extension I provide to the existing model through incorporating a second-stage decomposition.

6.1 Blinder-Oaxaca Decomposition

The Blinder-Oaxaca decomposition method has often been used to decompose the mean wage differential between groups based on gender or race into explained and unexplained portions. While it is frequently applied to wages, the decomposition technique can be used on any continuous variable and has been extended to include binary variables (e.g. promotion and labor-market participation).

In my paper, I will be using the twofold decomposition, which allows me to decompose the difference in means into two parts: the difference in endowments and the difference in coefficients. Moreover, I provide a simple extension of the traditional decomposition by applying it to a function within a function, allowing me to decompose the mean differential into more folds than the previous twofold decomposition.

6.1.1 First-Stage Decomposition

First, I will provide an explanation of the twofold Blinder-Oaxaca decomposition. For the remainder of this paper, I will also refer to this decomposition method as a "first-stage decomposition." I have two groups: male and female (denoted as M and F), an outcome variable (for the first stage, this is task assignment T; for the second stage, this is performance P), and a set of pre-work characteristics as predictors (denoted as Xs). I am interested in understanding how much of the difference in the mean outcome, denoted as $\bar{T_M} - \bar{T_F}$ where $\bar{T}$ is the mean value of the outcome variable, can be explained by differences in the predictor values between the two groups. A simplifying assumption here is that I am assuming a linear relationship between X and T.

The linear model for group M is as follows,

$$T_M = X_M \beta_M + \epsilon_M \tag{2}$$

where X is a matrix with rows denoting individual observations and columns denoting the predictors in the model with a constant, β is a vector of the slope parameters and intercept, and ϵ is the error term, where $E(\epsilon_M) = 0$.

Similarly, the linear model for group F is:

$$T_F = X_F \beta_F + \epsilon_F \tag{3}$$

where X, β , and ϵ are defined the same way as above. Then, I have that the difference in the mean between the two groups can be expressed as:

$$\bar{T}_M - \bar{T}_F = \bar{X}_M \hat{\beta}_M - \bar{X}_F \hat{\beta}_F \tag{4}$$

where $\bar{X}$ is a 1-by-k vector of the mean values of the predictors, $\hat{\beta}$ is a k-by-1 vector of the predicted coefficient values, and k is the total number of predictors in the model. Now, there are two possible ways to decompose the mean differential. I can either use group M's coefficients as the reference coefficients, or I can use group F's coefficients as the reference coefficients. If I use group M's coefficients as the reference, I can add and subtract $X_F \beta_M$ from the equation to arrive at my final decomposition, as seen below.

$$\bar{T}_M - \bar{T}_F = \bar{X}_M \hat{\beta}_M + \bar{X}_F \hat{\beta}_M - \bar{X}_F \hat{\beta}_M - \bar{X}_F \hat{\beta}_F \tag{5}$$

$$\bar{T}_M - \bar{T}_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_M + \bar{X}_F(\hat{\beta}_M - \hat{\beta}_F) \tag{6}$$

In the above equation, I decompose the difference in mean outcome between group M and F into two parts: the part due to differences in endowments ($(\bar{X}_M - \bar{X}_F)\hat{\beta}_M$), and the part due to differences in coefficients ($\bar{X}_F(\hat{\beta}_M - \hat{\beta}_F)$).

On the other hand, if I use group F's coefficients as the reference, my decomposition is as

follows.

$$\bar{T}_M - \bar{T}_F = \bar{X}_M\hat{\beta}_M + \bar{X}_M\hat{\beta}_F - \bar{X}_M\hat{\beta}_F - \bar{X}_F\hat{\beta}_F \tag{7}$$

$$\bar{T}_M - \bar{T}_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_F + \bar{X}_M(\hat{\beta}_M - \hat{\beta}_F) \tag{8}$$

In the above equations, the difference in endowments and differences in coefficients will now produce different composition results, due to different weights used. In general, the difference in endowments can be interpreted as the portion of the gap that would be eliminated if the two groups had the same Xs, while the difference in coefficients can be interpreted as the portion of the gap that would be eliminated if the two groups had the same returns on their Xs. However, the results from using different reference groups can be interpreted in different ways.

Using F as the reference group answers two questions: i) How would the average individual in group F have done if, leaving their returns unchanged, they had the same Xs as the average individual in group M, and ii) How would the average individual in group F have then done if they had the same Xs as the average individual in group M *and* the same average returns on their Xs as members of group M? Likewise, using M as the reference group explains how the average individual in group M would have done if they had the same Xs as the average individual in group F, as well as how they would have done if their Xs and returns to their Xs were the same as the average individual in group F.

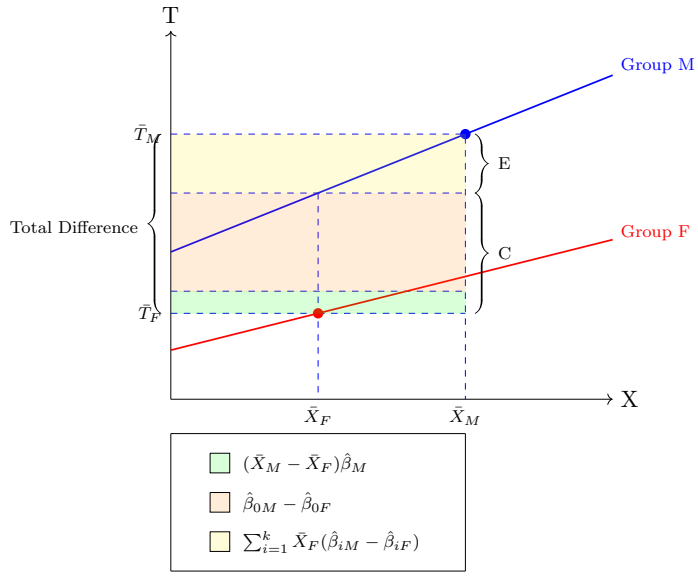
I chose to use group F (female) as the reference group, because it seems more plausible that women are facing negative discrimination, which would mean that the "baseline" level of task assignment should be that of the average male. The key assumption behind my choice is that the gap is caused by partners penalizing women for their gender by assigning them *less* work than they would have otherwise assigned, rather than leaving female task assignment unchanged and assigning men *more* work on the basis of their gender. Thus, the focus of my paper is on how female associates would have done if they had the same pre-work characteristics as men. While I show both graphical illustrations of the Blinder-Oaxaca decomposition from the perspective of

group M and group F in Figures 1a and 1b below, the following tables in Section 7 will only include decomposition results using group F (female associates) as the reference group. The detailed results for the decompositions using group M (male associates) as the reference group can be found in the Appendix.

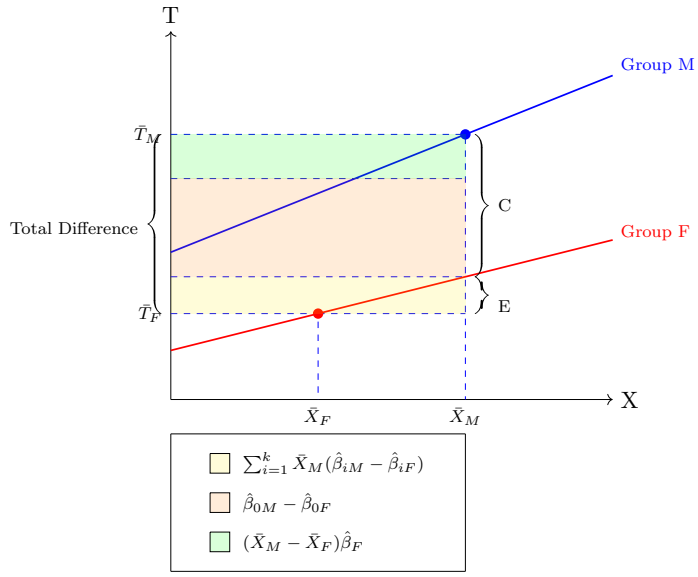
The graphical illustration of the decomposition is as follows. Figure 1a depicts the decomposed breakdown based on Group M as the reference group, while Figure 1b shows the breakdown based on Group F as the reference group. As can be seen in the comparison between the two figures, choosing a different reference group results in a different portion explained by the difference in endowments versus the difference in coefficients.

Blinder-Oaxaca decompositions typically do not differentiate between differences in the intercepts and differences in the other coefficients. However, I believe it is important to understand how the differences in intercepts can affect the total difference in the outcome variable. The difference in intercepts denotes the portion of the total gap in T that cannot be explained by the Xs that were chosen for the decomposition. This difference can be thought of as the difference in the returns for simply belonging in either Group M or Group F. If one believes that the predictors used in the model encompass all possible avenues through which T could be affected, then one may attribute differences in the intercept to bias or discrimination. However, if there are other differences in characteristics (that are not gender identity) between members of Group M and Group F that are not captured by the model, this could indicate other factors unrelated to the Xs are affecting T.

Figure 1: Illustration of Twofold Decomposition



(a) Group Male as Reference Group



(b) Group F as Reference Group

Notes: These are two graphical illustrations of the twofold Blinder-Oaxaca decomposition for an equation with k predictors. Panel A uses Group M as the reference group, while Panel B uses Group F as the reference group. E denotes the part of the total difference attributed to the difference in endowments, while C denotes the part attributed to the difference in coefficients.

6.1.2 Second-Stage Decomposition

This paper contributes to the current literature on the Blinder-Oaxaca decomposition by considering a decomposition on a function within a function. Specifically, I again define the two groups as M and F. Now, consider the initial model above for outcome variable T_i, which I defined as:

$$T_i = X_i\beta_i + \epsilon_i. \tag{9}$$

Now, assume there exists another outcome variable P, which is a function of T_is. I define the new model as:

$$P(T) = (X\beta + \epsilon)\gamma + \epsilon_p \tag{10}$$

where $X\beta + \epsilon$ is a vector containing the T_is and a constant, γ is a vector containing the slope parameters and intercept, and ϵ_p is the error term where $E(\epsilon_p) = 0$. Then, the mean difference in outcome P between group M and F is:

$$\bar{P}_M - \bar{P}_F = (\bar{X}_M\hat{\beta}_M)\hat{\gamma}_M - (\bar{X}_F\hat{\beta}_F)\hat{\gamma}_F. \tag{11}$$

Here, there are multiple directions I can take to reach our ultimate decomposition. Similar to the first-stage simple decomposition I outlined where I had the option of either setting M or F as the reference group, I can choose to weigh the difference in endowments and coefficients here in a variety of ways. For the simple decomposition above, I could add and subtract either $\bar{X}_F\hat{\beta}_M$ or $\bar{X}_M\hat{\beta}_F$ to arrive at one of two possible decomposition results. Here, there are six different options that I can add and subject; however, since I have chosen F as the reference group for my analysis, that limits the number of options to the following three: (1) $(\bar{X}_M\hat{\beta}_F)\hat{\gamma}_F$, (2) $(\bar{X}_F\hat{\beta}_F)\hat{\gamma}_M$, or (3) $(\bar{X}_F\hat{\beta}_M)\hat{\gamma}_F$. Support I choose (1) to add and subtract. Then, I get

$$\bar{P}_M - \bar{P}_F = (\bar{X}_M\hat{\beta}_M)\hat{\gamma}_M + (\bar{X}_M\hat{\beta}_F)\hat{\gamma}_F - (\bar{X}_M\hat{\beta}_F)\hat{\gamma}_F - (\bar{X}_F\hat{\beta}_F)\hat{\gamma}_F \tag{12}$$

which I can simplify as:

$$\bar{P}_M - \bar{P}_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_F\hat{\gamma}_F + (\bar{X}_M)(\hat{\beta}_M\hat{\gamma}_M - \hat{\beta}_F\hat{\gamma}_F). \tag{13}$$

Now I can do a first-stage Blinder-Oaxaca decomposition on the last section of the equation above, specifically $\hat{\beta}_M\hat{\gamma}_M - \hat{\beta}_F\hat{\gamma}_F$. As I outlined previously, I can either choose M or F as the reference group when conducting the decomposition, which gives me two possible options to add or subtract here: $\hat{\beta}_F\hat{\gamma}_M$ or $\hat{\beta}_M\hat{\gamma}_F$. If I choose the former, the decomposition can be simplified as:

$$\bar{P}_M - \bar{P}_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_F\hat{\gamma}_F + (\bar{X}_M)((\hat{\beta}_M - \hat{\beta}_F)\hat{\gamma}_M + \hat{\beta}_F(\hat{\gamma}_M - \hat{\gamma}_F)). \tag{14}$$

The equation above is equivalent to:

$$\bar{P}_M - \bar{P}_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_F\hat{\gamma}_F + \bar{X}_M(\hat{\beta}_M - \hat{\beta}_F)\hat{\gamma}_M + \bar{X}_M\hat{\beta}_F(\hat{\gamma}_M - \hat{\gamma}_F). \tag{15}$$

Therefore, I have decomposed the difference in mean outcome P between groups M and F into three sections: the difference in the Xs $(\bar{X}_M - \bar{X}_F)\hat{\beta}_F\hat{\gamma}_F)$, the difference in the returns to the Xs on T $(\bar{X}_M(\hat{\beta}_M - \hat{\beta}_F)\hat{\gamma}_M)$, and the difference in the returns to T on P $(\bar{X}_M\hat{\beta}_F(\hat{\gamma}_M - \hat{\gamma}_F))$.

Note that the weights on each of the three different sections (differences in pre-work characteristics, differences in returns to pre-work characteristics on tasks, and differences in returns to tasks on performance) are dependent on the prior choices I made about which variables to add and subtract from our equation. Therefore, there are a total of 12 different combinations of weights I could have used; however, the calculations in Table A2 in the Appendix show that there are in reality six different unique weight combinations, if I consider both group M and group F as reference groups. Using only group F as the reference group yields me three different unique weight combinations. For the remainder of the paper, I will only be considering these three options, as I initially chose to use female as the reference group.

When interpreting what each of the different models based on the different weights means, I will focus on two primary questions: i) How would the average individual in group F have done if they had the same returns to pre-work characteristics on tasks as the average individual in group M, holding all else equal? and ii) How would the average individual in group F have done if they

had the same returns to task assignment on performance as the average individual in group M, holding all else equal?

I show a graphical illustration of a second-stage Oaxaca decomposition of P on T as a function of Xs in Figure 2b. The breakdown of only one model (Model 1) is depicted in Figure 2b, though there are three possible models using F the reference group. For comparison, I also depict a simple first-stage Oaxaca decomposition of P on T using group F as the reference in Figure 2a. The graphical illustration in Figure 2a corresponds to the following decomposition:

$$\bar{P}_M - \bar{P}_F = (\bar{T}_M - \bar{T}_F)\hat{\gamma}_F + \bar{T}_M(\hat{\gamma}_M - \hat{\gamma}_F), \tag{16}$$

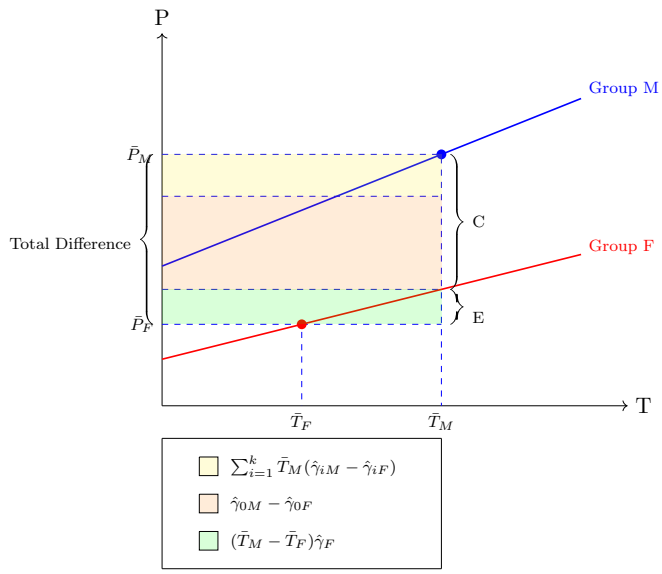
where $(\bar{T}_M - \bar{T}_F)\hat{\gamma}_F$ is the portion of the performance gap due to differences in task assignment, while $\bar{T}_M(\hat{\gamma}_M - \hat{\gamma}_F)$ is the portion of the performance gap due to differences in the returns to task assignment on performance.

Figure 2b is similar to Figure 2a, except the difference in T along the x-axis in Figure 2b is divided into two sections, specifically the part of the gap in T due to difference in coefficients (C) and the part of the gap due to difference in endowments (E). Moreover, while the part explained by differences in the returns to T on P are the same between both graphs, the section in Figure 2a that denotes the difference in P due to differences in T (the green section) is split into two sections in Figure 2b: one part due to differences in the initial Xs (the pink section) and one part due to differences in the returns to Xs on T (the purple section). This aligns with the theory that initial differences in treatment between male and female workers may result in later differences in subsequent stages. The combination of C and E determines the gap between $\bar{T}_F$ and $\bar{T}_M$, which then affects the total difference between $\bar{P}_F$ and $\bar{P}_M$. Moreover, the division between the sections denoted C and E affects the portion of the total difference in P that can be explained by the difference in the initial Xs, the returns to Xs on T, and the returns to T on P. For instance, if C explained a larger portion of the gap in T, then more of the total gap in P would be explained by $\bar{X}_F(\hat{\beta}_M - \hat{\beta}_F)\hat{\gamma}_F$, indicating the average individual in group F would have done much better if

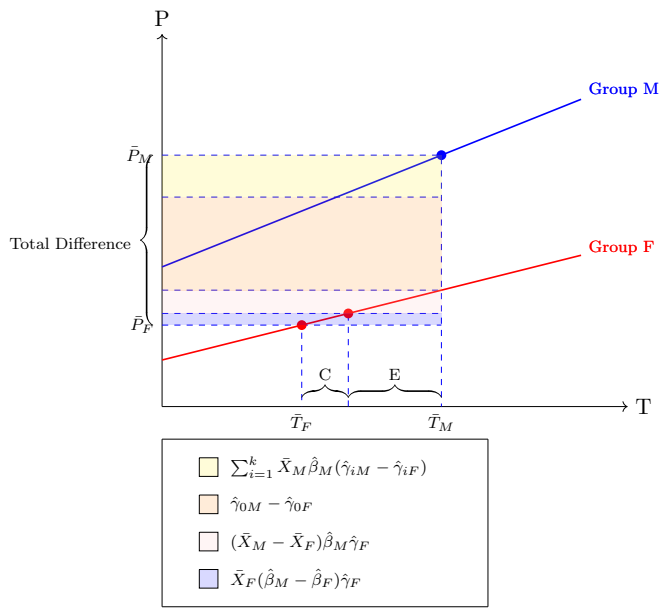
they had the same returns to Xs on T as the average individual in group M. This would mean the difference in returns to Xs are now explaining a larger portion of the gap in P, while differences in X are now explaining a smaller fraction of the difference.

Moving onto a more detailed explanation of Figure 2b, each colored portion explains a different component that contributes to the total gap in P. The pink section denotes how much of the total difference can be explained by the difference between the average P of group F and the average P of group F if they had the same average Xs as group M. The purple section denotes how much of the total difference can be explained by the difference between the average P of group F and the average P of group F if they had the same average returns to Xs on T as group M, holding all else constant. Similar to Figure 3, the orange and yellow sections denote the remainder, which is the portion of the total difference that can be explained by the differences in the intercepts and by differences in the returns to T on P between the two groups. Therefore in this example, the section of interest is the part in purple, as finding the area of this section helps me answer my first primary question.

Figure 2: Comparison of First-Stage versus Second-Stage Decomposition



(a) First-Stage Decomposition of P on T (F as Reference)



(b) Second-Stage Decomposition (F as Reference)

Notes: Panel A depicts a first-stage Blinder-Oaxaca decomposition for an equation with k predictors using group F as the reference group. Panel B depicts a second-stage decomposition for an equation with k predictors. E denotes the part of the total difference attributed to the difference in endowments, while C denotes the part attributed to the difference in coefficients.

7 Main Results

7.1 From Pre-Work Characteristics to Tasks

The results of the first-stage decomposition of tasks on pre-work characteristics are shown in Table 4. Choosing female as the reference group, if the average female associate had the same pre-work characteristics as the average male associate holding all else equal, their PC score would be 0.027 higher, dropping the total gap from 0.103 to 0.076. This can be interpreted in a more meaningful way as 26.2% of the gap between female and male associates being explained by differences in pre-work characteristics, while 73.8% of the gap can be explained by differences in the returns to pre-work characteristics.

Notably, the selection of a reference group changes the share of the total gap in task assignment that can be attributed to differences in endowments versus differences in coefficients. Choosing males as the reference group results in 45.6% of the gap being explained by differences in pre-work characteristics, while 54.4% of the gap can be explained by differences in the returns to pre-work characteristics on task assignment (shown in Appendix Table A3). It is crucial to note that none of the totals are statistically significant, which indicates that pre-work characteristics do a poor job in accounting for the gap in task delegation. However, it is unclear if Blinder-Oaxaca decomposition results must be statistically significant, as the majority of published papers that report this form of decomposition do not include standard errors in their results (Jann (2005)).

This result is surprising, since I expected early task assignment to be largely determined by pre-work characteristics, given the lack of other quantifiable metrics that supervisors have access to at this stage of an associate's career. One important thing to note is that my dataset could not take into account the "personality" of associates, so it is possible that partners are deciding task delegation based on the perceived personality traits of associates. However, given the existence of a statistically significant gap in task allocation, it seems unlikely that men would, on average have much more sought-after personality traits compared to women. Another possibility is that

task assignment is randomly distributed by partners to associates; however, the existence of the significant difference between male and female associates' tasks again suggests work delegation is likely not random. Therefore, it is unclear what else is driving the gap in task assignment. This result is similarly reflected in Lehmann (2011)'s paper that discusses the racial gap in task assignment; after controlling for law school GPA, law school rank, and law review participation, she finds that there continues to be a statistically significant gap in task assignment between Black and White associates.

Moreover, I attempted to uncover if I found these results because I was only studying the Blinder-Oaxaca decomposition, which only breaks down the decomposition at the mean, as opposed to the entire distribution. I run a counterfactual density kernel plot and find similar results as seen in Appendix Figure A2 and A3, which depict the counterfactual distributions for females and males respectively. The female counterfactual distribution denotes the distribution of tasks women would have if they had the same pre-work characteristics as men. There do not seem to be significant differences between the counterfactual distribution and the original distribution. This aligns with my decomposition results that show differences in pre-work characteristics cannot explain most of the difference in task assignment.

Table 4: Decomposition of Tasks on Pre-Work Characteristics

	Difference in Endowments		Difference in Coefficients		
Detailed Decomposition	$\beta_f(\bar{X}_M - \bar{X}_F)$	Share of Gap	$\bar{x}^M(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap	**Total Gap**
Year Undergrad	0.004	0.039	0.119	1.155	
	(0.013)		(0.152)		
Direct to Law School	-0.002	-0.019	0.000	0.000	
	(0.010)		(0.114)		
Law Class Rank	-0.002	-0.019	0.031	0.301	
	(0.015)		(0.130)		
Law School Rank	0.033	0.320	0.031	0.301	
	(0.029)		(0.077)		
Law Alumni Association	-0.009	-0.087	0.138	1.340	
	(0.012)		(0.220)		
Moot Court	-0.007	-0.068	-0.065	-0.631	
	(0.015)		(0.092)		
Pro Bono Law	-0.006	-0.058	0.035	0.340	
	(0.021)		(0.120)		
Student Government	0.001	-0.010	0.053	0.515	
	(0.010)		(0.156)		
Charity Org	0.015	0.146	0.028	0.272	
	(0.018)		(0.146)		
Part Time Law	-0.001	-0.010	-0.044	-0.427	
	(0.014)		(0.031)		
Constant	.	.	-0.318	-3.087	
			(0.449)		
Total	0.027	0.262	0.076	0.738	0.103
	(0.054)		(0.105)		

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".

7.2 From Tasks to Performance

Moving on to understanding the relationship between task allocation and performance assessment, I first conducted a simple first-stage decomposition of the two performance metrics from

Wave 2, billed hours and number of clients, as the outcome variable on tasks. As depicted in Table 1, the difference in the number of annual billed hours between male and female associates in Wave 2 is 333.275, which is significant at a 1% level, while the difference in number of clients between male and female associates in Wave 2 is 4.981, which is also significant at a 1% level.

The results are depicted in Table 5, broken down into differences in endowments and differences in coefficients. Differences in endowments, namely differences in task assignment, do not seem to be able to explain the performance differential, given that using female associates as the reference group yields less than 1.5% of the gap explained by endowments. While these results are not statistically significant, the confidence intervals suggest that at maximum, less than 10% of the difference in billed hours can be explained by differences in task assignment, which suggests the majority of the gap is due to external factors. Decomposing using male as the reference group yields a similar result, as seen in Appendix Table A6.

However, it is still important to understand if the performance differences can be attributed to differences in task assignment as a function of pre-work characteristics. If there was a portion of the gap that was able to be explained by differences in task assignment through conducting a second-stage decomposition, this would indicate that pre-work characteristics do have an effect on performance, even if task assignments independently do not.

Table 5: Decomposition of Performance on Tasks

Billed Hours	$\beta_f(\bar{X}_M - \bar{X}_F)$	Share of Gap
Endowments	4.048	0.012
	(12.301)	
Coefficients	329.227	0.988
	(65.851)	
Total Gap	333.275	1.000
Number of Clients	$\bar{x}_M(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Endowments	0.017	0.003
	(0.093)	
Coefficients	4.963	0.997
	(1.866)	
Total Gap	4.981	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".

Thus, I conducted a second-stage decomposition with the performance metrics as the outcome variable and task assignment as a function of pre-work characteristics as the predictor variable. The full results with all three models that use female as the reference group can be seen in Table 6.

In general, the models give very similar results; every model consists of a large share of the gap being explained by the difference in the returns to tasks on performance, with a minimal share of the gap being explained by either the difference in returns to pre-work characteristics on tasks or the difference in pre-work characteristics themselves. For example, focusing on billed hours in Model 1, -1.51% of the gap can be explained by differences in returns to pre-work characteristics, 98.79% can be explained by differences in returns to tasks on performance, and 2.73% can be explained by differences in pre-work characteristics themselves. Turning to the gap in the number

of clients for Model 1, virtually none of the gap can be explained by differences in returns to pre-work characteristics, 99.64% can be explained by differences in returns to tasks on performance, and 0.36% of the gap can be explained by differences in pre-work characteristics. This indicates that, holding all else constant, if female associates had the same returns to pre-work characteristics on tasks as male associates on average, I would actually expect their annual billed hours to decrease by around 5 hours, while I would expect their client numbers to have no change. Clearly, differences in the returns to pre-work characteristics cannot explain the performance gap.

In contrast, the largest difference is due to female and male associates having differences in performance, despite being assigned similar tasks. For instance, Table 6 would indicate that if female associates had the same returns to tasks on performance as male associates on average, holding all else constant, their annual billed hours would increase by 329.227 and number of clients would increase by 4.963, which would explain almost the entire performance differential. However, it is necessary to look at a more detailed decomposition of each of these parts in order to understand what makes up the largest portion of each of these totals. Since I am currently looking at the aggregate total of each section, the logical next step is to uncover which pre-work characteristics, returns to pre-work characteristics, or returns to task assignment matter more. Additionally, it is possible that different characteristics are canceling each other out, resulting in the small totals I see for the amount explained by the difference in returns to pre-work characteristics and the difference in pre-work characteristics. For example, it is possible that difference in moot court participation between male and female associates may be widening the gap in performance, but it is canceled out by difference in law school class ranks, which could be narrowing the gap in performance. Thus, it is important to explore the detailed decomposition of each of these sections in order to gain a more nuanced picture of what exactly is driving the performance differential.

Table 6: Decomposition of Performance on Tasks as Function of Pre-Work Characteristics

	Billed Hours			**Number of Clients**		
	Betas	Gammas	Preworks	Betas	Gammas	Preworks
	$w_b(\beta_M - \beta_F)$	$w_g(\gamma_M - \gamma_F)$	$w_p(\bar{X}_M - \bar{X}_F)$	$w_b(\beta_M - \beta_F)$	$w_g(\gamma_M - \gamma_F)$	$w_p(\bar{X}_M - \bar{X}_F)$
Model 1	-5.036	329.227	9.084	-0.001	4.963	0.018
Model 2	1.475	333.920	-2.119	-4.290	8.814	0.458
Model 3	6.167	329.227	-2.119	-0.441	4.963	0.458
Total Gap		333.275			4.981	

Notes: Beta refers to the difference in returns to pre-work characteristics on tasks, Gamma refers to the difference in returns to tasks on performance, and Prework refers to the difference in pre-work characteristics. The (w_b, w_g, w_p) values are ($\gamma_1^F \bar{X}^F$, $\beta_1^M \bar{X}^M$, $\beta_1^M \gamma_1^F$) for Model 1, ($\gamma_1^F \bar{X}^M$, $\beta_1^M \bar{X}^M$, $\beta_1^F \gamma_1^F$) for Model 5, and ($\gamma_1^M \bar{X}^M$, $\beta_1^F \bar{X}^M$, $\beta_1^F \gamma_1^F$) for Model 3.

The detailed decomposition of the differences in pre-work characteristics and differences in returns to pre-work characteristics on tasks are depicted in Appendix Table A4 and A5. Since these two categories relate primarily to the first decomposition of pre-work characteristics on tasks, I refer to them as "first-stage differences." As three different models exist, I chose only to depict the lower bound and upper bound values for each portion. This is defined as the smallest and largest values among the models for each category; for example, the lower bound for "Differences in 1st Stage Coefficients" for billed hours comes from Model 1, while the upper bound comes from Model 3. It is clear that none of the pre-work characteristics or returns on any of the pre-work characteristics are able to explain a significant portion of the differences in billed hours or number of clients. Looking at billed hours specifically, it seems as though the portions that account for the largest positive share are the intercept and the returns to law school rank, while the largest negative shares can be attributed to law class rank, direct entry into law school, and participation in college alumni association. However, no individual event other than the intercept is able to explain a significant portion of the difference in performance. A detailed decomposition of the contribution of differences in pre-work characteristics on the performance differential also reveals that none of the differences can explain more than 1.5% of the gap.

The detailed decomposition of the differences in returns to tasks on performance are depicted in Table 7. Since this has to do with the relationship between tasks and performance, I will refer to this as "second-stage differences." Again, the lower and upper bound values of the contribution of the returns to tasks on performance for the gap in performance are depicted. The first column of Table 7 depicts the lower bound for this contribution, and it can be interpreted as such: 101.36% of the gap can be explained by differences in the intercept of the second-stage coefficients, 10.47% of the gap can be explained by differences in the intercept of the first-stage coefficients, 1.29% can be explained by differences in the second-stage coefficients on the year of undergrad, and so on. Once more, the intercept seemingly explains an overwhelming share of the gap in performance. Thus, the largest source of the differences in returns to tasks on performance comes from the intercept.

This means that I cannot find a relationship between the difference in performance and the difference in task assignment as a function of pre-work characteristics, since the intercept being the largest source of the gap suggests that there are external factors causing the performance gap that are not related to task assignment. This result goes against my original hypothesis, as I had predicted that differences in task assignment would be able to explain a portion of the performance differential, given the interlinked relationship between the tasks that associates are working on and the number of hours they are able to bill or number of clients they are able to attract into the firm.

Table 7: Detailed Decomposition of Second-Stage Coefficients

	Billed Hours		**Number of Clients**	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Intercept	337.792	337.792	5.736	5.736
Beta Intercept	34.897	34.897	1.410	14.735
Year of Undergrad	4.312	3.998	-0.448	-1.327
Direct from Undergrad to JD	6.272	6.899	-0.051	-1.153
Law Class Rank	-7.082	-7.785	0.347	-4.567
Law School Rank	-34.028	-32.539	-0.801	-2.643
College Alumni Association	4.665	7.310	0.673	-0.047
Pro Bono Law	-3.328	-4.189	-0.266	-0.695
Student Government	0.289	1.553	0.026	-0.294
Moot Court	-6.964	-4.918	-0.737	-0.641
Charity Organization	-9.028	-9.955	-0.742	-0.193
Part-time Law Student	1.430	0.858	-0.184	-0.098
Overall	329.227	333.920	4.963	8.814

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. "Intercept" refers to the intercept from the regression of performance assessment on task assignment as a function of pre-work characteristics. "Beta Intercept" refers to the intercept from the regression of task assignment on pre-work characteristics.

There are a few reasons as to why I may not find differences in tasks to be able to explain differences in performance. One possible reason is that the majority of the difference comes from client-side discrimination against female associates. If a partner assigned similar tasks to male and female lawyers who also hold similar qualifications, but clients themselves prefer to work with male associates, this would cause men to have higher performance metrics. Another reason could be related to differences in other activities that are not directly documented in task assignment and mentorship, such as networking. For instance, if female and male lawyers were assigned similar tasks in the selection observable from the dataset, but had vastly different experiences and opportunities for networking, that may resolve the gender differences in performance assessment. In general, it

is likely that the other channels of discrimination I discussed in Section 2.4, such as differences in cultural capital, childcare and career aspirations, and client-side biases may be explaining the differences in performance that task assignment cannot.

This result is somewhat consistent with the findings from Azmat and Ferrer (2017), which note that university rank and judicial clerkship have negligible effects on the gap in performance and promotion. This seems to suggest that differences in pre-work characteristics are not able to explain the performance differential. Likewise, they find that women not receiving enough assignments does not seem to have an effect on the gender gap in billed hours either. While the number of assignments associates receive is different from the type of assignments they are assigned, there still may be a relationship between the two; for instance, female lawyers who report being assigned less tasks than desired may be the same lawyers who are being assigned less "desirable" tasks, which is why they want to be assigned more work to improve their abilities and demonstrate their competence.

7.3 Off-the-CV Decompositions

There may be other possible characteristics in the AJD dataset that could explain differences in performance, which are not directly reflected on a resume or through task assignment and mentorship. For instance, existing literature points to the effect of children on the gender wage gap, especially for highly skilled female workers. Thus, I chose various "off-the-CV characteristics" and used each one individually with task assignment in a first-stage decomposition of performance. The characteristics I chose to test included: sexual orientation, marital status, number of kids, father's education, mother's education, equity partner aspirations, non-equity partner aspirations, of-counsel aspirations, and binary variables that indicate whether the associate's mom or dad were born in the United States.

The results differed based on the performance metric used as the outcome variable. For billed hours, I found that sexual orientation, marital status, number of kids, non-equity partner aspirations, of-counsel aspirations, and having American-born parents all independently explained less

than 5% of the gap in the performance using female as the reference group. However, father's education, mother's education, and equity partner aspirations were all independently able to explain more than 20% of the performance differential when using female as the reference group. After combining these three characteristics with task assignment, I found that differences in endowments could explain 50.1% of the gap in performance. This result, depicted in Table 8, is statistically significant at the 1% level. While I need to do further investigation to understand why these three variables matter in explaining the gap in performance, this result seems to suggest that differences in aspirations and social capital seem to be important in determining the number of hours that associates bill.

Turning to number of clients, sexual orientation, number of kids, mother's education, equity partner aspirations, non-equity partner aspirations, of-counsel aspirations, and parents' birth location were all able to explain less than 5% of the gap in performance independently. However, father's education and marital status were each independently able to explain more 20% of the gap in performance when using female as the reference group. After combining these two characteristics with task assignment, the differences in endowments were able to explain 45.5% of the gap in performance. However, this result, as can be seen in Table 9, is not statistically significant. Thus, it is unclear if father's education and marital status are truly able to explain differences in the number of clients that associates are able to accrue. Further research is necessary to uncover what is driving the performance gap with regards to the number of clients. The results of the decomposition on "off-the-CV characteristics" for billed hours and number of clients using male as the reference group are shown in Appendix Table A7 and A8 respectively.

Part of my results in this section are consistent with previous literature; namely, Azmat et al. (2020) also find that far more male associates have strong aspirations to become partner, while female associates are much less likely to list becoming partner as an important aspiration. However, there has yet to be any literature that documents the effect of differences in parental education and marital status between male and female associates, which may be a relevant and interesting path

for future research.

Table 8: Detailed Decomposition of Billed Hours on Off-the-CV Characteristics

Endowments	$\beta_f(\bar{X}_M - \bar{X}_F)$	Share of Gap
Tasks	3.952	0.013
	(8.389)	
Mom Education	53.232	0.174
	(36.381)	
Dad Education	39.181	0.128
	(31.685)	
Equity Partner Aspirations	57.329	0.187
	(46.446)	
Total	153.694	0.501
	(62.520)	
Coefficients	$\bar{x}_M(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Tasks	-4.100	-0.013
	(10.295)	
Mom Education	-9.164	-0.030
	(99.690)	
Dad Education	-1.421	-0.005
	(76.980)	
Equity Partner Aspirations	-33.817	-0.110
	(60.737)	
Constant	201.579	0.657
	(130.667)	
Total	153.077	0.499
	(84.218)	
Total Gap	306.771	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap". "Mom Education" and "Dad Education" are categorical variables with the following nine levels: grade school, some high school, high school diploma, trade/vocational school, associate/two-year degree, bachelors/four-year degree, law degree, some graduate/professional school, and graduate/professional degree.

Table 9: Detailed Decomposition of Number of Clients on Off-the-CV Characteristics

Endowments	$\beta_f(\bar{X}_M - \bar{X}_F)$	Share of Gap
Tasks	0.161	0.032
	(0.841)	
Dad Education	1.383	0.278
	(1.953)	
Marital Status	0.724	0.145
	(0.944)	
Total	2.268	0.455
	(2.231)	
Coefficients	$\bar{x}_M(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Tasks	-1.046	0.214
	(0.852)	
Dad Education	-0.274	-0.055
	(1.958)	
Marital Status	-3.723	-0.761
	(3.012)	
Constant	7.756	1.557
	(4.099)	
Total	2.713	0.545
	(2.649)	
Total Gap	4.981	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap". "Marital Status" is a categorical level with the following seven levels: never married, married first time, remarried after divorce, domestic partnership, divorced, widowed, and other.

8 Conclusion

In this paper, I consider the effect of accumulated discrimination from pre-work qualifications to task assignment to performance in order to understand the gender gaps in large law firms. Substantial gender gaps in performance between male and female associates, with documented consequences on earnings and promotion, exist in these firms. Thus, it is important to understand the determinants that cause this performance differential in order to find targeted solutions to the issue.

My primary research question was: how much of the difference in workplace performance is due to accumulated discrimination from task assignment as a function of pre-work characteristics? To answer this question, I extend on the existing Blinder-Oaxaca decomposition model by considering the effects of accumulated discrimination through the use of a second-stage decomposition. Using a second-stage decomposition of performance, I find that almost none of the gap in billed hours or number of clients can be attributed to differences in task assignment as a result of pre-work characteristics.

I also explore two secondary questions: i) are differences in pre-work characteristics able to explain differences in task assignment, and ii) what are other "off-the-CV" factors that may explain the performance differential? To answer the first, I use a first-stage Blinder-Oaxaca decomposition and find that a few extracurricular activities, in particular moot court and charity organization leadership, can explain a portion of the gap in task assignment, but in total less than 30% of the task gap can be explained by differences in pre-work characteristics, a result that is also statistically insignificant. This suggests that worker qualifications are not the primary driver of task assignment; rather, other factors such as personality and motivation may be more vital in determining work delegation. With regards to the latter secondary question, I run multiple first-stage decompositions to find that differences in parental education and equity partner aspirations are able to explain half of the difference in annual billed hours between male and female associates, a result that is statistically significant. This suggests that other factors, such as worker ambition and social capital

may be playing a large role in shaping career outcomes.

All in all, my results reveal the difficulty of truly pinpointing the cause of gender differences in career outcomes within the legal field. Further investigation is necessary to uncover what can explain the performance differential. Potentially, client-side discrimination may be an influencing factor; therefore, attempting to understand the implicit and explicit bias that clients hold against female lawyers may be important in decomposing the gender gap. Additionally, cultural capital may be able to explain a portion of the difference, though given the vagueness of the term, there may be limitations to acquiring data on differences in cultural capital. While strong pre-work characteristics and favorable task assignment may still be important for all lawyers, these do not seem to be primary factors that result in the gender gap in performance metrics.

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9 Appendix

Table A1: Group Lasso Regression versus OLS Regression Coefficients

	Lasso Regression Coefficients	**OLS Regression Coefficients**
Year Begin Work	.	-0.069
Year Complete Undergrad	-0.010	-0.106
Years Between College & JD	.	-0.088
Law Class Rank 2	0.008	0.019
Law Class Rank 3	-0.010	-0.021
Law Class Rank 4	0.007	0.578
Law Class Rank 5	-0.008	-0.126
Law School Rank 2	-0.008	-0.057
Law School Rank 3	-0.001	0.293
Law School Rank 4	0.014	0.481
Law School Rank 5	0.038	1.005
Law School Rank 6	-0.000	-0.068
Activity: Alumni (Member)	0.011	0.011
Activity: Alumni (Leadership)	0.001	-0.420
Activity: Bar Association (Member)	.	-0.227
Activity: Bar Association (Leadership)	.	3.599
Activity: General Law Review (Member)	.	-0.264
Activity: General Law Review (Leadership)	.	0.107
Activity: Moot Court (Member)	0.011	0.032
Activity: Moot Court (Leadership)	0.295	0.448
Activity: Other Law Review (Member)	.	-0.005
Activity: Other Law Review (Leadership)	.	0.080
Activity: Political Advocacy (Member)	.	0.119
Activity: Political Advocacy (Leadership)	.	0.801
Activity: Political Party (Member)	.	0.480
Activity: Political Party (Leadership)	.	-1.021
Activity: Pro Bono Work (Member)	-0.014	0.013
Activity: Pro Bono Work (Leadership)	0.006	0.575
Activity: Public Interest Law (Member)	.	-0.265
Activity: Public Interest Law (Leadership)	.	-1.268
Activity: Race Org (Member)	.	-0.035
Activity: Race Org (Leadership)	.	-0.045
Activity: Student Gov't (Member)	-0.070	-0.452
Activity: Student Gov't (Leadership)	0.063	0.224
Major: Biology	.	0.045
Major: Business	.	-0.404

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Table A1 – continued from previous page

	Lasso Regression Coefficients	OLS Regression Coefficients
Major: Criminal Justice/Law	.	-0.626
Major: Engineering	.	-0.313
Major: Humanities	.	-0.399
Major: Science/Math	.	-0.500
Major: Social Science	.	-0.066
Direct to Law School	0.085	0.290
Bar Association (Member)	.	-0.031
Bar Association (Active Participant)	.	-0.465
Bar Association (Former Participant)	.	0.179
Charity Orgs (Member)	0.037	0.149
Charity Orgs (Active Participant)	0.312	0.881
Charity Orgs (Former Participant)	0.021	0.418
Civic Association (Member)	.	0.020
Civic Association (Active Participant)	.	-0.396
Civic Association (Former Participant)	.	-1.076
College Alumni (Member)	.	-0.040
College Alumni (Active Participant)	.	-0.384
College Alumni (Former Participant)	.	-0.603
Gender Orgs (Member)	.	-0.132
Gender Orgs (Active Participant)	.	-0.191
Gender Orgs (Former Participant)	.	0.379
Law Alumni (Member)	.	-0.222
Law Alumni (Active Participant)	.	0.679
Law Alumni (Former Participant)	.	1.409
Local Bar (Member)	.	0.200
Local Bar (Active Participant)	.	-0.400
Local Bar (Former Participant)	.	0.675
Political Advocacy (Member)	.	0.018
Political Advocacy (Active Participant)	.	0.374
Political Advocacy (Former Participant)	.	-0.352
Political Party (Member)	.	-0.138
Political Party (Active Participant)	.	-0.843
Political Party (Former Participant)	.	0.403
PTA (Member)	.	0.255
PTA (Active Participant)	.	-0.509
PTA (Former Participant)	.	-1.757
Service Orgs (Member)	.	0.168
Service Orgs (Active Participant)	.	-0.527
Service Orgs (Former Participant)	.	1.541
Substantive Bar Assocs (Member)	.	0.187

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Table A1 – continued from previous page

	Lasso Regression Coefficients	OLS Regression Coefficients
Substantive Bar Assocs (Active Participant)	.	1.329
Substantive Bar Assocs (Former Participant)	.	-2.184
Undergrad GPA Rank 2	.	-0.348
Undergrad GPA Rank 3	.	-0.156
Undergrad GPA Rank 4	.	0.308
Undergrad GPA Rank 5	.	-0.471
Undergrad GPA Rank 6	.	-0.282
Undergrad GPA Rank 7	.	0.000
Undergrad GPA Rank 8	.	-0.811
Undergrad Class Rank 2	.	0.206
Undergrad Class Rank 3	.	-0.259
Undergrad Class Rank 4	.	-0.431
Undergrad Class Rank 5	.	0.728
Law GPA Rank 2	.	-0.101
Law GPA Rank 3	.	-0.228
Law GPA Rank 4	.	-0.675
Law GPA Rank 5	.	-0.414
Law GPA Rank 6	.	-1.098
Activity: Other (Member)	.	-0.044
Activity: Other (Leadership)	.	-0.357
Interim: Family	.	-0.366
Interim: Jobs	.	-0.086
Interim: Graduate School	.	0.645
Interim: Military	.	0.918
Other Orgs (Member)	.	0.330
Other Orgs (Active Participant)	.	0.169
Other Orgs (Former Participant)	.	0.470
Part Time Law	0.112	-0.171
Doctorate Degree	.	1.114
LLM	.	-0.419
Masters Degree	.	0.100
MBA	.	-0.024
Clerkship	.	-0.676
First Job	.	-0.013

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. "Lasso Regression Coefficients" were derived from a group lasso regression with task assignment as the outcome variable. "OLS Regression Coefficients" were derived from running a linear regression of task assignment on all potential pre-work characteristics.

Table A2: Weights for Second-Stage Decomposition

Option 1	Option 2	Weight on Beta	Weight on Gamma	Weight on Xs
$\hat{\gamma}_M(\hat{\beta}_M\bar{X}_F)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^F\bar{X}^F$	$\beta_1^M\bar{X}^F$	$\beta_1^M\gamma_1^M$
$\hat{\gamma}_M(\hat{\beta}_M\bar{X}_F)$	$\hat{\gamma}_M\hat{\beta}_F$	$\gamma_1^M\bar{X}^F$	$\beta_1^F\bar{X}^F$	$\beta_1^M\gamma_1^M$
$\hat{\gamma}_M(\hat{\beta}_F\bar{X}_M)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^M\bar{X}^M$	$\beta_1^F\bar{X}^M$	$\beta_1^F\gamma_1^F$
$\hat{\gamma}_M(\hat{\beta}_F\bar{X}_M)$	$\hat{\gamma}_M\hat{\beta}_F$	$\gamma_1^M\bar{X}^M$	$\beta_1^F\bar{X}^F$	$\beta_1^F\gamma_1^M$
$\hat{\gamma}_M(\hat{\beta}_F\bar{X}_F)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^M\bar{X}^M$	$\beta_1^F\bar{X}^F$	$\beta_1^F\gamma_1^M$
$\hat{\gamma}_M(\hat{\beta}_F\bar{X}_F)$	$\hat{\gamma}_M\hat{\beta}_F$	$\gamma_1^M\bar{X}^F$	$\beta_1^F\bar{X}^F$	$\beta_1^M\gamma_1^M$
$\hat{\gamma}_F(\hat{\beta}_M\bar{X}_M)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^F\bar{X}^M$	$\beta_1^M\bar{X}^M$	$\beta_1^F\gamma_1^F$
$\hat{\gamma}_F(\hat{\beta}_M\bar{X}_M)$	$\hat{\gamma}_M\hat{\beta}_F$	$\gamma_1^F\bar{X}^F$	$\beta_1^M\bar{X}^M$	$\beta_1^M\gamma_1^F$
$\hat{\gamma}_F(\hat{\beta}_M\bar{X}_F)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^F\bar{X}^F$	$\beta_1^M\bar{X}^M$	$\beta_1^M\gamma_1^F$
$\hat{\gamma}_F(\hat{\beta}_M\bar{X}_F)$	$\hat{\gamma}_M\hat{\beta}_F$	$\gamma_1^F\bar{X}^F$	$\beta_1^M\bar{X}^F$	$\beta_1^M\gamma_1^M$
$\hat{\gamma}_F(\hat{\beta}_F\bar{X}_M)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^F\bar{X}^M$	$\beta_1^M\bar{X}^M$	$\beta_1^F\gamma_1^F$
$\hat{\gamma}_F(\hat{\beta}_F\bar{X}_M)$	$\hat{\gamma}_F\hat{\beta}_M$	$\gamma_1^M\bar{X}^M$	$\beta_1^F\bar{X}^M$	$\beta_1^F\gamma_1^F$

Notes: "Option 1" refers to one of six possible choices made during the second-stage decomposition, while "Option 2" refers to one of two possible choices made. A more detailed explanation can be found in Section 6.1.2. "Weight on Beta" refers to w_b in w_b in $w_b(\beta_M - \beta_F)$, "Weight on Gamma" refers to w_g in $w_g(\gamma_M - \gamma_F)$, and "Weight on Xs" refers to w_p in $w_p(\bar{X}_M - \bar{X}_F)$.

Table A3: Decomposition of Tasks on Pre-Work Characteristics (Male as Reference)

	Difference in Endowments		Difference in Coefficients		
Detailed Decomposition	$\beta_m(\bar{X}_M - \bar{X}_F)$	Share of Gap	$\bar{x}^F(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap	**Total Gap**
Year Undergrad	0.002	0.019	0.120	1.165	
	(0.018)		(0.150)		
Direct to Law School	-0.002	-0.019	0.000	0.000	
	(0.010)		(0.116)		
Law Class Rank	0.012	0.117	0.081	0.786	
	(0.020)		(0.115)		
Law School Rank	-0.017	-0.165	0.081	0.786	
	(0.024)		(0.063)		
Law Alumni Assoc	0.004	0.039	0.126	1.223	
	(0.007)		(0.218)		
Moot Court	0.007	0.068	-0.078	-0.757	
	(0.025)		(0.084)		
Pro Bono Law	0.009	0.087	0.020	0.194	
	(0.023)		(0.102)		
Student Government	0.017	0.165	0.038	0.369	
	(0.022)		(0.038)		
Charity Org	0.015	0.146	0.029	0.282	
	(0.016)		(0.146)		
Part Time Law	0.000	0.000	-0.045	-0.437	
	(0.002)		(0.031)		
Constant	.	.	-0.318	-3.087	
			(0.449)		
Total	0.047	0.456	0.056	0.544	0.103
	(0.055)		(0.106)		

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".

Figure A1: Density Plots of Male and Female's Principal Component Distributions

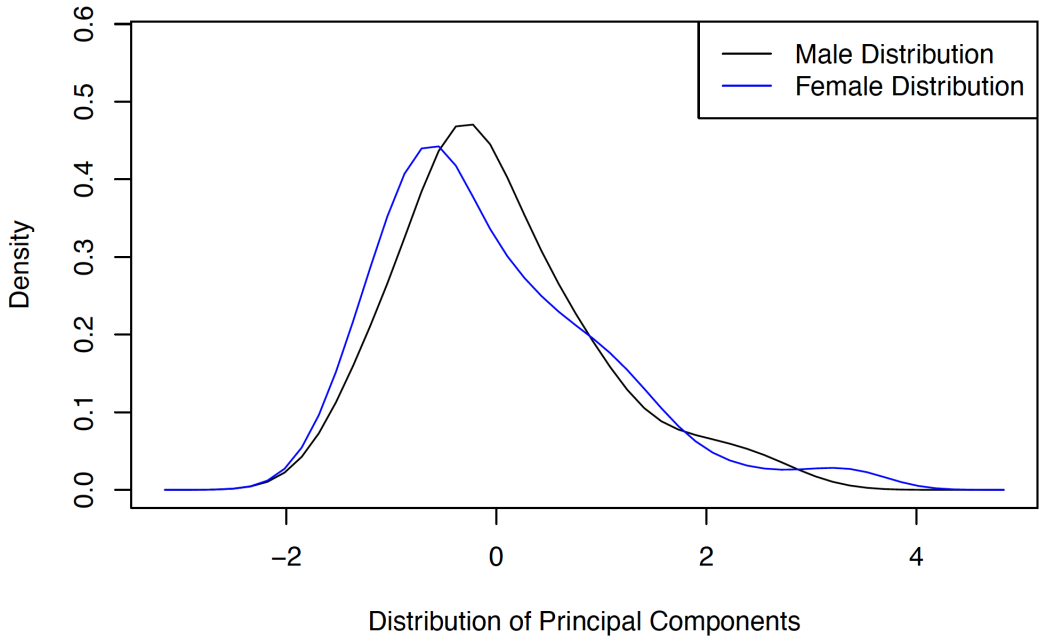
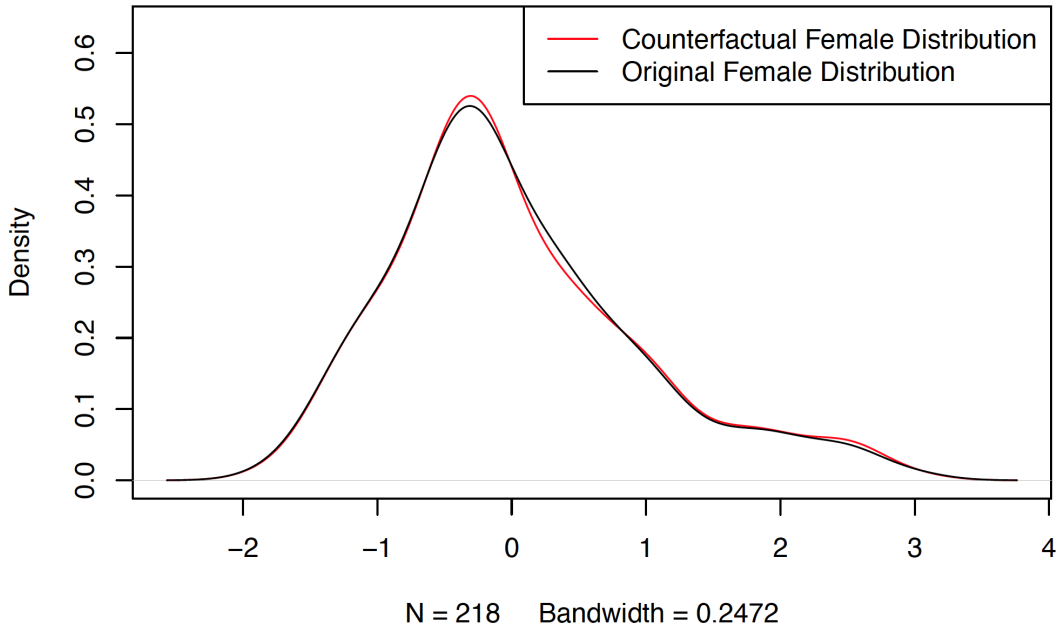
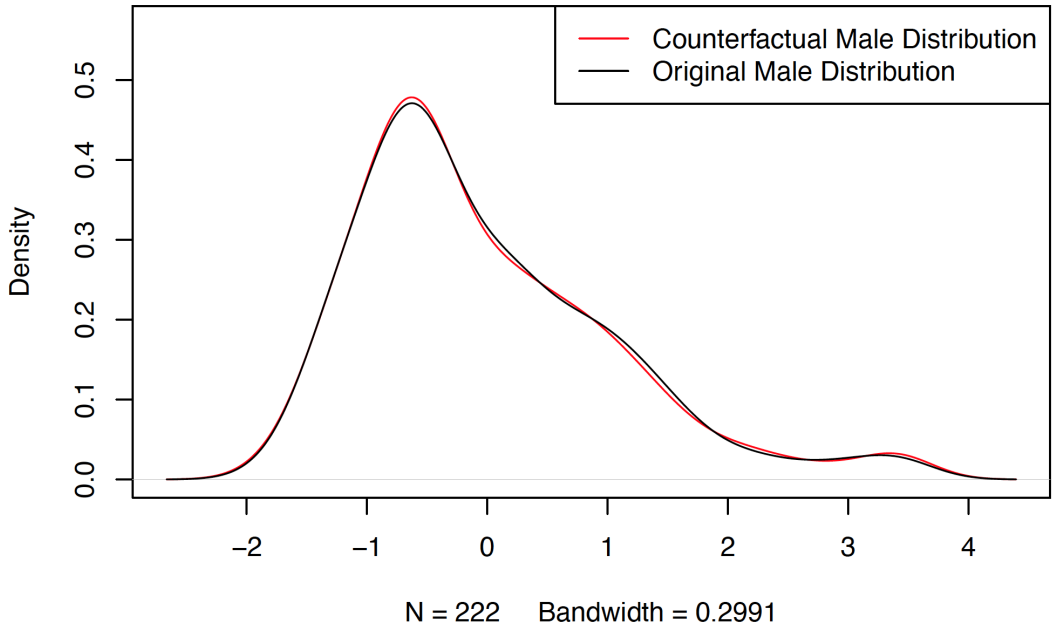


Figure A2: Counterfactual Density Plot (Female as Reference)



Notes: "Counterfactual Female Distribution" assumes that female associates had the same pre-work characteristics as male associates and then re-computes their principal component score distribution on this basis, holding all else constant.

Figure A3: Counterfactual Density Plot (Male as Reference)



Notes: "Counterfactual Male Distribution" assumes that male associates had the same pre-work characteristics as female associates and then re-computes their principal component score distribution on this basis, holding all else constant.

Table A4: Detailed Decomposition of First Stage Differences (Billed Hours)

	Difference in 1st Stage Coefficients ($\beta^M - \beta^F$)		Difference in Preworks ($\bar{X}^M - \bar{X}^F$)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Intercept	25.284	25.284	.	.
Year of Undergrad	1.162	0.072	0.162	-0.412
Direct from Undergrad to JD	-22.471	-20.428	-0.291	0.824
Law Class Rank	-24.455	-16.569	-2.107	-0.924
Law School Rank	36.868	37.091	0.414	1.956
College Alumni Association	-15.913	-10.261	-0.520	3.476
Pro Bono Law	-0.364	-0.081	-0.339	-1.132
Student Government	0.135	0.879	0.219	1.661
Moot Court	-3.614	-3.870	0.622	2.689
Charity Organization	0.685	-2.374	1.137	1.698
Part-time Law Student	-2.352	-3.920	-0.195	-0.752
Overall	-5.036	6.167	-2.119	9.084

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey.

Table A5: Detailed Decomposition of First Stage Differences (Number of Clients)

	Difference in 1st Stage Coefficients ($\beta^M - \beta^F$)		Difference in Preworks ($\bar{X}^M - \bar{X}^F$)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Intercept	-14.849	-1.525	.	.
Year of Undergrad	1.030	0.519	0.005	0.168
Direct from Undergrad to JD	1.237	0.331	0.001	0.249
Law Class Rank	5.606	0.833	0.031	2.955
Law School Rank	2.057	0.063	0.001	-0.285
College Alumni Association	0.622	0.036	-0.018	0.038
Pro Bono Law	0.478	0.062	0.000	0.361
Student Government	0.249	0.087	-0.011	0.171
Moot Court	-0.142	-0.133	-0.004	0.641
Charity Organization	-0.551	0.108	0.006	0.108
Part-time Law Student	-0.030	0.035	0.007	0.052
Overall	-4.290	-0.001	0.018	4.457

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey.

Table A6: Decomposition of Performance on Tasks (Male as Reference)

Billed Hours	$\beta_m(\bar{X}_M - \bar{X}_F)$	Share of Gap
Endowments	0.968	0.003
	(3.396)	
Coefficients	332.307	0.997
	(65.972)	
Total Gap	333.275	1.000
Number of Clients	$\bar{x}_F(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Endowments	0.167	0.034
	(0.869)	
Coefficients	4.814	0.966
	(1.921)	
Total Gap	4.981	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".

Table A7: Decomposition of Billed Hours on Off-the-CV Characteristics (Male as Reference)

Endowments	$\beta_m(\bar{X}_M - \bar{X}_F)$	Share of Gap
Tasks	0.997	0.003
	(5.026)	
Mom Education	-3.756	-0.012
	(24.999)	
Dad Education	-10.662	-0.035
	(27.426)	
Equity Partner Aspirations	8.151	0.027
	(35.982)	
Total	-5.271	-0.017
	(56.672)	
Coefficients	$\bar{x}_F(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Tasks	-1.146	-0.004
	(4.723)	
Mom Education	47.824	0.156
	(93.724)	
Dad Education	48.422	0.158
	(72.631)	
Equity Partner Aspirations	15.361	0.050
	(51.719)	
Constant	201.579	0.657
	(130.667)	
Total	312.041	1.017
	(87.225)	
Total Gap	306.771	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".

Table A8: Decomposition of Number of Clients on Off-the-CV Characteristics (Male as Reference)

Endowments	$\beta_m(\bar{X}_M - \bar{X}_F)$	Share of Gap
Tasks	0.161	0.032
	(0.841)	
Dad Education	1.383	0.278
	(1.953)	
Marital Status	0.724	0.145
	(0.944)	
Total	2.268	0.455
	(2.231)	
Coefficients	$\bar{x}_F(\hat{\beta}_M - \hat{\beta}_F)$	Share of Gap
Tasks	-1.046	0.214
	(0.852)	
Dad Education	-0.274	-0.055
	(1.958)	
Marital Status	-3.723	-0.761
	(3.012)	
Constant	7.756	1.557
	(4.099)	
Total	2.713	0.545
	(2.649)	
Total Gap	4.981	1.000

Notes: The sample is restricted to self-identified associates in Wave 1 with no missing gender information who responded to all three waves of the AJD survey. Standard errors are reported in parentheses. "Share of Gap" is found by taking the value found from the decomposition and dividing it by the value of the "Total Gap".