Rejection Communication and Women's Job-Search Persistence

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Abstract

We examine whether the reasons that employers provide for rejecting job candidates affect their likelihood of applying for future positions, and differential responses by gender. Through a randomized controlled field experiment among job candidates rejected for positions by a staffing company, we find that relative to men, women are less likely to apply for future positions after being rejected. Furthermore, we find that this gap is nearly eliminated by informing applicants that they were rejected for "fit" rather than "quality" or by providing no reason for the job rejection. We present survey evidence that workers view the quality message as demeaning and the no-reason message as ambiguous. Our findings lend support for hypotheses that women have relative tastes for non-competitive and transparent application procedures, and that gender disparity in job search persistence may be reduced by framing rejection in terms of fit.

1 Introduction

Despite decades of efforts, women's earnings and labor force participation lags behind men (Blau & Kahn 2017). Because much of this gap is explained by supply-side sorting effects (e.g., women are concentrated in lower paying fields) rather than direct discrimination, significant policy efforts have focused on fixing talent pipelines that yield fewer women candidates for open positions (Brands & Fernandez-Mateo 2017; Campero 2021; Fernandez & Campero 2017; Fernandez-Mateo & Fernandez 2016; Petersen & Saporta 2004). These efforts are increasingly recognizing that a paucity of qualified female applicants may be due to demand-side factors, such as the poor reputation of a job, organization, or industry for treating women (Fernandez-Mateo & Kaplan 2018).

Researchers, policymakers, and companies have naturally scrutinized whether women's negative perceptions of job opportunities be alleviated in the recruitment process: how a position is advertised, who applies, and how candidates are screened and selected. A relatively recent but promising literature suggests that organizations can attract female applicants to male-dominated jobs by making relatively modest changes to how they communicate with applicants, such as avoiding language in job postings that describe the work environment as competitive (e.g. Abraham & Stein 2020; Coffman et al. 2019; Flory et al. 2015; Garratt et al. 2013; Gaucher et al. 2011; Samek 2019; Wille & Derous 2018) and being transparent about the size or qualifications of the applicant pool (Bertrand 2011; Croson & Gneezy 2009; Gee 2019). These studies have largely cited women's relative aversion to employers that would highlight competition or obfuscate the search process, which may differentially affect the willingness of men and women to submit a job application. Risk aversion, underconfidence, or fear of rejection may prompt women to prematurely accept inferior offers (Cortés et al. 2021). Indeed, because most job applications result in rejection, this literature has also examined the effect of job rejection on women's likelihood of persisting in their job search.[1] These studies have found that women who are rejected for positions are less likely than men to apply for future opportunities in similar contexts (Brands & Fernandez-Mateo 2017; Yang et al. 2019). If women are less likely to re-apply after rejection, then the number of women available for subsequent job openings will gradually and continually decrease, and this will ultimately lead to substantial differences in the gender composition of candidate pools (Brands & Fernandez-Mateo 2017).

In the spirit of this prior research, we examine whether the way rejection is communicated can affect women's and men's perseverance in job search and their perceptions of the rejecting employer. To do so, we conduct a field experiment among applicants rejected for positions by a temporary staffing company. Over a 26 week study period, we randomly assign 7,837 rejected job applicants to one of three types of rejected messages: one emphasizing better quality among selected candidates, one emphasizing better fit, and one providing no explanation for why another candidate was selected. Our treatments are motivated by the common parlance of rejection messages, which are typically split among those that offer no explanation, a quality-related explanation, or a fit-related explanation (Aamodt & Peggans 1988). Our treatments are also motivated by popular claims and theoretical reasons to believe that men and women may respond differently to rejection (Brands & Fernandez-Mateo 2017; Kolev et al. 2019; Mohr 2014; Yang et al. 2019).

We find that women who were rejected with messages citing fit were significantly more likely to reapply for jobs than those who were rejected with messages citing quality or those rejected without a reason. These effects were specific to women: we found no significant or substantive differences in men's likelihood of applying to future jobs. Overall, women were far less likely to apply for positions than men after being rejected, but women who received the fit message reapplied for positions at similar rates as men.

[1] Glassdoor.com estimates that the average corporate job receives 250 applications, the vast majority of which conclude with rejection (Glassdoor 2015). Large companies, like Starbucks, send rejections to millions of job candidates every year (Ferguson et al. 2013).

To examine how jobseekers may be interpreting our messages, we conducted a separate survey on Amazon Mechanical Turk (AMT). Survey participants reacted negatively to the no-reason messages, typically citing their view that the message was vague, ambiguous, and left the candidate wanting to know more. However, survey respondents stated that they found the quality message was demeaning, rude, or made them feel inferior. Respondents reacted more positively to the fit message and were far less likely to view it as either demeaning or ambiguous.

Our experimental results are strongly consistent with the proposition that women are less likely than men to apply for similar roles after being rejected. However, the experiment also suggests that rejection messages that provide fit-related reasons may greatly reduce the gender gap in reapplications. Our survey suggests two mechanisms: that fit-related messages limit the detrimental effects of rejection on self-confidence and are less ambiguous than messages that provide no reason.

From a practical implications perspective, our results suggest that organizations can retain diverse applicant pools by rejecting candidates for fit (when possible and appropriate); this messaging will enhance the likelihood that women will apply for future positions and have minimal effects on men. Further fit related messaging is appealing because it appears to enhance applicant perceptions of the employer and its process, while also avoiding tailoring responses or engaging in algorithmic social engineering (Cowgill & Stevenson 2020). More broadly, our results extend evidence that theoretically-motivated, low-cost tweaks to the way employers conduct job searches may make job search more equitable.

2 Employer communication in screening

2.1 Background

Understanding how jobseekers interpret, adapt, and persevere in response to rejection is critical to understanding job search and the labor market. Economists, for instance, argue that rejections can cause unemployed workers to drop out of the labor force (the "disgruntled worker effect") or change what jobs they target, presumably as they update their beliefs regarding their aptitudes, labor market conditions, or their fit with their desired jobs (Bloemen 2005). Precisely how jobseekers respond to rejection, particularly whether they ascribe rejections to personal failures, has been associated with culture, age, sex, and coping resources (Brands & Fernandez-Mateo 2017; Jackson & Warr 1984; McKee-Ryan et al. 2005; Sharone 2013). If fewer women than men re-apply after rejection, then the number of women available for subsequent job openings will slowly and continually decline, which will eventually lead to large differences in the composition of candidate pools (Brands & Fernandez-Mateo 2017). Public policies and civic organizations that provide aid and encouragement to historically disadvantaged groups operate under the premise that closing a job search gap can reduce broader socioeconomic inequality. Similarly, employers may wish to maintain goodwill with rejected jobseekers, who could be future workers, clients, customers, or referrers (Aamodt & Peggans 1988; Benson et al. 2020; O'Reilly III & Pfeffer 1995).

In hiring, a relatively young but vibrant research stream finds that minor changes in how employers communicate with job applicants can achieve these desired goals. Field experiments have shown that women's propensity to apply for jobs is significantly lower when a job is described as competitive, that is, where the pay depends heavily on relative performance (Flory et al. 2015; Samek 2019). In a similar vein, a lab study conducted by Gaucher et al. (2011) finds that job advertisements were less appealing to women when its wording elicited stereotypically masculine traits by describing the work environment as "competitive" rather than "cooperative," the group as "dominant" versus a "community," and the development of "leadership" rather than "interpersonal" skills. These studies are largely believed to be driven by women's relative aversion to competitive environments (see Niederle & Vesterlund 2011, for a review). In a large-scale experiment on LinkedIn, Gee (2019) finds that disclosing the number of applicants for a position increases the likelihood that women (but not men) complete an application. Gee attributes this finding to the proposition that women are more ambiguity-averse than men, a finding corroborated in prior studies (Bertrand 2011; Croson & Gneezy 2009; Eckel & Grossman 2008; Garratt et al. 2013; Leibbrandt & List 2015; Schubert et al. 1999).

Despite evidence that minor changes in communication can elicit more applications and greater persistence among targeted groups, most of the evidence has come from job postings rather than rejection. Perhaps the closest related studies are Brands & Fernandez-Mateo (2017) and Yang et al. (2019) which find that in male dominated environments such as top management positions, women are less likely to pursue future opportunities in the context that has rejected them in the past. Following this work, Fernandez et al. (2019) use formal modelling to identify the conditions under which these gender differences contribute to women's underrepresentation over time. While these studies find evidence of gender gaps in reapplication after rejection and its long-term effects, prior studies have not examined the differential effect of the content of rejection messages on men and women. Understanding how different rejection messages affect women's and men's job search persistence can help us paint a more complete picture of the leaky pipeline and may help stem some of the leakage.

2.2 The theoretical content of established rejection messages

Relatively few studies have explored how employers reject job candidates. Nevertheless, available evidence suggest there are certain regularities in the content of job rejection messages. In an analysis of rejection letters, Aamodt & Peggans (1988) found that rejections commonly begin with a personalized salutation (74%) and a friendly statement, such as "thank you for applying" (91%). From there, employers typically turn to the reason for rejection. Those reasons are most commonly related to fit, quality, or provide no reason at all. Fit-related messages typically asserted there were "no suitable openings for you" (16%), "not enough fit between you and the position" (14%), or "other applicants had better fit" (3%). Quality-related messaging typically referred to the quality of the applicant pool (38%) or the applicant (19%). In a similar study, 30% of rejection notifications reported that other candidates were more qualified, and another 30% of rejection messages did not provide a reason for rejection (Jablin & Krone 1984).

From a theoretical standpoint, messages that emphasize the relative quality of the applicant, the relative fit of the applicant or that do not convey a reason for rejection, communicate different kinds of information which may in turn have implications for applicant behavior.

Quality-related messages underscore the relationship between the skills of the applicant being rejected and the skills of other applicants applying for the position. As a result, such messages prime the reader to think of the rejection in competitive terms, perhaps as a loss or personal failing along some common dimension of quality. Candidates may also view quality-related rejection messages as a signal that potential employers themselves would have a competitive or otherwise unattractive environment. In light of evidence that women are less likely to respond to advertisements that reference competition in the applicant pool or work environment, we anticipate that women will respond more unfavorably to rejection messages that cite the relative quality of the applicant to the selected candidates.

Fit-related messages differ from quality-related messages in that they draw less attention to the professional deficiencies of the applicant being rejected in relation to other applicants. Instead, they place the locus of the rejection on the relationship between the applicant being rejected and the attributes of the specific position. Fit-related rejection messages attribute the decision to perceived incompatibility rather deficiency. The image that comes to mind is one of (in)compatibility, rather than the failure of the applicant or the superiority of other applicants. As such, fit-related messages communicate less negative information to the candidate about their general prospects with other organizations, or with the rejecting organization should other opportunities emerge. Consistent with this line of reasoning, Jablin & Krone (1984) find that indirect messages like those that emphasize fit are socially preferred. Similarly, Brown (1993) finds that indirect messages are more face-saving and polite. Because they are more relational in nature and less emphasizing of the competitive environment, we anticipate that women may respond favorably to fit related messages.

Finally, we propose that messages that contain no explanation are theoretically distinct from messages that provide either quality or fit related reasons, in that they are inherently more ambiguous, less transparent, and leave room for greater speculation. Although we are not aware of any evidence specifically testing whether ambiguous rejections deter women from future applications, others have found evidence that women are more ambiguity-averse in other settings, including initial job applications (Exley & Kessler 2019; Gee 2019; Murciano-Goroff 2018; Niederle & Vesterlund 2007). In addition to the possibility that women are more averse to ambiguity in itself, ambiguity may be interpreted as a failure of employers to provide assurance that their application was evaluated fairly. Building on Gilligan's (1993) moral development theory, researchers have long proposed that men and women may differ in the relative importance they ascribe to different types of justice, with men being more attentive to distributive forms of justice (i.e., fairness with respect to outcomes) and women being more attentive to procedural justice (i.e., fairness with respect to processes) (Kulik et al. 1996). Recently, scholars have begun attending to more granular distinctions among different notions of justice, moving beyond the classical distributive/procedural dichotomy. The emerging picture suggests that relative to men, women appear to place greater weight on informational justice, which "focuses on the explanations provided to people that convey information about why procedures were used in a certain way or why outcomes were distributed in a certain fashion" (Colquitt et al. 2001: 427). We propose that messages that do not communicate a reason for rejection are less likely to perceived as informationally just. These considerations lead us to believe that women will generally respond unfavorably to job rejection messages that lack a reason for rejection.

3 Data and methods

3.1 Study design

Our study uses data from a randomized controlled trial conducted at a temporary staffing company in India, henceforth called Agile. Agile hires and places temporary workers at over 3,500 client firms for engagements that typically last six months to a year, and some temporary workers are ultimately hired by clients. The experiment was conducted over 26 weekly cohorts of rejected job candidates, beginning the week of February 17, 2020. The protocol for each cohort was as follows:

1. *Identifying the cohort population.* To fulfill client requests for temporary workers, Agile posts available positions on their web portal which allows candidates to search open positions. To apply for a position, the candidate creates an account and can optionally update their profile to report demographics. Agile screens candidates based on their profiles and then subsequently with interviews. The set of candidates rejected either during screening or interview in week t become a member of the week t's cohort the first week they are rejected.

2. *Randomization.* Rejected candidates are randomly assigned to receive one of three treatment messages: the *Fit* message, the *Quality* message, or the *No Reason* message (detailed below). Rejection messages are sent by SMS[2] through Agile's e-recruiting platform between 3:00 pm and 4:00 pm on the Thursday of week $t + 1$.[3] If the worker had already been rejected for

[2]For perspective, 41% of US employers plan to use text messages to schedule job interviews (Turczynski 2021).

[3]For the first two cohorts, only one job rejection message was sent to rejected candidates, and this message was sent 1 week after the hiring decision was made. The third cohort was for rejection decisions made between March 2

another position in a prior week, they receive the same treatment message that they received in their initial assignment.

3. *Follow up*. From week $t + 1$ and beyond, Agile tracks three primary outcomes: (1) whether the candidate applied for another position, (2) whether the candidate clicked on the rejection message's job listing URL, and (3) whether the candidate immediately continued their search by clicking on the message's search URL. We track the rejected candidates' reapplications until 8 weeks after the 26th and final cohort is rejected. We track job listing and search URL clicks one week after a rejection message messages was sent.

During the 26-week study period, 8,653 job applicants (6,387 male, 1,450 female, and 816 gender unknown) were rejected at least once. The rejections occurred for listings in 201 cities and for 294 job titles in a wide variety of fields, particularly work relating to sales, customer support, and office support.

3.2 Independent variables

The key independent variables are the three treatment messages $\{$*Fit*, *Quality*, *No reason*$\}$ and whether the applicant is female. The treatment messages are detailed below.

1. *Fit message*: Thank you for applying to the <role name> position <listing-url> at <Agile division name>. Candidates selected were closer matches for the position. We are sorry we cannot make you an offer at this time. Please apply to other positions by clicking <search-url>.

and March 8, 2020, when public attention was focused on COVID-19. Thus, at this point Agile started sending an additional (identical) follow up rejection message. These messages were sent 1 and 3 weeks following the week in which the rejection decision was made. Due to technical issues the second rejection message for cohort 3 and the first message for cohort 5 (both sent on the same day) were sent a day later than the regular schedule. In addition, for cohort 17, the dispatch of rejection messages and the collection of the click data occurred 1 week later than the regular cycle.

2. *Quality message*: Thank you for applying to the <role name> position <listing-url> at <Agile division name>. Candidates selected were better qualified for the position. We are sorry we cannot make you an offer at this time. Please apply to other positions by clicking <search-url>.

3. *No reason message*: Thank you for applying to the <role name> position <listing-url> at <Agile division name>. We are sorry we cannot make you an offer at this time. Please apply to other positions by clicking <search-url>.

The job listing and search URLs in the messages above are unique to the candidate and job posting, allowing us to track clicks. The listing URL redirects candidates to the original job posting to which the candidate applied. The job posting includes details such as the desired qualifications and the job description. Clicking on the listing URL would suggest that the candidate wants to review these details about the job for which they were rejected. The search URL redirects candidates to a job search landing page. We abbreviate role names so that the message fits in one SMS (e.g., "sales representative" becomes "sales rep").

We code gender from self-reported profile information by the candidate when available (32% of the cases). Where self-reported gender (male or female) is not available, we identify gender based on candidates' first names, using the `genderize.io` API (58% of the cases). We omit observations for which gender is neither available from the profiles nor genderize (9.4% of cases). When both profile and genderize codes are available, they match 95.4% of the time. This cross-validation exercise suggests that attenuation bias is minimal, and as long as the error is uncorrelated with job applications or URL clicks, any measurement error in coding female should yield conservative estimates.

Finally, we use a set of demographic, job preference, and skills-related variables from applicants' profiles to test for message randomization and as controls. *Post-COVID lockdown* denotes that the rejection message was sent after COVID-related lockdowns went into effect, the cohort that begins in week 8. *Married* takes a value of one if marital status is currently married, or zero if single, separated, or divorced. *Top 6 metro* denotes the applicant's address is in one of the largest metros in the rejected candidate data.[4] *Lists job preference*, *lists city preference*, and *lists skills* take a value of one if the candidate elected to fill this field in their optional profiles. Work experience takes four possible values, indicating either months of work experience is not reported in the candidate's profile, work experience is explicitly zero months, 1-35 months, or at least 36 months.

3.3 Dependent variables

We track three outcomes, each of which takes a value of one or zero, for applicant i in cohort t:

1. $APPLIED_{it}$: Indicates that the rejected candidate applied for a job within two months of receiving the rejection message.

2. $LISTING_{it}$: Indicates that the rejected candidate clicked on the job listing URL in the rejection message.

3. $SEARCH_{it}$: Indicates that the rejected candidate clicked on the job search URL in the rejection message.

3.4 Estimating treatment effects

Because we have a randomized experiment with three treatments, our main tests depend on the means and standard errors of the three outcomes (applied, listing, and search) for each treatment (fit, quality, and no reason). We partition population of rejected workers i into the subsamples of

[4] They are: Bengaluru (1040 applicants), Hyderabad (895), Delhi (873), Mumbai (836), Chennai (737), and Kolkata (497). These metros constitute the addresses of 31% of all rejected candidates. They also constitute six of the seven most populous Indian metropolitan areas; the seventh, Ahmedabad (172) is less represented in the data.

women and men (indexed by f for female and m for male), and run analyses separately for each subsample. We report the predictive margins from a linear probability model regression framework of the form:

$$\begin{aligned}
APPLIED_{ft} &= \beta_1 FIT_f + \beta_2 QUALITY_f + \beta_3 NOREASON_f + \mathbf{X}\beta + \epsilon_{ft} && (1)\\
LISTING_{ft} &= \beta_1 FIT_f + \beta_2 QUALITY_f + \beta_3 NOREASON_f + \mathbf{X}\beta + \epsilon_{ft} && (2)\\
SEARCH_{ft} &= \beta_1 FIT_f + \beta_2 QUALITY_f + \beta_3 NOREASON_f + \mathbf{X}\beta + \epsilon_{ft} && (3)\\
APPLIED_{mt} &= \beta_1 FIT_m + \beta_2 QUALITY_m + \beta_3 NOREASON_m + \mathbf{X}\beta + \epsilon_{mt} && (4)\\
LISTING_{mt} &= \beta_1 FIT_m + \beta_2 QUALITY_m + \beta_3 NOREASON_m + \mathbf{X}\beta + \epsilon_{mt} && (5)\\
SEARCH_{mt} &= \beta_1 FIT_{mt} + \beta_2 QUALITY_m + \beta_3 NOREASON_m + \mathbf{X}\beta + \epsilon_{mt} && (6)
\end{aligned}$$

Each dependent variable takes a value of one if the candidate applies for a job, clicks the listing URL, or clicks the search URL, respectively. FIT_i, $LISTING_i$, and $SEARCH_i$ indicate the treatment message sent to individual i. Note that, without controls in $\mathbf{X}\beta$, the coefficients β_1 through β_3 and their standard errors are equivalent to the means and standard errors of the dependent variable for their respective regressors. With controls, the coefficients are simply the conditional means and standard errors. In the robustness check, $\mathbf{X}\beta$ includes controls for: top-6 metro, lists job preference, lists city preference, lists skills, post-COVID lockdown, and work experience. Our hypothesis tests do not control for age or married status because these are optional fields that are rarely filled (21.7% and 19.9%); we include these in the randomization test alone.

Note that our analysis treats one observation as one unique individual; when a candidate is initially rejected in the study period, they receive a treatment message, we track their outcomes from the initial rejection, and they do not reenter the sample. This yields conservative results, simplifies the analysis, and removes the need to cluster standard errors or add individual fixed effects, as is typically found in studies using repeated observations within individuals. We use a linear probability model with predictive margins for ease of interpretation, testing, and convention.[5] We use robust standard errors to address that residuals are generally not identically or normally distributed in a linear probability model (Angrist & Pischke 2008; Davidson et al. 1993).

Our main tests evaluate whether each treatment arm is significantly different from the other two treatments combined. For instance, in equation (1), the significance test for β_1 is given by:

$$APPLIED_{ft} = \beta_0 + \beta_1 FIT_f + \mathbf{X}\beta + \epsilon_{ft} \tag{7}$$

where FIT_{ft} = 1 if rejected female f in cohort t was randomly assigned the fit message, and zero otherwise. Our supplementary analysis (reported in Table 5 and elaborated upon in Section 4, "Main results") examines statistically significant differences in applications, listing clicks, and search clicks for all pairwise combinations of $\{$female, male$\}$ $\times$ $\{$fit, quality, no reason$\}$.

3.5 Descriptive statistics

Table 1 reports summary statistics for the variables listed in the rows by the treatment listed in the columns.

We begin by examining the raw means across all treatment messages. Females constitute a relatively small share of temporary workers at Agile, and about 18.5% of rejected candidates in this period. Roughly half of the candidates come from the first seven weeks of the experiment, prior to COVID-related lockdowns in India on March 24th, 2020. The average age is 26 years, and most workers are early-career; 86% of workers are between the ages of 20 and 35. Workers apply for positions from dispersed locations; 32% come from the six largest metros represented in the data. 87% of workers elect to list a job preference. A majority of workers do indicate prior work experience, and 27% report some prior experience.

[5] See, for example, Brands & Fernandez-Mateo (2017) and Sorenson & Waguespack (2006) for similar procedures.

TABLE 1: MEANS OF INDEPENDENT VARIABLES BY MESSAGE

		By treatment message		
	All	Quality	Fit	No reason
Female	0.185	0.183	0.183	0.189
Post-COVID lockdown	0.517	0.516	0.531	0.505
Age	26.284	26.071	26.378	26.398
Married	0.344	0.338	0.359	0.336
Top 6 metro	0.319	0.312	0.321	0.322
Lists job preference	0.869	0.862	0.878	0.865
Lists city preference	0.091	0.086	0.095	0.093
Lists skills	0.218	0.218	0.220	0.217
Experience: missing	0.541	0.531	0.563	0.532
Experience: none	0.192	0.205	0.183	0.190
Experience 1-35 months	0.135	0.129	0.127	0.149
Experience: $\geq$ 36 months	0.130	0.135	0.125	0.129
Count	7,757	2,581	2,589	2,587

Note: p=0.083 for the test that the true probability of treatment is equal across columns for applicants who have experience of 1-35 months. No other tests are significant at the 10% level.

Table 1 also allows us to examine whether treatment messages are uncorrelated with observable characteristics, as they should be under random assignment. To do so, for each of the 12 variables listed in the rows, we test the joint hypothesis that the true means across treatment messages are equal. One of the tests—for experience between 1 and 35 months—yielded a p-value of 0.083. However, with 12 tests, it is likely that at least one will yield a p-value below 0.10 even if the null hypothesis were true, and none of the other tests yielded a p-value below 0.10. Therefore we conclude that the randomization was effective and omitted covariates should be uncorrelated with the treatment.

Table 2 examines the pairwise correlations among the outcomes of interest, treatment messages, female, and the controls. Turning first to column a, listing and search clicks are correlated with post-rejection application. This suggests that the listing and search clicks are a

TABLE 2: PAIRWISE CORRELATIONS

		a.	b.	c.	d.	e.	f.	g.
a.	Applied	1.000						
b.	Listing	0.081*	1.000					
c.	Search	0.068*	0.415*	1.000				
d.	Fit	0.003	0.014	0.009	1.000			
e.	Quality	-0.007	0.020	-0.007	-0.501*	1.000		
f.	No reason	0.004	-0.033*	-0.002	-0.499*	-0.500*	1.000	
g.	Female	-0.051*	-0.022	-0.003	-0.004	-0.003	0.007	1.000
h.	Post lockdown	0.011	0.004	-0.110*	0.002	0.014	-0.017	-0.118*
i.	Age	0.019	0.022	0.019	-0.023	0.008	0.015	-0.101*
j.	Married	-0.012	0.041	0.019	-0.008	0.021	-0.012	-0.056*
k.	Top metro	0.004	0.005	-0.023*	-0.010	0.005	0.005	0.032*
l.	Lists job preference	0.043*	-0.008	0.001	-0.008	0.020	-0.012	-0.038*
m.	Lists city preference	0.069*	0.030*	0.036*	-0.012	0.008	0.004	-0.055*
n.	Work experience	0.016	-0.001	-0.003	0.000	0.000	-0.001	-0.093*
o.	Lists skills	0.052*	0.035*	0.033*	-0.004	0.002	0.002	0.011
		h.	**i.**	**j.**	**k.**	**l.**	**m.**	**n.**
i.	Age	-0.001	1.000					
j.	Married	0.053*	0.584*	1.000				
k.	Top metro	0.118*	0.157*	0.035	1.000			
l.	Lists job preference	0.003	-0.032	-0.002	0.006	1.000		
m.	Lists city preference	0.011	0.092*	0.025	0.055*	0.116*	1.000	
n.	Work experience	0.057*	0.622*	0.373*	0.113*	0.084*	0.168*	1.000
o.	Lists skills	-0.094*	0.041	-0.015	0.050*	-0.124*	0.092*	0.034*

* $p<0.05$

meaningful intermediary outcome, either because the the URLs themselves effectively nudge workers to continue their search, or because both URL clicks and reapplications capture rejected candidates' unobserved true interest in continuing their search. For the full uncontrolled sample, messaging is not correlated with applications. However, the overall population is heavily weighted toward men (who may be unaffected) and our key tests concern women. Women are substantially less likely to apply for positions after being rejected compared to men. Applicants who list job preferences, location preferences, or skills are more likely to apply; filling out these voluntary fields may reflect differences in preferences or effort in searching for a position. Moving across columns, the three outcomes (applied, search, and listing) are significantly correlated with each other. Pairwise correlations between the three treatments are near -0.5 as expected. Women tend to be slightly younger and less likely to be married or fill out voluntary information. Reporting voluntary fields are generally positively correlated with each other, suggesting candidates who fill their profile generally answer its questions.

4 Main results

Table 3 presents the main results for the six regressions presented in equations (1) through (6) without controls. Recall that the predictive margins in a linear probability model with treatment dummies yield the within-treatment means and standard errors for men and women.

Results for women. Column 1 of Table 3 shows the main result of the main analysis: the probability that women apply for a job after receiving different treatment messages. Women who receive the fit message have a substantially and statistically significantly higher probability of reapplying for a position within two months: applications after rejection was 10.8% for the fit message versus 6.7% for the quality message or 7.3% for the no reason message. The net gap is 3.73%, with a standard error of 1.65% (p=0.024). This evidence is consistent with our hypothesis, that the Fit message avoids a competitive framing and encourages future applications. We do not find support for the hypothesis that relative to rejection letters that provide a reason for rejection, letters that do not provide a reason for rejection will discourage future applications. Although the fit message appears increase the probability that a candidate applies for a job, we do not find the same results in columns 2 and 3, which test for the secondary outcomes of clicking on the URLs. Women who receive the quality message are significantly more likely to click the URL linking to the job post for which they are rejected, possibly to make sense of the candidate pools who may

TABLE 3: SEARCH PERSISTENCE BY REJECTION MESSAGE AND SEX, NO CONTROLS

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Message sent	Applied	Listing	Search	Applied	Listing	Search
1: Fit	0.108**	0.0275	0.0571	0.120	0.0508*	0.0574
	(0.0143)	(0.00753)	(0.0107)	(0.00709)	(0.00478)	(0.00507)
2: Quality	0.0674	0.0484**	0.0568	0.125	0.0464	0.0516
	(0.0115)	(0.00986)	(0.0106)	(0.00720)	(0.00457)	(0.00481)
3: No Reason	0.0735	0.0224*	0.0469	0.129	0.0348***	0.0577
	(0.0118)	(0.00670)	(0.00956)	(0.00732)	(0.00400)	(0.00509)
Observations	1438	1438	1438	6319	6319	6319

Notes: Robust standard errors in parentheses. Significance tests compare the listed treatment with the other two jointly.
*: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

be attracted to the job. We do not find substantial or significant differences for the share of women who click the URL to continue their job search.

Results for men. Column 4 shows two important features of reapplication rates for men. First, by comparing the coefficients in columns 1 and 4 we see that men overall are far more likely to apply for positions after being rejected than women (further evidence can be found in the pair-wise comparisons shown in Table 5). Second, differences in application rates between treated messages among men are very small and not statistically significant. In other words, the results suggest that men are generally more likely to reapply for jobs regardless of which message they receive. Turning to URL clicks, column 5 suggests men are more likely to click on the listing link if they receive the fit message and less likely to do so if they receive no reason for their prior rejection. This contrasts with women (column 2), who are significantly more likely to click the listing link when they receive the quality message. We find no significant differences in search clicks across treatments (column 6), and coefficients are similar to those for women.

TABLE 4: SEARCH PERSISTENCE BY REJECTION MESSAGE AND SEX, PREDICTIVE MARGINS

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Message sent	Applied	Listing	Search	Applied	Listing	Search
1: Fit	0.108**	0.0275	0.0562	0.121	0.0509*	0.0577
	(0.0143)	(0.00754)	(0.0106)	(0.00709)	(0.00478)	(0.00503)
2: Quality	0.0669	0.0484**	0.0575	0.125	0.0462	0.0521
	(0.0115)	(0.00984)	(0.0107)	(0.00714)	(0.00455)	(0.00480)
3: No Reason	0.0733	0.0225*	0.0471	0.128	0.0348**	0.0569
	(0.0118)	(0.00674)	(0.00957)	(0.00726)	(0.00400)	(0.00501)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1438	1438	1438	6319	6319	6319

Notes: Robust standard errors in parentheses. Significance tests compare the listed treatment with the other two jointly.
*: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Results for models with controls. Table 4 shows results controlling for post-COVID lockdown, top metro, listing job experience, listing city preference, listing skills, and work experience. Like Table 3, we present predictive margins, which now report the means and standard errors conditioned on the controls. As expected, controls have very little effect on the experimentally manipulated coefficients. For the main result in column 1, the six coefficients and standard errors change by less than one tenth of a percent after introducing controls. Intuitively, this is because the treatments are nearly uncorrelated with the controls, and incidentally, the controls themselves are weak predictors of application and so do not explain much of the residual variation. The strongest predictors of reapplication are listing job preferences, listing city preferences, and listing skills. However, a partial F-test cannot reject the hypothesis that all controls have no effect in column 1, and precisely estimated small effects for men. We present the full regressions with controls in Appendix Table A1.

Results for pairwise tests. Table 5 presents pairwise tests for differences in coefficients, taken from the simple model without controls presented in Table 3. These gender-message pairwise differences include all combinations of differences for the two samples (women and men), and three treatment messages (fit, quality, and no message). Cells represent the coefficient listed in the column minus the coefficient listed in the row. Because the main analysis's linear probability models do not have controls, the differences in coefficients are simply the differences in means.

Panel 1 examines differences in applications for gender-message pairs, the coefficient on female fit (F-Fit) is substantially and significantly larger than those for female quality (F-Quality) and female no reason (F-No reason). In contrast, the coefficient for F-Fit is only between 1.3% and 2.1% smaller than those for men in any treatment, and these differences are not statistically significant. To estimate the gap in applications that may be reduced by providing the fit message, we note that the overall gender gap in applications for those *not* receiving the fit message is 5.66%. The gender gap for those who *do* receive the fit message is 1.26%. The point estimate for the reduction of the gender gap is 77.6%.

This result calls attention to another interpretation: providing women the fit message essentially brings their probabilities of applying for a new position to be similar to that of men, eliminating most of the gender gap. Put another way, among the six combinations of gender and message, women receiving quality and no reason messages are distinctively *less* likely to apply for a new position compared to either women receiving the fit message or men. Also notably, the differences in coefficients for men are small and not significant, providing evidence that men's probability of reapplying does not depend on the type of rejection message. Put together, this suggests that all rejected candidates could be given the fit message, which increases the probability that women apply for new positions and does not reduce the probability for men.

Panel 2 examines differences in listing clicks. Although the fit message was most effective at eliciting subsequent applications from women, the quality message elicited a significantly higher probability of clicking on the listing for which the worker was rejected. Once again, men are substantially and significantly more likely to click on the listing after being rejected. Men are significantly more likely to click the listing URL when they are provided the fit message. Panel 3 shows that there are no significant difference in search clicks by gender or message. Intuitively, these shares are about equal to universal mean of 5.61% for all six gender-message pairs.

All results are very similar when we compare coefficients from the model with controls (shown in Appendix Table A2).

5 Examining mechanisms

The previous section presents evidence that messaging affects the probability that women apply for new positions. Based on prior theoretical work, we proposed that the fit, quality, and no-reason messages commonly used by employers are likely to generate different responses to rejected job seekers. In particular, we proposed that these messages convey different magnitudes of competitiveness and ambiguity, which would in turn affect the propensity for women to reapply to positions. However, it is not necessarily certain that the experimental messages were being interpreted in this way, and even if they were, it is not obvious that competitiveness and ambiguity would be the most salient differences among the messages. Therefore, we implemented a follow-up experiment that serves both as a manipulation check—affirming our messages were interpreted in a way that matches the theories—and also as a check that existing theories account for the most salient differences among the most common forms of rejection identified in audit studies (e.g. Aamodt & Peggans 1988; Jablin & Krone 1984).

To investigate how the three types of rejection messages were interpreted by workers, we conducted a survey on Amazon Mechanical Turk. In the survey, we presented the three rejection messages and asked 100 respondents to describe in 20 words or fewer their sentiment to an employer that would use each of the messages. This yielded a data set of 300 descriptions: one description per message, times three messages, times 100 respondents.

To generate categories from the open-ended responses, we first referred to the theoretical proposition that the messages should vary in the degree they are perceived as competitive or ambiguous, and found seven common ways that these two concepts were conveyed. Common responses relating to competition and superiority include that the rejection message made the respondent (1) feel deficient, or the message was perceived as (2) demeaning, (3) rude, or (4) polite. Common responses relating to ambiguity include that the message (5) is explicitly ambiguous, (6) was missing an explanation, or (7) was generic. These seven subcategories also strongly reflected the full set of responses that we observed.[6]

Three raters independently categorized each of the 300 messages. To ensure that the categories depended on the description of the message, and not the message itself, the order of the 300 descriptions was randomized and the raters were blinded to the message prompt that generated the survey respondents' descriptions. The raters coded dummy variables for each of these seven subcategories. A description was considered to affirm a particular subcategory if there was agreement between any two raters. The three raters agreed between 82% and 93% of the time for each of the seven subcategories, with an average of 86% (kappa = 0.58).

Figure 1 reports the means and standard errors for the seven subcategories by experimental condition. Panel A of Figure 1 suggests that relative to the fit and the no reason messages, survey respondents stated that they perceived that the quality message made them feel deficient or found it demeaning or rude. Further, we find relative to the quality and the no reason messages, respondents found the fit message to be polite. Pairwise t-tests confirm that these differences are statistically significant with $p < 0.01$.

Panel A also hints at whether the quality message was primarily affecting candidates' self-perceptions or perceptions of the employer. This is important in itself, as messages that affect the candidate estimation of the employer suggest the applicant simply wouldn't apply to that employer, whereas effects on self-perceptions would seemingly generalize to the type of opportunities a jobseeker would pursue in the future. We find respondents reported the quality

[6]These results are available upon request.

message as *both* demeaning to the applicant and rude on the part of the employer. This suggests respondents interpret the message as a signal about oneself and the employer.

Panel B indicates that relative to the fit and the quality messages, survey participants found the no reason message to be ambiguous, missing an explanation, and generic. Once again, all differences were significantly different with $p < 0.01$.

Together, the results from our survey suggest that job seekers' interpretation of our rejection messages are aligned with the theoretical explanations provided. We conclude that the quality message was salient for making candidates feel deficient, under-qualified, and came across as rude. Respondents perceived the fit message to be distinctively polite. The no-reason message came across as sharing too little and generic; respondents often reported that they wanted and deserved to know more.

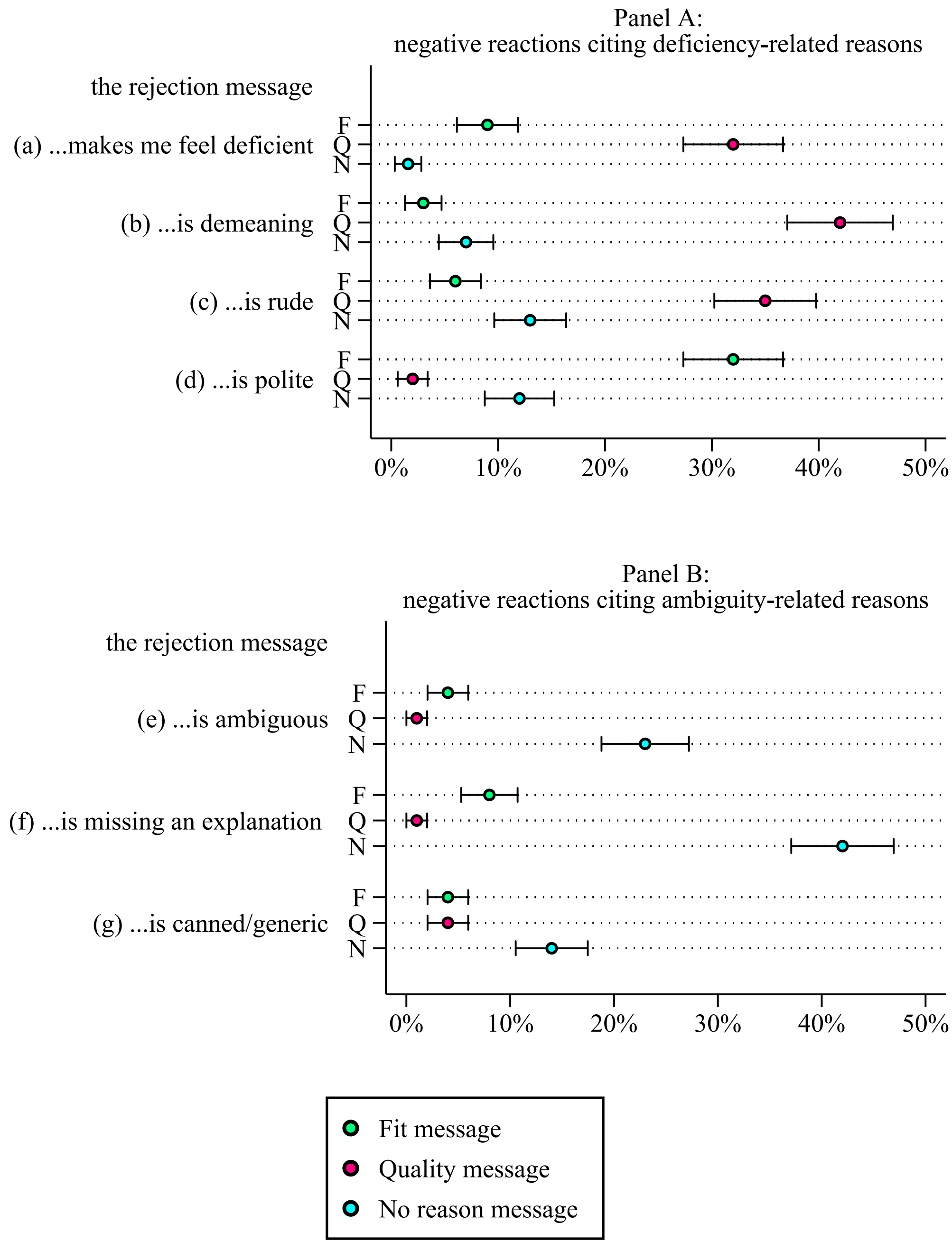
TABLE 5: PAIRWISE DIFFERENCES IN COEFFICIENTS (COLUMN MINUS ROW)

	F-Fit	F-Qual	F-No	M-Fit	F-Qual
Panel 1: Applied					
F-Quality	.0405**				
	(.0183)				
F-No reason	.0344*	-.0061			
	(.0185)	(.0165)			
M-Fit	-.0127	-.0531***	-.047***		
	(.0159)	(.0135)	(.0138)		
M-Quality	-.0175	-.058***	-.0519***	-.0049	
	(.016)	(.0136)	(.0138)	(.0101)	
M-No reason	-.0209	-.0614***	-.0553***	-.0083	-.0034
	(.016)	(.0136)	(.0139)	(.0102)	(.0103)
Panel 2: Listing click					
F-Quality	-.0209*				
	(.0124)				
F-No reason	.005	.026**			
	(.0101)	(.0119)			
M-Fit	-.0233***	-.0023	-.0283***		
	(.0089)	(.011)	(.0082)		
M-Quality	-.0189**	.0021	-.0239***	.0044*	
	(.0088)	(.0109)	(.0081)	(.0066)	
M-No reason	-.0073**	.0136	-.0124**	.0159**	.0115*
	(.0085)	(.0106)	(.0078)	(.0062)	(.0061)
Panel 3: Search click					
F-Quality	.0002				
	(.0151)				
F-No reason	.0101	.0099			
	(.0143)	(.0143)			
M-Fit	-.0003	-.0006	-.0105		
	(.0118)	(.0118)	(.0108)		
M-Quality	.0055	.0053	-.0046	.0058	
	(.0117)	(.0117)	(.0107)	(.007)	
M-No reason	-.0006	-.0009	-.0108	-.0003	-.0061
	(.0118)	(.0118)	(.0108)	(.0072)	(.007)

Notes. Cells show the coefficient listed in the column minus the coefficient listed in the row.

* $p < 0.1$, ** $p < 0.05$, ** $p < 0.01$

FIGURE 1: NEGATIVE REACTIONS TO THE REJECTION MESSAGES



NOTES: Open-ended responses were categorized into seven reactions, four relating to feelings of deficiency (Panel A) and three relating to ambiguity (Panel B). Point estimates on the horizontal axis represent the share of survey respondents for each type of messages whose open-ended responses fall into these categories. Brackets represent standard errors.

6 Conclusion

To better understand the effect of the content of commonly used job rejection messages on men's and women's likelihood to reapply to future positions this study uses a combination of a randomized controlled field experiment and a survey. The study focuses on three rejection message that are commonly used by employers—ones that refer to quality, fit and that do not provide a reason for the rejection. We theorized that the quality message primes the reader to think of the rejection in competitive terms, as it suggests that other candidates had superior qualifications. In contrast, the fit message appears less negative and focuses on the compatibility between the organization and the individual. The message that does not provide a reason for rejection is ambiguous. Given women's ambiguity aversion, we hypothesized that women would respond more favorably to messages that provide a reason—the quality and fit messages—relative to the message that did not provide a reason for the rejection. Further, between the quality and fit messages, we hypothesized that since women tend not to prefer non-competitive environments, they would respond more favorably to the fit message relative to the quality message.

We found that women overall were less likely to reapply to positions post rejection. This finding is consistent with prior by Brands & Fernandez-Mateo (2017), who find in the context of top management positions, women are less likely to reply to the same organization post-rejection. Furthermore, in line with our hypothesis, we found that women responded more positively to the fit message relative to the other two message. Finally, while women responded more positively to the fit message relative to the no reason message, we did not find a significant difference in the response to the quality message relative to the no reason message. This may be because women tend to align their self-ratings based on feedback(Croson & Gneezy 2009; Flory et al. 2015; Niederle & Vesterlund 2007, 2011; Reuben et al. 2017), while men continue to inflate their self-images (Mayo et al. 2012). We employ a survey to help validate our theory. Our survey indicates that the rejection message that does not offer a reason is perceived as ambiguous, missing an explanation and canned. The quality message is perceived as demeaning, rude and inadequate, and the fit message as polite.

Our study has several strengths. First, the exogenous random assignment of the treatments removes extraneous factors and the resulting endogeneity, allowing for causal inference (Brewer 1985; Karahanna et al. 2018). Second, the experiment was conducted unobtrusively, and the subjects were not aware that they were part of a study, thus actor-observer bias was eliminated. Third, since the study was conducted as a field experiment in the subjects' naturally occurring environment, it provides for a high level of realism (Karahanna et al. 2018). A limitation of our study is that we are unable to test if candidates' reapplications eventually led to them being selected for the job; a study involving reapplications and eventual selection would require a very large sample and a long time horizon. Another limitation is that we are unable to explore if rejection by one employer affects rejected candidates' future applications to other employers. We leave this to future work. Notwithstanding these limitations, our study makes several contributions to research and practice.

Our study contributes to the literature on gender differences in job applications. Previous research has found that women are less likely to apply to jobs (Mohr 2014), are less likely to self-promote themselves in recruitment settings (Exley & Kessler 2019; Murciano-Goroff 2018), and are less likely to re-apply in the same context after rejection (Brands & Fernandez-Mateo 2017; Yang et al. 2019). We extend this literature by showing that women's likelihood of applying after job rejection depends on the content of the rejection message. Importantly, we find that providing women a fit related rejection message brings their probabilities of applying for a new position to be similar to that of men, eliminating most of the gender gap in applications after rejection.

Rejection is widespread in the labor market, and small differences in being willing to be considered for jobs could eventually lead to large differences in the composition of candidate pools; if more men than women decide to re-apply after rejection, then the number of women available for subsequent job openings will slowly and continually decline (Brands & Fernandez-Mateo 2017). Our study provides a novel insight into a source of leakage in the pipeline for female workers—the content of rejection messages. Importantly, our study identifies which commonly used rejection messages are likely to worsen or diminish the gender gaps in the applicant pool. The study's findings point to simple measures that can be used by employers to maintain the diversity of their candidate pool. While previous research suggests that care needs to be taken in the choice of the content of job advertisements in order to encourage female applications (Flory et al. 2015; Gaucher et al. 2011; Samek 2019; Wille & Derous 2018), our findings suggest that similar attention needs to be paid to the content of rejection messages. Given our study's context, we expect our findings to be generalizable to early career candidates in roles such as sales, customer support, and office support.

Our study is also relatively "low-dimensional," in that we only examine three major types of messages. In contrast, the methods that employer use to follow up with rejected candidates vary widely. For instance, quality-related rejection might be accompanied by an affirmation, such as that the committee was impressed by one's qualifications, but that the process was highly selective. Employers could also seemingly signal that they value rejected applicants by making rejection letters more personal, which could also have different effects on different groups' search persistence. We hope that the evidence we present will encourage future scrutiny of the application process.

References

Aamodt, M. G. & Peggans, D. L. (1988). Rejecting applicants with tact. *Personnel Administrator*, 33(4), 58–60.

Abraham, L. & Stein, A. (2020). Words matter: Experimental evidence from job applications. *Working Paper*.

Angrist, J. D. & Pischke, J.-S. (2008). *Mostly harmless econometrics*. Princeton university press.

Benson, A., Sojourner, A., & Umyarov, A. (2020). Can reputation discipline the gig economy? experimental evidence from an online labor market. *Management Science*, 66(5), 1802–1825.

Bertrand, M. (2011). New perspectives on gender. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics*, volume 4 (pp. 1543–1590). Elsevier.

Blau, F. D. & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of economic literature*, 55(3), 789–865.

Bloemen, H. G. (2005). Job search, search intensity, and labor market transitions an empirical analysis. *Journal of Human resources*, 40(1), 232–269.

Brands, R. A. & Fernandez-Mateo, I. (2017). Leaning out: How negative recruitment experiences shape women's decisions to compete for executive roles. *Administrative Science Quarterly*, 62(3), 405–442.

Brewer, M. B. (1985). Experimental research and social policy: Must it be rigor versus relevance? *Journal of Social Issues*, 41(4), 159–176.

Brown, T. (1993). Unkind cuts: Rethinking the rhetoric of academic job rejection letters. *College English*, 55(7), 770–778.

Campero, S. (2021). Hiring and intra-occupational gender segregation in software engineering. *American Sociological Review*, 86(1), 60–92.

Coffman, K. B., Collis, M., & Kulkarni, L. (2019). *When to Apply?* Harvard Business School.

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: a meta-analytic review of 25 years of organizational justice research. *Journal of applied psychology*, 86(3), 425.

Cortés, P., Pan, J., Pilossoph, L., & Zafar, B. (2021). *Gender differences in job search and the earnings gap: Evidence from business majors*. Technical report, National Bureau of Economic Research.

Cowgill, B. & Stevenson, M. T. (2020). Algorithmic social engineering. In *AEA Papers and Proceedings*, volume 110 (pp. 96–100).

Croson, R. & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, 47(2), 448–74.

Davidson, R., MacKinnon, J. G., et al. (1993). Estimation and inference in econometrics. *OUP Catalogue*.

Eckel, C. C. & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results*, 1, 1061–1073.

Exley, C. L. & Kessler, J. B. (2019). *The gender gap in self-promotion*. Technical report, National Bureau of Economic Research.

Ferguson, M., Hitt, L. M., & Tambe, P. (2013). *The talent equation: Big data lessons for navigating the skills gap and building a competitive workforce*. McGraw Hill Professional.

Fernandez, R. M. & Campero, S. (2017). Gender sorting and the glass ceiling in high-tech firms. *Ilr Review*, 70(1), 73–104.

Fernandez, R. M., Rubineau, B., & Kuppuswamy, V. (2019). Expanding pools or expanding tools? rejection response dynamics and the gender segregation of talent pipelines. *Working Paper*.

Fernandez-Mateo, I. & Fernandez, R. M. (2016). Bending the pipeline? executive search and gender inequality in hiring for top management jobs. *Management Science*, 62(12), 3636–3655.

Fernandez-Mateo, I. & Kaplan, S. (2018). Gender and organization science: Introduction to a virtual special issue. *Organization Science*, 29(6), 1229–1236.

Flory, J. A., Leibbrandt, A., & List, J. A. (2015). Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions. *The Review of Economic Studies*, 82(1), 122–155.

Garratt, R. J., Weinberger, C., & Johnson, N. (2013). The state street mile: Age and gender differences in competition aversion in the field. *Economic Inquiry*, 51(1), 806–815.

Gaucher, D., Friesen, J., & Kay, A. C. (2011). Evidence that gendered wording in job advertisements exists and sustains gender inequality. *Journal of personality and social psychology*, 101(1), 109.

Gee, L. K. (2019). The more you know: Information effects on job application rates in a large field experiment. *Management Science*, 65(5), 2077–2094.

Gilligan, C. (1993). *In a different voice: Psychological theory and women's development*. Harvard University Press.

Glassdoor (2015). *Fifty HR and recruiting stats that make you think*.

Jablin, F. M. & Krone, K. (1984). Characteristics of rejection letters and their effects on job applicants. *Written communication*, 1(4), 387–406.

Jackson, P. R. & Warr, P. B. (1984). Unemployment and psychological ill-health: The moderating role of duration and age. *Psychological medicine*, 14(3), 605–614.

Karahanna, E., Benbasat, I., Bapna, R., & Rai, A. (2018). Editor's comments: opportunities and challenges for different types of online experiments. *MIS Quarterly*, 42(4), iii–x.

Kolev, J., Fuentes-Medel, Y., & Murray, F. (2019). *Is blinded review enough? How gendered outcomes arise even under anonymous evaluation*. Technical report, National Bureau of Economic Research.

Kulik, C. T., Lind, E. A., Ambrose, M. L., & MacCoun, R. J. (1996). Understanding gender differences in distributive and procedural justice. *Social Justice Research*, 9(4), 351–369.

Leibbrandt, A. & List, J. A. (2015). Do women avoid salary negotiations? evidence from a large-scale natural field experiment. *Management Science*, 61(9), 2016–2024.

Mayo, M., Kakarika, M., Pastor, J. C., & Brutus, S. (2012). Aligning or inflating your leadership self-image? a longitudinal study of responses to peer feedback in mba teams. *Academy of Management Learning & Education*, 11(4), 631–652.

McKee-Ryan, F., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: a meta-analytic study. *Journal of applied psychology*, 90(1), 53.

Mohr, T. S. (2014). Why women don't apply for jobs unless they're 100% qualified. *Harvard Business Review*, 25.

Murciano-Goroff, R. (2018). Missing women in tech: The labor market for highly skilled software engineers. *Working Paper*.

Niederle, M. & Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The quarterly journal of economics*, 122(3), 1067–1101.

Niederle, M. & Vesterlund, L. (2011). Gender and competition. *Annu. Rev. Econ.*, 3(1), 601–630.

O'Reilly III, C. & Pfeffer, J. (1995). Southwest airlines (a). *Stanford Case Study HR1A*.

Petersen, T. & Saporta, I. (2004). The opportunity structure for discrimination. *American Journal of Sociology*, 109(4), 852–901.

Reuben, E., Wiswall, M., & Zafar, B. (2017). Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender. *The Economic Journal*, 127(604), 2153–2186.

Samek, A. (2019). Gender differences in job entry decisions: A university-wide field experiment. *Management Science*, 65(7), 3272–3281.

Schubert, R., Brown, M., Gysler, M., & Brachinger, H. W. (1999). Financial decision-making: are women really more risk-averse? *American economic review*, 89(2), 381–385.

Sharone, O. (2013). Why do unemployed americans blame themselves while israelis blame the system? *Social forces*, 91(4), 1429–1450.

Sorenson, O. & Waguespack, D. M. (2006). Social structure and exchange: Self-confirming dynamics in hollywood. *Administrative Science Quarterly*, 51(4), 560–589.

Turczynski, B. (2021). Hr statistics: Job search, hiring, recruiting & interviews, https://zety.com/blog/hr-statistics (accessed: July 28, 2021).

Wille, L. & Derous, E. (2018). When job ads turn you down: how requirements in job ads may stop instead of attract highly qualified women. *Sex Roles*, 79(7), 464–475.

Yang, A. T., Leung, D. M., & Bao, J. (2019). Approaching or avoiding: Gender asymmetry in reactions to prior job search. *Working Paper*.

7 Appendix

TABLE A1: SEARCH PERSISTENCE BY REJECTION MESSAGE AND SEX, PREDICTIVE MARGINS

	(1) Applied		(2) Listing		(3) Search	
1: F-Fit	0		0		0	
2: F-Qual	-0.0413**	(0.0208)	0.0206	(0.0130)	0.00108	(0.0147)
3: F-Ctrl	-0.0349*	(0.0206)	-0.00535	(0.0129)	-0.00943	(0.0146)
4: M-Fit	0.00646	(0.0164)	0.0228**	(0.0103)	0.00790	(0.0116)
5: M-Qual	0.0110	(0.0164)	0.0182*	(0.0102)	0.00200	(0.0116)
6: M-Ctrl	0.0137	(0.0164)	0.00681	(0.0103)	0.00699	(0.0116)
Top-6 metro	-0.00428	(0.00787)	0.00162	(0.00493)	-0.00774	(0.00559)
Lists job preference	0.0309***	(0.0110)	-0.000818	(0.00688)	0.000780	(0.00780)
City preference	0.0525***	(0.0135)	0.0187**	(0.00844)	0.0313***	(0.00956)
Lists skills	0.0346***	(0.00930)	0.0194***	(0.00582)	0.0162**	(0.00660)
Post-COVID lockdown	-0.00486	(0.00752)	0.00211	(0.00470)	-0.0468***	(0.00533)
Exp: missing	0		0		0	
Exp: 0 months	0.0125	(0.00990)	-0.00147	(0.00620)	-0.00825	(0.00702)
Exp: 1-35 months	0.0376***	(0.0116)	-0.00200	(0.00729)	0.00293	(0.00826)
Exp: ≥ 36 months	0.0183	(0.0122)	-0.00355	(0.00762)	-0.00878	(0.00864)
Constant	0.0681***	(0.0180)	0.0222**	(0.0113)	0.0731***	(0.0128)
Observations	7757		7757		7757	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A2: PAIRWISE DIFFERENCES IN COEFFICIENTS WITH CONTROLS (COLUMN MINUS ROW)

	F-Fit	F-Qual	F-No	M-Fit	F-Qual
Panel 1: Applied					
F-Quality	.0413**				
	(.0184)				
F-No reason	.0349*	-.0064			
	(.0186)	(.0165)			
M-Fit	-.0065	-.0478***	-.0414***		
	(.0161)	(.0137)	(.0139)		
M-Quality	-.011	-.0524***	-.046***	-.0046	
	(.0161)	(.0136)	(.0139)	(.0101)	
M-No reason	-.0137	-.055***	-.0486***	-.0072	-.0026
	(.0162)	(.0138)	(.014)	(.0101)	(.0102)
Panel 2: Listing click					
F-Quality	-.0206*				
	(.0124)				
F-No reason	.0054	.0259**			
	(.0101)	(.0119)			
M-Fit	-.0228**	-.0023	-.0282***		
	(.0089)	(.011)	(.0082)		
M-Quality	-.0182**	.0024	-.0235***	.0047*	
	(.0089)	(.011)	(.0082)	(.0066)	
M-No reason	-.0068**	.0138	-.0122**	.016**	.0113*
	(.0086)	(.0108)	(.0079)	(.0062)	(.0061)
Panel 3: Search click					
F-Quality	-.0011				
	(.015)				
F-No reason	.0094	.0105			
	(.0143)	(.0143)			
M-Fit	-.0079	-.0068	-.0173		
	(.012)	(.0117)	(.0109)		
M-Quality	-.002	-.0009	-.0114	.0059	
	(.0119)	(.0116)	(.0108)	(.0069)	
M-No reason	-.007	-.0059	-.0164	.0009	-.005
	(.012)	(.0117)	(.0109)	(.0071)	(.0069)

Notes. Cells show the coefficient listed in the column minus the coefficient listed in the row.

* $p < 0.1$, ** $p < 0.05$, ** $p < 0.01$