Breaking Down Information Inequality: Evidence from a Field Experiment in the Technology Industry

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Abstract

The under-representation of women within the technology sector has long been acknowledged as a pertinent concern, prompting the exploration of gender-specific information provision on job search platforms as a potential remedy. Our hypothesis posits that such gender-specific data offers valuable insights into in-group experiences, particularly for numerical minorities, albeit at the expense of potentially obscuring general information. Conducting a randomized experiment on a professional job search platform, we scrutinize the overall impact of this trade-off. Our findings reveal that the inclusion of gender-specific information derived from employee surveys diminishes user engagement on the platform, albeit with a less pronounced effect on women compared to men. To delve into the underlying mechanism, we conduct a subsequent survey, which unveils that both genders perceive aggregated job market information as more general. However, women exhibit a (relatively heightened) interest in disaggregated job market information, suggesting a nuanced perspective on the informational value of gender-specific data in the job search context.

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1 Introduction

The under-representation of women in the technology industry is well-documented, not only by scholars but also by practitioners (Correll and Mackenzie, 2016). Although many companies view recruiting a diverse workforce as important, those employers face challenges in doing so (Bloomfield et al., 2021; Fanning et al., 2021). To address this problem, researchers and practitioners have argued that technologies such as job platforms may serve to reduce inequality. These job platforms are believed to economize the search process because they provide individuals access to information about a wide range of companies and their job openings. Individuals use them early on in the job search, wherein they use platforms to learn about companies and to apply for jobs. In the later stages of the hiring process, they are used by individuals to assess their job offers and to make decisions on whether to negotiate salary (Wang and Sterling, 2023). In sum, scholars and practitioners have argued there is promise in these platforms, such as Indeed, Glassdoor, Blind and others, because they reduce information inequality.

In this paper, we study the link between information aggregation and job search behavior across numerical majority and minority groups. Aggregating information, which we refer to herein as the clustering information into a representative whole by combining data on segments or groups, is common in accounting and pervasive in many other contexts (e.g., Yelp Ratings) (Arya and Glover, 2014). Individuals make decisions based on information, including product purchases, portfolio choices, and their career pursuits based on aggregate rankings or scores (Stigler, 1962). Averaging people's consumer reactions, preferences and opinions is one dominant way to summarize a vast amount of information (e.g., mean of analyst forecasts or mean of Glassdoor reviews) (Huang et al., 2020). This aggregation mechanism might (unintentionally) generate information inequality if people's experiences diverge across groups in the numerical majority and minority. Imagine you observe a restaurant review with an average score of 4.5. You are a local resident. You know that most of the reviews come from tourists who have different tastes. Only observing an average score

of 4.5 might be less informative for you than for tourists because the scores have (unintentionally) more weight on tourists' opinions. Disaggregating the overall average score–i.e., into local and non-local reviews–might be more informative for you than for tourists for decision-making purposes.

Job search platforms typically provide users with aggregated information. But, platforms also have taken steps recently to provide group-specific information (e.g., ratings disaggregated across social groups), based on the belief that this will be even more valuable to platform users. Harkening back to the Yelp example except turning our attention to gender, information women might receive in the technology industry, on average, may be less useful to them than men. To the degree that information (e.g., rankings of employers) is provided, these may be more representative of the sentiments of the numerical majority than the numerical minority. Further, women tend to have less access to the type of information that they might value from their in-group—i.e., such as what firms might be more female-friendly, where there is an inclusive culture, and whether firms engage in organizational practices that can create a track record of promotions for women and support for their careers (Fernandez and Weinberg, 1997; Barbulescu and Bidwell, 2013; Folke and Rickne, 2016). It is believed that by disaggregating information, platforms can convey information in cost-efficient ways not just to those that are a part of the numerical majority but also to those that are a part of the numerical minority (Garcia et al., 2018). On the flip side, aggregated information could prove more beneficial than gender-specific insights, particularly if members within a group remain curious about the perspectives of both in-group and out-group members. Both group may share common experiences. Additionally, comprehending the viewpoints and sentiments of those outside one's immediate group can aid in coordinating with colleagues in varied organizational settings.

To quantitatively examine this question about the relationship between (dis)aggregated information, gender and job search behavior, we place an informational field experiment among technology workers. By placing a field experiment, we can overcome a couple of

challenges that might otherwise be present in assessing the effects of information disaggregation on job search behavior (Lourenço, 2016; Li and Sandino, 2018; Choi et al., 2023). Usually, it is difficult to observe how job search activities are directly affected by employer information, including across individuals that are members of different demographic groups. In addition, it is difficult to (randomly) alter information provided by multiple companies at the same time (Lourenço, 2019). By placing a field experiment on an online platform, we observe various job seekers' real-world reactions to gender-specific information about various employers.

Our experiment alters knowledge about "great places" to work on Blind, a platform of over 7 million working professionals in tech in North America and Asia. To a control "aggregated information" group, we provide information about great places to work (i.e., a "top 20" rankings list). To a treatment group we provide the same information disaggregated by gender, or from herein what we term gender-specific information. From March 2022 to May 2022, we seeded 56,095 Blind users with disaggregated information of the two main types. The main type is information that was aggregated across Blind users, regardless of their genders, about the best technology companies to work for based on real employee reviews. In a second set of conditions (across two "treatments"), we seeded Blind users with the same information but we disaggregated it in gender-specific ways (i.e., a "top 20" rankings list by gender).

We observe a decrease in job search interests and activities on the platform in response to gender-specific information. Users exhibit lower engagement with the "By Gender" employer ranking notification, both in terms of the extensive margin (interest) and the intensive margin (click-through rates on employers' overview and job opportunity links). This trend holds true for both female and male users. The disengagement from disaggregated rankings applies uniformly across all employers, irrespective of their rank. However, we note that this effect is somewhat attenuated for women. Moreover, there is no statistically significant decline in click per session observed on the "By Gender" or "Side-by-Side" ranking pages. Our

cross-sectional analyses reveal that female job seekers with high job search interests tend to show increased interest in gender-specific information and that men tend to show increased interest in gender-specific information when their employers have lower male-dominated environments. These findings underscore the differential impact of gender-specific information on numerical minorities and majorities, likely stemming from information inequality, and highlight a potential trade-off in providing disaggregated job market information.

We conduct a follow-on survey to explore how breaking down job market information by gender affects engagement and job search activities in both genders, with a less pronounced effect observed for women. The survey involved 931 participants from STEM and business industries, randomly shown either disaggregated or aggregated data. Participants are asked about their opinions on these displays and their interest in seeking employment at the firms. Two main findings emerge: firstly, the differential impact of gender-specific information on engagement by gender is consistent across industries, with individuals showing less engagement when such information is provided. Secondly, gender-specific information is perceived as less useful and more difficult to understand, although both men and women acknowledged its social value. Notably, women find gender-specific information as interesting as aggregated data, unlike men. These findings suggest a potential divergence in preferences between general and gender-specific labor market information for women and men, although both ultimately prefer aggregated information for its general content.

Overall, our paper makes a number of contributions. In the accounting literature this study has yields important insights. Recruiting talented workers is viewed as a fundamental control system (Campbell, 2012). The platform interacts with the fundamental control system throughout the process: hiring (e.g., Indeed), engagement (e.g., Glassdoor), and interviews (e.g., Blind). The platform provides job market information to job seekers intermediating the hiring process. The specific way to measure job market information is of accounting researchers' interest as well. Our study suggests that contrary to studies that have found promising effects of disaggregating information in other domains around corpo-

rate disclosure (Berger, 2011), doing so across all sub-groups does not have the same impact. While researchers have argued that it is important to reduce inequalities that stem from social networks, including those that provide job information, the difficulty of doing so through impersonal channels such as job platforms is laid bare in this study (Rubineau and Fernandez, 2015; Sterling and Merluzzi, 2019). This raises important questions about the fortitude of inequality in labor markets, and whether platform technologies, which nonetheless have been argued to have equalizing impacts, are in fact, bringing these to fruition (see Castilla and Rho (2023) for additional discussion).

As a human capital disclosure perspective, the paper's findings provide insights to corporate managers. The importance of corporations communicating non-financial information with workers has gotten more and more attention (Cardinaels et al., 2018; Cai, 2023). The SEC's new regulations on human capital disclosure have emphasized the demand for human capital information, especially diversity, equity, inclusion metrics (Bourveau et al., 2022; Choi et al., 2022; Goldman and Zhang, 2021). Our study points out that, during this (either internal or external) communication with workers, managers may want to consider a subtle trade-off between aggregated and disaggregated non-financial information. Finally, we use a field experiment and a survey approach to address a socially significant research question with implications for job-seekers and policy. This is in line with the recommendations of recent review papers in the accounting literature (Floyd and List, 2016; Lourenço, 2019; Armstrong et al., 2022).

2 Institutional Setting and Theoretical Foundation

2.1 Gender Inequality, Information, and Platform

Despite decades of attention from scholars and policy makers, there remains a large gender gap in STEM workforce participation. While some STEM fields have seen an increase in women's employment, women remain especially under-represented in the high technology

industry, an industry that has a disproportionately positive contribution to GDP growth in the U.S. and a number of countries (Correll and Mackenzie, 2016). The lack of women in the technology industry is well-documented. Women only make up 18% of executives in tech firms, and only account for 27% of professionals in Silicon Valley tech firms, the well-established agglomeration area of technology firms in the U.S (EEOC 2014).

One problem leading to this lack of representation is the deficits faced by some in receiving information. Researchers find there is a lack of information about corporations' workforce dynamics, cultures, and human resource management practices that are useful to job-seekers. This lack of information has been noticed by regulators. In August 2020, the SEC updated the reporting requirements for public companies by making changes to Regulation S-K. One of the amendments was to Item 101, which is the first item in the 10-K report and requires companies to describe their business. Under the new amendment, companies must also describe their human capital resources if they are important to their business. The amendment became effective for the 2020 fiscal year 10-K reports filed on or after November 9, 2020. The SEC has not specified any particular subtopics or metrics to be disclosed. Rather, it follows a principle-based approach. Companies may choose to disclose topics such as training and development, retention strategies, labor relations, COVID-19 strategy, and workplace safety.

This lack of transparency by companies influences job-seekers and especially women, who receive less information about job opportunities than men (Gallen and Wasserman, 2021). Studies find that women lack the social networks and peer-to-peer relationships in male-dominated fields like engineering, that can provide private information about employers–i.e., what the day-to-day work involves, what skills are required, and the culture and norms at firms (McDonald et al., 2009; Obukhova and Kleinbaum, 2022). Further, studies suggest that even if women do receive this information, the information they receive may be less relevant to them. Women that are able to successfully enter into networks in male-dominated fields often receive information from those of their 'out-group' or men, rather than women

(Obukhova and Kleinbaum, 2022). As a result, they lack information about employers when they look for jobs, influencing the degree to which individuals are well-matched at firms (Rivera, 2012). They may have less information on firms that might be viewed as more female-friendly, and lack knowledge on firms that have a strong record of promoting women and supporting their careers.

Platforms are argued to provide information to a broader, more public audience, and dislodge information from more private channels, which may be disproportionately valuable for women.[1] By reducing information frictions, platforms are believed to provide information that reduces inequality. Platforms are argued to reduce labor market "frictions"— the matching of employees with employers—which could lessen inequality (see discussions in Burdett and Mortensen (1998) and Sørensen (2007)). Labor market frictions come about when information fails to be conveyed to actors on either side—i.e., the demand and supply side—of the labor market. Labor market frictions lead to extended open vacancies, high levels of unemployment, and skills and cultural "mismatch" between employees and firms (Autor, 2001; Gee, 2019).

However, an important way labor market frictions might be reduced is through the disaggregation of information on platforms. Every summary statistic is an aggregation of some set of informational observations or inputs. By disaggregation, we refer to creating different versions of a given summary statistic by incorporating or emphasizing different subsets of these informational observations. For example, review platforms often present the uniform average of all available reviews for a given product or business (this is what we refer to as the "aggregated average"). When we disaggregate reviews by gender, we separately collect the reviews left by men and women to construct two different averages using only the reviews left by each gender. For the purposes of this exposition, we consider the case where users

[1]Platforms have not been viewed as a panacea for reducing inequality *per se*. Some of the attention to date has focused on potential risks of exploitation of workers on platforms (Kalleberg and Dunn, 2016; Katz and Krueger, 2019), as well as to the potential abuse of workers (see discussion in Cameron and Rahman (2022)).

would only be able to observe the disaggregated rating based on their own gender [2].

In this work, we study information disaggregation on platforms in labor markets. There has been a great deal of attention to platforms and disaggregation. A number of platforms now provide gender-specific information.[3] For example, Glassdoor started to present an average review score by various individual characteristics including gender in 2020. To date, however, no study to our knowledge has directly investigated the impact of providing in-group gender information on job search.

The purpose of disaggregation is to filter out information with limited relevance to the intended audience of the summary statistic. If men's and women's experiences with a company are markedly different, leading to divergent ratings, the aggregated average could misrepresent the typical experience of either gender. This is because it incorporates all reviews to create a singular average, even if those underlying reviews come from reviewers who have systematically different experiences than the focal user's gender. While the aggregated rating is a biased representation of both genders' experiences at a given company, it more closely represents, on average, the view of the gender in the numerical majority (which is men in our context). Disaggregation would separately construct average reviews left by men and women. By creating gender-specific averages, we exclude reviews left by the other gender, and only include reviews left by users who have more similar experiences and/or preferences as the focal user. They are unbiased representations of each gender's experience at a company, which may be particularly beneficial for the numerical minority gender (which is women in our context).

Disaggregation reduces the number of observations used for a given statistic, which could lead to significant drawbacks. Although reviews from men and women might show considerable differences on average, they could still exhibit systematic correlations. This implies that reviews from men might still offer insights into what women might experience at the

[2]Even if they observe both disaggregated ratings, it is possible users do not incur the cognitive cost of processing and/or combining those different disaggregated averages.

[3]See the online appendix.

same company and vice-versa. For example, suppose that men tend to be generous in how they rate companies, and that the average male review for any given company corresponds to the average female review plus some fixed constant. In this example, a company rated relatively highly by men would also be rated relatively highly by women. These male reviews would therefore prove informative to women if they had to choose from a set of alternative companies based on how they were rated. Consequently, a gender-specific average might overlook the informative value found in the broader set of reviews, making it potentially less insightful than the aggregated average that includes all reviews.

Another concern with disaggregation is its impact on the variances of summary averages. For instance, particularly in situations where women are under-represented, the female-specific, disaggregated average would be based on a small number reviews, often resulting in a higher variance compared to the more stable aggregated average that encompasses all reviews. If users place significant importance on the variance of the information they consult, then examining the disaggregated average could be less beneficial than considering the aggregated rating. In essence, disaggregation, while aiming to provide targeted information, may reduce its informativeness for certain audiences. We elaborate on these points using a stylized model in Appendix D.

2.2 Relevant Theories

Our theorizing is informed by the information theory literature in economics and organizational behavior (Stigler, 1962; Mortensen, 1988; deHaan et al., 2021; Gillis et al., 2021; Bryan et al., 2022). Information theory suggests that while information is valuable, it comes at a cost. Specifically, labor economists focus on the search involved in attaining information, and under what conditions such search is valuable or detrimental.[4] According to informa-

[4]Gee (2019) finds that when job seekers see how many other people are applying for a job on LinkedIn, they are more willing to apply for those jobs, using a field experiment with 2.3 million LinkedIn users. Gee (2019) discusses that limited information about employers and its consequences in the job market is not well discussed, especially with field experimental settings mentioning a few exceptions, including Flory et al. (2015), which is about competitive workplaces and female workers.

tion theories, women would need to search longer than men to learn where they might want to work because what would generally be known about a company (e.g., "company [XX] treats its employees well") would be affected by the demographic composition of the workforce. Specifically, women in tech might receive less valued information about a company from other workers, because the average worker is male in the U.S. (EEOC, 2014), and their experiences would be told from this vantage (Gallen and Wasserman, 2021). Further, women are more isolated from information channels and receive less information overall. For instance, studies find that women lack social networks and peer-to-peer relationships in male-dominated fields, and these networks and relationships can yield nuanced information about employers.

Nevertheless, there are several reasons to believe that information disaggregation may not have these expected effects. One possibility is that general information might be more valuable than gender-specific information if in-group members are still interested in both in-group and out-group members' thoughts (Brewer, 1999; Tropp and Bianchi, 2006). For example, understanding out-group members' thoughts and opinions can be helpful when coordinating with team members in diverse organizations (Charness and Chen, 2020). Additionally, when people are presented with information about multiple groups, this can lead to greater levels of cognitive complexity and overload (Kahneman, 1973; Schick et al., 1990; Umar, 2022). In a laboratory experiment, Chervany and Dickson (1974) document that graduate students took a longer time for and had less confidence in their production decisions when (disaggregated) production data were presented to them, instead of simple descriptive statistics. Finally, in STEM fields, studies find that there is a strong belief in meritocratic ideals for workers across social groups (Castilla and Benard, 2010; Blair-Loy and Cech, 2022). By disaggregating information by gender, there may be a sense among individuals that this is out-of-step with meritocratic norms (Leibbrandt and List, 2018). This might lead to backlash among individuals in these domains.

Based on the the above arguments, the overall effect of disaggregation is empirically

ambiguous. Further, the literature and these arguments suggest that women would receive greater gains from disaggregated information compared to men, and this would be evidenced in their job search activities across the type forms of information. Specifically, we expect that women in the technology industry would be more apt to pursue job search activity at employers where their in-group rated an employer highly.

3 Experimental Design and Results

3.1 Experimental Methods

We ran our experiment on Blind, an anonymous job search and discussion platform headquartered in Northern California (Kim and Leach, 2020). Blind has millions of users worldwide with a high number of daily active users, but our research and experiment focus on US users.[5] The platform's mission centers around transparency and breaking down professional barriers, providing users with the ability to discuss their employers and job markets while maintaining complete anonymity.[6] Similar to LinkedIn, users can share important job market information such as career choices, job offers, and interview questions. To access the site's full features, users must indicate their current employer, but the platform does not store any information about users other than their current employer.

Our research not only conducted an experiment on the platform but also utilized the real world data obtained from Blind about their perceptions of companies. To conduct the research, we began designing the experiment in 2021. In order to run the experiment, the research team, in partnership with software engineers, designed the push notifications and landing pages. We collaborated on the design and execution of the study for a period of approximately 12 months. Our sampling frame consists of all users on the platform that

[5]Our geographical analysis in the online appendix indicates that about 80% of sessions come from the US. See www.teamblind.com.

[6]Our keyword analysis in the online appendix indicates that Blind users are highly interested in compensation, career advice, and interviews (Choi et al., 2022).

left a review about their current employer and self-identified their gender by January 1, 2022. Although the platform covers multiple industries, the presence of the platform in the technology industry is especially salient: the top employers getting reviews are mostly technology companies. Its major reviews are collected on companies through a "Pulse" survey, which is a job satisfaction survey sent to employees, initiated by the platform instead of an employer. The 56,095 individuals, who participated in a "Pulse" survey, are the sample for the experiment. We preregistered our experiment in the AEA RCT registry.

During the experiment, individuals received push notifications about technology company ratings. The message-based experimental approach is widely used in the literature (Hallsworth et al., 2017; Guzman et al., 2020). Push notifications are an alert generated by Blind, which notify the user of a new message on their phone. The experiment randomized the nature of the push notifications that a user received across the control and treatment conditions. In the control condition, the user received a push notification about company ratings that were not disaggregated by gender. Specifically, the push notification was for the "Top 20 Employers Ranked through Blind Pulse". For the treatment conditions, the users received the same push notification, except that they were notified the platform was listing the "Top 20 Employers By Gender Ranked through Blind Pulse".[7]

After receiving the push notifications, all users have the option of opening the message to see company rankings. In the control condition, they see a "Top 20" list (see Figure 2) at the second stage. In the treatment conditions the push notification is the same. What differs is the rankings pages after individuals open the push notifications. In the (second-stage) control condition, we show users a "Top 20 employers" page consisting of the aggregate rankings for all users on the platform. The (second-stage) first treatment condition provides a ranking of the same 20 companies, but only provides rankings by users of the same gender as the focal user (referred to as "Own-Group"). Users in the first treatment could view the rankings of

[7]Prior to running the experiment, we conducted one pilot test with about 600 participants to examine those participants' understanding of employer ranking pages in general and by gender. The pilot test results indicate the usefulness of these ranking pages for job search. We also pretested functionality, as well as similar looking between the control and treatment conditions, for push notifications.

the other gender by clicking on a button at the bottom of the page, which redirected them to a separate rankings page. The (second-stage) second treatment condition also provides a ranking of the same 20 companies, but not only for the same in-group gender as the focal user but also for the out-group gender. The (second-stage) second treatment shows rankings for both men and women disaggregated and side-by-side (referred to as "Side-By-Side"). The second treatment condition was included for a few reasons. Namely, we wished to control for the possibility that users would engage more or less based on the number of users providing a ranking. In the (second-stage) control and treatment conditions, the number of ratings was identical. The only difference was that in the Side-By-Side condition, these rankings are disaggregated by gender.

Across the top 20 employers, the correlation between the Aggregated rankings and male rankings is approximately 0.82, while the correlation between the Aggregated rankings and female rankings is approximately 0.68. This difference in correlations matches the pattern of male experiences being better captured by Aggregated ratings as compared to female experiences at firms. Consistent with our theoretical predictions, this suggests that the information value of disaggregating ratings and its delivery by gender should be higher for women than for men. The diverging views on employers between male and female workers is documented by Glassdoor in 2023. The inaugural Glassdoor Equity Xray report indicates that the difference in employee reviews between men and women on average is meaningfully higher in the technology industry than in other industries.[8]

3.2 Experimental Variables

There are two main dependent variables we examined in the experiment: engagement and job search activity. The first dependent variable, engagement, is measured as the click-through rate (CTR) of the push notification. This is a common way of measuring job

[8]https://www.glassdoor.com/research/equity-xray/. The report states that at two-thirds of the companies, men rated the company higher on average than women. For the remaining third, women reported higher average ratings.

seekers' (Lambrecht and Tucker, 2019) as well as consumers' (Wu et al., 2022) interests across the economics and marketing literature. CTR is measured per platform-user as a binary variable.

The second dependent variable, job search activity, is measured by actual search behavior. After individuals click-through, they open what we refer to as the "landing page". On this page, there were links to all of the companies in the Top 20 list. Users can engage through the "See More" button, which redirects users to the respective company landing review page on Blind. There is also an "Apply Now" button, which redirects users to the respective career page on the company's website. We are able to observe all of these behaviors through the platform, and we measure the clicks as an indication of job search activity. One limitation of these data sets is that, as already mentioned, the users are anonymous. We are not able to connect their subsequent movements to other companies based on information seeded in this experiment. Even if that were to occur, job movements would only be expected to be loosely coupled to treatment condition, given the numerous factors that affect job movement. However, we are able to track user engagement with our experimental variables based on coarse, group identifiers. These are based on gender, who their employers were before the start of the experiment, and how they rated those employers. We kept track of user engagement via Google Analytics with the group identifier during their visits. Even in the absence of tracking actual job changes, this allows us to focus on what presumably would be a tighter association with our information treatments.

3.3 Randomization and Covariates

Using random number generation, we assign 18,699, 18,737, and 18,659 users to Baseline, Own-Group, and Side-By-Side, respectively. We assessed the effectiveness of this randomization across three observable characteristics. First, we check gender with a dummy variable if the user identifies as a woman ("Woman"). Second, we assess the score from 0 to 100 the user gave their current employer ("Review Score"). Third, to assess the recency of user ac-

tivity, we create a dummy variable to indicate whether they created their review in the prior 90 days ("Recent Review"). In Table 1, we find that there were no significant differences in the average of these characteristics across the treatment conditions (Tests across all users by treatment condition-ANOVA *Woman* Statistic: 1.89, P-Value 0.15; ANOVA *Review Score* Statistic: 0.61, P-Value 0.54; ANOVA *Recent Review* Statistic: 2.16, P-value 0.12.). This suggests that the sample is balanced and the randomization was effective across the control and treatment conditions.

3.4 Job Search Engagement

We estimate a linear probability model given that our dependent variable is a binary variable of click-through or job search activity(Jeziorski and Moorthy, 2018). We use treatment conditions, gender, and their interactions as independent variables. The regression specification is as follows:

$$P(Click_i) = \beta_1 Treatment_i + \beta_2 Female_i + \beta_3 Treatment_i \cdot Female_i + \epsilon_i$$

where i represents a platform user.[9]

We find that users of both genders were less likely to click on the By-Gender push notification, to be directed to the rankings pages compared to the Baseline. The left column of Table 2 shows that the probability of men clicking on the By-Gender push decreases by about 3% in absolute terms as compared to the Baseline (i.e., Aggregated) rankings push. The (relative) effect size is substantial as it corresponds to a drop of approximately -33%. We see a similar story for women, as shown in the second column. The probability of women clicking on the By-Gender push decreases by about 1% in absolute terms as compared to the Aggregated rankings push. This corresponds to a drop of approximately -16%. We formalized this observation by running a difference-in-differences equation, shown in the last column of Table 2, where we compare the changes in engagement across the By-Gender

[9]We use a regression specification to analyze experimental results (Guzman et al., 2020). In the online appendix, we find that our results are robust to a logistic regression specification.

and Aggregated rankings push notifications across men and women. We see that female engagement decreases by a significantly smaller amount as compared to men.

We can also analyze the clicking behavior of users, conditional on their arrival on the rankings page. A click is a meaningful measure of intensive engagement with the rankings, potentially directing users to more detailed information about the top companies ("View More") or to the career page of the company ("Apply Now"). Table 3 analyzes the propensity of clicking this job search link on the rankings page. In the third column, we show that there is a 3.4% absolute decrease in the probability of job search links created by a male user containing a click on the Own-Gender rankings page as compared to the Aggregated rankings. This corresponds to a 21% decrease relative to the baseline click-through rate. For the Side-By-Side rankings pages, there is a 4.5% absolute decrease in the probability of job search links created by men having a click, which corresponds to a 28% relative decrease. In terms of job search links created by women, we do not see any significant difference in clicking behavior across job search links in Table 3. As we did for the previous analysis, we can combine these results into a single difference-in-differences regression. In the last column, we compare the changes in engagement between the Own-Gender, Side-by-Side, and Baseline rankings pages and across men and women. The signs for *Woman* interactions with the treatment rankings page indicators are positive; however, they are not significant.[10]

Our results are not limited to a few top employers on the ranking pages. The drop-off in overall click propensity shown may be explained by users being less engaged across the whole ranking page or by users systematically shifting their attention to smaller portions of the list instead. For example, one potential explanation is that users could be restricting their engagement to the top companies under the treatment conditions. We show the probability of a user clicking on a ranking (both the respective "See more" and "Apply now" buttons), conditional on that user starting a session in Figure 4. Users in the treatment conditions

[10]We conduct F-test to examine both of the interaction terms' statistical significance. Considering our binary dependent variables, we conduct ANOVA tests alternatively and find qualitatively the same results, which are reported in the online appendix.

decrease clicking across the entire list of 20 rankings, not just in selected parts. In all, there is no support for the prediction that providing gender-specific information prompts higher interest and job search activity. Instead, we find that providing gender-specific information decreased engagement, especially for male users. Returning back to the stylized model in Section **??**, these results bring our attention to the potential benefit of additional reviews left by the opposite gender providing more information about overall job satisfaction, which can be meaningful even for numerical minority groups.

3.5 Cross-sectional Heterogeneity

We conduct two different types of cross-sectional tests to explore heterogeneity across users: how they rate their current employer and the proportion of women at their company who left reviews on Blind.

For the first type, we classify users into a category based on how they rated their current employer. The rationale is that users who are likely to have greater job mobility are users who 1) are dissatisfied with their current employer or 2) are highly skilled in their profession, leading to greater demand for their employment. Users who are dissatisfied in their current roles are likely to rank their current employers poorly. Likewise, users who are highly skilled may rate their current employers highly due to their skills being appreciated by management in order to keep them at the company. We operationalize this by constructing a variable *Tail Review* as an indicator if a user rated their current employer lowly or highly.

Table 4 shows that user who either rate their current employer lowly or highly are systematically more likely to engage with the treatment by-gender push notification, as compared to users who rate their company as more average. This pattern holds when we restrict our analysis to only including men or only including women. Considering those job seekers with tail reviews are more interests in moving to another job because of their dissatisfaction or them being desired by other companies, this cross-sectional result is consistent with the usefulness of gender-specific information especially for job seekers with high job search interest.

This job search interest effect is stronger for women considering the statistically significant coefficient of Tail Review for women.

We additionally study how the proportion of women at a user's company might affect their propensity to engage with By-Gender information considering that numerical minorities value gender-specific information. However, there are two potential issues that would prevent substantive analysis: 1) we currently do not have ground-truth measures of the proportion of women at each company, and 2) we are not able to track every user's company due to the previously mentioned technological constraints. In order to address the first issue, we constructed proxies for the proportion of women at each company using Blind data. Using these proxies, we calculated *Female Composition Percentage* as the proportion of female reviews to male and female reviews. For the second point, we limit our analysis to *only* the users who work at companies we are able to fully observe. We are only able to capture a focal user's company if they belong to the Top 20 companies defined based on the number of reviews by users due to technological constraints.

In Table 5, we find that men who work at companies with more women had decreased engagement in general, relative to companies with fewer women. This is the case for both the Baseline and By-Gender ranking push notifications. However, men at these companies with more women are more likely to click on the By-Gender push notification than the Baseline push notification. On the other hand for women, we see no such pattern in engagement as a function of the proportion of female reviewers. These effects could potentially be idiosyncratic to the specific set of users at large companies, but we nonetheless find them informative. It is in line with the idea that being a numerical minority requires a trade-off between general and gender-specific labor market information, and such trade-off is even present for men.

We conduct another cross-sectional analysis to explore the potential impact of divergent (among gender) job satisfactions on individuals' engagement with gender-specific information, specifically in relation to their current employers. The underlying rationale for this

analysis was that users' perception of the value of general information may be influenced by the extent of gender-based disparities in job satisfaction within their workplaces. To assess users' beliefs, we utilize the differential job satisfaction levels reported within their respective current employers. Our untabulated results, however, do not indicate any discernible differences in the results between users employed at companies with significant gender differentials and those with more balanced gender ratings.[11] These results may be consistent with that the perception of gender disparities in job satisfaction is a technology industry-wide phenomenon, instead of a firm-specific phenomenon.

4 Follow-on Survey

To understand the mechanisams behind our results, we implement a follow-on survey. We survey research participants on Prolific to understand why platform users are not more engaged with the disaggregated information compared to the aggregated information. This allows us to assess possible explanations in light of our experimental findings.

4.1 Survey Design

We conduct a follow-on study in order to understand the trade-off between general and gender-specific labor market information. We conduct a survey on Prolific using the Engagement Motivation Scale (EMS). Prolific is a survey vendor commonly used by academic researchers (Barcellos and Kadous, 2022). The EMS scale is adapted from the Consumer Motivation Scale (CMS) developed by Barbopoulos and Johansson (2017) that measures consumer behavior in various contexts (Ding et al., 2020). The scale is broken into three overarching goals that drive behavior—Gain, Hedonic, and Normative—with fine-grained sub-goals and motives attached to each one (Barbopoulos and Johansson, 2017).

To map the CMS framework onto our own study, we first conducted two pretests. We

[11] Refer to the online appendix.

presented the same push notifications and rankings pages to survey participants and asked them to respond to open-ended questions. They detailed their preferences for one version or the other. These responses were then analyzed using inductive coding to extract the main themes. Once finished, four themes were identified: Informativeness, Job Search, Disinterest in Gender, and Equality. Users perceived the informativeness of employer rankings either connecting to or not connecting to job search activities. Users also expressed their interest or disinterest in gender-specific information. These themes were then mapped onto the individual motivation items of the EMS. Overall, 15 motives were identified across the three main goals of the EMS. Because our study focused on information value in decision making, we draw from additional existing frameworks in the accounting literature that characterized this process: Decision Usefulness, Information Consumption, and Social Value (Libby and Luft, 1993; Rennekamp, 2012). These three concepts are also mapped onto the 15 motives from the EMS. After an initial pretest of our EMS, we decide to shorten the number of motives used due to shared similar concepts in the motives, and revised the wording of our motivation items to fit the content of both the push notification design and company ranking page design. After this final round, our EMS contains 8 total motivation items: Useful, Informative, Relevant, Easy to Understand, General, Interesting, Aligns with my Values, and Promotes Inclusion.

4.2 Survey Results

The follow-on survey on Prolific was conduct in the fall of 2022. We select survey participants working in the technology, finance, business industries. These industries are chosen because they are male-dominant and STEM-intensive industries. Similar to the survey experiment, we randomly present 931 Prolific participants with a screenshot of a push notification, followed by a screenshot of the respective rankings page linked to that push notification. Table 6 provides demographic characteristics of the sample. After viewing each of the screenshots, we ask participants to evaluate the push notifications and rankings pages.

Figure 5 indicates that, based on the average score, participants generally perceive the By-Gender push notification as informative, easy to understand, and containing general information. However, Table 7 documents that the By-Gender push notification is perceived as less easy-to-understand and containing less general information than the Baseline push notification. This suggests that aggregated labor market information is viewed as more decision-useful. Disaggregated labor market information is more inclusive regardless of survey participants' gender. When survey participants evaluate the ranking pages, the Side-By-Side ranking page is perceived as containing all three features (i.e., average scores higher than 4) in Table 8: decision usefulness, information consumption, and social values. But as shown, disaggregated labor market information is still less decision-useful than the Baseline condition (i.e., the aggregated labor market information).

These survey results provide two potential mechanism explanations for our experimental findings. As for the overall engagement reduction for gender-specific information, disaggregated labor market information is perceived as less useful, and viewed as containing less general information. This result is consistent with the argument that in-group members may not only seek information about their own group but also that of out-group members. Going one step further with our speculation, it may be that workers are more familiar with their in-group than their out-group, which leads them to be more interested in aggregated information. In addition, the survey results suggesting disaggreaged information is more difficult to understand suggests participants faced information complexity and cognitive overload. In other words, it may require more cognitive effort for users to process in-group and out-group information at the same time.

While the first two explanations align with the overall decline in engagement, it does not fully elucidate the differing impacts on women and men. When we compare men's and women's differential responses to general and gender-specific information in Tables 7 and 8, we find that women view gender-specific information as interesting as general information. This survey result brings our empirical findings back to our theoretical prediction. There is

support that the numerical minority group appreciates disaggregated labor market information more than the numerical majority group, which is consistent with our cross-sectional analyses in Tables 4 and 5 as well.

Regarding the further job search activities on the ranking pages, we document in the online appendix that all three key criteria matter. In other words, relevant (decision usefulness), interesting (information consumption), and aligning with my values (social values) are positively associated with job seekers' willingness to engage with these companies. Interestingly, "Promotes Inclusion" is a perceived distinctive feature of gender-specific information by both genders, but this feature is not associated with the likelihood to further engage in job search activities. In terms of gender differences, female job-seekers are neutral about aggregated and disaggregated labor market information for job-search motivating features (i.e., relevant and interesting). Again, results in Tables 7 and 8 suggest that female platform users may trade-off between losing general information and getting gender-specific information for job search activities.

5 Conclusion

We conduct an original experiment on a widely used labor market platform to examine the relationship between gender-specific information and job search activity in the technology industry. Our objective was to explore the potential benefits of disaggregating employee reviews by gender, which have been argued to reduce information inequality in an era of increasing platform usage in labor markets. Yet, there has been a dearth of research on the impact of platforms on labor markets and the influence of information provision on job search behavior. Overall, our experiment reveals a sophisticated finding: instead of generating increased interest and prompting job search activity, the provision of gender-specific information on the platform led to decreased interest and job search activity. These results indicate a statistically significant decline in engagement and job search behavior, with

a relatively less significant effect observed for female workers.

To better understand these nuanced findings, we conduct a cross-sectional test, employ a follow-on survey, and explore three potential mechanisms for these effects: the benefit of general information, the benefit of disaggregated information for a numerical minority group, and information overload due to disaggregation. While none of these arguments alone fully explain all of our findings, they together aid our understanding of the results. Through the survey, we find that survey participants, regardless of gender, perceived the treatment conditions with gender-specific information as less useful compared to the control conditions. Despite the platform offering information that might be considered more exclusive and harder to access, it is deemed as having less utility. Consequently, it was less likely to drive an increase in job search behavior overall. Nonetheless, women recognize some benefits of gender-specific information. The cross-sectional analysese support this benefit especially numerical minorities with high job search interests.

Taking into account all the results and these nuanced explanations, this study makes significant contributions to literature in accounting as well as labor market and organizational inequality. We argued and developed a theoretical model that would predict the benefit and cost of disaggregation under a reasonable condition. We find the net effect of disaggregation on workers is negative, but our finding suggests a potential of disaggregated job market information to reduce information inequality across numerical minorities and majorities in the technology industry. At a time when there is significant focus on platforms using artificial intelligence to improve labor market outcomes through information facilitation, our findings highlight the potential opportunitieis and challenges in reducing information inequality through the provision of disaggregated information. The numerical minority group seems to face a trade-off between losing general information and gaining gender-specific information. In summary, disaggregating information presents a complex dynamic. In light of this, our study raises important new questions for scholars. Empirically evaluating the potential benefit of additional reviews by the opposite gender in the context of the stylized model would be

informative to balance the trade-off of gender-specific information in different circumstances. The broad applicability of our results to STEM jobs, as well as those students pursuing these jobs, warrants further investigation in other industries.

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A Experiment Design and Variable Description

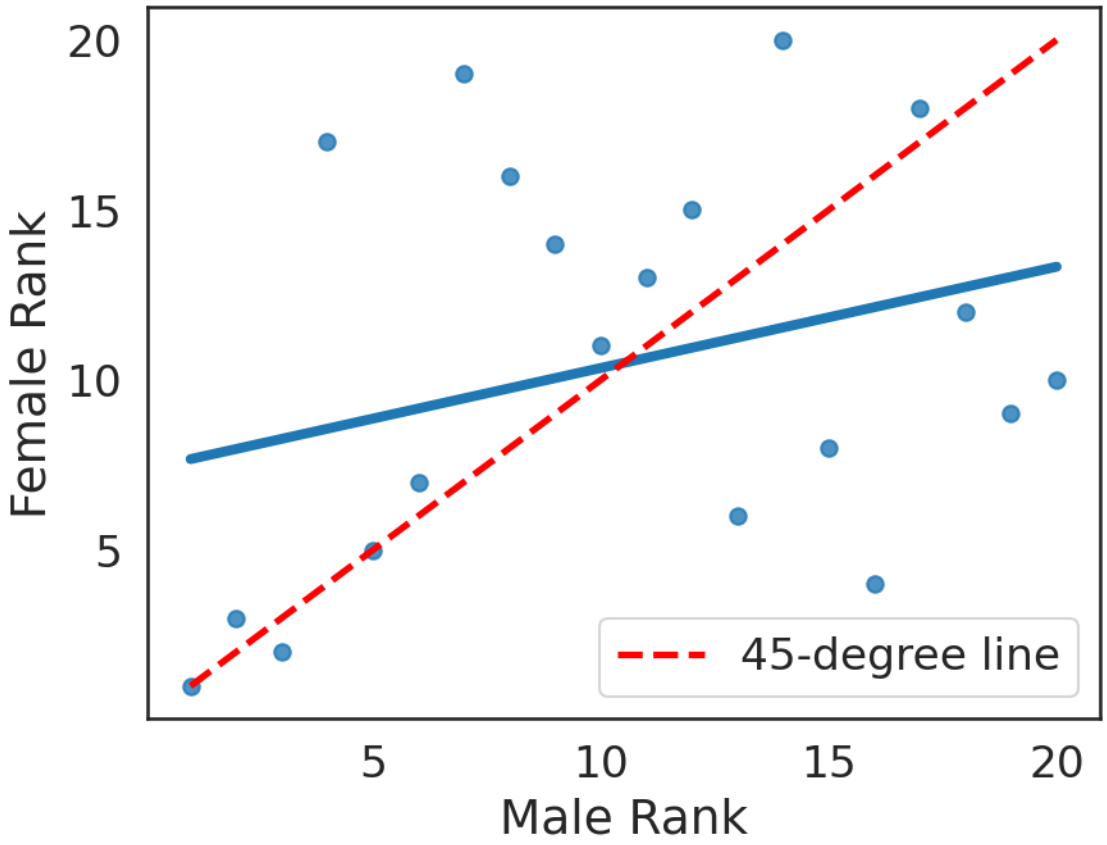
Panel A: Experiment Design

Condition	Push Notification	Condition	Rankings Page
Baseline (Aggregated)	The push notification is for "Top 20 Employers Ranked through Blind Pulse".	Baseline (Aggregated)	Show a "Top 20 employers" page consisting of the aggregate rankings for all users on the platform
By Gender	The push notification is for "Top 20 Employers By Gender Ranked through Blind Pulse".	Own Group	Show a "Top 20 employers" page consisting of the rankings by users of the same gender on the platform as the focal user
		Side By Side	Show a "Top 20 employers" page consisting of the rankings by male and female users separately

Panel B: Variable Description

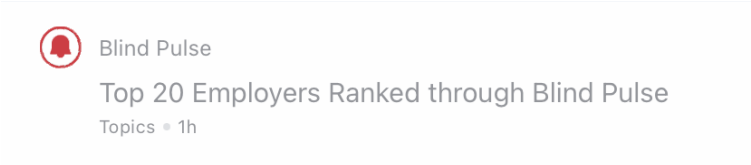
Variable	Definition	Source
User Starts Session	The user clicks on the served push notification to go to the rankings page	Blind
Session with Click	The likelihood that a realized session contains a click	Blind
Women	An indicator if a user is a woman	Blind
Large Company	A company that is top 20 in terms of reviewership on Blind	Blind
Small Company	A company that is not top 20 in terms of reviewership on Blind	Blind
Female Composition Percentage	The ratio of female reviewers over male and female reviewers for each employer	Blind
Information Features	Useful, Practical, Relevant, Easy to Read, General, Interesting, Aligns with my values, Promotes inclusion	Prolific Survey

B Figures

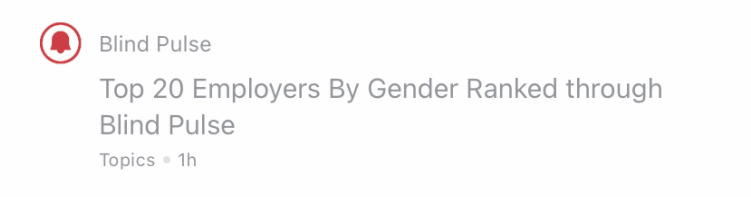


Notes: This figure compares rankings as determined by different reviewer genders on Blind. Each point is a single company from the top 20 company list we compiled. The X-axis is the ranking, only among those 20 companies, as determined by male reviewers on Blind. The Y-axis is the ranking as determined by female reviewers. The blue line is the OLS fit. The red dashed line is the 45-degree line.

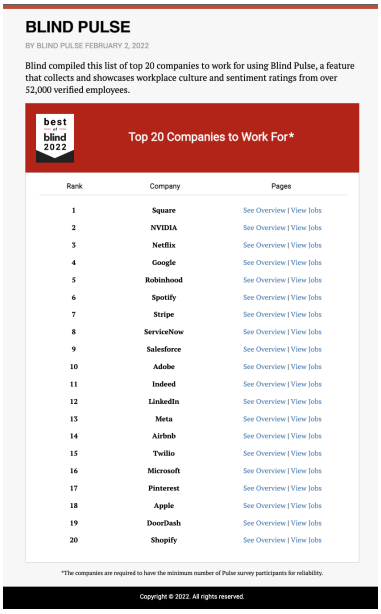
Figure 1: Correlation Between Top Company Ranks



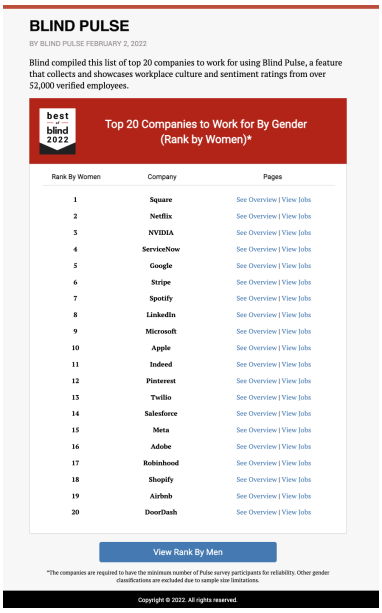
(a) Baseline Push



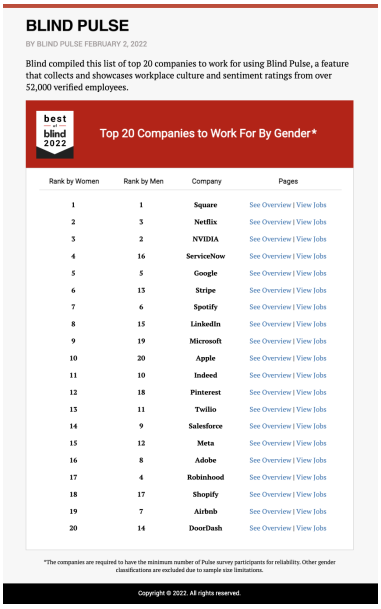
(b) By-Gender Push



(c) Baseline Rankings



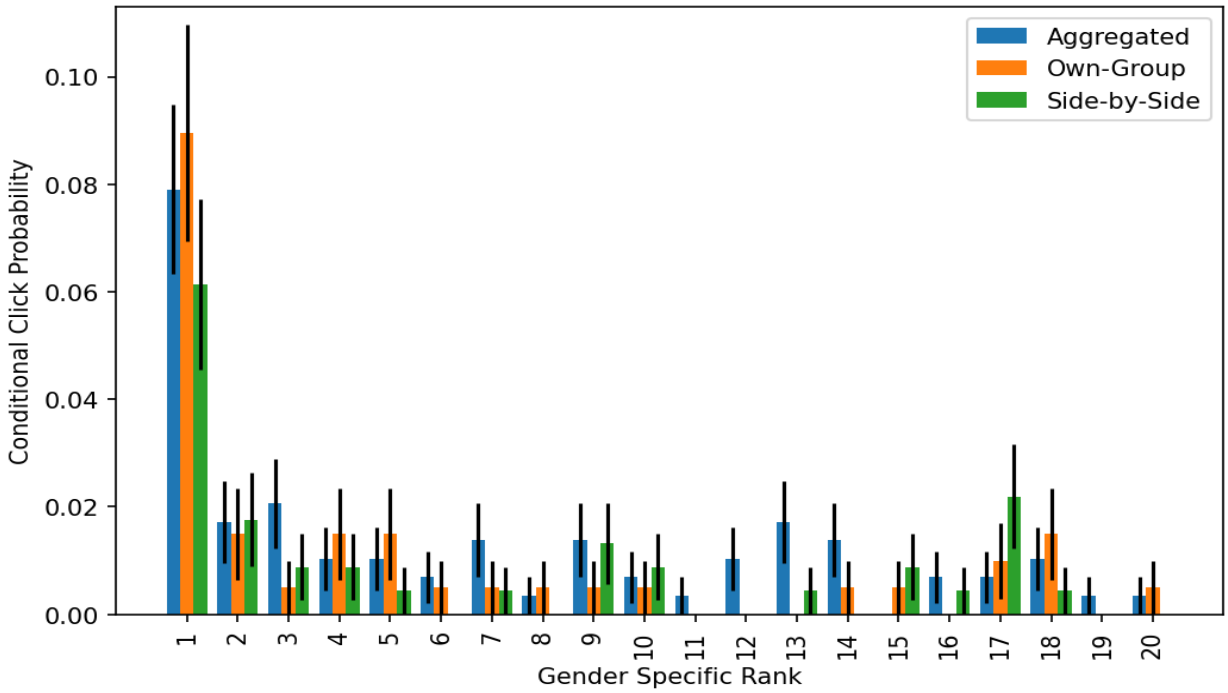
(d) Own-Group Rankings



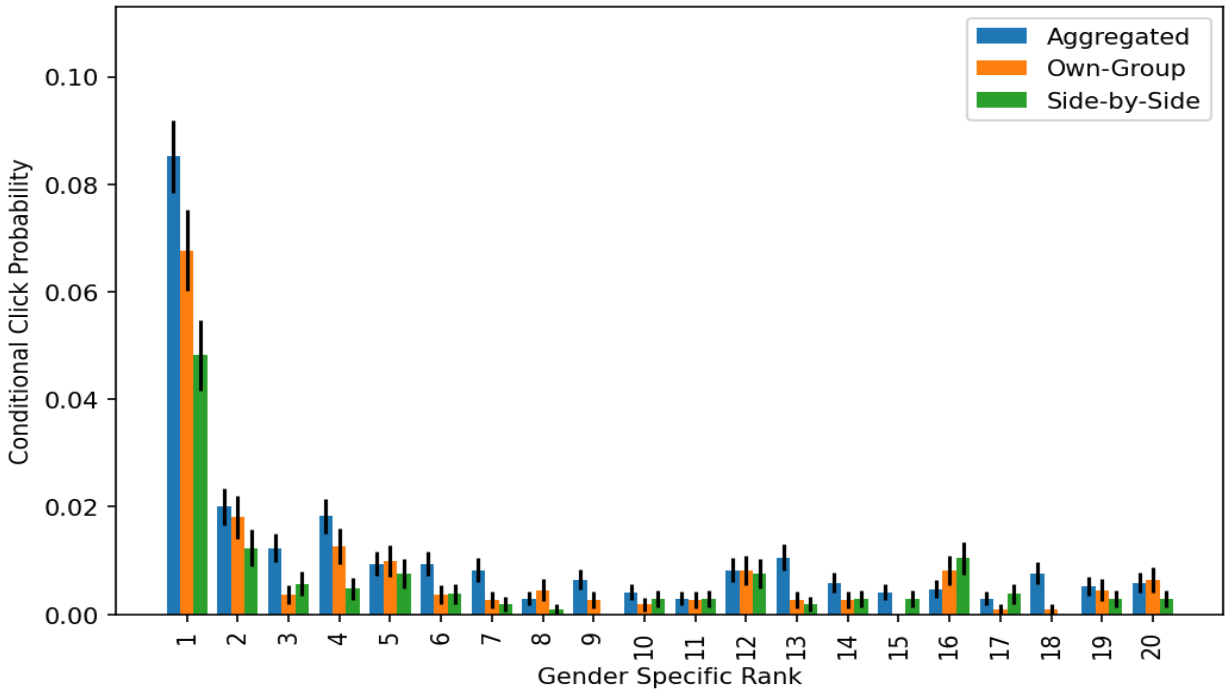
(e) Side-By-Side Rankings

Notes: This figure contains screenshots of push notifications and ranking pages served to female users. a) general information, b) the gender specific information, c) the aggregated rankings, d) the by-gender rankings for one gender only, and e) lists both gender rankings side-by-side. Men would receive their own gender specific rankings.

Figure 2: Control and Treatment Conditions



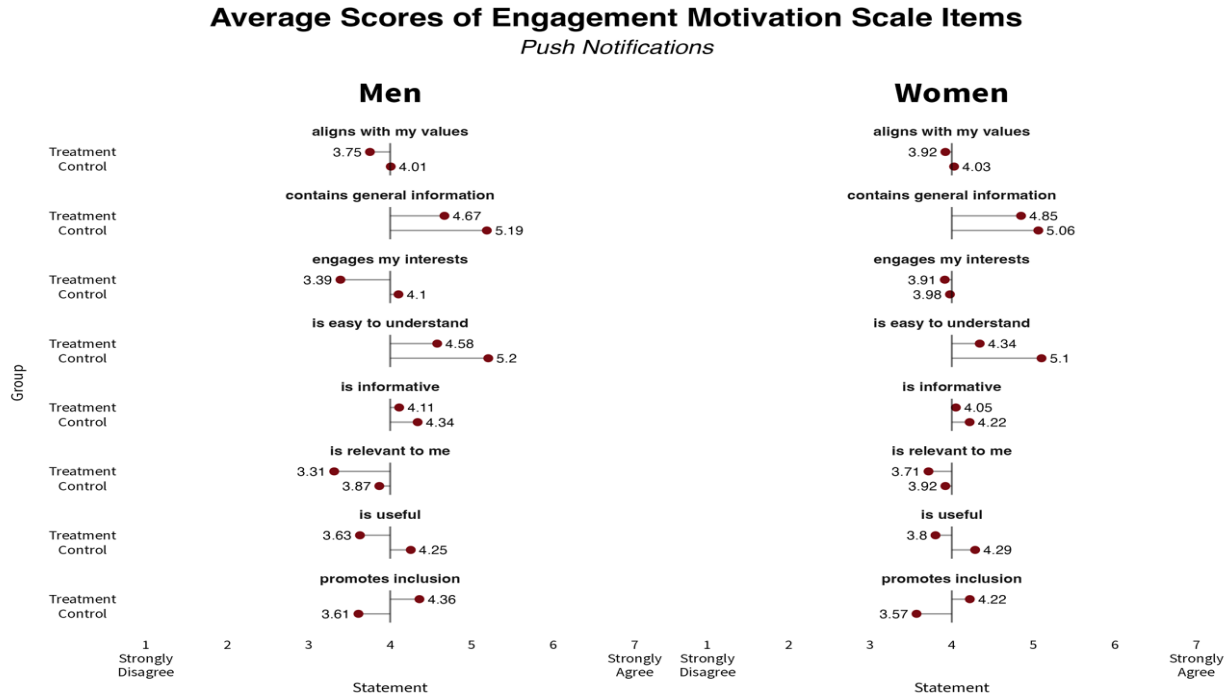
(a) Female Click Likelihood



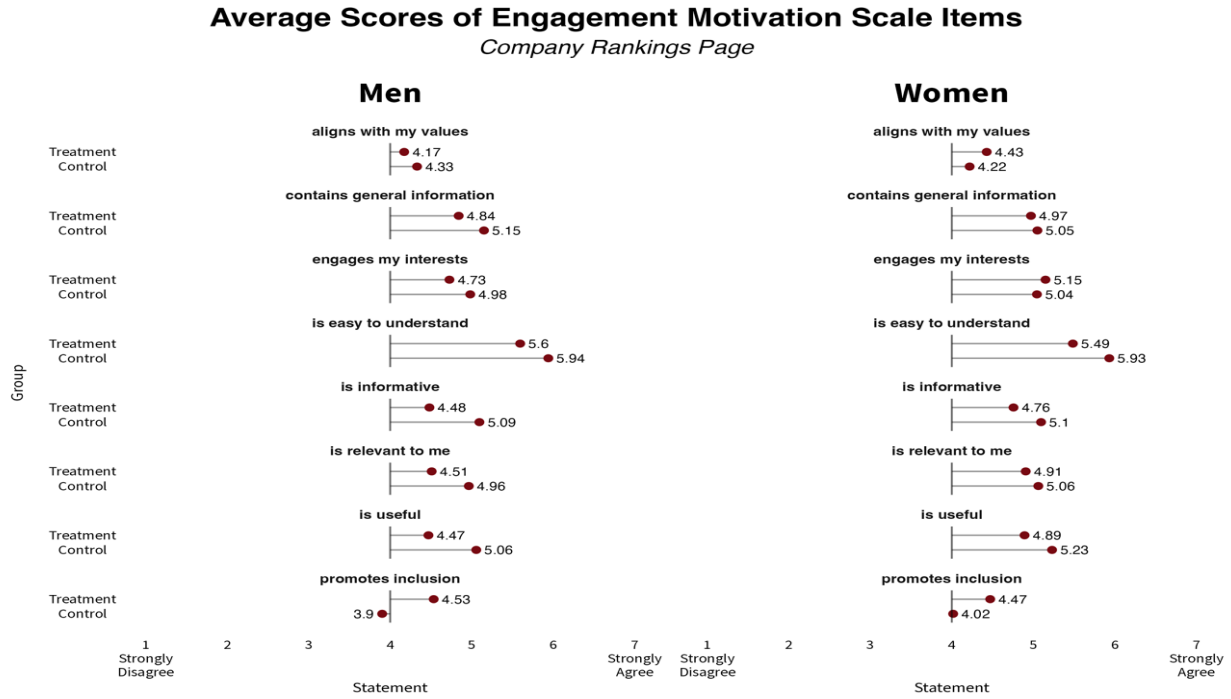
(b) Male Click Likelihood

Notes: This figure contains the likelihoods a company being clicked on in a session broken down by rank. Each x-axis tick mark represents the same company across all three types of bars, and the x-axis tick marks are ordered by Own-Gender rank. Error bars are standard errors.

Figure 4: Click Likelihood on the Ranking Page



(a) Push Notification



(b) Company Rankings Page

Figure 5: Comparison of Engagement Motivation Scale Ratings for Treatment and Control Conditions by Gender. Prolific Users.

C Tables

Table 1: Balance Across Conditions

	Condition	Count	Average Review Score	Average Recent Review	Average Large Company
Men	Baseline	15,268	67.2114	0.2300	0.4002
	Own-Group	15,291	67.2544	0.2368	0.4011
	Side-By-Side	15,105	67.1034	0.2399	0.3933
ANOVA			0.2316	2.1560	1.1637
(P-Value)			(0.7931)	(0.1157)	(0.3123)

	Condition	Count	Average Review Score	Average Recent Review	Average Large Company
Women	Baseline	3,431	63.2395	0.2273	0.3517
	Own-Group	3,446	64.1334	0.2391	0.3418
	Side-By-Side	3,554	63.8350	0.2279	0.3570
ANOVA			1.6575	0.8574	0.9148
(P-Value)			(0.1906)	(0.4242)	(0.4006)

Notes: This table describes covariates across treatment conditions divided by user gender. In the main body text, we present ANOVA tests across all users. Review Score represents a user's individual score for their company. Large Company is an indicator if the user works at the top 20 companies on Blind by reviewer base. Recent Review is an indicator if the user signed up within 3 months of the experiment. We were only able to track the company names of users from within those 20 companies in order to reduce the technological complexity of launching the experiment.

Table 2: Probability of Clicking on the Push Notification

	User Starts Session			
	All Users	Women	Men	All Users
By-Gender Push	-0.0296***	-0.0112**	-0.0337***	-0.0337***
	(0.00246)	(0.00509)	(0.00279)	(0.00279)
Woman				-0.0310***
				(0.00491)
By-Gender Push × Woman				0.0225***
				(0.00580)
Constant	0.0926***	0.0673***	0.0983***	0.0983***
	(0.00212)	(0.00428)	(0.00241)	(0.00241)
N	56,095	10,431	45,664	56,095
R^2	0.003	0.000	0.004	0.004

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the linear probability model of a user starting a session by clicking on the push notification. The baseline is the control push notification. Note that we combine the two treatments into one indicator variable, since both treatments received the same push notification. The first column restricts the sample to users who are men, the second column restricts the sample to users who are women, and the last two columns use both men and women.

Table 3: Probability of a Session Having a Click

	Session with Click			
	All Users	Women	Men	All Users
Own-Group	-0.0271**	0.0114	-0.0340**	-0.0340**
	(0.0123)	(0.0332)	(0.0132)	(0.0132)
Side-By-Side	-0.0426***	-0.0293	-0.0451***	-0.0451***
	(0.0120)	(0.0299)	(0.0131)	(0.0131)
Woman				-0.00793
				(0.0226)
Own-Group×Woman				0.0454
				(0.0357)
Side-By-Side×Woman				0.0158
				(0.0326)
Constant	0.155***	0.148***	0.156***	0.156***
	(0.00810)	(0.0208)	(0.00879)	(0.00879)
N	4,589	720	3,869	4,589
R^2	0.003	0.002	0.003	0.003

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the linear probability model of a session on the rankings page having any click on it. The baseline is the aggregate rankings page. The second column restricts the sample to users who are women, the third column restricts the sample to users who are men, and the first and last columns use both men and women. We test if the coefficients of Own-Group × Woman and Side-By-Side × Woman are jointly different than 0 ($F(2, 4583) = 0.81$; P-Value = 0.4438). Therefore, there is no evidence of treatment heterogeneity across men versus women in terms of affecting the likelihood of a session containing a click.

Table 4: Probability of Clicking on Push Notification by Own Rating

	User Starts Session		
	Men	Women	All Users
By-Gender Push	-0.0387***	-0.0234***	-0.0360***
	(0.00376)	(0.00733)	(0.00336)
Tail Review	-0.00430	-0.0193**	-0.00772*
	(0.00484)	(0.00852)	(0.00424)
By-Gender Push× Tail Review	0.0110**	0.0253**	0.0141***
	(0.00561)	(0.0101)	(0.00494)
Constant	0.100***	0.0767***	0.0961***
	(0.00327)	(0.00632)	(0.00292)
N	45,664	10,431	56,095
R^2	0.004	0.001	0.003

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Notes: This table describes the linear probability model of a user starting a session as a function of treatment status, as well as how they rated their current employers. The variable *Tail Review* is an indicator if the user rated their current employer either lowly or highly. The cutoff to be a tail review is a score below 53.4 or above 83.7. These thresholds were chosen prior to the start of the experiment, because there were technological constraints in how many categories that defined groups of users which we could monitor.

Table 5: Probability of Clicking on the Push Notification by Gender Diversity at Current Company

	User Starts Session		
	Men	Women	All Users
By-Gender Push	-0.0887***	0.0116	-0.0750***
	(0.0268)	(0.0473)	(0.0235)
Female Comp. Perc.	-0.408***	-0.133	-0.390***
	(0.134)	(0.226)	(0.117)
By-Gender Push × Female Comp. Perc.	0.319**	-0.0938	0.267*
	(0.157)	(0.268)	(0.136)
Constant	0.170***	0.0873**	0.161***
	(0.0230)	(0.0397)	(0.0202)
N	18,186	3,654	21,840
R^2	0.005	0.001	0.004

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes is the linear probability model of a user starting a session by clicking on the push notification. The baseline is the control push notification. Note that only users from the top 20 companies by size are included, because those are the only users we were able to track with their company name in the experiment. The Female Comp. Perc. is the ratio of female reviewers to the sum of male and female reviewers on Blind. The first column restricts the sample to users who are men, the second column restricts the sample to users who are women, and the last column use both men and women.

Table 6: Prolific Participant Demographics

Gender	
Man	599
Woman	313
Non-binary	12
Transgender Man	5
Transgender Woman	1
Other	1
Race	
White	671
Asian	110
Black	73
Mixed	54
Other	20
Unknown	3
Employment Sector	
Information Technology	333
Science, Technology, Engineering & Mathematics	188
Finance	168
Business Management & Administration	124
Marketing & Sales	118

Notes: This table describes the reported demographics of the participants on Prolific.

Table 7: Differences in EMS across Push Notifications

	By-Gender Push		
	Men	Women	Difference
Useful	-0.641***	-0.520***	0.121
	(0.129)	(0.179)	(0.220)
Informative	-0.251*	-0.161	0.0904
	(0.131)	(0.181)	(0.224)
Relevant	-0.561***	-0.250	0.311
	(0.136)	(0.182)	(0.230)
Easy to Understand	-0.667***	-0.724***	-0.0563
	(0.133)	(0.188)	(0.229)
General	-0.543***	-0.303*	0.239
	(0.110)	(0.160)	(0.192)
Interesting	-0.711***	-0.117	0.594**
	(0.138)	(0.191)	(0.236)
Aligns with my Values	-0.250**	-0.111	0.139
	(0.109)	(0.138)	(0.181)
Promotes Inclusion	0.742***	0.674***	-0.0678
	(0.120)	(0.163)	(0.204)
N	599	313	912

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes how the EMS variables vary across push notifications. We ran 8 SUR regressions with the outcome of each one being a EMS variable. The focal EMS variable was regressed onto a *By-Gender Push* dummy, which was 1 if the participant was rating the By-Gender Push, and a constant. Each row in this table corresponds to the coefficient on the dummy variable for the respective outcome EMS variable. The EMS variables are on a discrete scale from 1 to 7 with 7 being the highest. We do not report the constant terms. The difference reported represents the interaction term between $Woman$ and the EMS variables in a regression combining both men and women.

Table 8: Differences in EMS across Rankings Pages

	Side-By-Side Rankings		
	Men	Women	Difference
Useful	-0.574***	-0.364**	0.210
	(0.128)	(0.165)	(0.214)
Practical	-0.629***	-0.335**	0.294
	(0.119)	(0.161)	(0.202)
Relevant	-0.461***	-0.161	0.300
	(0.126)	(0.159)	(0.209)
Easy to Read	-0.350***	-0.399***	-0.0486
	(0.0995)	(0.142)	(0.172)
General	-0.315***	-0.0863	0.228
	(0.113)	(0.159)	(0.194)
Interesting	-0.241*	0.0706	0.311
	(0.132)	(0.172)	(0.222)
Aligns with my Values	-0.159	0.222	0.381**
	(0.110)	(0.153)	(0.189)
Promotes Inclusion	0.640***	0.485***	-0.155
	(0.116)	(0.165)	(0.200)
N	599	313	912

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes how the EMS variables vary across rankings pages. We ran 8 SUR regressions with the outcome of each one being a EMS variable. The focal EMS variable was regressed onto a *Side-by-Side* dummy, which was 1 if the participant was rating the Side-by-Side page, and a constant. Each row in this table corresponds to the coefficient on the dummy variable for the respective outcome EMS variable. The EMS variables are on a discrete scale from 1 to 7 with 7 being the highest. We do not report the constant terms. The difference reported represents the interaction term between $Woman$ and the EMS variables in a regression combining both men and women.

D Stylized Model

We present a stylized model to illustrate a condition and rationale in which job seekers might prefer to view an own-gender, *disaggregated* rating for a company as opposed to an *aggregated* rating before applying to that company. The goal of the job seekers is to collect sufficiently detailed information about what their own potential experience of working at the company would be, while simultaneously balancing costs, before deciding whether or not to apply.

Assume, without loss of generality, that the job seeker is a woman and deciding whether to apply to company X. Importantly, she may initially believe that the typical experiences for women and men are systematically different at X. Let her prior of the gender-specific experiences of working at X be a multivariate normal with mean $\bar{\mu}_W$ and $\bar{\mu}_M$ for women and men, respectively. The variance-covariance matrix of the prior is represented by $\bar{\Sigma}$. $\bar{\Sigma}_{11}$ is the prior variance in the female experience, $\bar{\Sigma}_{22}$ is the prior variance in the male experience, and $\bar{\Sigma}_{12}$ is the prior covariance. She chooses to incur a fixed cost c to observe one of either the disaggregated or aggregated rating for the focal company X before deciding to apply to company X.

We now turn to describing the likelihood functions of the aggregated and disaggregated ratings. We assume that each individual review left on the platform is a draw from a normal distribution with known variance that is centered on the gender-specific experience of the focal reviewer. A review left by a woman would be a draw from $\mathrm{N}(\mu_W, \sigma^2_{r_W})$, and a review left by a man would be a draw from $\mathrm{N}(\mu_M, \sigma^2_{r_M})$.

We can separately average the reviews for X left by women and men, respectively, to form:

$$s_W \sim N(\mu_W, \sigma^2_W := \frac{\sigma^2_{r_W}}{N_W})$$
$$s_M \sim N(\mu_M, \sigma^2_M := \frac{\sigma^2_{r_M}}{N_M}),$$

where N_W is the number of female reviewers and N_M is the number of male reviewers. Note that s_W and s_M are the *disaggregated ratings* for women and men. Since the seeker is a woman, she would observe s_W under the disaggregated rating option.

On the other hand, the status quo on review platforms is to use a flat average across all reviews (what we call the *aggregated* rating). This means that all the reviews are equally-weighted into one average value, irrespective of the gender of the reviewer. This flat average can be represented as the weighted average of the two disaggregated ratings. Let s_A be the aggregated rating; $s_A = \gamma s_W + (1-\gamma)s_M$, where γ represents the proportion of female reviewers for X. s_A is distributed as:

$$s_A \sim N(\gamma\mu_W + (1-\gamma)\mu_M, \sigma^2_A := \gamma^2\sigma^2_W + (1-\gamma)^2\sigma^2_M + 2\gamma(1-\gamma)\sigma_{WM})$$

where σ_{WM} is the covariance between s_W and s_M. The aggregated rating is a biased measure of experience for both genders if women and men have different experiences of working at X. One important observation is that the smaller the proportion of female reviews, the

more biased the aggregated rating is in representing the female experience, and it moves closer towards depicting the male experience. This intuition is the underlying rationale for why numerical minorities might receive more beneficial information from observing the disaggregated ratings as opposed to the aggregated ratings.

Given the likelihoods for s_W, s_M, and s_A, we can now find the respective posteriors, which would represent the beliefs over the female working experience at X after different possible ratings observations. After observing either the aggregated rating or the disaggregated ratings, the posterior is normally distributed.

$$\dot{\Sigma}|s_A = \big(\bar{\Sigma}^{-1} + \frac{1}{\sigma_A^2}\begin{bmatrix}\gamma^2 & \gamma(1-\gamma)\\ \gamma(1-\gamma) & (1-\gamma)^2\end{bmatrix}\big)^{-1}$$
$$\dot{\mu}|s_A = \big(\begin{bmatrix}\bar{\mu}_W & \bar{\mu}_M\end{bmatrix}\bar{\Sigma}^{-1} + \frac{s_A}{\sigma_A^2}\begin{bmatrix}\gamma & (1-\gamma)\end{bmatrix}\big)\dot{\Sigma}|s_A$$

describe the variance and mean of the posterior after observing the aggregated ratings. While

$$\dot{\Sigma}_{11}|s_W = \frac{1}{\frac{1}{\bar{\Sigma}_{11}} + \frac{1}{\sigma_W^2}}$$
$$\dot{\mu}_W|s_W = (\frac{\bar{\mu}_W}{\bar{\Sigma}_{11}} + \frac{s_W}{\sigma_W^2})\dot{\Sigma}_{11}|s_W$$

describe the posterior for the own-gender ratings. These posterior distributions describe how satisfied the experience of working at X would appear after viewing a specific ratings type.

To structure how the job seeker evaluates the different alternatives, we provide an example where the job seeker has a Constant Absolute Risk Aversion (CARA) utility function with parameter α. The benefit of applying to X after observing each rating can be ordered by the certainty equivalent:

$$\dot{\mu}_S - \frac{\alpha}{2}\dot{\Sigma}_S$$

where S is one of either $\{A, W, M\}$.[12]

She evaluates which rating type to choose before observing any specific rating information using only her anticipated posterior variance. This is because her expectation of $\dot{\mu}_S - \frac{\alpha}{2}\dot{\Sigma}_S$ is taken over her prior. Call $\hat{\mu}_S = \int \dot{\mu}_S dF(s_S|\bar{\mu}, \bar{\Sigma})$, and let $\hat{\Sigma}_S = \int \dot{\Sigma}_S dF(s_S|\bar{\mu}, \bar{\Sigma})$ for a given ratings type S: $\hat{\mu}_S = \bar{\mu}$. Therefore, if we focus on the female components of the simplified posterior variances, we arrive at:

[12]We are motivated by examples where seekers do not know what companies are good or bad for them. Therefore, if the seeker would neither search for information nor apply under their prior, they would pick the outside option with utility set to 0. The seeker will only choose to observe a rating if she expects to apply to X after viewing that rating.

$$\hat{\Sigma}_W = \frac{1}{\frac{1}{\bar{\Sigma}_{11}} + \frac{1}{\sigma_W^2}} \tag{1}$$

$$\hat{\Sigma}_A = \frac{-(\gamma-1)^2\bar{\Sigma}_{12}^2 + \bar{\Sigma}_{11}((\gamma-1)^2\bar{\Sigma}_{22} + \sigma_M^2 + 2\gamma(\sigma_{WM} - \sigma_M^2) + \gamma^2(\sigma_M^2 + \sigma_W^2 - 2\sigma_{WM}))}{\bar{\Sigma}_{22} + \sigma_M^2 + \gamma^2(\bar{\Sigma}_{11} - 2\bar{\Sigma}_{12} + \bar{\Sigma}_{22} + \sigma_M^2 + \sigma_W^2 - 2\sigma_{WM}) + \gamma(2\bar{\Sigma}_{12} - 2(\bar{\Sigma}_{22} + \sigma_M^2 - \sigma_{WM}))} \tag{2}$$

We want to explain the benefit of information disaggregation for numerical minorities with one simple scenario. We consider the case where $\bar{\Sigma}_{12} = 0$ and $\sigma_{WM} = 0$. In that sense, adding male reviews through aggregation only acts as noise for female seekers. Equation 2 becomes:

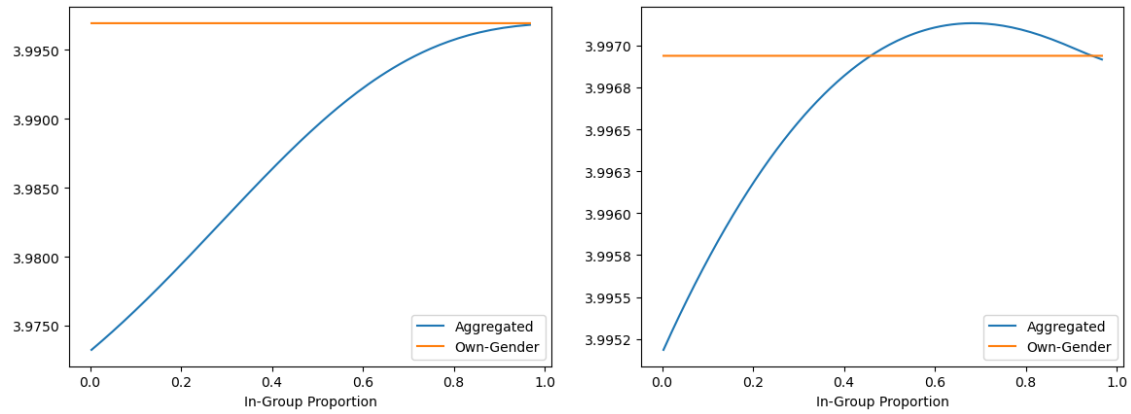
$$\hat{\Sigma}_A = \frac{1}{\frac{1}{\bar{\Sigma}_{11}} + \frac{1}{\frac{(\gamma-1)^2}{\gamma^2}(\bar{\Sigma}_{22}+\sigma_M^2)+\sigma_W^2}}$$

while $\hat{\Sigma}_W$ remains the same as before. We can see that for any given γ between 0 and 1, $\hat{\Sigma}_A > \hat{\Sigma}_W$, suggesting that she would be more likely to choose the disaggregated rating when she desires a tighter posterior. This tighter expected posterior translates to a greater expected utility of disaggregated ratings.[13]

To analytically see that those job seekers belonging to the gender in the numerical minority might benefit more from disaggregation than those in the numerical majority, we make further assumptions that $\sigma_{r_M} = \sigma_{r_W}$ and that N_W is fixed. The first assumption means that men's and women's reviews have equal variance in how they rate the company. Secondly, changes in γ are achieved by adding or removing male reviewers (i.e. changing N_M), as opposed to changing the total number of female reviewers. With these assumptions, the difference between $\hat{\Sigma}_A$ and $\hat{\Sigma}_W$ is largest when γ is small. This is because when γ is small, the aggregated rating is mostly incorporating reviews from the other gender, which are essentially noise for the seeker. Under this set-up, the benefits of disaggregation are most strongly felt by those seekers in the numerical minority. As γ increases, the difference in the expected variance of the two ratings decreases.

We expand on this point through an numerical exercise with relaxed parameter value assumptions. In other words, we would expect the correlation described by $\bar{\Sigma}$ and σ_{WM} to be somewhere in the interior of the interval of 0 to 1. We can describe when this occurs with the following inequality which describes when the expected posterior variance of the disaggregated rating is smaller than that of the aggregated rating.

[13]We note that it is possibility that she would choose to observe neither the disaggregated nor aggregated rating if $\bar{\mu}_W - c - \frac{\alpha}{2}\hat{\Sigma}_{11} < 0$.



(a) $\bar{\Sigma}_{12} = 0.4$ **(b)** $\bar{\Sigma}_{12} = 0.7$

Notes: Expected certainty equivalent for the posteriors. The certainty equivalent for the CARA utility function is $\mu - \frac{\alpha}{2}\sigma^2$. The priors are described by: $\bar{\mu}_W = 4$, $\bar{\mu}_M = 4$, $\bar{\Sigma}_{11} = \bar{\Sigma}_{22} = 0.75$. $N_W = 30$ and N_M ranges from 1 to 10000. $\sigma^2_{r_W} = \sigma^2_{r_M} = 2$.

Appendix D Figure 1: Example Expected Certainty Equivalents

$$\begin{aligned}\bar{\Sigma}_{12} \leq & \frac{\gamma\bar{\Sigma}_{11}\sigma_W^2}{(\gamma-1)(\bar{\Sigma}_{11}+\sigma_W^2)} \\ & + \Big[\frac{\bar{\Sigma}_{11}^2(\bar{\Sigma}_{11}((1-2\gamma+\gamma^2)\bar{\Sigma}_{22}+\gamma(2\sigma_{WM}-2\sigma_M^2)+\sigma_M^2+\gamma^2(\sigma_M^2-2\sigma_{WM}))}{(\gamma-1)^2(\bar{\Sigma}_{11}+\sigma_W^2)^2} \\ & + \frac{\bar{\Sigma}_{11}^2(\sigma_W^2((1-2\gamma+\gamma^2)\bar{\Sigma}_{22}+\gamma(2\sigma_{WM}-2\sigma_M^2)+\sigma_M^2+\gamma^2(\sigma_W^2+\sigma_M^2-2\sigma_{WM})))}{(\gamma-1)^2(\bar{\Sigma}_{11}+\sigma_W^2)^2}\Big]^{0.5}\end{aligned} \tag{3}$$

There is an upper bound on the prior covariance expressed by Equation (3) that shows when the job seeker would prefer the disaggregated rating over the aggregated rating. Heuristically, the job seeker balances the trade-off where additional reviews left by the opposite gender provide more information. However, the degree to which that information is useful depends on the job seeker's beliefs of how systematically related the experiences are between men and women at X. If she believes that the experiences are unrelated, adding more information from the opposite gender adds noise to the rating, making it less desirable to view for the seeker. In Figure 1, we present numerical examples of the respective variances for values that we believe to be empirically relevant to our setting of interest. It is clear that disaggregated, own-gender ratings tend to be better than aggregated ratings. However, we note that this upper bound is not likely to hold generally with large correlations described by $\bar{\Sigma}$ close to 1.[14]

[14]Once again, we can also see that in each of the graphs that as *gamma* increases, the difference between the disaggregated rating variance and aggregated rating variance tends to shrink towards 0.

Breaking Down Information Inequality: Evidence from a Field Experiment in the Technology Industry

Online Appendix

Online Appendix A: Gender Inequality

The economics and organizational behavior literature suggests multiple potential causes for the lack of women in the technology sector (Bertrand et al., 2010). Alongside "glass ceilings", "labyrinths", and "cliffs" no other metaphor has captured greater attention in gender studies across social science disciplines as the "pipeline." Fewer women enroll in majors in college that lead to work in high technology fields (Brenøe and Zölitz, 2020), a finding that occurs despite men and women having similar performance in math and science classes in secondary institutions. Even as more women enter undergraduate and advanced degree programs that yield credentials to enter well-paid, male-dominated STEM fields, notions of pipeline problems can be heard reverberating across post-secondary institutions, workplaces, and corporate boardrooms. The number of women earning degrees to enter high-paying STEM fields has increased, but data indicate that women with degrees in quantitative STEM courses are less likely to enter these fields than men, and if they do enter, they are less likely to remain (Hunt, 2016).

While early literature focused on explanations, such as the abilities of women compared to men in STEM fields, sociologists and other social scientists noted that documented evidence of females' and males' mathematics and science abilities evidenced little difference, and therefore research about women's lack of representation in the STEM workforce turned to structural explanations. Studies find women face challenges in locating good places to work. Studies argue that the culture of these industries also alienates women from working in those environments. In the tech sector, in particular, companies can have "chilly" climates, and toxic workplaces, that isolate women in STEM domains. There is also bias and discrimination on the part of employers that might lead employers to overlook women as viable hires or to hire women but pay them less than men in ways that reduce their commitment to staying in the STEM workforce (Rudman and Glick, 2001; Bertrand and Duflo, 2017). For this reason, establishing and providing information on where there are more friendly climates is viewed as one avenue to disrupt these processes. The notion is that if individuals can gain knowledge from others in their in-group, they might be more engaged with where to work and pursue workplace opportunities where they are better matched.

References

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Brenøe, A. A. and U. Zölitz (2020). Exposure to more female peers widens the gender gap in stem participation. *Journal of Labor Economics 38*(4), 1009–1054.

Hunt, J. (2016). Why do women leave science and engineering? *ILR Review 69*(1), 199–226.

Rudman, L. A. and P. Glick (2001). Prescriptive gender stereotypes and backlash toward agentic women. *Journal of social issues 57*(4), 743–762.

Online Appendix B: Prolific Survey Instrument

Survey

DESCRIPTION: You are invited to participate in a research study on the effects of information on job seeking behaviors. There are no right or wrong answers.

TIME INVOLVEMENT: Your participation will take approximately 5-8 minutes.

RISKS AND BENEFITS: There are no risks associated from the study. We cannot and do not guarantee or promise that you will receive any benefits from this study.

PARTICIPANT'S RIGHTS: If you have read this form and have decided to participate in this project, please understand your participation is voluntary and you have the right to withdraw your consent or discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled.

If you agree to participate in this research, please click forward below.

Optional: Print a copy of this page for your records.

Introductory Questions

In this survey you will see some information about companies. This type of information could be found in an email or be sent to you on a mobile device. Click next to proceed with the survey.

1. Based on what you just read, where could this information about companies come from?

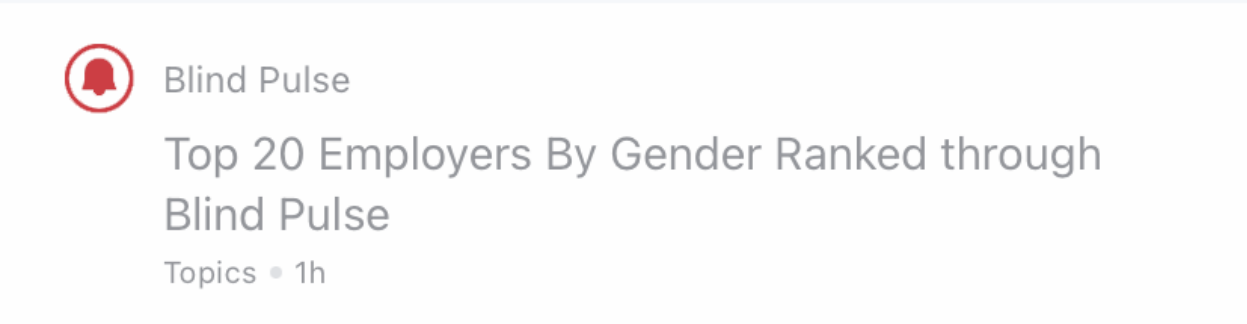
   ☐ Email

   ☐ Newspaper

   ☐ Billboard

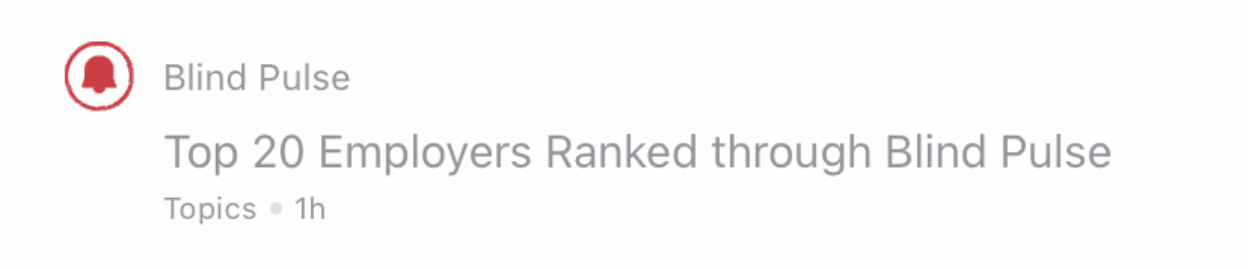
Treatment Condition 1: Push Notification by Gender

Please review the push notification image below.



Treatment Condition 2: General Push Notification

Please review the push notification image below.



Consumer Motivation Scale Questions (Both Treatment Conditions)

2. We will now ask you to rate the following items below based on the above image.

The message in this notification...

is useful	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is informative	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is relevant to me	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is easy to understand	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
contains general information	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
engages my interests	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
aligns with my values	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
promotes inclusion	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree

3. Please answer the following question:

How likely are you to click on this notification?

Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

4. Please explain why you chose the answers above.

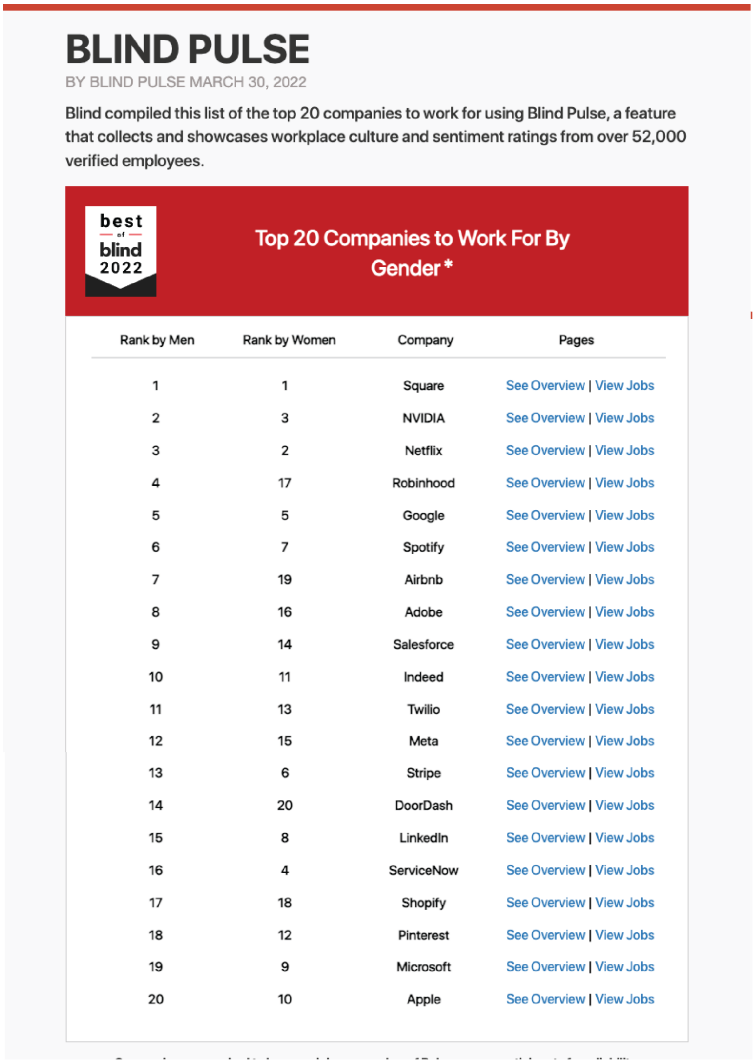
Transition to next section (Both Treatment Conditions)

You click on the push notification. On the next screen, you will see what happens when you do so.

Hit forward to go to the next screen.

Treatment Condition 1a: M/W Rankings Page

You are taken to a screen that shows the following panel of company rankings. Please review the image below.



BLIND PULSE

BY BLIND PULSE MARCH 30, 2022

Blind compiled this list of the top 20 companies to work for using Blind Pulse, a feature that collects and showcases workplace culture and sentiment ratings from over 52,000 verified employees.

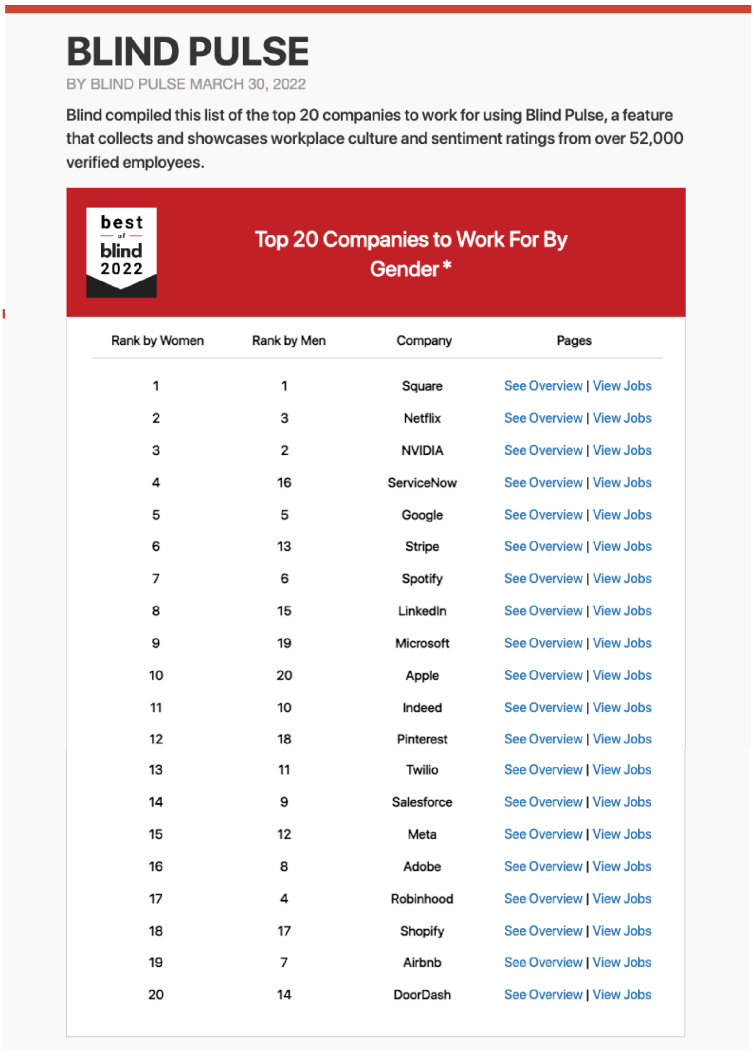
best of blind 2022

Top 20 Companies to Work For By Gender *

Rank by Men	Rank by Women	Company	Pages
1	1	Square	See Overview | View Jobs
2	3	NVIDIA	See Overview | View Jobs
3	2	Netflix	See Overview | View Jobs
4	17	Robinhood	See Overview | View Jobs
5	5	Google	See Overview | View Jobs
6	7	Spotify	See Overview | View Jobs
7	19	Airbnb	See Overview | View Jobs
8	16	Adobe	See Overview | View Jobs
9	14	Salesforce	See Overview | View Jobs
10	11	Indeed	See Overview | View Jobs
11	13	Twilio	See Overview | View Jobs
12	15	Meta	See Overview | View Jobs
13	6	Stripe	See Overview | View Jobs
14	20	DoorDash	See Overview | View Jobs
15	8	LinkedIn	See Overview | View Jobs
16	4	ServiceNow	See Overview | View Jobs
17	18	Shopify	See Overview | View Jobs
18	12	Pinterest	See Overview | View Jobs
19	9	Microsoft	See Overview | View Jobs
20	10	Apple	See Overview | View Jobs

Treatment Condition 1b: W/M Rankings Page

You are taken to a screen that shows the following panel of company rankings. Please review the image below.



BLIND PULSE

BY BLIND PULSE MARCH 30, 2022

Blind compiled this list of the top 20 companies to work for using Blind Pulse, a feature that collects and showcases workplace culture and sentiment ratings from over 52,000 verified employees.

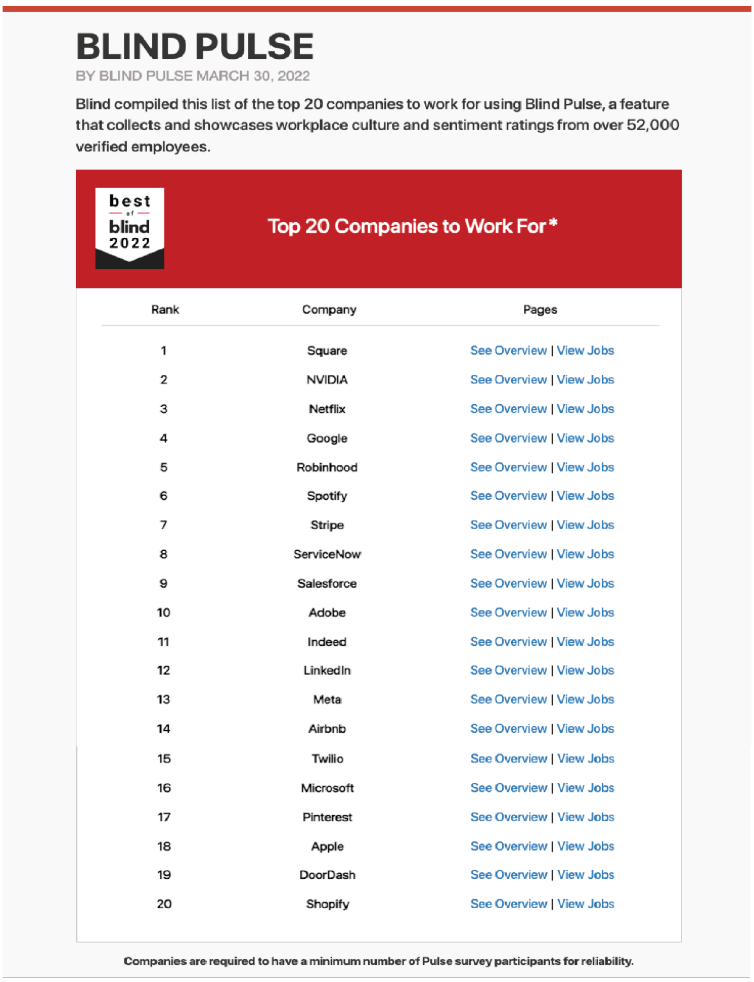
best of blind 2022

Top 20 Companies to Work For By Gender *

Rank by Women	Rank by Men	Company	Pages
1	1	Square	See Overview | View Jobs
2	3	Netflix	See Overview | View Jobs
3	2	NVIDIA	See Overview | View Jobs
4	16	ServiceNow	See Overview | View Jobs
5	5	Google	See Overview | View Jobs
6	13	Stripe	See Overview | View Jobs
7	6	Spotify	See Overview | View Jobs
8	15	LinkedIn	See Overview | View Jobs
9	19	Microsoft	See Overview | View Jobs
10	20	Apple	See Overview | View Jobs
11	10	Indeed	See Overview | View Jobs
12	18	Pinterest	See Overview | View Jobs
13	11	Twilio	See Overview | View Jobs
14	9	Salesforce	See Overview | View Jobs
15	12	Meta	See Overview | View Jobs
16	8	Adobe	See Overview | View Jobs
17	4	Robinhood	See Overview | View Jobs
18	17	Shopify	See Overview | View Jobs
19	7	Airbnb	See Overview | View Jobs
20	14	DoorDash	See Overview | View Jobs

Treatment Condition 2: Aggregate Rankings Panel

You are taken to a screen that shows the following panel of company rankings. Please review the image below.



BLIND PULSE

BY BLIND PULSE MARCH 30, 2022

Blind compiled this list of the top 20 companies to work for using Blind Pulse, a feature that collects and showcases workplace culture and sentiment ratings from over 52,000 verified employees.

best of blind 2022

Top 20 Companies to Work For*

Rank	Company	Pages
1	Square	See Overview | View Jobs
2	NVIDIA	See Overview | View Jobs
3	Netflix	See Overview | View Jobs
4	Google	See Overview | View Jobs
5	Robinhood	See Overview | View Jobs
6	Spotify	See Overview | View Jobs
7	Stripe	See Overview | View Jobs
8	ServiceNow	See Overview | View Jobs
9	Salesforce	See Overview | View Jobs
10	Adobe	See Overview | View Jobs
11	Indeed	See Overview | View Jobs
12	LinkedIn	See Overview | View Jobs
13	Meta	See Overview | View Jobs
14	Airbnb	See Overview | View Jobs
15	Twilio	See Overview | View Jobs
16	Microsoft	See Overview | View Jobs
17	Pinterest	See Overview | View Jobs
18	Apple	See Overview | View Jobs
19	DoorDash	See Overview | View Jobs
20	Shopify	See Overview | View Jobs

Companies are required to have a minimum number of Pulse survey participants for reliability.

Consumer Motivation Scale Questions (Both Treatment Conditions)

5. How much do you agree or disagree with the following statements about the ranking below?

This information as presented...

is useful	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is practical	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is relevant to me	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is easy to read	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is general	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
is interesting	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
aligns with my values	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
promotes inclusion	Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree

6. Please answer the following question:

How likely are you to click on this notification?

Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

7. Please explain why you chose the answers above.

Demographic Questions

8. Do you currently work in the tech industry?

☐ No, I do not work in the tech industry

☐ Yes, I work in the tech industry

9. What is your job title?

10. Do you work for a company below? (We will not ask which company you work for.)

- Adobe
- Airbnb
- Apple
- DoorDash
- Google
- Indeed
- LinkedIn
- Meta
- Microsoft
- Netflix
- NVIDIA
- Pinterest
- Robinhood
- Salesforce
- ServiceNow
- Shopify

- Spotify
- Square
- Stripe
- Twilio

☐ Yes

☐ No

11. What is your employer size?

☐ 10-24

☐ 25-99

☐ 100-499

☐ 500-999

☐ 1000+

12. Do women make up more than 20% of your company's workforce?

☐ Yes

☐ No

☐ I'm not sure

13. To which gender do you most identify?

☐ Man

☐ Woman

☐ Transgender Man

☐ Transgender Woman

☐ Non-binary / Third gender

☐ Not listed (please specify)

14. What is your ethnicity?

☐ Hispanic

☐ Not Hispanic

☐ Decline to self-identify

☐ Not listed (please specify)

15. What is your race? Select all that apply.

☐ White or Caucasian

☐ Black or African American

☐ Hispanic or Latinx

☐ Asian

☐ Native American or Indigenous

☐ Pacific Islander or Native Hawaiian

☐ Decline to self-identify

☐ Not listed (please specify)

16. What is the highest level of education you have completed?

☐ Less than high school

☐ High school graduate/GED

☐ Some college

☐ 2-year college degree

☐ 4-year college degree

☐ Master's degree

☐ Doctoral degree

☐ Professional degree (JD, MD)

☐ Other (please specify)

17. In what country do you currently work?

Final Bot Check

18. This questions is to prevent bot submissions. Please fill in the blank.
This survey was about _____ seeking behaviors.

Online Appendix C: Additional Tables and Figures

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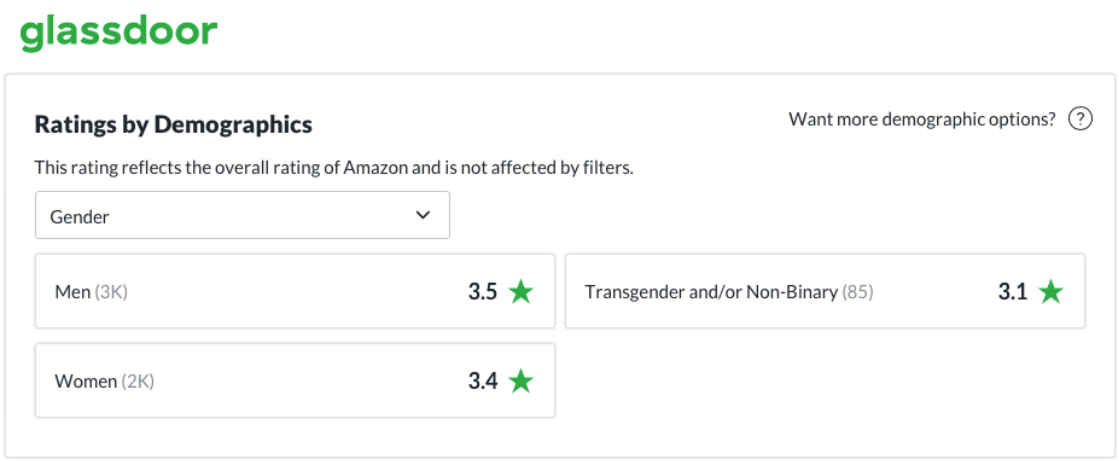
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1 Gender-Specific Company Ratings



O. A. Figure 1: Gender-Specific Ratings from Glassdoor

Forbes

RANK	NAME	INDUSTRIES	EMPLOYEES	YEAR FOUNDED
1.	Tampa General Hospital	Healthcare & Social	8,000	1927
2.	REI	Clothing, Shoes, Sports Equipment	15,000	1938
3.	Crocs	Clothing, Shoes, Sports Equipment	5,770	2002
4.	EBSCO Information Services	Business Services & Supplies		1984
5.	Carvana	Retail and Wholesale	21,000	2012
6.	L'Oreal USA	Packaged Goods	12,000	1909
7.	AstraZeneca	Drugs & Biotechnology	83,100	1953
8.	Loyola University Chicago	Education	5,138	1870
9.	SAP	IT, Internet, Software & Services	107,415	1972
10.	MD Anderson Cancer Center	Healthcare & Social	22,000	1941
11.	Lululemon Athletica	Clothing, Shoes, Sports Equipment	16,530	1998
12.	BlueCross BlueShield of Tennessee	Insurance	6,000	1945
13.	Steelcase	Engineering, Manufacturing	11,100	1912
14.	Help At Home	Healthcare & Social	30,000	1975
15.	Cisco Systems	IT, Internet, Software & Services	38,000	1984

O. A. Figure 2: Gender-Specific Rankings from Forbes

2 Keyword Searches on Blind

O. A. Table 1: Keyword Search Behavior

Num. Searches	52,550,949
Num. Unique Searched Companies	4,947
% Searches about a Company	48.5%
% Searches about Top Ranked Company	22.8%
% Searches from Top Ranked Company Employee	40.3%

We describe English keyword search behavior Blind's search bar by *all* users on the platform from late June 2018 to early March 2021. The Top Ranked Companies are those 20 that are listed in our experiment conditions. Exact substring matching (independent of case) was used to determine if a keyword contained a company name.

3 User Geographic Location

O. A. Table 2: Proportion of Sessions by Country

Country	
United States	0.7616
India	0.1088
Canada	0.0451
United Kingdom	0.0238
Brazil	0.0071
Other	0.0533

We show the distribution of sessions in the experiment by country based on Google Analytics data. The table lists out the top five countries.

4 Differences between Ratings left by Men and Women

O. A. Table 3: Ratings Differences by Gender

	Log. Rating
Woman	-0.0617***
	(0.00417)
Company FE	Y
N	51,311
R^2	0.161

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We regress the individual ratings left for the reviewer's current company on the gender identity of the reviewer, while controlling for company fixed effects. Some observations were dropped due to the inclusion of company fixed effects. We find that women systematically rate their current companies lower than men do.

5 Main Results with Logit Regressions

O. A. Table 4: Probability of Clicking on the Push Notification

	User Starts Session			
	All Users	Women	Men	All Users
By-Gender Push	-0.418***	-0.194**	-0.457***	-0.457***
	(0.0330)	(0.0857)	(0.0358)	(0.0358)
Woman				-0.412***
				(0.0734)
By-Gender Push × Woman				0.263***
				(0.0928)
N	56,095	10,431	45,664	56,095

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

This table describes the propensity to click on the push notification and start a session. Each column represents a different subset of users. It is analogous to the analysis in the main paper, except using a logistic regression.

O. A. Table 5: Probability of a Session Having a Click

	All Users	Women	Men	All Users
Own-Group	-0.224**	0.0881	-0.286**	-0.286**
	(0.103)	(0.254)	(0.114)	(0.114)
Side-By-Side	-0.371***	-0.255	-0.394***	-0.394***
	(0.108)	(0.263)	(0.119)	(0.119)
Woman				-0.0616
				(0.178)
Own-Group × Woman				0.374
				(0.278)
Side-By-Side × Woman				0.139
				(0.289)
N	4,589	720	3,869	4,589

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

This table describes the propensity to for a session on a rankings page to have a click. Each column represents a different subset of users. It is analogous to the analysis in the main paper, except using a logistic regression.

6 Relationship Between Current Company Gender Ratings Divergence and Engagement

O. A. Table 6: Probability of Clicking on the Push Notification with Company Gender Ratings Divergence

	User Starts Session		
	All Users	Women	Men
By-Gender Push	-0.0221**	-0.0111	-0.0240**
	(0.00905)	(0.0187)	(0.0102)
Company Gender Diff	0.00219	-0.000282	0.00273
	(0.00186)	(0.00355)	(0.00211)
By-Gender Push × Company Gender Diff	-0.00222	0.00172	-0.00307
	(0.00217)	(0.00438)	(0.00245)
Constant	0.0875***	0.0657***	0.0916***
	(0.00770)	(0.0153)	(0.00871)
N	21,840	3,654	18,186
R^2	0.003	0.000	0.004

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

This table describes the likelihood of a user clicking on a push notification, based on its content (i.e. treatment condition) and where that user currently works. It is possible that by observing men and women having different experiences at their current company, users may be more likely to believe that men and women have systematic differences in experiences across other companies. The variable *Company Gender Diff* is the absolute difference between the average male and female ratings at the relevant company. We note that there is no relationship between the divergence in ratings at the current company a user works at and the propensity to engage with any push notification, including the By-Gender push notification. Also note that we can only observe users who work at the top 20 companies by reviewer size (large companies).

O. A. Table 7: Probability of a Session Having a Click with Company Gender Ratings Divergence

	Session with Click		
	All Users	Women	Men
Own-Group	-0.0513	-0.0411	-0.0504
	(0.0482)	(0.114)	(0.0524)
Side-By-Side	-0.0568	0.0953	-0.0805
	(0.0465)	(0.125)	(0.0495)
Company Gender Diff	-0.00486	0.0112	-0.00689
	(0.00721)	(0.0191)	(0.00775)
Own-Group × Company Gender Diff	0.00610	0.0191	0.00342
	(0.0113)	(0.0291)	(0.0122)
Side-By-Side× Company Gender Diff	0.00272	-0.0195	0.00603
	(0.0109)	(0.0303)	(0.0116)
Constant	0.178***	0.0836	0.190***
	(0.0316)	(0.0763)	(0.0342)
N	1,805	242	1,563
R^2	0.003	0.011	0.006

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

This table describes the likelihood of a user clicking on a rankings, based on its content (i.e. treatment condition) and where that user currently works. The variable *Company Gender Diff* is the absolute difference between the average male and female ratings at the relevant company. We note that there is no relationship between the divergence in ratings at the current company a user works at and the propensity to engage with any rankings page. Also note that we can only observe users who work at the top 20 companies by reviewer size (large companies).

7 Relationship Between Company Size and Engagement

O. A. Table 8: Probability of Clicking on the Push Notification by Current Company Size

	User Starts Session			
	M Large Comp.	M Small Comp.	W Large Comp.	W Small Comp
By-Gender Push	-0.0356***	-0.0325***	-0.00455	-0.0148**
	(0.00448)	(0.00357)	(0.00856)	(0.00633)
Constant	0.102***	0.0959***	0.0646***	0.0688***
	(0.00387)	(0.00308)	(0.00708)	(0.00537)
N	18,186	27,478	3,654	6,777
R^2	0.004	0.003	0.000	0.001

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the linear probability model of a user starting a session by clicking on the push notification broken down by company size. The baseline is the control push notification. A large company is measured as the Top 20 companies on Blind by reviewer base. A small company is a company that does not fall into this list. W stands for Women and M stands for Men.

8 ANOVA Contrasts of Engagement across Gender

O. A. Table 9: Difference in Engagement across Gender by Experimental Condition

Panel A: Woman vs. Man in Push Notification Engagement

Push Condition	
Control	-0.030
	(0.004)
By-Gender	-0.008
	(0.003)

Standard errors in parentheses

Panel B: Woman vs. Man in Rankings Page Engagement

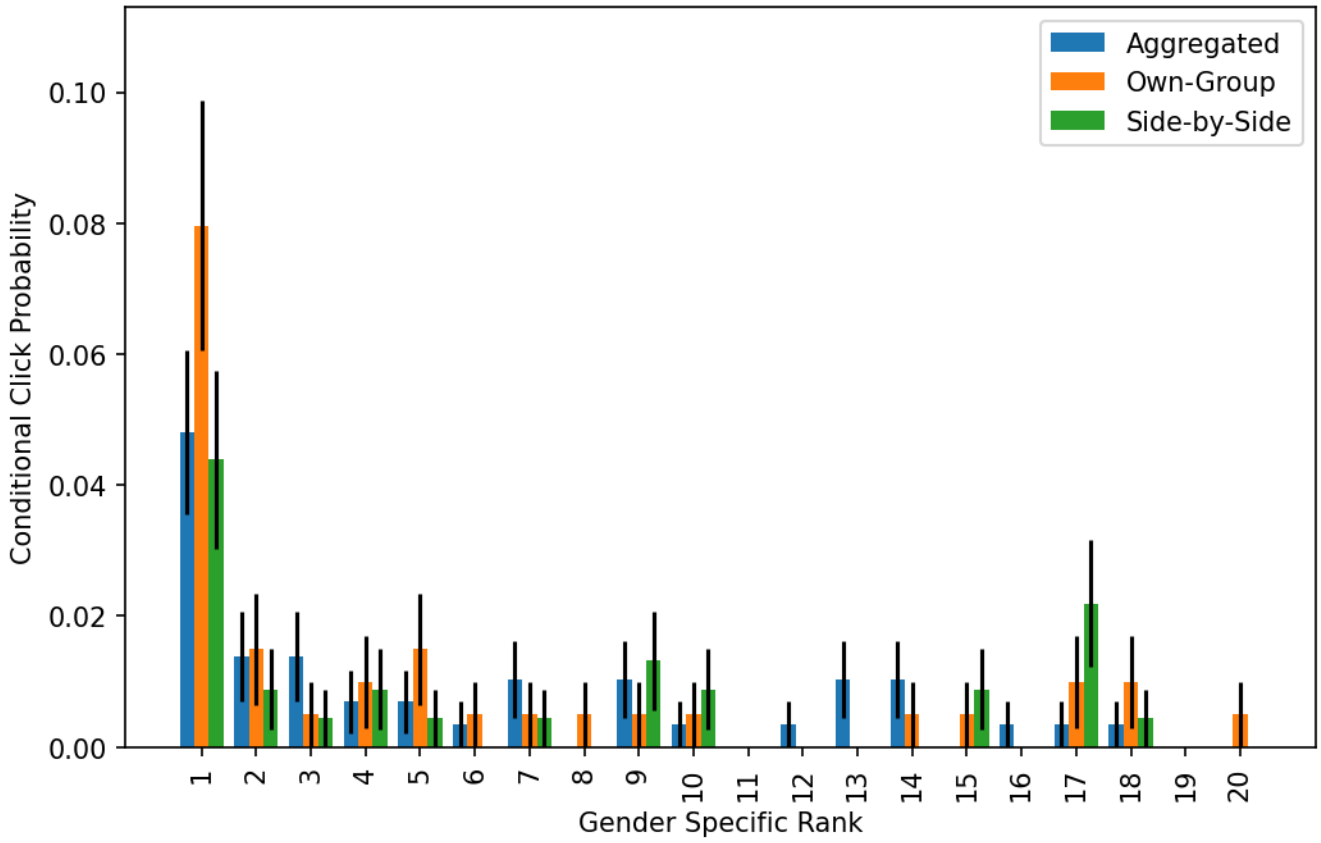
Rankings Page Condition	
Control	-0.007
	(0.022)
Own-Gender	0.037
	(0.027)
Side-By-Side	0.007
	(0.023)

Standard errors in parentheses

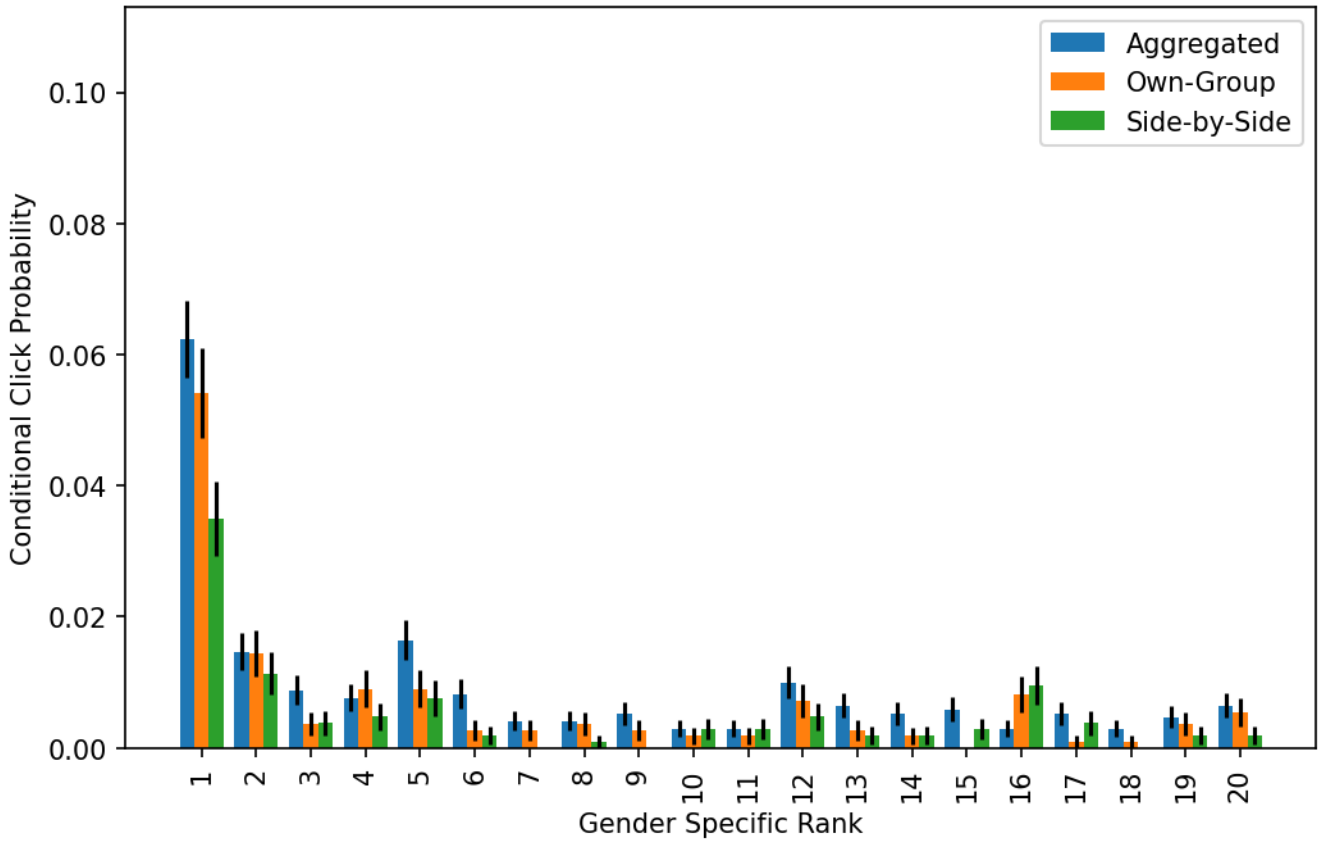
9 Rankings Page Click Likelihoods by Button

In the main results, we presented the probabilities of clicking on *either* the "overview" or "view jobs" buttons as a function of rank conditional on starting a session. In this section, we separately report the probabilities for the two kinds of buttons.

Overview Button Click Probability by Rank

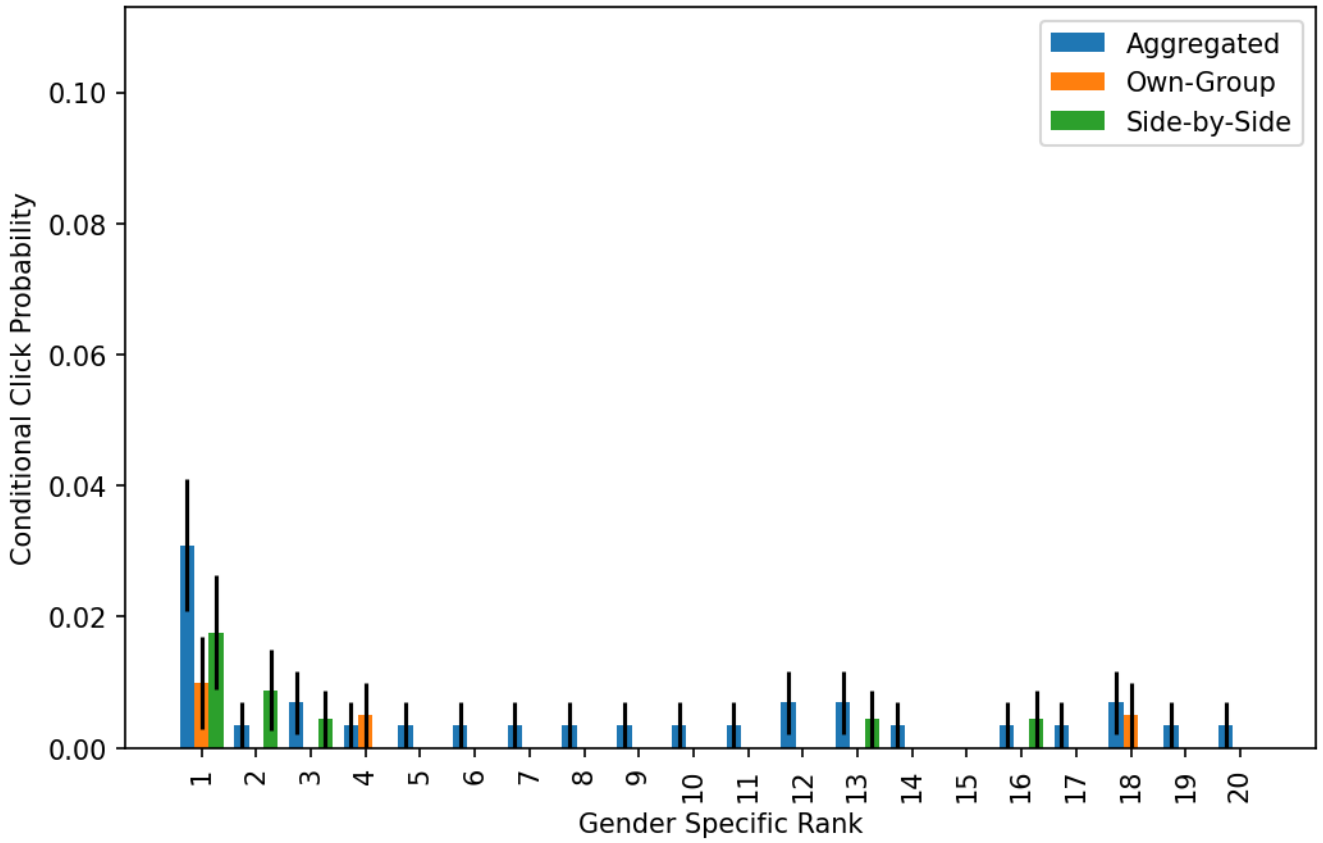


O. A. Figure 3: Rankings Page Overview Button Click Likelihood for Women

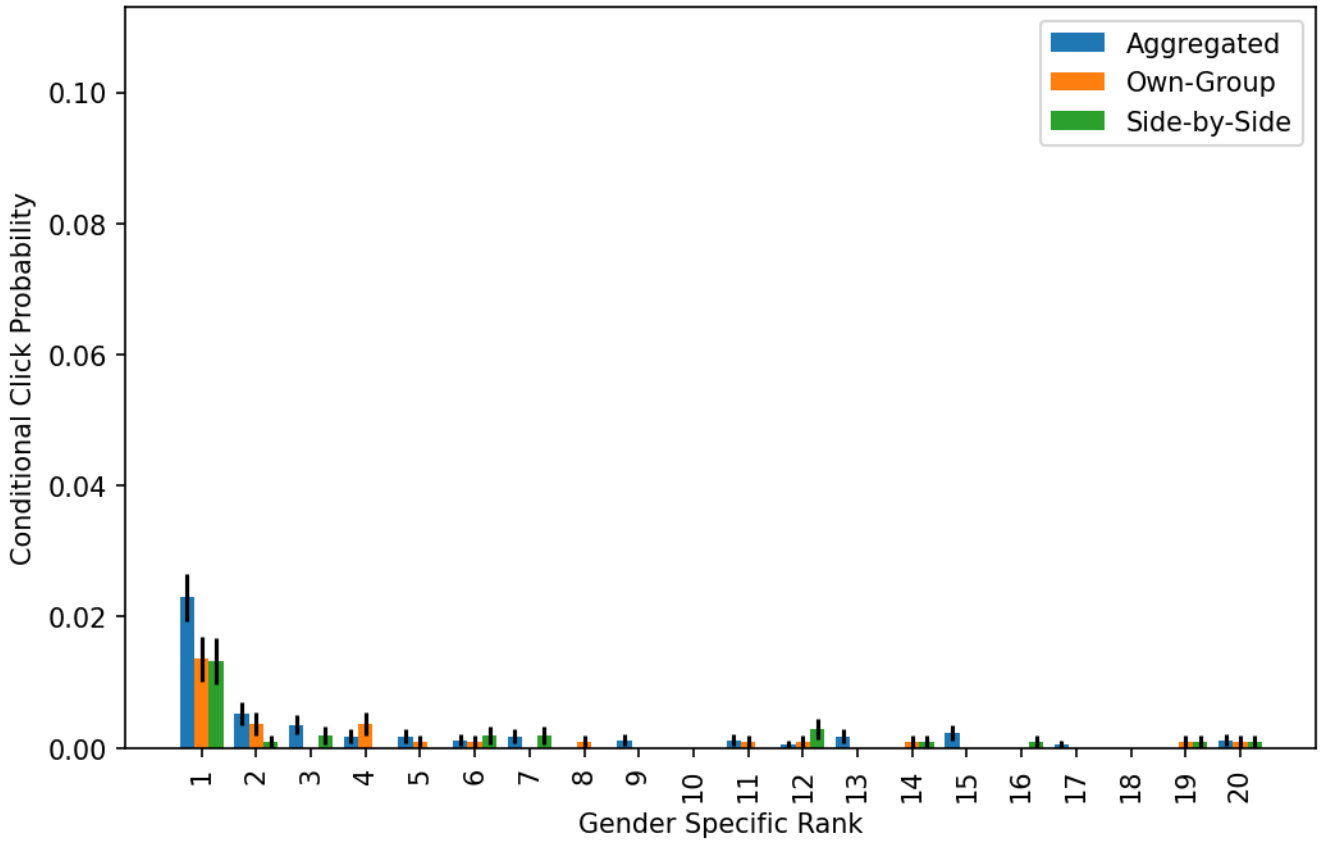


O. A. Figure 4: Rankings Page Overview Button Click Likelihood for Men

View Jobs Click Probability by Rank



O. A. Figure 5: Rankings Page View Jobs Button Click Likelihood for Women



O. A. Figure 6: Rankings Page View Jobs Button Click Likelihood for Men

10 Description of Free Response Answers from Survey



(a) Word Cloud from Pre-Testing Surveys



(b) Word Cloud from Pre-Testing Surveys for Push Notifcations



(c) Word Cloud from Pre-Testing Surveys for Ranking Pages

O. A. Figure 7: Word Clouds

11 EMS Ratings by Gender

O. A. Table 12: Push Notification Click Likelihood by Gender

	By-Gender Push Click Likelihood
Useful	0.249***
	(0.0583)
Informative	0.102**
	(0.0439)
Relevant	0.288***
	(0.0571)
Easy to Understand	-0.0229
	(0.0349)
General	-0.00341
	(0.0390)
Interesting	0.452***
	(0.0580)
Aligns with my Values	-0.00146
	(0.0513)
Promotes Inclusion	-0.0609*
	(0.0332)
Woman	-0.0699
	(0.375)
Woman×Useful	-0.147
	(0.0999)
Woman×Informative	-0.0399
	(0.0806)
Woman×Relevant	-0.116
	(0.0942)
Woman×Easy to Understand	0.0277
	(0.0631)
Woman×General	-0.0108
	(0.0707)
Woman×Interesting	0.259***
	(0.0940)
Woman×Aligns with my Values	0.0623
	(0.106)
Woman×Promotes Inclusion	0.00240
	(0.0700)
N	912
R^2	0.655

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the relationship between EMS variables and push notification click likelihood by gender for self-identified men and women. The sample comes from the Prolific survey. The outcome variable is self-reported click likelihood. Ethnicity and employment sector fixed effects are included.

O. A. Table 13: Rankings Page Click Likelihood by Gender

	Side-By-Side Rankings Page Click Likelihood
Useful	-0.0384
	(0.0775)
Practical	0.0689
	(0.0672)
Relevant	0.344***
	(0.0674)
Easy to Read	0.0205
	(0.0583)
General	-0.0150
	(0.0512)
Interesting	0.406***
	(0.0700)
Aligns with my Values	0.327***
	(0.0735)
Promotes Inclusion	-0.0646
	(0.0488)
Woman	-0.950*
	(0.575)
Woman×Useful	0.358**
	(0.145)
Woman×Practical	-0.0575
	(0.119)
Woman×Relevant	0.00527
	(0.126)
Woman×Easy to Read	0.0798
	(0.0875)
Woman×General	-0.0423
	(0.0837)
Woman×Interesting	-0.163
	(0.125)
Woman×Aligns with my Values	-0.0340
	(0.124)
Woman×Promotes Inclusion	0.0567
	(0.107)
N	912
R^2	0.513

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the relationship between EMS variables and rankings page click likelihood by gender for self-identified men and women. The sample comes from the Prolific survey. The outcome variable is self-reported click likelihood. Ethnicity and employment sector fixed effects are included.

12 EMS Ratings by Employment Sector

O. A. Table 14: Push Notification Click Likelihood by Employment Sector

	By-Gender Push Click Likelihood
Useful	0.156**
	(0.0705)
Informative	0.121**
	(0.0538)
Relevant	0.147**
	(0.0628)
Easy to Understand	0.0308
	(0.0460)
General	-0.00398
	(0.0557)
Interesting	0.620***
	(0.0625)
Aligns with my Values	0.0170
	(0.0689)
Promotes Inclusion	-0.0104
	(0.0457)
Tech Worker	0.464
	(0.345)
Tech Worker × Useful	0.0561
	(0.0947)
Tech Worker × Informative	-0.0783
	(0.0731)
Tech Worker × Relevant	0.211**
	(0.0880)
Tech Worker × Easy to Understand	-0.0681
	(0.0597)
Tech Worker × General	-0.00776
	(0.0687)
Tech Worker × Interesting	-0.130
	(0.0899)
Tech Worker × Aligns with my Values	-0.0112
	(0.0907)
Tech Worker× Promotes Inclusion	-0.0731
	(0.0594)
N	912
R^2	0.654

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the relationship between EMS variables and push notification click likelihood by employment sector for self-identified men and women. The sample comes from the Prolific survey. The outcome variable is self-reported click likelihood. Ethnicity and gender fixed effects are included.

O. A. Table 15: Rankings Page Click Likelihood by Employment Sector

	Side-By-Side Rankings Page Click Likelihood
Useful	0.153
	(0.104)
Practical	0.104
	(0.0853)
Relevant	0.356***
	(0.0844)
Easy to Read	0.109*
	(0.0629)
General	-0.0208
	(0.0608)
Interesting	0.273***
	(0.0887)
Aligns with my Values	0.260***
	(0.0849)
Promotes Inclusion	0.0292
	(0.0631)
Tech Worker	1.223**
	(0.544)
Tech Worker×Useful	-0.131
	(0.135)
Tech Worker×Practical	-0.0624
	(0.113)
Tech Worker×Relevant	-0.0310
	(0.115)
Tech Worker×Easy to Read	-0.0892
	(0.0870)
Tech Worker×General	-0.0140
	(0.0801)
Tech Worker×Interesting	0.130
	(0.119)
Tech Worker×Aligns with my Values	0.0743
	(0.116)
Tech Worker×Promotes Inclusion	-0.113
	(0.0867)
N	912
R^2	0.509

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table describes the relationship between EMS variables and ranking page click likelihood by employment sector for self-identified men and women. The sample comes from the Prolific survey. The outcome variable is self-reported click likelihood. Ethnicity and gender fixed effects are included.