Gender Wage Gap in Online Gig Economy and Gender Differences in Job Preferences

Completed Research Paper

Chen Liang
Arizona State University
Tempe, Arizona, US
chen.liang.4@asu.edu

Yili Hong
Arizona State University
Tempe, Arizona, US
hong@asu.edu

Bin Gu
Arizona State University
Tempe, Arizona, US
bin.gu@asu.edu

Jing Peng
University of Connecticut
Storrs, Connecticut, US
jing.peng@uconn.edu

Abstract

We explore whether there exists gender wage gap in the gig economy and examine to what degree gender differences in job application strategy could account for the gap. With a large-scale dataset from a leading online labor market, we show that females only earn around 81.4% of the hourly wage of their male counterparts. We further investigate three main aspects of job application strategy, namely bid timing, job selection, and avoidance of monitoring. After matching males with females using the propensity score matching method, we find that females tend to bid later and prefer jobs with a lower budget. In particular, the observed gender difference in bid timing can explain 7.6% of the difference in hourly wage, which could account for 41% of the gender wage gap (i.e. 18.6%) observed by us. Moreover, taking advantage of a natural experiment wherein the platform rolled out the monitoring system, we find that females are less willing to bid for monitored jobs than males. To further quantify the economic value of the gender difference in avoidance of monitoring, we run a field experiment on Amazon Mechanical Turk (AMT), which suggests that females tend to have a higher willingness to pay (WTP) for the avoidance of monitoring. The gender difference in WTP for the avoidance of monitoring can explain 8.1% of the difference in hourly wage, namely, 44% of the observed gender wage gap. Overall, our study reveals the important role of job application strategies in the persistent gender wage gap.

Keywords: gender wage gap, job application strategy, gig economy, quasi-natural experiment

Introduction

There is a growing literature documenting the gender wage gap in the labor market. As the previous literature suggests, while employers exhibit less discrimination against females in the hiring process, females still earn a lower wage than males in the same positions (Goldin and Rouse 2000; Kuhn and Shen 2012). Therefore, an emerging school of thought is that "*gender wage gap is caused mainly by women's choice, not discrimination.*"[1] In the same vein, more studies are suggesting that the gender wage gap is

[1] https://www.campusreform.org/?ID=9827
This report reads "*The American Association of University Women (AAUW) has finally admitted that the "gender pay gap" is caused primarily by women's choices, not discrimination. In fact, the AAUW's own research suggests*

partially attributable to motherhood penalty, gender differences in career plans, or preferences for non-monetary attributes in a job, such as flexibility (Mas and Pallais 2017), work-from-home (Mas and Pallais 2017), and workplace competitiveness (Niederle and Vesterlund 2007,2011; Flory et al. 2014).

Given that gender pay gap is a longstanding phenomenon, the new gig economy, which is thriving in many industries (e.g., ridesharing, temporary lodging, outsourcing), seems to provide an efficient way to reduce the gender wage gap. Owing to the market openness and the emphasis on spot-market based short-term employment in gig economy, many scholars predict that gender differences in career development, as well as the gender wage gap, will be smaller in the gig economy (e.g. Goldin and Rouse 2000). Specifically, it's predicted but not empirically confirmed that workers tend to have more flexible work hours and locations in the gig economy, making motherhood penalty less likely to become an obstacle to career development. As the booming gig economy is projected to comprise a large portion of the future of work[2], it is imperative to examine whether there is a gender wage gap in the gig economy. Moreover, given that females tend to have much more flexibility in gig work than in traditional workplace, the gig economy also provides us an unprecedented opportunity to explore factors other than motherhood penalty or compensation differential for flexibility that might influence the gender wage gap, which is critical to policy prescription to further narrow the gender wage gap. In particular, as the gig economy, especially the online gig economy platform, enables workers from all over the world to seek a wider diversity of remote jobs posted by employers from various countries, this provides a unique setting to dig into potential gender differences in job application strategy, which is hitherto little explored. To this end, with the advantage of the availability of large-scale micro-level granular data in the online gig economy (Hong and Pavlou 2017), we attempt to explore several critical aspects of gender differences in job application strategy and their impact on the gender wage gap. Specifically, we examine whether there are gender differences in job application strategy and to what extent such gender differences can account for the gender wage gap in the gig economy (if any). In particular, we are interested in the following questions:

1) Is there a gender wage gap in the gig economy?
2) Whether and to what extent the gender wage gap is driven by gender differences in job application strategy?

In this paper, we take advantage of a comprehensive dataset from a leading gig economy platform, a quasi-natural experiment, and a supporting field experiment to answer the above research questions. First, we infer workers' genders based on their profile images[3] with human labeling. We find that there is a gender wage gap based on the historical hiring data. This result is consistent when we control for various workers' characteristics. We find that, on average, females earn 81.4% of the hourly wage of their male counterparts.

Second, we recover each worker's consideration set of jobs based on our comprehensive dataset. It is notable that although there are a few studies analyzing employers' preference for workers in the online labor market (Chan and Wang 2017), workers' behaviors are yet to be explored, e.g., gender differences in job preference, likely due to the lack of data regarding workers' consideration sets. In our study, because the platform restricts workers to only bid for jobs with at least one skill requirement matched with their own skill sets, we are able to reconstruct the whole list of contemporaneous jobs which were available for workers to bid. Based on the recovered consideration sets, we find that females tend to bid later and prefer jobs with a lower hourly wage budget, compared to males. This result is consistent when we only use the matched sample and use an alternative proxy for bid timing. In particular, the result shows that the observed gender difference in bid timing can lead to a decrease of 7.58% in hourly wage, which could roughly account for 40.75% of the observed gender wage gap (i.e. 18.6%).

Third, we find that females prefer to bid jobs without monitoring based on a quasi-natural experiment and that females tend to have a higher willingness to pay (WTP) for the avoidance of monitoring through a field experiment. Specifically, hinging on the exogenous shock when the platform implemented the monitoring system on all the hourly jobs, we observe that females are less willing to bid for monitored jobs based on a difference-in-differences (DID) estimation and difference-in-difference-in-differences (DDD) estimation.

---

that only about 7% of the observed pay gap can be attributed to discrimination, with simple economic factors accounting for the remainder."

[2] "Independent work: Choice, necessity, and the gig economy" https://www.mckinsey.com/featured-insights/employment-and-growth/independent-work-choice-necessity-and-the-gig-economy

[3] We find consistent results when we use the first name of workers to infer gender.

In particular, we take fixed-price jobs as the control group and incorporate the interaction of the monitoring treatment with contractual forms across jobs and the worker's gender. To further quantify the economic value of the gender difference in WTP for the avoidance of monitoring than males, we conduct a randomized field experiment on Amazon Mechanical Turk (AMT). We randomly provide two hourly jobs for workers on AMT (Turkers), in which only one requires monitoring. We also randomize the wage premium offered by the job with the monitoring requirement, which varies between $-2 and $5. The result suggests that females have a higher WTP for the avoidance of monitoring than males, which lends support to our finding from the quasi-natural experiment. In fact, the gender difference in WTP for the avoidance of monitoring can explain roughly 8.13% of the hourly wage, which is equivalent to 43.71% of the observed gender wage gap.

Our paper contributes to three related strands of literature. First, our study contributes to the literature on gender wage gap (Blau and Kahn 2017; Mas and Pallais 2017; Wiswall and Zafar 2015, 2017) by providing new explanations for the gender wage gap that are unrelated to gender discrimination, i.e., gender differences in bid timing, job selection, and the avoidance of monitoring. Second, this study also contributes to the literature on the online labor market by showing the importance of workers' job preferences. Although employers' preference of workers has been recently explored (Chan and Wang 2017; Hong and Pavlou 2017), there is little research exploring the preference from the supply side (i.e., workers' preference for jobs). Our study advances the previous literature on online labor markets by documenting gender differences in job application strategy and how they may explain the gender wage gap. Lastly, this paper also contributes to the literature on compensation differential (Bonhomme and Jolivet 2009; Mas and Pallais 2017). Our study takes advantage of both a quasi-natural experiment and a field experiment to show the gender difference in WTP for the avoidance of monitoring, a non-wage aspect which has hardly been explored in the compensation differential literature.

Theoretical Background

Gender Wage Gap

The gender wage gap has been established long ago. According to the estimates from the Institute for Women's Policy Research, women are still paid 20% less than their male counterparts in the same position in 2015[4]. In fact, based on the statistics from the Census Bureau, the female-to-male earnings ratio, which has not been updated since 2007, is 0.805[5]. The persistence of gender pay gap is difficult to explain because the explanations for the wage gap provided by the previous literature, such as gender differences in occupation choice and preference for flexibility, seem to be less relevant in today's society, especially in gig economy. For instance, even in the IT industry, which tends to provide workers a relatively flexible work schedule, women are still systematically paid less than men and are promoted more slowly.

There is a large body of literature exploring the causes of the gender wage gap. First, discrimination from the demand side has found to be one of the key explanations. Regarding the mechanisms of discrimination, the findings from the previous literature are still mixed. Some studies suggest that only statistical discrimination (Gupta and Smith 2012; Castillo et al. 2013) contributes to the gender wage gap while some other papers lend support to the taste-based discrimination explanation (Goldin and Rouse 2000; Marom et al. 2016). Second, a growing literature suggests that gender differences in worker confidence and compensation differential also help to account for the gender wage gap, which will be discussed below.

Gender Wage Gap and the Gig Economy

The emerging gig economy is expected to help to decrease the gender wage gap by increasing work schedule flexibility and reducing the motherhood penalty (Goldin and Rouse 2000). According to a report from Hyperwallet, a gig-work payment platform, 86% of females believe that they can earn equal pay to males in the gig economy, while only 41% of females think so in traditional workplace[6]. Moreover, Chan and Wang (2017) found that employers prefer to hire female workers in feminine-typed jobs and even gender-neutral jobs in an online gig economy platform, which suggests that discrimination is less likely to be a serious

[4] https://iwpr.org/publications/the-gender-wage-gap-2015-annual-earnings-differences-by-gender-race-and-ethnicity

[5] https://iwpr.org/wp-content/uploads/2017/09/C459_9.11.17_Gender-Wage-Gap-2016-data-update.pdf

[6] "The Future of Gig Work is Female," available at www.hyperwallet.com

obstacle to females. That being said, females are still found to pay an invisible cost owing to gender differences in preference-based characteristics, such as females' lower willingness to work more hours in the car-hailing service industry when the hourly wage is high (Cook et al. 2018). However, it is still unknown whether females still earn less than males in online gig economy platforms wherein the hourly wage is less dependent on the working time and location. Given that the effect of discrimination in online gig economy platforms has already been explored in the prior study (Chan and Wang 2017), in this paper, we will focus on examining key factors that contribute to the gender wage gap other than the gender discrimination in online gig economy platforms.

Gender Wage Gap and Gender differences in Confidence and Avoiding Uncertainty

Gender differences in worker confidence and avoidance of uncertainty are found to be key contributing factors of the gender wage gap. First, gender differences in confidence may lead to gender differences in competitiveness and the wage gap. For instance, Niederle and Vesterlund (2007) identified gender differences in competitiveness in a lab experiment. They found that although there are no significant gender differences in performance, women show less preference for the competitive tournament. Further, they explained that gender differences in competitiveness were caused by the differences in confidence and attitudes toward competition instead of gender differences in risk aversion (Niederle and Vesterlund 2011). In line with this study, Flory et al. (2014) found that gender differences in preferences for uncertainty and competition jointly drive gender differences in job-entry choices. Moreover, some contingent factors influence the size of gender differences, including whether the job involves teamwork or has overt gender associations, and his/her age, etc. (Flory et al. 2014). Inspired by this stream of literature, we expect that there might exist gender differences in job application strategy due to gender differences in confidence and avoidance of uncertainty suggested in the previous literature and explore the subsequent impact on the gender wage gap.

Gender Wage Gap and Gender difference in Compensation Differential/Preference

Meanwhile, the gender wage gap can also be caused by compensation differential. Research in this space has focused on how gender differences in preference for various non-wage job characteristics may account for the gender wage gap. This is also referred to as cross-gender compensation differential. Cross-gender compensation differential means that females and males may have different WTP for different nonwage job attributes (Arnould and Nichols 1983), which subsequently leads to their different job choices and wages. For example, gender differences in work flexibility have been found to help to explain the gender wage gap. Marini and Fan (1997) found that gender differences in worker characteristics (including occupational aspirations, job-related skills, and credentials) explain roughly 30% of the gender wage gap. More recently, Wiswall and Zafar (2017) found that females show a stronger preference for work flexibility and job stability whereas males prefer potential earnings growth. Moreover, such gender differences in preference also indirectly lead to gender differences in college major choices and subsequent income (Wiswall and Zafar 2017). In the same vein, Mas and Pallais (2017) find a significant gender difference in WTP for working from home but an insignificant gender difference in WTP for scheduling flexibility in their large-scale field experiment. Given that most jobs in the gig economy tend to have high scheduling flexibility and allow working-from-home, we focus on potential gender differences in WTP for the avoidance of monitoring, which has become increasingly important with the popularity of online, IT-enabled monitoring systems.

Research Methodology

Research Framework

We first explore whether a gender wage gap exists in the gig economy. Then, we examine whether there are gender differences in job application strategy and how these differences may contribute to the gender wage gap. Table 1 summarizes our research framework. Next, we explain them in turn.

Table 1. Research Framework and Empirical Identification Strategy

Key concepts	Research questions	Data source	Empirical model
Gender wage gap	Is there a gender wage gap in the gig economy?	Observational data from Freelancer.com	Fixed-effect model with the worker country and month two-way fixed effects
Gender differences in job application strategy	1) Do females prefer to bid jobs with a smaller hourly wage budget? 2) Do females prefer to bid later?	Observational data from Freelancer.com	Propensity score matching between female and male workers Linear probability model with fixed effects on the consideration set
	3) Do females prefer to bid jobs without monitoring?	Observational data from Freelancer.com with a quasi-natural experiment	Propensity score matching between female and male workers; propensity score matching between fixed-price and hourly jobs Differences-in-Differences and triple differences estimator based on a quasi-natural experiment
		A field experiment on AMT	Mixture logit model

Table 1. Research Framework and Empirical Identification Strategy

Observational Data

Our data for the main analysis were collected from Freelancer.com, one of the leading online gig economy platforms. In Freelancer, all jobs are awarded based on a reverse auction mechanism wherein employers post jobs first and workers bid for those jobs of their interest. When posting the job, the employer provides the project title, project description, required skills, and project budget. To reduce the potential confounding effects of various job requirements, we limit our sample to the "IT, software & website" category, which is the most popular category in Freelancer, in terms of number of jobs and transactions. Given that we attempt to explore the gender difference in job preference, we focus on jobs that can be done remotely.[7] Our final dataset includes a majority of the IT jobs posted in Freelancer between October 2013 and November 2014. Users of Feelancer.com come from over 100 countries. Before making the first bid on the platform, they are required to list those skills they acquired and upload their profile images. Our dataset includes various job- and user- level characteristics as reported in Table 2.

Table 2. Definitions and Summary Statistics of Related Variables

Variable	Variable definition	Mean	SD	Min	Median	Max
chosen_bid	A dummy variable (0,1); =1 if the worker bids for the job or not	0.005	0.069	0.000	0.000	1.000
employer_norating	A dummy variable (0,1); =1 if the employer has not any reviews written by previous workers hired by him/her	0.080	0.272	0.000	0.000	1.000
log(employer_review)	The number of reviews for the employers entered by previous workers (log-transformed)	3.255	1.207	0.000	3.178	6.071
employer_overall_rating	The average overall ratings for the employer (in the range of [0-5])	4.884	0.470	0.000	4.996	5.000
log(max_budget)	The maximum of hourly wage for this job set by the employer (log-transformed)	2.300	1.275	0.000	2.197	5.994
female	A dummy variable (0,1); =1 if the worker is a female	0.146	0.353	0.000	0.000	1.000
log(title_length)	Number of characters in the job title (log-transformed)	3.472	0.412	2.398	3.466	4.796
log(desc_length)	Number of characters in the job description (log-transformed)	5.312	0.918	2.773	5.242	8.101

[7] Local jobs only accounts for less than 0.01% of all the jobs posted on the platform.

log(skills_count)	Number of necessary skills listed by the employer (log-transformed)	1.509	0.315	0.693	1.609	1.792
featured_job	A dummy variable; =1 if this job is featured prominently on the job catalog page	0.005	0.071	0.000	0.000	1.000
NDA	A dummy variable; =1 if this job requires NDA (Non-Disclosure Agreement)	0.000	0.012	0.000	0.000	1.000
log(daystoend)	Number of days between the bid date and the date when the auction is closed (log-transformed)	1.361	0.594	0.000	1.386	3.135
log(auction_duration)	Number of days wherein the job is open for bid (log-transformed)	2.089	0.106	0.693	2.079	3.135
log(hourly_wage)	The hourly wage of the awarded bid (log-transformed)	2.247	0 .983	0 .693	2.303	7.600

Notes: a) Due to the overdispersion in the "*log(max_budget)*" variable, we dropped the outliers based on 99th percentile cutoff; b) Given that the consideration set of each worker's bid decision is very large (close to 200 jobs), the mean value of chosen_bid is relatively low. If chosen_bid is equal to 0.005, it means that the worker chooses one job to bid among all the 200 jobs for which s/he could bid. c)We label the gender of each user based on his/her profile image. we hired student workers and MTurk workers to label workers' genders based on their profile images. For each image, there are at least two persons to label them. For those images we could not identify their genders based on the profile images or there is some inconsistency between the labels of the same image, we label their genders as "unknown". We find consistent results when we use the first name of workers to infer gender.

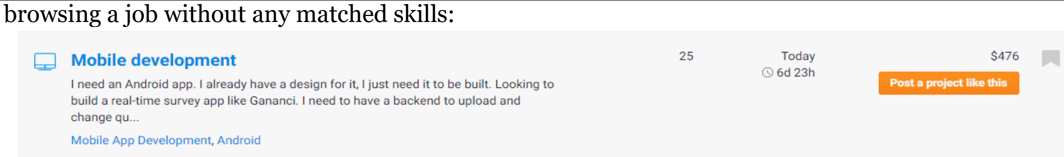
Table 2. Definitions and Summary Statistics of Related Variables

Construction of Workers' Consideration Sets

To explore workers' job application strategy, we compile the whole dataset and reconstruct each worker's consideration set based on the platform regulation policy (Figure 1). In general, there are two main restrictions imposed on the workers' job selection. First, the job should be open for bids at that time. Second, the worker has at least one skill matched with the skill requirements of the project. As such, we take advantage of the comprehensiveness of our dataset, which includes both the detailed auction duration, job skill requirements and all workers' skill sets, and construct workers' consideration sets as follows:

To begin with, we first find a list of active workers and their bids during our observation window. Specifically, the worker j is considered as an active worker at day t only if s/he bid at least once on that day. Further, we find all the IT jobs which were open to bidding when s/he made the bid decision. Lastly, we check whether the worker has at least one skill matched with the job skill requirements to finalize his/her consideration set. According to the platform regulation, the worker could bid for all the jobs satisfying with these two restrictions. In essence, we examine female and male workers' revealed preference for job characteristics based on the actual bid decisions they made, given all the open jobs fitted with their skills.[8]

When browsing a job without any matched skills:



With browsing a job with at least one matched skill, the "bid now" button is displayed:

Figure 1. A Screenshot from Freelancer.com for Jobs with/without Matched Skills

[8] To ensure that workers can bid for all the jobs in the consideration set, we only limit to those jobs which do not use sealed auctions and are described in English. Additionally, since the "hireme" jobs are posted for targeted workers, we also rule out these jobs from our sample.

Experimental Data for the Analysis of Gender Differences in WTP

We conduct a field experiment on Amazon Mechanical Turk. In total, we have recruited 300 participants, among which 276 have completed the experiment. The experiment follows a between-subject design with 15 treatments by varying wage premium of the job with monitoring (Table 3). For each treatment group, participants will be provided a short introduction of the monitoring system and two job options shown randomly. When the participant is choosing between two hourly choices with different wages, his/her WTP to avoid monitoring can only be driven by his/her distaste for monitoring. To ensure the internal validity of randomization, we ensure the comparability of participants in different treatment groups across various wage premium cases.

Table 3. Treatment Design of the Field Experiment		
Single choice question	Job option design	Wage premium of the job with monitoring
	An hourly job without monitoring or an hourly job with monitoring	Wage premiums ∈[-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5]

Table 3. Treatment Design of the Field Experiment

Measures and Models

Measuring the Gender Wage Gap

To measure the gender wage gap in the gig economy, we explore whether female workers systematically earn a lower hourly wage in all the hourly job transactions made on Freelancer.com. Specifically, we use the log-transformed hourly wage based on those awarded bids as the dependent variable and the $Female_i$ dummy is the key independent variable of our interest. We employ the following linear regression model to estimate the effect of gender on hourly wage:

$$\log(wage_{it}) = \alpha_{it} + \beta_1 Female_i + controls(\text{Worker}_i) + \varepsilon_{it} \tag{1}$$

According to the literature on the gender wage gap, we attempt to calculate the adjusted gender wage gap which needs to be corrected for differences in payment due to country or occupation, differences in period, and differences in human capital (Freeman and Oostendorp 2000; O'Neill 2003; Oostendorp 2004; Blau and Kahn 2017). To adjust for the country or period differences, we control for the worker country and month two-way fixed effects and cluster standard errors accordingly. Given that our observations come from the same type of jobs (online IT jobs), the occupation differences among our sample is relatively small. To correct for human capital, we assume that the worker's rating, experience and tenure can serve as good proxies for the worker's human capital. Accordingly, we further add the control for various time-varying covariates regarding worker i, such as the number of reviews entered by previous employers, the average rating, the tenure measured in the month unit, the primary language set by worker i, verification measures and the length of the tagline on worker i's profile, etc. A significant coefficient of the dummy $Female_i$ suggests that there is a gender wage gap in the gig economy.

Gender Differences in Bid Timing and Budget Preference

To further explore whether there are gender differences in bid timing and budget preference among all hourly IT jobs, we estimated the heterogeneity in female and male workers' preference for jobs' characteristics. Particularly, we examine the impact of the $log(daystoend_{ij})$ dummy and the $log(maxbudget_{ij})$ dummy on the probability of worker i bidding for the job j. We control for the fixed-effects of the consideration set of each bid with the linear probability model. In particular, the decision of worker i bidding for job j is modeled as follows:

$$Worker_{it}\_bid\_for\_job_j = \alpha_{it} + \beta_1 \log(daystoend_{ij}) + \beta_2 \log(maxbudget_{ij}) + \beta_3 \log(daystoend_{ij}) * Female_i + \beta_4 \log(maxbudget_{ij}) * Female_i + controls(job_j) + \varepsilon_{itj} \tag{2}$$

where α_{it} means the fixed effect of the consideration set facing worker i at time t, and $Female_i$ dummy denotes whether worker i is a female inferred based on his/her profile image. $controls(job_j)$ include various related characteristics of all the jobs in the consideration set, such as the employer's country dummy, the number of reviews and average rating of the employer of job j, the maximum budget of hourly wage listed by the employer, the length of job title and description, the number of skills required by the job, whether this job is featured. ε_{itj} is the error term clustered at the consideration set faced by worker i at time t. We are interested in the coefficient of two interaction terms (β_3 and β_4) which denote whether females prefer to bid later and bid jobs with a smaller hourly job budget compared to their male counterparts.

Gender Differences in Avoidance of Monitoring in the Quasi-Natural Experiment

We estimate gender differences in avoidance of monitoring by taking advantage of the exogenous shock when the platform requires all workers hired for hourly jobs need to install and use the monitoring system. And this monitoring system is not available for fixed-price jobs. Specifically, we employ the DID estimation and the DDD estimation to check whether females are less willing to work under monitoring. First, in the DID estimation framework, we are interested in the coefficient of the interaction term (β_2), which denotes that whether female workers are less willing to bid for hourly jobs after the implementation of monitoring systems by taking the fixed-price jobs as the control group. Here, we employ the propensity score matching to control for the selection on observables among job types and only use highly comparable fixed-price jobs as the counterfactual.

$$Worker_{it}\_choice\_on\_job_j = \alpha_{it} + \beta_1 Hourly_j + \beta_2 After_{it} \times Hourly_j + controls(Job_j) + \varepsilon_{itj} \quad (3)$$

Further, we also match male and female workers based on their reputation and various profile information. Based on the comparable females and males within the matched sample, we explore the difference in the treatment effect of monitoring on males and females in term of job preference:

$$Worker_{it}\_choice\_on\_job_j = \alpha_{it} + \beta_1 Hourly_j + \beta_2 Female_i \times Hourly_j + \beta_3 After_{it} \times Hourly_j + \beta_4 Female_i \times After_{it} \times Hourly_j + controls(Job_j) + \varepsilon_{itj} \quad (4)$$

We compare the difference in preference for hourly jobs for males before and after the implementation of monitoring systems (DD_{male}) with the difference in preference for hourly jobs for females before and after (DD_{female}). In other words, $\mathrm{DDD} = \mathrm{DD}_{female}$-$\mathrm{DD}_{male}$, which will be captured by the coefficient of the triple interaction (β_4). Note that, compared to the traditional DDD estimation, the term $After_{it} \times Female_i$ is omitted because it is nested in the time-varying fixed effect α_{it}. If we observe a significantly negative coefficient of DDD (β_4), it suggests that females tend to have a stronger avoidance of monitoring than their male counterparts, which means that females prefer to bid for jobs without monitoring.

Gender Differences in WTP for Avoidance of Monitoring in the Field Experiment

Following the modeling framework of Mas and Pallais (2017), the probability of workers choosing a job with monitoring when the wage premium of the monitored job is ΔW as follows:

$$P(Y_i = 1) = \Pr(\beta \Delta W_i + \delta X - Z_i > 0)\,(1-\eta) + \eta/2 \quad (5)$$

where represents the probability that the worker is inattentive. η denotes the probability that the user is inattentive, in which case the user makes decision randomly. X is a vector of various job characteristics other than the hourly wage and the monitoring condition, Z_i is the disutility for worker i if s/he works under monitoring. $\Delta W_i + \delta X - Z_i$ is the utility of worker i choosing a monitored job with the utility for a job without monitoring normalized to zero. Further, we can get the likelihood function of the above probability is $\ln \prod_i \left(P(Y_i = 1)\right)^{Y_i} \left(1 - P(Y_i = 1)\right)^{1-Y_i}$ and use the maximum likelihood estimation to identify μ and σ, which represent the mean and standard deviation of the distribution of WTP, respectively.

Empirical Results Regarding Gender Wage Gap

The Existence of Gender Wage Gap

As Table 4 shows, the coefficient of the "female" dummy is significantly negative, which suggests that females systematically earn a lower wage than males. We control for workers' reputation and experience in Model 1 and additional characteristics of their profiles in Model 2. The result is highly consistent. Based on the result of Model 2, on average, females can only earn 81.4% of the wage of their male counterparts, which is very close to the gender wage gap found in the general fulltime job in the US (i.e., 80%)[9].

Table 4. Evidence of Gender Wage Gap in the Gig Economy				
Dependent variable: log(hourly_wage)				
Model	(1)		(2)	
Job type	hourly		hourly	
female	-0.208**	(0.099)	-0.205**	(0.101)
log(bidder_overall_rating)	0.021	(0.094)	0.020	(0.091)
log(bidder_count_rating)	0.055*	(0.029)	0.055*	(0.032)
bidder_primary_language_eng	0.020	(0.252)	0.020	(0.248)
log(bidder_tenure_month)	0.150***	(0.036)	0.162***	(0.037)
log(length_tagline)			0.085	(0.059)
identity_verified			-0.050	(0.068)
phone_verified			0.024	(0.297)
preferred_freelancer			0.041	(0.078)
log(milestone_percentage)			0.009	(0.034)
Observations	1,300		1,288	
R-squared	0.047		0.053	
Bidder country dummy	yes		yes	
Month fixed effects FE	yes		yes	
Notes: a) Here, log(length_tagline) denotes the length of the tagline on worker i's profile, which can be considered as the short headline of the self-introduction on the profile page; b) Robust standard errors clustered by the bidder country and month two-way fixed effects are reported in parentheses; c) * p<0.1, ** p<0.05, *** p<0.01.				

Table 4. Evidence of Gender Wage Gap in the Gig Economy

Empirical Results Regarding Gender Differences in Job Application

Model-free Evidence

To provide some model-free evidence on gender differences in job application strategy, we summarize the sample statistics of the bid order measure and the maximum of wage budget for male and female worker respectively. As Table 5 shows, females tend to have a higher bid order and bid for jobs with smaller hourly wage budgets. "Bid_order" denotes the sequence in which the bidders' bids were submitted. The higher bid order implies the latter bid. To further examine whether there exist gender differences in bidding strategy, we will present our result with econometric models introduced in the previous section.

Table 5. Model-free Evidence of Gender Differences in Job Application Strategy								
	Male workers				Female workers			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
bid_order	12.57	13.25	1.00	109.00	13.61	13.97	1.00	89.00
max_budget	13.79	10.48	0.00	50.00	13.25	10.14	0.00	50.00

Table 5. Model-free Evidence of Gender Differences in Job Application Strategy

Sample Matching

To ensure the similarity between females and males, we employ the propensity score matching method to match females with males, and match fixed-price jobs with hourly jobs. As suggested in Table 6, we match males and females based on their reputation, experience, verification, primary language, primary currency and whether they have the "preferred freelancer" badges, most of which serve as proxies for their human capital and the credibility of their identity or work. The balance check result and the density distribution of

[9] Based on the report from American Association of University Women (AAUW), females working in full-time jobs usually get paid 80% of the wage earned by males (source: https://www.aauw.org/research/the-simple-truth-about-the-gender-pay-gap/).

the propensity score suggest that after the matching, females and males are highly comparable in most of the observable characteristics displayed to the employers.

Table 6. Balance Check for Propensity Score Matching between Females and Males

Variable	Sample	Mean: Female	Mean: Male	%bias	% reduced |bias|	t-test: t	t-test: p>|t|
registration_month	Unmatched	635.910	629.490	27.400		7.070	0.000
	Matched	635.910	636.200	-1.200	95.500	-0.300	0.768
current_reviews	Unmatched	14.587	15.650	-1.500		-0.430	0.669
	Matched	14.587	15.798	-1.700	-14.000	-0.260	0.795
avg_rating	Unmatched	2.082	2.207	-5.200		-1.440	0.149
	Matched	2.082	1.953	5.400	-3.800	1.150	0.251
payment_verified	Unmatched	0.006	0.009	-4.600		-1.770	0.076
	Matched	0.006	0.006	0.000	100.000	0.000	1.000
identity_verified	Unmatched	0.004	0.011	-7.800		-2.870	0.004
	Matched	0.004	0.004	0.500	93.100	0.240	0.808
phone_verified	Unmatched	0.001	0.001	-1.600	-70.600	-0.610	0.542
	Matched	0.001	0.002	-2.700		-0.820	0.414
preferred_freelancer	Unmatched	4.916	4.940	-8.300	95.500	-3.340	0.001
	Matched	4.916	4.917	-0.400		-0.100	0.918

Notes: 1) Results of Nearest Neighbor (1) Matching Method without replace are presented. 2) Due to length limitation, results regarding some variables are omitted, including the "primary_language_Eng" and "primary_currency_US" dummies. The means of both variables are not significantly different across groups.

Table 6. Balance Check for Propensity Score Matching between Females and Males

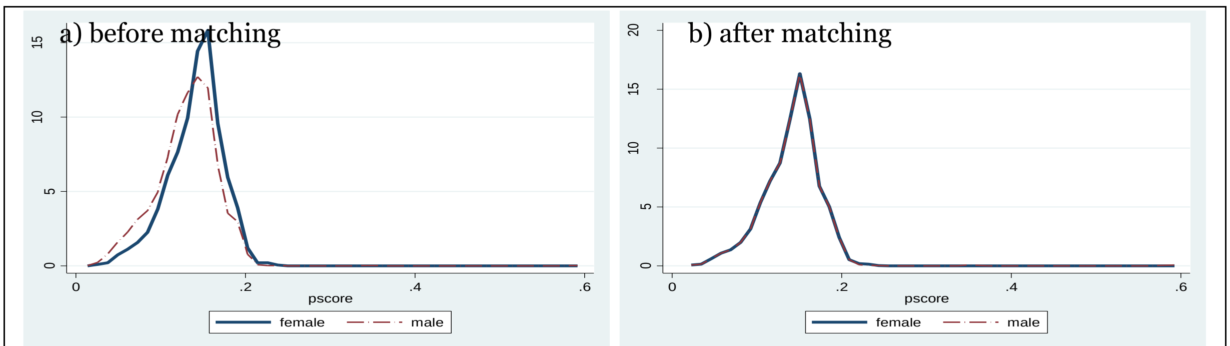


Figure 2. Density of Propensity Score of Being Female (before and after Matching)

Similarly, given that we use fixed-price jobs as the control group in our analysis for the quasi-natural experiment wherein Freelancer.com rolled out its monitoring system for hourly jobs, we deploy the propensity score matching method to match two types of jobs. We match two types of jobs based on various characteristics which are suggested to be correlated with the contract type by the previous literature (Banerjee and Duflo 2000; Gopal and Sivaramakrishnan 2008; Lin et al. 2016; Roels et al. 2010), such as employers' reputation, project size (the total amount of project), the complexity of job (the number of skills required), whether employers have a concrete idea of the job (the length of job title and description), and so on. As suggested by Figure 3 and Table 7, the density of the propensity score and the mean of all observable covariates are highly comparable in two groups after matching.

Table 7. Balance Check for PSM Between Fixed-Price Jobs and Hourly Jobs

Variable	Sample	Mean: Hourly	Mean: Fixed-price	%bias	% reduced |bias|	t-test: t	t-test: p>|t|
employer_developed	Unmatched	0.381	0.762	-83.300		-35.970	0.000
	Matched	0.381	0.379	0.600	99.300	0.190	0.852
title length	Unmatched	31.968	35.346	-20.400		-8.100	0.000
	Matched	31.968	32.164	-1.200	94.200	-0.420	0.674
job_desc length	Unmatched	270.970	455.200	-41.600		-15.500	0.000
	Matched	270.970	285.680	-3.300	92.000	-1.490	0.136

employer tenure month	Unmatched	25.497	32.570	-25.300	95.200	-9.630	0.000
	Matched	25.497	25.158	1.200		0.460	0.645
employer overall rating	Unmatched	4.916	4.940	-8.300	95.500	-3.340	0.001
	Matched	4.916	4.917	-0.400		-0.100	0.918
primary_language_Eng	Unmatched	0.947	0.902	17.000	85.700	6.570	0.000
	Matched	0.947	0.953	-2.400		-0.970	0.331
auction_duration	Unmatched	7.996	7.646	7.400	99.500	2.480	0.013
	Matched	7.996	7.994	0.000		0.010	0.995
total paid amount of the project (/$100)	Unmatched	1.764	2.752	-6.700	67.100	-2.410	0.016
	Matched	1.764	2.090	-2.200		-1.240	0.214
skills_count	Unmatched	3.530	3.317	15.300	79.100	6.410	0.000
	Matched	3.530	3.486	3.200		1.070	0.287
Notes: 1) Results of Nearest Neighbor (1) Matching Method without replace are presented. 2) Due to length limitation, results regarding some covariates are omitted, including the "featured_job", "urgent", "NDA", and "payment_verified" dummies. The means of all these variables are not significantly different across groups.							

Table 7. Balance Check for PSM Between Fixed-Price Jobs and Hourly Jobs

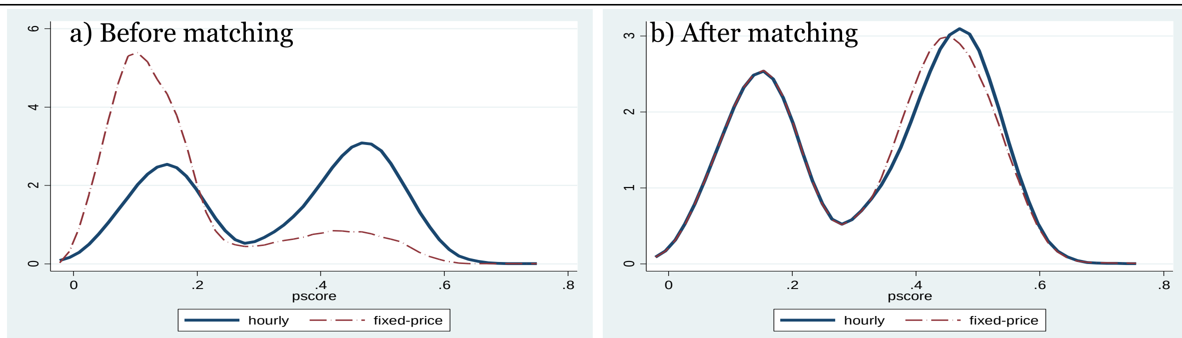


Figure 3. Density of Propensity Score of Being an Hourly Job (before and after Matching)

Results on Gender Differences in Bid Timing and Budget Preference

After matching male workers with female workers, we explore whether there exist gender differences in job application strategy and how such differences may contribute to the gender wage gap. Specifically, we are interested in whether females prefer to bid later and to bid jobs with a smaller wage budget. To answer these two research questions, we examine the heterogeneity of job preference across genders. As Table 8 shows, as the number of days between the bid decision date and the end of the auction increases (i.e. the earlier state of auction duration), male workers are more likely to bid for that job. However, the negative coefficient of the interaction term between *log(daystoend)* and the female dummy suggests that females tend to bid later than males. Based on the estimation of Column (3) of Table 8, as the number days until the end of auction increases 10% (i.e., the earlier stage of auction), the probability of bidding for this job among female workers is 8% (=10%*0.004/0.005) lower than that among male workers. Moreover, we also observe a negative coefficient of the interaction between *log(max_budget)* and the female dummy, which implies that females tend to prefer jobs with lower hourly wage budgets compared to their male counterparts.

Table 8. Gender Differences in Job Application Strategy

Dependent variable: whether the worker chose to bid for the job or not

Sample	Female & male matched sample	Female & male matched sample	Female & male matched sample	Female & male full sample
Job type	hourly	hourly	hourly	hourly
Variables	(1)	(2)	(3)	(4)
log(daystoend)	0.008*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.009*** (0.000)
log(daystoend)*female		-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)
log(max_budget)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
log(max_budget)* female	-0.001** (0.000)		-0.001** (0.000)	-0.001** (0.000)

employer_norating	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
log(employer_review)	0.001**	(0.000)	0.001**	(0.000)	0.001**	(0.000)	0.000**	(0.000)
employer_overall_ rating	0.001	(0.002)	0.001	(0.002)	0.001	(0.002)	0.001	(0.001)
log(auction_duration)	0.000	(0.005)	0.001	(0.005)	0.001	(0.005)	-0.006***	(0.003)
log(title_length)	-0.002**	(0.001)	-0.002**	(0.001)	-0.002**	(0.001)	-0.002***	(0.001)
log(desc_length)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.001**	(0.000)
log(skills_count)	0.003**	(0.001)	0.003**	(0.001)	0.003**	(0.001)	0.001	(0.001)
featured_job	-0.022***	(0.008)	-0.022***	(0.008)	-0.022***	(0.008)	-0.008**	(0.005)
consideration set FE	yes		yes		yes		yes	
employer country FE	yes		yes		yes		yes	
Observations	42,545		42,545		42,545		150,706	
R-squared	0.292		0.292		0.292		0.270	
Adjusted R-squared	0.085		0.085		0.085		0.066	
Residual Std. Error	0.062		0.062		0.062		0.064	

Notes: a) Robust standard errors clustered by the consideration set of each bid decision are reported in parentheses; b) The "NDA" dummy is omitted because of the lack of variation. Among all the hourly jobs in the matched workers' consideration set, all jobs do not require NDA. c)Because we control for the fixed effect of the consideration set of each bid, the worker's fixed effect is omitted. d) The dependent variable, chosen_bid, the dummy denoting whether the worker chose to bid for the job or not) is relatively small (its mean is 0.005). As such, even the magnitude of the coefficient is small, its marginal effect measured with percentage change can be large. e)* p<0.1, ** p<0.05, *** p<0.01.

Table 8. Gender Differences in Job Application Strategy

Based on the revealed preference indicated by workers' actual bids, we found that females tend to bid later and bid for jobs with a smaller hourly wage budget. Though females' preference for jobs with smaller budgets is intuitively found to contribute to the gender wage gap, the implication of females' late bid behavior on the gender wage gap is still unclear. To this end, we further explore the impact of late bids on the probability of being hired by employers to infer the economic value of late bids. We employed the linear probability model to estimate the effect of bid timing (i.e. late bids) and controlled for the job fixed-effects in Model 1 and controlled for the employer fixed-effects in Model 2. In Table 9, the result shows that employers are less likely to hire the worker as the bidding time becomes later. In addition, the previous model-free evidence suggests that the average bid order of females is 13.61, which is 8.27% higher than the average bid order of males. Based on the result of Model 2 of Table 9, females need to decrease their bid price by 7.58%[10] to compensate the negative effect of bid order increasing 8.27%, which could account for roughly the 40.75%[11] of out of the 18.6% gender wage gap observed by us.

Table 9. The Negative Effect of Late Bids

Dependent variable: whether the employer awarded the job to the worker or not

Job type	hourly		hourly	
Model	(1)		(2)	
log(bid_order)	-0.014***	(0.004)	-0.033***	(0.004)
log(bid_amount)	-0.047***	(0.007)	-0.036***	(0.006)
log(milestone_percentage)	-0.028***	(0.003)	-0.030***	(0.003)
log(bidder_current_reviews)	0.003	(0.002)	-0.004**	(0.002)
log(bidder_avg_rating)	0.004*	(0.002)	0.010***	(0.002)
preferred_freelancer	0.048***	(0.007)	0.046***	(0.007)
female	0.000	(0.006)	0.001	(0.006)
Constant	0.265***	(0.025)	0.293***	(0.023)
Observations	14,447		14,447	
Bidder country dummy	yes		yes	
Employer fixed effects			yes	
Job fixed effects	yes			

[10] (0.033*0.0827/0.036) * 100%=7.58%
[11] 7.58%/18.6%=40.75%

R-squared	0.033	0.039
Notes: a) All the bids submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to jobs with only one winner. b) Robust standard errors clustered by jobs are reported in parentheses; c) * p<0.1, ** p<0.05, *** p<0.01.		

Table 9. The Negative Effect of Late Bids

Results on Gender Differences in Avoidance of Monitoring

Another gender difference of our key interest is workers' avoidance of monitoring. Specifically, if females have a stronger avoidance of monitoring, they may be less willing to bid for hourly jobs or accept a lower wage job which does not require monitoring in other platforms or markets, which subsequently lowers their labor participation or average hourly wage in the gig economy. Based on the result of Model 1 and Model 2 with the DID estimation, females are significantly less willing to bid for hourly jobs after the implementation of the monitoring system, with the trend in their preference of the fixed-price jobs as the counterfactual. Moreover, we further explore gender differences in avoidance of monitoring with the DDD estimation by taking the difference between the differences-in-differences (DD) observed in the female sample and the DD observed male sample. As the result of Model 3 shows, females are less willing to bid for hourly jobs after the implementation of monitoring systems. Given that monitoring systems are mandatory for all hourly jobs on Freelancer.com after the implementation and it is difficult to observe the outside option for most female workers, we turn to a field experiment to observe gender differences in WTP for avoidance of monitoring and infer its impact on the gender wage gap accordingly.

Table 10. Gender Differences in Avoidance of Monitoring

Dependent variable: whether the worker chose to bid for the job or not						
Sample	Female full sample		Female matched sample		Female & male matched sample	
Job type	All hourly& fixed-price jobs		Matched hourly& fixed-price jobs		Matched hourly& fixed-price jobs	
Model	(1)		(2)		(3)	
hourly	0.003**	(0.002)	0.004**	(0.002)	-0.003	(0.002)
after*hourly	-0.003**	(0.002)	-0.004**	(0.002)	0.002	(0.002)
hourly*female					0.007***	(0.003)
after*hourly*female					-0.006**	(0.003)
employer_norating	0.001	(0.001)	0.001	(0.001)	-0.000	(0.001)
log(employer_review)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)
employer_overall_ rating	0.001**	(0.000)	0.001	(0.000)	0.001*	(0.000)
log(max_budget)	0.000***	(0.000)	0.000	(0.000)	0.000***	(0.000)
log(title_length)	-0.000	(0.001)	-0.001	(0.001)	-0.001*	(0.001)
log(desc_length)	0.000	(0.000)	0.000	(0.000)	0.001*	(0.000)
log(skills_count)	-0.001	(0.001)	-0.001	(0.001)	0.000	(0.001)
featured_job	-0.011***	(0.004)	-0.01*	(0.004)	-0.014***	(0.004)
NDA	-0.02***	(0.009)	omitted		omitted	
log(daystoend)	0.008***	(0.000)	0.007***	(0.001)	0.009***	(0.000)
log(auction_duration)	-0.009***	(0.001)	-0.005***	(0.002)	-0.009***	(0.001)
consideration set FE	yes		yes		yes	
employer country FE	yes		yes		yes	
Observations	105,479		52,221		101,420	
R-squared	0.089		0.188		0.159	
Adjusted R-squared	0.035		0.092		0.062	
Residual Std. Error	0.064		0.057		0.065	
Notes: a) Robust standard errors clustered by the consideration set of each bid decision are reported in parentheses; b) * p<0.1, ** p<0.05, *** p<0.01.						

Table 10. Gender Differences in Avoidance of Monitoring

Results on Gender Differences in WTP for Avoidance of Monitoring

To further show that there exist gender differences in avoidance of monitoring, we conducted a field experiment by providing all participants two hourly job options and asking them to choose the one they preferred. Following the previous literature, we took the potential inattentive participants in our experiment into consideration (Mas and Pallais 2017) and estimated the mean WTP of males and females with a mixture model. Specifically, we assumed that a small proportion of inattentive participants randomly chose one from the two given job options and estimated the inattentive rate and the distribution of WTP among those attentive participants. In particular, based on the difference in the probability of choosing a job with monitoring as the wage premium of the job with monitoring changes, we estimate the mean and standard deviation of female and male participants' willingness to pay for the avoidance of monitoring. As the result of maximum likelihood logit model shows, an average female is willing to pay $1.779 for the avoidance of monitoring while an average male is only willing to pay $1.276. The gender difference in WTP for the avoidance of monitoring is around $0.503, which is significant at the 0.05 significance level based on 1,000 bootstrap samples. In particular, according to the prior study on AMT, the mean hourly wage is $6.19 for all those paid work (Hara et al. 2018). Therefore, the gender difference in WTP for the avoidance of monitoring is equivalent to 8.13% of the average hourly wage on AMT. In other words, females are willing to accept an hourly job without monitoring by offering 8.13% discount in their hourly wage.

Table 11. Gender Differences in WTP for Avoidance of Monitoring

Dependent variable: Willingness to pay for the avoidance of monitoring			
Variables	female	male	Difference
Mean (μ)	$ 1.779 (0.138)	$ 1.276 (0.188)	$0.503 (0.227)
SD (σ)	$ 1.223 (0.135)	$ 0.891 (0.169)	
Note: Standard errors are calculated based on 1000 bootstrap samples.			

Table 11. Gender Differences in WTP for Avoidance of Monitoring

Robustness Checks

We conduct several robustness checks to further support our finding. Due to the space limitation, we only summarize the estimation strategies and results.

First, we use an alternative measure to show females' preference to bid later than males. Specifically, we construct another measure, *log(daysfromstart)*, which represents the number of days between the start date of the auction and the bid decision date. We again find a negative coefficient for the main effect of *log(daysfromstart)* and a positive coefficient for the interaction term between *log(daysfromstart)* and the gender dummy, which suggests that females tend to bid later than males.

Second, instead of merely inferring the workers' genders based on their profile images, we predict each worker's gender based on his/her first names by taking advantage of the Facebook profile name database (Tang et al. 2013; Chan and Wang 2017). Following the previous literature (Chan and Wang 2017), we limit to those first names with a gender probability higher or equal to 95%, based on which we can reliably infer the worker's gender. Further, we rerun all the models with the sample of those workers whose genders can be consistently predicted with both profile images and first names. All the results are highly consistent with our main finding.

Third, we also try to rerun the model with alternative models. For one thing, we explore gender differences in job application strategy by controlling the bidder-day two-way fixed effects instead of the consideration set fixed effects. We still find highly consistent results. For another, we use *log(bid_order)* as the dependent variable and control for job fixed-effect, worker country fixed-effect and all other related bid characteristics. We find that the coefficient of the "female" dummy is significantly positive, which suggests that females tend to bid later than males.

Fourth, we test the parallel trend assumption using the approach proposed by Autor (2003) and find that all the relative time coefficients are not significant prior to the implementation of the monitoring system and most relative time coefficients are significantly negative after the implementation. This implies that the pre-existing treatment trend is not an issue in our study.

Finally, we employ alternative matching methods, including Coarsened Exact Matching (CEM) and the propensity score matching with five nearest neighbors, to match males with females, and fixed-price jobs with hourly jobs. The result is highly consistent.

Overall, all the robustness checks lend support to our finding that females tend to bid later, prefer jobs with lower wage budget, and have a higher WTP for the avoidance of monitoring than males.

Discussion

In this paper, we explore whether there is a gender wage gap in the gig economy and examine whether there are gender differences in job application strategy which could account for the persistent gender wage gap. First, we show that females can only earn around 81.4% of the hourly wage of their male counterparts. Second, we find that females tend to bid later and prefer jobs with a smaller hourly wage budget based on both the model-free evidence and the empirical results of the linear probability model with the consideration set fixed-effect. We further find that the observed gender difference in bid timing can lead to a decrease of 7.58% in hourly wage, which could roughly account for 40.75% of the gender wage gap (i.e. 18.6%) observed by us. Third, we examine the gender difference in avoidance of monitoring with a quasi-natural experiment and a field experiment. We find that females are less willing to bid for hourly jobs than males and tend to have a higher willingness to pay for the avoidance of monitoring. The gender difference in WTP for the avoidance of monitoring can explain roughly 8.13% of the hourly wage, which is equivalent to 43.71% of the observed gender wage gap. On the whole, our study underscores the important impact of gender differences in job application strategy on the gender wage gap.

Our paper contributes to several streams of literature. First, our paper contributes to several streams of literature. First, our study adds to the literature on gender wage gap and highlights new explanatory factors for the gender wage gap other than gender discrimination, i.e. gender differences in bid timing, job selection, and avoidance of monitoring. The existing literature mainly focusing on the traditional employment relationship suggests that discrimination, WTP for flexibility (Mas and Pallais 2017), motherhood penalty and career choices (Blau and Kahn 2017) could help to explain the gender wage gap. On top of that, some scholars predict that the gig economy is an emerging labor market design which helps to narrow the gender wage gap owing to the flexibility and remoteness of its on-demand employment relationship (Goldin and Rouse 2000; Goldin 2014). In contrast, a recent study on the gig economy suggests that the gender wage gap still exists. Using a large-scale dataset from a gig economy platform which provides offline car-hailing service (i.e. Uber), Cook et al. (2018) find that, gender differences in experience and willingness to work extra hours when the hourly wage is high, mainly explain the gender wage gap. However, given that workers tend to have limited freedom to choose jobs in the car-hailing platform, the existence and potential impact of gender differences in job application strategy is hitherto little explored in their study. Given that the freedom of choosing jobs based on preference is such a common primary feature shared by most gig economy platforms, our study focuses on potential gender differences in job application strategy and points out that gender differences in bid timing, job selection, and WTP for the avoidance of monitoring help to explain the gender wage gap in gig-economy.

Second, this paper contributes to the literature on the online labor market by providing a framework to recover workers' consideration sets and underscores the importance of workers' job preference. Though employers' preference of workers has been recently explored (Chan and Wang 2017; Hong and Pavlou 2017), there is little research exploring the preference from the supply side (i.e. workers' preference for jobs). We extend this prior work by taking advantage of a comprehensive dataset and the platform policy to recover workers' consideration sets. We further demonstrate gender differences in job application strategy from three aspects, including bid timing, job budget preference and avoidance of monitoring. Our study advances the previous literature on online labor markets by documenting gender differences in job application strategy, which has strong academic and managerial implications for the online labor market.

Lastly, our study also expands the literature on compensation differential. Prior studies have found compensation differential in several non-wage job amenities in traditional employment relationship (Bonhomme and Jolivet 2009), such as flexibility (Mas and Pallais 2017), unemployment benefits (Hall and Mueller 2015), and non-wage job value (Sorkin 2017). Given that online monitoring is prevalent in most online labor markets, we focus on potential compensation differential in avoidance of monitoring, a non-wage aspect which has hardly been explored in the previous compensation differential literature. Taking the implementation of the monitoring system as an exogenous shock, we find that females are less willing to bid for jobs with monitoring, compared to males. We further conduct a field experiment on AMT to explicitly estimate gender differences in WTP for the avoidance of monitoring. Our finding suggests that gender differences in WTP for the avoidance of monitoring is likely to persistently contribute to the gender wage gap.

Meanwhile, we acknowledge several limitations of this study. For instance, we note that our results are limited by the IT job sample and it should be cautious to generalize the results to other job categories, especially those feminine-typed jobs. Further, it might not be appropriate to generalize the results to other offline labor markets until sufficient evidence is available. Last but not least, although our analysis points to a strong relationship between these gender difference in job preference and the gender wage gap, we admit that we cannot rule out all the possible unobserved factor influencing both the gender difference in job application strategy and the gender wage gap. We believe our study helps to suggest the potential ways to reduce the wage gap instead of concluding the drivers of the gender wage gap.

References

~~Arnould, R.J. and Nichols, L.M., 1983. "Wage-risk premiums and workers' compensation: A refinement of estimates of compensating wage differential". *Journal of Political Economy*, (91:2), pp.332-340.~~

~~Autor D.H. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, (21:1), pp.1-42.~~

~~Azmat, G. and Petrongolo, B., 2014. "Gender and the labor market: What have we learned from field and lab experiments?". *Labour Economics*, 30, pp.32-40.~~

~~Banerjee, A. V., and Duflo, E. 2000. "Reputation Effects and the Limits of Contracting: A Study of the Indian Software Industry". *The Quarterly Journal of Economics*, (115:3) 989-1017.~~

~~Blau, F.D. and Kahn, L.M., 2017. "The gender wage gap: Extent, trends, and explanations". *Journal of Economic Literature*, (55:3), pp.789-865.~~

~~Bonhomme, S. and Jolivet, G., 2009. "The pervasive absence of compensating differentials". *Journal of Applied Econometrics*, (24:5), pp.763-795.~~

~~Chan, J. and Wang, J., 2017. "Hiring preferences in online labor markets: Evidence of a female hiring bias". *Management Science*. Articles in Advance, pp. 1–22.~~

~~Castillo, M., Petrie, R., Torero, M. and Vesterlund, L., 2013. "Gender differences in bargaining outcomes: A field experiment on discrimination". *Journal of Public Economics*, (99), pp.35-48.~~

~~Cook, C., Diamond, R., Hall, J., List, J.A. and Oyer, P., 2018. "*The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers*" (No. repec: eel: stabus: 3637).~~

~~Flory, J. A., Leibbrandt, A., & List, J. A. 2014. "Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions," The Review of Economic Studies, (82:1), pp.122-155.~~

~~Goldin, C. and Rouse, C., 2000. "Orchestrating impartiality: The impact of 'blind' auditions on female musicians," American Economic Review, (90:4), pp.715-741.~~

~~Goldin, C., 2014. "A grand gender convergence: Its last chapter". *American Economic Review*, (104:4), pp.1091-1119.~~

Gopal2008 Gopal, A., and Sivaramakrishnan, K. 2008. "Research Note-On Vendor Preferences for Contract Types in Offshore Software Projects: The Case of Fixed Price vs. Time and Materials Contracts". *Information Systems Research,* (19:2), pp.202-220.

~~Gupta, N.D. and Smith, N., 2002. "Children and career interruptions: The family gap in Denmark". *Economica*, (69:276), pp.609-629.~~

~~Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C. and Bigham, J.P., 2018. A Data-Driven Analysis of Workers' Earnings on Amazon Mechanical Turk. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, ACM*, pp.449-463.~~

~~Hall, R. and Mueller, A.I., 2015. "Wage Dispersion and Search Behavior (No. 9527)". IZA Discussion Papers.~~

Hong2015 Hong, Y., Wang, C. and Pavlou, P.A., 2015. "Comparing open and sealed bid auctions: Evidence from online labor markets," Information Systems Research, (27:1), pp.49-69.

Hong2017a Hong, Y. and Pavlou, P.A., 2017. "On Buyer Selection of Service Providers in Online Outsourcing Platforms for IT Services," Information Systems Research, (28:3), pp.547-562.

Heinz, M., Normann, H.T. and Rau, H.A., 2016. "How competitiveness may cause a gender wage gap: Experimental evidence". *European Economic Review*, (90), pp.336-349.

Kuhn, P. and Shen, K., 2012. "Gender discrimination in job ads: Evidence from china," The Quarterly Journal of Economics, (128:1), pp.287-336.

Lin, M., Liu, Y., and Viswanathan, S. 2016. "Effectiveness of Reputation in Contracting for Customized Production: Evidence from Online Labor Markets. *Management Science*, (64:1), pp. 345-359.

Marini, M.M. and Fan, P.L., 1997. "The gender gap in earnings at career entry". *American Sociological Review*, pp.588-604.

Marom, D., Robb, A. and Sade, O., 2016. "Gender dynamics in crowdfunding (Kickstarter): Evidence on entrepreneurs, investors, deals and taste-based discrimination". Working Paper.

Mas, A. and Pallais, A., 2017. "Valuing alternative work arrangements," American Economic Review, (107:12), pp.3722-59.

Niederle, M. and Vesterlund, L., 2007. "Do women shy away from competition? Do men compete too much?". *The Quarterly Journal of Economics*, (122:3), pp.1067-1101.

Niederle, Muriel, and Lise Vesterlund, 2011. "Gender and competition." *Annual Review of Economics* (3:1), pp. 601-630.

Wiswall, M. and Zafar, B., 2014. "Determinants of college major choice: Identification using an information experiment", *The Review of Economic Studies*, (82:2), pp.791-824.

Wiswall, M. and Zafar, B., 2015. "How do college students respond to public information about earnings?". *Journal of Human Capital*, (9:2), pp.117-169.

Wiswall, M. and Zafar, B., 2017. "Preference for the workplace, investment in human capital, and gender," The *Quarterly Journal of Economics*, (133:1), pp.457-507.

Roels, G., Karmarkar, U.S. and Carr, S., 2010. "Contracting for collaborative services". *Management Science*, (56:5), pp.849-863.

Sorkin, I., 2017. "Ranking firms using revealed preference". *The Quarterly Journal of Economics*. (132:1), pp:1-63.

Tang J, Gao H, Hu X, Liu H (2013). "Exploiting homophily effect for trust prediction", *Proc. 6th ACM Internat. Conf. Web Search Data Mining* (ACM, New York), pp.53 -62.

Zafar, B., 2011. "How do college students form expectations?". *Journal of Labor Economics*, (29:2), pp.301-348.