# FIRM CHARACTERISTICS, GENDER SORTING, AND LABOR MARKET INEQUALITY\*

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#### ABSTRACT

The movement toward gender equality has stalled. Building on theoretical arguments about how demand-side processes shape supply-side behavior, we propose a distinct mechanism for continued gender labor market stratification. Specifically, we foreground the importance of firm characteristics in shaping the companies to which men and women submit job applications. Drawing on unique panel data, we document that women apply for jobs at companies with worse compensation packages than men. We then demonstrate that this pattern is contingent on another company attribute: its work-life balance. We find that women are less likely than men to apply for jobs at companies with good compensation packages if those companies also have low work-life balance, but are equally likely to apply for jobs at companies with good compensation packages and good work-life balance. We then use survey-experimental data to show that these patterns are unlikely to be driven by individual-level preferences. Rather, we argue they are driven by structural constraints.

## FIRM CHARACTERISTICS, GENDER SORTING, AND LABOR MARKET INEQUALITY

Gender inequality in the labor market persists, even though significant progress toward equality was made in the latter part of the 20<sup>th</sup> Century (England 2010). Women still earn less than men – even after accounting for occupational sex segregation – and they are underrepresented in leadership positions within firms and on corporate boards. Addressing this empirical pattern, a significant body of scholarship has probed the mechanisms driving the persistence of gender inequality. Indeed, researchers have provided powerful insights about how, why, and where disparities between men and women emerge and are maintained in the world of work (Correll et al. 2007; Ridgeway 2011).

One set of explanations for gender inequality emphasizes the behavior of firms and employers. Generally referred to as demand-side mechanisms, the employer-based processes scholars have found to perpetuate gender inequality include discrimination against women (Neumark et al. 1995; Correll et al. 2007), the devaluation of the work that women do (Kilbourne et al. 1994; England et al. 1994), as well as workplaces premised on gendered "ideal worker" norms of complete devotion and commitment to one's work (Williams 2001). But, employers are not the only actors involved in perpetuating gender inequality. Examining the supply-side of the labor market, scholars point to gendered selection processes that lead men and women in to different occupations (see Badgett and Folbre 2003), women being cut off from important network-based resources (Fernandez and Sosa 2005), and the increasing importance of intensive parenting – particularly intensive mothering – that has become a central part of modern family life (Lareau 2003) as key dynamics that are implicated in continued gender inequality. Together, existing scholarship provides compelling evidence that multiple factors – on both sides of the labor market – are involved in maintaining disparities between men and women.

A recent set of theoretical insights in this area, however, have illuminated the ways that the actions of employers and workers are not independent of one another. Specifically, demandside forces are often directly implicated in the supply-side dynamics of the labor market. Constraints imposed by employers and workplaces may turn in to what appear to be gendered "preferences," differentially shaping the supply-side behavior of men and women (Correll 2004). Certain occupational environments that prioritize and accentuate particular forms of masculinity, for example, may lead women to "choose" other types of work. Further, workplaces that reinforce "ideal worker" norms and provide limited support for workers' lives outside of the workplace – caring for young children or taking care of aging parents, which are responsibilities that fall disproportionately on women – may push women to retreat from the labor force altogether (Stone 2007). These arguments shed light on the complex intersection of supply- and demand-side forces in influencing the patterns that perpetuate gender inequality.

In this article, we propose a distinct mechanism for gender inequality that builds on arguments about the ways that demand-side processes shape supply-side behaviors in the labor market. Specifically, we foreground the importance of firm characteristics in shaping the decisions that men and women make about the companies to which they submit job applications and, thus, the companies at which they ultimately work. We imagine that both men and women are likely to be interested in working at companies with generous compensation and benefits packages. Working at these companies is likely to maximize a worker's returns in the labor market. Yet, the demands that individuals face outside of the workplace – for housework, caregiving, and other obligations – fall disproportionately on women. These social and structural constraints may produce conditions where women also need to consider the work-life balance at a prospective company, not just how well it compensates its employees. These work-life balance

concerns, by contrast, may not be particularly salient for men, given the way that masculinity norms are structured around breadwinning (Thébaud 2010). Indeed, maximizing his pay and benefits is often deemed the best way for a man to care for his family. In other words, how a firm structures its work-life balance may intersect with broader social patterns of the division of household labor to influence the companies where women work, but not necessarily the companies where men work. Indeed, we argue that the anticipation of work-life balance or the lack thereof at a company may influence gender sorting processes during individuals' job searches. In turn, women may be over-represented at firms with worse compensation packages – particularly when those firms have poor work-life balance – which has important implications for gender earnings inequality.

Our argument and analysis proceeds in three parts. First, we examine whether women, on average, apply to companies with worse compensation packages than men. We document gender differences in the companies to which men and women apply, both with and without controlling for a host of covariates, including occupational sex segregation. Second, we examine how the work-life balance of a company intersects with its compensation and benefits packages to produce gender disparities in the likelihood that workers will apply for jobs there. Third, we use separate data from an original survey experiment to demonstrate that the patterns we detect in the observational survey data are unlikely to be driven by the individual-level preferences of men and women. Rather, we argue, the structural contexts within which men and women live and work produce a system where men and women sort into different types of firm, a process that is implicated in perpetuating gender earnings disparities.

The rest of this article is structured as follows. Next, we introduce our data and methods. We then turn to presenting our results. First, we draw on unique survey data about individuals'

job search behavior that is matched to information about the companies to which they submit applications. Second, we present evidence from an original survey experiment that captures men's and women's preferences about working at different types of companies. Finally, we conclude by discussing the implications of these findings for scholarship on gender inequality the labor market.

## **DATA & METHODS**

## The National Longitudinal Survey of Job Search: Observational Survey Data

To gain empirical traction on the argument outlined above, we first draw on a unique dataset matching information from an original panel survey tracking a national sample of job seekers with ratings from Glassdoor.com of the companies to which they submitted applications.<sup>1</sup> The survey data come from the National Longitudinal Survey of Job Search (NLSJS). The NLSJS follows a national sample of 2,060 job seekers over an 18-month period. This data collection effort was conducted in collaboration with Gfk (formerly Knowledge Networks). The sampling design for the Gfk panel – referred to as KnowledgePanel – is based on a combination of random-digit dial (RDD) methods and address-based sampling (ABS) methods, with a sampling frame that covers approximately 97 percent of all U.S. households (Knowledge Networks 2011).

The NLSJS consists of 9 survey waves conducted between February 2013 and November 2014. The first 7 waves were conducted roughly 6 weeks apart over the course of approximately 8 months. The eighth wave was conducted one year after the baseline, and the final survey (wave 9) took place six months later (roughly 18 months after the baseline survey). The target

<sup>&</sup>lt;sup>1</sup> Glassdoor Inc. generously shared their rating data with us to make these analyses possible.

population for the NLSJS was non-institutionalized adults ages 18 through 64 who were residing in the United States and who had looked for work over the previous four weeks.<sup>2</sup>

For our purposes, one of the most important components of the NLSJS is that, at each wave, respondents were asked to provide information about the five most recent jobs they had applied to in the past four weeks. Respondents were asked a series of questions about each application that they submitted, including the name of the company to which the application was submitted. Thus, we are able to match data from other sources using the name of the company to which the individual submitted an application. This is what we do with the ratings of companies from Glassdoor.com.

Glassdoor.com is an online database that includes worker-provided information about companies, including company reviews. Workers are able to provide their own evaluations of companies where they currently work or previously worked. Among the ratings that workers provide about companies are their compensation and benefits packages as well as their work-life balance, rated on a scale from 1 to 5. For our primary analyses, we construct measures of the average compensation and benefits score and the average work-life balance score for each company. For our analyses, these average evaluations are standardized to have a mean of zero and a standard deviation of one. We then match these scores to the company names of the applications submitted by the job seekers in the NLSJS. This data structure enables us to

<sup>&</sup>lt;sup>2</sup> To recruit participants for the NLSJS, Gfk sampled 19,509 of its KnowledgePanel members and sent email invitations to this group to screen them for eligibility. Of those 19,509 individuals, 11,231 (57.6%) completed the screening items. We screened individuals for eligibility on two items. First, the respondent had to provide informed consent. Second, the respondent had to have been looking for work in the four weeks prior to participating in the survey. Of the 11,231 respondents who completed the screening items, 2,092 (18.6%) were eligible to participate in the NLSJS. Of those eligible for participation, 2,060 (98.5%) completed the survey. The NLSJS also oversampled African American respondents. Similar descriptions of these data are utilized in working papers that utilize these data (e.g., Pedulla and Pager 2019).

examine how the companies that men and women job seekers apply to vary in terms of their compensation and benefits packages as well as their work-life balance.

The detailed data collected by the NLSJS also enable us to adjust for potential confounding factors as well as probe additional mechanisms and processes driving gender sorting. Given the important role that occupational sex segregation plays in influencing gender labor market inequality, we will examine whether workers' current or previous occupations explain gender sorting in to different types of firms. The baseline survey of the NLSJS asked respondents about their current or most recent job title using an open text response. These open text responses were then sent to trained coders at the University of Wisconsin Survey Center who classified the responses into three-digit SOC codes for occupations. In our analyses, when we control for current/prior occupation, we use the two-digit SOC codes for major occupational categories.

The NLSJS also contains key socio-demographic information that is likely relevant to the types of jobs people apply for. Much of this information was collected by Gfk from their panel of standing respondents. Other information was collected as part of the NLSJS itself. Given our interest in gender inequality, we will draw on a measure of respondents' sex collected by Gfk. This is a binary measure, where respondents classified themselves as either male or female. Additionally, we are able to control for respondents' race, age (and age-squared), and education. We also include controls for two application-specific pieces of information that may be related to gender and the types of firms to which an individual applied. First, the NLSJS asked respondents to provide information about how they heard about the opening for a given application that they submitted. We include a binary variable in our models for whether the respondent heard about an opening through a network-based channel (e.g., family or friends) compared to a formal channel

(e.g., the internet). Second, we include as a control whether or not the job seeker reported knowing someone at the company to which they we applying. We also include controls for the survey wave in which a respondent submitted a given application. Finally, we control for the number of reviews available for each company on Glassdoor.com (logged).

# Survey-Experimental Data on Workplace Preferences

After presenting data from the NLSJS, we will turn to evidence from an original survey experiment. In the survey experiment, we presented respondents in two occupations - managerial roles and administrative assistant roles – with the profiles of two companies. They were told that a position at their skill level was available at the company. They were presented with a short description of the company as well as numeric ratings about the company along five dimensions: compensation and benefits, work-life balance, culture and values, senior management, and career opportunities. These are the same characteristics about which companies are evaluated on Glassdoor.com, where we obtained information about the companies in the NLSJS. We randomly manipulated the scores for the companies to be either high or low on compensation and benefits and work-life balance. The other company characteristics remained consistent. After evaluating each company profile (the order of the profiles was randomly assigned) each respondent was asked how likely they would be to apply for a job at the company on a five-point scale ranging from "Extremely Likely" to "Extremely Unlikely." This item is our primary dependent variable because it captures respondents' preferences about working at a company in a more abstract way than occurs in an actual job search.<sup>3</sup>

<sup>&</sup>lt;sup>3</sup> Respondents were also asked a set of questions about what they thought about the company, which are not analyzed here given that our primary analytic interest is in workers' preferences about the types of companies they may want to work at.

We conducted the survey experiment through Qualtrics' panel services in January of 2019. We recruited respondents who were both currently in the labor force (either working or looking for work) and whose current (or most recent) job type was either in a clerical or administrative support position or in a professional or managerial position. Two respondents were missing data on either their gender or their likelihood of applying for a job at the company and, thus, are removed from the analysis. Thus, our analytic sample contains 1,010 respondents who evaluated 2,020 company profiles.

# RESULTS

Our presentation of results will proceed in two steps. First, we will analyze the observational survey data from the NLSJS studying people's job search behaviors. These data capture information about the companies to which individuals actually apply. Second, we will turn to our survey-experimental data. These data are well-suited for capturing the preferences individuals have about the types of companies where they may work.

# The National Longitudinal Survey of Job Search

We begin our analysis by examining the types of companies to which individuals apply in the NLSJS. Table 1 presents results for whether men and women apply to companies that differ in terms of the compensation and benefits packages that they provide. The dependent variable in Table 1 is the standardized average compensation and benefits score at the company to which a respondent submitted an application. Model 1 examines whether there are differences between men and women, only controlling for the number of reviews the company received on Glassdoor and the survey wave. We see a large, negative and statistically significant coefficient for being a woman. Indeed women, on average, apply to companies that are approximately a quarter of a standard deviation lower in terms of the compensation and benefits than men. Model 2 includes socio-demographic and application-related controls. Here, we see a large attenuation in the gender gap, which is cut in half from Model 1, although it remains highly statistically significant. In Model 3, we include controls for respondents' current or previous occupation. Again, the coefficient for being a woman attenuates by nearly half after accounting for respondents' occupations. Yet, the association between being a woman and the compensation and benefits package at the company to which job seekers applied is still negative and statistically significant. Thus, on average, women apply to companies with worse compensation packages than men and a significant portion of the gender gap – although by no means all of it – is explained by socio-demographic characteristics and occupational sex segregation.

#### [Table 1 About Here]

Next, we examine whether another key characteristics of the company – its work-life balance – may further influence the ways that men and women sort into companies with differing levels of compensation and benefits packages. To do this, we conceptualize firms as varying on two primary axes: compensation/benefits and work-life balance. In Figure 1, we plot the ratings of the companies for all applications in the NLSJS data along these two axes. We break the figure in to four quadrants, split at the mean on each variable. Quadrant 1 is for applications to firms with good compensation packages and good work-life balance. Quadrant 2 is for applications to firms with good work-life balance, but below average compensation packages. Quadrant 3 is for applications to firms with good compensation packages, but below average work-life balance. Quadrant 4 is for applications to firms with below average compensation packages *and* below average work-life balance.

## [Figure 1 About Here]

Quadrant 1 is likely what would be conceived of as applications to the best companies – those firms with good compensation and benefits alongside good work-life balance. We might expect that women and men will be equally represented in submitting applications to this group of companies, since the companies in this quadrant offer the suite of things that are likely important to both men and women. However, in Quadrant 3 – high compensation and benefits, but below average work-life balance – our theory would predict that women would be underrepresented compared to men. Our theory would also predict that women may end up being more likely to apply to companies with high work-life balance and low compensation.

We examine these possibilities in Table 2. The dependent variable in Table 2 is a variable capturing which quadrant of Figure 1 an application was submitted to (the excluded category is Quadrant 1). We utilize a multinomial logit model with clustered standard errors to estimate the models in Table 2. In Model 1, we include the full set of controls from Table 1. Here, we see that women are statistically significantly *less* likely than men to submit applications to companies in Quadrant 3 (compared to Quadrant 1): companies with good compensation and benefits packages, but below average work-life balance. Thus, we find support for our argument that part of what drives women's under-representation in firms with good compensation packages is that they also account for a company's work-life balance in assessing where to apply. Thus, women are less likely to apply to jobs at companies with good compensation packages if the company is going to limit their ability to balance the competing demands of work and family life. In the second part of Model 1 in Table 2, we see that women are also statistically significantly more likely than men to apply for jobs at companies with good work-life balance and below average compensation and benefits.

## [Table 2 About Here]

In Figure 2, we present the predicted probabilities of men and women submitting applications to each type of company from Model 1 in Table 2, holding all covariates at their mean. Consistent with the findings in Table 2, the figure demonstrates that women are underrepresented in submitting applications to companies with above average compensation packages if the company has low work-life balance. And, women are over-represented in submitting applications to companies with below average compensation, but above average work-life balance.

# [Figure 2 About Here]

In Model 2 in Table 2, we test the robustness of our cut-off points for determining what it means for a company to have high compensation and benefits or high work-life balance. In Model 1, the cut-off was the median on both variables. In Model 2, we change the cut-off to be the 75<sup>th</sup> percentile on each variable. In other words, we classify high compensation/high work-life balance companies as those that are above the 75<sup>th</sup> percentile on both compensation and benefits and work-life balance. We then re-estimate the same multinomial logit model that was used in Model 1, but with this updated dependent variable. The results indicate that, consistent with Model 1, women are less likely than men to apply for companies with high compensation and benefits packages if those companies do not also have good work-life balance. However, our other finding from Model 1 – that women were more likely to apply to companies with high work-life balance and low compensation – does not hold with this updated dependent variable.

# The Survey Experiment: Detecting Workers' Preferences

Our argument throughout has been that the gendered process of firm sorting that we are capturing is driven by the gender-differentiated structural constraints faced by men and women. Yet, a competing hypothesis could be that men and women have different preferences about compensation and work-life balance that drive their decisions about the companies to which they apply. Thus, one could argue that it is individual-level preferences, rather than a set of structural constraints, that drive our findings. To gain direct empirical traction on this issue, we will turn to our survey-experimental data.

First, we graphically present the gender-differentiated stated likelihood of applying for a job at a company where the compensation and benefits and work-life balance of the company have been exogenously manipulated. Figure 3 presents the mean values of their likelihood of applying for a job at the company for men and women, separately, in each of the four quadrants of potential companies: 1) high compensation/high work-life balance, 2) high compensation/low work-life balance, 3) low compensation/high work-life balance, and 4) low compensation/low work-life balance. What becomes immediately apparent is that men and women have an equal stated likelihood of applying for jobs at companies with high compensation packages, regardless of the work-life balance at that company. Interestingly, it appears as if women are more reluctant than men to apply for jobs at companies with low-compensation, regardless of the company's work-life balance.

# [Figure 3 About Here]

In Table 3, we test for this possibility using a linear regression model with standard errors clustered by respondent. The dependent variable is a respondent's likelihood of applying for a job at the company. The independent variables are which of the four types of companies the

respondent was evaluating (e.g., high compensation and low work-life balance), the gender of the respondent, and an interaction between the two. The results show that men have limited responsiveness to the compensation and work-life balance characteristics of the company, but that women are, indeed, relatively less likely to apply for jobs at companies with low compensation, regardless of the company's work-life balance. Together, we take these results as evidence that when asked about their preferences regarding working at companies with differing levels of compensation and work-life balance, women do *not* demonstrate preferences for higher levels of work-life balance. If anything, women appear to prioritize the compensation and benefits of a company more than men. These findings present evidence that runs counter to what would be expected if the findings from the observational job search data were being driven by the preferences of men and women, rather than by the structural constraints that they face when actually searching for work.

### [Table 3 About Here]

#### **DISCUSSION & CONCLUSION**

The results presented above reveal that women, on average, apply for jobs at companies with lower levels of compensation and benefits. While socio-demographic characteristics and occupational sex segregation account for a significant portion of this gap, gender disparities remain. We argue that the social and structural constraints placed on women's employment by the demands of childcare, housework, and other forms on unpaid labor result in women applying to companies where there is reasonable work-life balance. When work-life balance at a company is good, women and men are equally likely to apply to the companies with the best compensation and benefits packages. However, when work-life balance is below average, women are less

likely than men to deem those companies with the best compensation packages as places they would or could work. Thus, women are less likely to apply for jobs in certain types of high compensation, high benefits firms. This pattern holds across different cut-off points with regard to what constitutes "good" compensation and "good" work-life balance.

Additionally, we present survey-experimental evidence that captures men's and women's preferences about the types of companies that they would like to work at with regard to compensation and benefits and work-life balance. Counter to the findings in the observational survey data, the survey experiment indicates that women do *not* prefer companies with better work-life balance more than men. If anything, women appear to have stronger preferences for working at the highest compensating firms, regardless of those firms' work-life balance.

Together, the evidence we present indicates that these labor market processes are *not* due to women's preferences about wanting bettering work-life balance than men. Rather, we argue that the social and structural constraints placed on women to be primarily responsible for housework, child care, and other types of unpaid work shape the types of companies to which they submit applications. In turn, these processes play an important role in perpetuating gender inequality because they result in women applying for and, thus, ultimately working at, firms with lower compensation packages.

Firms play a key role in shaping the distribution of rewards among workers. And, the evidence presented here indicates that how firms are structured in terms of their compensation and benefits as well as their work-life balance have real consequences for the types of workers who are able to consider working there. Indeed, the findings presented above have important implications for understanding gender inequality in earnings, benefits, and economic standing. Ultimately, these findings point to the ways that demand-side processes – the structure and

organization of workplaces, their policies, and their practices – interact with the non-work demands experienced by men and women to shape supply-side behaviors, perpetuating gender inequality in the labor market.

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# **FIGURES & TABLES**

| Table 1. Random effects models of compensation scores |              |              |              |  |
|---|--------------|--------------|--------------|--|
|   | (1)          | (2)          | (3)          |  |
|   | Standardized | Standardized | Standardized |  |
|   | compensation | compensation | compensation |  |
|   | score        | score        | score        |  |
| Woman   | -0.249***    | -0.133***    | -0.0781*     |  |
|   | (0.0372)     | (0.0357)     | (0.0381)     |  |
| <i>Ref</i> = <i>Less than high school</i>             |              |              |              |  |
| High school   |              | $0.181^{*}$  | $0.171^{*}$  |  |
| -   |              | (0.0753)     | (0.0699)     |  |
| Some college  |              | 0.403***     | 0.372***     |  |
| C C   |              | (0.0745)     | (0.0700)     |  |
| Bachelor's degree or higher                           |              | 0.634***     | 0.590***     |  |
|   |              | (0.0755)     | (0.0737)     |  |
| Constant  | 0.0630       | -1.162***    | -0.954***    |  |
|   | (0.0507)     | (0.213)      | (0.220)      |  |
| Previous occupation                                   | No           | No           | Yes          |  |
| Demographic controls                                  | No           | Yes          | Yes          |  |
| Wave fixed effects                                    | Yes          | Yes          | Yes          |  |
| Observations  | 9124         | 9124         | 9124         |  |

# Table 1. Random effects models of compensation scores

Standard errors in parentheses

All standard errors clustered on applicant. The sample is restricted to companies that had at least 10 reviews on Glassdoor.com. Each model includes a control variable for the logged number of Glassdoor.com reviews available for the company. Demographic controls include the applicant's age, square of age, marital status, race/ethnicity, and presence of children under the age of twelve. Models 2 and 3 also include controls for whether the applicant used an informal network-based search method to apply to the position and whether they know someone working at the company.

Source: NLSJS, Glassdoor Inc.

 $p^{+} p < 0.10, p^{*} > 0.05, p^{**} > 0.01, p^{***} > 0.001$ 

|   | (1)                    | (2)                  |
|---|------------------------|----------------------|
| <i>Ref</i> = <i>High comp, high work-life</i> | Compensation           | Compensation         |
|   | quadrant, median split | quadrant, 75th       |
|   |                        | percentile split     |
| High comp, low work-life                      |                        |                      |
| Woman   | -0.253*                | -0.380**             |
|   | (0.117)                | (0.134)              |
| <i>Ref</i> = <i>Less than high school</i>     |                        |                      |
| High school                                   | 0.131                  | -0.432               |
| -   | (0.326)                | (0.339)              |
| Some college                                  | -0.0112                | -0.386               |
|   | (0.317)                | (0.326)              |
| Bachelor's degree or higher                   | -0.590+                | -0.747*              |
| c c   | (0.322)                | (0.328)              |
| Constant                                      | -1.892**               | -0.315               |
|   | (0.718)                | (0.809)              |
| Low comp, High work-life                      |                        |                      |
| Woman   | $0.308^{*}$            | -0.0206              |
|   | (0.122)                | (0.156)              |
| Ref = Less than high school                   | (0.122)                | (0.100)              |
| High school                                   | 0 108                  | -0 0769              |
|   | (0.251)                | (0.423)              |
| Some college                                  | -0.0643                | -0 147               |
|   | (0.237)                | (0.412)              |
| Bachelor's degree or higher                   | -0.376                 | -0.0789              |
| Bacheror & acgree of mighter                  | (0.241)                | (0.413)              |
| Constant                                      | 1 068                  | 1 242                |
| Constant                                      | (0.713)                | (0.969)              |
| Low comp. Low work-life                       | (0.715)                | (0.909)              |
| Woman   | 0 140                  | -0.0621              |
| woman   | (0.146)                | (0.124)              |
| Rof - Loss than high school                   | (0.100)                | (0.124)              |
| High school                                   | 0.460*                 | 0.702**              |
| riigii school                                 | (0.227)                | (0.267)              |
| Some college                                  | 0.800***               | (0.207)              |
| Some conege                                   | (0.221)                | (0.257)              |
| Bachelor's degree or higher                   | (0.221)<br>_1 607***   | (0.237)<br>-1.7/2*** |
| Dacheror 5 degree or might                    | -1.097                 | -1.743               |
| Constant                                      | (0.230)                | (0.237)              |
| Constant                                      | (0.595)                | 2.413                |
| Dravious accuration                           | (0.383)<br>Vac         | (0.728)<br>Vac       |
| Previous occupation                           | Yes                    | res                  |
| Demographic controls                          | Yes<br>V               | res<br>Var           |
| wave fixed effects                            | Yes                    | res                  |
| Ubservations                                  | 9124                   | 9124                 |

# Table 2. Multinomial logistic regression models of applications by compensation and worklife balance quadrants

Standard errors in parentheses

All standard errors clustered on applicant. The sample is restricted to companies that had at least 10 reviews on Glassdoor.com. Each model includes a control variable for the logged number of Glassdoor.com reviews available for the company. Demographic controls include the applicant's age, square of age, marital status, race/ethnicity, and presence of children under the age of twelve. Both models also include controls for whether the applicant used an informal network-based search method to apply to the position and whether they know someone working at the company.

Source: NLSJS, Glassdoor Inc.

 $p^{+}p < 0.10, p^{*} < 0.05, p^{**} > 0.01, p^{***} > 0.001$ 

|                                  | (1)                         |
|----------------------------------|-----------------------------|
| Ref = High comp, high work-life  | Likely to apply (1-5 scale) |
| Quadrant:                        |                             |
| High comp, low work-life         | 0.174                       |
| Low comp high work life          | (0.152)                     |
| Low comp, nign work-nie          | 0.0310                      |
| Low comp, low work-life          | 0.113                       |
|                                  | (0.170)                     |
| Woman                            | 0.0495                      |
|                                  | (0.130)                     |
| Interactions:                    |                             |
| High comp, low work-life X Woman | -0.391*                     |
|                                  | (0.169)                     |
| Low comp, high work-life X Woman | -0.124                      |
|                                  | (0.164)                     |
| Low comp, low work-life X Woman  | -0.444*                     |
|                                  | (0.187)                     |
| Constant                         | 3.225***                    |
|                                  | (0.119)                     |
| Observations                     | 2020                        |

# Table 3. Linear regression model of stated likelihood of applying to company bycompensation / work-life quadrant and gender

Standard errors in parentheses All standard errors clustered on applicant Source: Survey-experimental data  $^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$ 





FIGURE 2





