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Taking a Pass: How Proportional Prejudice and Decisions Not to Hire Reproduce Sex Segregation*

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Taking a Pass: How Proportional Prejudice and Decisions Not to Hire Reproduce Sex Segregation

Abstract

We propose and test a theory of how decisions not to hire reproduce sex segregation through what we term *proportional prejudice*. We hypothesize that employers are less likely to hire anyone when the applicant pool contains a large proportion of gender atypical applicants – that is, applicants from a different gender than the typical job holder – because they view this as a signal of a poor quality applicant pool. Analyses, of over seven million job applications for over 700,000 jobs by over 200,000 freelancers on an online platform for contract labor support our contention. A survey experiment isolates the mechanism: Applicant pools with a larger proportion of gender atypical applicants were perceived as less likely to contain people who "seemed skilled enough for the job." We conclude by demonstrating how our theory explains the mixed findings as to whether gender atypical job seekers are disadvantaged in the hiring process.

Keywords
Occupational sex segregation, hiring decisions, cultural schema, gig economy

Introduction

The tendency for men and women to work in different types of jobs explains much of the gender gaps in pay (England et al. 1994; Petersen and Morgan 1995), access to the most influential organizational positions (Huffman, Cohen and Pearlman 2010), and assignment to less permanent jobs (Haveman, Broschak and Cohen 2009). As such, understanding the roots of occupational sex segregation is a key concern of labor market research. The lack of women in relatively high-paying information technology and programming jobs in particular has been lamented by researchers, the popular press, and employing companies alike. Women currently make up about half of the U.S. workforce but only 24 percent of the workforce in science, technology, engineering, and math (STEM) fields; while 40 percent of men with STEM college degrees work in STEM jobs, only 26 percent of women do (Beede et al. 2011).

The point of hire is a crucial step in the process of sex segregation (Fernandez and Weinberg 1997; Petersen, Saporta and Seidel 2005). As Blau and Ferber (1987):51 explain, “Once men and women are channeled into different types of entry jobs, the normal everyday operation of the firm will virtually ensure sex differences in productivity, promotion opportunities, and pay.” Scholars have even gone so far as to suggest that hiring could be the most prominent source of disadvantage. As Lazear (1991):13 states with regard to the processes that lead to segregation, “My view is that hiring is the most important; promotion second, and wages are third.” For employers with a “taste” for discrimination, hiring has been said to represent an “opportunity” because, compared to decisions about promotions and wages, there is less documentation, documentation is more ambiguous, and the person discriminated against is less likely to file a complaint (Lazear 1991; Petersen and Saporta 2004). Thus, it is vitally important for researchers to understand how employer hiring decisions affect sex segregation.

Most theories of how employer hiring decisions shape sex segregation assume the employers reproduce sex segregation *directly* through decisions to hire individual applicants, yet employers make another relevant decision more or less simultaneously: *whether or not to hire* to any applicant from the pool they receive. We know that when evaluating individual applicants, employers often rely on visible social characteristics because they inform conceptions of the "kind of person" who can successfully perform a particular job (Gorman 2005; Turco 2010). Decisions not to hire are even more susceptible to these beliefs because they often involve evaluating the quality of an entire applicant pool, which, by virtue of the larger number of individuals involved, requires assimilating a larger amount of information (Botelho and Abraham forthcoming). We propose and test the novel argument that employers are more likely to decide not to hire anyone when a large proportion of applicants are from a different gender than the typical job holder (henceforth, "gender atypical applicants") because they view this as a signal of a poor quality applicant pool, a tendency we term *proportional prejudice*.

The absence of theorizing around decisions not to hire may have muddled the conclusions reached by previous studies of sex segregation. If decisions not to hire are correlated with the proportion of women in the applicant pool, as we hypothesize, then theoretical attention to these decisions could reconcile the mixed findings on the extent to which employers reproduce sex segregation. More specifically, while field experiments suggest that job seekers are less likely to receive callbacks when they apply for jobs widely associated with the opposite gender (Petit 2007; Riach and Rich 2006), statistical analyses of organizational hiring data tend to find that employers in gender-typed industries hire men and women at rates equivalent to their representation in the applicant pool (e.g., Fernandez-Mateo and Fernandez 2016; Fernandez, Castilla and Moore 2000; Petersen, Saporta and Seidel 2000). In other words, gender atypical job seekers appear to experience a disadvantage when they submit their applications but employers do not seem to privilege one gender over the other when they decide which applicants to hire. Incorporating employer decisions not to hire into our theorization of the hiring process – cases included in the former studies but not in the latter – may help explain this puzzle. If employers are more likely to decide not to hire when gender atypical job applicants are overrepresented, employers can reproduce sex segregation even if they eventually hire men and women at rates equivalent to their representation in the applicant pool.

In this article, we propose and test the argument that employer decisions not to hire anyone reproduce sex segregation through an analysis of the hiring of freelancers in an online market for temporary contract labor, *Elance.com*. This unique data source allows us to address many of the limitations of past hiring research. Unlike many traditional datasets, we have access to unusually detailed data on the hiring process and can observe which applicants apply to which job postings, which postings end with an offer of employment, and which applicants are hired for postings that end with an offer of employment, all while controlling for visible measures of applicant ability. And unlike most datasets with such detailed data, our dataset spans multiple employers and includes a wide breadth of different job types. The nature of work on this platform also eliminates many alternative explanations. Given that applicants apply directly to jobs, hiring decisions are unlikely to reflect intermediaries' efforts to 'steer' women and men to gender-typed jobs (Fernandez-Mateo and King 2011), and given that work is virtual, hiring decisions are unlikely to reflect interpersonal processes that occur during in-person interviews (Rivera 2012) or employer reluctance to hire women for jobs requiring geographic mobility (Rivera 2017). Finally, given that on this platform employers are usually individuals or very small organizations, organizational factors like corporate policies (Dobbin, Kim and Kalev 2011;

Kalev 2014) or the existing gender composition of firms (Beckman and Phillips 2005) are unlikely to impact hiring decisions.

We analyze all of the transactions conducted on *Elance.com* in 2012, which amounted to 792,650 posted jobs, by 249,506 employees who received 7,699,370 job applications from 292,518 freelancers (39% of them female). We show that decisions not to hire are more likely when there is a larger proportion of gender atypical applicants (e.g., mostly women for a programming job and mostly men for a writing job). Using a complementary survey experiment, we find evidence that this relationship can be attributed to proportional prejudice: Subjects assessed applicant pools with a large proportion of gender atypical applicants as less likely to contain the "kind of people" with the skills for the job.

We then demonstrate that our theory of proportional prejudice may help explain why some studies find that gender atypical job seekers are disadvantaged even though others show employers hire men and women at equal rates. We do so by showing that women are less likely to be hired for male-typed IT & Programming jobs and more likely to be hired for female-typed Writing & Translation jobs when we include jobs for which employers decided not to hire anyone but that the female disadvantage disappears when we exclude these cases. Taken together, our study suggests that, in this online labor market, employers reproduce sex segregation through decisions not to hire when there are a large proportion of gender atypical applicants in the pool, findings with important implications for research on sex segregation and discrimination, as well as practical implications for employers seeking to create a more equitable workforce.

Do Employer Hiring Decisions Reproduce Sex Segregation?

The persistent tendency for men and women to work in different types of jobs has long been attributed to the decisions of employers. Up until the 1964 Civil Rights Act, the majority of American employers had jobs that explicitly excluded one sex (Goldin 1990). With the removal of legal barriers, shifting attitudes, and equalizing educational attainment (Cotter, Hermsen and Vanneman 2011; Jacobs 1996; 2003), a large body of work suggests that overt discrimination has been replaced by unconscious yet widespread cultural beliefs about what men and women are known to be like that disadvantage women when they seek employment in male-dominated fields and vice versa (Gorman 2005; Gorman 2006; Ridgeway 2011). This research suggests that sex segregation today is less the result of discrimination and more a consequence of employers' unintentional reliance on these cultural beliefs when making hiring decisions, particularly in the absence of complete information (Heilman 1995; Petersen and Togstad 2006; Reskin 2000). Yet the most empirically rigorous tests of this argument have come to seemingly contradictory conclusions about the extent to which employers reproduce sex segregation.

Field experiments – usually audit and correspondence studies that bring an experimental causal approach to real world job openings – have generally found evidence that applications from gender atypical applicants are less likely to receive callbacks than similarly-qualified gender typical ones, suggesting that employer hiring decisions reproduce sex segregation. In Neumark, Bank, and Van Nort's (1996) landmark study, when matched pairs of equally qualified men and women applied for jobs as servers in the same restaurants, men had significantly more success than women getting job offers at high-paying restaurants whereas women had significantly more success at low-paying restaurants. Similar results were found in studies of jobs culturally associated with a single gender. Riach and Rich (2006) found that employers were less likely to hire women for “male” engineering jobs and more likely to do so for “female” secretarial jobs; Petit (2007) found that financial service firms were less likely to hire young women for “male” management jobs and more likely to do so for “female” assistant jobs.

In contrast, the most rigorous analyses of observational data on hiring outcomes have generally found that employers do not privilege one gender over the other when deciding whom to hire, suggesting that employer hiring decisions may no longer be a key driver of sex segregation. When using observational data to address this question, the most empirically rigorous approaches account for applicant actions that occur prior to hiring decisions – i.e., the decisions of men and women to apply for specific jobs – by including demographic information on the pool of applicants who have applied for a particular position (Fernandez and Sosa 2005). Statistical analyses of observational data from employers operating in male-dominated fields – including an executive search firm (Fernandez-Mateo and Fernandez 2016), a high technology company (Petersen, Saporta and Seidel 2000) and BioPharma firm (Fernandez and Abraham 2011) – all found that, when the gender composition of the applicant pool is accounted for, men and women were equally likely to be hired. Similar patterns were evident in analyses of hiring data from organizations in female-dominated fields, including a large public service organization (Petersen, Saporta and Seidel 2005) and a retail bank’s customer service division (Fernandez, Castilla and Moore 2000). In a rare study of multiple firms, Fernandez and Campero (forthcoming) found that women were slightly less likely to be hired by small and mid-sized technology firms but argue that employer hiring decisions play a relatively minor compared to the decisions of individuals to apply.

Taken together, these findings – that gender atypical applicants experience a disadvantage but that employers hire men and women at rates proportional to the rates at which they apply –

present a confusing picture if we assume that employers reproduce sex segregation *directly* through decisions whom to hire. Yet if we theorize that employers reproduce sex segregation *indirectly* through decisions not to hire, the picture becomes clearer: audit and correspondence studies find that atypical applicants experience a disadvantage because they include job openings for which employers decided not to hire in their analyses – employers rarely tell applicants about these decisions, so all researchers know is that their fictitious résumé was not selected – while analyses of company hiring data do not find this disadvantage because they only analyze openings filled during the study period. By focusing on how employers decide whom to hire, researchers have obscured an important and, to our knowledge, unstudied mechanism of sex segregation – employer decisions whether to hire at all.

From Whom to Hire to Whether to Hire

Theories of how employers affect sex segregation tend to focus on their decisions about which job applicant to hire, but ignore another important decision employers make more or less simultaneously: whether or not to hire anyone from the applicant pool they receive. The former decisions are, of course, intertwined with the latter but the latter are distinct in that they involve evaluating the entire applicant pool, which, by virtue of the larger amount of individuals involved, requires assimilating a larger amount of information. Applicant pools are the unordered[1] set of applicants an employer considers for a particular position. Hiring decisions are typically made after evaluating this slate[2] of applicants and thus hiring outcomes are sensitive to

[1] The lack of ordering differentiates an applicant pool from a queue Reskin, B. 1990. *Job queues, gender queues: Explaining women's inroads into male occupations*: Temple University Press..

[2] Hiring decisions can also be structured as a sequence, where employer decisions to hire are made on each applicant as they apply over time Sterling, Adina D. 2014. "Preentry Contacts and the Generation of Nascent Networks in Organizations." *Organization science* 26(3):650-67.. We suspect that the decision-making

the composition of the pool; the applicants contained within are in direct competition with one another for the job in question.

Though the process of evaluating the applicant pool may vary from employer to employer – some may go through a structured, sequential screening process, while others may take a more ad-hoc or iterative approach – the larger amount of information involved evaluating a pool increases the amount of effort an employer must spend to assimilate all available pertinent information, or the *search costs*. When search costs are higher, evaluating quality is more difficult and evaluators are more likely to rely on visible social characteristics (Botelho and Abraham forthcoming; Simcoe and Waguespack 2011). For example, because it is not feasible to read résumés, call references and conduct interviews for all of the applicants in a pool, employers may just glance at applicant names, education, and most recent work experiences, a more cursory approach that is more susceptible to unconscious cultural beliefs about particular social groups. Yet we know very little about the extent to which these beliefs affect employer decisions whether to hire from the applicant pool they receive.

Past studies of how employers decide whom to hire offer a theoretical starting point. When making decisions about individual job applicants, employers evaluate whether the applicant can perform the job in question. Though this process is typically portrayed as a rational assessment of applicant quality (Moss and Tilly 2001), applicant quality is often not directly observable, leading employers to infer quality based on what they can observe (Kanter 1977; Ridgeway 2011). When visible social characteristics are widely believed to be associated with desired qualities, they can shape hiring decisions without discriminatory intent because they unconsciously inform conceptions of the "kind of person" who can successfully perform a

processes in these cases will largely be consistent with our theory, yet depart in ways which we elaborate on in the discussion.

particular job (Gorman 2005). For example, given widespread belief that men have better mathematic skills and women have better verbal skills (Baird 2012; Correll 2001; Correll 2004; Hyde and Mertz 2009), men come to be seen as the right "kind of people" for mathematically-intensive programming jobs and women as the right "kind of people" for verbally-intensive writing jobs. Employers then rely on fit with these culturally available *schema* – i.e., mental structures that represent objects and provide assumptions regarding their attributes and relationships (DiMaggio 1997) – when evaluating applicants for these jobs (Heilman 1983; Turco 2010), reproducing existing social divisions (Rivera 2012). For example, men are seen as a better fit and more likely to be hired when employer selection criteria include qualities culturally associated with men (e.g., quantitative skills) while women are seen as a better fit and more likely to be hired when criteria include qualities culturally associated with women (e.g., verbal skills) (Gorman 2005).

When deciding whether a pool contains sufficiently qualified applicants, employers may be even more likely to rely on whether applicants seem like the right "kind of people" for the job because of the higher search costs. The larger amount of information involved in evaluating the quality of a pool – theoretically, all the available pertinent information on all the applicants in the pool – increases search costs and the likelihood employers will rely on visible social characteristics. Indeed, previous research suggests that women are more likely to be disadvantaged by decisions made during hiring stages with higher search costs, such as when employers construct long lists from applicant pools, but are less so during those with lower search costs, such as when employers decide whom to offer employment from among those interviewed (Fernandez-Mateo and Fernandez 2016; Fernandez-Mateo and King 2011; Fernandez and Mors 2008).

Employers may believe that, in an ideal applicant pool, most applicants will fit their schema of the right "kind of person" for the job, and when the qualities needed to perform the job are widely associated with particular social groups, then these schema will be too. Though we know little about how employers evaluate applicant pools, emerging research suggests that employers pay less attention to applicants who differ from the "kind of people" culturally associated with the jobs in question. Employers put less effort into opening and reading the résumés of applicants from minority groups (Bartoš et al. 2016) and ignore pools generated through public postings because they believe that those outside the elite East Coast universities from which they recruit are ill-suited for the job (Rivera 2015). Whether relying on schema is actually beneficial is very unclear because it rests on the assumption that social characteristics associated with right "kind of person" reflect real differences in the distribution of ability in the population, which is not necessarily the case. Furthermore, the demographic composition of applicant pools tends to systematically differ from that of job holders because applicant pools include individuals who are not currently in the workforce like students who tend to be younger, more female, and more racially diverse (Gastwirth 1981).

We expect that when deciding whether to hire, employers rely on whether a large proportion of job applicants fit their schema of the right "kind of people" for the job, a tendency we term *proportional prejudice.* When an applicant pool contains a large proportion of gender atypical applicants, employers may believe the pool is not of sufficient quality to hire because it does not seem to contain the right "kind of people," whereas when an applicant pool contains a large proportion of gender typical applicants, employers may believe the pool *is* of sufficient quality because it confirms their expectations about what "good" applicants should look like. For instance, if employers believe the right "kind of people" for programming jobs are men and the right “kind of people” for writing jobs are women, they may infer that a larger proportion of male applicants signals a highly skilled pool for a programming job and a larger proportion of female applicants signals a highly skilled pool for a writing job. As a consequence, when they receive an applicant pool that is mostly male for a writing job or mostly female for a programming job, they may be more likely to decide not to hire anyone from the pool and in this way, reproduce existing patterns of sex segregation.

Scope Conditions

Our proposed theory of proportional prejudice is most applicable when the hiring contexts meets the following three conditions. First, our theory is predicated on the fact that employers are limited in their ability to evaluate in detail all the information on all the job applicants they receive. Therefore, it likely more applicable in instances where there is broad set of job applicants who apply and are not vetted in any way. With a wide breadth of job applicants, there is a greater likelihood the employer will make a cursory assessment of whether the pool is worth examining in detail. Given that a nationwide survey of employers reported that the average job opening attracts 75 résumés and more than half of those surveyed spend two minutes or less reviewing each application (Haefner 2008), this is likely broadly applicable.

Second, for our theory to apply, the decision not to hire must be available to employers. If deciding to not hire is costly to an employer, say under extremely tight labor market supply conditions or if an employer is facing tremendous growth, then the employer will likely spend additional time examining the applicant pool to identify a candidate. Recent studies suggest that circumstances in which this condition is met are relatively widespread. For example, Andrews et al. (2008) documented that 34% of 17,759 job vacancies listed between 1985-1992 on a Youth Career Services employment service in Lancashire, England resulted in no applicant being hired.

At the other end of the employment spectrum, executive recruiting, Fernandez-Mateo and Fernandez (2016) detail how a search firm started with 218 open positions but only made 112 job offers, suggesting that employers decided not to hire for 49% of the jobs. More generally, according to a new report from Indeed and the Centre for Economic and Business Research (CEBR), about 43 percent of job openings are filled within the first 30 days but the remaining 57 percent of job openings will likely stay unfilled for three months or more. Relatedly, our theory is more likely to apply in situations where the cost of advertising a job and receiving applicants is low. As a result of the transition from newspaper to internet job postings, the cost of advertising jobs has declined – some of the largest recruitment websites like *Indeed.com* even allow employers to post jobs for free. Proportional prejudice is likely less salient when these costs are high.

Third, our theory also necessarily implies that the job being filled is gendered. Because we posit that employers will use the gender of job applicants to quickly surmise whether to investigate in more detail, gender needs to appear relevant to the task at hand. Relatedly, for an employer to use gender in their initial screening process, the gender of the job applicants must be visible. This condition is likely met in a wide variety of contexts because many jobs are gendered and gender is readily visible through the first names contained on standard résumés. Our theory is likely less applicable when a job is regarded as gender neutral or when gender is not visible in the selection process, such as the "blind" auditions used by top symphony orchestras (Goldin and Rouse 2000).

An Online Job Market for Contract Labor

We examined job application and employment activity on the largest platform for the hiring of online temporary workers, Elance.com, which connects skilled freelance workers with employers seeking to hire them. Elance was founded in 1999 as the first platform to connect freelancers worldwide with employers of temporary contract labor for virtual work tasks. It has since merged with oDesk in 2014 (the other largest online platform for temporary contract work) and the combined entity was renamed UpWork in 2016. Upwork is now the largest platform in the virtual contract labor space with over $1 billion in hiring transactions completed in 2015, compared to their next largest competitor, Freelancer, with approximately $138 million in hiring transactions. There are currently over twelve million freelancers and five million employers registered on the website with over two million jobs posted each year. Employers, 43% of whom are individuals and 42% small companies of about five employees, seek to employ freelancers through job posting they place on the platform.

An investigation of online job seeking and employment practice is timely. As the Pew Research Center reports, over 45% of adults have applied for employment online, and internet based employment resources now rival personal and professional networks as the top source for job information for individuals contemplating a job search (Smith 2015). The phenomenon of temporary "gig-economy" work, in general, and skilled freelancing in particular, has seen rapid recent growth as an employment relationship. A recent investigation revealed that a full 15.8% of the U.S. labor force consider themselves employed in non-standard work in 2015, up from 10.1% in 2005, which includes skilled temporary contract labor and part-time employment (Katz and Krueger 2016). Other estimates that include individuals who dabble part-time in counts of self-employed freelancers suggest up to 53 million individuals have attempted to freelance at least part-time (Freelancers Union 2015). While only a proportion of the overall freelance market, online platforms that enable temporary contract work are growing tremendously quickly (Farrell and Greig 2016). Scholars suggest that this trend is replacing traditional work relationships with a market-based, on-demand workforce (Cappelli 1999), and industry analysts and consultants have all identified them as being a critical sector of the job market (Gartside et al. 2013), leading the popular press to suggest we are in 'the age of the virtual worker.'

A hiring event begins with an employer listing a job posting on the platform (see Figure 1 for a sample job posting). There is no cost to posting a job on the platform. Job postings include a description of the work that needs to be completed along with details regarding timing and cost expectations. All job postings are classified within one, and only one, job category, which parallels generally understood divisions of offline jobs as well. There are eight job categories: Sales & Marketing, Admin Support, Writing & Translation, IT & Programming, Design & Multimedia, Finance & Management, Engineering & Manufacturing, and Legal[3]. The top three job categories by volume are Writing & Translation, Design & Multimedia, and IT & Programming, which encompass approximately 80.5% of all the jobs posted in 2012. Employers rely on these job categories to search for freelancers to hire and freelancers use them to browse for available jobs.

[Insert Figure 1 about here]

Below the job categories are job sub-categories that more specifically classify job postings. All job postings are also listed under one, and only one, job sub-category, which are nested in one and only one job category. The top three job sub-categories under IT & Programming are Web Programming, Web Design, and Mobile Application Development; the top three job sub-

[3] Legal jobs comprise 0.77% and Engineering & Manufacturing jobs comprise 1.06% of all jobs in 2012. For brevity, we do not report these job categories.

categories that appear in Writing & Translation are Web Content, Article Writing, and Translations. In all, there are 162 job sub-categories, nested in the above eight job categories. A full list of job sub-categories within job categories, appears in the Appendix.

Once a job posting is listed, any and all freelancers are free to apply. Employers may also invite specific freelancers to apply. When applying for a job, each freelancer enters a price at which they are willing to complete the work and writes a paragraph or two of text to the employer, which is linked to their online profile. Though the mean bid for a job was $752,810.90, due to some clear outliers, the mean employers paid for a job was approximately $335 during this time period.

Figure 2 depicts employers' view of the applicant pool for a job posting. The order of applicants is initially sorted chronologically, with the earliest applicant first, though an employer can manually sort by the bid price or ratings. At this stage of the hiring process, the employer will only see job applicants' photos, their hourly rate, summaries of past jobs, their level score, and their feedback star ratings. On average, each job posting received 9.7 job applicants, with a maximum of 687 applicants. However, many jobs received only one job applicant because an employer invited a particular freelancer to apply in order to hire them specifically. This occurred approximately 3% of the time. Removing these cases resulted in an average of 13 job applicants for each competitive job posting.

[Insert Figure 2 about here]

Employers can examine the freelancers who applied to their job more closely by clicking on individual applicants, which brings them to each applicant's Profile Page (see Figure 3). This is a freelancer's online résumé and is available to any potential employer. It includes (among other details) a photograph and name or logo of the freelancer,[4] their past experience on the platform, star ratings received from past employers, and a level score. The level score is generated by the platform's proprietary algorithm that takes into account star ratings, past experiences, past repeat employers, price history, and bidding success.

[Insert Figure 3 about here]

A job posting is active for about a week, during which time an employer has the option of deciding whether or not to hire anyone who has applied. Despite the number of job applicants and the availability of detailed information about their past work experiences, employers on the platform claim the biggest hiring challenge they face is finding qualified talent (Johnson et al. 2015). In a survey of employers who had used the platform in October of 2015, 49% (by far, the modal response) of the 1,543 respondents indicated "Finding a qualified freelancer for your job" when answering: "Which step(s) in the hiring process did you find most challenging?" Of those who claimed finding qualified talent was the most challenging step, 30% (the top response) indicated "not enough qualified candidates/choice" or "too many unqualified applicants."

Current Study

Elance provided us with data from their operational database from their inception to mid-2013. For this study, we examine all job posting, applying, and hiring activity that occurred on this website for 2012. We use 2012 activity because this was the last full year of hiring transaction data we received, allowing us to account for potential seasonal differences in the types of jobs employer may hire for on this platform. Data from all website activity since the founding of this platform in late 1999 are incorporated in the analyses when appropriate; for

[4] There are both individual freelancers and organizations on the platform, for simplicity we refer to both as "freelancers." Organizations comprise approximately 20% of the applicants. Instead of photos and actual names, organizations display logos and the name of the organization – which cannot be identified with a specific gender.

example, measures of freelancer past experiences are calculated from the time they entered the platform. Available information included unique identifiers of each employer and freelancer, all the jobs posted on the website including its category and sub-category, which freelancers bid on which jobs, and details from freelancer applications like the price at which they were willing to work, and who (if anyone) was eventually hired. We were also able to account for observable measures of ability and experience, as the website tracks all feedback ratings as well as past experiences on the platform visible to an employer. For the period under study, there were 792,697 posted jobs, by 249,505 employees who received 7,696,296 job applications from 292,518 freelancers.

In our observation window, approximately 42% of all job postings ended without an offer of employment being extended. There are three considerations to put this into perspective. First, online hiring is a relatively novel phenomenon, so some employers may be experimenting with the platform by posting a job without the intention of hiring anyone. The percent of jobs ending with no offers being extended by employers who have hired at least once on this platform is 33%, much more in line with extant studies on non-hiring. Second, since there is no cost to posting a job, employers may see this as an inexpensive way to gather information about a job they may be considering filling offline. We address these possibilities empirically below. Finally, and more germane to our argument, employers may not be satisfied with the job applicants they received and may choose to not hire anyone and instead re-post the job again in the hopes of drawing a better set of applicants. We explore the implications of employer decisions to not hire anyone in more detail below.

Gender Coding

The platform does not store, nor explicitly highlight, the gender of a freelancer. Instead, employers can infer this from a freelancer's name and photo visible on their profile, reported in Figure 3. We used these two indicators to code the gender of each freelancer. We scraped the names and photos of all freelancers on the Elance platform active in 2012. We used two techniques to code for gender. First, we used the website Gender API (www.gender-api.com), which has a database of 1,877,782 names, covering over 178 countries, to code the first name of the freelancer for gender. The API returns a percent likelihood that a name is matched either as a female or male, and we set a cutoff at 75%. This yielded an identifiable gender for 71% of all freelancers by their first name.

We then used the freelancer's photo to identify gender for the remaining 29% freelancers. We presented the photos to MTURK workers, who were paid to identify the gender of the individual. Pretesting of gender coding for a subset of freelancers produced a 91% rate of consensus between two independent online raters, so we used one rater for the majority of the photos. Of the remaining 29% of freelancers, we were able to visually identify 40% of them from their photos.

The two combined techniques therefore allowed us to identify the gender of approximately 83% of the freelancers in our study window. Visual inspection of the photos that were unable to be coded for a gender revealed that they are companies operating with a firm name and a graphic logo. See Figure A.1 in the Appendix for an example of a company profile. They are therefore not individuals and, reasonably, neither male nor female. We coded these entities as a 'company' in our dataset. Figure 4 reports on the male and female breakdown of active freelancers on the website in 2012 as well as their application activity. Overall, 39% of the individual freelancers on the website were women, who accounted for 36% of the application activity.

[Insert Figure 4 about here]

Gender-Typed Jobs

We use job categories to identify female- and male-typed jobs. Following past research (Correll 2001; Gorman 2005), we operationalize the jobs posted in the Writing & Translation category as female-typed and jobs posted in the IT & Programming category as male-typed. To ensure this categorization was accurate in our setting, we investigated the actual percentages of women and men freelancers on the platform who worked in these job categories, with the expectation that there would be a greater percentage of female freelancers active in the female typed-job category than for male-typed jobs. We found that 21% (13,123/62,277) of the freelancers who applied to at least one IT & Programming job were female but 52% (30,403/58,362) of the freelancers who applied to at least one Writing and Translation job were women, which, compared with the 39 percent of female freelancers on the platform as a whole, confirms that these jobs are gendered on this platform.

Reconciling Study Context with Scope Conditions

Our setting corresponds well with the previously outlined scope conditions. First, employers are limited in their ability to evaluate each job applicant in detail because even though the average job is priced relatively low ($335), the average posting receives about 13 applicants, if it receives more than one. This suggests it is relatively costly for an employer to examine every applicant in detail. Supplemental analyses confirm that employers only closely examine an average of about three job applicants for each job. Second, an employer bears almost no cost for not offering employment to any job applicant in this context because posting a job on the platform is free. Third, we have chosen to focus exclusively on the two job categories that are gendered female and male – Writing & Translation and IT & Programming – and the gender of job applicants is visible to employers through the prominent display of applicant first names and photographs.

Analytical Strategy

We set out to demonstrate whether and how employer decisions not to hire reproduce sex segregation through a two-stage analytic strategy. In the first set of analyses, we provide support for our proposed theory of proportional prejudice. With data from the Elance platform, we show that having a greater proportion of gender atypical job applicants leads to a greater likelihood of an employer deciding not to hire anyone. With a complementary online survey experiment, we test the proposed mechanism: that employers believe an applicant pool with a greater proportion of gender atypical job applicants is less likely to contain the "kind of people" with the skills for the job. In the second set of analyses, we analyze job posting, applying, and hiring behavior on the Elance platform and show how we reach different conclusions as to whether employers reproduce sex segregation when we include cases that end with decisions not to hire anyone and when we exclude them.

Analysis 1: Proportional Prejudice and Decisions Not to Hire

In the following first set of analyses, we show that the decision by an employer to not hire to any job applicant is a function of the proportion of gender atypical job applicants in the pool by examining the hiring activity of employers on Elance with statistical models. We bolster our arguments with the use of several robustness checks for spuriousness. Then, we use an experimental approach to isolate the mechanism through a complementary online survey.

Dependent variable. The dependent variable of interest is whether an employer decides to hire anyone from the set of job applicants they receive. The level of analysis is the job-posting, with the outcome coded =1 if the employer decides not to award the job to anyone in the applicant pool and =0 if the employer decides to do so.

Independent variable. Our independent variable of interest is the proportion of gender atypical job applicants each job posting received. We operationalize this as the percentage of female job applicants who applied to each job posting. This is measured as the number of female job applicants each job posting received divided by the total number of job applicants of known gender. This variable ranges from 0 to 1 for each job posting. We report the density of jobs by the percentage of female job applicants, for each high-level job category in Figure 5.

[Insert Figure 5 about here]

Two features of the distributions ae notable. First, across all job categories, there is a reasonable distribution of jobs that span the percentage of females who apply. Specifically, the distributions all approach Gaussian, though with differing means. Second, there is a distinct difference in the distribution of the proportion of females applying to IT & Programming jobs versus Writing & Translation jobs. The mean percentage of female job applicants for jobs in Writing & Translation is about 56% while the mean for IT & Programming is 23%. In short, employers are likely to receive a greater proportion of job applications from women than from men for a Writing & Translation job compared to an IT & Programming job.

We report the graphical relationship between the likelihood of a job posting ending without any applicant being extended an offer of employment and the percent of female job applicants they receive. We divided the percentage of female job applicants into 10% bins (i.e. 0-10%, 11-20%, etc.) and report the results for IT & Programming jobs and Writing & Translation jobs separately. The non-parametric binomial point estimates, with 95% Confidence Intervals, of the likelihood that the jobs within a 10% bin end with no job offers being extended are reported in Figure 6.

[Insert Figure 6 about here]

The results are dramatic. As shown in Figure 6, the percentage of female job applicants increases as we move right along the horizontal axis. As the percentage of female job applicants increases, there is a significant, monotonic increase in the likelihood of an employer choosing not to hire anyone among their set of job applicants, for IT & Programming jobs. Conversely, this relationship is the opposite for Writing & Translation jobs, where the likelihood of an employer hiring anyone among a set of job applicants increases with a greater proportion of female job applicants.

Control variables. We explore this relationship more rigorously with statistical models. To do so, we also include the identical control variables used in the regressions above at the level of all female and male applicants, to account for the potential differences among men and women who apply. We include the dollar amount of all the *average bids* overall and by females, males, and companies. To account for potential differences in the quality of the applicants, we include the *average star rating* and *average level score* of female, male, and company applicants. We also include the average *number of past jobs* completed in both the bidding sub-category (relevant experience) and the overall experience for female, male, and company applicants. We also included 162 job sub-categories fixed effects into the regressions.

To the extent that the number of job applicants applying to each job is correlated with the proportion of female job applicants (the variable of interest), we need to account for the total number of job applicants a job receives. We do so by including a dummy variable for the number of job applicants applying to each job. In essence, we estimate the effects of the proportion of female job applicants, within all jobs that received the same number of job applicants. More substantively, we included dummy indicator variables for the number of applicants for job, from 2 to 687 job applicants. Including a simple linear control variable for the number of job applicants does not change results. Summary statistics and correlations are reported in Tables 1 and 2.

[Insert Tables 1 and 2 about here]

Models and Results

We model this dichotomous outcome with a logistic regression. Heterogeneity among employers, who may vary on their overall seriousness to hiring on the platform and their preferences for female or male freelancers, is accounted for with the use of an employer fixed-effects specification. We are therefore estimating the *within* employer likelihood of them choosing to hire anyone or not, from repeatedly observing variation in their job posting and hiring behaviors and the proportions of gender atypical applicants they receive. In order to further account for potential heterogeneity between employers who may hire in on job category and not the other, we limit the set of observations to only employers who have posted and hired for jobs in *both* the IT & Programming and Writing & Translation job categories.

Table 3 reports the fixed-effects logistic regression estimates of the likelihood of a job posting ending with a decision not to hire anyone. Model 1 includes only the control variables, which generally behave as expected. The greater the average bid price for the job, the more likely an employer will choose not to hire anyone. The greater the average bids of the female, male, and company job applicants, the greater likelihood an employer will also choose not to hire anyone. The average level score of female job applicants is not significant, though having higher quality male applicants and companies in the applicant pool increases the likelihood no one will be hired (but the effect of female job applicants becomes positive in later models). The effect of the average amount of job category specific experience is negative for female and male applicants and companies, suggesting applicants with more experience are likely to increase the likelihood an employer decides to hire from that pool. The greater number of bids decreases the likelihood of an employer choosing not to hire anyone, perhaps because they have a greater selection of applicants. Finally, having anyone in the applicant pool who has worked previously with the employer also decreases the likelihood the employer will not choose to hire anyone.

[Insert Table 3 about here]

In line with our expectations, a greater proportion of female applicants increases the likelihood of an employer deciding not to hire anyone for male-typed jobs and decreases the likelihood for female-typed jobs. Models 2, 3, and 4 include, in a stepwise fashion, the percent female in the applicant pool, an indicator for whether the job was a Writing & Translation job (=1) or an IT & Programming one, and the interaction between these two, respectively. The percentage of female job applicants, in Model 2, reduces the likelihood of an employer deciding to not to hire anyone. However, with the inclusion of the indicator for the type of job in Model 3, this variable now is estimated to have a positive effect by increasing the likelihood an employer will choose to not hire anyone. Finally, the interaction in Model 4 provides support for our argument. Specifically, the main effect of the percentage of female job applicants on the likelihood of an employer deciding not to hire anyone for IT & Programming jobs is positive and significant while the interaction of proportion female and a writing job is negative and significant. There is a differential effect of the proportion of female applicants has on the likelihood of an employer deciding not to hire anyone for Writing & Translation jobs when compared to IT & Programming. Specifically, for IT & Programming jobs, a standard deviation increase from the mean of 23% of female job applicants increases by 20% the likelihood that a job posting will end with no hire from the employer. Conversely, for Writing & Translation jobs, a one standard deviation increase over the mean of 56% female job applicants for a Writing & Translation job, we observe a 16% *decrease* in the likelihood of a job posting ending without an offer of employment to anyone.

[Insert Figure 7 about here]

To visualize this effect across the complete distribution, we plot the marginal effects (with 95% CIs) of the percentage of females in the applicant pool on the estimated likelihood of a job posting ending with an employer deciding not to hire anyone in Figure 7, parametric estimates that are within employer. The top, upward sloping, solid blue line depicts that, accounting for observables set at their means, the greater the percentage of female applicants in the pool, the greater the likelihood that an employer will decide to not extend hire anyone for an IT & Programming job. This has the opposite effect for Writing & Translation jobs. The red dashed line interval indicates that the greater percentage of female applicants in the pool, there is a commensurate reduction in the likelihood of a job posting ending with no offer of employment.

Robustness Checks

Skill differences. An alternative explanation for the findings above is that female freelancers are, on average, better at writing tasks and that male freelancers are, on average, better at programming. While the regressions above control for all indicators of skill and ability by including the average category experience and level score of the females and males that apply to each of the jobs posted, a skeptical reader may be concerned with how much overlap there is between the men and women applying to each of these jobs. Put another way, the ideal experiment would be to examine only jobs where the visible skills and ability of the men and women applying are as identical as possible and see if the effect of the proportion of female job applicants exerts the same effect on the likelihood of an employer deciding to not hire.

To address this issue, we first calculated the differences in the means of female and male jobs applicants in job category experience and level score within each individual Writing & Translation and IT & Programming job. Specifically, for every job posting, we subtracted the mean of these measures for all female job applicants from the mean of all male job applicants. If female and male applicants were identically matched on these indicators of skill and ability, we should expect the mean of these differences to be statistically indistinguishable from zero. To visualize this, we plotted the histogram of the number of jobs by this measure of difference between male and female job applicants (results are reported in Figure A.2 in the Appendix).

While there are a substantial number of jobs where the average female and male job applicants are essentially identical (i.e., jobs where the difference is very close to zero), there are notable deviations. Specifically, for IT & Programming jobs, the mean of the differences between female and male applicant programming job experience for all jobs is -0.6, suggesting that the average female applicant has less experience than the average male applicant. For Writing & Translation jobs, the mean difference between female and male applicant writing job experience is 17.5, suggesting that female job applicants, on average, have significantly more relevant job experience than male applicants in Writing (t-tests confirm that -0.6 versus 17.5 is significantly, $p<0.001$, different). This pattern of results, while less dramatic, holds when we compare the average level score of the female and male job applicants by Programming versus Writing jobs (mean of -.72 versus .51, $p<0.001$). In short, there are jobs where the differences between female and male applicants are significant and in a direction that may confound our findings, i.e., more qualified women in writing and more qualified men in programming.

To address this concern, we ran the identical models as reported above on a subset of the jobs where the female and male job applicants were as similar as possible on these three measures of ability and skill. We identified job postings where the differences between the female and male applicant pools were within one standard deviation of zero for both male and female job experience and level score, which resulted in a subset of 125,850 job postings for both IT & Programming and Writing & Translation jobs. Put another way, we *only* examined job postings where the female applicants and male applicants were similar to one another in job category experience and level score. Results run on this matched subject of jobs, reported in Table A.1 in the Appendix, do not significantly differ from our main findings.

Employer learning. A related question is whether the employers on this platform are 'learning' about the potential gender differences in skill and ability for gender-typed jobs, and thereby acting 'rationally' by excluding gender atypical applicant pools from further consideration. We believe this effect is due to general and widespread cultural beliefs regarding gender and skills, however, the results could be limited to the employers who have spent time hiring and interacting with freelancers on this platform, which may reflect 'actual' differences in abilities. We reason that if our argument were true, then the effect of proportional prejudice should be reflected in both employers who are familiar and not familiar with hiring on the website. If the effect were replicated for those unexperienced with the platform, then there is little evidence that this phenomenon is isolated to this platform only. In analyses unreported for brevity, we find the identical effect for both employers who have never hired on the platform with those that are more experienced hiring on the platform, supporting our argument that these beliefs are widespread and general, rather than a response to learning about differences on the platform.

Limited range. A reader may be concerned that the differences in the distributions of the proportions of women and men applying to the different job types may suggest that our findings are limited in the ranges of proportions we observe. For example, there are very few jobs where women comprise over 50% of the applicant pool in Programming. To address this issue, we ran identical analyses, but on quartile splines of the observed distribution of proportions of women and men (i.e. 0-25% female, 25-50% female, 50-75%, 75%+ female). Results, unreported for brevity, continue to support our contentions across the whole spectrum.

Isolating the Mechanism: Proportional Prejudice

Our previous analyses show that a greater proportion of gender atypical applicants increases the likelihood of an employer deciding not to hire anyone. These results are consistent with our theoretical argument that employers believe gender atypical applicant pools are less likely to contain the "kind of people" with the skills for gender-typed jobs. Robustness checks provide additional support for these claims. To test proportional prejudice more directly, we used an online survey experiment that mimics the decision-making process of an employer faced with a slate of applicants in this online labor market. We manipulate the proportion of women in the applicant pool and the type of job for which the employer is hiring in an experimental setting. We test the main effect that being presented with a large proportion of gender atypical job applicants increases the likelihood subjects will decide not to hire anyone. We measure our mechanism by demonstrating how the relationship between the proportion of gender atypical job applicants in the pool and subjects' likelihood of deciding not to hire was dramatically attenuated below the level of significance ($p<0.05$) by subjects' assessment of the suitability of the applicants they received.

Method

We conducted an online experiment where we mimicked the virtual environment experienced by employers on the Elance platform. In total, 185 adults from Amazon Mechanical Turk ($Mean_{age} = 34$, s.d. = 11; 55% male) participated in exchange for $0.25 each. We limited our subject pool to those residing in the U.S. as over 50% of the employers on the Elance platform are based in the United States.

Procedure

We employed a 2 (Male versus Female-typed job) x 2 (Gender Typical versus Gender Atypical applicant pool) between participant design. In the Male-typed job scenario we asked subjects to evaluate applicants who applied for a job offer "to code you a computer program that will automate the copying of information from a website into a database." Subjects in the Female-typed job scenario were asked to evaluate applicants for a job offer "to assist you in writing and editing a 400-page novel." We presented subjects the exact same webpage, reported in Figure 2, that an employer would see when viewing job applicants on Elance. To vary the typicality of the gender of the applicant pool, we altered the photos and names of freelancers to be either 80% male or 80% female. For the Gender Typical condition we presented the applicant pool consisting of 80% men for the male-typed computer programming job and 80% women for the female-typed writing job; for the Gender Atypical condition, we presented the applicant pool consisting of 80% women for the male-typed computer programming job and 80% men for the female-typed writing job. All other visible cues, such as experience and quality measures, remained exactly the same. To ensure consistency, all freelancers were Caucasians between the ages of 20-30. Experimental materials are available from the authors.

To measure a subject's perception of the overall quality of the applicant pool, we asked the extent the subject agreed (5-point Likert scale) with the following statement: "The freelancers that applied seemed skilled enough for my job." To measure a subject's likelihood of hiring a job applicant from the applicant pool, we asked "Of the applicants I received, I am" with responses being, "Very likely to hire at least one," "Somewhat likely to hire at least one," "Somewhat Unlikely to hire anyone - may post job again, and "Very Unlikely to hire anyone - rather post job again," coded as 1, 2, 3, 4 respectively.

Results and Discussion

Confirming our statistical tests above, we find that subjects who were presented with a majority of gender atypical job applicants were more likely to indicate a significantly greater likelihood of choosing to not hire anyone among the applicants they received (N=92, $\text{Mean}_{Atypical}$ = 1.76. s.d.=0.05, $p<0.001$) than subjects who received a majority of gender typical job applicants (N=93, $\text{Mean}_{Typical}$ = 1.34, s.d.=0.08). We also find that subjects who were presented with a majority of gender atypical job applicants were also significantly more likely to indicate the applicant pool they received was less skilled ($\text{Mean}_{Atypical}$ = 2.09. s.d.=0.09, $p<0.001$) than those who received a majority of gender typical job applicants ($\text{Mean}_{Typical}$ = 1.61, s.d.=0.07). Figure 9 reports these results graphically.

[Insert Figure 8 about here]

We next tested whether subjects' impression of skill level of the applicant pool was the reason they decided whether or not to hire. We used a linear probability model to estimate this effect, though because the outcome of the decision to hire was ordinal in nature (i.e. 1, 2, 3, 4) we also confirmed the results with an order logistic regression (results are identical). We report the results of the Linear Probability Model in Table 5.

[Insert Table 5 about here]

As expected, when subjects were faced with a greater proportion of gender atypical job applicants, they were less likely to hire anyone among the pool, despite controlling for all observable indicators of ability. Model 1 reports the positive and significant effect of the job applicant condition (Greater Proportion Gender Atypical =1) on the likelihood of the subject choosing to not hire (=1) from the applicants they received. Model 2 reports the positive and significant effect of subjects' perceptions of the skill level of the applicant pool they received, indicating that this swayed their decisions whether to hire anyone. More telling, the indicator for whether the condition was a greater proportion gender typical or atypical declines in significance. This attenuation allows us to conclude that the mechanism driving the effect is as hypothesized. In unreported models (available from the authors) we included additional controls, such as the age and education level of the subject, and an indicator for whether it was a writing versus programming job, in the same regressions and the results were unchanged. As a final check, we ran the same analyses only on subjects who indicated that they had previous experience hiring freelancers online (N=62). There were no significant differences in results between this population and the general Mturk population.

Analysis 2: The Impact of Decisions Not to Hire on Sex Segregation

Having demonstrated that employers are more likely to decide to not hire when the applicant pool has a higher proportion of gender atypical applicants, we now show how proportional prejudice partially explains why some studies conclude that employers drive sex segregation and others do not. We do so by examining the hiring outcomes for individual job applicants on the same Elance platform and comparing the outcomes of job applicants from female and male freelancers *unconditional* on whether any applicant was hired with the outcomes of female and male freelancers *conditional* on an applicant being hired. In other words, we compare differences in outcomes by gender when we include cases for which employers decided not to hire anyone to differences in outcomes when we exclude these cases. These two approaches parallel the outcomes of field experiments that find disadvantages for gender atypical applicants and the outcomes of statistical analyses of company hiring data, which necessarily condition on a set of hired applicants and find that employers hire men and women at rates equivalent to the rates at which they apply.

Hiring Outcomes Including Jobs Where Employers Decided Not to Hire

Dependent variables. For the second set of analyses, we examine the extent to which there are differences in hiring outcomes for female and male applicants, which would suggest that employers drive sex segregation. Our dependent variable of interest is whether a freelancer was hired or not, conditional on applying to a job posting. For each job application submitted, the outcome is set =1 if that freelancer was hired, versus 0 if not.

Independent variables. We are interested in estimating the likelihood that, controlling for observable bid, quality, and experience, a female versus male freelancer is hired. The independent variable of interest is the freelancer's gender: male versus female. Job applicants are also classified as being a company, and therefore without a gender. We include these three dichotomous, mutually exclusive, and completely exhaustive designations as indicator variables, with males as the omitted category.

The moderator is whether the type of job the applicant is applying to is male or female-typed. As we mention above, we coded all jobs that were posted in Writing & Translation as a female-typed job (=1) and jobs that were posted in IT & Programming as a male-type jobs (=0).

Control variables. We also included control variables at the level of each individual job application. Specifically, we control for the *bid*, i.e., the price at which the freelancer was willing to work (+0.01, logged). Because many freelancers indicate they are willing to work for free, perhaps for the experience, we also include an indicator if the *bid was zero* (=1). We also include extensive controls for freelancer skills and experience. For measures of reputation, we include the *average star ratings* at the time of applying and an indicator as to whether or not the freelancer had *no star ratings* at all (=1). We also include an Elance generated *level score* which is calculated by the website and a function of the freelancer's past experience, star ratings, and also bidding success. We include an indicator as to whether the freelancer had *no level score* (=1). For experience, we include the total *number of past jobs* a freelancer has completed (+ 0.01, logged) as well as the *number of past jobs in focal category*, i.e., the job category they are applying for (+ 0.01, logged). We also include an indicator as to whether or not the applying freelancer and the employer have *worked together previously* (=1), as working together should ameliorate any uncertainties of quality of the freelancer. Finally, as noted above, even within each of the job categories of Writing & Translation and IT & Programming, there could be variation in the gender typicality of the job sub-categories within each of these categories. To account for this, we included the 162 job sub-category fixed-effects into the regressions. Summary statistics and correlations are reported in Tables 6 and 7.

[Tables 6 and 7 about here]

Models and Results

We modeled the job applicant level dichotomous outcome, whether the freelancer who applied for the job was hired or not, as a logistic regression. To account for employer heterogeneity in their overall likelihood of hiring a female or male freelancer, we utilized an employer fixed-effects specification. We only included jobs posted by employers who had hired in both IT & Programming and Writing & Translation job categories in the past and pooled both types of jobs together into the regression. In total, we are left with 4,211,343 job applications.

In our first set of analyses, we estimated the likelihood of a female versus male freelancer being hired on ALL job applications, pooling both jobs that ended with someone being hired with those that ended with an employer deciding not to hire. This mimics what a job seeker would experience and the results attained through field experiments because both applicants and researchers sending matched applications to job postings would likely not know whether the employer had decided to not hire anyone. Results of the fixed-effect logistic regressions are reported in Table 8.

Model 1 presents the base model of the likelihood of being hired, conditional on applying to a job posting in the IT & Programming or Writing & Translation job categories. The control variables generally behave as expected. The more an applicant bids, the less likely they will be hired, though bidding zero is such a poor signal of confidence, it dramatically reduces the applicant’s chance of being hired. Better star rating feedback scores and level scores lead to a greater chance of being hired, while having no feedback reduces an applicant’s likelihood of being hired, likely because when an employer doesn’t leave feedback after a job, it is construed as poor feedback unsaid. However, having no level score increases one’s chance of being hired, perhaps because employers on this platform are willing to try out new freelancers. Level scores are only designated after a certain number of jobs, so is not necessarily a signal of poor quality. Consistent with the category spanning literature in labor markets (Leung 2014; Zuckerman et al. 2003), additional general experience decreases a freelancer's likelihood of being hired, but additional job experience in the focal job category increases the likelihood. Unsurprisingly, working together previously with an employer increases the likelihood of being hired again. Finally, applications by a company are less likely to be hired, perhaps because the marketing focus of the platform is individual freelancers and employers who use the platform are more likely to want to use individual freelancers.

[Insert Table 8 about here]

In line with the results of field experiments, we find that female applicants are more likely than male applicants to be hired in response to female-typed job openings while male applicants are more likely than female applicants to be hired for male-typed job openings. Models 2, 3 and 4 investigate the likelihood of a female job applicant being hired overall and whether this varies by the type of job they are applying for. We first include the indicator of a female job applicant, then add an indicator (=1) if the application was to a Writing & Translation job, and finally, we include the interaction term of gender of the freelancer and whether it was to a Writing & Translation versus an IT & Programming job. In Model 2, we see that the coefficient for female job applicant is not significant, suggesting that a female job applicant is not more or less likely than a male job applicant to be hired in response to a job opening, conditional on applying to a job. Model 3 demonstrates that applying to a Writing & Translation job is not more or less likely to end with someone being hired compared to an IT & Translation job. Finally, the results in Model 4 demonstrate that a female job applicant is more likely than an equally qualified and experienced male job candidate to be hired in response to a posting for a Writing & Translation job. Specifically, a female applicant is 5% more likely (1-exp(0.11-0.06)) to be hired than a similarly qualified male applicant. Conversely, females are 6% less likely (1-exp(-0.06)) to be hired when applying to an IT & Programming job than equally qualified male freelancers. Together, this set of analyses suggests that female applicants are disadvantaged compared to male applicants for male-typed jobs while male are disadvantaged compared to female ones for female-typed jobs.

Hiring Outcomes Excluding Jobs Where Employers Decided Not to Hire

We now examine how these results change conditional on an employer deciding to hire someone. These results would parallel the approach taken by studies of company hiring data, within which job applicants who were hired are compared to those who were not hired for jobs that were ultimately filled. To account for this, we modeled the outcome of being hired as a conditional logit, grouped by job posting, in essence, a McFadden choice model (1984). This modeling strategy most accurately reflecting the decision an employer makes when choosing among a set of job applicants and requires an employer receives more than one job applicant and hires one of the applicants, otherwise there would be no variation in the outcome variable within the group and these observations are dropped from the analysis. Modeling the outcome in this manner necessarily eliminates from consideration job postings where no applicant was hired from our analysis set. Given these limitations, we are left with a total of 27,004 jobs in IT & Programming and 22,419 Writing & Translation jobs.

Fixed-effects models grouped by job posting eliminate variation at the application level of the job category in which the job was originally posted. We therefore split the sample of jobs postings into IT & Programing jobs and Writing & Translation jobs and run separate regression models and compare the coefficients for a female job applicant to one another. We include the same control variables as above. As before, to account for heterogeneity between employers who may only hire in the female or male-typed jobs, we further limit our sample to employers who have hired for *both* Writing & Translation and IT & Programming parent job categories. Results of the McFadden choice models are reported in Table 9.

[Insert Table 9 about here]

In line with the results of studies of company hiring data, we find that, conditional on someone being hired for a job, there is no significant difference for female applicants compared to male applicants in their likelihood of being hired for male-typed jobs, though female applicants are still significantly more likely than male applicants to be hire for female-typed jobs. Models 1 and 3 report results of the control variables and are run on the separate populations of IT& Programming jobs and Writing & Translation jobs respectively. The control variables behave generally as expected, and mimic the results from the above analyses reported in Table 6; for brevity, we avoid repeating the discussion of their effects. Models 2 and 3 include an indicator for whether the job applicant was a male or female, for IT & Programming jobs and Writing & Translation jobs respectively. In Model 2, we see that a female applicant (compared to a male applicant) does not experience a significant difference in her likelihood of being hired for an IT& Programming job, conditional on a job applicant being hired for that job. Conversely, in Model 4 female job applicants are significantly more likely to be hired than similarly qualified male applicants when they apply for Writing & Translation jobs, conditional on any applicant being hired. Specifically, they are about 23% (1-exp(0.24)) more likely.

To put the results from the two preceding analyses into perspective, Figure 9 reports the point estimates (and 95% CIs) of the coefficients for a female (compared to a male) applicant being hired for IT & Programming versus Writing & Translation job posting – unconditional and conditional on whether anyone was hired for the job posting. Here, we can compare the changes in the effect that the gender of the job applicant has on their likelihood of being hired or not, for all jobs and for jobs that ended with an offer of employment. Beginning on the left side, we note that unconditional logistic regression estimates of the likelihood a female freelancer will be hired for an IT & Programming job, designated by the open circle, is significantly negative and also significantly less than the conditional likelihood of them being hired if a job posting concluded with an offer of employment, as designated by the closed circle. In contrast, the unconditional logistic regressions demonstrate that female freelancers are significantly more likely to be hired than male freelancers for Writing & Translation jobs, though when only considering job postings where someone was hired, this female advantage increases significantly.

[Insert Figure 9 about here]

Discussion and Conclusion

By analyzing uniquely detailed data from an online platform for hiring skilled temporary contract labor, this study sheds light on a novel way in which employers reproduce sex segregation through proportional prejudice. We propose and statistically test the novel argument that employers are more likely to decide not to hire when there are a large number of gender atypical applicants in the pool they receive. A complementary survey experiment provides support for our mechanism: Subjects were more likely to decide not to hire anyone when applicant pools had a large proportion of gender atypical applicants because they believed these pools were less likely to contain applicants who "seemed skilled enough for my job." These findings contribute to theory and research on sex segregation, discrimination, and online labor markets.

Our findings contribute to the large literature on occupational sex segregation by identifying a novel source of its persistence. Building on the insight that employers rely on applicants' fit with the culturally available schema of the typical job holder when deciding *whom* to hire (Gorman 2005; Rivera 2012; Turco 2010), we argue that employers rely on the same schema when deciding *whether* to hire from the applicant pool they receive. We show that hiring patterns in the largest online labor market are consistent with this argument and provide preliminary evidence for the mechanism of proportional prejudice through an online survey experiment. In doing so, we shed light on a previously ignored source of sex segregation and answer calls (e.g., Reskin 2003) to isolate the mechanisms that produce gender differences in employment outcomes.

Our study also contributes to the broader research on discrimination by offering a novel explanation for why the two most empirically rigorous approaches – field experiments and analyses of organizational hiring data – come to seemingly contradictory conclusions. When jobs for which employers decided not to hire anyone were included in the analysis, we find a significant hiring disadvantage for women in male-typed jobs, but when these cases are not included, we find that men and women are equally likely to be hired for these jobs. By identifying a previously overlooked difference in how the two approaches treat employer decisions not to hire anyone, we show that women can experience a disadvantage even when employers hire men and women at rates equivalent to their representation in the applicant pool because sex segregation can be reproduced through decisions not to hire. Given that similarly mixed results are present in hiring research on the effects of race (Pager 2007), we suspect that decisions not to hire and the proportional prejudice they engender are an unstudied source of discrimination beyond gender. When jobs are culturally associated with a social group and membership in that group is readily visible to employers, a larger proportion of applicants from outside that group may signal a lower skilled pool to employers. On the platform we study, for example, race and age are highly visible from photographs and could trigger proportional prejudice but social class and sexual orientation are less visible and thus less likely to do so.

This study also provides novel insight into how applicant pools impact sex segregation. Most studies that assess the role of employers in sex segregation rely on statistical analyses of large datasets and attribute the residual gender difference in employment outcomes, after controlling for all other potential influences, to employers (for reviews see Reskin 1993; Reskin and Bielby 2005). Yet most of these "post-hire" studies analyze data on people who have already been hired; we can only determine the extent to which employer hiring decisions reproduce existing social divisions if we account for applicant actions that operate prior to these decisions (Fernandez and Sosa 2005). Few studies of sex segregation have visibility into who applies to which jobs (Fernandez and Campero forthcoming; Petersen, Saporta and Seidel 2005) and of those that do, most focus on the *vertical* sorting of women into higher versus lower levels within a single organization (e.g., "glass ceilings"). We, in contrast, are able to examine the *horizontal* sorting of women and men into different types of jobs (e.g., "glass walls") *across* multiple employers. In doing so, we extend the generalizability of these findings and show that applicant pools impacts "glass walls" in addition to "glass ceilings."

Our findings also have implications for the surprising hiring advantage for women in male-typed jobs documented in recent studies of online markets. Women were found to be more likely to raise capital successfully than male founders for technological projects on an online crowdsourcing platform (Greenberg and Mollick 2016), receive higher ratings than their male counterparts for mathematically-intensive database and web analytic tasks on an online freelance platform (Hannák et al. 2017) and be on an equal playing field with male candidates for programming jobs on another online freelance platform (Chan and Wang forthcoming). We too found that female job candidates were on an equal playing field for programming jobs *until* we included jobs for which employers decided not to hire anyone and the female disadvantage resurfaced. Such findings suggest that, in online markets, the female hiring disadvantage manifests more in decisions not to hire than in whom to hire.

We expect that decisions whether to hire are generally more likely to rely on culturally-available schema than decisions whom to hire and the latter may be even less vulnerable in online labor markets than traditional ones for multiple reasons. Employers in online labor markets may be more amenable to female job seekers because of the inherent flexibility in work arrangements and geographic freedom. Additionally, these platforms remove the potential influence of human resources managers and other intermediaries, such as headhunters (Fernandez-Mateo and King 2011), who may 'steer' female applicants away from certain jobs. Online hiring platforms also provide employers with quantitative metrics of performance for all applicants at the individual level, which are likely better predictors of future performance in this task-based labor market than résumés are in traditional ones and may reduce the ambiguity that disadvantages female candidates (Gorman 2006). Finally, given that online temporary employment offers no opportunities for advancement, long-term retention, or leadership positions, women's lack of disadvantage may not be surprising. Future research can examine the ways in which online markets reduce or exacerbate unequal outcomes or provide skilled employment opportunities that heretofore did not exist.

Our findings also have important practical implications. Though efforts have been made to create more equitable outcomes by gender and race (Koput and Gutek 2010), many attempts do not produce their intended results (Kalev, Dobbin and Kelly 2006). There are a myriad of potential avenues to promote inclusion and the extent to which a strategy is successful or not depends on properly identifying the source of the problem (Fernandez and Fernandez-Mateo 2006). To design successful policies that increase women's representation, we need to isolate mechanisms that produce gender differences (Reskin 2003). By revealing how decisions whether to hire can reproduce sex segregation, our study highlights the need to develop strategies that promote inclusion during these decisions. For example, online labor markets could aggregate their individual-level applicant performance metrics into pool-level metrics and use them to compare the pools employers receive to pools generated by similar job postings, thereby providing employers with a more objective measure of pool quality and lowering the chance they will rely on proportional prejudice.

This article has limitations that can guide future research. Like most other studies of the effects of cultural schema (Budig and England 2001; Cech 2013; Gorman 2005), we cannot empirically demonstrate causality because direct measures are not available our dataset. Instead, we show that gender differences in hiring patterns are consistent with this argument and conducted a complementary survey experiment that supports our proposed mechanism, both with a convenience sample of MTurk workers and a sample of MTurk workers who have experience hiring freelancers online through Elance or similar websites. We hope that future research will examine the process underlying how employers decide whether to hire in greater depth. Additionally, we find, contrary to our expectations, the hiring disadvantage for men in female-typed writing jobs does not disappear. We suspect this is because women are more likely to approach the job application process through efforts to develop closeness and connection with their partner, which is particularly important for virtual tasks (Ng and Leung 2015) and, we suspect, for writing tasks, given that writing is about communicating with others. Future research can hopefully clarify this unexpected finding.

Our focus in this article is hiring decisions that are structured as a *slate*, i.e., made at a particular point in time regarding a set of applicants, rather than a *sequence*, i.e., made on each applicant as they apply over time. When hiring decisions are made sequentially, an employer is less able to decide to not to hire from the complete applicant pool because they do not have prior knowledge of who will eventually apply. As such, we suspect proportional prejudice will work in a different way. Rather than inspiring employer decisions not to hire from the pool received, it will extend the amount of time it takes for a position to be filled. With a greater proportion of gender atypical applicants applying, an employer will likely review a greater number of job applicants before being convinced a suitable one is identified.

Our paper demonstrates why it is important for scholars to identify how sex segregation is occurring within the large, complex process of hiring. Using a unique dataset, we show how, in this context, women and men are disadvantaged by employer decisions not to hire anyone rather than employer decisions about whom to hire. Of course, employers impact sex segregation at many other stages: from the way job descriptions are written and the way employers market themselves to candidates, to the sourcing process (e.g. referrals), interviews, and ultimate hiring decisions. This study examines one piece of this much larger puzzle. By highlighting a new way that sex segregation is reproduced, our study demonstrates the need for researchers to continue to search for subtle but pernicious processes that constrain the advancement of both sexes in today's workforce.

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Figure 1

Sample job posting for an IT & Programming job

Scraping data from a website

IT & Programming > Other IT & Programming

Job Status: Selecting Candidate

Posted: Sat, Nov 23, 2013

Location: Anywhere

Start: Immediately

My Team (1)

Budget: Less than $500

Fixed Price Job

Elance Escrow Protection

W9 Not Required

6 invited

Hi there,

I need someone to scrape data from a website and provide the data and the code used to me. The code should be in Python or Perl.

Specifically, I need the following four datafields scraped from the metacritic.com website, for only the movies.

- Movie Title
- Production Company
- Release Date
- Home Release Date

I have attached a sample screenshot of the page from which this data will come from. Note, I've circled the fields I would need scraped.

Webpage: http://www.metacritic.com/movie/the-worlds-end/details

Title: The World's End
Production: Relativity Media
Release Date: Aug 23, 2013
Home Release Date: Nov 19, 2013

Figure 2

Illustrative Applicant Pool for IT & Programming job

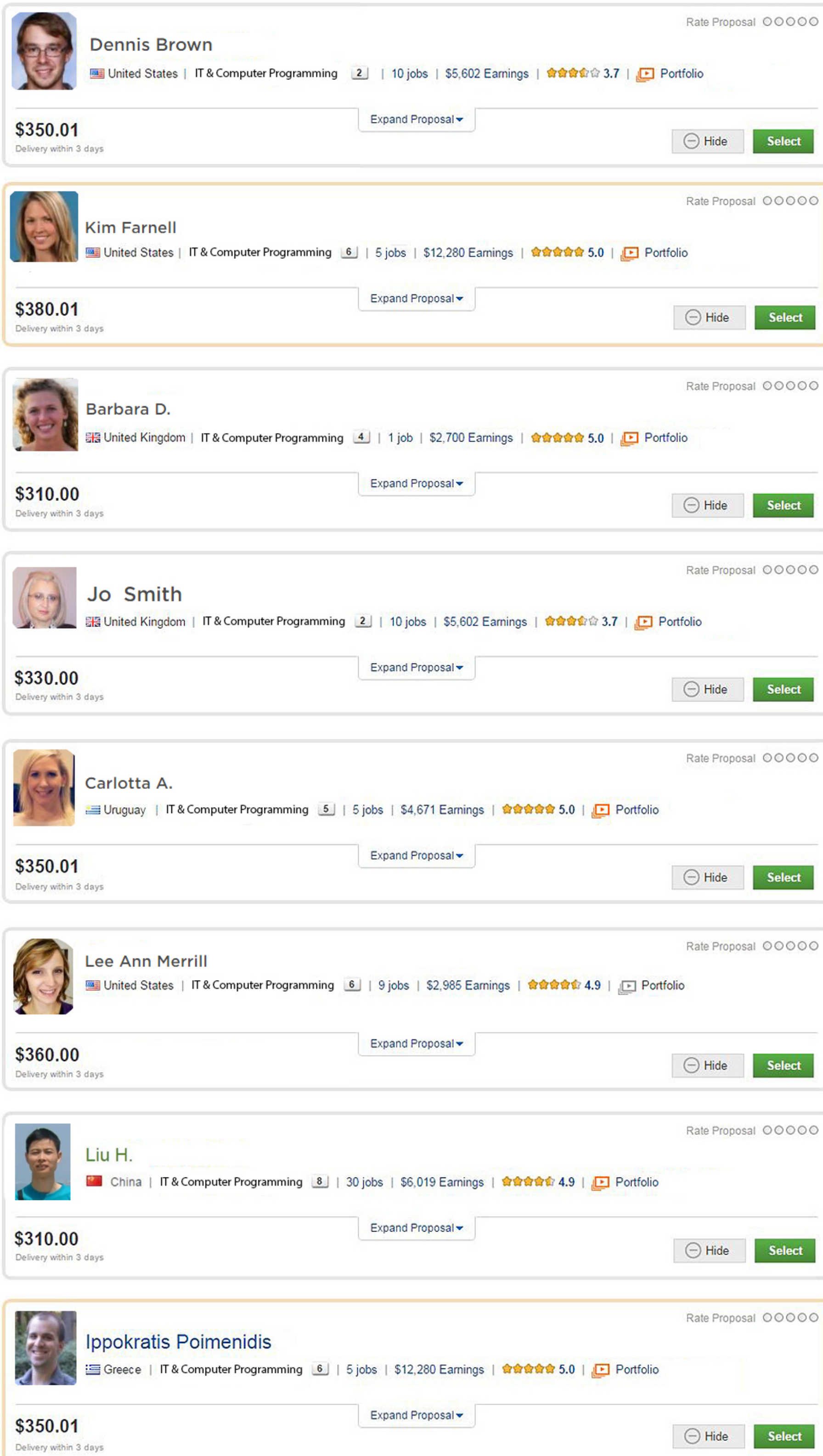


Figure 3
Freelancer Profile Page

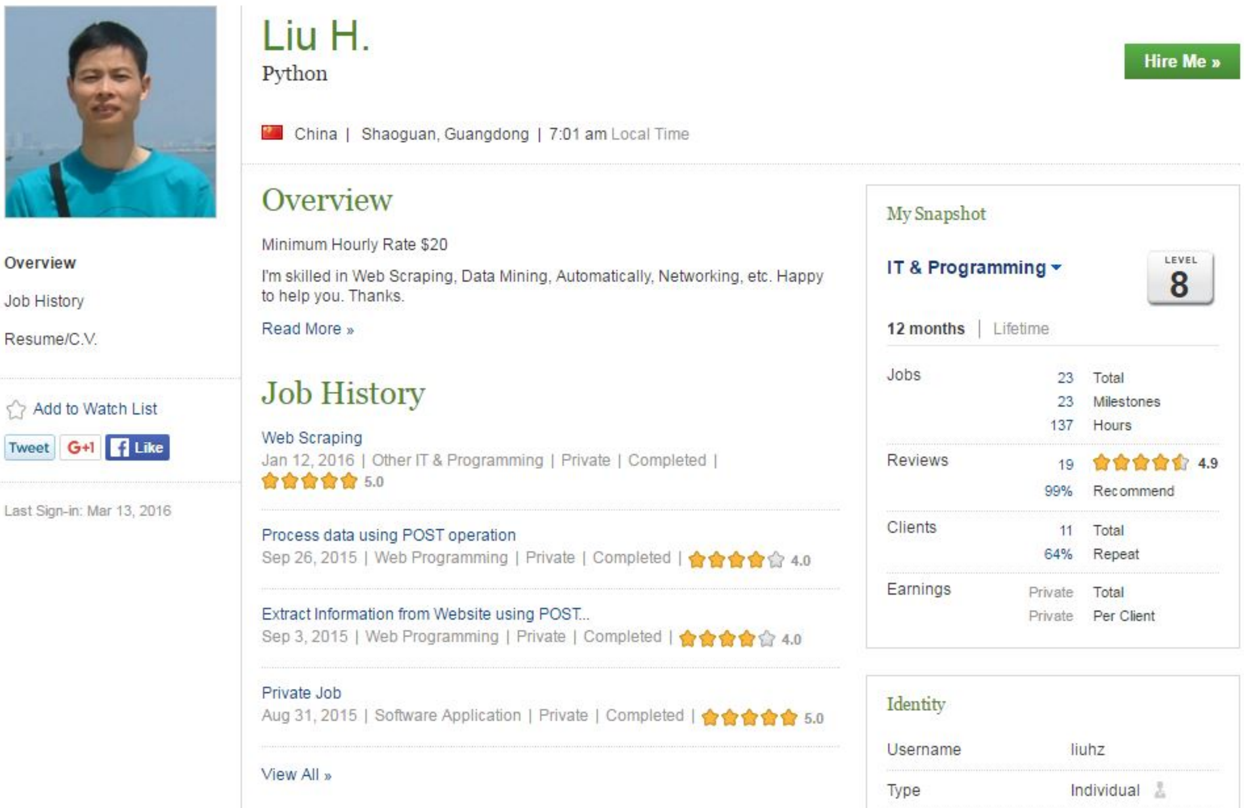


Figure 4

Gender Composition and Application Activity of Individual Freelancers in 2012

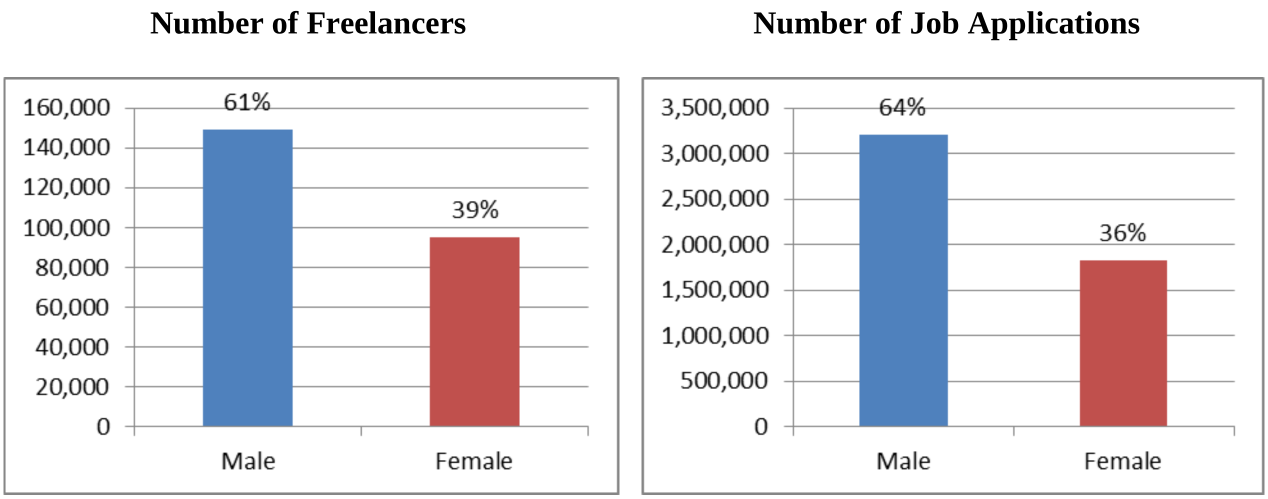


Figure 5

Histograms of the Number of Jobs by Proportion of Female Job Applicants

(By top six high-level job categories, Peaks at 0 and 100% - single applicant jobs - removed)

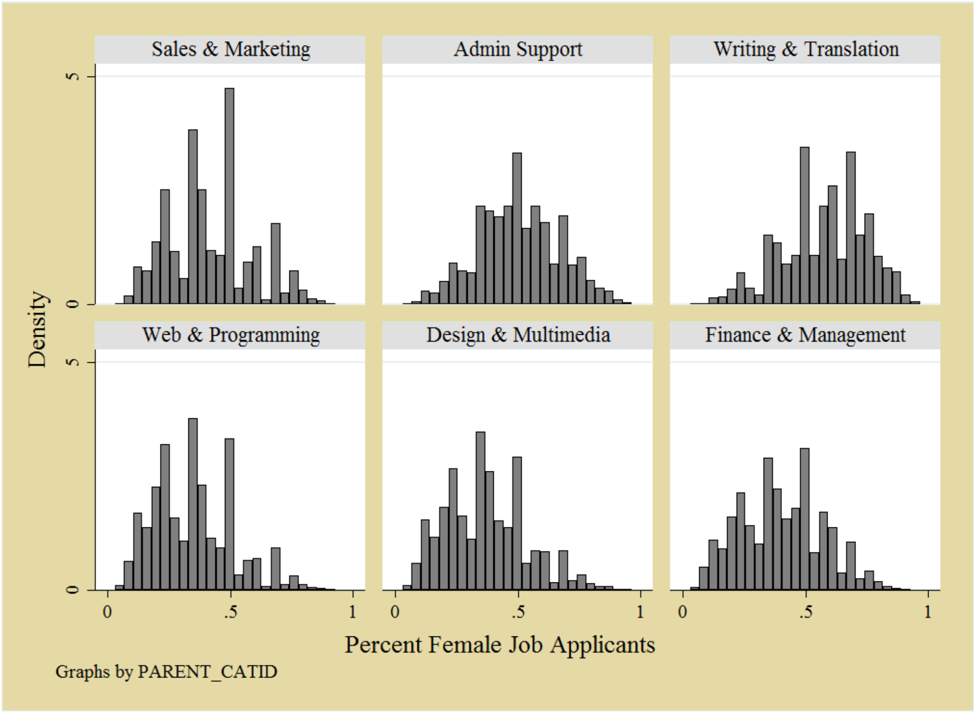
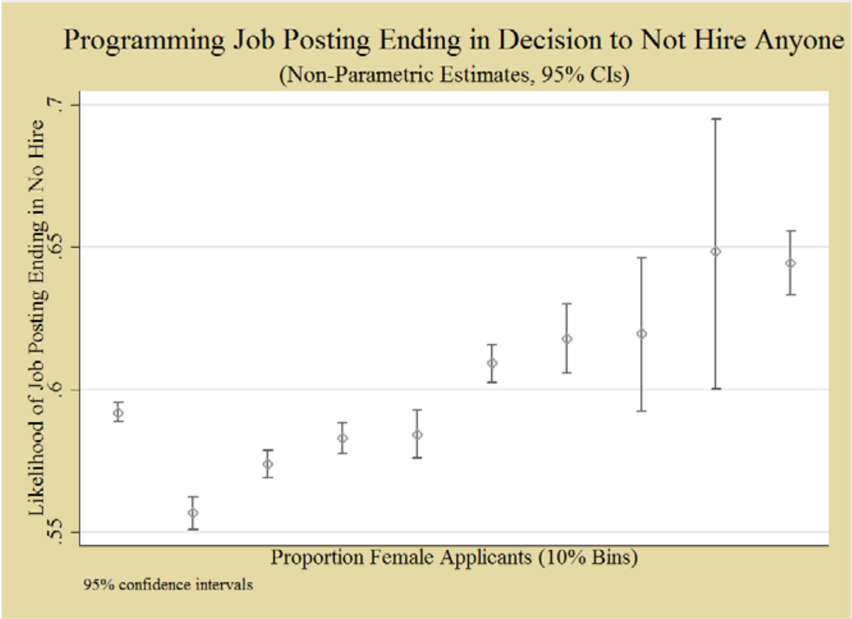


Figure 6
Non-parametric Estimates of Job Posting Ending with
Employer Decision to Not Hire Anyone
(With 95% Confidence Intervals, By 10% Bins of Percentage Female Applicants)



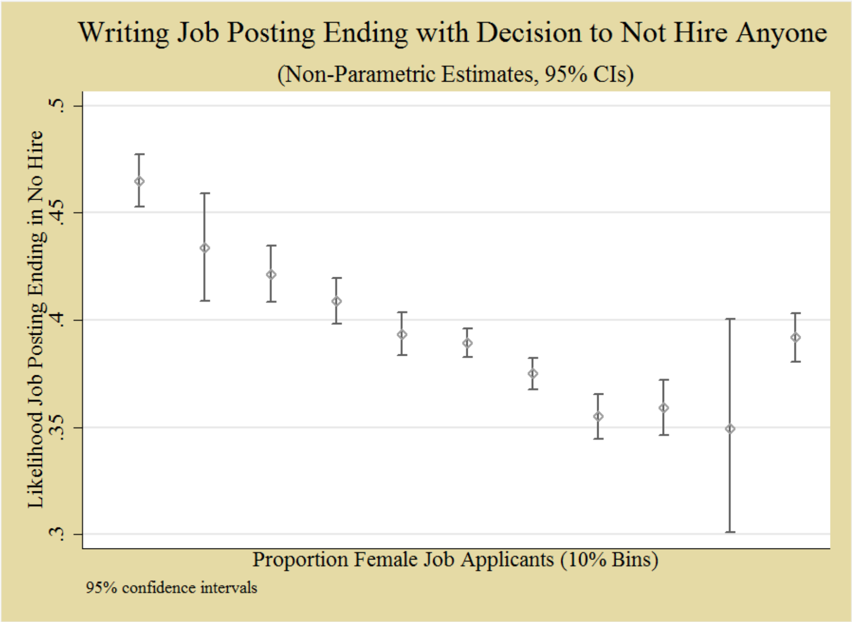


Table 1
Job Level - Summary Statistics
(N=70,224)

Variable	Mean	Std. Dev.	Min	Max
Non-Hire	0.335	0.472	0	1
Average bid (logged)	5.212	2.122	-4.605	13.885
Average female bid (logged)	4.706	2.936	-4.605	13.835
Average male bid (logged)	4.976	2.652	-4.605	13.885
Average company bid (logged)	5.008	2.666	-4.605	13.122
Average female level score	5.495	2.881	1	16
Average male level score	5.574	2.729	1	18
Average company level score	5.450	2.5949	1	18
Average female category experience	33.955	82.693	0	1279
Average male category experience	24.495	45.476	0	794
Average company category experience	26.775	53.177	0	858
Number of bids	9.335	11.895	1	687
Worked together previously	0.334	0.471	0	1
Percent female applicant pool	0.374	0.345	0	1
Writing job (Not programming)	0.428	0.494	0	1

Table 2
Job Level - Correlations
(N=70,224)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	**Non-Hire**	1						
(2)	**Average bid**	0.175	1					
(3)	**Average female bid**	0.069	0.287	1				
(4)	**Average male bid**	0.102	0.465	0.306	1			
(5)	**Average company bid**	0.094	0.418	0.259	0.402	1		
(6)	**Average female level score**	0.010	0.051	-0.004	0.002	0.006	1	
(7)	**Average male level score**	0.071	0.145	0.024	0.026	0.034	0.242	1
(8)	**Average company level score**	0.088	0.164	0.045	0.064	0.050	0.207	0.306
(9)	**Average female category experience**	-0.025	-0.020	-0.025	-0.031	-0.028	0.450	0.125
(10)	**Average male category experience**	-0.004	0.044	-0.007	-0.027	-0.014	0.153	0.490
(11)	**Average company category experience**	0.035	0.050	-0.001	-0.015	-0.016	0.155	0.170
(12)	**Number of bids**	0.005	0.163	0.046	0.067	0.063	-0.012	0.027
(13)	**Worked together previously**	-0.149	-0.051	-0.022	-0.033	-0.036	0.031	0.022
(14)	**Percent female applicant pool**	-0.103	-0.163	-0.047	-0.071	-0.064	0.025	-0.074
(15)	**Writing job (Not programming)**	-0.172	-0.236	-0.063	-0.090	-0.087	0.071	-0.154

		(8)	(9)	(10)	(11)	(12)	(13)	(14)
(8)	**Average company level score**	1						
(9)	**Average female category experience**	0.099	1					
(10)	**Average male category experience**	0.193	0.276	1				
(11)	**Average company category experience**	0.406	0.277	0.304	1			
(12)	**Number of bids**	0.022	0.041	0.093	0.092	1		
(13)	**Worked together previously**	0.013	0.048	0.048	0.039	0.068	1	
(14)	**Percent female applicant pool**	-0.142	0.003	-0.077	-0.143	-0.067	0.025	1
(15)	**Writing job (Not programming)**	-0.249	0.039	-0.150	-0.253	-0.055	0.033	0.602

Table 3
Within-Employer Fixed-Effects GEE Logit Estimates of the Likelihood a Job Posting Ending with Decision to Not Hire Anyone
(IT & Programming and Writing & Translation jobs pooled)

	(1)	(2)	(3)	(4)
Average bid (logged)	0.2847***	0.2847***	0.2847***	0.2848***
	(0.0118)	(0.0119)	(0.0119)	(0.0119)
Average female bid (logged)	-0.0352***	-0.0352***	-0.0352***	-0.0368***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Average male bid (logged)	-0.0498***	-0.0499***	-0.0499***	-0.0489***
	(0.0054)	(0.0054)	(0.0054)	(0.0055)
Average company bid (logged)	-0.0444***	-0.0444***	-0.0444***	-0.0449***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Average female Star rating	-0.0749***	-0.0749***	-0.0749***	-0.0737***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)
Average male Star rating	-0.1479***	-0.1478***	-0.1478***	-0.1465***
	(0.0085)	(0.0085)	(0.0085)	(0.0086)
Average company Star rating	-0.1128***	-0.1128***	-0.1128***	-0.1121***
	(0.0088)	(0.0088)	(0.0088)	(0.0088)
Average female level score	0.0247***	0.0247***	0.0247***	0.0249***
	(0.0042)	(0.0042)	(0.0042)	(0.0041)
Average male level score	0.0733***	0.0733***	0.0733***	0.0729***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Average company level score	0.0565***	0.0565***	0.0565***	0.0568***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
Average female experience	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Average male experience	-0.0003**	-0.0003**	-0.0003**	-0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Average company experience	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Average female category experience	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average male category experience	-0.0016***	-0.0016***	-0.0016***	-0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Average company category experience	0.0002	0.0002	0.0002	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Any Worked together previously	-0.8414***	-0.8414***	-0.8414***	-0.8400***
	(0.0308)	(0.0308)	(0.0308)	(0.0307)
Percent female applicant pool		-0.0034	-0.0034	0.3487***
		(0.0564)	(0.0564)	(0.0807)
Writing job (Not Programing, =1)			-0.5118***	-0.2602
			(0.1416)	(0.1477)
Writing job x Percent female pool				-0.6836***
				(0.1136)

Constant	-1.1361***	-1.1340***	-0.6222***	-0.7632***
	(0.1181)	(0.1235)	(0.1718)	(0.1733)
Job Sub-Category Fixed-Effects?	Yes	Yes	Yes	Yes
Number Applicant Fixed-Effects?	Yes	Yes	Yes	Yes
Number Jobs	70224	70224	70224	70224
Number Employers	23243	23243	23243	23243
Chi^2	4423.7	4426.5	4426.5	4441.9

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 7
Marginal Probability of Job Posting Ending in Decision to Not Hire Anyone
(By Job-Type, Other variables at means, 95% CI)

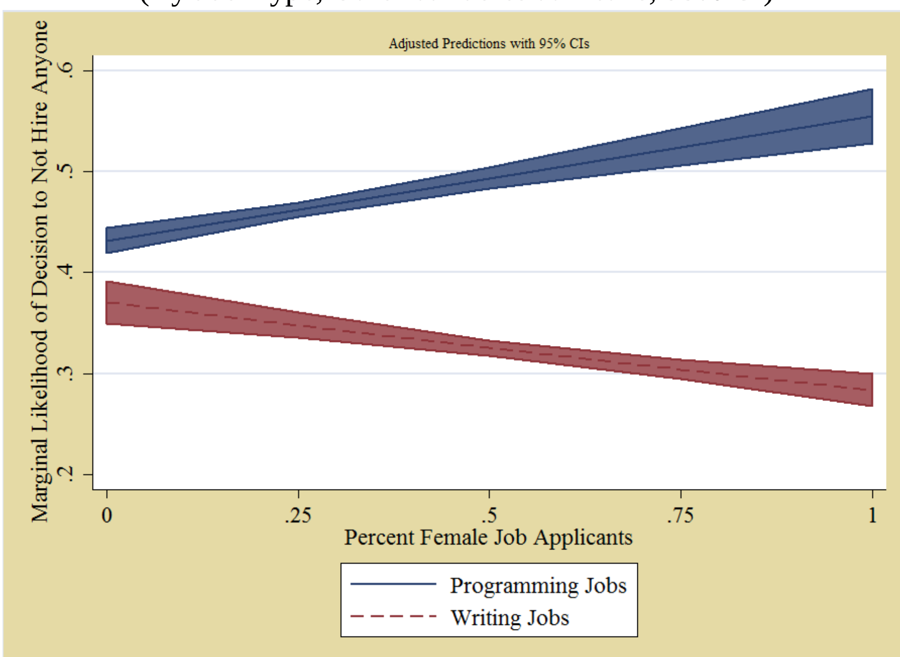
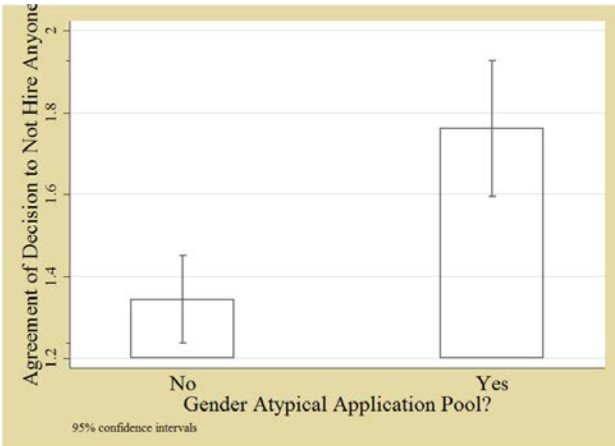


Figure 8

Agreement to Not Hire from Applicant Pool
(Gender Typical versus
Gender Atypical Applicant Pools)



Perceptions of Applicant Pool Skill
(Gender Typical versus
Gender Atypical Applicant Pools)

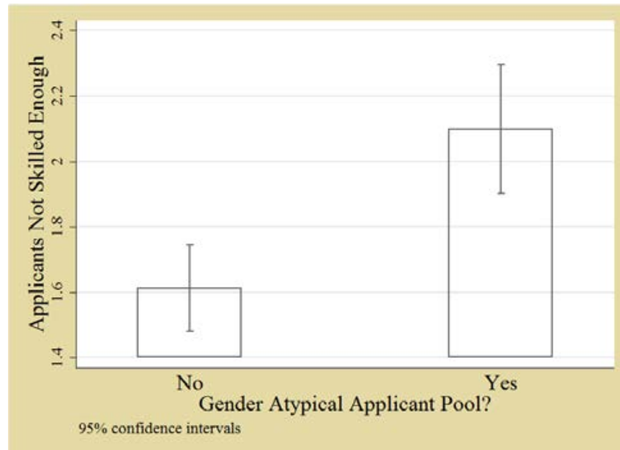


Table 5
Linear Probability Estimates of Agreement to Not Hire Anyone from Applicant Pool
(Pooled Subjects)

	(1)	(2)
Majority Gender Atypical Applicant Pool (=1)	0.417***	0.128
	(0.099)	(0.073)
Applicant Pool Not Skilled Enough (=1)		0.595***
		(0.043)
Constant	1.344	0.384
	(0.070)	(0.086)
Observations	185	185
R^2	0.088	0.551

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6
Application Level – Summary Statistics
(N=4,211,343)

Variable	Mean	Std. Dev.	Min	Max
Hired (=1)	0.068	0.252	0	1
Bid amount (logged)	3.579	4.595	-4.605	19.191
Bid was zero	0.222	0.415	0	1
Average star rating	3.547	2.051	0	5
No star rating	0.246	0.431	0	1
Level score	4.612	4.073	0	18
No level score	0.177	0.382	0	1
No. past jobs (logged)	1.644	3.563	-4.605	9.447
No. past jobs in focal category (logged)	0.020	3.616	-4.605	7.155
Previously worked together	0.030	0.171	0	1
Organization	0.378	0.485	0	1
Female	0.221	0.415	0	1
Writing job (Not Programming)	0.286	0.452	0	1

Table 7
Application Level – Correlations
(N=4,211,343)

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	**Hired (=1)**	1.000					
(2)	**Bid amount (logged)**	0.090	1.000				
(3)	**Bid was zero**	-0.137	-0.950	1.000			
(4)	**Average star rating**	0.114	0.010	-0.011	1.000		
(5)	**No star rating**	-0.108	-0.012	0.011	-0.989	1.000	
(6)	**Level score**	0.046	-0.124	0.157	0.565	-0.561	1.000
(7)	**No level score**	-0.038	-0.018	0.010	-0.418	0.423	-0.525
(8)	**No. past jobs (logged)**	0.084	-0.026	0.038	0.836	-0.842	0.710
(9)	**No. past jobs in focal category (logged)**	0.079	-0.030	0.046	0.659	-0.661	0.667
(10)	**Previously worked together**	0.506	0.046	-0.073	0.091	-0.085	0.074
(11)	**Organization**	-0.036	-0.012	0.041	0.093	-0.114	0.073
(12)	**Female**	0.032	0.022	-0.053	-0.050	0.062	-0.061
(13)	**Writing job (Not Programming)**	0.064	0.038	-0.137	-0.073	0.083	-0.114

		(7)	(8)	(9)	(10)	(11)	(12)
(7)	**No level score**	1.000					
(8)	**No. past jobs (logged)**	-0.416	1.000				
(9)	**No. past jobs in focal category (logged)**	-0.350	0.824	1.000			
(10)	**Previously worked together**	-0.041	0.106	0.112	1.000		
(11)	**Organization**	-0.079	0.127	0.111	-0.028	1.000	
(12)	**Female**	0.048	-0.079	-0.088	0.024	-0.416	1.000
(13)	**Writing job (Not Programming)**	0.092	-0.122	-0.168	0.038	-0.196	0.324

Table 8
Within-Employer Fixed-Effects GEE Logit Estimates
of the Likelihood of a Job Applicant Being Hired
(Clustered Std Errors, Conditional on Freelancer Submitting a Job Application,
IT & Programming and Writing & Translation jobs pooled)

	(1)	(2)	(3)	(4)
Bid amount (logged)	-0.3141***	-0.3141***	-0.3157***	-0.3157***
	(0.0225)	(0.0221)	(0.0188)	(0.0188)
Bid was zero	-6.5316***	-6.5314***	-6.5514***	-6.5503***
	(0.2974)	(0.2922)	(0.2523)	(0.2523)
Average star rating	0.3767***	0.3767***	0.3769***	0.3762***
	(0.0099)	(0.0099)	(0.0099)	(0.0099)
No star rating	-0.0898	-0.0899	-0.0896	-0.0936
	(0.3138)	(0.3162)	(0.3165)	(0.3166)
Level score	0.0522***	0.0522***	0.0525***	0.0520***
	(0.0123)	(0.0122)	(0.0117)	(0.0117)
No level score	0.3357***	0.3357***	0.3366***	0.3373***
	(0.0799)	(0.0795)	(0.0774)	(0.0775)
No. past jobs (logged)	-0.1335***	-0.1335***	-0.1335***	-0.1336***
	(0.0217)	(0.0218)	(0.0219)	(0.0219)
No. past jobs in focal category (logged)	0.0214***	0.0214***	0.0210**	0.0210**
	(0.0063)	(0.0064)	(0.0072)	(0.0072)
Previously worked together	4.2131***	4.2131***	4.2134***	4.2136***
	(0.0925)	(0.0926)	(0.0931)	(0.0931)
Organization (=1)	-0.1309***	-0.1306***	-0.1311***	-0.1329***
	(0.0177)	(0.0247)	(0.0257)	(0.0256)
Female (=1)		0.0007	0.0061	-0.0581***
		(0.0206)	(0.0106)	(0.0114)
Writing job (=1)			-0.0167	-0.0487
			(0.0368)	(0.0376)
Female x Writing job				0.1140***
				(0.0130)
Constant	-2.4823***	-2.4825***	-2.4707***	-2.4560***
	(0.1113)	(0.1057)	(0.0854)	(0.0856)
Number Job Applications	4211343	4211343	4211343	4211343
Number Employers	165100	165100	165100	165100
Chi^2	44405.4	46582.7	46889.2	46936.5

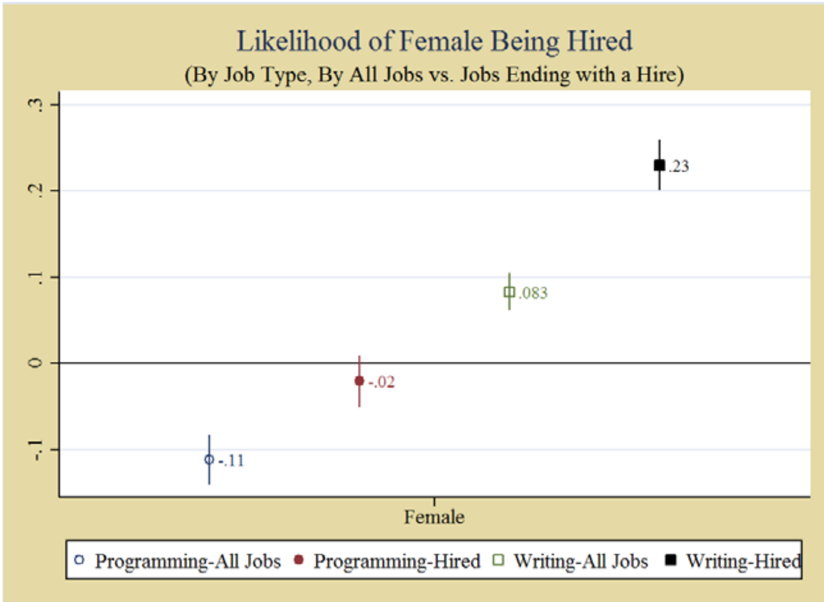
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9
Within-Job Posting Conditional Logit Estimates of Likelihood of Being Hired
(Conditional on any Job Applicant Being Hired)

	Programming Jobs		Writing Jobs	
	Model 1	Model 2	Model 3	Model 4
Bid amount (logged)	-0.5077***	-0.5078***	-0.5177***	-0.5209***
	(0.0091)	(0.0091)	(0.0091)	(0.0091)
Bid was zero (=1)	-9.0358***	-9.0364***	-7.8603***	-7.8879***
	(0.1188)	(0.1188)	(0.1108)	(0.1110)
Average star rating	0.3206***	0.3208***	0.2284***	0.2222***
	(0.0189)	(0.0189)	(0.0194)	(0.0195)
No star rating (=1)	-0.1775*	-0.1782*	-0.2705**	-0.3024***
	(0.0879)	(0.0879)	(0.0908)	(0.0909)
Level score	0.0205***	0.0204***	-0.0020	-0.0035
	(0.0028)	(0.0028)	(0.0035)	(0.0035)
No level score (=1)	0.3804***	0.3809***	0.1164***	0.1153***
	(0.0238)	(0.0239)	(0.0242)	(0.0242)
No. past jobs (logged)	-0.0857***	-0.0857***	-0.0849***	-0.0864***
	(0.0054)	(0.0054)	(0.0051)	(0.0051)
No. past jobs in focal category (logged)	0.1138***	0.1137***	0.1105***	0.1104***
	(0.0041)	(0.0041)	(0.0035)	(0.0035)
Previously worked together (=1)	2.4130***	2.3313***	2.0753***	2.0750***
	(0.0155)	(0.0155)	(0.0156)	(0.0156)
Organization (=1)	-2.5796***	-2.5836***	-1.3826***	-1.2503***
	(0.0271)	(0.0275)	(0.0233)	(0.0248)
Female (=1)		-0.0183		0.2358***
		(0.0151)		(0.0146)
Number Applications	428453	428453	329893	329893
Number Jobs	27004	27004	22419	22419
Pseudo-r^2	0.2557	0.2557	0.1487	0.1507
Log-Likelihood	-54151.5	-54151.1	-55532.4	-55401.2
Chi^2	37214.4	37215.2	19398.3	19660.8

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9
Comparison of Likelihood of Female Job Applicant Being Hired
(By Job-Type and By Whether Anyone was Hired)



Appendix

Figure A.1
Profile Page for an Organization, No Gender

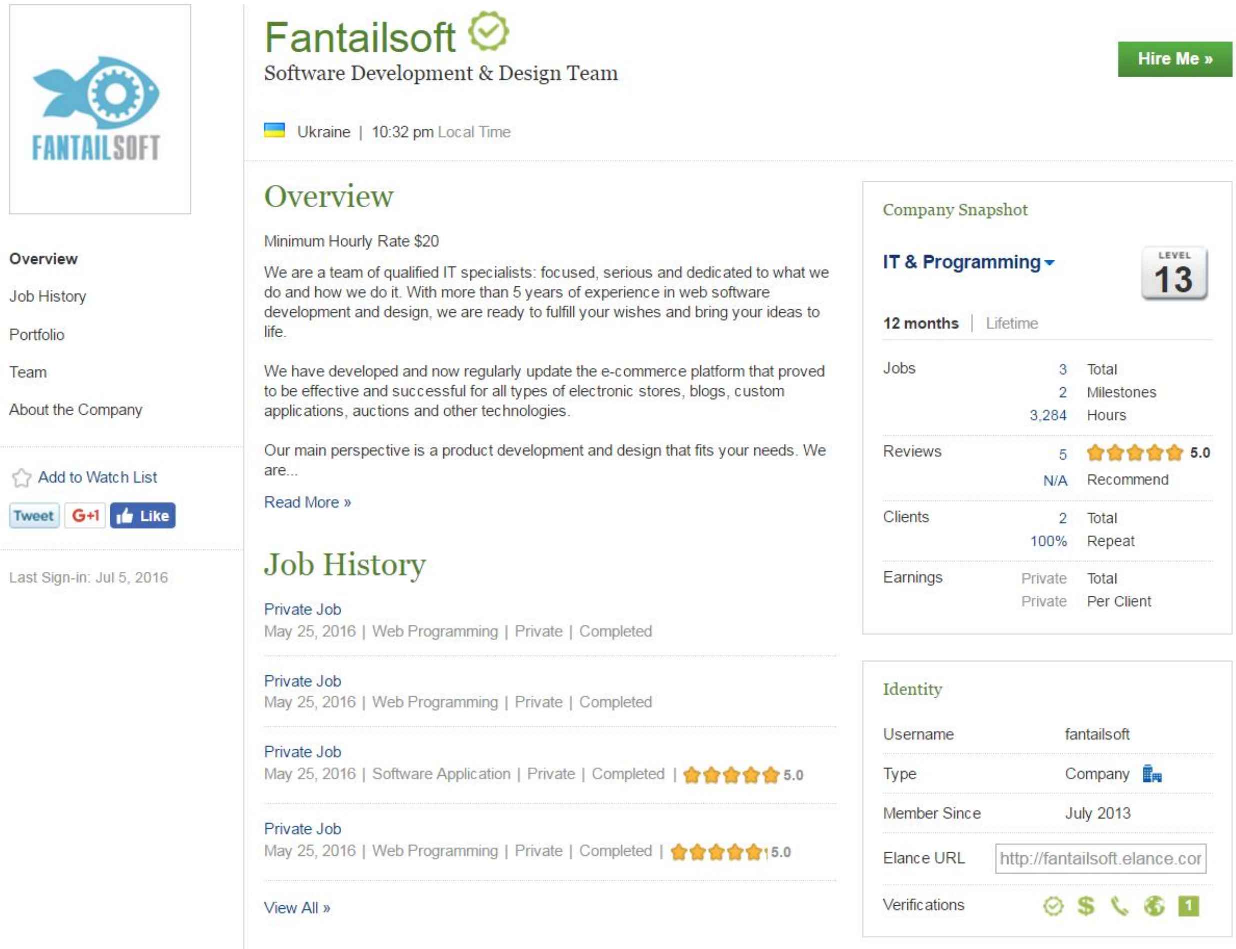
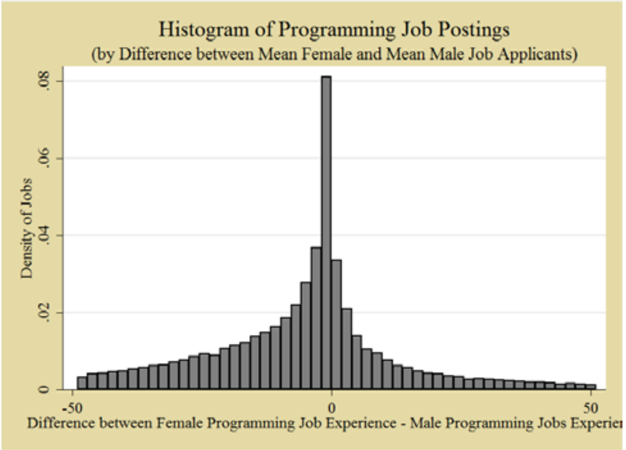
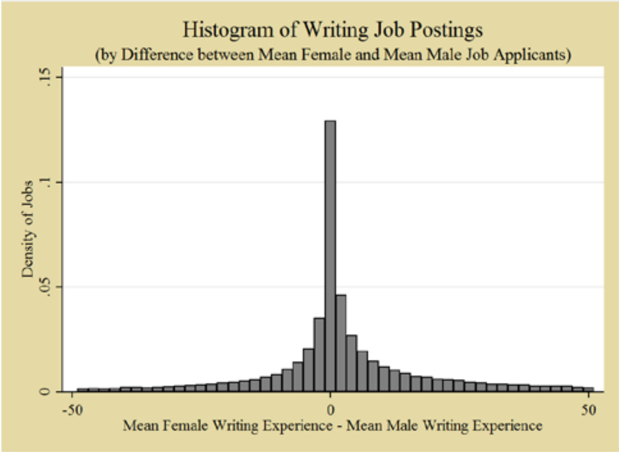
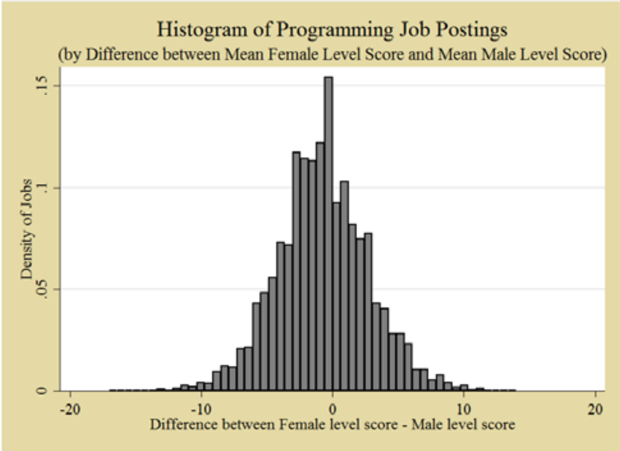


Figure A.2
Histogram of the Past Job Category Experiences and the Level Score Differences Between Female and Male Freelancers for 2012
Differences in Job Category Experience
(Mean of Female Applicants – Mean of Male Applicants)





Differences in Level Score
(Mean of Female Applicants – Mean of Male Applicants)



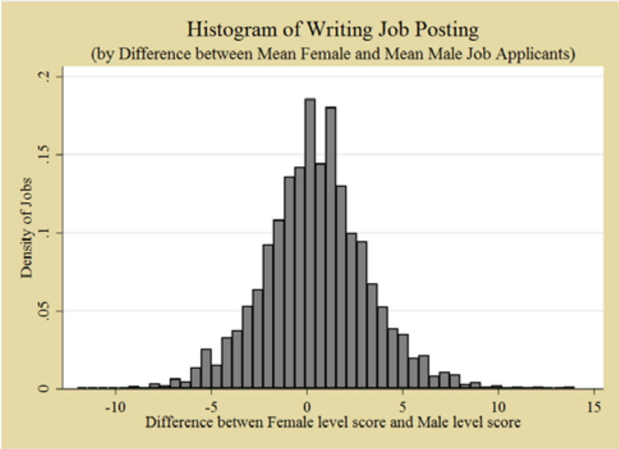


Table A.1
Within-Employer Fixed-Effects Logit Estimates of the Likelihood a Job Posting Ending with Decision to Not Hire Anyone
(IT & Programming and Writing & Translation jobs pooled. Subset of Jobs of Similar Female and Male applicant pool quality)

	(1)	(2)	(3)
Number Bids	-0.0008	-0.0004	0.0004
	(0.0012)	(0.0012)	(0.0012)
Average bid (logged)	0.3622***	0.3215***	0.3192***
	(0.0202)	(0.0204)	(0.0204)
Average female bid (logged)	-0.0442***	-0.0401***	-0.0414***
	(0.0064)	(0.0065)	(0.0065)
Average male bid (logged)	-0.0897***	-0.0760***	-0.0742***
	(0.0113)	(0.0114)	(0.0115)
Average company bid (logged)	-0.0371***	-0.0371***	-0.0361***
	(0.0093)	(0.0093)	(0.0093)
Average female Star rating	-0.0639***	-0.0653***	-0.0638***
	(0.0135)	(0.0136)	(0.0136)
Average male Star rating	-0.1191***	-0.1420***	-0.1429***
	(0.0162)	(0.0164)	(0.0164)
Average company Star rating	-0.0898***	-0.0905***	-0.0900***
	(0.0160)	(0.0161)	(0.0161)
Average female level score	0.0319**	0.0440***	0.0442***
	(0.0106)	(0.0107)	(0.0107)
Average male level score	0.0929***	0.0951***	0.0960***
	(0.0125)	(0.0125)	(0.0126)
Average company level score	0.0869***	0.0738***	0.0743***
	(0.0096)	(0.0097)	(0.0097)
Average female experience	-0.0003	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)
Average male experience	-0.0007**	-0.0008**	-0.0008**
	(0.0003)	(0.0003)	(0.0003)
Average company experience	-0.0002	-0.0002	-0.0001
	(0.0002)	(0.0002)	(0.0002)
Average female category experience	-0.0021*	-0.0025*	-0.0027**
	(0.0010)	(0.0010)	(0.0010)
Average male category experience	-0.0005	-0.0011	-0.0010
	(0.0011)	(0.0011)	(0.0011)
Average company category experience	0.0006	-0.0003	-0.0004
	(0.0007)	(0.0007)	(0.0007)
Any Worked together previously	-0.4377***	-0.4332***	-0.4326***
	(0.0428)	(0.0429)	(0.0430)
Percent female applicant pool	-0.6128***	0.1388	0.5565***
	(0.0887)	(0.1043)	(0.1435)
Writing job (Not Programing, =1)		-0.6333***	-0.2638**

		(0.0458)	(0.0981)
Writing job x Percent female pool			-0.8744***
			(0.2060)
Number Jobs	24352	24352	24352
Number Employers	5357	5357	5357
Psuedo-R^2	0.0532	0.0631	0.0640
Log-Likelihood	-9305.1	-9207.5	-9198.5
Chi^2	1045.1	1240.2	1258.3

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Elance Job Sub-Categories

ADMIN SUPPORT

Bulk Mailing
Customer Response
Data Entry
Event Planning
Fact Checking
Mailing List Development
Office Management
Other - Administrative Support
Presentation Formatting
Research
Transcription
Travel Planning
Virtual Assistant
Word Processing

DESIGN AND MULTIMEDIA

3D Graphics
Animation
Banner Ads
Brochures
Card Design
Cartoons and Comics
Catalogs
CD and DVD Covers
Commercials
Corporate Identity Kit
Digital Image Editing
Direct Mail
Displays and Signage
Emails and Newsletters
Embedded Video/Audio
Graphic Design
Illustration
Label and Package Design
Logos
Menu Design
Music
Other - Design
Other - Multimedia Services
Page and Book Design
Photography and Editing
Podcasts
Presentation Design
Print Ads
Radio Ads and Jingles
Report Design
Sketch Art
Stationery Design
Videography and Editing
Viral Videos
Voice Talent

ENGINEERING AND MANUFACTURING

Architecture
CAD
Civil and Structural
Contract Manufacturing
Electrical
Industrial Design
Interior Design
Mechanical
Other - Architecture and Engineering

FINANCE AND MANAGEMENT

Accounting and Bookkeeping
Billing and Collections
Budgeting and Forecasting
Cost Analysis and Reduction
Financial Planning
Financial Reporting
HR Policies and Plans
Management Consulting
Other - Management and Finance
Outsourcing Consulting
Process Improvement
Stock Option Plans
Supply Chain Management
Tax

LEGAL

Bankruptcy
Business and Corporate Contracts
Criminal
Family
Immigration
Incorporation
Landlord and Tenant
Litigation
Negligence
Other - Legal
Patent, Copyright and Trademarks
Personal Injury
Real Estate
Tax Law
Wills, Trusts and Estates

SALES AND MARKETING

Advertising
Branding
Business Plans
Business Skills
Business Software
Competitive Analysis
Corporate Training
Diversity Training
Email and Direct

Marketing
Grassroots Marketing
Lead Generation
Management
Training
Market Research and Surveys
Marketing and Sales Consulting
Marketing Collateral
Marketing Plans
Media Buying and Planning
Media Training
Other - Sales and Marketing
Other - Training and Development
Policies and Manuals
Pricing
Product Research
Programming Languages
Project Management
Promotions
Public Relations
Retailing
Sales Presentations
Sales Training
Search and Online Marketing
Technical Training
Telemarketing
Tradeshows and Events

IT AND PROGRAMMING

Application Development
Blogs
Database Development
Ecommerce Website
Enterprise Systems
Flash Animation
Handhelds and PDAs
HTML Emails
Network Administration
Online Forms
Other - Programming
Other - Website Development
Project Management
Quality Assurance
Scripts and Utilities
Security
SEO and SEM
Simple Website
System Administration
Technical Support
Usability Design
Web Design
Web Programming
Website QA
Wireless

WRITING AND TRANSLATION

Test Writing
Academic Writing
Article Writing
Children's Writing
Copywriting
Creative Writing
E-books and Blogs
Editing and Proofreading
Ghost Writing
Grant Writing
Newsletters
Other - Writing Services
Press Releases
Report Writing
Resumes and Cover Letters
Sales Writing
Speeches
Technical Writing
Translation
User Guides and Manuals
Web Content