Article

Social Science Computer Review
1-19

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/0894439319895757
journals.sagepub.com/home/ssc
SAGE

"This Gig Is Not for Women": Gender Stereotyping in Online Hiring

Hernan Galperin[1]

Abstract

This study examines gender segregation in the context of the so-called gig economy. In particular, it explores the role that stereotypes about male and female occupations play in sorting men and women into different jobs in an online freelance marketplace. The findings suggest that gender stereotypes are particularly salient in online hiring because employers typically contract for short-term, relatively low-value jobs based on limited information about job applicants. These conditions trigger the use of cognitive shortcuts about intrinsic gender characteristics linked to different skills and occupations. The results corroborate that female candidates are less likely to be hired for male-typed jobs (e.g., software development) but more likely to be hired for female-typed jobs (e.g., writing and translation) than equally qualified male candidates. Further, the study investigates three mechanisms predicted to attenuate the female penalty in male-typed jobs. The penalty is found to be self-reinforcing, as it perpetuates gender imbalances in worker activity across job categories that strengthen the sex typing of occupations.

Keywords

gig economy, gender discrimination, online labor, women in STEM

Sorting into different jobs and industries has become the single most important factor accounting for the remaining gaps in earnings and career trajectories between men and women (Blau & Kahn, 2017; Goldin, 2014; Penner, 2008). Why are women less likely to work in higher paying occupations (e.g., in Science, Technology, Engineering and Math fields) and in the more dynamic firms? One line of argument emphasizes the cultural and institutional factors that shape career choices (Akerlof & Kranton, 2010; Blickenstaff, 2005; Fuller, 2017). This line of argument attributes observed differences in labor market outcomes to self-selection in educational trajectories (the "pipeline") and subsequent career choices (e.g., preference for jobs with flexible hours).

Another line of argument emphasizes gender discrimination by employers at the time of hiring or in promotions within organization. Discrimination in hiring has been attributed to various factors,

[1] University of Southern California, Los Angeles, CA, USA

Corresponding Author:
Hernan Galperin, University of Southern California, 3502 Watt Way, Los Angeles, CA 90089, USA.
Email: hgalperi@usc.edu

including pure employer distaste (Becker, 1957), threats to professional status (Goldin, 2002), and noisy signals of worker productivity (Aigner & Cain, 1977). In turn, the “glass ceiling” argument emphasizes gender bias in advancement to leadership positions within organizations that ultimately result in lower wages and truncated careers for women (Cotter, Hermsen, Ovadia, & Vanneman, 2001).

This study analyzes gender segregation in the context of the so-called gig economy. In particular, it explores the role that stereotypes about “male” and “female” occupations play in sorting men and women into different jobs in an online freelance marketplace. Online work is still nascent but has grown exponentially in recent years. Pew Research Center (2016) reports that 8% of working-age Americans (about 16 million people) have earned money from online gigs. In the UK, the overall incidence of online gig work was estimated at 4.4% or about 2.8 million workers (UK Department for Business, Energy & Industrial Strategy, 2018). Across the European Union (EU)-28, 1 in 10 adults has generated income through a gig platform, and while for most this represents a sporadic source of secondary income, 2% of the EU adult population (about 8 million people) works more than 20 hr a week or earns at least half of their income online (Eurpean Commission, 2018).

There is considerable debate about how the rise of nonstandard work and the platformization of employment will affect gender gaps in wages and career trajectories (Branch & Hanley, 2017; Leung & Koppman, 2018). Some scholars postulate that online hiring may mitigate the mechanisms that penalize women in traditional organizations. For example, since long-term worker attachment to a particular organization is of limited importance in spot contracting, the motherhood penalty may be significantly reduced (Cullen, Humphries, & Pakzad-Hurson, 2018). Further, the value of social connections in hiring and promotions (the “old boys club”) is significantly more limited in the gig economy, where worker–employer interactions tend to be one-off and highly impersonal (Horton, Kerr, & Stanton, 2018).

The findings of this study nonetheless point in the opposite direction. They suggest that gender stereotypes are particularly salient in online freelance platforms because employers typically hire for short-term, relatively low-value jobs based on limited verifiable information about alternative job applicants. These conditions trigger the use of cognitive shortcuts about intrinsic gender characteristics associated with different skills and occupations. Based on the examination of proprietary data from an online hiring platform spanning several occupational categories, the results indicate that women are significantly less likely to be hired for male-typed jobs (e.g., software development) but more likely to be hired for female-typed jobs (e.g., writing and translation) than equally qualified male candidates. The mechanism is self-reinforcing, as it perpetuates gender imbalances in worker activity across job categories that strengthen the sex typing of occupations.

This study contributes to several related fields of scholarship. First, it suggests that the rise of online work in the past decade, coupled with larger social trends favoring precarious employment, may exacerbate gender occupational segregation. For example, if women face higher barriers in the competition for STEM-related jobs in online platforms, incentives for acquiring these skills in the first place will diminish as the gig economy expands, thus compounding the pipeline problem. Second, the study contributes to our understanding of how stereotyping and discrimination operate in online platforms more generally, adding to the body of evidence from studies of social media (Caers & Castelyns, 2010), peer-to-peer vacation rentals (Edelman, Luca, & Svirsky, 2017), and electronic auction platforms (Kricheli-Katz & Regev, 2016), among others. In broader terms, the findings have implications for policy efforts seeking to create more and better employment opportunities for women in mid of rapid technological change affecting the quantity and quality of labor demand.

Literature Review and Hypotheses

Gender in Conventional Hiring

Hiring involves a two-side matching process. At the heart of hiring lies an information asymmetry problem since the true ability and productivity of a job candidate cannot be directly observed. Employers thus rely on noisy information signals, some of which are self-reported by candidates (e.g., the information contained in résumés) and some of which are provided by third parties (e.g., educational certificates or recommendations from previous employers). In traditional hiring, an initial "paper" screening of résumés is followed by a series of job interviews, where employers seek to elicit more information about skills and productivity from a selected pool of candidates (Penner, 2008).

Current scholarship suggests that overt discrimination against women in hiring and promotion has largely given way to subtler and often unconscious forms of bias associated with cultural stereotypes about gender-appropriate occupations (Cejka & Eagly, 1999). These stereotypes are beliefs about intrinsic differences between men and women that form expectations about the types of jobs that men and women will excel at. Broadly speaking, these stereotypes tend to map onto the existing gender composition of occupations.

Scholars have revealed a close link between stereotypes as descriptive generalizations ("what women and men *are* like") and stereotypes as prescriptive classifications ("how women and men *should be* like"). In the context of hiring, group generalizations result in beliefs regarding the expected abilities and job performance of male and female job candidates (Diekman & Eagly, 2000; Heilman, 2012). The prediction that emanates from this body of research is that women will be less likely to be hired for male-typed occupations and, conversely, more likely to be hired for female-typed occupations. This prediction is in fact a composite of two intertwined mechanisms. Descriptive stereotypes about what women *are* create a perceived "lack of fit" between female attributes and male-typed occupations (Heilman, 1983). The second and more subtle mechanism is the composition of the applicant pool for different jobs, which tends to reinforce the gender typing of occupations and favor applicants of the gender that dominates the pool (Campero & Fernandez, 2018).

Interestingly, however, attempts to empirically validate gender discrimination in hiring have often obtained mixed results. The evidence from experimental studies with small populations overwhelmingly supports the lack-of-fit hypothesis, uncovering significant penalties for women seeking jobs in predominantly male occupations (Isaac, Lee, & Carnes, 2009). Further, these studies show that penalties increase when female applicants violate prescribed gender stereotypes, particularly when evaluated by male employers (Tyler & McCullough, 2009).

While these studies suffer from the usual shortcomings of laboratory experiments in the social sciences (Falk & Heckman, 2009), the evidence is also compelling from audit and correspondence field experiments, in which researchers send otherwise identical pairs of applications to job openings and compare callback or offer rates for men and women. For example, in a landmark study in the food service industry, Neumark, Bank, and Van Nort (1996) find that men are more likely to receive callbacks and job offers from high-end restaurants than female applicants, while women are more likely to receive callbacks and offers from low-end establishments. In a similar experiment across several job categories, Riach and Rich (2006) find negative discrimination against women in a male-dominated job category (engineering) and positive discrimination in the female-dominated (secretarial) and gender-neutral (accounting) categories. Similarly, Booth and Leigh (2010) find that positive discrimination in favor of female candidates increases with the overall share of women in the occupation.

Audit and correspondence studies also suffer from various weaknesses (Azmat & Petrongolo, 2014). As Bertrand and Duflo (2016) note, real-life workers adjust job-searching strategies to expected outcomes, resulting in nonrandom application to available jobs. In addition, audit and correspondence studies typically focus on entry-level jobs, yet gender discrimination arguably increases with job hierarchy (Cotter et al., 2001). Finally, audit and correspondence studies typically lack information about the full pool of applicants, which may result in biased estimations (Heckman & Siegelman, 1993).

An alternative approach is the examination of hiring outcomes within one or multiple firms, controlling for the observable characteristics of all job applicants. These studies offer less consistent results than laboratory experiments and audit or correspondence methods. For example, Petersen, Saporta, and Seidel (2005) find no hiring discrimination against women in a large service organization. Similarly, Penner (2008) reports no significant gender differences in salaries offered at hiring in a large financial services firm, while Fernandez and Abraham (2011) find no evidence of gendered hiring in a large pharmaceutical firm. A study of an MBA cohort by Barbulescu and Bidwell (2013) finds no evidence that women are less likely to be hired in the finance industry. In general, these studies attribute observed differences in the gender composition of jobs to imbalances in the pool of candidates, thus supporting the pipeline argument regarding different career preferences between male and female workers.

As study by Fernandez and Campero (2017) is of particular relevance for it offers a unique looking glass into hiring practices for a large sample of firms in a male-dominated industry (the IT industry). The findings reveal discrimination against female candidates for IT/engineering jobs at the initial screening stage. However, the female penalty vanishes thereafter, with women equally likely to receive a job offer conditional on having been invited for a job interview. These results suggest potential differences in selection mechanisms at each stage in the hiring process. More specifically, they suggest that gender stereotypes are more likely to be activated in the "paper" screening of large pools of candidates, as opposed to selection within a smaller pool of applicants in the information-rich context of a job interview.

Gender in Online Hiring

Transposing the above findings to the online hiring context is far from trivial due to several fundamental differences in the information signals available to parties. Conceptually, hiring can be broken down into three distinct stages: recruitment, selection, and negotiation/acceptance of job offer. In the gig economy context, there are important differences with respect to conventional hiring that may alter the role and salience of gender stereotypes at each of these stages. Building on these differences, several scholars hypothesize that online labor platforms could potentially mitigate the mechanisms that penalize women in male-typed occupations.

Consider the recruitment process. Previous research has consistently shown that referrals based on personal networks play a key role in conventional hiring, which tends to perpetuate the demographic profile of occupations (Granovetter, 1974). In addition, employers may choose to advertise and recruit selectively in ways that bias the applicant pool in favor of certain groups of individuals. By contrast, information about available jobs in online platforms is significantly more transparent and is generally available to all potential candidates. Further, while some online platforms allow employers to introduce filters that limit the visibility of the jobs posted, these filters typically relate to required skills or maximum wages rather than the demographic characteristics of potential candidates. Put simply, the value of social connections and the "old boys club" is significantly attenuated in online hiring (Cullen et al., 2018).

Turning to selection, Agrawal, Horton, Lacetera, and Lyons (2013) hypothesize that the transparency and standardization in the presentation of information about alternative job applicants in online hiring favors selection on the basis of verified individual skills and reputation (e.g., rating from previous employers) rather noisy signals drawn from résumés and personal interviews. In addition, Cullen, Humphries, and Pakzad-Hurson (2018) argue that spot contracting significantly reduces the female penalty associated with motherhood or part-time work by making considerations of long-term commitment to an organization irrelevant. More broadly, the flexibility of online employment is believed to favor labor force participation by qualified female workers, thus potentially rebalancing the composition of applicant pools in male-dominated occupations (Organization for Economic Cooperation and Development, 2017).

Finally, online hiring significantly reduces the scope for employer–employee bargaining, as wages are typically set by the employer in advance or established through online reverse auctions. This is important because previous research attributes part of the gap in wages and career trajectories to gender differences in willingness to negotiate (Babcock & Laschever, 2003). In fact, most online labor platforms actively discourage direct communication between employers and job seekers prior to hiring due to concerns about the parties contracting outside the platform. By limiting opportunities for bargaining, online hiring may thus favor the selection of female applicants.

On the other hand, other differences between conventional and online hiring may exacerbate gender segregation into different types of jobs. This is particularly apparent in the process of filtering and selecting candidates. Consider a prospective employer seeking a freelancer for a logo design job valued at around US$140 (the average value found for this category in our data set). Within a few hours of posting the job, the employer will likely receive proposals from several dozen freelancers from around the world. Given the relatively small value of the contract, the small odds of repeated worker–employer matches, and the seemingly infinite pool of alternative candidates across different online hiring platforms, the employer is unlikely to carefully scrutinize the attributes of each individual candidate. Rather, stereotypes that link group characteristics with the skills required to complete the job provide a cognitive shortcut that greatly simplifies selection.

Previous research has consistently found the activation of stereotypes to be more likely under conditions of limited information and low attention to task. In particular, the Fiske and Neuberg (1990) model highlights the critical role that attention plays in decision-making. The model distinguishes between two cognitive paths, one that uses preexisting social categories—which are closely related to stereotypes—and a second that requires the examination of an individual's attributes regardless of group affiliation. According to the model, attention "mediates the extent to which people use relative stereotypic or relatively more individuating processes" (Fiske & Neuberg, 1990, p. 6).

Hancock and Dunham (2001) apply this model of impression formation to computer-mediated communication and find that the dearth of social cues in electronic (compared to face-to-face) interactions increases deindividuation. Overall, this suggests that the combination of limited information, limited cognitive resources applied to selection, and the impersonal context inherent to online hiring will tend to raise the salience of an applicant's gender as a heuristic cue.

Extant studies of online hiring have detected employer bias along a number of dimensions. For example, Gefen and Carmel (2008) find geographical discrimination against foreign applicants in an online programming marketplace. When jobs are offshored, employers prefer workers from countries with minimal cultural distance (rather than lower costs), such as U.S. employers hiring programmers in Canada and Australia. Similar findings are reported by Hong and Pavlou (2014) and Lehdonvirta, Barnard, Graham, and Hjorth (2014). Other studies center on the factors that mitigate employer bias in online hiring. For example, Mill (2011) finds that feedback from previous contracts significantly reduces the effect of geographical location on hiring. Similarly, Agrawal, Lacetera, and Lyons (2013) find that the benefit of platform-verified information from previous employers is disproportionately larger for applicants from less developed countries.

A small number of studies have specifically addressed gender bias in online hiring. Overall, the results suggest a small but significant female advantage, though the findings are unable to disambiguate the theoretical tension regarding hiring in male-typed occupations. For example, Leung and

Koppman (2018) find positive discrimination in favor of women in female-dominated job categories. However, findings for male-dominated categories are inconclusive. The authors theorize that this result is driven by employers' propensity to leave jobs unfilled when the gender composition of the applicant pool differs from stereotypical expectations. Similarly, Chan and Wang (2018) find a small but significant female hiring advantage, which the authors attribute to women being perceived by online employers as more cooperative and trustworthy, thus mitigating uncertainty about the information provided by job applicants. This advantage nonetheless dissipates as employers gain more experience in online hiring.

A different interpretation is proposed by Urwin and Cerqua (2018) who also find a hiring bias in favor of women that is particularly large in female-dominated occupations (but is found to be negligible in male-dominated job categories). The authors hypothesize that, if online employers utilize heuristics that tend to favor women, the effect must fall as the value of the job rises because of the closer scrutiny of applicants expected in higher value projects. Their findings corroborate that the female advantage decreases monotonically in significance and size as job value increases, and this result spans across job categories. The authors interpret this finding as evidence that the female advantage in online hiring is mainly driven by cognitive shortcuts used by employers when hiring for one-off jobs that tend to be of small value and limited in duration.

Research Hypotheses

Based on the above review of the literature, this study tests the following hypotheses regarding gender cues in online hiring:

Hypothesis 1: Controlling for observable applicant characteristics, women will be less likely to be hired in male-typed job categories and more likely to be hired in female-typed job categories.

The main assumption underlying this hypothesis is that, in the context of a hiring process characterized by rapid contracting, limited information about individual candidates and small contract values, gender stereotypes about the occupations that men and women are best qualified for will become highly salient. This will result in a hiring advantage for female applicants in female-typed jobs (e.g., writing and translation) and a hiring penalty against women in male-typed jobs (e.g., software programming).

Hypothesis 2: Female job applicants will benefit relatively more from the availability of information based on previous jobs completed in the platform.

Previous research suggests that even small amounts of additional information regarding workers' ability can significantly affect hiring outcomes in online platforms (Pallais, 2014). In particular, other studies suggest that reputational information based on previous job contracts and platform-verified information regarding work experience can significantly reduce bias against negatively stereotyped applicants (Agrawal, Lacetera, & Lyons, 2013). This hypothesis seeks to validate whether this mechanism mitigates perceived lack of fit, thus increasing the hiring odds of female freelancers applying for male-typed jobs.

Hypothesis 3: As employers gain experience in online hiring, the bias against female candidates in male-typed jobs will decrease.

This hypothesis conceptualizes online hiring as a dynamic learning process through which employers not only observe the abilities of hired freelancers but also update beliefs about group characteristics. Social psychology research has shown that impression formation is not static and evolves over time as a result of repeated interactions or events (Denrell, 2005). In the online hiring context, Leung (2018) finds that repeated (positive) interactions with freelancers from one country increase the likelihood of subsequent hires from the same country. The key assumption is that, in job categories with limited supply of qualified workers, employers will sample from various candidate profiles and thus adjust prior beliefs based on actual performance. Along these lines, this hypothesis postulates that the activation of gender stereotypes by employers will diminish with online hiring experience, thus favoring female applicants in male-typed occupations.

Hypothesis 4: As the value of the job increases, the bias against female candidates in male-typed jobs will decrease.

Following Urwin and Cerqua (2018), it is hypothesized that employers will be less likely to activate gender stereotypes and more likely to select candidates on individual characteristics, as the value of the job increases. In other words, the closer scrutiny of individual candidates expected in higher value jobs will tend to favor female applicants against equally qualified male applicants in male-typed occupations.

Data and Methods

Sample Characteristics

This study is based on the examination of anonymized data from Nubelo, an online freelance platform based in Spain that was acquired by Freelancer.com in December 2016 (and subsequently folded into its main platform). Nubelo matched employers who listed short-term jobs (the labor demand side) with freelance workers who bid for these jobs (the supply side). The model differed from crowdsourcing platforms (such as Amazon's Mechanical Turk) in which jobs are disaggregated into small tasks and offered at a fixed price to multiple workers on a first come, first served basis.

In Nubelo, employers would screen candidates and select a single freelancer based on the value of the bids and the information visible on candidates' profile pages. These pages contained two types of personal information. First, platform-verified information based on previous jobs completed on the platform, including a summary feedback score from past employers. In addition, freelancers were invited (but not required) to upload personal information to their profiles such as a narrative description of skills, a sample portfolio, and a personal picture. This information was voluntarily provided and not validated by the platform.

Our data set includes records for all transactions in Nubelo for a 44-month period between March 2012 and December 2015. This includes information on 1,051 jobs listed and the 22,215 bids to these jobs placed by 6,707 applicants. Similar to other platforms, Nubelo actively discouraged interactions between prospective employers and freelance workers prior to hiring. Therefore, most of the information visible to employers at the time of hiring is available in our data set.

An important exception, however, concerns the information voluntarily provided by freelancers in their personal profile pages. Our data set only contains a coarse measurement of this information given by the percentage of profile completeness, which Nubelo calculated by assigning a certain percentage value to different information categories (e.g., a personal picture added 20% to the profile completeness, a description of skills added another 20%, and so forth). This is an important limitation given previous findings about information content (rather than simply amount) in impression formation and, in particular, whether the information confirms or violates gender stereotypes (Rudman & Phelan, 2008). This limitation is further elaborated upon in the interpretation of results in the Discussion and Limitations section.

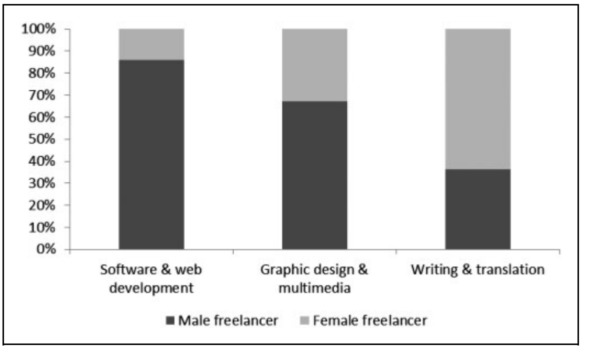

Figure 1. Share of bids by gender and job category.

Nubelo did not collect demographic information from workers, such as age, race, or gender, due to concerns about potential discrimination in hiring. However, employers could easily infer the gender of job candidates from first names and/or profile photos. For the purposes of this study, gender was automatically coded by contrasting first names against a database of common Spanish names (it is worth noting that there are no gender-neutral names in the Spanish language). For a variety of reasons, slightly less than 5% of names did not result in a match. These cases were manually coded by examining the information contained in workers' online profiles. Overall, gender could not be established for less than 1% of the freelancers in the data set.

Jobs listings were classified by Nubelo into 10 categories. In practice, however, three categories concentrated about 92% of the bid activity: Graphic and Multimedia Design (43.8%), Software and Web Development (28%), and Writing and Translation (20.4%). The analysis thus focuses on these three job categories, which present the following gender breakdown in bid activity (Figure 1).

This breakdown generally conforms to gendered occupation stereotypes identified by previous studies. Broadly speaking, women's traits are believed to be well suited for jobs that require emotional sensitivity, creativity, and verbal skills, while men's traits are associated with technology-related occupations (Correll, 2001; Gorman, 2005). In our data set, about 88% of the bids for jobs in Software and Web Development (e.g., JavaScript programming, Android app development) come from male applicants. By contrast, about 63% of the bids to Writing and Translation jobs (e.g., audio transcription, proofreading) were placed by female applicants. In the Graphic and Multimedia Design category, where jobs typically involve a combination of technical and creative skills (e.g., video editing and special effects, and HTML design), male bidders still outnumber female applicants by about 2 to 1.

Variables and Empirical Strategy

The dependent variable is the probability of being hired, conditional on submitting a bid. This binary outcome is modeled as a choice model, where employers can either hire or not hire a job applicant conditional on his or her bid amount and individual characteristics. Because choices are interdependent at the level of individual jobs, the models are estimated using a conditional logit specification (McFadden, 1974). These clusters estimate at the individual job level, thus limiting bias stemming from unobservable differences across jobs (Greene, 1990).

Since the research questions relate to differences in male and female outcomes, job postings that only received bids from either male or female candidates are dropped out of the sample. In other words, our estimates are based on a subsample of jobs for which there are competing bids between male and female job applicants. Table 1 presents summary statistics for the model variables.

Table 1. Descriptive Statistics.

Variable	Mean	*SD*	Min.	Max.
Hired (*yes* = 1)	0.041	0.199	0	1
Bid amount (log)	4.837	1.426	−4.60	9.588
Feedback score	4.709	0.400	1.67	5
Profile completeness	0.819	0.152	0.2	1
Previous job experience (yes=1)	0.355	0.478	0	1
Worker experience	1.875	5.664	0	57
Employer experience	1.566	1.759	1	27
Project amount (log)	4.279	1.242	−4.60	8.446
Female (*yes* = 1)	0.360	0.480	0	1

The variable *Hired* is a binary outcome variable which indicates a successful job bid (=1). As shown, the overall odds of being hired (about 4%) are quite low. This figure is in line with previous studies of online hiring in similar job platforms (e.g., Agrawal, Lacetera, & Lyons, 2013; Chan & Wang, 2018) and suggests intense competition among freelancers (Graham, Hjorth, & Lehdonvirta, 2017) and significant market power exercised by employers (Dube, Jacobs, Naidu, & Suri, 2018).

Our main variable of interest is *Female* (=1), and the covariates capture other information about job candidates that is visible to employers at the time of hiring. *Bid amount* is the amount of the bid submitted by the applicant to a specific job (logged). *Feedback score* refers to the average feedback score received by the freelancer from past employers (1–5 scale) at the time of the bid (conditional on having been hired in the past). As shown, the distribution is highly skewed toward the maximum score of 5 ($\bar{x} = 4.709$, $SD = 0.4$). This is consistent with previous studies which find reputation scores in online marketplaces to be highly inflated (Agrawal, Horton, Lacetera, & Lyons, 2013).

As noted above, *profile completeness* computes the degree to which job applicants had completed their personal profiles (regardless of the actual content). *Previous job experience* is a binary variable representing whether or not the worker has been previously hired at the time of bidding (=1), while *worker experience* refers to the number of previous jobs completed at the time of bidding. *Project amount* is the average value of the previous jobs completed by the worker at the time of bidding (logged). Finally, *employer experience* refers to the number of previous jobs posted by the employer at the time of bidding.

Results

Table 2 introduces the baseline model (Model 1) which presents the (log) odds of being hired across all job categories conditional on the observable covariates. All the covariates are highly significant, and, in all but one case, the direction of the effect is as expected. A higher bid is associated with lower hiring odds. Applicants with more experience and stronger reputation are more likely to be hired. Having previously worked in higher value projects also increases the hiring odds, possibly because employers interpret this as a signal of higher worker quality.

Somewhat surprisingly, a more complete profile is associated with lower hiring odds. This result can be attributed to a number of factors. First, the variable is inherently noisy since it does not capture variations in the type or quality of the information included in personal profiles. In particular, it fails to capture whether the content reinforces or challenges gendered job stereotypes. On the other hand, the result is in line with previous findings that suggest that online employers heavily discount nonverified information voluntarily provided by job candidates (e.g., Gefen & Carmel, 2008). Model 2 shows that excluding this variable only marginally alters the results in Model 1.

Turning to the main outcome of interest, the results corroborate that the overall odds of being hired are higher for female applicants. More specifically (using Model 2 coefficients), female

Table 2. Probability of Being Hired (Conditional Logit Coefficients).

Variable	Model 1	Model 2	Model 3	Model 4
Bid amount (log)	−0.302*** (0.0384)	−0.294*** (0.0379)	−0.323*** (0.0382)	−0.326*** (0.0384)
Feedback score	0.969*** (0.0476)	0.937*** (0.0445)	0.932*** (0.0438)	0.938*** (0.044)
Job experience (*yes* = 1)	1.082*** (0.115)	1.102*** (0.115)	1.073*** (0.116)	1.091*** (0.117)
Worker experience	0.0174*** (0.00545)	0.0133** (0.00529)	0.0156*** (0.0053)	0.0169*** (0.00533)
Employer experience	−0.0384*** (0.01)	−0.0386*** (0.01)	−0.0394*** (0.00975)	−0.0418*** (0.00977)
Project amount (log)	0.218*** (0.0439)	0.220*** (0.0439)	0.192*** (0.0431)	0.197*** (0.0434)
Female (*yes* = 1)	0.268** (0.106)	0.292*** (0.106)	0.374*** (0.108)	0.534*** (0.118)
Profile completeness	−1.233*** (0.477)	—	—	—
Software/web development (*yes* = 1)			0.581*** (0.121)	0.797*** (0.134)
Female × Software/Web Development				−1.119*** (0.35)
Constant	−4.296*** (0.463)	−5.253*** (0.278)	−5.253*** (0.274)	−4.248*** (0.46)
Job fixed effects	Yes	Yes	Yes	Yes
Number of bids	9,476	9,476	9,476	9,476

Note. Standard errors in parentheses. *$p < .1$. **$p < .05$. ***$p < .01$.

applicants are about 34% (exp(0.292) = 1.339) more likely to be hired than male applicants, controlling for bid amount and other observable worker characteristics. This result validates the key role that trust plays in online markets. As Diekmann, Jann, Przepiorka, and Wehrli (2013) argue, the traditional mechanisms that mitigate trust problems in economic transactions (such as social networks, credit-scoring institutions, and dispute settlement courts) are of limited relevance in online markets that connect anonymous buyers and sellers for one-off exchanges around the globe. Because women are stereotypically perceived as more trustworthy and less likely to cheat (Davison & Burke, 2000), online employers assign a smaller risk to female applicants.

Models 3 and 4 explore variations in hiring odds across job categories. The focus is on the Software and Web Development category, for a number of reasons. First, this is a male-typed category for which the gender imbalance in bid activity (88% male/12% female) is most apparent (see Figure 1). This is also the highest wage category, where the average contract value (about US$350) is about twice that of the other categories. To test differences in outcomes for different job categories, Model 3 introduces a job category dummy (*Software and Web Development* = 1), whereas Model 4 introduces a term that captures the interaction between gender (*Female* = 1) and the Software and Web Development category.

The results in Model 3 are essentially similar to those in Model 2, with only relatively small variations in coefficient magnitude. The large positive coefficient for the Software and Web Development dummy reflects the technical skills typically required to compete for these jobs, which pushes up wages and limits competition. On average, Software and Web Development jobs receive about half the bids compared to jobs in the two other large categories (Writing and Translation and Graphic and Multimedia Design).

Table 3. Probability of Being Hired (Conditional Logit Coefficients) Across Job Categories.

Variable	Software and Web Development	Graphic and Multimedia Design	Writing and Translation
Bid amount (log)	−0.544*** (0.10)	−0.323*** (0.07)	−0.104 (0.08)
Feedback score	1.004*** (0.11)	0.965*** (0.10)	1.170*** (0.11)
Profile completeness	−0.907 (0.96)	−1.107 (0.79)	−2.054** (1.02)
Job experience (*yes* = 1)	0.858*** (0.24)	0.981*** (0.19)	1.741*** (0.27)
Worker experience	0.012 (0.02)	0.026*** (0.01)	0.017 (0.02)
Employer experience	−0.078*** (0.02)	−0.010 (0.03)	−0.043* (0.02)
Project amount (log)	0.331*** (0.11)	0.192** (0.09)	0.215* (0.11)
Female (*yes* = 1)	−0.573* (0.34)	0.193 (0.17)	0.435* (0.25)
Constant	−3.774*** (0.97)	−4.969*** (0.82)	−5.496*** (1.00)
Job fixed effects	Yes	Yes	Yes
Number of bids	2,004	4,950	1,927

Note. Standard errors in parentheses.
$^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

The main result of interest is the interaction term between *Female* and *Software and Web Development* in Model 4, which is negative and highly significant ($p < .01$). This suggests that, controlling for bid amount and other observable candidate characteristics, female applicants are significantly less likely to be hired for jobs in Software and Web Development. Combining the main effect of female with the interaction effect for this job category, we obtain an estimate of the total female hiring penalty in Software and Web Development jobs. The penalty amounts to about 50%, which expressed in odds means that the hiring odds for women in this category are only about half relative to the odds of similar male candidates ($\exp(-1.12 + 0.53) = 0.55$).

In order to validate these findings, Table 3 presents results from separate estimations of the baseline model (Model 1) across the three main job categories. The first column shows estimates for jobs in Software and Web Development only, which corroborate that the hiring odds for female applicants in this category are only about half ($\exp(-0.573) = 0.56$) relative to the odds of men. The second column replicates the model for jobs listed under Graphic and Multimedia Design. As shown, in this more gender-balanced category, the coefficient for *Female* is not statistically significant. Finally, the third column presents baseline model coefficients for jobs in Writing and Translation. In this female-typed job category, the gender effect is reversed, with women about 54% ($\exp(0.435 = 1.54)$) more likely to be hired than male applicants.

Figure 2 presents coefficient point estimates of the (log) hiring odds of female freelancers in each of the three job categories (from Table 3) along with 95% confidence intervals (CIs). The figure offers a simple visualization of how the hiring odds for women change from negative to neutral to positive in the male-typed (Software and Web Development), gender-neutral (Graphic and Multimedia Design) and female-typed (Writing and Translation) job categories, respectively. Overall, these results corroborate Hypothesis 1: women are more likely to be hired for jobs stereotyped as "female"—and for which the overall share of female workers in the platform is larger—but less likely to be hired for jobs associated with male skills.

Hypothesis 2 postulates that previous job experience can mitigate the female hiring penalty in male-typed jobs. According to this hypothesis, when more information about the past performance of individual job candidates is available, online employers will be less likely to activate stereotypes that substitute for the lack of reliable information about workers' abilities. While the availability of more information about past performance will benefit male and female job applicants alike (relative

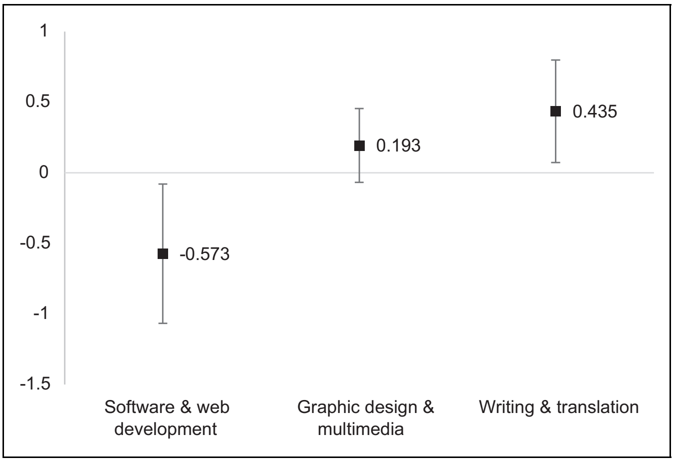

Figure 2. Conditional logit coefficient estimates and 95% confidence interval for female applicants by job category.

to candidates for which this information is not available), Hypothesis 2 predicts that women will benefit relatively more due to the reduction in the salience of stereotypes in hiring.

Contrary to expectations, however, the findings reveal that previous job experience does not alter the male hiring advantage in the Software and Web Development category. Using the same covariates from the baseline model, Figure 3 plots point estimates and 95% CIs for the hiring odds of men and women at different levels of job experience in Software and Web Development. As expected, the hiring odds increase with experience for both male and female workers. However, female workers do not benefit relatively more. If anything, the male odds appear to be increasing with experience at a slightly faster rate, though comparisons at different levels of job experience reveal that these differences are not statistically significant.

Does employer experience in online hiring mitigate the female penalty in male-typed jobs? To explore this question (postulated in Hypothesis 3), Figure 4 presents point estimates and 95% CIs for the hiring odds of men and women in the Software and Development category across different levels of employer experience (measured in number of previous jobs listed by the employer, regardless of hiring outcome). In contrast to the results for Hypothesis 2, the figure suggests that increased employer experience in online hiring is associated with a smaller bias against female workers in male-typed jobs, with the odds for male and female applicants gradually converging as employer experience grows.

Finally, Hypothesis 4 postulates that the female penalty in male-typed jobs will decrease as the value of the job increases. Figure 5 presents point estimates and 95% CIs for the hiring odds of men and women across project values in Software and Web Development. As shown, the hiring odds increase for both male and female applicants as job value rises, likely because higher value jobs require more technical expertise, which limits the applicant pool. However, the results do not support Hypothesis 4, as no statistically significant differences are detected between the odds for female and male applicants along the project value distribution. Hence, contrary to expectations, female job seekers do not benefit from the closer scrutiny of individual candidates that employers can be expected to make in higher value projects.

Discussion and Limitations

Structural changes in labor markets are increasingly pushing workers to seek piecemeal work in the gig economy. At the center of this new form of economic organization are online platforms that

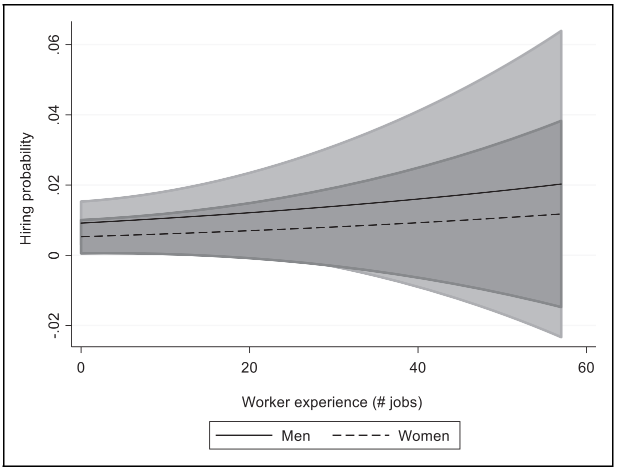

Figure 3. Point estimates and 95% confidence interval for hiring odds by gender and previous job experience in Software and Web Development category.

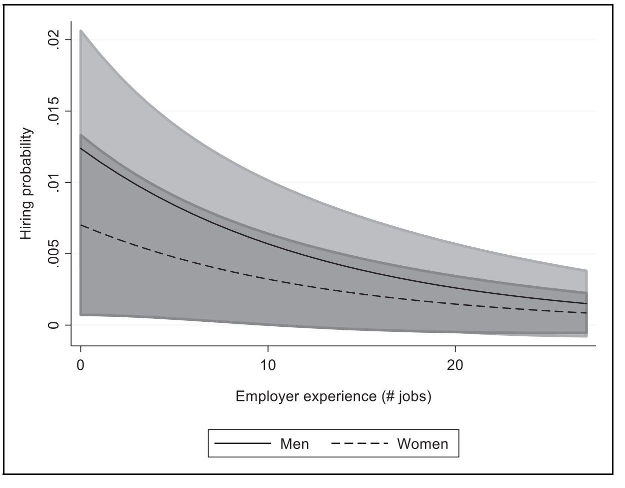

Figure 4. Point estimates and 95% confidence interval for hiring odds by gender and previous employer experience in Software and Web Development category.

intermediate between prospective employers and job seekers. These platforms present a novel context in which previous findings about gender bias in hiring must be tested. While researchers have already made significant progress, much remains to be understood as the gig economy expands further into the fabric of modern economies (Kalleberg & Vallas, 2018).

Gig work is often described as a desirable alternative to traditional employment that offers schedule flexibility, monetization of underutilized resources, better work/family balance, and entrepreneurial opportunities (e.g., World Bank, 2018). Further, these characteristics are often linked to female preferences for flexible employment, along traditional social norms that determine the division of labor within families. This is hardly a novel linkage, as shown by Hatton (2011), who traces the feminization of contingent work to the emergence of temporary work agencies in the postwar period.

Historical analysis reveals that occupational segregation has fallen sharply since the 1950s as a result of more qualified women entering the labor force as well as less discrimination in hiring and

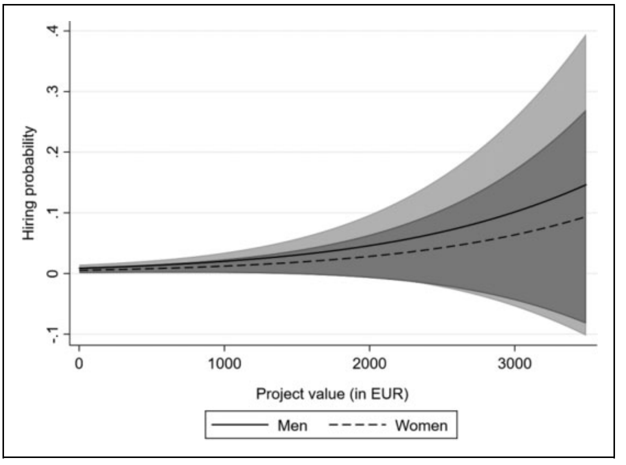

Figure 5. Point estimates and 95% confidence interval for hiring odds by gender and project value in Software and Web Development category.

promotion within organizations (Blau, Brummund, & Liu, 2012). However, women continue to face numerous challenges in male-dominated occupations, particularly those associated with STEM skills. For example, Beede et al. (2011) find that only 26% of women with STEM degrees worked in a STEM job, compared to 40% of men. Higher barriers to entry and higher exit rates suggest that the challenges to women in male-dominated occupations extend beyond personal career choices (Xie, Fang, & Shauman, 2015).

Online labor platforms are a fast-paced hiring environment in which one-off, low-value transactions are the norm. Whether these conditions are likely to mitigate or exacerbate gender sorting into different occupations is theoretically ambiguous. On the one hand, online hiring reduces the value of personal networks as well as the parenthood penalty that disproportionately affects women in traditional hiring. On the other, a low-information context in which employers hire for small gigs from a large pool of applicants may favor the activation of gender stereotypes regarding fit for different jobs.

The findings suggest that online hiring is unlikely to mitigate gender sorting into different occupations. In particular, they suggest that women will continue to face a significant hiring penalty in male-typed occupations associated with STEM skills. The estimates suggest that the winning odds of female applicants in Software and Web Development are only about half relative to similarly qualified male applicants. By contrast, the effect is reversed in the female-typed Writing and Translation job category (and the magnitude is similar), suggesting that sorting effects are bidirectional and create distinctive incentives for male and female freelance workers in online labor platforms.

Previous research suggests that several mechanisms can potentially attenuate sorting effects in online hiring. The first mechanism is the increased availability of job performance information from past employers, which studies suggest tends to benefit negatively stereotyped groups (e.g., Agrawal, Lacetera, & Lyons, 2013). The results however indicate that this mechanism benefit men and women equally and therefore do not contribute to mitigate sorting effects. This finding needs to be carefully interpreted against the backdrop of the study's limitations. For example, it is possible that the relatively small sample of women that compete for jobs in Software and Web Development is simply not large enough to capture the effects of increased information from previous job performance. Another concern relates to variations in the types of jobs within this category that are not captured in the analysis. For example, previous job experience in Android app development may not translate into advantages when applying for .NET programming jobs. Further research is required to validate this finding.

By contrast, the second attenuation mechanism identified by previous research acted as predicted. The female penalty in Software and Web Development falls as employer experience in online hiring increases. This corroborates findings by Leung (2018) which suggest that online employers continually update expectations and adjust choices based on past results. Put differently, the less experienced the employer, the more it is likely to fall back on gender stereotypes when hiring in sex-typed occupations.

Finally, previous research suggests that stereotype activation will be less likely in higher value projects because of closer employer scrutiny of individual applicants. This can be expected to favor negatively stereotyped groups, as is the case of female applicants in the Software and Web Development category. Contrary to expectations, the odds of female applicants (relative to male applicants) remain essentially unchanged across job value and even appear to decrease slightly on the higher end of the job value distribution. This suggests that increased cognitive resources from employers do not necessarily result in a more level playing field for women (as predicted for example by Urwin and Cerqua, 2018). For example, while employers can be expected to screen individual candidates more closely as the value of the job rises, it is also likely that employers are less willing to risk hiring negatively stereotyped candidates in higher value jobs. Further research is required to disentangle the net effect of these alternative explanations.

An important limitation to this study is the inability to observe the content of the information contained in job applicants' online profiles. As noted, the data set only contains a coarse measurement about the degree to which an applicant has completed its profile page. The concern is that employers' choices may also be driven by such content and, in particular, by content that either increases or decreases the salience of stereotyped gender attributes (Heilman & Stopeck, 1985).

This important limitation is nonetheless moderated by several factors. First, previous studies find that employers heavily discount the information on applicants' profile pages that is not validated by the platform (Agrawal, Lacetera, & Lyons, 2013; Gefen & Carmel, 2008). In fact, the comparison between Models 1 and 2 (Table 2) reveals that the coefficients for our variables of interest are essentially unaffected by the inclusion of the profile completeness variable. Finally, this variable is not significant in the estimates for our main job category of interest (Software and Web Development) in Table 3. Taken together, these factors partly attenuate the inability of the estimates to account for the content of the information in applicants' online profiles.

Conclusion

There is some evidence that for many women, particularly in less-advanced regions, gig work has amplified employment opportunities, facilitating access to labor markets and increasing the likelihood that individual skills will be matched with jobs (Galperin & Greppi, 2018). Gig work may also open job training opportunities for those seeking to enter a new field or resume their careers, which tend to be disproportionately female (Ferenstein, 2018). Online work may also alter women's career preferences by shielding women from hostile work environments in male-dominated occupations (World Bank, 2018).

Despite these potential benefits, the evidence in this study raises concerns about the exacerbation of sorting mechanisms that ultimate truncate women's careers in STEM-related fields. Along these lines, there is already survey evidence that young STEM-educated women seek online employment significantly below their educational qualifications (International Labor Organization, 2018). As the gig economy expands globally across industries and occupations, efforts to reduce gender inequality in wages and careers must account for rapid changes in the nature of hiring and employment that new technologies bring about.

Acknowledgments

The author thanks Guillermo Cruces, Catrihel Greppi and the reviewers for their comments.

Data Availability

The original data set was provided by Nubelo, an online freelance marketplace acquired by Freelancer.com in December 2016. The data are available upon request from the author (hgalperi@usc.edu).

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author received no financial support for the research, authorship, and/or publication of this article.

Software Information

The data were processed using Stata Version 15.0. The .do file is available upon request from the author (hgalperi@usc.edu).

References

Agrawal, A., Horton, J., Lacetera, N., & Lyons, E. (2013). *Digitization and the contract labor market: A research agenda* (NBER Working Paper 19525). NBER.

Agrawal, A., Lacetera, N., & Lyons, E. (2013). *Does information help or hinder job applicants from less developed countries in online markets?* (NBER Working Paper 18720). NBER.

Aigner, D., & Cain, G. (1977). Statistical theories of discrimination in labor markets. *ILR Review*, *30*, 175–187.

Akerlof, G. A., & Kranton, R. E. (2010). *Identity economics: How our identities affect our work, wages, and well-being*. Princeton University Press.

Azmat, G., & Petrongolo, B. (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics*, *30*, 32–40.

Babcock, L., & Laschever, S. (2013). *Women don't ask: Negotiation and the gender divide*. Princeton University Press.

Barbulescu, R., & Bidwell, M. (2013). Do women choose different jobs from men? Mechanisms of application segregation in the market for managerial workers. *Organization Science*, *24*, 737–756.

Becker, G. S. (1957). *The economics of discrimination* (2nd ed.). University of Chicago Press.

Beede, D., Julian, T., Langdon, D., McKittrick, G., Khan, B., & Doms, M. (2011). *Women in STEM: A gender gap to innovation*. Economics and Statistics Administration, U.S. Department of Commerce.

Bertrand, M., & Duflo, E. (2016). *Field experiments on discrimination* (Working Paper NBER 22014). NBER.

Blau, F., Brummund, P., & Liu, A. Y. (2012). *Trends in occupational segregation by gender 1970–2009* (Working Paper NBER 17993). NBER.

Blau, F., & Kahn, L. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, *55*, 789–865.

Blickenstaff, J. C. (2005). Women and science careers: Leaky pipeline or gender filter? *Gender and Education*, *17*, 369–386.

Booth, A., & Leigh, A. (2010). *Do employers discriminate by gender? A field experiment in female-dominated occupations* (IZA Discussion Paper 4690). Institute for the Study of Labor (IZA).

Branch, E. H., & Hanley, C. (2017). A racial-gender lens on precarious nonstandard employment. In A. L. Kalleberg & S. P. Vallas (Eds.), *Precarious work (research in the sociology of work)* (Vol. *31*, pp. 183–213). Emerald.

Caers, R., & Castelyns, V. (2010). LinkedIn and Facebook in Belgium: The influences and biases of social network sites in recruitment and selection procedures. *Social Science Computer Review*, *29*, 437–448.

Campero, S., & Fernandez, R. M. (2018). Gender composition of labor queues and gender disparities in hiring. *Social Forces*. doi:10.1093/sf/soy097

Cejka, M. A., & Eagly, A. (1999). Gender-stereotypic images of occupations correspond to the sex segregation of employment. *Personality and Social Psychology Bulletin*, *25*, 413–423.

Chan, J., & Wang, J. (2018). Hiring preferences in online labor markets: Evidence of a female hiring bias. *Management Science*, *64*, 2973–2994.

Correll, S. (2001). Gender and the career choice process: The role of biased self-assessments. *American Journal of Sociology*, *106*, 1691–1730.

Cotter, D. A., Hermsen, J. M., Ovadia, S., & Vanneman, R. (2001). The glass ceiling effect. *Social Forces*, *80*, 655–681.

Cullen, Z. B., Humphries, J. E., & Pakzad-Hurson, B. (2018, January). *Gender and sorting in the on-demand economy*. Presented at ASSA Annual Meeting, Atlanta, GA.

Davison, H., & Burke, M. (2000). Sex discrimination in simulated employment contexts: A meta-analytic investigation. *Journal of Vocational Behavior*, *56*, 225–248.

Denrell, J. (2005). Why most people disapprove of me: Experience sampling in impression formation. *Psychological Review*, *112*, 951–978.

Diekman, A. B., & Eagly, A. (2000). Stereotypes as dynamic constructs: Women and men of the past, present, and future. *Personality and Social Psychology Bulletin*, *26*, 1171–1188.

Diekmann, A., Jann, B., Przepiorka, W., & Wehrli, S. (2013). Reputation formation and the evolution of cooperation in anonymous online markets. *American Sociological Review*, *79*, 65–85.

Dube, A., Jacobs, J., Naidu, S., & Suri, S. (2018). *Monopsony in online labor markets* (NBER Working Paper 24416). NBER.

European Commission. (2018). *Platform workers in Europe: Evidence from the COLLEEM survey*. Luxembourg: Publications Office of the European Union.

Edelman, B., Luca, M., & Svirsky, D. (2017). Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics*, *9*, 1–22.

Falk, A., & Heckman, J. J. (2009). *Lab experiments are a major source of knowledge in the social sciences* (IZA Discussion Paper No. 4540). Institute for the Study of Labor (IZA).

Ferenstein, G. (2018). *Automation could create a more inclusive economy through high-skilled side work*. Brookings.

Fernandez, R. M., & Abraham, M. (2011). *Glass ceilings and glass doors? Internal and external hiring in an organizational hierarchy* (MIT Sloan Research Paper 4895-11). MIT Press.

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

Fiske, S., & Neuberg, S. L. (1990). A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. *Advances in Experimental Social Psychology*, *23*, 1–74.

Fuller, S. (2017). Segregation across workplaces and the motherhood wage gap: Why do mothers work in low-wage establishments? *Social Forces*, *96*, 1443–1476.

Galperin, H., & Greppi, C. (2018). Geographical discrimination in the gig economy. In M. Graham (Ed.), *Digital Economies at Global Margins* (pp. 295–318). Cambridge, MA: MIT Press.

Gefen, D., & Carmel, E. (2008). Is the world really flat? A look at offshoring in an online programming marketplace. *MIS Quarterly*, *32*, 367–384.

Goldin, C. (2002). *A pollution theory of discrimination: Male and female differences in occupations and earnings* (Working Paper NBER 8985). NBER.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, *10*, 1091–1119.

Gorman, E. H. (2005). Gender stereotypes, same-gender preferences, and organizational variation in the hiring of women: Evidence from law firms. *American Sociological Review*, *70*, 702–728.

Graham, M., Hjorth, I., & Lehdonvirta, V. (2017). Digital labour and development: Impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transfer: European Review of Labour and Research*, *23*, 135–162.

Granovetter, M. (1974). *Getting a job: Study of contacts and careers*. University of Chicago Press.

Greene, W. (1990). *Econometric analysis*. Prentice Hall.

Hancock, J. T., & Dunham, P. J. (2001). Impression formation in computer-mediated communication revisited: An analysis of the breadth and intensity of impressions. *Communication Research*, *28*, 325–347.

Hatton, E. (2011). *The temp economy: From Kelly girls to permatemps in postwar America*. Temple University Press.

Heckman, J., & Siegelman, P. (1993). The urban institute audit studies: Their methods and findings. In M. Fix & R. Struyk (Eds.), *Clear and convincing evidence: Measurement of discrimination in America* (pp. 187–258). The Urban Institute Press.

Heilman, M. E. (1983). Sex bias in work settings: The lack of fit model. *Research in Organizational Behavior*, *5*, 269–298.

Heilman, M. E. (2012). Gender stereotypes and workplace bias. *Research in Organizational Behavior*, *32*, 113–135.

Heilman, M. E., & Stopeck, M. H. (1985). Attractiveness and corporate success. Different causal attributions for males and females. *Journal of Applied Psychology*, *70*, 379–388.

Hong, Y., & Pavlou, P. (2014). *Is the world truly 'flat'? Empirical evidence from online labor markets* (Fox School of Business Research Paper No. 15-045).

Horton, J., Kerr, W. R., & Stanton, C. (2018). Digital labor markets and global talent flows. In G. H. Hanson, W. R. Kerr, & S. Turner (Eds.), *High-skilled migration to the United States and its economic consequences* (pp. 71–108). University of Chicago Press.

Intenational Labor Organization. (2018). *Digital labour platforms and the future of work: Towards decent work in the online world*. Author.

Isaac, C., Lee, B., & Carnes, M. (2009). Interventions that affect gender bias in hiring: A systematic review. *Academic Medicine: Journal of the Association of American Medical Colleges*, *84*, 1440–1446.

Kallelberg, A., & Vallas, S. P. (2018). Probing precarious work: Theory, research, and politics. In A. L. Kalleberg & S. P. Vallas (Eds.), *Precarious work (research in the sociology of work)* (Vol. 31, pp. 1–30). Emerald.

Kricheli-Katz, T., & Regev, T. (2016). How many cents on the dollar? Women and men in product markets. *Science Advances, 2*, *e1500599*.

Lehdonvirta, V., Barnard, H., Graham, M., & Hjorth, I. (2014, September). *Online labour markets—Leveling the playing field for international service markets?* Presented at the Internet, Politics, and Policy Conference, Oxford, England.

Leung, M. (2018). Hiring as a dynamic experiential learning process in an online market for contract labor. *Management Science*, *64*, 5461–5959.

Leung, M., & Koppman, S. (2018). Taking a pass: How proportional prejudice and decisions not to hire reproduce gender segregation. *American Journal of Sociology*, *124*, 762–813.

McFadden, D. L. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*, 303–328.

Mill, R. (2011). *Hiring and learning in online global labor markets* (NET Institute Working Paper No. 11-17). Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1957962

Neumark, D., Bank, R. J., & Van Nort, K. D. (1996). Sex discrimination in restaurant hiring: An audit study. *The Quarterly Journal of Economics*, *111*, 915–941.

Organization for Economic Cooperation and Development. (2017). *Going digital: The future of work for women*. Author.

Pallais, A. (2014). Inefficient hiring in entry-level labor markets. *American Economic Review*, *104*, 3565–3599.

Penner, A. (2008). Race and gender differences in wages: The role of occupational sorting at the point of hire. *The Sociological Quarterly*, *49*, 597–614.

Petersen, T., Saporta, I., & Seidel, M. (2005). Getting hired: Sex and race. *Industrial Relations: A Journal of Economy and Society*, *44*, 416–443.

Pew Research Center. (2016). *Gig work, online selling and home sharing*.

Riach, P. A., & Rich, J. (2006). *An experimental investigation of age discrimination in the French labour market* (IZA Discussion Papers 2522). Institute for the Study of Labor (IZA).

Rudman, L. A., & Phelan, J. E. (2008). Backlash effects for disconfirming gender stereotypes in organizations. *Research in Organizational Behavior*, *28*, 61–79.

Tyler, J. M., & McCullough, J. D. (2009). Violating prescriptive stereotypes on job resumes: A self-presentational perspective. *Management Communication Quarterly*, *23*, 272–287.

UK Department for Business, Energy & Industrial Strategy. (2018). *The characteristics of those in the gig economy*. BEIS.

Urwin, P., & Cerqua, A. (2018). Unpicking the gender hiring bias in online labor markets. *Academy of Management Proceedings*, *1*, 16137.

World Bank. (2018). *World development report 2019: The changing nature of work*. Author.

Xie, Y., Fang, M., & Shauman, K. (2015). STEM education. *Annual Review of Sociology*, *41*, 331–357.

Author Biography

Hernan Galperin (PhD, Stanford University) is an associate professor at the Annenberg School for Communication, University of Southern California, where he is also a director of the Annenberg Research Network on International Communication. He is also affiliated with the USC Annenberg Innovation Lab, the USC Price Center for Social Innovation, and the USC Spatial Analysis Lab. E-mail: hgalperi@usc.edu