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An Empirical Analysis of Prominent Theories on the Gender Promotion Gap: Evidence from Panel Data on Law Graduates

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An Empirical Analysis of Prominent Theories on the Gender Promotion Gap

Evidence from Panel Data on Law Graduates

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Abstract

Women have unique, valuable information and insights that lead to their having different priorities and making different decisions than their male counterparts. Despite the fact that women have overtaken men in college attendance, there is a gender disparity in high powered positions that can be seen in many professions. Male and female lawyers, though exhibiting similar levels of competency, are promoted at different rates, exemplifying a trend throughout the world that is also closely related to the gender wage gap. The gender promotion gap is a topic that has been widely theorized upon, though never fully and satisfactorily explained. This paper assesses a wide array of proposed theories on the gender disparity in promotion using a single empirical dataset. I find that there is a 13 percentage point difference in promotion between men and women. Women may be subject to implicit, self-confirming bias that ends in an equilibrium where women, despite being of equal skill level, are promoted less frequently than their male counterparts due to task assignment early in their career. Male composition of firm does not affect task assignment, which contradicts theories on women's decision making. Controlling for task assignment does not reduce this gap as would be expected from prior literature. Ultimately, I find that the gap is reduced to 6 percentage points when controlling for billable hours, which are negatively affected by having children and spending time doing household chores. However, the persisting 6 percentage point gap remains unexplained.

I. Introduction

Despite the fact that women have overtaken men in college attendance (Flashman 2013), there is a gender disparity in high powered positions that can be seen in many (white collar) professions: the corporate and financial world (Bertrand, Goldin, and Katz 2010), the political sphere (Fox and Lawless 2010), the medical field (Reed et al. 2011), and the legal profession (Spurr 1990) to name a few. Bertrand and Hallock (2001) find that the gender wage gap among top executives is at least 45%. Much of this gap is explained by the dearth of female CEOs, Chairs, Vice-Chairs, and Presidents and by the fact that females are not executives in large corporations. Even in a study solely examining top executives, women are not promoted to the highest positions in large firms. Blau and Devaro (2007) find that, in a large sample of establishments, women are less likely to be promoted than men, but there are no gender differences in wage growth, "with or without promotions." The objective of this paper is to empirically assess prominent economic theories of the gender disparity in promotion.

The gender promotion gap is not well understood; it is a topic that has been widely theorized upon, though never fully and satisfactorily explained. This paper contributes to the field as the first (to my knowledge) to assess a wide array of proposed theories on the gender disparity in promotion using a single empirical dataset. Various theories have been proposed to explain the gender disparity in promotion, though many have not been fully tested outside of behavioral studies and theoretical models; there is no empirical evidence that can fully explain why this gap has come about. It is difficult to test these theories in an empirical study because there do not exist many natural experiments that lead to random variation in causes of the gender promotion gap. This paper seeks to utilize a very rich set of variables that are closely tied to prominent theories of gender discrimination. Other empirical studies have not had access to the broad range of variables

associated with explaining the gender disparity in promotion. The dataset used in this paper follows a large group of lawyers over their professional career, up to the point where they should have been promoted to partner. If they have not been promoted by their late career, it is unlikely that they will ever be promoted to partner. This dataset is advantageous because it has collected information that is extremely important, but not often observable, when assessing theories attempting to explain the gender gap in promotion.

The theory I endeavor to asses first and foremost is one of statistical discrimination by task assignment. Theoretical literature (Coate and Loury 1993, Arrow 1972, Bjerk 2008) would suggest that women may be subject to implicit, self-confirming bias that ends in an equilibrium where women, despite being of equal skill level, are promoted less frequently than their male counterparts due to task assignment and inability or lack of opportunity to signal their skill. I employ an empirical dataset that is able to assess this theory because it includes the tasks to which individuals were assigned in their early career. Given the literature, I would expect to find significant differences in tasks assigned to women and men; however, there is little variation by gender within task assignment in the empirical data. Possibly due to this lack of variation by gender, I do not find any effect on the gender gap in promotion to be driven by task assignment during individuals' early careers.

I then break down task assignment by male composition of firm because experimental evidence suggests that women are more likely to volunteer for worse tasks than their male counterparts when they are in a group of mixed gender but volunteer with the same likelihood when only among other women (Babcock 2016). I am able to assess this theory in conjunction with statistical discrimination by task because my dataset includes information on the male composition of the firm. Despite finding that the number of women working in male-dominated

firms decreases over time, I find that male composition does not cause variation in task assignment, and thus does not offer an explanation as to why the gender gap persists.

Another experiment suggests that women self-select into worse tasks in order to make themselves more attractive in the marriage market (Bursztyn et al. 2017). These women only do so when they believe their decisions will be observed by a possible future spouse. The dataset I employ contains information on an individual's preferences for work/life balance, enabling me to control for the possibility that women are self-selecting into lower-powered positions in order to work less and appear as more attractive candidates for marriage. Though there is little variation in task assignment between men and women, I find that controlling for a work/life balance preference and utilizing the same male-composition data as above has no effect.

The theory presented by Bertrand, Goldin, and Katz (2010) provides evidence from data on people in the U.S. corporate and financial sectors, suggesting that a possible cause of gender wage differences is related to career interruptions, especially due to childbearing. I am able to utilize data on career interruptions (and whether or not these interruptions were driven by children) to consider the ideas presented by Bertrand, Goldin, and Katz (2010); indeed, career interruptions are able to explain part of the gender disparity in promotion. Hours billed offers the largest explanation for this promotion gap, explaining about half of the difference in promotion between men and women. Children and household responsibilities cause quite a bit of the gender difference in billable hours, and thus affect the gender promotion gap through billable hours.

Finally, I utilize data determining the region in which an individual resides to proxy for sexism to attempt to explain the remaining 6 percentage point gap in promotion. Pan (2015) utilizes variation in sexism by region to test correlation between taste-based discrimination and gender disparities in occupation. Similarly, I utilize this variation in sexism to assess the correlation

between taste-based discrimination and the size of the unexplained gap in promotion. I find that there is a negative correlation between the two: when sexism in a region is higher, the unexplained gap in promotion is lower, leading me to believe that the gender gap in promotion is driven, in part, by a firm's sexism.

This paper finds that no one theory can fully explain the gender promotion gap. Initially I find a 13 percentage point gap between men and women who make partner. Despite a rich dataset, allowing for the assessment of the most prominent theories of the gender disparity in promotion, there remains a 6 percentage point difference in promotion between men and women that cannot be explained by any prominent theory or combination thereof.

Women and men have different preferences and are thus likely to make different decisions affecting the socio-economic sphere (Duflo 2012); this gender promotion gap does not allow for these different decisions to be made at a high level, thus reducing the overall impact of women's experiences on society. Esther Duflo (2012) reviews the existing literature on women as decision-makers and how their different preferences lead to different outcomes. Women who have higher relative incomes than their husbands (and thus bargaining power) tend to make decisions that lead to larger improvements in child health. It is clear from evidence in household decision-making that women have different preferences than men, so as policymakers, women "will prefer policies that better reflect their own priorities" (Duflo 2012). Regardless of whether or not these policies result in unambiguously positive outcomes for society overall, it is clear that having women in high-powered roles where they can act on their different preferences will lead to positive outcomes for women. Thus, the dearth of women in these high-level positions negatively impacts female outcomes.

To the extent that the legal profession is a vehicle for social change it is important for women to have a voice in this field. Duflo (2012) relays the importance of the legal environment in providing bargaining power to women within marriages through divorce, property, and pension laws. If women live in an environment where they are able to get divorced without negative societal repercussions, are able to own their own property, and can receive a pension directly, not only will unmarried or previously-married women be able to succeed, married women's bargaining power *within* their marriage will increase and they will be able to enforce their own priorities within the household. Additionally, Boyd, Epstein, and Martin (2010) find evidence that female judges make different decisions than their male counterparts and that serving on a bench with a female judge can change the way a male judge behaves. The evidence they find points to an "informational" premise; "women possess unique and valuable information emanating from shared professional experiences" (Boyd, Epstein, and Martin 2010). The gender disparity in promotion prevents this information from being used to benefit society.

II. Theories of Gender Disparity in Promotion

The gender wage gap has generated to an extremely large body of literature. This paper will focus on how differing standards, methods, and rates of promotion have given rise to the gender differences in the workforce. This paper builds both on statistical discrimination literature and experimental literature on the promotion rate of women. There are a multitude of explanations as to why women are promoted to high level jobs less often than their male counterparts.

There is an extensive literature that proposes gender difference in task assignment may be an important explanation for gender differences in promotion. When a worker arrives at a firm, their type is unobservable. Yet firms face an incentive to match workers to tasks that match their

abilities. Introspection suggests that if you give a young worker the chance to appear in court as 1st or 2nd chair or formulate strategy with senior members of the firm and/or clients, it substantially increases the likelihood that they would be promoted. Indeed, Xia Li (2016) confirms that there are tasks in law firms that are generally considered "good" (see Tables for list of good tasks), or on the promotion track. However, firms cannot observe the true type of their workers, so they must use other observable characteristics in deciding task assignment. Firms can observe output, but this may not accurately reflect ability, rather it could reflect exogenous shocks. Firms must continually update their prior beliefs based on signals from their workers and make decisions based on threshold rules. There is no restriction on what observable trait may be used by firms to infer worker-type. Thus, many models utilize race as an observable characteristic that may predict latent ability.

Indeed, Coate and Loury (1993) consider how affirmative action affects employers' negative stereotypes. Their model supposes that racial minorities are hired equally to their white counterparts and receive equal pay for equal work, but due to affirmative action, the standard for hiring minority groups is lower, or perceived as lower, than that for preferred workers. Employers have negative stereotypes about these minorities and thus utilize their observable characteristic of race to predict their ability. Then race proxies for ability, so minority workers are assumed to be "worse" than their white counterparts, and are assigned to worse tasks—less highly rewarding jobs. These stereotypes may be self-confirming for two reasons: 1) because there may be a lower hiring standard for minority workers, they might actually be less qualified and 2) because they see that they are not on track for promotion, they invest less in the company. These minority workers observe that they have been given tasks that do not lead to promotion and are incentivized to work less. Then the firm sees this outcome and assumes that they were correct in labeling minority

workers as less-skilled. Thus, we will reach an equilibrium in which these negative stereotypes about minorities are self-confirming, minorities will continue to be given tasks that are not on the promotion track, and the racial promotion disparity will continue *ad infinitum*.

Similar dynamics may play a role in the promotional gender gap by utilizing gender as an observable characteristic rather than race. My model tests the idea that women are not given tasks on the "promotion track" for fear that they will experience more career interruptions than their male counterparts. Indeed, this is a common assumption in the theoretical literature. Lazear and Rosen's (1990) gender-specific model of statistical discrimination theorizes that promotion choice is based on both ability and a worker's likelihood of remaining on the job. According to their model, "women of equal ability have a lower probability of promotion than men" because, despite their level of ability, they are presumed to be more likely to exit the workforce. Thus, women must signal greater ability than their male counterparts in order to be promoted. Even if workers were able to signal their actual ability, firms may utilize the observable characteristic of gender and assign women worse tasks on the assumption that women are more likely leave their job. Because women are assigned worse tasks, they may invest less in the company (and towards promotion) and are thus more likely to work less, have longer or more frequent career interruptions, and possibly drop out of the workforce. This could explain an equilibrium in which women are promoted less frequently than their male counterparts. As in Coate and Loury (1993), this equilibrium is self-fulfilling, that is, employers expect women to have frequent, lengthy career interruptions and so assign them worse tasks, and because they are assigned to worse tasks women do indeed have lengthier and more frequent career interruptions. In this type of equilibrium, the employer's observations ex-post match their beliefs ex-ante and it becomes very difficult to deviate from this equilibrium that does not truly reflect women's abilities in the labor market.

My focus on task assignment is driven by the prominence of task assignment in many literatures attempting to explain the gender promotion gap. David Bjerk (2008) proposes a model of statistical discrimination in which discrimination in promotion practices could occur if minorities have: 1) less ability to precisely signal their skill or 2) fewer opportunities for signaling. Bjerk calls this phenomenon "sticky floors." His model is supported by Altonji (2005) whose model predicts that sensitivity to skill signaling is dependent upon the skill level of the job. This is relevant to the model of statistical discrimination that I test because when women are given worse tasks or placed on the non-promotion track they have fewer opportunities to signal their skill level and this could act as an additional explanation of why they make partner more infrequently than their male counterparts. For instance, it is difficult for a woman to signal her skill as a lawyer if she is doing routine research and memo writing, but it may be much easier if she is assigned first or second chair. Women who are assigned worse tasks are then less able to signal their skill and, because senior partners have less information with which to make decisions, women get promoted to partner less frequently.

The pattern of promotion and wage inequality persists across a variety of job sectors. Malkiel and Malkiel (1973) find that women receive equal pay for equal work, but end up with a gendered wage gap due to their lower average job levels. In 1981 Cabral et al. find that male employees in fiduciary institutions tend to be more qualified than their female counterparts, but cannot fully explain the difference in compensation. Their data show that women experience arbitrary differences from men in both their pay and job assignment. Through the richness of my dataset, I can test for possible alternative theories that may eliminate the arbitrariness found by Cabral et al. Subsequent research by Olson and Becker (1983) uses the Quality of Employment Panel, 1973-1977. They compare constrained and unconstrained estimates to conclude that they

cannot reject the hypothesis that the coefficients determining promotion for men and women are equal. However, they do confirm that when the intercept varies by gender, it is not the same for men and women, which could be explained by women being held to a higher promotion standard or by employers expecting men to perform better than women when promoted. Thus, all else equal, though the returns from promotion are similar for men and women (that is men are not better off than women if both are promoted), men are promoted more frequently than their female counterparts and the processes by which they are promoted are not the same.

Similar research by Cannings (1988) finds that "female managers in one large Canadian company are distinctly less likely than their male colleagues to be promoted, and, furthermore, that their disadvantage is not primarily the result of differential probability 'returns' to particular *acquired* attributes." My model will be able to confirm that acquired attributes do not drive the gender gap in promotion because, as I will show below, men and women look very similar across acquired attributes, especially those that predict skill level such as GPA, law school rank, etc. Groshen (1991) finds that, across five industries, wages of males and females performing the same jobs differ only by one percent and that the largest source of the female/male wage gap is the association between wages and proportion female in occupations. She also finds that "even people who choose integrated occupations work primarily with members of their own sex" which leads to a gender wage gap. My dataset provides information on the individual's mentor's gender, which will enable me to see if women working closely with other women, or relying on them for help in signaling their skill in order to be promoted, can explain any of the gender disparity in promotion.

A study done on the legal profession by Spurr (1990) finds evidence of statistical discrimination. The difference in productivity between male and female lawyers is negligible, but the standard for promotion for females is much more demanding than that for males. Spurr utilizes

a model in which the standard of productivity is held constant but the probability that a person will have achieved y amount of successes is allowed to vary. The standard y needed for promotion is 56.5% higher for women than for men. Spurr cites reasons for a higher standard of promotion similar to those found in Lazear and Rosen's model: "a higher probability that women will leave the firm after being promoted, thereby depriving the firm of valuable firm-specific human capital." My dataset enables me to test for this directly by looking at women's work experience, history of unemployment, and how frequent and lengthy their career interruptions have been. I can also look at a variable indicating whether or not an individual plans to stay at the firm for 5 or more years.

The idea that there is self-selection into tasks is a complicating factor in empirical analysis of the gender disparity in promotion. It is difficult to disentangle gender differences in task assignment that are driven by firms trying to assign tasks to maximize profits from women self-selecting into tasks due to their own preferences. In fact, Babcock et al. (2016) conduct a laboratory study and find "women are more likely to volunteer, more likely to be asked to volunteer, and more likely to accept direct requests to volunteer" for worse tasks than their male counterparts. Women are then more likely to end up performing worse tasks. This likelihood to volunteer for worse tasks disappears when women are in groups solely composed of women; in fact, their volunteer rates become identical to their male counterparts, suggesting that the male composition of a firm could be a driving factor in women being assigned to worse tasks.

Bursztyn, Fujiwara, and Pallais (2017) utilize an experimental survey to test their hypothesis that single women in an MBA program avoid career-enhancing actions in order to be more appealing in the marriage market. They find that women who are not married or in long-term relationships report that they desire a lower salary and are willing to travel less than their married counterparts when they believe that their answers will be shared with their male classmates.

Additionally, in class assignments where achievements are private, single women score as well as their married counterparts, but in public grades (like participation) they score lower. This suggests that women who are looking for a partner are willing to sacrifice actions that promote success in their careers in order to appear more attractive to possible spouses. These theories of self-selection are important because they shed light on different incentives leading to women accepting or even requesting "worse" tasks. However, the dataset that I will be using includes information on individuals' preferences for work/life balance, marital status, and satisfaction with task assigned, which allow me to control for gender-based selection into tasks that would not usually be considered attractive.

A closely related idea is that potential career interruptions are child-related. Women have a comparative advantage in the household and may be more likely to leave their job because, compared to their male counterparts, they would be more effective doing household work. This may be observed simply by an individual's gender, and could explain why women may be assigned to worse tasks. The dataset I employ includes data on whether women, in fact, do more work in the household. Winter-Ebmer and Zweimuller (1997) find that the risk of childbearing in Austria cannot explain the crowding out of women into lower hierarchical positions. Yet Bertrand, Goldin, and Katz (2010) look at the gender wage gaps among professionals in the financial and corporate sectors and find that the cause of gender wage differences are related to childbearing. They report gender differences due to: a male advantage in training and labor market returns to such training, "gender differences in career interruptions combined with large earnings losses associated with any career interruption," and gender differences in weekly hours worked. Additionally, the presence of children results in less accumulated experience, greater career interruptions, shorter work hours, and earnings declines for women but not for men. Finally, Gangl and Ziefle (2009)

find, in a study comparing the United States, the United Kingdom, and Germany, that motherhood results in wage penalties between 9% and 18% per child.

An additional theory presented by Borjas and Bronars (1989) suggests consumer discrimination as an impetus for lower minority wages in self-employment. Because majority consumers discriminate against minority suppliers, these minorities must set their price points lower. This can be easily translated to consumer discrimination in law firms. If clients do not want to work with female lawyers, then these women will bring in fewer clients (and less revenue), thus decreasing their ability to make partner in the firm. The data I use includes revenue brought in and number of clients both brought in by and working with an individual. I am able to use this data to asses a theory of consumer discrimination.

Discrimination due to gender, though often suggested as a possible explanation for the gender disparity in both promotion and wages, is extremely difficult to assess. Pan (2015) utilizes regional variation in both sexism and tipping points to test the correlation between sexism and the role of tipping in gender segregation in occupations. Additionally, Bertrand, Kamenica, and Pan (2015) suggest that women who have higher incomes than their husbands have less happy marriages and are more likely to get divorced. This is truer in regions with high sexism. I will use a similar idea to take advantage of the regional variation in law firms in order to test for regional taste-based discrimination in the promotion of women to partner. For example, I expect that more of the gender based promotion gap will be explained for individuals working in the South than will be explained for individuals working in the Northeast because there is more sexism in the South than the Northeast.

Both the theoretical and empirical evidence presented above suggest that utilizing a model of statistical discrimination based on a woman's (perceived) higher likelihood to experience career

interruptions due to childbearing could have important explanatory purposes in regard to the gender wage gap that seems to have stagnated. Additionally, women could be self-selecting into worse tasks due to being in male-dominated firms (possibly in order to appear more desirable in the marriage market). The gender disparity in promotion may be driven in part by consumer discrimination and accepted gender norms. This paper aims to utilize a uniquely rich dataset to assess all of these theories on the gender disparity in promotion.

III. Data and Descriptive Statistics

Data

The legal profession is a field historically dominated by men. However, since the 1980s female participation has increased. Less than 3% of lawyers were female from 1950 through 1970; by 1984, they had grown to be 13% of all lawyers and by 2000, women represented 30% of lawyers in America (Curran (1986), 25; Schmidt (2000), 1). In 1980, only 13.7% of law school faculty were female but by 1986 that had increased to 20% (Chused (1988), 538). By 1996, 43.5% of J.D. and LL.B. degrees were awarded to women (Schmidt (2000), 1). This trend mimics national trends in white collar positions; women have made progress in traditionally male-dominated fields with high salaries. Despite the advances made by women in the legal profession, there is evidence that women are not being promoted to the highest level jobs within their firms.

The dataset I use is attractive for several reasons; it is the first and only national, longitudinal study of lawyers in the United States, the After the JD (AJD). The individuals within this dataset were drawn from a nationally representative group of lawyers entering the legal field in 2000 who graduated with their J.D. between 1998 and 2000. The AJD only includes individuals who entered a state bar in 2000. The AJD utilized a two-stage sampling approach, first selecting

to obtain a wide geographic and population size distribution of geographic areas, and then selecting individuals who met the requirements of the study within those geographic parameters. Finally, the AJD included an oversample of lawyers from minority groups (Black, Latin@, and Asian American) (AJD I Restricted Codebook, 3). Due to their sampling approach, the AJD data is nationally representative of lawyers in the United States who began their careers in 2000.

The first wave of data was collected in 2002 by mail questionnaires, web surveys, and telephone follow-up interviews (AJD I Restricted codebook, 4). Wave I of the AJD (hereafter referred to as "early career") had a 71% response rate for a total of 4,538 valid responses (Dinovitzer, 90). The AJD national sample matches the expected racial composition of young lawyers as would be predicted from results of the 2000 Census. Comparing gender composition to that found in American Bar Association data finds very similar results as well (Dinovitzer AJDI, 90). This allows me to generalize the results of my tests to all lawyers in the United States who began their careers in 2000 and provides insight into promotion mechanisms within other white collar careers in the United States. The second wave of data (hereafter referred to as "mid-career") was collected in 2007-2008 with a 50.6% response rate (AJDII, 12). This time period represents the point in a lawyer's career when they often decide if they will continue to work in a private firm and pursue partnership or leave to a nonprivate firm. Finally, the third wave of data (hereafter referred to as "late career") was collected in 2012 and had a 53% response rate for individuals who had previously responded to either AJD1 or AJD2 (ICPSR). The datasets include weight variables to account for attrition and ensure the dataset remains nationally representative. After the three waves were collected, there are 2,410 individuals who responded in every wave.

This dataset is unique in that it follows such a large group of individuals over a long period of time. It allows me to follow individuals' careers as they progress over time and test various

theories as to why women are promoted more infrequently than their male counterparts. The dataset includes GPA, assigned tasks (see page 39 for a list of tasks), billable hours, interaction with senior associates or partners, and whether or not the individual made partner which lets me test the theory of statistical discrimination. It includes data on the male composition of firms which allows me to look at whether or not women are self-selecting away from promotion due to societal expectations. It also includes marital status, number and age of children, whether an individual has worked part time due to children or taken parental leave, and hours spent doing household chores which allows me to assess theories about childcare on female promotion. Additionally, it contains data on how many clients each individual has and has brought in, and how much client revenue each individual brings in, which allows me to assess the theory of consumer discrimination. I utilize the GSS Male Sexism Index (1977-1998) by region as presented by Pan (2015) to explore if variation in sexism by region can explain variation in the gender promotion gap by region. These data come from the General Social Survey from 1977 to 1998.

Descriptive Statistics

Male and female respondents look very similar across demographics, which is to be expected. Table 1 displays the overall mean for demographic variables, the averages for each gender, and the difference between male and female means. Men and women are very similar across age and marital status. There are slightly more women who are nonwhite than their male counterparts, though the standard deviations are quite high and thus this difference is fairly negligible. Men and women have no difference in whether or not the job they are in during their early career is their first job, and there is no difference in their average GPAs. On average, men and women went to similarly ranked schools and have a similar educational debt. Women tend to

work in slightly smaller firms and are paid slightly less than their male counterparts in their early career, but these differences are negligible. Neither women nor men often make partner in their early career, which is to be expected, though there is already slight difference between the two groups. These similarities imply that the baseline characteristics and performance of individuals should not be driving their differences in promotion rates.

Table 2 displays the overall mean for variables that have to do with children and career interruptions, these means by gender, and the difference between the means for men and women. On average, men have more children than women early in their careers. There is no difference in the rate at which men and women work part time, but women work part time in order to care for children more often than their male counterparts. Women also work slightly fewer hours per week than men. I have included hours billed from men and women during mid-career as the variation there is quite stark and is important. Men bill more hours than their female counterparts during their mid-careers. The variable "Stay for 5+ years" is used as a proxy for whether or not an individual wants to make partner. If they do, they will most likely plan to stay at their current firm for 5 or more years. There is no difference in wanting to stay for 5+ years between men and women in their early careers. Because there is some variation by gender among number of children, working part time due to children, hours worked weekly, and hours billed it is possible that these may be causing the promotion gap.

Although there is literature that suggests men and women differ along task assignment in their early careers, Table 3 shows that men and women actually perform similar tasks. For example, men and women are equally assigned to appear in court as 1st or 2nd chair and there is no gendered difference between individuals assigned to do routine research and memo writing. Moreover, men and women are equally satisfied with the tasks they are assigned, suggesting that

women are not being assigned tasks that they feel are worse than those their male counterparts are assigned. My ability to observe which task individuals are assigned in their early career is an extremely important feature of this dataset. This allows me to test the theory of statistical discrimination. However, because men and women do not differ by task, my expectations for the results of this theory are somewhat different than what the literature may suggest. However, it is possible that task assignment differs depending on the male composition of the firm. I will explore this further below.

Table 4 displays the average rate of making partner throughout time for individuals overall, by gender, and the difference between genders for each stage of their career. Clearly, the difference increases. In their early careers, neither men nor women make partner very often, which is to be expected. Even so, women make partner less frequently than their male counterparts. By their mid-career, men and women differ in making partner by 6.4 percentage points. This is the trend I expected to find, and the trend that the literature suggests. By their late careers, individuals should have made partner if they decided to stay in a private firm. If they have not made partner by their late career, it is unlikely that they will make partner. By their late career, men and women differ in making partner by 11 percentage points. This trend confirms that women do indeed make partner less frequently than their male counterparts and motivates the rest of this paper.

Table 11 presents the GSS Male Sexism Index for white-collar workers by region. It is clear that sexism does indeed vary by region. For instance, there is more sexism in the southern regions than anywhere else in the country. By contrast, the Pacific region has the least sexism. It is important to note these differences, as I make use of this variation later.

IV. Methodology

In this section, I detail the methodology used to assess various theories of the gender promotion gap. My definition of promotion is making partner in a private firm but my regressions pool private and nonprivate firms for the sake of precision. My main specification is an OLS regression model:

$$(*) \qquad Y_i = \beta_0 + \beta_1 Female_i + \beta_2 Nonprivate_i + \beta_3 Female_i * Nonprivate_i + \beta_4 X_i + \varepsilon_i$$

Where Y_i is a dummy variable for whether or not the individual i has made partner by their late career, $Female_i$ is a dummy variable for gender where female=1, and $Nonprivate_i$ is an indicator for being in a nonprivate firm during the individual i's early career. I control for being in a private firm during i's early career because there could be gender-based selection out of the private sector. Attempting to estimate the gender difference among only those women who *remain* in private firms is extremely difficult, so I utilize an indicator for whether or not the individual is in a private firm during their early career. This indicator leads to estimates that can be interpreted as the gender differences between men and women who begin in the private sector, that is, those individuals who begin their careers intending to join the ranks of those lawyers working in the private sector in their late career. This indicates a desire to make partner from early in an individual's career. β_1 is the coefficient for the female-male gap for individuals in private firms who make partner, and X_i, in the baseline specification, represents a vector of demographic controls including age, a quadratic for age, marital status, race, firm size, law school rank, GPA, participation in general law review, and an indicator for having had a clerkship during law school. I add to this specification a control for whether or not the individual planned on staying with the firm for 5+ years as a proxy for whether or not they want to make partner, hours billed during their mid-career, hours worked during their mid-career, and, finally, task assigned. In order to decrease noise, I add a specification

where I control for "good task" rather than individual task assigned. Most of the specifications I test will include this baseline specification.

I expect β_1 to be negative, to reflect the male-female gap in promotion. As I add controls I expect β_1 to change as these controls explain the gender gap. If it is true that task assignment explains the promotion gap, then I would expect that controlling for task will significantly decrease the magnitude of β_1, possibly to zero. However, based on the (lack of) gender differences in task assignment within the data, I do not expect task assignment to have a large impact on β_1.

I then assess the effect of male composition of a firm on the likelihood of women being assigned to better or worse tasks. I utilize a similar OLS regression model, this time including all triple and pairwise interactions among *Female*, *Nonprivate*, and *Male Composition Below Median*. The dependent variable in this specification varies by column and is each task (1-10), "good task," and partner during late career. In a similar vein, I utilize regression (*), separated by quartiles of male composition. Next, I look at the effect of controlling for career interruptions, especially due to children. I utilize the same regression model (*) and add controls for work experience, total years of unemployment, and various forms of parental leave. Men and women differ over billed hours, and I test if this is due to children. I utilize a triple-interaction approach again, interacting *Female$_i$*, *Nonprivate$_i$*, and *No Children$_i$* (an indicator variable for having children, where having children=0). The dependent variable is hours billed in mid-career and β_1 is the coefficient for the male-female gap in billed hours for individuals in private firms who have children. I then utilize an OLS regression to assess the effect of client revenue brought in by an individual on the gender promotion gap. This specification is the same as that of regression (*), but I add a control for having a female mentor. I use a similar OLS linear regression with multiple interactions to use regions as a proxy for sexism to see if the remaining gap is explained by sexism with E. North

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Central as the base region. I run another version of this regression where I control for the importance of work/life balance in accepting a position.

Finally, I use a Oaxaca decomposition to reveal the gender promotion gap that is left unexplained, even after all of the possible theories I assess. A Oaxaca decomposition exploits the fact that regression lines always pass through the true mean (Figure 3). It compares the regression lines for two groups (in this case, male and female) by looking at the difference in promotion rate between the two. This difference is made up of two parts: the "explained" and the "unexplained." The "explained" part is drawn from the difference in the male mean and female mean for the independent variable. The "unexplained" part is the additional difference in promotion rate derived from the difference in the slope of the regression line for men and women, that is, the differing returns to the independent variable for men and women. I run a Oaxaca decomposition grouping by demographics, labor supply, tasks, work/life balance, an indicator for children, an indicator for doing the majority of household chores, whether or not an individual had a female mentor, variables to control for revenue per client, and region. I run it twice, once with women as the primary group and once with men as the primary group. Figure 3 provides the graphical intuition behind the Oaxaca method. The mathematical intuition is as follows:

$$\bar{Y}_F = \hat{\beta}_F \bar{X}_F$$

$$\bar{Y}_M = \hat{\beta}_M \bar{X}_M$$

$$\bar{Y}_F - \bar{Y}_M = \hat{\beta}_F \bar{X}_F - \hat{\beta}_M \bar{X}_M$$

$$\bar{Y}_F - \bar{Y}_M = \hat{\beta}_F \bar{X}_F - \hat{\beta}_M \bar{X}_F + \hat{\beta}_M \bar{X}_F - \hat{\beta}_M \bar{X}_M$$

$$\bar{Y}_F - \bar{Y}_M = (\hat{\beta}_F - \hat{\beta}_M)\bar{X}_F + \hat{\beta}_M(\bar{X}_F - \bar{X}_M)$$

Where $\bar{Y}$ is the mean percentage of males/females promoted given $\bar{X}$, the mean input variable for males/females. The "explained" part of the Oaxaca decomposition is the coefficient $\hat{\beta}_M$,

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modifying the difference due to men and women's different endowments. The "unexplained" part is the $(\hat{\beta}_F - \hat{\beta}_M)$, the differences in covariates given the same input. This particular example corresponds to the first two columns in Table 12. The last two columns in Table 12 are weighted by $\bar{X}_M$. I provide weights by male average and weights by female average because it is possible that the distribution of women places very few women at the male mean or vice versa, and using both weights provides a good check to ensure a correct estimate of $\bar{Y}$.

V. Results

Main Results on Gender Difference due to Task Assignment

The first theory I test is one of statistical discrimination through task assignment; the results are shown in Table 5. The coefficient of interest is *Female* and column 1 shows there is an unadjusted 13 percentage point gap in promotion between men and women in private firms. Column 2 adds demographic controls, which do not explain any of this gap, and very little is explained when I control for individuals wanting to remain at the firm for 5+ years in column 3. This control, wanting to stay for 5+ years, is added as a proxy for the desire to make partner. Generally, if an individual is planning to remain at their firm for five or more years, their ultimate goal is to make partner. In column 4, I control for hours billed during an individual's mid-career, which significantly decreases the promotion gap to about a 6 percentage point difference. The prominent theories of statistical discrimination through task assignment would suggest that controlling for tasks should eliminate much of the remaining gap in promotion; women are assigned worse tasks due to a firm's previous beliefs, namely that women will experience longer and more frequent career interruptions. Because of these beliefs, women are set on a "non-promotion track," which, when observed by female individuals, incentivizes them to invest less in

the firm. This causes women to meet the belief that they will experience longer and more frequent career interruptions, fulfilling the firm's hypothesis and leading to a gender gap in promotion. However, Table 3 shows that there is little difference in task assignment between men and women. Because of this lack of variation by gender, I cannot expect what the literature would suggest, and predict that when I control for task assignment, the gap will remain. Indeed, I find in column 6 that controlling for task does *not* explain the gender promotion gap. I control only for tasks 1-4 and 6-8 because tasks 1-4 are considered "good" tasks, while tasks 6-8 are considered "bad" tasks. In column 7, I group these good tasks and control for doing a good task, in order to give slightly more power to the variable of task assignment, though it still does not explain the gap between men and women making partner.

Despite there being little empirical evidence to support the idea that tasks affect women's promotion through the mechanism of statistical discrimination overall, it is important to consider the possibility of male composition affecting task assignment. The idea behind this stems both from Babcock et al. (2016) who propose that women are more likely to volunteer for worse tasks when in a group with men and also from Bursztyn, Fujiwara, and Pallais (2017) who find that women self-select away from career-enhancing actions in order to be more appealing in the marriage market when their male peers can see those actions. Indeed, I find an interesting trend when comparing the number of women in male-dominated firms during their early career to the number of women in male-dominated firms during their mid-career. We can see in Figure 1 that in women's early careers, fewer work in firms with male composition below the median than do during their mid-careers and in women's mid-careers, fewer work in firms with male composition above the median than do during their early careers. Thus, there seems to be a tendency to select away from male-dominated firms once women have gained some experience in the legal

workforce. Driven by the theory of male composition affecting task and by the trends in my own data, I consider how male composition can affect task assignment.

The first row of Table 6 shows the effect of being a woman in a male-dominated private firm on task assignment. If male composition does affect the tasks women are assigned as theorized, I expect the coefficient on *Female* to be negative for good tasks (1-4), and positive for bad tasks (6-8). This effect is significant for few tasks, and of the tasks that would be considered the worst (tasks 6-8), two have negative coefficients, meaning that women in male-dominated private firms are less likely to be assigned those tasks. The pattern seems to make more sense when restricted simply to "good task" and "bad task" but these are only significant at the 10% level and "bad task" is loosely defined as not being in "good task." The coefficient on partner agrees with the results from Table 4, but is not different from the effect of simply being a woman in a private firm. Thus, I conclude that being female in a male-dominated firm does not alter task assignment from that of the average firm.

Finally, to fully assess the effect of being a woman in a male-dominated firm on promotion, Table 7 separates individuals by their firm's quartile of male-composition. If women were given worse tasks in more male-dominated firms, we would expect that controlling for tasks in the 3rd and 4th quartiles (columns 5-8) would explain more of the gender gap in promotion than in the 1st and 2nd quartiles (columns 1-4), where we should see little to no change. However, there is no difference in the gender gap between specifications where tasks are and are not controlled for, regardless of whether I control for task assignment in early or mid-career.

Results on Career Interruptions

Bertrand, Goldin, and Katz (2010) find that career interruptions caused by children have a detrimental effect on women's careers. I will now assess how much of the gender gap this idea can help to explain. Each column of Table 8 controls for demographics. Column 1 controls for work experience, column 2 for unemployment, columns 3-6 for different measures of parental leave (an indicator for having taken parental leave, an indicator for having taken parental leave for 3+ months, and an indicator for having taken paid parental leave for 3+ months), and columns 7 and 8 for the importance of work/life balance during early and mid-career respectively. If career interruptions, especially those caused by children, explain the promotion gap, I expect to see the magnitude of the coefficient on *Female* decrease when I control for these various forms of interruptions. However, none of these variables explain the remaining gap, as is most obvious in column 9. Yet they could still be impacting women's promotion.

Because billed hours explains about half of the gap in promotion, in Table 9 I look at what effect children have on billed hours. I expect the coefficient on *Female* to be negative, meaning that women who have children and work in private firms bill fewer hours than their male counterparts in private firms with children. Additionally, the coefficient on doing the majority of household chores should be negative. The mean hours billed during individuals' mid-career is 1554.48, so column 1 of Table 9 shows about a 20% loss in hours billed from being a woman with children in a private firm. In column 4, I control for number of children and doing the majority of the housework, which explains more of the gap in hours billed as well. Being the primary member of the household doing chores lowers billed hours by about 10%, but also decreases the magnitude of the effect of having children on billed hours (though by less than 10%). The magnitude of the coefficient on billed hours gets smaller when I control for whether or not an individual does the

majority of the household chores, as some of the difference in billed hours due to children could be explained by time spent doing housework. Since having children and doing the majority of the housework do cause women to have fewer billed hours, it seems plausible that children do affect women's promotion through their effect on their mother's billed hours.

Results on Consumer Discrimination

Since many private law firms base promotion to partner on whether or not an individual will be able to both obtain and retain high-revenue clients for the firm, I look at whether or not being in the 50th, 75th, or 90th percentiles of revenue per client has any effect on the gender disparity in making partner. If theories of consumer discrimination prove true, the magnitude of the coefficient on *Female* should decrease when controls for revenue per client are added. It is possible that these clients are discriminating against female lawyers, which in turn does not allow these women to be promoted at the same rate as their male counterparts. In Table 10 it is clear that, while revenue per client does affect whether or not individuals make partner, it does not explain the gender promotion gap. Column 1 shows the same baseline specification that I begin with in each table. Column 2 controls for the gender of the individual's mentor. If a woman has a female mentor, and consumers discriminate against women, her mentor may not be able to help her make important connections with clients. Mentor gender does negatively affect individuals' likelihood of making partner, but it does not explain the gender wage gap. Column 3 controls for revenue brought in by new clients, which proxies for the ability to obtain clients. It does not explain the gender disparity in promotion. Column 4 controls for revenue brought in by old clients: an individual's ability to retain clients. This also does not explain the gender gap in promotion.

In column 6, I control for revenue per client, which has less to do with how many clients an individual brings in and more to do with how "important" a client they are. This alone does not explain the gender promotion gap, so in columns 7, 8, and 9 I assess whether or not controlling for being in the upper tails of revenue per client can explain the promotion gap for women. It may be that women can't draw in clients at this upper tail of the distribution. Individuals who bring in revenue per client above the median are significantly more likely to make partner, and this increases with the cutoff. Individuals in the 75th revenue per client quartile are more likely to make partner than those in the 50th quartile, and individuals in the 90th quartile are still more likely than those in the 75th. However, this does not explain the gender promotion gap, leading me to believe that, while revenue per client is an important factor in considering promotion, it does cause the promotion gap between men and women.

Results on Regional Sexism

Finally, I look at sexism by region to see if areas with higher sexism can explain more of the gender gap than areas with lower sexism. There are two possible mechanisms at play here. One idea is that if sexism is higher in a certain region, firms could be discriminating against women, which is why they may not make partner as often. If more of the gap is explained in regions with higher sexism, this could be evidence that taste-based discrimination is playing a role. Table 11 presents the coefficients for the male/female gap in promotion by region, using E. North Central as the base region, as well as the white-collar male sexism in that region taken from the GSS Male Sexism Index (Pan 2015). Indeed, Figure 2 shows that there is a regional correlation between the unexplained gender gap and sexism, suggesting that sexism does play a role in whether or not women make partner, though if it is due to the firm is unclear from this regression.

Another, less straightforward, mechanism suggests that with higher sexism, women are less likely to want to make partner because it may make their marriage less happy. There is evidence from Bertrand, Kamenica, and Pan (2015) that if women become the primary earner, their marriages become less happy and more likely to fail. Thus, in a more sexist area, this is more likely to occur. In Table 12, I assess the likelihood of this mechanism by including a control for how important women consider work/family balance to be when taking a job, using East North Central as the base region. Controlling for work/life balance does not seem to have any explanatory power, so the explanation granted by using region as a proxy for sexism most likely stems from sexist practices by the firm.

Results on the Oaxaca Decomposition

Thus far, this paper has assessed the most prominent theories on the gender disparity in promotion, yet an unexplained gap persists. This suggests that we still do not fully understand the socio-economic forces driving the gender inequality in the workforce. Despite the lack of a full understanding, it is clear that there is indeed a large gap in promotion that cannot be explained by women's preferences. I have shown that billed hours is the only thing that can satisfactorily explain part of the gender promotion gap, and that it is most likely driven by children and time spent doing household chores. I utilize a Oaxaca decomposition to more fully summarize how much of the gender disparity in promotion each theory explains and what is left unexplained after all theories are accounted for. The Oaxaca decomposition can assess the relative importance of the different mechanisms suggested throughout the paper for driving the gender promotion gap and display what fraction of the gap is explained by each theory.

Table 13 displays the results of this Oaxaca decomposition. The first column is the explained difference in promotion with women as the primary group. Labor supply accounts for most of the explained gap in promotion, which is to be expected because it includes billed hours, the only part of the regression with true explanatory power. The second column is the unexplained difference in promotion with women as the primary group. Labor supply and an indicator for children have the largest unexplained effect on the gender disparity in promotion. This means that if women provide the same labor supply as their male counterparts (that is, they have the same average work experience, unemployment, parental leave, and hours billed), their returns to labor supply are 8% lower than their male counterparts. Similarly, women are punished more harshly than their male counterparts for having children; their returns are about 8% lower if they have children than if their male counterparts have children. In fact, women make lower returns to labor supply, task assigned, work/life balance, children, and household work than their male counterparts, but receive higher rewards than men for having a female mentor and bringing in a higher revenue per client. These results support the theory proposed by Bertrand, Goldin, and Katz (2010). Columns 3 and 4 of Table 13 present the same results, but use men as the primary group. There is no difference between the two, so I can conclude that the Oaxaca decomposition is able to accurately predict outcomes for each group at the other's mean.

An important caveat to the results of the Oaxaca distribution is the relatively large contributions of missing variable indicators to the gender gap. One possible explanation might be that men and women face different time constraints. Thus, women have higher returns to leaving questions unanswered in the survey because their missing values indicate that they spend their time differently (and possibly more productively) than their male counterparts. We know that women spend more time caring for children and doing household chores than their male

counterparts, and that they record fewer billable hours. All of these claims to a woman's time contribute to the gender promotion gap and therefore it is plausible that they have less time to spend on surveys.

The contribution of missing variable indicators is especially important to note for the unexplained gap. Without controlling for missing values, the unexplained gender gap is 22 percentage points, but with the controls for missing variables, it is reduced to only 3 percentage points. In the regressions run earlier, many of the coefficients on the missing indicator variables are very imprecise with large standard errors. Thus, it is difficult to know how to interpret these outcomes, as we should not take them at face value due to their statistical imprecision.

VI. Conclusion

I have examined various theories that attempt to explain the gender disparity in promotion; due to the richness of the AJD dataset I have been able to assess the most prominent theories both separately and concurrently within one panel dataset. This has allowed me to assess theories that have not been widely tested outside of experimental studies. Male and female lawyers, though exhibiting similar levels of competency, are promoted at different rates, exemplifying a trend throughout the world that is also closely related to the gender wage gap. I find that there is a 13 percentage point difference in promotion between men and women. This gap is reduced to 6 percentage points when I control for billable hours.

The first theory I tested is one of statistical discrimination by Coate and Loury (1993). Although women are as qualified as their male counterparts, they are not given tasks on the "promotion track" for fear that they will experience more career interruptions than their male counterparts. Because they then observe that they are not on the promotion track, they invest less

in the company and do experience more career interruptions, which appear less costly since women do not believe they will be promoted regardless. The associates who assigned the women these tasks observe their higher rates of career interruptions, which confirm their belief that women have more career interruptions, and an equilibrium is reached in which women are given worse tasks and promoted more infrequently than their male counterparts. To test this theory, I control for task assigned. There is little variation by gender in tasks assigned and performed within the data, and, in light of this, it is unsurprising that controlling for task does not explain 6 percentage point gender gap in promotion.

I then test to see if there is more variation by gender in task assigned if a woman is working in a private, male-dominated firm. This stems from a theory presented by Babcock et al. (2016). In a laboratory study, they find that men and women are equally likely to volunteer for "worse" tasks if women are in a group composed solely of other women, but if they are in an environment with men, women are more likely to volunteer for worse tasks. I do not find evidence that being a woman in a male-dominated firm leads to assignment to worse tasks. There is no observable pattern in task assignment, even related to the male composition of a firm.

A model suggested by Bertrand, Goldin, and Katz (2010) finds that much of the wage disparity in the financial and corporate sector can be explained by women's longer and more frequent career interruptions, mainly due to child-bearing. I control for work experience, unemployment spells, and different measures of parental leave in order to determine the effect of career interruptions on the promotion gap, but it remains at around 6 percentage points. Bertrand et al. also find that gender differences in weekly hours worked (also due to childbearing and child-rearing) have explanatory power over the gender wage gap. Although I do not find hours worked to have a large explanatory effect, I do find that being a woman in a private firm with children

lowers billed hours by about 20%. Additionally, being the primary member of the household to do chores lowers billed hours by about 10.5%.

Borjas and Bronar's (1989) theory of consumer discrimination postulates that consumers are less willing to patronize minorities. Thus, important clients at law firms may select away from female attorneys. If these women cannot bring in revenue from clients, they will not be promoted. There is no explanation of the gender promotion gap associated with revenue per client, even if individuals are bringing in revenue in the 50th, 75th, or 90th percentiles. The gender gap in promotion remains at 6 percentage points.

I use region to proxy for sexism to see if the explained gender gap in promotion for individuals in regions with higher rates of sexism is smaller than for those in regions with lower rates of sexism. Indeed, there is a correlation between the sexism of a region and that region's explanatory power over the gender gap in promotion. There is no additional explanation gained by controlling for the importance of work/life balance, so I conclude that regional sexism is correlated with firms' promotion decisions causing a gender gap.

Finally, a Oaxaca decomposition confirms the fact that, though some of these theories can offer a partial explanation of the gender disparity in promotion, none of them (and, indeed, no combination of them) can offer a complete explanation. There is still some cause of the gender promotion gap that no theory has yet explained. Despite the fact that there is still an unexplained gap in promotion for men and women, this paper sheds light on many prominent theories and compare them to one another within a single dataset. While I can only speculate on the true driving force behind the gender disparity in promotion, there are complex mechanisms at play that combine both economic and societal forces. What is clear is that there is a disparity in promotion that is not driven solely by any one prominent theory, or by a woman's desires.

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Tables

<u>Good Tasks</u>

Task 1: Appearing in court as 1st or 2nd chair

Task 2: Formulating strategy with seniors and/or clients

Task 3: Traveling to meet clients, interview witnesses, or court appearances

Task 4: Assigning and/or supervising attorneys or paralegals

<u>Bad Tasks</u>

Task 6: Work limited to routine research and memo writing

Task 7: Spending 100+ hours reviewing discovered documents

Task 8: Writing motions or taking depositions

<u>Neutral Tasks</u>

Task 5: Responsible for keeping client updated

Task 9: Drafting transactional documents

Task 10: Handling entire matter on your own

Table 1
Demographic Summary Statistics

	Early Career			
Variable	Total	Male	Female	Male/Female Difference
Age	25.4627	25.6371	25.2876	0.3495
	(13.4492)	(13.4827)	(13.4188)	(26.9017)
Married	0.4564	0.4847	0.4281	0.0566
	(0.4982)	(0.5)	(0.495)	(0.9950)
Nonwhite	0.2975	0.256	0.3392	-0.0832
	(0.4573)	(0.4366)	(0.4736)	(0.9109)
Indicator for First Job	0.6244	0.615	0.6337	-0.0187
	(0.4844)	(0.4868)	(0.482)	(1.0695)
GPA	2.245	2.2068	2.2835	-0.0767
	(1.8302)	(1.8003)	(1.8597)	(3.6604)
Law School Tier (1-4)	3.1195	3.1412	3.0979	0.0433
	(1.1884)	(1.2424)	(1.1324)	(2.6372)
Educational Debt ($)	49169.54	47560.75	50783.68	-3222.93
	(44080.75)	(43464.12)	(44650.7)	(88120.9691)
Firm Size (lawyers)	133.4241	139.1334	127.6958	11.4376
	(305.713)	(293.9801)	(317.068)	(611.4466)
Salary ($)	62330.74	66340.45	58307.7	8032.75
	(54847.3)	(54910.38)	(54510.91)	(109422.8617)
Partner	0.0091	0.0124	0.0058	0.0066
	(0.0951)	(0.1108)	(0.0761)	(0.8184)
Observations	2410	1207	1203	2410

Standard deviations in parentheses
Notes: The first column of data contains the means of each demographic variable for the total sample population. The second column of data contains the means of each demographic variable for the males in the sample population. The third column of data contains the means of each demographic variable for the females in the sample population. The fourth column of data contains the difference in means of each demographic variable between males and females in the sample population. The indicator for first job implies that the job the respondent has while answering the survey is their first job in the law field. Most law schools grade on a curve, so actual GPA is less important than noting it is very similar between men and women. In Law School Tier, Tier 1 is the best.

Table 2
Summary Statistics Pertaining to Children and Career Interruptions

Variable	Early Career			
	Total	Male	Female	Male/Female Difference
Number of Children	0.3311	0.4234	0.2386	0.1848
	(0.7644)	(0.8623)	(0.6388)	(1.5180)
Part Time	0.0199	0.0108	0.0291	-0.0183
	(0.1397)	(0.1033)	(0.1681)	(0.2789)
Part Time due to Children	0.1328	0.0804	0.1854	-0.105
	(0.9246)	(0.7427)	(1.0745)	(1.8466)
Hours Worked (weekly)	30.2602	31.4872	29.0291	2.1992
	(23.0208)	(22.8512)	(23.1339)	(45.9856)
Hours Billed (in 2006)	668.760	804.872	532.195	272.677
	(916.702)	(972.71)	(835.223)	(1813.3840)
Salary ($)	62330.74	66340.45	58307.7	8032.75
	(54847.3)	(54910.38)	(54510.91)	(109422.8617)
Stay for 5+ years	0.2498	0.2883	0.2111	0.0772
	(0.433)	(0.4532)	(0.4083)	(0.8627)
Partner	0.0091	0.0124	0.0058	0.0066
	(0.0951)	(0.1108)	(0.0761)	(0.8184)
Observations	2410	1207	1203	2410

Standard deviations in parentheses

Notes: The first column of data contains the means of each demographic variable pertaining to children and career interruptions for the total sample population. The second column of data contains the means of each demographic variable pertaining to children and career interruptions for the males in the sample population. The third column of data contains the means of each demographic variable pertaining to children and career interruptions for the females in the sample population. The fourth column of data contains the difference in means of each demographic variable pertaining to children and career interruptions between males and females in the sample population. Stay for 5+ years is an indicator variable for whether or not the respondent wants to remain at the firm for five or more years. Hours Billed is from mid-career to provide intuition for why it is important that men and women differ along hours billed.

Table 3
Descriptive Statistics by Tasks

Variable	Total	Male	Female	Male/Female Difference
Good Task	.2838	.2833	.2843	-0.001
	(.4509)	(.4508)	(.4513)	(0.9021)
Task 1: Appearing in court as 1st or 2nd chair	.1137	. 1102	. 1172	-0.007
	(.3175)	(.3133)	(.3218)	(0.6351)
Task 2: Formulating strategy with seniors and/or clients	.2037	.2071	.2003	0.0068
	(.4029)	(.4054)	(.4004)	(0.8059)
Task 3: Traveling to meet clients, interview witnesses, or court appearances	.1398	.1384	.1413	-0.0029
	(.3469)	(.3454)	(.3485)	(0.6939)
Task 4: Assigning and/or supervising attorneys or paralegals	.0784	.0787	.0781	0.0006
	(.2689)	(.2694)	(.2685)	(0.5379)
Task 5: Responsible for keeping client updated	.249	.2428	.2552	-0.0124
	(.4325)	(.4289)	(.4362)	(0.8651)
Task 6: Work limited to routine research and memo writing	.0743	.0713	.0773	-0.006
	(.2623)	(.2574)	(.2672)	(0.5246)
Task 7: Spending 100+ hours reviewing discovered documents	.0307	.0232	.0382	-0.015
	(.1726)	(.1506)	(.1918)	(0.3448)
Task 8: Writing motions or taking depositions	.1216	.1301	.1131	0.017
	(.3269)	(.3365)	(.3168)	(0.6536)
Task 9: Drafting transactional documents	.0975	.0978	.0973	0.0005
	(.2967)	(.2971)	(.2964)	(0.5935)
Task 10: Handling entire matter on your own	.1539	.1533	.1546	-0.0013
	(.361)	(.3604)	(.3617)	(0.7221)
Satisfied with Tasks Performed	.5407	.5352	.5461	-.0109
	(.4984)	(.499)	(.4981)	(0.9970)
Observations	2410	1207	1203	2410

Standard deviations in parentheses

Notes: The first column of data contains the percentage of individuals assigned to each given task for the total sample population. The second column of data contains the percentage of individuals assigned to each given task for the males in the sample population. The third column of data contains the percentage of individuals assigned to each given task for the females in the sample population. The fourth column of data contains the difference in percentage of individuals assigned to each given task between males and females in the sample population. "Good Tasks" include Tasks 1-4.

Table 4
Differences in Partner Rates Across Time

Partner Rates	Early Career	Mid-Career	Late Career	Observations
Total	0.0091	.0921	0.2178	2410
	(0.0951)	(.2892)	(0.4129)	
Male	0.0124	.1243	0.2734	1207
	(0.1108)	(0.33)	(0.4459)	
Female	0.0058	.0599	0.1621	1203
	(0.0761)	(0.2373)	(0.3687)	
Male/Female Difference	0.0066	0.0644	0.1113	2410
	(0.1902)	(0.5750)	(0.8184)	

Standard deviations in parentheses

Notes: The first column of data contains the percentage of individuals promoted to partner for each sample population during their early career. The second column of data contains the percentage of individuals promoted to partner for each sample population during their mid-career. The third column of data contains the percentage of individuals promoted to partner for each sample population during their late career. The fourth column of data contains the number of observations per each sample population.

Table 5
Gender Difference in Promotion

Dependent Variable: Partner during Late Career

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.133***	-0.130***	-0.124***	-0.0666***	-0.0592***	-0.0581***	-0.0588***
	(0.0226)	(0.0225)	(0.0224)	(0.0206)	(0.0209)	(0.0210)	(0.0209)
Nonprivate Firm	-0.308***	-0.257***	-0.262***	-0.136***	-0.134***	-0.122***	-0.128***
	(0.0246)	(0.0368)	(0.0365)	(0.0337)	(0.0338)	(0.0346)	(0.0343)
Female * Nonprivate	0.0824**	0.0738**	0.0727**	0.0439	0.0418	0.0407	0.0413
	(0.0321)	(0.0319)	(0.0317)	(0.0289)	(0.0289)	(0.0291)	(0.0290)
Stay for 5+ years			0.104***	0.0630***	0.0637***	0.0635***	0.0646***
			(0.0196)	(0.0179)	(0.0179)	(0.0181)	(0.0181)
Hours Billed				0.000152***	0.000147***	0.000144***	0.000146***
				(1.48e-05)	(1.50e-05)	(1.51e-05)	(1.51e-05)
Hours Worked					0.00113*	0.00111*	0.00109*
					(0.000644)	(0.000647)	(0.000646)
Task 1						-0.0570*	
						(0.0299)	
Task 2						0.0203	
						(0.0232)	
Task 3						0.0412	
						(0.0286)	
Task 4						-0.0338	
						(0.0307)	
Task 6						0.00291	
						(0.0297)	
Task 7						-0.0128	
						(0.0441)	
Task 8						0.0205	
						(0.0285)	
Good Task							0.00981
							(0.0212)
Demographic Controls	N	Y	Y	Y	Y	Y	Y
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.107	0.132	0.144	0.291	0.293	0.296	0.294

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Each column represents the same baseline regression on a dummy variable for making partner during an individual's late career. Controls are added by column. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, and having had a clerkship during law school. The variable "Stay for 5+ years" indicates whether or not an individual planned on staying with their firm for 5+ years.

Table 6
Effect of being Female in a Private, Male-dominated Company on Task

Dependent Variable:	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10	Good Task	Bad Task	Partner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	-0.0184	-0.0202	-0.0335	-0.0120	-0.00419	-0.00644	0.00960	-0.0357*	0.0466**	-0.0283	-0.0408*	0.0408*	-0.0606**
	(0.0197)	(0.0243)	(0.0218)	(0.0179)	(0.0248)	(0.0173)	(0.0118)	(0.0210)	(0.0193)	(0.0208)	(0.0247)	(0.0247)	(0.0243)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.212	0.257	0.195	0.096	0.327	0.105	0.046	0.154	0.132	0.323	0.385	0.385	0.292

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column represents the same regression on the task indicated during an individual's early career. Column 13 is a regression on making partner during an individual's late career.
Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, and having had a clerkship during law school.
Good Tasks
Task 1: Appearing in court as 1st or 2nd chair
Task 2: Formulating strategy with seniors and/or clients
Task 3: Traveling to meet clients, interview witnesses, or court appearances
Task 4: Assigning and/or supervising attorneys or paralegals
Bad Tasks
Task 5: Responsible for keeping client updated
Task 6: Work limited to routine research and memo writing
Task 7: Spending 100+ hours reviewing discovered documents
Task 8: Writing motions or taking depositions
Task 9: Drafting transactional documents
Task 10: Handling entire matter on your own

Table 7
Effect of Gender on Making Partner separated by Quartile of Male Composition

Early Career

Dependent Variable: Partner during Late Career	1st Quartile	1st Quartile	2nd Quartile	2nd Quartile	3rd Quartile	3rd Quartile	4th Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.0820	-0.0709	-0.0404	-0.0525	-0.0186	-0.0115	-0.0763***	-0.0800***
	(0.0568)	(0.0571)	(0.0543)	(0.0566)	(0.0511)	(0.0519)	(0.0294)	(0.0296)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	N	Y	N	Y	N	Y	N	Y
Observations	332	332	282	282	316	316	1,480	1,480
R-squared	0.373	0.423	0.373	0.389	0.379	0.415	0.265	0.272

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Early Career, nonmissing

Dependent Variable: Partner during Late Career	1st Quartile	1st Quartile	2nd Quartile	2nd Quartile	3rd Quartile	3rd Quartile	4th Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.0820	-0.0709	-0.0404	-0.0525	-0.0186	-0.0115	0.00172	-0.0430
	(0.0568)	(0.0571)	(0.0543)	(0.0566)	(0.0511)	(0.0519)	(0.0751)	(0.0794)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	N	Y	N	Y	N	Y	N	Y
Observations	332	332	282	282	316	316	226	226
R-squared	0.373	0.423	0.373	0.389	0.379	0.415	0.285	0.324

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Mid-Career

Dependent Variable: Partner during Late Career	1st Quartile	1st Quartile	2nd Quartile	2nd Quartile	3rd Quartile	3rd Quartile	4th Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.0717*	-0.0641	-0.0817	-0.0915	-0.0579	-0.0597	-0.0601*	-0.0615*
	(0.0402)	(0.0406)	(0.0602)	(0.0623)	(0.0546)	(0.0557)	(0.0313)	(0.0319)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	N	Y	N	Y	N	Y	N	Y
Observations	563	563	320	320	418	418	1,109	1,109
R-squared	0.280	0.302	0.348	0.381	0.250	0.266	0.303	0.307

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Mid-Career, nonmissing

Dependent Variable: Partner during Late Career	1st Quartile	1st Quartile	2nd Quartile	2nd Quartile	3rd Quartile	3rd Quartile	4th Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.0717*	-0.0641	-0.0817	-0.0915	-0.0579	-0.0597	0.0375	0.0274
	(0.0402)	(0.0406)	(0.0602)	(0.0623)	(0.0546)	(0.0557)	(0.0809)	(0.0850)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	N	Y	N	Y	N	Y	N	Y
Observations	563	563	320	320	418	418	305	305
R-squared	0.280	0.302	0.348	0.381	0.250	0.266	0.296	0.312

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Every column represents the same regression on making partner during an individual's late career. Each regression is restricted to a specific quartile of a firm's male composition so only individuals in firms within that quartile are included. Columns 1, 3, 5, and 7 do not control for task while columns 2, 4, 6, and 8 do. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, and having had a clerkship during law school. Control for tasks includes the following tasks:
Task 1: Appearing in court as 1st or 2nd chair, Task 2: Formulating strategy with seniors and/or clients, Task 3: Traveling to meet clients, interview witnesses, or court appearances, Task 4: Assigning and/or supervising attorneys or paralegals, Task 5: Responsible for keeping client updated, Task 6: Work limited to routine research and memo writing, Task 7: Spending 100+ hours reviewing discovered documents, Task 8: Writing motions or taking depositions, Task 9: Drafting transactional documents, and Task 10: Handling entire matter on your own. There are many instances of missing responses, so quartiles are rather uneven in the upper table, which is why I include the lower table. Only the individuals whose responses are nonmissing are included in the lower table.

Table 8
The Effect of Career Interruptions on Partner

Dependent Variable: Partner during Late Career	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.0657***	-0.0672***	-0.0555***	-0.0576***	-0.0649***	-0.0710***	-0.0661***	-0.0660***	-0.0542**
	(0.0207)	(0.0202)	(0.0207)	(0.0217)	(0.0215)	(0.0212)	(0.0207)	(0.0207)	(0.0220)
Nonprivate Firm	-0.124***	-0.149***	-0.126***	-0.120***	-0.123***	-0.124***	-0.125***	-0.124***	-0.143***
	(0.0345)	(0.0339)	(0.0344)	(0.0346)	(0.0346)	(0.0346)	(0.0346)	(0.0346)	(0.0339)
Female * Nonprivate	0.0428	0.0522*	0.0379	0.0400	0.0433	0.0456	0.0428	0.0422	0.0454
	(0.0290)	(0.0284)	(0.0289)	(0.0292)	(0.0291)	(0.0291)	(0.0290)	(0.0290)	(0.0286)
Hours Billed	0.000149***	0.000143***	0.000141***	0.000149***	0.000149***	0.000150***	0.000149***	0.000150***	0.000139***
	(1.49e-05)	(1.46e-05)	(1.49e-05)	(1.49e-05)	(1.49e-05)	(1.49e-05)	(1.49e-05)	(1.50e-05)	(1.47e-05)
Work Experience		-0.0440***							-0.0434***
		(0.00872)							(0.00873)
Work Experience Quadratic		0.00191***							0.00189***
		(0.000626)							(0.000628)
Total Years of Unemployment			0.000211						-0.00462
			(0.00783)						(0.00784)
Has Taken Parental Leave				0.0227					0.0280
				(0.0193)					(0.0193)
On Parental Leave for 3+ Months					-0.00203				-0.00990
					(0.0253)				(0.0277)
On Paid Parental Leave for 3+ Months						0.0358			0.0486
						(0.0302)			(0.0327)
Importance of work/life balance (2000)							0.00472		
							(0.0223)		
Importance of work/life balance (2006)								0.00554	0.00450
								(0.0199)	(0.0194)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.295	0.327	0.303	0.296	0.295	0.296	0.295	0.295	0.333

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column represents the same baseline regression on a dummy variable for making partner during an individual's late career. Controls are added by column. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, clerkship, stay for 5+ years. Control for tasks includes the following tasks: Task 1: Appearing in court as 1st or 2nd chair, Task 2: Formulating strategy with seniors and/or clients, Task 3: Traveling to meet clients, interview witnesses, or court appearances, Task 4: Assigning and/or supervising attorneys or paralegals, Task 5: Responsible for keeping client updated, Task 6: Work limited to routine research and memo writing, Task 7: Spending 100+ hours reviewing discovered documents, Task 8: Writing motions or taking depositions, Task 9: Drafting transactional documents, and Task 10: Handling entire matter on your own.

Table 9
Effect of Children on Billed Hours

Dependent Variable: Hours Billed (in 2006)	(1)	(2)	(3)	(4)
Female	-347.4***	-350.9***	-287.7***	-291.6***
	(64.81)	(65.72)	(66.50)	(67.37)
Nonprivate Firm	-682.6***	-683.7***	-679.0***	-680.4***
	(89.44)	(89.54)	(89.21)	(89.30)
No Children	-81.33	-99.45	-59.26	-79.72
	(68.87)	(88.85)	(68.96)	(88.84)
Female * Nonprivate	147.7	148.9	142.3	143.7
	(95.40)	(95.50)	(95.16)	(95.25)
Female * No Children	94.42	98.00	48.16	52.21
	(97.27)	(97.92)	(97.86)	(98.50)
Nonprivate * No Children	39.09	39.62	40.09	40.71
	(97.25)	(97.28)	(97.00)	(97.03)
Female * Nonprivate * No Children	25.30	24.15	27.90	26.59
	(137.0)	(137.1)	(136.7)	(136.7)
Number of Children		-9.221		-10.41
		(28.56)		(28.49)
Does Majority of Household Work			-162.4***	-162.4***
			(44.30)	(44.31)
Demographic Controls	Y	Y	Y	Y
Observations	2,410	2,410	2,410	2,410
R-squared	0.189	0.190	0.195	0.195

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column represents the same baseline regression on hours billed during an individual's mid-career. Controls are added by column. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, clerkship, stay for 5+ years. The mean hours billed during individuals' mid-career is 1554.48, col. 1 shows about a 20% loss in hours billed from being a woman with children in a private firm. Col. 4 shows about a 10% loss in hours billed from doing the majority of the household work, but also decreases the magnitude of the effect of having children on billed hours (though by less than 10%).

Table 10
Effect of Mentor Gender and Revenue brought in by Client on Partner Rates

Dependent Variable: Partner during Late Career	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.0657***	-0.0609***	-0.0570***	-0.0618***	-0.0608***	-0.0617***	-0.0608***	-0.0601***	-0.0615***	-0.0605***
	(0.0207)	(0.0207)	(0.0205)	(0.0206)	(0.0206)	(0.0206)	(0.0206)	(0.0206)	(0.0206)	(0.0206)
Nonprivate Firm	-0.124***	-0.122***	-0.134***	-0.122***	-0.129***	-0.129***	-0.125***	-0.126***	-0.127***	-0.125***
	(0.0345)	(0.0344)	(0.0342)	(0.0344)	(0.0344)	(0.0344)	(0.0344)	(0.0344)	(0.0344)	(0.0344)
Female * Nonprivate	0.0428	0.0482*	0.0396	0.0418	0.0419	0.0427	0.0392	0.0392	0.0414	0.0396
	(0.0290)	(0.0289)	(0.0287)	(0.0289)	(0.0289)	(0.0289)	(0.0289)	(0.0289)	(0.0289)	(0.0289)
Hours Billed (in 2006)	0.000149***	0.000142***	0.000153***	0.000143***	0.000146***	0.000147***	0.000141***	0.000144***	0.000146***	0.000140***
	(1.49e-05)	(1.49e-05)	(1.47e-05)	(1.49e-05)	(1.48e-05)	(1.49e-05)	(1.50e-05)	(1.49e-05)	(1.49e-05)	(1.50e-05)
Female Mentor		-0.0661***								
		(0.0201)								
Revenue brought in by new clients			3.61e-07***							
			(6.97e-08)							
Revenue brought in by old clients				3.36e-08*						
				(2.01e-08)						
Total revenue brought in by clients					6.23e-08***					
					(1.89e-08)					
Total revenue brought in per client						2.30e-07**				1.04e-07
						(9.75e-08)				(1.15e-07)
50th Percentile of revenue per client							0.118***			0.0777
							(0.0363)			(0.0482)
75th Percentile of revenue per client								0.144***		0.0412
								(0.0472)		(0.0718)
90th Percentile of revenue per client									0.181**	0.0433
									(0.0721)	(0.0971)
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for Tasks	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.295	0.300	0.309	0.299	0.303	0.301	0.303	0.302	0.302	0.304

Standard errors in parentheses

Notes: Each column represents the same baseline regression on a dummy variable for making partner during an individual's late career. Controls are added by column. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, clerkship, stay for 5+ years. Control for tasks includes the following tasks:
Task 1: Appearing in court as 1st or 2nd chair, Task 2: Formulating strategy with seniors and/or clients, Task 3: Traveling to meet clients, interview witnesses, or court appearances, Task 4: Assigning and/or supervising attorneys or paralegals, Task 5: Responsible for keeping client updated, Task 6: Work limited to routine research and memo writing, Task 7: Spending 100+ hours reviewing discovered documents, Task 8: Writing motions or taking depositions, Task 9: Drafting transactional documents, and Task 10: Handling entire matter on your own.

Table 11
Sexism Index by Region

Region	Male/Female Promotion Gap	GSS Male Sexism Index: White Collar Sexism
New England	0.167 (0.0629)	-0.241
Middle Atlantic	-0.116 (0.181)	-0.083
E. North Central (Base Region)	-0.112 (0.0397)	-0.162
W. North Central	0.0427 (0.0879)	-0.125
South Atlantic	-0.0231 (0.0595)	-0.027
E. South Central	-0.0138 (0.129)	-0.019
W. South Central	0.122 (0.0624)	-0.032
Mountain Division	0.0966 (0.245)	-0.06
Pacific	0.230 (0.0947)	-0.117

Standard errors in parentheses

Notes: This table displays the coefficient for male/female promotion gap by region using E. North Central as the base region, and each region's measure of white collar sexism. This Male Sexism index comes from that used by Pan (2015). She reports that "the GSS Male Sexism Index is constructed based on male answers to the full set of eight gender-related questions in the General Social Survey in [sic] from 1977 to 1998." The white-collar index "restricts the index to males whose reported occupation in the GSS is white-collar."

Table 12
Importance of Work/Life Balance on Regional Explanation

Dependent Variable: Partner during Late Career	(1)	(2)	(3)
Female	-0.112***	-0.112***	-0.112***
	(0.0397)	(0.0397)	(0.0397)
Importance of work/life balance in early career		-0.00494	
		(0.0224)	
Importance of work/life balance in mid-career			0.00208
			(0.0199)
Demographic Controls	Y	Y	Y
Control for Tasks	Y	Y	Y
Observations	2,410	2,410	2,410
R-squared	0.314	0.314	0.315

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column represents the same baseline regression on a dummy variable for making partner during an individual's late career. Controls are added by column. Demographic Controls include age, a quadratic for age, married, nonwhite, firm size, law school rank, GPA, participation in general law review, clerkship, stay for 5+ years. This regression uses E. North Central as the base region. Each specification includes triple interactions for region, gender, and nonprivate firm. This is the specification used to obtain coefficients for how much of the gender gap is explained by region. Regions defined by U.S. Census Bureau, see Figure 4 for map. Control for tasks includes the following tasks: Task 1: Appearing in court as 1st or 2nd chair, Task 2: Formulating strategy with seniors and/or clients, Task 3: Traveling to meet clients, interview witnesses, or court appearances, Task 4: Assigning and/or supervising attorneys or paralegals, Task 5: Responsible for keeping client updated, Task 6: Work limited to routine research and memo writing, Task 7: Spending 100+ hours reviewing discovered documents, Task 8: Writing motions or taking depositions, Task 9: Drafting transactional documents, and Task 10: Handling entire matter on your own.

Table 13
Oaxaca Decomposition on Gender Promotion Gap

| | $\bar{X}_F$-$\bar{X}_M$ | | $\bar{X}_M$-$\bar{X}_F$ | |
| | (1) | (2) | (3) | (4) |
VARIABLES	Explained Gap	Unexplained Gap	Explained Gap	Unexplained Gap
Demographics	0.0042647	0.7481961	-0.0042647	-0.7481961
Labor Supply	-0.0523547	-0.0821121	0.0523547	0.0821121
Tasks	0.0017127	-0.0254945	-0.0017127	0.0254945
Work/Life Balance	-0.0018335	-0.061289	0.0018335	0.061289
Kids	0.0037993	-0.080317	-0.0037993	0.080317
Household Work	-0.0034282	-0.0335841	0.0034282	0.0335841
Female Mentor	-0.0107309	0.0054565	0.0107309	-0.0054565
Client Revenue	-0.0105624	0.0246144	0.0105624	-0.0246144
Region	-0.0017271	0.0059144	0.0017271	-0.0059144
Missing	-0.0316526	0.1867281	0.0316526	-0.1867281
Constant		-0.7227094		0.7227094
Total (Without Missing)	-0.0708601	-0.2213247	0.0708601	0.2213247
Total (Including Missing)	-0.1025127	-0.0345966	0.1025127	0.0345966

Notes: Columns 1 and 2 display the results from a Oaxaca decomposition on the gender promotion gap (the dependent variable being a dummy for making partner during an individual's late career) using female as the baseline mean. Columns 3 and 4 display the results from a Oaxaca decomposition on the gender promotion gap (the dependent variable being a dummy for making partner during an individual's late career) using male as the baseline mean.
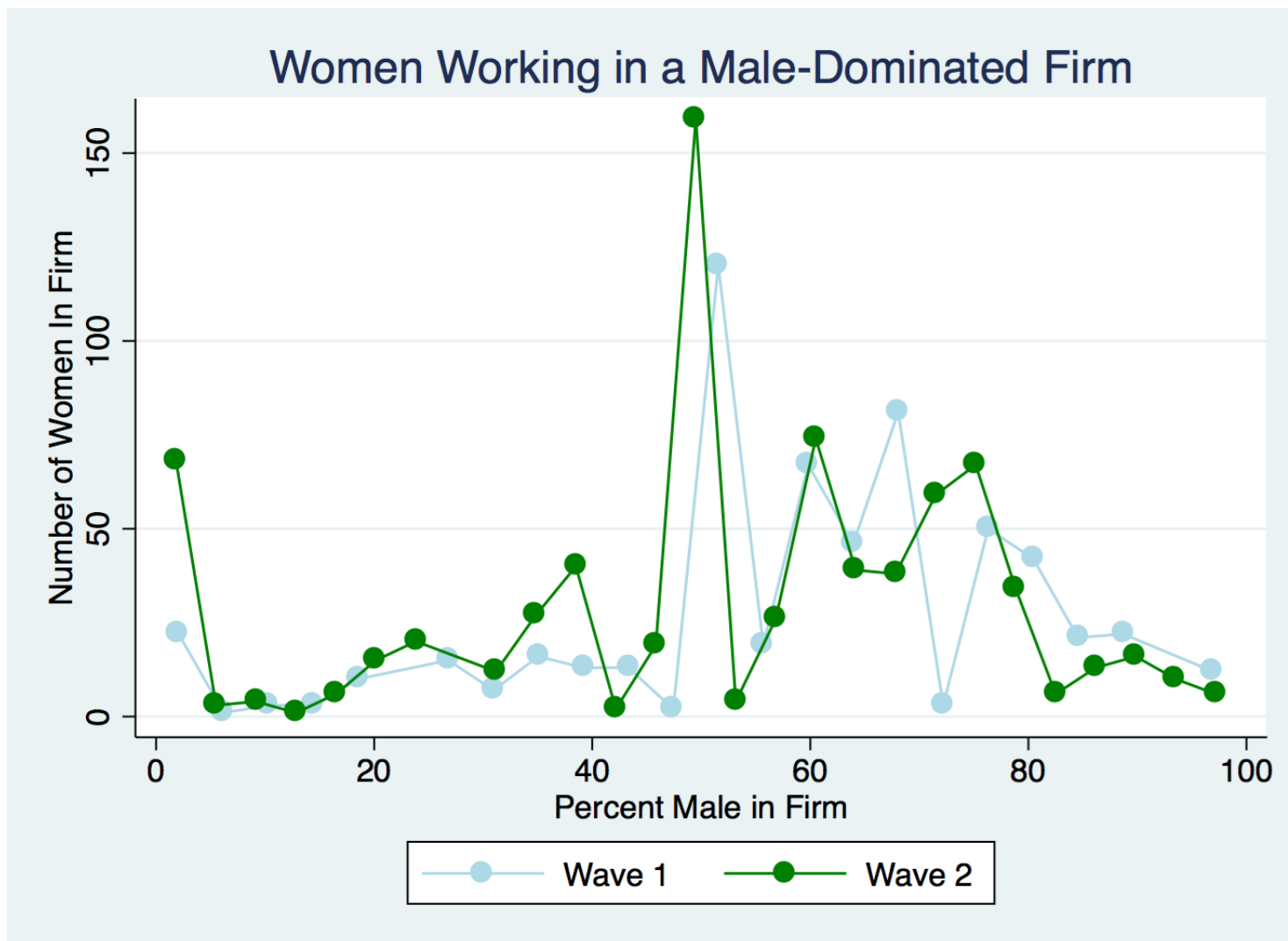
Notes: Wave 1 is women with nonmissing values for male composition of firm during their early career and Wave 2 is women with nonmissing values for male composition of firm during their mid-career. Each line shows the number of women in firms with the corresponding percent male. In women's early careers, fewer work in firms with male composition below the median than do during their mid-careers and in women's mid-careers, fewer work in firms with male composition above the median than do during their early careers.
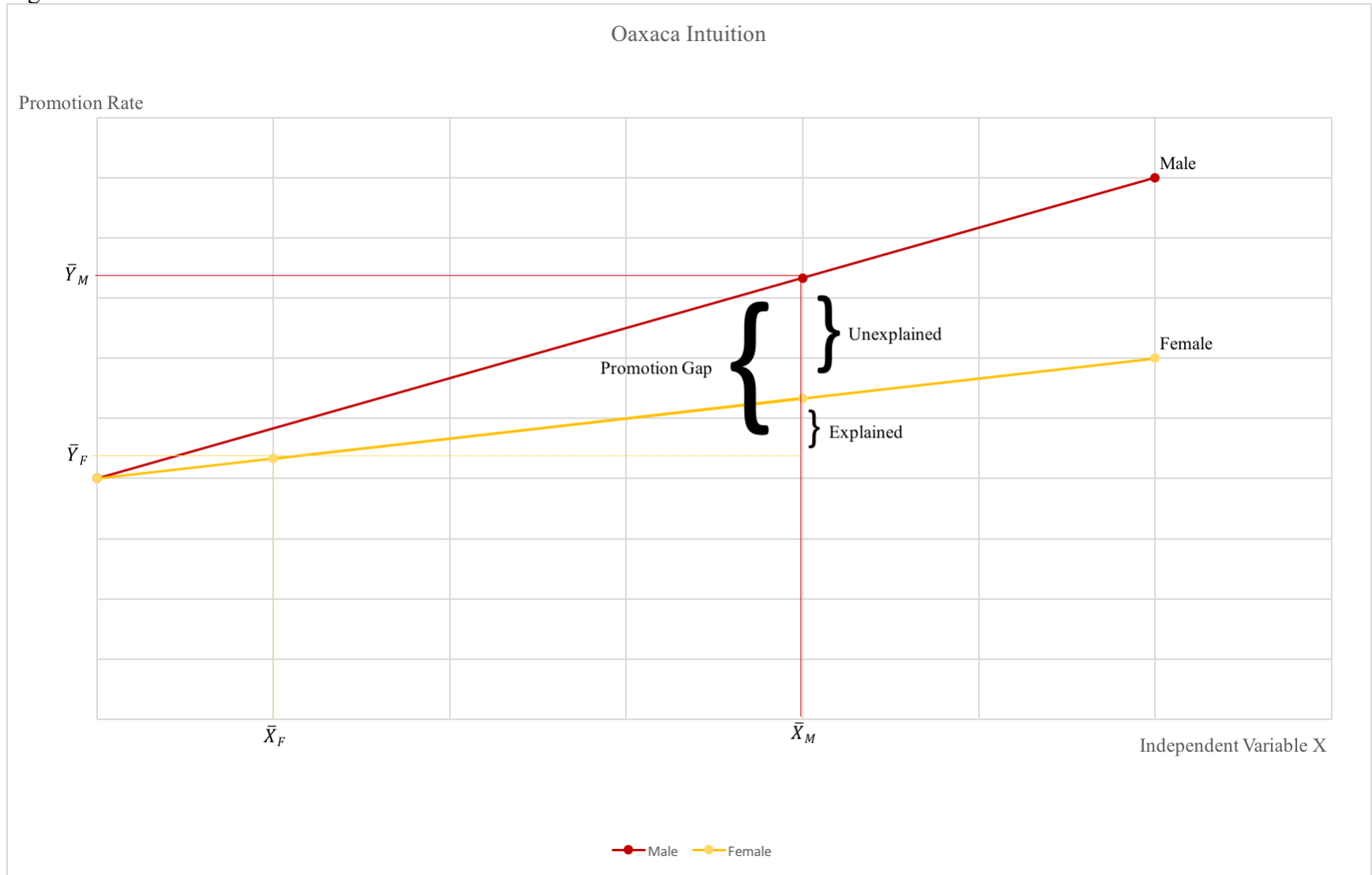
Figure 2
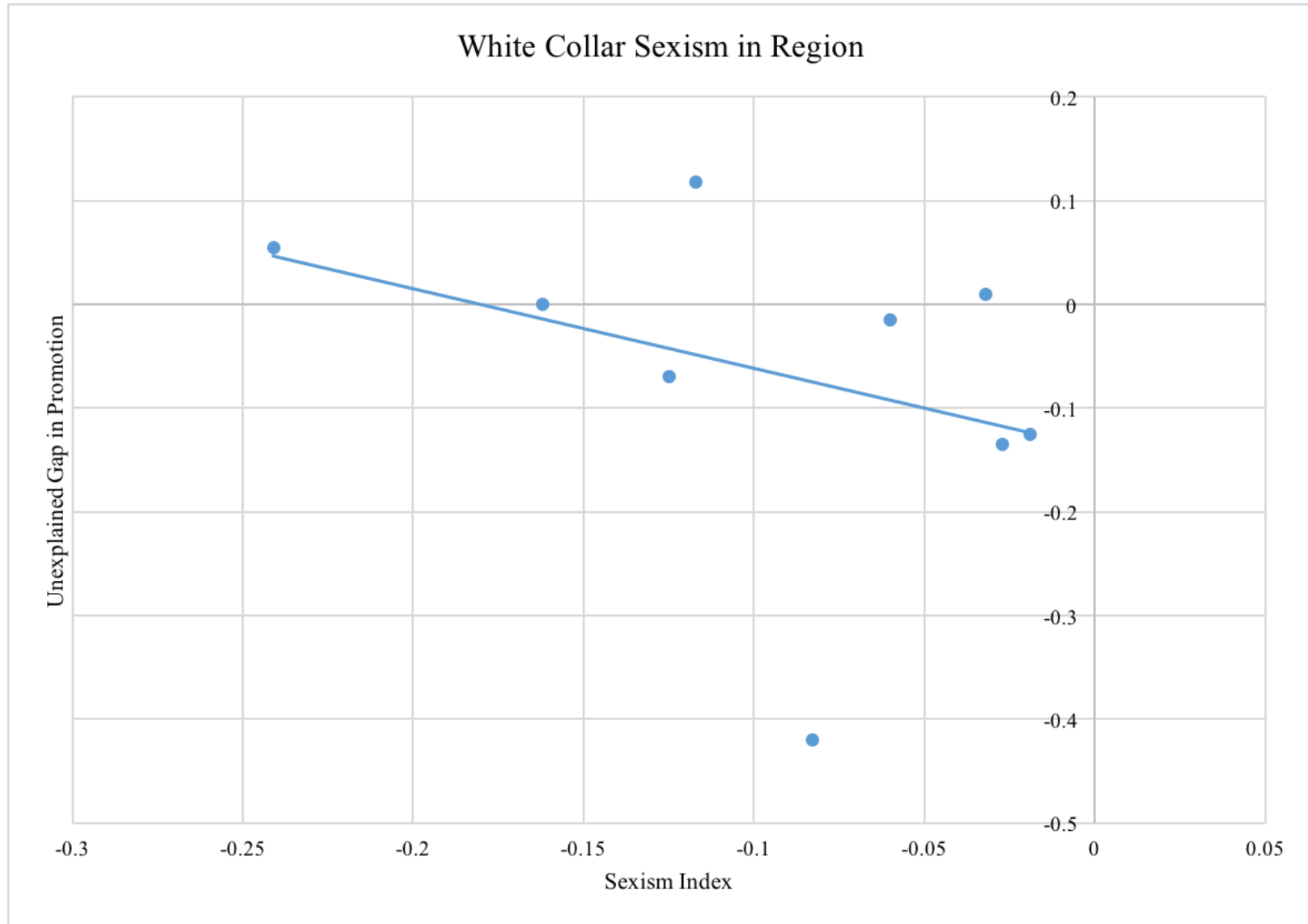
Notes: This graph displays a scatter plot of the unexplained gap in promotion against the GSS Male Sexism Index for White-collar workers by region. There is a negative correlation between seism and the unexplained gender gap in promotion.

Figure 3

Oaxaca Intuition

Promotion Rate

$\bar{Y}_M$

$\bar{Y}_F$

Male

Female

Unexplained

Promotion Gap

Explained

$\bar{X}_F$

$\bar{X}_M$

Independent Variable X

Male   Female

Notes: This graph is purely for demonstration purposes to provide intuition into how a Oaxaca decomposition works. It is not demonstrative of actual results in this paper.

Figure 4
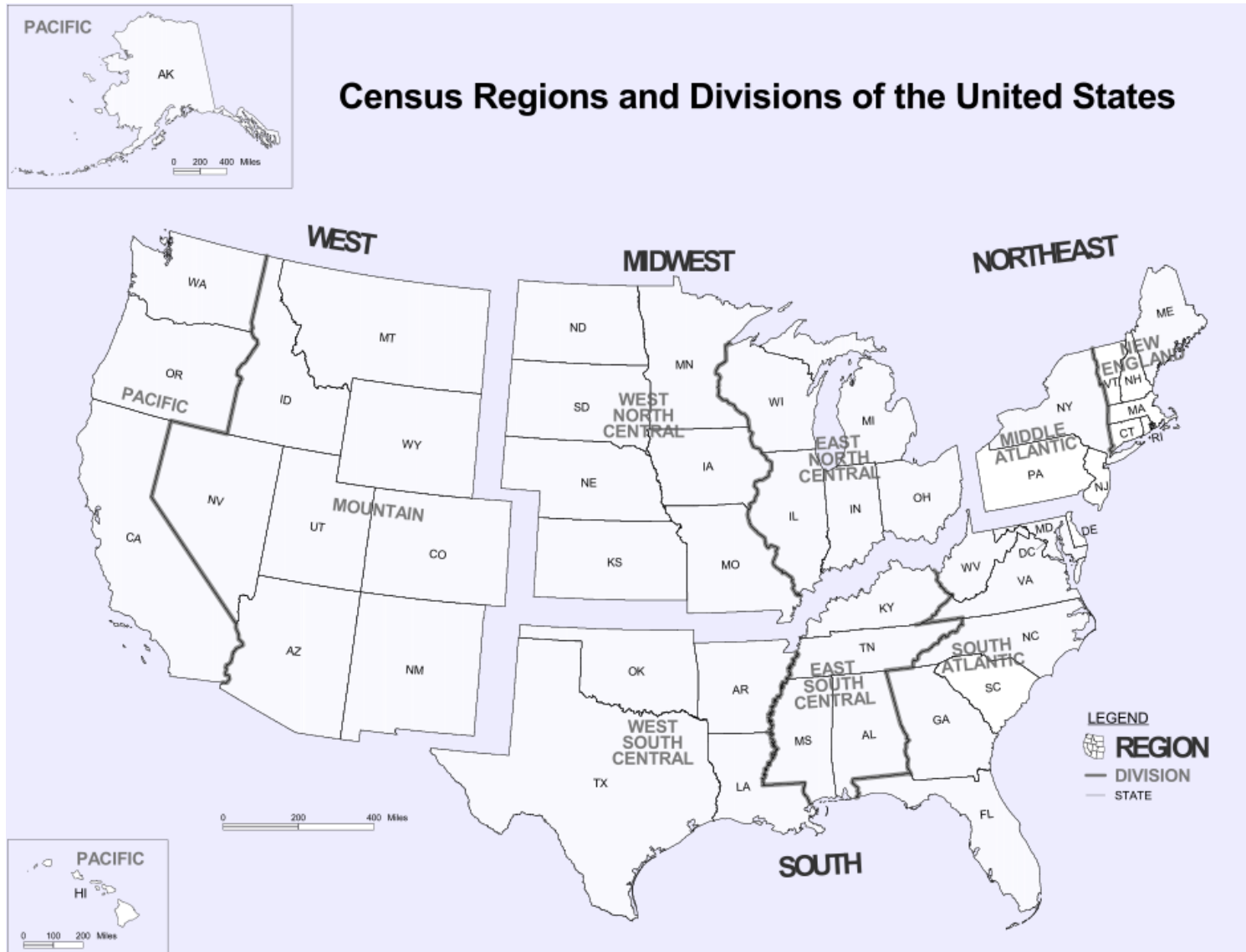
Notes: Map created by the U.S. Census Bureau. It is in the public domain. According to the sexism index utilized by Pan (2015), white collar sexism is highest in the southern regions and lowest in New England.