

Understanding Gender Differences in Pricing Strategies in Online Labor Marketplaces

Eureka Foong*

foong.eureka@tc.u-tokyo.ac.jp
Tokyo College, University of Tokyo
Tokyo, Japan

Elizabeth M. Gerber

egerber@northwestern.edu
Northwestern University
Evanston, Illinois

ABSTRACT

The growing online gig economy provides ways for women to participate in a flexible, remote workforce and close the offline gender pay and participation gap. While women in online labor marketplaces earn about as much overall as men, women set lower bill rates suggesting gender differences in pricing strategies. In this study, we surveyed 392 freelancers in the United States (US) on the popular marketplace platform, Upwork, to understand strategies used to set hourly bill rates. We did not find gender differences in pricing strategies that were significantly related to bill rate. Instead, we found that other factors, such as full-time freelancer status and level of self-esteem, may help explain gender differences in bill rates. To better support equity and fairness in the growing gig economy, CHI researchers must identify, assess, and address the complex interaction between societal conditions in online labor markets.

CCS CONCEPTS

• Human-centered computing → Empirical studies in collaborative and social computing.

KEYWORDS

Gender, gig economy, freelancing, online labor marketplaces, online work, pricing, survey, bill rate

ACM Reference Format:

Eureka Foong and Elizabeth M. Gerber. 2021. Understanding Gender Differences in Pricing Strategies in Online Labor Marketplaces. In *CHI Conference on Human Factors in Computing Systems (CHI '21)*, May 8–13, 2021, Yokohama, Japan. ACM, New York, NY, USA, 16 pages. <https://doi.org/10.1145/3411764.3445636>

1 INTRODUCTION

Across the world, women continue to receive lower pay and participate in the workforce at lower rates than men, which can lead to losses in productivity and diversity in leadership [121]. Two important factors that contribute to lower pay and participation include women taking breaks from the workforce to start their families and

women doing unpaid household labor [11, 16, 46]. These factors make it more challenging for women to participate in paid labor, especially if jobs disproportionately reward workers for their ability to work long hours in person [19, 46].

The growing online gig economy could provide new ways for women to participate in a flexible and remote freelance workforce [39, 74]. In marketplaces such as Upwork [108] and Fiverr [1], freelancers can apply and be hired to complete hundreds of short-term projects in a variety of domains, such as web development, writing, and graphic design [113]. Compared to the offline labor market, freelancers construct online profiles to attract potential clients, which can include their history of work on and off the platform, customer reviews, and bill rates for services. These bill rates are publicly displayed on freelancers' profiles allowing for clients, as well as freelancers, to easily compare their rates with other freelancers, and for women to set comparable wages to men.

Despite this new opportunity for women to see other's bill rates and set comparable wages to men, women do not. In one study, the median woman in an online labor marketplace in the US set a bill rate that was 13.5% lower than the median man's bill rate, a gap that could not be entirely explained by differences in work experience, education level, and job category [39]. Nevertheless, women also earned about as much as men after factoring in their total hours worked, suggesting that they may be using lower bill rates as a pricing strategy for attracting work opportunities [39].

To understand potential gender differences in the pricing strategies freelancers use to choose their bill rates, we surveyed 392 freelancers in the US on the popular marketplace platform, Upwork. The freelancers rated and ranked the importance of different pricing strategies for choosing bill rate.

We contribute to an ongoing conversation on ethical online work (e.g., [64, 107]) by providing the first overview of pricing strategies for rate-setting in online labor marketplaces. While prior work hypothesized that pricing strategies contribute to gender differences in rate-setting online, we show that multiple variables (e.g., part-time status, importance of freelancing as a source of income)—and not just pricing strategies—could contribute to gender rate gaps [39, 123]. We build on prior work in human-computer interaction (HCI; e.g., [67, 105]) by showing how freelancers adapt to platform constraints when pricing their services by considering both offline (e.g., expertise, expected profits) and online (e.g., on-platform work experience) contexts. To better support equity and fairness in the growing gig economy, CHI researchers must identify, assess, and address the complex interaction between societal conditions in online labor markets.

*Previously affiliated with Northwestern University

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

CHI '21, May 8–13, 2021, Yokohama, Japan

© 2021 Association for Computing Machinery.

ACM ISBN 978-1-4503-8096-6/21/05...\$15.00

<https://doi.org/10.1145/3411764.3445636>

2 BACKGROUND

Below we describe research on gender inequities in the offline and online labor markets, the lack of research on freelancer's pricing strategies, and features of the labor marketplace, Upwork, on which this study is based.

2.1 Focus on Binary Gender Differences

In the current work, we focus on binary gender differences in pricing behavior, as decades of prior work have suggested biases in how men and women behave and are perceived based on binary gender roles [29, 34]. Nevertheless, it is important to acknowledge here the marginalization of non-binary and/or transgender perspectives more broadly in the labor market [17, 65]. For example, in a 2015 survey by the National Center for Transgender Equality, about 30% of transgender respondents who held a job were fired or denied promotions in the workplace due to their gender identity [65]. On Upwork, non-binary and/or transgender freelancers could similarly experience pricing differently from binary gender freelancers. However, given our study's focus and, as described later, our ability to recruit only a small number of participants who described themselves as non-binary and/or transgender, we could not draw conclusions about this population. We urge future research to address these limitations by contrasting the current findings with the pricing behaviors and experiences of workers who are non-binary and/or transgender.

2.2 Gender Inequities Exist In The Offline And Online Labor Market

2.2.1 Gender Inequities Exist In The Offline Labor Market. Across the world, including the US, women are being paid less than men in part because they lack flexible work opportunities [121]. In 2016, the median woman in the US earned only 82% as much as the median man's weekly earnings [109].

Multiple institutional, social, and psychological factors contribute to these gender disparities, despite legal efforts to stem workplace discrimination [16, 48]. For example, the lack of flexible work opportunities contributes to gender pay gaps by disproportionately rewarding workers with continuous years of work experience (e.g., without breaks, for example to start a family) or who can commit to long hours of face-to-face work [47]. Men also tend to have higher salary expectations than women because they perceive bringing more value to the labor market [88, 99] and have an elevated sense of entitlement to wages [81, 88]. Men are also more likely than women to base their salary expectations on their level of self-esteem [88], which could lead to gender pay disparities given that higher self-esteem predicts higher salary and job satisfaction [94]. Moreover, women may have lower salary expectations because they may sense backlash when advocating for higher pay [115]. The lack of the transparency in pay rates within organizations also makes it more likely for gender to influence pay by making it more difficult for workers to advocate for themselves (e.g., [15, 18]). Besides that, women tend to be over-represented in lower-paying job categories, such as education [60].

Other factors, such as age, part-time status, and location, could also relate to gender inequities in pay in the offline labor market. Research suggests that women of childbearing age (i.e., 20–40 years

old) earn significantly less relative to men due to increased childcare responsibilities [46]. In addition, women may be more likely than men to work part-time for more flexible working hours [21, 87], which leads to lower pay rates due to perceptions of poorer productivity [76]. Differences in location could also influence expected income levels by influencing living costs and access to job opportunities [111]. Together, these factors contribute to complex gender dynamics in pay in the offline marketplace.

2.2.2 Online Gig Economy Provides Flexible Ways To Participate In Paid Remote Work. The online gig economy could provide new ways for women to join the flexible and remote workforce by lowering barriers to participating in paid work [59]. The gig economy consists of online and location-based applications that distribute opportunities for short-term labor to tens of millions of project-based freelancers [9]. In this paper, we focus on platforms that offer a range of occupational contexts and skills (e.g., Upwork), compared to platforms with fixed rates and contexts (e.g., Uber [2]), as these platforms provide workers with opportunities to develop professional skills. On these platforms, freelancers convey their skills through work profiles, select bill rates for their services, apply to jobs, and browse the profiles of other freelancers [9]. For example, a mother caring for her young child at home could post her profile and bill rate on Upwork soliciting work as a freelance writer, while another woman caring for her aging mother could post her profile soliciting work as a graphic designer.

2.2.3 Gender Inequities Persist In The Online Gig Economy. Despite these new opportunities for women to participate in the online gig economy, gender disparities persist online. For example, in online labor marketplaces such as Fiverr and TaskRabbit, women receive fewer customer reviews than men, influencing their appearance in search results on the platform [52]. Similarly, Jahanbakhsh and colleagues [64] found that low-performing women in a simulated online work task received lower performance ratings than men, while Ge and colleagues [44] found evidence of gender discrimination of ridesharing passengers, in which women were offered longer and more expensive rides than men. Some online tools that automate recruiting, such as Amazon's artificial intelligence recruiting tool, have also been shown to prefer the resumes of men compared to women [28]. Cook and colleagues [24] found that female drivers on Uber earned significantly less than male drivers because of differences in their driving activity, such as driving at less lucrative times of the day (e.g., in the daytime). In contrast, Thebault-Spieker and colleagues [107] did not find evidence that workers on Amazon Mechanical Turk were evaluating fellow workers differently based on gender or race. Together, these studies suggest a need for more critical engagement with gender dynamics in online labor platforms (e.g., [98]).

Most recently, researchers suggest that differences in *pricing strategies* in online labor marketplaces could contribute to specific gender gaps in the bill rates workers set for themselves online [39]. In one study of Upwork, where workers set hourly bill rates on their profiles, the median woman set a bill rate that were 13.5% less than the median man's bill rate, a gap that could not be entirely explained by work experience, education level, or job category [39]. However, women may have been using lower bill rates as a strategy to attract potential clients, as they also worked enough hours to earn as much

revenue as men. This suggests that freelancers' pricing strategies may play a critical role in explaining gender rate gaps online.

2.3 Lack of Research on Freelancers' Pricing Strategies

Despite the potentially critical role of pricing strategies, scholars currently have limited insight into how freelancers choose their bill rates online. While some researchers have described different structures that freelancers can use to receive payment for their services (e.g., a fixed or flat rate, an hourly rate) as well as different strategies for freelancers to increase their competitiveness in the marketplace (e.g., forming partnerships with other freelancers, lowering rates) [13, 102, 114], none have investigated the prevalence of different strategies nor whether gender differences in pricing strategies exist. Practitioner guides on online businesses and freelancing further urge individuals to consider the value of their services to potential clients when pricing themselves, but the merits of this approach have yet to be empirically verified [14, 45, 66, 78, 90, 101]. Moreover, prior work suggests that multiple factors, such as work experience, time spent on platform, and employer feedback, predict hiring behavior (e.g., [3, 10, 120]), and therefore could also be critical to freelancers' pricing decisions. In this novel study, we seek to understand the variety of factors that could influence freelancers' pricing strategies online and test the hypothesis that gender differences in strategies contribute to gender rate gaps online.

2.4 Studying Pricing Strategies on Upwork

In line with prior work [39], we focus on the experiences of freelancers in the US on Upwork, one of the largest English-speaking online labor marketplaces in the world [6]. On Upwork, freelancers create public profiles that display information such as their hourly bill rate in US Dollars, a self-description, education and work history, and projects in their portfolio. To be considered for work, freelancers submit proposals or bids to jobs using "connects," a virtual currency that regulates the number of freelancers who can apply for a job [33]. At the time of the study, freelancers were given 60 free connects each month and could purchase more through a premium subscription plan (USD\$49.99/month as of January 2021). Depending on the nature of the job, freelancers may either be asked by a client to propose an hourly or a fixed rate to complete a project. Clients can then choose to interview and hire freelancers who submitted proposals. In short, the Upwork platform provides an appropriate setting to examine freelancers' pricing strategies.

3 RESEARCH QUESTIONS

To better understand the freelancers' pricing strategies in online labor marketplaces, we asked the following research questions:

- RQ1: What pricing strategies do freelancers use to determine their hourly bill rate in online labor marketplaces?
- RQ2: How do gender and job category relate to the importance of different pricing strategies?
- RQ3: How do the importance of pricing strategies and other factors (e.g., age, education) relate to bill rate?

4 FORMATIVE STUDY

To identify pricing strategies, we triangulated between prior literature, blogs for freelancers, and survey data with a convenience sample of freelance graphic designers. Below, we describe the formative, open-ended survey we developed to understand pricing strategies freelancers use to determine their bill rate.

4.1 Formative Survey Method

We recruited seven freelance graphic designers (3 men, 3 women, 1 non-binary) in the US via Upwork. All participants were freelance graphic designers who had taken part in a prior study we conducted on Upwork. At this stage, we were less concerned about the diversity of the sample, as freelancers regardless of focus share similar approaches to freelance work [105]. We asked participants the following open-ended questions: 1) why they chose their hourly bill rate on their Upwork profile, 2) why they did not choose a higher and lower bill rate, and 3) if they had ever proposed a rate different than the one on their profile (and if so, why). To elicit concrete moments in participants' lives [117], we asked participants to refer to the current bill rate on their profile page while completing the survey. We also asked about freelancers' work experience and their demographic background (see Method for Large Survey). Once we began to uncover patterns in freelancers' answers, we stopped recruiting participants and began developing statements to describe these pricing strategies by integrating participants' phrases and concepts from the literature. More details on the development of each of these strategies can be found in the Supplemental Materials.

4.2 Formative Survey Data Analysis

As we collected the survey data, we compiled participants' answers on a spreadsheet and began to notice similarities between the answers and strategies from strategic marketing that *companies* use to price their products and services [25]. For example, some companies price their products based on the costs for making those products (cost-based pricing), while others choose prices based on the value the products will bring to customers (value-based pricing) [25]. Therefore, applying Strauss's constant comparison method [103], we compared themes from our data to relevant literature in strategic marketing, practitioner guides on pricing for freelancers, resources on gender differences in negotiation, and peer-reviewed articles on online labor marketplaces to form pricing strategies [8, 14, 25, 45, 52, 78, 101].

4.3 Formative Survey Findings

Our analysis revealed seven types of pricing strategies that freelancers use to determine their bill rate (Table 1). Similar to how a company might consider several factors (e.g., cost, strategic positioning, value proposition) to differentiate their products and services [25, 89], a freelancer considers several factors (e.g., overhead costs, potential business value to clients) when setting their bill rate. While some of these pricing strategies are similar to those in the strategic marketing (e.g., cost-based, value-based, dynamic pricing), others are unique to the Upwork platform. For example, freelancers might consider platform features, such as platform fees, when choosing their bill rate (platform-based pricing). Based on these seven pricing strategy categories, we developed a full survey

Pricing Strategy	Definition of Pricing Strategy	Example	Gender Differences Predicted
Value-Based Pricing	Based on the value the service will bring to a client or the value of one's unique qualities over competitors	<i>"I feel that I am an accomplished designer that would command a premium rate."</i> (PSP1, man)	✓ Men will find more important than women (H1) ✓ Freelancers with higher self-esteem will find more important (H2)
Cost-Based Pricing	Based on the costs of providing a service including living expenses and costs related to job flexibility (e.g., how much time it will take to complete a job).	<i>"...since I run my own business, I have to set a rate that is high enough to cover my living expenses."</i> (PSP6, woman)	✓ Women will find more important than men (H3)
Strategic Positioning	Convey an impression to clients (e.g., to appear knowledgeable, professional, approachable, or expensive)	<i>"...I am trying to market my value as a new, junior designer at an approachable hourly rate."</i> (PSP5, non-binary)	✗
Competition-Based Pricing	Based on the prices set by others seen as competitors to one's services	<i>"I looked at the going rate of other designers on Upwork..."</i> (PSP1, man)	✗
Demand-Based Pricing	Based on the perception of the demand for a service in the market	<i>"...I tried a lower rate, and got low quality clients. I also tried a higher rate but did not get much response..."</i> (PSP2, woman)	✗
Dynamic Pricing	Temporary rate that changes over time to achieve a marketing goal, such as attracting clients when one has little existing work experience	<i>"I eventually want to charge higher than \$65 but waiting to get more jobs on Upwork as well as good feedback."</i> (PSP6, woman)	✗
Platform-Based Pricing	Based on the features of the online platform, such as platform fees and appearance in search results	<i>"I originally had my rate set to \$12, however, Upwork collects 30% of my earnings so I felt obliged to up my rating."</i> (PSP7, woman)	✗

Table 1: Our formative study revealed seven types of pricing strategies that freelancers use to determine their hourly bill rate in an online labor marketplace. Based on prior literature, we expected to find gender differences in two of these pricing strategies—value-based and cost-based pricing.

instrument with survey items that corresponded to each strategy (see Method for Main Survey).

4.3.1 Pricing Strategies with Predicted Gender Differences. Although our analysis revealed seven types of pricing strategies, our literature review suggested gender differences in only two of these strategies (Table 1); we encourage readers to view the Supplemental Materials for a full overview of the pricing strategy categories not listed here. First, we predicted that men (H1) and freelancers with higher levels of self-esteem (H2) would perceive value-based pricing strategies as more important than women and freelancers with lower self-esteem. We also predicted that women would perceive cost-based pricing strategies as more important than men (H3). Below, we describe these hypotheses and strategies in greater detail.

Value-based Pricing. Value-based pricing is pricing based on: 1) the value that a product or service would bring to customers, or 2) the value of one's unique qualities over competitors [25, 45, 54, 78, 101]. For instance, when setting her bill rate, a freelance designer could consider how much a firm would benefit from having their logo redesigned and set a rate that is commensurate with that potential business value. Another freelance writer might consider his unique expertise in writing for older audiences and set his bill rate based on that unique value. A graphic designer with more than

10 years of work experience used value-based pricing to justify his \$45/hour bill rate:

"I feel that I am an accomplished designer that would command a premium rate." (PSP1, man)

Men and freelancers with higher levels of self-esteem may find value-based pricing strategies more important to determining their bill rate [37, 99]. Research on negotiation suggests that the ability to take the perspective of an opponent while considering one's own goals predicts the likelihood of negotiating a deal [42, 43]. However, women tend to feel less competent about their abilities than men in negotiations unless the task is framed in terms of more "feminine" qualities, such as the ability to manage interpersonal relationships [37]. Moreover, men tend to have higher salary expectations than women because they perceive bringing more value to the labor market [56, 99]. Therefore, we predict that:

H1: Men will find value-based pricing more important than women when setting their hourly bill rate.

We also expect that self-esteem, or global feelings of self-worth, may predict the use of the value-based pricing strategy. Researchers have hypothesized that self-esteem can influence salary expectations [55, 99]; in one study, men were more likely to relate their self-pay to their self-esteem or self-worth, while women were more likely to relate their pay to their performance on a specific task

[88]. As discussed earlier, these differences could lead to gender pay disparities given that higher self-esteem predicts higher salary and job satisfaction [94]. Moreover, women may have lower salary expectations because they may sense backlash when advocating for higher pay [115]. Hence, we also predict that:

H2: Freelancers with higher self-esteem will find value-based pricing more important to setting their bill rate than freelancers with lower self-esteem.

Cost-based Pricing. Cost-based pricing is pricing based on the costs of providing a product or service. For example, a freelance web developer might consider the costs of their computer equipment and software subscriptions when choosing how much to bill a client. One digital content creator in our formative survey considered the cost of living expenses when choosing her bill rate on Upwork:

“...since I run my own business, I have to set a rate that is high enough to cover my living expenses.” (PSP6, woman)

We predict that women will be more likely than men to consider the costs of providing their services when choosing a bill rate. Women tend to be more risk averse than men, choosing options that minimize losses, rather than maximize gains [95]. Hence, women may be more sensitive to costs they incur as freelancers (e.g., paying for insurance, equipment). For online freelancers, cost-based pricing could also include costs related to job flexibility, such as the amount of time it takes to complete a project. HCI research suggests that workers are willing to lower their rates in exchange for more time to complete a job [123]. Women may be further influenced by flexibility-related costs due to their increased time spent on unpaid household labor [110]. Therefore, we predict that:

H3: Women will find cost-based pricing, such as pricing based on their needs for job flexibility, more important to determining their hourly bill rate than men.

Again, we encourage readers to view the Supplemental Materials for a full overview of the pricing strategy categories not listed here.

5 METHOD FOR LARGE SURVEY

Next, we conducted a large survey of freelancers in the US on Upwork. Below we describe the recruitment methods, the survey instrument, and our approach to data analysis.

5.1 Recruitment

We recruited participants via two job postings on Upwork between April 1 and April 20, 2020. Based on prior work, we recruited freelancers in two job categories with similar median bill rates: “Writing” (with a gender rate gap) and “Design and Creative” (without a rate gap) [39]. We advertised the task as completing a general survey about pricing behavior. To attract participants with a variety of bill rates, we compensated participants beyond the median rates for these job categories (i.e., \$28–\$30/hour, [39]). Participants were paid \$18.75 for completing the 20-minute survey, after accounting for Upwork’s 20% fee, for a profit of approximately \$45/hour. In addition to receiving proposals from interested participants, we sent individual invitations to freelancers by using search filters provided by Upwork (e.g., “content writing” and “design”). We hired a representative sample by reviewing all freelancers who applied to

our post and hiring those within a certain strata (e.g., estimated age, work experience, gender), based on their profile pages, to create a balanced sample [30, 32].

5.2 Survey Instrument

We measured participants’ pricing strategies by asking them to rate and rank the importance of 27 different survey statements (see Supplemental Materials).¹ We asked participants to rate on a scale of 1 (not very important) to 5 (very important) how important or unimportant each statement was in determining their hourly bill rate on their Upwork profile. Participants could also answer that they did not know the meaning of a statement. To prevent question order effects [32], we randomized the order in which we displayed the pricing strategy categories. To mitigate ceiling effects, participants also chose and ranked the top five statements.² We also asked participants to explain why they ranked these statements in this way, any other factors that influenced their pricing behavior, and how effective they perceived their pricing strategies to be on a scale of 1 (“very ineffective”) to 5 (“very effective”).

In line with best practices in HCI [97], we captured participants’ gender by providing checkboxes and several options (i.e., “Man,” “Woman,” “Non-binary,” “Prefer Not to Disclose,” and “Prefer to Self-Describe”). We also asked participants for their primary job category, current hourly bill rate, approximately when they joined the platform, their earnings on the platform, and demographic variables that could be potential covariates to pay, as discussed in the Background (e.g., highest level of education, years of work experience, marital status, age range, number of children, and zip code as a proxy for location). Participants were also asked whether they were freelancing part-time (i.e., less than 35 hours/week) or full-time, in addition to rating the importance of freelancing as a source of income [80]. Based on prior work, we also presented a modified four-item self-esteem measure [88].³

5.3 Overview of Data Analyses

In this section, we describe our data preparation, validity and reliability checks, and data analysis approach.

5.3.1 Data Preparation and Formatting. We received a total of 399 responses and removed participants who were younger than 18 years old ($n=3$, 0.8%) and who did not disclose their gender ($n=4$, 1%). Therefore, the sample we report in our description and RQ1 sections consisted of 392 participants (60% women, 38.8% men, 1.2% self-described or non-binary). To format our data, we estimated the number of years participants had been on the platform given their approximate month and year of joining Upwork. Following

¹To better capture the meaning of one of our survey items (i.e., “I considered that Upwork limits the number of jobs I can submit a proposal to on Upwork”), we added an extra platform-based strategy item halfway through the study ($n=226$; i.e., “I considered that I have to pay for ‘connects’ to submit more proposals on Upwork”). We included both statements to capture the experiences of as many freelancers as possible.

²Due to technical limitations, we were unable to add the additional platform-based strategy survey item to this ranking task. However, our analysis suggested that freelancers did not rank a similar survey item (i.e., “I considered that Upwork limits the number of jobs I can submit a proposal to on Upwork.”) very highly in comparison to other survey items; only 6.9% of participants ($n=27$) had named this statement as one of their top five strategies. Therefore, omitting this additional item would likely not have had a significant impact on the rankings of the top strategies.

³An example of an item on this measure is: “I wish I could have more respect for myself as a freelancer.”

prior work, we assigned urban-rural classification codes to each participant based on their zip code [69, 93]. To prepare the data for validity and reliability checks ($n=319$), we further removed participants who said their hourly bill rate was exactly \$0 ($n=2$), did not disclose information to at least one survey item (i.e., “*Prefer not to disclose*”) ($n=23$), set their freelancer status as “*I used to freelance, but I do not currently freelance*” or “*I have never freelanced before*” ($n=34$), had a self-described or non-binary gender ($n=5$), or reported a job category other than “Writing” or “Design & Creative” ($n=22$). To prepare the data for the linear regressions in RQ2 and RQ3 (described later, $n=314$), we further removed outliers whose hourly bill rate was 1.5 times above the interquartile range ($n=5$; $m=\$99$, $\max=\$125$).

5.3.2 Validity and Reliability of Survey Items. To determine a factor structure of pricing strategies for RQ2 and RQ3, we conducted confirmatory factor analyses (CFA). An initial CFA using the Lavaan package in R [92] found that the survey items did not load well onto the original pricing strategy categories (Comparative Fit Index, CFI=0.55, Tucker-Lewis Index, TLI=0.48, root mean square error of approximation, RMSEA=0.10, $p<0.05$; see Supplemental Materials). Following best practices [71], we ran another CFA after dropping 15 low-loading items, which showed an improved model fit (CFI=0.96, TLI=0.92, RMSEA=0.06, n.s.; see Supplemental Materials). Although dropping items is expected for exploratory research such as this [32], we discuss plans to improve the survey instrument later in this paper.

Next, we computed Cronbach’s alpha to determine the reliability of the remaining survey items [26]. First, we dropped one platform-based pricing item due to the high number of missing values (i.e., “*I considered that I have to pay for connects to submit more proposals on Upwork,*” $n=192$). We then computed Cronbach’s alpha for the four remaining strategy categories containing at least two survey items [26]. For three of the pricing strategy categories (i.e., strategic positioning, demand-based, and value-based pricing) with moderate levels of reliability (i.e., $\alpha>0.65$), we averaged the ratings of the items into a composite rating [32]. Because the two survey items under cost-based pricing had low reliability ($\alpha=0.57$), we considered each item as a separate measure. Finally, because the three remaining categories (i.e., competition-based, platform-based, and dynamic pricing) contained a single survey item each, we added three additional individual survey items as separate measures for comparison. Table 2 summarizes the survey items included in the regressions to address RQ2 and RQ3 (discussed later).

5.3.3 Approach to Data Analyses.

Describing the Sample and the Prevalence of Pricing Strategies. First, we used descriptive statistics and non-parametric tests (e.g., Mann-Whitney [83], Chi-square [84]) to describe the characteristics of our sample. To address RQ1, we used descriptive statistics to understand which individual survey items were the top strategies chosen by participants. We then reviewed the open-ended responses of participants who gave these survey items high ratings (i.e., 4 or 5).

Understanding Gender’s Relationship to Pricing Strategies. Following prior survey research in HCI [27, 86], we conducted a multivariate linear regression in R [106] to predict the ratings of the

importance of the different pricing strategies based on factors such as gender, Upwork job category, and work experience ($n=314$). A multivariate linear regression allowed us to compare coefficients across separate regression models to understand gender’s overall relationship to pricing strategies [5]. We included the pricing strategy categories and survey items in Table 2 as dependent variables, as well as several predictors (e.g., gender, job category, gender by job category interaction, age, work experience).⁴⁵⁶

Predicting Bill Rate. To address RQ3, we conducted a five-step hierarchical linear regression in R [106] to understand how sets of predictors (e.g., pricing strategies, control variables) separately contributed to the variance in bill rate ($n=314$) [70, 77]. In the first step of the regression, we did not include any predictors. In the second step, we included control variables (e.g., age, work experience). In the third step, we added gender, while in the fourth step, we added the gender and Upwork job category interaction. In the fifth step, we added the ratings of the pricing strategy categories and survey items (Table 2). We log transformed hourly bill rate to better approximate a normal distribution. The Variance Inflation Factors for each predictor were below 4, which did not suggest multicollinearity issues in the dataset [41]. We then conducted an ANOVA of the models to compare the influence of each additional set of predictors.

6 FINDINGS

Below we describe our sample, the prevalence of pricing strategies, the relationship between gender and job category and pricing strategies, and the relationship between pricing strategies and other factors and bill rate.

6.1 Description of the Sample

In general, participants were representative of writers and designers in the US, and as expected [16], men and women differed on some characteristics, such as work experience and part-time freelancer status.

6.1.1 Participants Representative of Writers and Designers in the US. Participants were representative of writers and designers in the US [7, 112]. About half identified “Writing” ($n=191$) and “Design & Creative” ($n=178$) as their primary job category.⁷ The gender distribution of the writers (62.3% women, 36.1% men, 1.6% self-described) and designers (57.3% women, 42.1% men, 0.6% self-described) in the sample was representative of the population of writers and designers on Upwork [7, 39, 112]. More than a third of participants had more than 10 years of work experience (38.5%), and about half (54%) had less than three years of experience working as freelancers. The

⁴To reduce the complexity of this model, we transformed several categorical predictors (e.g., work experience, age range, hours worked on Upwork) into binary variables. For example, we divided participants into those who had self-esteem above and at or below the median on a four-point scale ($Mdn=3.5$).

⁵To provide an adequate sample size, we imputed missing values for the pricing strategy ratings ($n=91$) and Upwork tenure in years ($n=14$) to equal the median for each respective measure.

⁶We additionally dropped urban-rural classification as a predictor due to a high number of missing values ($n=96$).

⁷Henceforth, we will refer to participants as “writers” and “designers” for simplicity, although participants in the “Design & Creative” category included various types of creative professionals. Participants also identified other primary job categories on Upwork, such as “Sales & Marketing” and “Administrative Support” ($n=23$).

Pricing Strategy Category	Survey Item(s)	M	SD	Mdn	Cronbach's Alpha
Strategic Positioning	"I wanted my rate to make me appear knowledgeable to potential clients." "I wanted my rate to make me appear professional to potential clients."	3.98	0.94	4.00	0.89
Demand-Based Pricing	"I considered the types of clients I got when I set a higher or lower rate on my Upwork profile in the past." "I considered the number of clients I got when I set a higher or lower rate on my Upwork profile in the past."	3.37	1.17	3.50	0.79
Value-Based Pricing	"I chose my rate based on how much business value my services would bring to potential clients (e.g., with my services, a potential client would earn \$XXX more in revenue, gain brand recognition, etc.)." "I considered the unique qualities I have over my competitors and how much potential clients would pay for these qualities."	3.79	0.99	4.00	0.65
Cost-Based Pricing*	"I wanted to avoid getting offered too many jobs as I do not have enough time to complete them all."	2.23	1.31	2.00	0.57
	"I considered how much flexibility I need to complete my work (e.g., time needed to complete a job)."	3.63	1.24	4.00	
Competition-Based Pricing	"I chose my rate based on the rates of other similar freelancers on Upwork."	3.55	1.25	4.00	-
Platform-Based Pricing	"I considered that Upwork limits the number of jobs I can submit a proposal to on Upwork."	3.05	1.41	3.00	-
Dynamic Pricing	"I set a lower price than I normally would have to attract more clients, but I plan to increase this over time."	3.69	1.30	4.00	-
Additional Individual Survey Items Included in Regression Analyses					
-	"I chose my rate based on the rates of other similar freelancers or agencies outside of Upwork." (originally a competition-based pricing item)	3.39	1.25	4.00	-
-	"I chose my rate so that I would appear in as many search results on Upwork as I could." (originally a platform-based pricing item)	2.97	1.25	3.00	-
-	"I set a higher price than I normally would have to show prestige, but I plan to decrease this over time." (originally a dynamic pricing item)	1.91	1.13	1.00	-

Table 2: A summary of the final 11 strategy categories and survey items included in the linear regression models to address RQ2 and RQ3. We averaged the ratings of the survey items in the strategic positioning, demand-based pricing, and value-based pricing categories that showed moderate reliability ($\alpha > 0.65$). The cost-based pricing survey items (*) were considered as separate measures in regression models due to low reliability. We included three additional individual survey items in the regression models, even though they did not initially load highly onto factors in our confirmatory factor analysis.

majority of the sample were part-time freelancers (70.7%), between 25-34 years of age (39.6%), had a bachelor's degree (49.1%), were single (49.6%), had no children (69.5%), lived in metropolitan areas (90.7% of participants who provided zip code), and had worked more than 0 hours on the platform (65%, $n=137$). Among workers who provided the information ($n=374$), almost a third ($n=117$) had started working on the platform within the past month. A correlation matrix is provided in the Supplemental Materials.

6.1.2 Gender Differences in Median Bill Rate as Expected. As anticipated, we found a gender gap in median bill rate for writers, but not designers. Female writers asked for 83.3% ($Mdn=\$25.00$, $M=\$31.25$, $SD=\$21.09$) of what male writers asked for in median hourly bill rate ($Mdn=\$35.00$, $M=\$35.86$, $SD=\$20.64$), $U=3424.5$, $p<0.05$. In comparison, self-described or non-binary writers asked for \$20.00 in median hourly bill rate. We did not find any gender disparities in the median hourly bill rate for male and female designers ($Mdn=\$35.00$,

$U=3539.5$, n.s. The self-described designer in this sample asked for \$40.00 in hourly bill rate.

6.1.3 Women More Likely to Freelance Part-Time and Had Less Work Experience than Men. Significantly more women reported freelancing part-time and having between one and three years of work experience compared to men. Using Chi-square analyses [84], we found that a significantly higher proportion of women reported freelancing part-time (80.4% of women) compared to men (55.8% of men, $\chi^2=24.48$, $p<0.001$). Significantly more women also had between one and three years of work experience (24.3% of women) compared to men (11.2% of men, $\chi^2=12.18$, $p<0.05$). While most freelancers reported finding freelance work as at least somewhat important as a source of income, female writers ($Mdn=5$) found it relatively less important at the time of the survey compared to male writers ($Mdn=5$), $U=3466.5$, $p<0.05$, but this was not a significant

difference for designers, $U=3707.5$, n.s. We did not include self-described or non-binary participants in the Chi-square analyses due to the small size of these participants in the sample ($n=5$).

By running a Mann-Whitney test, we found no significant gender differences in overall self-esteem for women ($Mdn=3.25$) or men ($Mdn=3.5$), $U=16288.5$, n.s. Chi-square analyses found no other significant gender differences in earnings on Upwork ($\chi^2=6.92$, n.s.), importance of freelancing at the moment ($U=16377.5$, n.s.), years of work experience as a freelancer ($\chi^2=5.2$, n.s.), age range ($\chi^2=3.5$, n.s.), education level ($\chi^2=9.43$, n.s.), marital status ($\chi^2=2.26$, n.s.), number of children ($\chi^2=0.51$, n.s.), or location ($\chi^2=3.36$, n.s.).

6.2 RQ 1: What Pricing Strategies Do Freelancers Use Online?

Our results suggest that freelancers considered multiple pricing strategies choosing their hourly bill rate. Most survey items (78%, $n=21$) were at least somewhat important ($Mdn=4$) to determining bill rate and the survey items received an average rating of 3.56 ($SD=1.16$). Freelancers found their pricing strategies to be somewhat effective ($M=3.46$, $SD=0.93$, $Mdn=4$).⁸ Below, we discuss participants' top strategies (see Supplemental Materials for full list of survey items).

6.2.1 Freelancers Considered Their Expertise On and Outside of Upwork. Freelancers across various stages of their careers considered their work experience on and off Upwork when pricing themselves. More than half of participants said their level of expertise was one of the top five factors (60.5% of participants, $n=237$, mean rank=2.52), with 17.9% ($n=70$) saying it was their top factor. For example, a female writer between the ages of 45–54 who had worked less than 100 hours since joining Upwork two months earlier tried to find a balance between her extensive work experience and her *inexperience* on Upwork:

“I chose my hourly rate based on my more than 20 years of work as a full-time journalist while also taking into consideration the fact that I’ve only been freelancing for a few months...” (P227)

Many participants felt the need to make these trade-offs because they wanted to attract new clients. One female writer between the ages of 18 and 24 explained:

“I’m relatively new to Upwork...I chose a lower hourly pay to attract actual jobs and prove my worth. My plan is to attract people who want small jobs for little pay, put in a lot of effort, get splendid reviews, and then move my game up to higher-pay gigs.” (P220)

This occasionally frustrated freelancers who felt their expertise entitled them to higher rates. One male writer between the ages of 18 and 24 said:

“I’m just starting my career out on Upwork...I price my rates like this because I know how to write. I just don’t have the experience needed to charge the prices I want. I’d like to portray the value to my potential clients but nothing I seem to do works for me.” (P193)

⁸Across both job categories, women ($Mdn=4$) perceived their pricing strategies to be about as effective as men ($Mdn=3.5$), $U=16749.5$, n.s.

In summary, freelancers take into account their online and offline work experience when choosing their bill rate. This was understandable, given that almost a third ($n=117$) of the sample had only started working on the platform within the past month, but over half ($n=209$) had at least five years of offline work experience.

6.2.2 Freelancers Considered Upwork’s Fee. In addition to work experience, participants found it very important to consider Upwork’s 20% platform fee ($M=4.46$, $SD=0.90$, $Mdn=5$) and, consequently, how much they would need to charge clients to earn a profit ($M=4.27$, $SD=0.98$, $Mdn=5$). Across job categories, nearly two-thirds of participants said that Upwork’s fee was one of the top factors influencing their hourly bill rate (61.5%, $n=241$, mean rank=2.98). A female designer who has worked more than 100 hours in seven years on the platform said:

“At \$32 per hour, taking into account the 20% Upwork takes, I will net approximately \$25 per hour. After estimated taxes, that is approximately \$20 per hour, which is approximately...\$40,000 per year (at 40 hours per week with two weeks off). This adds up to the amount it will take to cover my expenses.” (P208)

Participants wanted to ensure that their profits made it worthwhile to engage in all the activities involved with working on Upwork, which include searching for jobs, paying for “connects” (i.e., platform currency that allows freelancers to submit job proposals), and paying Upwork’s fee. As one graphic designer who set his rate at \$30, or \$5 below the median for the designers, said:

“The first thing I consider when determining my hourly price is profit. If I’m spending a portion of my time applying to jobs and paying for connects on UpWork, and then UpWork takes a fee, I need to make sure I have enough remaining at the end of the day to make it worth my while.” (P7)

In short, many freelancers considered Upwork’s fee when choosing their bill rate, as this fee would substantially affect their profits. For example, the median graphic designer on Upwork in the US with a bill rate of \$35/hour would pay Upwork \$7 for each hour they work, making their effective rate \$28/hour. Considering this fee was important to freelancers so that they could ensure profit from their efforts.

6.2.3 Freelancers Wanted to Appear Approachable Given Competition from Other Freelancers. Freelancers said appearing approachable to clients was a top factor contributing to their bill rate ($n=46$, 11.7%). Some of these concerns stemmed from a desire to set competitive rates in a global market. For example, one female designer chose a lower bill rate (i.e., \$25, or \$10 below the median) because she wanted to appear approachable to new clients and be competitive with freelancers outside of the US, but did not find her strategy effective:

“I chose my hourly rate mainly because clients don’t want to pay much at all because of the freelance designers overseas that charge \$5 an hour. If I charge too low, I’m afraid clients think I’m not as experienced, and I have over 20 years of extensive experience. I keep changing my rate to appear approachable. Not really thinking to raise my hourly rate, but to actually

lower it. I have not gotten a single job as of yet on Upwork. So far two scammers. I stopped applying for projects. Now four years later I'm back to try it again." (P201)

In some cases, freelancers used their knowledge of the platform's features to orchestrate a favorable impression through their hourly rate. For instance, a female designer who had worked between 10 and 99 hours on Upwork understood her \$30 bill rate on her profile did not have to reflect the actual rate she listed in her job proposals. She used this to her advantage by proposing rates that were slightly lower than her listed bill rate so clients would feel they were getting a "deal" for her services:

"...As a way to receive attention on my bids... I often undercut myself by a dollar or two so the client will see, after viewing both my bid and profile, that maybe he is getting a deal off my usual rate...I feel that the undercut price (the rate in my bid) might show them that I want to do it for more than just their money, but that I truly value my own knowledge and experience as much as the next person..." (P160)

Across different types of work, freelancers considered similar factors when choosing their bill rate, including their experience on and outside the platform, Upwork's fee, and their desire to appear approachable yet knowledgeable to potential clients.

6.3 RQ 2: How do Gender and Job Category Relate to Pricing Strategies?

While gender and job category separately predicted the importance of different pricing strategies to freelancers, the interaction *between* gender and job category did not. A multivariate linear regression predicting pricing strategy ratings found a significant relationship between gender, Upwork job category, and self-esteem, and freelancers' pricing strategies. We found a statistically significant MANOVA effect for gender, Pillai's trace=0.09, $F(11, 290)=2.54$, $p<0.01$, Upwork job category, Pillai's trace=0.07, $F(11, 290)=2.07$, $p<0.05$, and self-esteem above the median, Pillai's trace=0.08, $F(11, 290)=2.26$, $p<0.05$. However, we did not find a statistically significant effect for the interaction between gender and job category, Pillai's trace=0.05, $F(11, 290)=1.25$, $p=0.25$ (full results in the Supplemental Materials). Below, we report the pricing strategies where there were significant differences based on gender and job category.⁹

6.3.1 Relationship between Gender and Pricing Strategies. Contrary to our hypotheses, we did not find a significant relationship between gender and value-based pricing (H1) (Table 3). Controlling for factors, such as work experience and education, women ($M=3.75$, $SD=1.01$, $Mdn=4.0$) found value-based pricing strategies about as important as men ($M=3.86$, $SD=0.95$, $Mdn=4.0$), $b=0.10$, $t(300)=0.62$, n.s. We also did not find a significant relationship between gender and either of the cost-based pricing survey items (H2) (Table 3). Women said it was equally important to them ($M=2.23$, $SD=1.32$, $Mdn=2.0$) to avoid getting offered too many jobs as men ($M=2.24$,

$SD=1.30$, $Mdn=2.0$), $b=-0.10$, $t(300)=-0.45$, n.s. Women also found it as important to consider how much flexibility they need to complete their work ($M=3.72$, $SD=1.24$, $Mdn=4.0$) as men ($M=3.49$, $SD=1.21$, $Mdn=4.0$), $b=0.16$, $t(300)=0.79$, n.s.

Instead, demand-based pricing was the only pricing strategy with significant gender differences after taking into account other control variables. Being a woman predicted a significant 0.52-point increase in the importance of demand-based pricing, which was measured using two survey items on a 5-point scale (i.e., "I considered the types of clients I got when I set a higher or lower rate on my Upwork profile in the past," "I considered the number of clients I got when I set a higher or lower rate on my Upwork profile in the past"). On average, women rated the importance of these strategies significantly higher ($M=3.46$, $SD=1.14$, $Mdn=3.50$) than men ($M=3.28$, $SD=1.18$, $Mdn=3.50$), $b=0.52$, $t(300)=2.98$, $p<0.01$. In addition, there were significant gender differences on the following platform-based pricing strategy survey item: "I chose my rate so that I would appear in as many search results on Upwork as I could", $b=0.34$, $t(300)=1.70$, $p<0.1$. Women reported the importance of this strategy as higher ($M=3.04$, $SD=1.25$, $Mdn=3$) than men ($M=2.89$, $SD=1.24$, $Mdn=3.0$).

6.3.2 Relationship between Gender, Job Category, and Pricing Strategy. We did not find substantial evidence that gender differences within Upwork job categories accounted for significant differences in pricing strategy. As noted above, we did not find a significant MANOVA effect of gender's interaction with job category, Pillai's trace=0.05, $F(11, 290)=1.25$, n.s. Nevertheless, being a female writer predicted a significant 0.54-point decrease on one of the platform-based survey items (i.e., "I chose my rate so that I would appear in as many search results on Upwork as I could"), $b=-0.54$, $t(300)=-1.92$, $p<0.1$. Being a female writer also predicted a 0.57-point decrease in the importance of demand-based pricing strategies, $b=-0.57$, $t(300)=-2.32$, $p<0.05$. Again, however, we did not find substantial evidence overall that there were significant gender differences in pricing strategies between writers and designers.

6.3.3 Relationship between Self-Esteem and Value-Based Pricing Strategy. In line with our hypothesis (H2), having more self-esteem than the median freelancer on Upwork predicted significantly higher ratings of the importance of the value-based pricing strategy (Table 3), $b=0.33$, $t(300)=2.64$, $p<0.01$. At the same time, higher levels of self-esteem also predicted lower ratings for the following dynamic pricing strategy: "I set a lower price than I normally would have to attract more clients, but I plan to increase this over time", $b=-0.33$, $t(300)=-2.00$, n.s. In short, self-esteem seemed to have a significant impact on predicting the importance of the value-based pricing strategy.

6.4 RQ 3: How do Pricing Strategies and Other Factors Relate to Bill Rate?

The control variables (e.g., work experience, part-time or full-time freelancer status), gender, job category, and ratings of the pricing strategies were all helpful factors in predicting freelancers' bill rates on Upwork. Using a five-step hierarchical linear regression predicting log transformed bill rate, we found that several pricing strategies and control variables had a significant relationship with freelancers' hourly bill rate. Introducing the control variables

⁹Because we do not report on the survey items that were not included in this regression, we present men's and women's average ratings all individual survey items in the Supplemental Materials.

Pricing Strategy	Adj. R ²	F	Selected Predictors from Model								
			Gender – Woman			Gender * Upwork Job Category			Self-Esteem - Above Median		
			β	Std. err	t	β	Std. err	t	β	Std. err	t
Strategic Positioning (Category)	0.006	1.148	0.07	0.15	0.46	0.14	0.21	0.66	0.11	0.12	0.96
Demand-Based Pricing (Category)	0.059	2.512	0.52**	0.17	2.98	-0.57*	0.25	-2.32	-0.21	0.14	-1.54
Value-Based Pricing (Category)	0.033	1.810	0.10	0.16	0.62	-0.12	0.23	-0.54	0.33**	0.13	2.64
"I wanted to avoid getting offered too many jobs as I do not have enough time to complete them all." (Cost-Based Pricing)	-0.009	0.781	-0.10	0.22	-0.45	-0.05	0.31	-0.15	-0.15	0.17	-0.87
"I considered how much flexibility I need to complete my work (e.g., time needed to complete a job)." (Cost-Based Pricing)	-0.002	0.949	0.16	0.20	0.79	0.14	0.28	0.51	-0.08	0.16	-0.53
"I chose my rate based on the rates of other similar freelancers on Upwork." (Competition-Based Pricing)	0.049	2.253	0.23	0.20	1.17	0.25	0.28	0.89	-0.18	0.15	-1.19
"I considered that Upwork limits the number of jobs I can submit a proposal to on Upwork." (Platform-Based Pricing)	0.068	2.754	0.38+	0.22	1.71	0.16	0.31	0.53	-0.25	0.17	-1.45
"I set a lower price than I normally would have to attract more clients, but I plan to increase this over time." (Dynamic Pricing)	0.043	2.079	0.26	0.21	1.24	-0.19	0.30	-0.63	-0.33*	0.17	-2.00
"I chose my rate based on the rates of other similar freelancers or agencies outside of Upwork."	0.035	1.879	0.11	0.19	0.59	0.11	0.27	0.42	-0.08	0.15	-0.51
"I chose my rate so that I would appear in as many search results on Upwork as I could."	0.027	1.662	0.34+	0.20	1.70	-0.54+	0.28	-1.92	-0.16	0.16	-1.03
"I set a higher price than I normally would have to show prestige, but I plan to decrease this over time."	0.024	1.582	-0.30	0.18	-1.64	0.12	0.26	0.46	-0.14	0.15	-0.94

Table 3: A summary of the multivariate linear regression with details for each individual regression predicting ratings of different pricing strategy categories and survey items. Women found the demand-based pricing strategy significantly more important than men. The number of observations ($n=314$), degrees of freedom of the residuals (i.e., 300) and the degrees of freedom of the model (i.e., 13) were the same across all models. + $p<0.1$, * $p<0.05$, ** $p<0.01$

to the baseline regression contributed significantly to the model, $F(11, 302)=12.40$, $p<0.001$ and accounted for approximately 25% of the variance in bill rate. Introducing gender improved the regression model, $F(1, 301)=3.17$, $p=0.08$, as did introducing the gender and Upwork job category interaction, $F(1,300)=3.42$, $p=0.07$. At the fifth step of the regression, the importance ratings of the pricing strategies contributed significantly to the regression model, $F(11,289)=9.82$, $p<0.001$, explaining an additional 19% of the variance in bill rate beyond just the control variables. Together, these variables accounted for 42% of the variance in bill rate (see Supplemental Materials for ANOVA).

6.4.1 Pricing Strategies and Factors that Predicted Higher Bill Rates. Taking these variables into account, our regression model showed that freelancers who found value-based, $b=0.10$, $t(289)=3.46$, $p<0.001$, and strategic positioning pricing strategies, $b=0.10$, $t(289)=3.60$, $p<0.001$, more important set significantly higher bill rates than freelancers who did not find these strategies as important (Table 4). Similarly, freelancers who found it more important to choose their rates based on the rates of other similar freelancers outside of Upwork also set significantly higher bill rates, $b=0.05$, $t(289)=2.19$, $p<0.05$. The regression model also showed that having at least a bachelor's degree, $b=0.13$, $t(289)=2.28$, $p<0.05$, being a full-time freelancer, $b=0.13$, $t(289)=2.20$, $p<0.05$, finding freelance work as at least somewhat important to covering one's expenses, $b=0.18$, $t(289)=2.39$, $p<0.05$, and having higher self-esteem than the median freelancer, $b=0.14$, $t(300)=2.51$, $p<0.05$, predicted significantly higher bill rates.

6.4.2 Pricing Strategies and Factors that Predicted Lower Bill Rates. In contrast, freelancers who found it more important to choose their

rates based on the rates of other similar freelancers on Upwork set significantly lower bill rates, $b=-0.06$, $t(289)=-2.51$, $p<0.05$ (Table 4). Likewise, freelancers who found it more important to temporarily set a lower rate to attract clients (dynamic pricing), to appear in as many search results on Upwork as possible (platform-based pricing), to consider that Upwork limits the number of jobs they can submit a proposal to, and to consider the amount of flexibility (i.e., time needed to complete a job; cost-based pricing) to complete their work set significantly lower bill rates (Table 4). We also found that having a longer tenure on Upwork predicted significantly lower bill rates, $b=-0.02$, $t(289)=-2.16$, $p<0.05$. As expected, we found a significant interaction between gender and Upwork job category, indicating that female writers set significantly lower bill rates than other freelancers, $b=-0.21$, $t(289)=-2.13$, $p<0.05$.

7 DISCUSSION

Motivated to understand the potential for the growing online gig economy to close the offline gender participation and pay gap, we found that the online gig economy cannot escape societal conditions. Below we summarize the major implications of this work future labor research, on- and off-platform design interventions, and policy.

7.1 Implications for Future Labor Research

7.1.1 Looking Beyond Pricing Strategies to Understand Gender Rate Gaps. Future labor research must look beyond pricing strategies to better understand gender rate gaps online. We hypothesized that pricing strategies could help explain gender rate gaps online, expecting that men would find value-based pricing strategies more important than women (H1), while women would find cost-based

Predictor	β	Std. Err.	t	p
Control Variables				
Upwork Job Category - Writing	0.02	0.08	0.29	0.77
Gender - Woman	0.06	0.07	0.87	0.39
Marital Status - Single	-0.03	0.06	-0.42	0.67
Education - At Least Bachelor's	0.13	0.06	2.28	0.02*
Work Experience - Above 5 Years	0.08	0.06	1.35	0.18
Freelance Status - Full-Time	0.13	0.06	2.20	0.03*
Earnings on Upwork (Above 0)	0.03	0.05	0.61	0.54
Tenure on Upwork (Years)	-0.02	0.01	-2.16	0.03*
Importance of Freelancing as a Source of Income - At Least Somewhat	0.18	0.07	2.39	0.02*
Self-Esteem - Above Median	0.14	0.06	2.51	0.01*
Number of Children - Above 0	0.09	0.07	1.25	0.21
Age - Above 35	0.07	0.07	0.99	0.32
Upwork Job Category - Writing * Gender - Woman	-0.21	0.10	-2.13	0.03*
Importance Ratings of Pricing Strategies				
Strategic Positioning (Category)	0.10	0.03	3.60	0.00***
Demand-Based Pricing (Category)	0.00	0.03	0.10	0.92
Value-Based Pricing (Category)	0.10	0.03	3.46	0.00***
"I wanted to avoid getting offered too many jobs as I do not have enough time to complete them all." (Cost-Based Pricing)	0.03	0.02	1.52	0.13
"I considered how much flexibility I need to complete my work (e.g., time needed to complete a job)." (Cost-Based Pricing)	-0.06	0.02	-2.67	0.01**
"I chose my rate based on the rates of other similar freelancers on Upwork." (Competition-Based Pricing)	-0.06	0.02	-2.51	0.01*
"I chose my rate based on the rates of other similar freelancers or agencies outside of Upwork."	0.05	0.02	2.19	0.03*
"I considered that Upwork limits the number of jobs I can submit a proposal to on Upwork." (Platform-Based Pricing)	-0.04	0.02	-1.94	0.05+
"I chose my rate so that I would appear in as many search results on Upwork as I could."	-0.07	0.02	-3.15	0.00**
"I set a lower price than I normally would have to attract more clients, but I plan to increase this over time." (Dynamic Pricing)	-0.08	0.02	-3.86	0.00***
"I set a higher price than I normally would have to show prestige, but I plan to decrease this over time."	0.01	0.02	0.58	0.56

Table 4: Results of the fifth step in the hierarchical linear regression model predicting log transformed bill rate. Several control variables and pricing strategies predicted significantly lower and higher log transformed bill rates. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

pricing strategies more important than men (H3). Instead, we only found significant gender differences in the importance of demand-based pricing, a strategy that did not significantly predict bill rate. Other factors, such as full-time freelancer status, had a greater impact on bill rates. For example, women were more likely than men to be freelancing part-time or to find freelancing less important, which predicted lower bill rates. Future work should investigate why part-time workers, the majority of whom were women in our study, set lower rates online. For example, if part-time workers set lower rates because of how they think others will perceive them for their part-time status, similar to how women hold lower salary expectations than men [38], platforms may want to guide workers to focus on other aspects, such as their work experience, during rate-setting.

Furthermore, future work should continue to investigate how value-based pricing and self-esteem might influence online pricing behavior regardless of gender. As predicted, we found that self-esteem predicted the importance of value-based pricing strategies (H2), which predicted higher bill rates. Although we did not find gender differences in value-based pricing or self-esteem, future work should investigate these factors given their profound impact on bill rate and the possibility that our survey was unable to capture participants' actual self-esteem or value-based pricing behaviors. Additionally, it is important to note that these and other factors included in the study explained at most only 42% of the variance in bill rate and less than 7% of the variance in the importance of pricing strategies, demonstrating the potential for studying other possible predictors of rates and pricing strategies in future research, such as race and socioeconomic status.

7.1.2 Gendered Behavior Persists Online. Contrary to prior work [104], our data suggest that being in a virtual environment does not always reduce the salience of gender in interactions. We did not expect to find gender differences in demand-based pricing strategies because all freelancers should be able to “test” the demand for their rate on Upwork. Therefore, we speculate that women on Upwork found demand-based pricing more important than men because they may have placed more value on the quality of their clients. We speculate that, with more limited time for paid work [110], women on Upwork may be more motivated to find flexible and valuable opportunities to grow their skills [72], and may set rates based on demand to appear more competitive and be hired for high quality jobs. With limited time, women on Upwork may also adopt a demand-based strategy instead of finding “referents” (i.e., other freelancers with similar qualities) to which to compare their rates [49].

Critically, this suggests that researchers must study the gig economy through the lens of gender and other dimensions of potential inequity, such as age, race, and socio-economic status [31]. Users in the gig economy already face unconscious biases [35, 52]; for example, African-American names are more likely to be turned down for short-term accommodations on the Airbnb platform [35]. This study demonstrates that not only discrimination, but *pricing strategies* could perpetuate gender inequities online. By not taking the lens of gender, age, race, and status in our research, we stand to disregard valuable insights into workers’ motivations, behaviors, and outcomes on these platforms [12].

7.1.3 Freelancers Must Develop Financial Gig Literacies to Adapt to Online Work. We further build on prior work by showing how freelancers develop financial “gig literacies” such as pricing strategies to earn a living online. Prior work suggests that freelancers learn to adapt to the affordances of online work platforms by developing “gig literacies” [105], sharing knowledge within networked communities [50, 51], and augmenting their work practices with technologies [36]. Our work is the first to show how freelancers modify their *pricing behavior* to succeed as freelancers online. For example, many freelancers in our study lowered their rates given their limited on-platform work experience, despite having extensive *off-platform* work experience. To extend these findings, we aim to explore the impact of accommodating these online factors on freelancers’ lives. For example, how does setting a lower rate than one feels one deserves influence job satisfaction? If a freelancer chooses to lower their rate, how will they respond if they do not see an increase in their number of clients? Understanding how freelancers adapt to these platform constraints can help us design systems that support the livelihoods of millions of workers [68, 74, 96, 105].

7.2 Implications for Design

7.2.1 On-platform Design Interventions. By intervening in processes like rate-setting, platforms can more directly support a diverse workforce, attracting and retaining high quality talent [62]. For example, platforms could encourage more women to increase their rates and mitigate rate gaps by providing feedback and strategies for increasing workers’ rates [73, 116]. Platforms could nudge workers (e.g., [4]) with below-average rates to raise their rates

through value-based pricing, such as by reminding them to consider their unique qualities or value to businesses before setting their rates, in line with prior work on gender and negotiation [8]. To encourage lower rates, these systems might consider reminding users that they need “connects” to submit new job proposals. Additional research is needed to understand not only the effectiveness of these strategies, but also the limitations of introducing these interventions on the platform (e.g., reducing freelancers’ autonomy).

Our work also suggests that, regardless of gender, freelancers share similar concerns when choosing their bill rate, including balancing their level of expertise off and on the platform, and weighing their expected profits given platform fees. These findings echo prior work in HCI, which suggest that gender can influence participation in some sociotechnical systems, such as peer production communities (e.g., Wikipedia) and social Q&A sites (e.g., StackOverflow) [22, 40, 53], but may not always lead to biases in other systems (e.g., ratings on micro-task markets [107]). Based on these results, platforms should consider helping *all* freelancers, regardless of gender, choose profitable bill rates based on their level of expertise and the variety of costs of working on the platform (e.g., time and money spent on proposals. Additionally, platforms could assign reputation scores based on offline work to support those who lack on-platform work experience.

7.2.2 Off-platform Design Interventions. Following prior research on ethical gig work [63, 82], we see opportunities for *off-platform* tools to increase the transparency of rate gaps to online freelancers [15], similar to how websites display average salaries for employees (e.g., Glassdoor). The tools could also encourage coordination between gig workers [63]. We also imagine tools that help *clients* price their tasks to avoid offering lower rates for part-time jobs [75, 118], as we found that part-time freelancers were more likely to set lower bill rates than full-time freelancers. By existing outside of online labor platforms, such off-platform interventions could utilize more sensitive data (e.g., gender of freelancers) to offer valuable insights to freelancers and clients, much like how prior HCI interventions, such as Turkopticon, helped online workers exchange honest reviews of past employers [63].

7.3 Implications for Policy

Our work also offers implications for future policy on online labor marketplaces. As other scholars have argued [61, 119], steps must be taken by governments to offer legal protections on online workers’ pay rates. These protections might include a minimum rate for part-time jobs to ensure that part-time freelancers receive commensurate pay as full-time freelancers, standardizing work tasks and rates to improve transparency, and protecting workers against bill rate discrimination based on gender to promote fairer wages [58, 62]. Nonetheless, enacting these protections will be challenging. Regulating bill rates will require a concerted effort from governments across the globe, given country-level differences in workers’ rates and tasks [57, 100]. Furthermore, it may be difficult for governments to recognize online workers as employees worthy of employment-based protections. In November 2020, California passed a proposition that enables online labor platforms, like Uber, to withhold valuable employment benefits, minimum wages, and other income protections from workers [23, 85]. Nevertheless, there

could be other promising ways to extend protections to freelancers; for instance, through the CARES Act, the US provided financial assistance to online workers during the COVID-19 pandemic [91]. Cooperative, worker-owned platforms and fair-trade certifications could also protect workers' welfare by actively involving workers in developing and enforcing minimum rates [20, 79, 119, 122]. We believe that effective policy will require creative solutions that acknowledge the global nature of online work and extend protections to *all* workers, regardless of their employment status.

7.4 Limitations and Future Work

While this study overcomes the limitations of prior work by collecting self-reported data [39], we look forward to improving and extending the study's design. First, we plan to recruit participants beyond the US and these job categories, as this may have caused some pricing strategies to be more prevalent than others. Moreover, the reliability and validity of several survey items was only moderate, indicating that future work can be done to improve the survey instrument. For example, we imagine hosting a workshop with freelancers to generate potential alternative survey items to measure pricing strategies. Because the survey was conducted during a global pandemic, the sample may not accurately represent freelancers on the Upwork platform. By only recruiting participants who had applied to our job posting, we may have excluded freelancers who were unable to submit a proposal. Finally, we plan to collect data on factors not captured in this survey, such as race, ethnicity, and socioeconomic status [87]. These changes will allow us to build a more robust survey instrument and extend our findings to other domains and countries.

8 CONCLUSION

Freelancers use multiple pricing strategies when choosing their bill rates online. Nevertheless, gender differences in pricing strategies may not fully account for gender rate gaps online. Instead, gender differences in other factors, such as full-time freelancer status, self-esteem, and the importance of freelancing as a source of income, predicted higher rates and may help explain gender rate gaps online. To support equity in the online gig economy, CHI researchers must identify and continue to assess the complex relationship between gender and these factors in online labor marketplaces.

ACKNOWLEDGMENTS

We would like to thank our study participants on Upwork, our reviewers, members of the Delta Lab at Northwestern University, Darren Gergle, Jeremy Birnholtz, Joy Kim, Zachary Gibson, and Kimberly Mak for their time and feedback. This study was generously supported by the National Science Foundation (IIS 1530837), Northwestern University, and Adobe Research.

REFERENCES

- [1] [0000]. Fiverr. <https://www.fiverr.com/>
- [2] [0000]. Making career moves? Sign up to be a Uber Driver or get a ride to the airport | Uber. <https://www.uber.com/>
- [3] Kumar Abhinav, Alpana Dubey, Sakshi Jain, Gurdeep Virdi, Alex Kass, and Manish Mehta. 2017. CrowdAdvisor: a framework for freelancer assessment in online marketplace. In *Proceedings of the 39th International Conference on Software Engineering: Software Engineering in Practice Track (ICSE-SEIP '17)*. IEEE Press, Buenos Aires, Argentina, 93–102. <https://doi.org/10.1109/ICSE-SEIP.2017.23>
- [4] Alessandro Acquisti, Idris Adjerid, Rebecca Balebako, Laura Brandimarte, Lorie Faith Cranor, Saranga Komanduri, Pedro Giovanni Leon, Norman Sadeh, Florian Schaub, Many Sleeper, Yang Wang, and Shomir Wilson. 2017. Nudges for Privacy and Security: Understanding and Assisting Users. In *Choices Online. Comput. Surveys* 50, 3 (Aug. 2017), 44:1–44:41. <https://doi.org/10.1145/3054926>
- [5] Abdelmonem Afifi, Susanne May, and Virginia A. Clark. 2003. *Computer-Aided Multivariate Analysis, Fourth Edition*. CRC Press. Google-Books-ID: Gejr3l40mHsC.
- [6] Ajay Agrawal, John Horton, Nicola Lacetera, and Elizabeth Lyons. 2015. Digitization and the Contract Labor Market: A Research Agenda. In *Economic Analysis of the Digital Economy*. University of Chicago Press, 219–250. <https://doi.org/10.7208/chicago/978026206981.003.0008>
- [7] AIGA, Google, and Accurat. 2019. *Design Census 2019: Understanding the state of design and the people who make it*. Technical Report. AIGA. <https://designcensus.org/data/2019DesignCensus.pdf>
- [8] Linda Babcock and Sara Laschever. 2009. *Women Don't Ask: Negotiation and the Gender Divide*. Princeton University Press. Google-Books-ID: k6vd7PJUFmYC.
- [9] The World Bank. 2019. *The Changing Nature of Work*. Technical Report. International Bank for Reconstruction and Development / The World Bank. <http://documents.worldbank.org/curated/en/816281518818814423/pdf/2019-WDR-Report.pdf>
- [10] Rajiv D. Banker and Iny Hwang. 2008. Importance of Measures of Past Performance: Empirical Evidence on Quality of e-Service Providers. *Contemporary Accounting Research* 25, 2 (2008), 307–337. <https://doi.org/10.1506/car.25.2.1> eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1506/car.25.2.1>
- [11] Roxana Barbulescu and Matthew Bidwell. 2012. Do Women Choose Different Jobs from Men? Mechanisms of Application Segregation in the Market for Managerial Workers. *Organization Science* 24, 3 (June 2012), 737–756. <https://doi.org/10.1287/orsc.1120.0757>
- [12] Shaowen Bardzell. 2010. Feminist HCI: Taking Stock and Outlining an Agenda for Design. In *Proceedings of the ACM Conference on Human Factors in Computing Systems*. 1301–1310.
- [13] T Barker, R Bernard, MG Flanders, R Moschak, and N Wycislo. 2003. Growing your practice by managing business relationships. In *STC's 50th Annual Conference Proceedings*. 93–98.
- [14] A. J. Beltis. [0000]. Everything You Need to Know About Value-Based Pricing. <https://blog.hubspot.com/sales/value-based-pricing> Library Catalog: blog.hubspot.com.
- [15] Morten Bennesen, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2019. *Do Firms Respond to Gender Pay Gap Transparency?* Working Paper 25435. National Bureau of Economic Research. <https://doi.org/10.3386/w25435>
- [16] Francine D. Blau and Kahn, Lawrence M. 2016. *The Gender Wage Gap: Extent, Trends, and Explanations*. Technical Report 21923. National Bureau of Economic Research. 1–77 pages. <https://www.nber.org/papers/w21913.pdf>
- [17] Kate Bornstein. 2013. *My New Gender Workbook: A Step-by-Step Guide to Achieving World Peace Through Gender Anarchy and Sex Positivity*. Taylor & Francis.
- [18] Emilio J. Castilla. 2015. Accounting for the Gap: A Firm Study Manipulating Organizational Accountability and Transparency in Pay Decisions. *Organization Science* 26, 2 (Feb. 2015), 311–333. <https://doi.org/10.1287/orsc.2014.0950>
- [19] YoonKyung Chung, Barbara Downs, Danielle H. Sandler, and Robert Sienkiewicz. 2017. *The Parental Gender Earnings Gap in the United States*. Technical Report 17-68. Center for Economic Studies, U.S. Census Bureau. <https://ideas.repec.org/p/cen/wpaper/17-68.html>
- [20] Nithin Coca. 2016. Cooperatives 4.0 – a 'fair trade' alternative to the exploitative gig economy? <https://www.equaltimes.org/cooperatives-4-0-a-fair-trade>
- [21] Sharon R Cohany. 1996. Workers in alternative employment arrangements. *Monthly Labor Review* 119, 10 (Oct. 1996), 31–45.
- [22] Benjamin Collier and Julia Bear. 2012. Conflict, Criticism, or Confidence: An Empirical Examination of the Gender Gap in Wikipedia Contributions. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work (CSCW '12)*. ACM, New York, NY, USA, 383–392. <https://doi.org/10.1145/2145204.2145265>
- [23] Kate Conger. 2020. Uber and Lyft Drivers in California Will Remain Contractors. *The New York Times* (Nov. 2020). <https://www.nytimes.com/2020/11/04/technology/california-uber-lyft-prop-22.html>
- [24] Cook, Cody, Diamond, Rebecca, Hall, Jonathan, List, John A., and Paul Oyer. 2018. *The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers*. Technical Report Working Paper No. 3637. <https://www.gsb.stanford.edu/faculty-research/working-papers/gender-earnings-gap-gig-economy-evidence-over-million-rideshare>
- [25] David Cravens and Nigel Piercy. 2012. *Strategic Marketing* (10 edition ed.). McGraw-Hill Education, New York.
- [26] Lee J. Cronbach. 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16, 3 (Sept. 1951), 297–334. <https://doi.org/10.1007/BF02310555> Company: Springer Distributor: Springer Institution: Springer Label: Springer

- Number: 3 Publisher: Springer-Verlag.
- [27] Laura A. Dabbish and Robert E. Kraut. 2006. Email Overload at Work: An Analysis of Factors Associated with Email Strain. In *Proceedings of the 2006 20th Anniversary Conference on Computer Supported Cooperative Work (CSCW '06)*. ACM, New York, NY, USA, 431–440. <https://doi.org/10.1145/1180875.1180941> event-place: Banff, Alberta, Canada.
 - [28] Jeffrey Dastin. 2018. Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters* (Oct. 2018). <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>
 - [29] Kay Deaux and Brenda Major. 1987. Putting gender into context: An interactive model of gender-related behavior. *Psychological Review* 94, 3 (1987), 369–389. <https://doi.org/10.1037/0033-295X.94.3.369>
 - [30] David M. Diez, Christopher D. Barr, and Mine Çetinkaya Rundel. 2015. *OpenIntro Statistics: Third Edition* (3 edition ed.). OpenIntro, Inc.
 - [31] Tawanna Dillahunt, Airi Lampinen, Jacki O'Neill, Loren Terveen, and Cory Kendrick. 2016. Does the Sharing Economy Do Any Good?. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work and Social Computing Companion (CSCW '16 Companion)*. ACM, New York, NY, USA, 197–200. <https://doi.org/10.1145/2818052.2893362>
 - [32] Don A. Dillman, Jolene D. Smyth, and Leah Melani Christian. 2014. *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method* (4 edition ed.). Wiley, Hoboken.
 - [33] Time Doctor. 2019. Upwork Connects Pricing Changes: A Complete Guide. <https://biz30.timedoctor.com/upwork-connects/> Library Catalog: biz30.timedoctor.com Section: Business.
 - [34] Alice H Eagly and Valerie J Steffen. 1984. Gender Stereotypes Stem From the Distribution of Women and Men Into Social Roles. *Journal of Personality and Social Psychology* 46, 4 (1984), 735–754.
 - [35] Benjamin Edelman, Michael Luca, and Dan Svirsky. 2017. Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment. *American Economic Journal: Applied Economics* 9, 2 (April 2017), 1–22. <https://doi.org/10.1257/app.20160213>
 - [36] Ingrid Erickson and Mohammad Hossein Jarrahi. 2016. Infrastructuring and the Challenge of Dynamic Seams in Mobile Knowledge Work. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*. ACM, New York, NY, USA, 1323–1336. <https://doi.org/10.1145/2818048.2820015> event-place: San Francisco, California, USA.
 - [37] Sandra R. Farber and Monica Rickenberg. 1999. Under-Confident Women and Over-Confident Men: Gender and Sense of Competence in a Simulated Negotiation. *Yale Journal of Law and Feminism* 11, 2 (1999), 271–304. <https://heinonline.org/HOL/P?h=hein.journals/yjfm11&i=277>
 - [38] Janell C. Fetterolf and Alice H. Eagly. 2011. Do Young Women Expect Gender Equality in Their Future Lives? An Answer From a Possible Selves Experiment. *Sex Roles* 65, 1 (April 2011), 83. <https://doi.org/10.1007/s11199-011-9981-9>
 - [39] Eureka Foong, Nicholas Vincent, Brent Hecht, and Elizabeth M. Gerber. 2018. Women (Still) Ask For Less: Gender Differences in Hourly Rate in an Online Labor Marketplace. *Proc. ACM Hum.-Comput. Interact.* 2 (Nov. 2018), 53:1–53:21. <https://doi.org/10.1145/3274322>
 - [40] Denae Ford, Alisse Harkins, and Chris Parmin. 2017. Someone like me: How does peer parity influence participation of women on stack overflow?. In *2017 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*. 239–243. <https://doi.org/10.1109/VLHCC.2017.8103473>
 - [41] John Fox. 2020. car package | R Documentation. <https://www.rdocumentation.org/packages/car/versions/3.0-9>
 - [42] Adam D. Galinsky, William W. Maddux, Debra Gilin, and Judith B. White. 2008. Why It Pays to Get Inside the Head of Your Opponent: The Differential Effects of Perspective Taking and Empathy in Negotiations. *Psychological Science* 19, 4 (April 2008), 378–384. <https://doi.org/10.1111/j.1467-9280.2008.02096.x>
 - [43] Adam D. Galinsky and Thomas Mussweiler. 2001. First offers as anchors: The role of perspective-taking and negotiator focus. *Journal of Personality and Social Psychology* 81, 4 (2001), 657–669. <https://doi.org/10.1037/0022-3514.81.4.657>
 - [44] Yanbo Ge, Christopher R. Knittel, Don MacKenzie, and Stephen Zoepf. 2016. *Racial and Gender Discrimination in Transportation Network Companies*. Technical Report w22776. National Bureau of Economic Research. <https://doi.org/10.3386/w22776>
 - [45] Kevin Geary. 2020. How Value Based Pricing Works (With Examples). <https://digitalambition.co/value-based-pricing/> Library Catalog: digitalambition.co Section: Revenue Generation.
 - [46] Claudia Goldin. 2014. A Grand Gender Convergence: Its Last Chapter. *American Economic Review* 104, 4 (April 2014), 1091–1119. <https://doi.org/10.1257/aer.104.4.1091>
 - [47] Claudia Goldin and Lawrence F. Katz. 2016. A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation. *Journal of Labor Economics* 34, 3 (July 2016), 705–746. <https://doi.org/10.1086/685505>
 - [48] Claudia Goldin, Sari Pekkala Kerr, Claudia Olivetti, and Erling Barth. 2017. The Expanding Gender Earnings Gap: Evidence from the LEHD-2000 Census. *American Economic Review* 107, 5 (May 2017), 110–114. <https://doi.org/10.1257/aer.p20171065>
 - [49] Paul Goodman. 1974. An Examination of Referents Used in the Evaluation of Pay. *Organizational Behavior and Human Performance* 12 (1974), 170–195.
 - [50] Mary L. Gray and Siddharth Suri. 2019. *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. Houghton Mifflin Harcourt. Google-Books-ID: 8AmXDwAAQBAJ.
 - [51] Mary L. Gray, Siddharth Suri, Syed Shoaib Ali, and Deepti Kulkarni. 2016. The Crowd is a Collaborative Network. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*. ACM, New York, NY, USA, 134–147. <https://doi.org/10.1145/2818048.2819942>
 - [52] Anikó Hannák, Claudia Wagner, David García, Alan Mislove, Markus Strohmaier, and Christo Wilson. 2017. Bias in Online Freelance Marketplaces: Evidence from TaskRabbit and Fiverr. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 1914–1933. <https://doi.org/10.1145/2998181.2998327>
 - [53] Libby Hemphill and Jahna Otterbacher. 2012. Learning the Lingo?: Gender, Prestige and Linguistic Adaptation in Review Communities. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work (CSCW '12)*. ACM, New York, NY, USA, 305–314. <https://doi.org/10.1145/2145204.2145254>
 - [54] Andreas Hinterhuber. 2004. Towards value-based pricing—An integrative framework for decision making. *Industrial Marketing Management* 33, 8 (Nov. 2004), 765–778. <https://doi.org/10.1016/j.indmarman.2003.10.006>
 - [55] Mary Hogue, Cathy Dubois, and Lee Fox-Cardamone. 2010. Gender differences in pay expectations: the roles of job intention and self-view. *Psychology of Women Quarterly* 34, 2 (June 2010), 215–227. <https://search-proquest-com.turing.library.northwestern.edu/docview/759516220/4E99E279902F4842PQ/69?accountid=12861>
 - [56] Mary Hogue, Janice D. Yoder, and Steven B. Singleton. 2007. The Gender Wage Gap: An Explanation of Men's Elevated Wage Entitlement. *Sex Roles* 56, 9 (May 2007), 573–579. <https://doi.org/10.1007/s11199-007-9199-z>
 - [57] John Horton, William R Kerr, and Christopher Stanton. 2018. Digital Labor Markets and Global Talent Flows. In *High-Skilled Migration to the United States and Its Economic Consequences*. University of Chicago Press, 71–108.
 - [58] Laura Huizar and Tsedeye Gebreselassie. 2016. What a \$15 Minimum Wage Means for Women and Workers of Color. (2016), 13.
 - [59] Hyperwallet. 2017. *The Future of Gig Work is Female*. Technical Report. Hyperwallet. 18 pages. <https://tinyurl.com/y5sl32fu>
 - [60] Institute for Women's Policy Research. 2018. *The Gender Wage Gap by Occupation 2017 and by Race and Ethnicity*. Technical Report C467. Institute for Women's Policy Research. https://iwpr.org/wp-content/uploads/2018/04/C467_2018-Occupational-Wage-Gap.pdf
 - [61] International Labor Organization. 2018. Helping the gig economy work better for gig workers. http://www.ilo.org/washington/WCMS_642303/lang--en/index.htm
 - [62] Panagiotis Ipeirotis and John Horton. 2011. The Need for Standardization in Crowdsourcing. 4. http://john-joseph-horton.com/papers/the_need_for_standardization_in_crowdsourcing.pdf
 - [63] Lilly C. Irani and M. Six Silberman. 2013. Turkopticon: interrupting worker invisibility in amazon mechanical turk. In *Proceedings of ACM Conference on Human Factors in Computing Systems (CHI 2013)*. ACM Press, 611. <https://doi.org/10.1145/2470654.2470742>
 - [64] Farnaz Jahanbakhsh, Justin Cranshaw, Scott Counts, Walter S. Lasecki, and Kori Inkpen. 2020. An Experimental Study of Bias in Platform Worker Ratings: The Role of Performance Quality and Gender. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. <https://doi.org/10.1145/3313831.3376860>
 - [65] Sandy James, Jody Herman, Susan Rankin, Mara Keisling, Lisa Mottet, and Ma'ayan Anafi. 2016. *The Report of the 2015 US Transgender Survey*. Technical Report. National Center for Transgender Equality, Washington D.C. <https://www.transequality.org/sites/default/files/docs/usts/USTS%20Full%20Report%20-%20FINAL%201.6.17.pdf>
 - [66] Jongick Jang. 2017. The Emergence of Freelancer Cooperatives in South Korea. *Annals of Public and Cooperative Economics* 88, 1 (March 2017), 75–89. <https://doi.org/10.1111/apce.12143>
 - [67] Mohammad Hossein Jarrahi and Will Sutherland. 2019. Algorithmic Management and Algorithmic Competencies: Understanding and Appropriating Algorithms in Gig Work. In *Information in Contemporary Society (Lecture Notes in Computer Science)*, Natalie Greene Taylor, Caitlin Christian-Lamb, Michelle H. Martin, and Bonnie Nardi (Eds.). Springer International Publishing, Cham, 578–589. https://doi.org/10.1007/978-3-030-15742-5_55
 - [68] Mohammad Hossein Jarrahi, Will Sutherland, Sarah Beth Nelson, and Steve Sawyer. 2020. Platformic Management, Boundary Resources for Gig Work, and Worker Autonomy. *Computer Supported Cooperative Work (CSCW)* 29, 1 (April 2020), 153–189. <https://doi.org/10.1007/s10606-019-09368-7>
 - [69] Isaac Johnson, Connor McMahon, Johannes Schöning, and Brent Hecht. 2017. The Effect of Population and "Structural" Biases on Social Media-based Algorithms: A Case Study in Geolocation Inference Across the Urban-Rural Spectrum.

- In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. Association for Computing Machinery, Denver, Colorado, USA, 1167–1178. <https://doi.org/10.1145/3025453.3026015>
- [70] Bonmae Kim. 2016. Hierarchical Linear Regression | University of Virginia Library Research Data Services + Sciences. <https://data.library.virginia.edu/hierarchical-linear-regression/>
- [71] Rex B. Kline. 2015. *Principles and Practice of Structural Equation Modeling, Fourth Edition*. Guilford Publications. Google-Books-ID: Q61ECgAAQBAJ.
- [72] Alison M. Konrad. 2013. Work-life interface and flexibility: Impacts on women, men, families, and employers. In *The Oxford handbook of diversity and work*. Oxford University Press, New York, NY, US, 366–390.
- [73] Laura J. Kray, Adam D. Galinsky, and Leigh Thompson. 2002. Reversing the Gender Gap in Negotiations: An Exploration of Stereotype Regeneration. <https://doi.org/10.1006/obhd.2001.2979>
- [74] Otto Kässi and Vili Lehdonvirta. 2016. *Online Labour Index: Measuring the Online Gig Economy for Policy and Research*. Technical Report 74943. <https://mpra.ub.uni-muenchen.de/74943/>
- [75] Matthew Lease, Jessica Hullman, Jeffrey P Bigham, Michael Bernstein, Juho Kim, Walter S Lasecki, Saeideh Bakhshi, and Tanushree Mitra. 2013. Mechanical Turk is Not Anonymous. (2013), 15.
- [76] Michael K. Lettau. 1997. Compensation in part-time jobs versus full-time jobs What if the job is the same? *Economics Letters* 56, 1 (Sept. 1997), 101–106. [https://doi.org/10.1016/S0165-1765\(97\)00098-0](https://doi.org/10.1016/S0165-1765(97)00098-0)
- [77] Ulman Lindenberger and Ulrich Pötter. 1998. The complex nature of unique and shared effects in hierarchical linear regression: Implications for developmental psychology. *Psychological Methods* 3, 2 (1998), 218–230. <https://doi.org/10.1037/1082-989X.3.2.218> Place: US Publisher: American Psychological Association.
- [78] Peggy Lomerson. 2019. Value-based pricing will change your business: here's what it is and how it works. <https://millo.co/value-based-pricing> Library Catalog: millo.co.
- [79] Annie Lowrey. 2017. What the Gig Economy Looks Like Around the World. *The Atlantic* (April 2017). <https://www.theatlantic.com/business/archive/2017/04/gig-economy-global/522954/> Section: Business.
- [80] Ning F. Ma and Benjamin V. Hanrahan. 2019. Part-Time Ride-Sharing: Recognizing the Context in which Drivers Ride-Share and its Impact on Platform Use. *Proceedings of the ACM on Human-Computer Interaction* 3, GROUP (Dec. 2019), 247:1–247:17. <https://doi.org/10.1145/3361128>
- [81] Brenda Major. 1989. Gender Differences in Comparisons and Entitlement: Implications for Comparable Worth. *Journal of Social Issues* 45, 4 (1989), 99–115.
- [82] Akash Mankar, Riddhi J Shah, and Matthew Lease. 2017. Design Activism for Minimum Wage Crowd Work. (June 2017). <https://arxiv.org/abs/1706.10097> arXiv: 1706.10097.
- [83] H. B. Mann and D. R. Whitney. 1947. On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *Annals of Mathematical Statistics* 18, 1 (March 1947), 50–60. <https://doi.org/10.1214/aoms/1177730491> Publisher: Institute of Mathematical Statistics.
- [84] Mary L. McHugh. 2013. The Chi-square test of independence. *Biochemia Medica* 23, 2 (June 2013), 143–149. <https://doi.org/10.11613/BM.2013.018>
- [85] Diane Mulcahy. 2018. How U.S. Law Needs to Change to Support the Self-Employed and Gig Economy. *Harvard Business Review* (July 2018). <https://hbr.org/2018/07/how-u-s-law-needs-to-change-to-support-the-self-employed-and-gig-economy> Section: Policy.
- [86] Anne Oeldorf-Hirsch and Darren Gergle. 2020. 'Who Knows What': Audience Targeting for Question Asking on Facebook. *Proceedings of the ACM on Human-Computer Interaction* 4, GROUP (Jan. 2020), 1–20. <https://doi.org/10.1145/3375191>
- [87] June O'Neill and David M. O'Neill. 2012. *The Declining Importance of Race and Gender in the Labor Market: The Role of Employment Discrimination Policies*. Rowman & Littlefield. Google-Books-ID: iltoHi_hcrIC.
- [88] Brett Pelham and John Hettis. 2001. Underworked and Overpaid: Elevated Entitlement in Men's Self-Pay. *Journal of Experimental Social Psychology* 37 (2001), 93–103.
- [89] Nigel F. Piercy, David W. Cravens, and Nikala Lane. 2010. Thinking strategically about pricing decisions. *Journal of Business Strategy* 31, 5 (Jan. 2010), 38–48. <https://doi.org/10.1108/02756661011076309>
- [90] Pawel Popiel. 2017. "Boundaryless" in the creative economy: assessing freelancing on Upwork. *Critical Studies in Media Communication* 34, 3 (2017), 220–233. <https://doi.org/10.1080/15295036.2017.1282618>
- [91] Alex Rosenblat. 2020. Gig Workers Are Here to Stay. It's Time to Give Them Benefits. *Harvard Business Review* (July 2020). <https://hbr.org/2020/07/gig-workers-are-here-to-stay-its-time-to-give-them-benefits> Section: Economics & Society.
- [92] Yves Rosseel. 2012. lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software* 48, 1 (May 2012), 1–36. <https://doi.org/10.18637/jss.v048.i02> Number: 1.
- [93] Charles J Rothwell, Jennifer H Madans, and Irma E Arispe. 2013. *2013 NCHS Urban–Rural Classification Scheme for Counties*. Technical Report. National Center for Health Statistics. 81 pages.
- [94] Katarina Salmela-Aro and Jari-Erik Nurmi. 2007. Self-esteem during university studies predicts career characteristics 10 years later. *Journal of Vocational Behavior* 70, 3 (June 2007), 463–477. <https://doi.org/10.1016/j.jvb.2007.01.006>
- [95] Paola Sapienza, Luigi Zingales, and Dario Maestri. 2009. Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences* 106, 36 (Sept. 2009), 15268–15273. <https://doi.org/10.1073/pnas.0907352106> Publisher: National Academy of Sciences Section: Social Sciences.
- [96] Steve Sawyer, Michael Dunn, Isabel Munoz, Fabian Stephany, Raghav Raheja, Gabrielle Vaccaro, and Vili Lehdonvirta. 2020. Freelancing Online During the COVID-19 Pandemic. (July 2020). <https://www.microsoft.com/en-us/research/publication/freelancing-online-during-the-covid-19-pandemic/>
- [97] Morgan Klaus Scheuerman, Katta Spiel, Oliver Haimson, Foad Hamidi, and Stacy Branham. 2019. HCI Inclusive Gender Guidelines. <https://www.morgan-klaus.com/sigchi-gender-guidelines>
- [98] Morgan Klaus Scheuerman, Kandra Wade, Caitlin Lustig, and Jed R. Brubaker. 2020. How We've Taught Algorithms to See Identity: Constructing Race and Gender in Image Databases for Facial Analysis. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (May 2020), 058:1–058:35. <https://doi.org/10.1145/3392866>
- [99] Linda Schweitzer, Sean Lyons, Lisa K.J. Kuron, and Eddy S.W. Ng. 2014. The gender gap in pre-career salary expectations: a test of five explanations. *Career Development International* 19, 4 (Aug. 2014), 404–425. <https://doi.org/10.1108/CDI-12-2013-0161>
- [100] M. Six Silberman, Lilly Irani, and Joel Ross. 2010. Ethics and Tactics of Professional Crowdfork. *XRDS* 17, 2 (Dec. 2010), 39–43. <https://doi.org/10.1145/1869086.1869100>
- [101] Jagpreet Singh. 2017. Council Post: Value-Based Pricing: Two Easy Steps To Implement And Two Common Pitfalls To Avoid. *Forbes* (July 2017). <https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2017/07/27/value-based-pricing-two-easy-steps-to-implement-and-two-common-pitfalls-to-avoid/> Section: Leadership.
- [102] John Storey, Graeme Salaman, and Kerry Platman. 2005. Living with enterprise in an enterprise economy: Freelance and contract workers in the media. *Human Relations* 58, 8 (Aug. 2005), 1033–1054. <https://doi.org/10.1177/0018726705058502>
- [103] Anselm Strauss and Juliet M. Corbin. 1997. *Grounded Theory in Practice*. SAGE. Google-Books-ID: TtRMolAapBYC.
- [104] Alice P. Stuhlmacher, Maryalice Citera, and Toni Willis. 2007. Gender Differences in Virtual Negotiation: Theory and Research. *Sex Roles* 57, 5 (Sept. 2007), 329–339. <https://doi.org/10.1007/s11199-007-9252-y>
- [105] Will Sutherland, Mohammad Hossein Jarrahi, Michael Dunn, and Sarah Beth Nelson. 2019. Work Precarity and Gig Literacies in Online Freelancing. *Work, Employment and Society* (Nov. 2019), 0950017019886511. <https://doi.org/10.1177/0950017019886511> Publisher: SAGE Publications Ltd.
- [106] R Core Team. 2013. R: A Language and Environment for Statistical Computing. <http://www.R-project.org/>
- [107] Jacob Thebault-Spieker, Daniel Kluver, Maximilian A. Klein, Aaron Halfaker, Brent Hecht, Loren Terveen, and Joseph A. Konstan. 2017. Simulation Experiments on (the Absence of) Ratings Bias in Reputation Systems. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW (Dec. 2017), 101:1–101:25. <https://doi.org/10.1145/3134736>
- [108] Upwork. [0000]. Freelancing in America: 2019. <https://www.slideshare.net/upwork/freelancing-in-america-2019/1> Library Catalog: SlideShare.
- [109] US Bureau of Labor Statistics. 2017. *Highlights of women's earnings in 2016*. Technical Report 1069. US Bureau of Labor Statistics. <https://www.bls.gov/opub/reports/womens-earnings/2016/pdf/home.pdf>
- [110] US Bureau of Labor Statistics. 2018. *American Time Use Survey - 2017 Results*. Technical Report USDL-18-1058.
- [111] US Bureau of Labor Statistics. 2019. May 2019 Metropolitan and Nonmetropolitan Area Occupational Employment and Wage Estimates. <https://www.bls.gov/oes/current/oesrcma.htm> Library Catalog: www.bls.gov.
- [112] Data USA. 2020. Writers & authors | Data USA. <https://datausa.io/profile/soc/writers-authors> Library Catalog: datausa.io.
- [113] Melissa A. Valentine, Daniela Retelny, Alexandra To, Negar Rahmati, Tulsee Doshi, and Michael S. Bernstein. 2017. Flash Organizations: Crowdsourcing Complex Work by Structuring Crowds As Organizations. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 3523–3537. <https://doi.org/10.1145/3025453.3025811>
- [114] Caroleen Vaughan. 1997. National writers union guide to freelance rates & standard practice. *Technical Communication* 44, 2 (May 1997), 180–183.
- [115] Mary E. Wade. 2001. Women and Salary Negotiation: The Costs of Self-Advocacy. *Psychology of Women Quarterly* 25, 1 (March 2001), 65–76. <https://doi.org/10.1111/1471-6402.00008>
- [116] Georgina Waylen. 2018. Nudges for gender equality? What can behaviour change offer gender and politics? *European Journal of Politics and Gender* 1, 1–2 (July 2018), 167–183. <https://doi.org/10.1332/251510818X15272520831229>
- [117] Robert S. Weiss. 1995. *Learning From Strangers: The Art and Method of Qualitative Interview Studies*. Simon and Schuster. Google-Books-ID: i2RzQbiEiD4C.

- [118] Mark E. Whiting, Grant Hugh, and Michael S. Bernstein. 2019. Fair Work: Crowd Work Minimum Wage with One Line of Code. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing* 7, 1 (Oct. 2019), 197–206. <https://www.aaai.org/ojs/index.php/HCOMP/article/view/5283> Number: 1.
- [119] Alex J. Wood, Vili Lehdonvirta, and Mark Graham. 2018. Workers of the Internet unite? Online freelancer organisation among remote gig economy workers in six Asian and African countries. *New Technology Work and Employment* 33, 2 (July 2018), 95–112. <https://doi.org/10.1111/ntwe.12112> WOS:000438217500001.
- [120] Alex Wood-Doughty. 2016. *Do Employers Learn from Public, Subjective, Performance Reviews?* SSRN Scholarly Paper ID 2848536. Social Science Research Network, Rochester, NY. <https://doi.org/10.2139/ssrn.2848536>
- [121] World Economic Forum. 2017. *The global gender gap report: 2017*. Technical Report. World Economic Forum, Geneva. OCLC: 1012177619.
- [122] World Economic Forum. 2019. The gig economy: how to make it more fair in 4 steps. <https://www.weforum.org/agenda/2019/11/gig-economy-in-4-steps/>
- [123] Ming Yin, Siddharth Suri, and Mary L. Gray. 2018. Running Out of Time: The Impact and Value of Flexibility in On-Demand Crowdwork. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, 430:1–430:11. <https://doi.org/10.1145/3173574.3174004>