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DISCUSSION PAPER SERIES

IZA DP No. 17434

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ABSTRACT

Gender Differences in Preferences for Flexible Work Hours: Experimental Evidence from an Online Freelancing Platform*

We conduct an experiment on a major international online freelancing labor market platform to study the impact of greater flexibility in choosing work hours within a day on female participation. We post identical job advertisements (for 320 jobs) covering a wide range of tasks (80 distinct tasks) that differ only in flexibility and the wage offered. Comparing the numbers of applicants for these jobs, we find that while both men and women prefer flexibility, the elasticity of response for women is twice that for the men. Flexible jobs receive 24 percent more female applications and 12 percent more male applications compared to inflexible jobs. Critically, these changes come at no cost to the quality of applications. In fact, we find suggestive evidence that flexible jobs attract higher quality female candidates. Our findings have important implications for explaining gender differences in labor market outcomes and for equity initiatives in firms.

JEL Classification: J22, O14, J16, L86

Keywords: workplace flexibility, online freelancing jobs, female labor force participation

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1 Introduction

Women are more likely to be employed in jobs that offer flexibility in choosing work hours, are part-time, or require lower commute times (Booth and Van Ours 2013; Le Barbanchon et al. 2021; Meekes and Hassink 2022). In Figure A1, we illustrate this using data from the American Working Conditions Survey (AWCS). AWCS respondents were asked if they had any choice in deciding their work hours. As Figure A1 shows, women are 15 percent less likely to be in jobs that provide no flexibility in choosing work hours. Does this sorting and employment pattern reflect a stronger preference among women for jobs that provide work-time flexibility and does the labor supply of women respond more to these non-pecuniary benefits than men?

The answer to this question has important implications. First, gender differences in response to various non-pecuniary benefits could explain part of the wage gap (Petrongolo 2019; Humphries et al. 2024). Women may have higher valuations for non-pecuniary benefits like worker-determined schedule flexibility, perhaps because of the social norms around household chores allocation. Schedule flexibility might allow women to better balance household responsibilities with work for pay (Sullivan 2019).[1] Men and women may sort into different jobs in response to such non-pecuniary benefits, and firms may make lower wage offers to employees to compensate for the provision of expensive non-pecuniary benefits (Penner et al. 2022). Second, the limited provision of such non-pecuniary benefits may prevent women from joining the formal labor force, generating a gender gap in employment. Female labor force participation in many developing countries, particularly in Asia, remains low even after accounting for the level of economic development and educational attainment. Multiple studies document that frictions in the labor market that often lead to the limited provision of non-pecuniary benefits that women prefer explain part of the gender education and employment gap (Gupta 1993; Macpherson and Hirsch 1995; DeLeire and Levy 2004; Grazier and Sloane 2008; Kleinjans 2009; Borker 2018). Third, the last decade has seen an increase in the provision of flexible working arrange-

[1] Gender differences in attributes such as competitiveness, risk preference, and willingness to negotiate, which are relevant to wage determination, could also play a role (Croson and Gneezy 2009; Azmat and Petrongolo 2014; Exley and Kessler 2019). However, the exact sources of these attribute differences are often unknown. They could be driven by personality traits shaped by social institutions, like difference in degrees of competitiveness in matrilineal and patrilineal societies, or have evolutionary roots. Gender differences in preference for schedule flexibility could also be a product of social norms or have other drivers. In this study, we remain agnostic about the sources of these differences.

ments. Several factors, like technological change, labour laws, and COVID-19 induced experimentation have contributed to this change. Gender difference in the elasticity of labor supply in response to flexible working arrangements has implications for the composition and the diversity of the workforce. Firms and policy-makers interested in responding optimally to these changes must therefore understand gender differences in response to these work arrangements (Cook et al. 2021; Gottlieb et al. 2021).[2]

Despite the far-reaching implications, answering this question is empirically challenging. We only observe the *equilibirum* gender distribution of employees and the final package of pecuniary and non-pecuniary benefits that workers receive. Several observed and unobserved demand- and supply-side factors play a role in determining the equilibrium. For example, we may observe an equilibrium with a higher proportion of women in flexible, low-paying desk jobs as opposed to in less flexible, high-paying construction jobs. However, this sorting could also result from a higher productivity of men in brawn-intensive jobs. Therefore, an association between certain non-pecuniary benefits and shares of female employees across firms, industries, or sectors of the economy does not necessarily imply that women respond more to these benefits than men. Another complication in identifying the labor supply response to a *specific* non-pecuniary benefit, like schedule flexibility, using observed real-world job choices is that jobs typically vary along several dimensions of non-pecuniary benefits. Jobs that offer schedule flexibility may also have lower travel requirements or could have offices located in safer neighborhoods. As a result, it is even more difficulty to infer gender difference in preference for a *specific* non-pecuniary benefit from observed choices (Mas and Pallais 2017; Wiswall and Zafar 2018; Wasserman 2019; Adams-Prassl 2020; He et al. 2021).

In this study, we address these empirical challenges using a natural field experiment that focuses on a specific non-pecuniary benefit - the flexibility in choosing work hours during the day.[3] We conducted our experiment on a major online freelance labor market platform. The experiment involved posting four otherwise identical job advertisements for each of 80 distinct tasks (resembling typical tasks on the platform) that vary only in

[2]Some studies argue that increased flexibility in working arrangements may increase gender disparities by reinforcing existing gender norms (Lott and Chung 2016; Chung 2019). Men might use it to work and earn more while women might be expected to contribute more to household work now that their work arrangements are flexible.

[3]For a description of natural field experiments, see List (2007), Al-Ubaydli and List (2012), and Al-Ubaydli and List (2015).

their flexibility and the wage offered.[4] Flexible jobs ("high-flexibility") allowed the freelancer applicants to choose any two-hour window during the day on a pre-specified date to complete the task. Inflexible jobs ("low-flexibility") required the work to be completed during a pre-specified two-hour period of our choosing on a pre-specified date. The jobs also differed in the wage offered. A "high-wage" job posting offered a lump-sum one-time payment of USD 40 and a "low-wage" job posting offered a lump-sum one-time fee of USD 30. In total, we made 320 job postings for 80 distinct tasks.[5] We collected information about the number of male and female applicants for each of the job postings as well as several applicant-level characteristics. Since the different job postings for each task varied only along the dimension of flexibility or the wage offered, we can attribute any difference between male and female application numbers (and composition) to these dimensions of pecuniary and non-pecuniary benefits.

We find that flexible jobs attract a higher number of applications from both men and women, implying that flexibility matters for both genders. However, there was a gender difference in the elasticity of the response to flexibility. Compared to inflexible jobs, flexible jobs see a 24% rise in the number of female applicants as opposed to a 12% rise in the number of male applicants. Thus, compared to men, a larger proportion of women (of the workers in the platform) find flexibility a binding constraint. Flexibility also makes the applicant pool more gender diverse, leading to a 1.5 percent rise in the proportion of female applicants. We find that women with a self-reported hourly wage rate on the platform that is higher than what we offer are more likely to apply for flexible jobs. There is suggestive evidence that higher self-reported hourly wage is a proxy for the quality of the worker, indicating that flexible jobs attract higher quality women applicants. The quality of male applicants was no worse in flexible jobs. Women are also more likely to put more effort into applications for a flexible job. Compared to inflexible jobs, women are more likely to make an application before men and to include their previous work samples in the application for a flexible job.

Our findings extend the literature on gender differences in preference for non-pecuniary

[4]These tasks covered a wide range of activities, such as proofreading, writing, and coding.

[5]The four jobs corresponding to each task were posted at the same time and on the same day of the week, but in different weeks, using the same user account. We randomized the 80 tasks across days of the week and across client user accounts. The order of posting the four jobs for a specific task was also random. Each job posting was open for one day, after which we hired one applicant at random to complete the job and paid the promised wage.

benefits in the labour market. Multiple studies highlighted the importance of non-pecuniary benefits for women using non-experimental methods (Goldin and Katz 2011; Flabbi and Moro 2012; Bronson 2014; Goldin 2014; Sullivan and To 2014; Lavetti and Schmutte 2016; Sorkin 2018). But as mentioned above, they fail to empirically disentangle the response to flexibility from other unobserved characteristics of the worker, firm and jobs.[6] These studies are also unable to identify the role of a *specific* non-pecuniary benefit. Our experiment allows us to overcome these challenges.[7] Recent studies have used experiments to elicit stated preferences (and willingness to pay) for various job characteristics reach broadly similar finding - women have a higher willingness to pay for non-pecuniary job benefits like flexibility (Mas and Pallais 2017; Maestas et al. 2018; Wiswall and Zafar 2018). Wiswall and Zafar (2018) use a sample of students from a top US university and find that women are willing to give up a higher salary for better job stability and flexibility. Maestas et al. (2018) use the American Working Conditions Survey and find that women have a stronger preference for jobs that are physically less demanding and have more paid leave. These studies validate that the stated preferences reflect true underlying preferences by looking at the match between stated preferences and real job attributes. But even when stated preferences match real job attributes, we do not observe the choice set of jobs respondents in these surveys choose from in the real world. The choice set may be impacted by other supply side factors. The concern that stated preferences are not incentive-compatible is not completely alleviated.

We add to this literature by focusing on workers' revealed preferences for flexibility. In this, our study complements He et al. (2021), who conducted a similar field experiment by posting job advertisements for a regular full-time job in the IT sector on a Chinese job board. They find that married females have a stronger preference for flexible jobs than married males. But our study also differs from He et al. (2021) in important ways. First, flexible work hours in a full-time job can impact promotions and career progression, especially for women (Goldin 2014). Such costs of choosing flexible work hours may deter applicants, especially women from responding to a job advertisement that provides flexibility in a regular full-time job. In our setting of a gig economy, there are no such costs for choosing flexible work hours. Second, the preference for flexible work hours in a regular

[6]For a interdisciplinary literature review of the topic, see Chung and Van der Lippe (2020).

[7]More broadly, our findings are also related to the large literature that investigates gender differences in attributes like risk preferences and competitiveness that have implications for labour market outcomes (Croson and Gneezy 2009; Azmat and Petrongolo 2014; Exley and Kessler 2019).

office job could merely reflect other preferences, like a distaste for commute at specific hours. The costs of commuting could also vary across genders and locations. In our setting where the freelancers work online, a preference for flexibility is not confounded by the potential differential distaste for commuting at specific hours. Finally, He et al. (2021) focus on a specific job in a specific sector. Different preferences around flexibility may drive people sorting into different sectors. Therefore, the extent to which experimental-introduced flexibility would generate an effect depends on the sector. Our experiments involves a range of job types, thus making our findings more generalizable.

Our study is closely related to a recent literature that attempts to understand the demand for flexibility in the gig economy. Chen et al. (2020) use random experimental variation in surge pricing for Uber rides to estimate the variation in labour supply elasticity of Uber drivers at different times of day. Using a combination of a natural field experiment and structural estimation to recover preference parameters, they find that female Uber drivers have a higher valuation of the flexibility to change their work schedule in response to unexpected shocks. Angrist et al. (2021) use a natural field experiment that allows a randomly selected set of Uber drivers the option of fixed-rent Uber lease instead of sharing a percentage of their earned ride fares. The authors find that Uber drivers prefer to share a percentage of the ride fares to avoid having to drive at specific times or for specific duration to recover the fixed rent. Chen et al. (2019) and Chen et al. (2021) use the variation in the elasticity of labour supply decisions at different times of the day, conditional on the expected wage, to infer that the reservation wage varies across different times of the day, indicating a valuation for flexibility. Female drivers, they find, have a higher valuation for flexibility. Our findings complement these studies. However, apart from the differences in the setting (US Uber drivers as opposed to online freelancers all over the world), the aversion to drive at certain hours of the day in their setting could be related to the varying nature of the job, like contact with drunk passengers, across hours of the day. In our experiment, since the jobs are all online, the characteristics (and thus the cost) of the job remains the same across both flexible and non-flexible postings.

Lastly, our study also adds to a recent and growing multidisciplinary literature that focuses on various aspects of the gig economy and specifically the online freelance labor market (Stanton and Thomas 2016, 2020; Cook et al. 2021; Stanton and Thomas 2021). In general, this literature notes that there is only limited data about online freelance workers. We add to this literature by collecting a rich set of data about applicants and their applications. In addition, we also focus on the role that flexibility may play in limiting the participation of women in online labor markets.[8]

2 Conceptual Framework

We begin with a simple conceptual framework to help set priors. Assume that there are n two-hour time slots during the day during which a freelancer can complete the task we advertise. In our inflexible job ads, we specify the two-hour slot in which the hired freelancer must work. In the flexible jobs, the applicants can choose to work during any two-hour window during the day. Let us denote the set of possible time slots by $S = (1, 2, 3, ..., n)$.

Workers have an opportunity cost of working during these time slots. Such an opportunity cost captures the pecuniary costs of working, such as forgone wages from alternative occupations, and non-pecuniary costs, such as delays in childcare or other family obligations. There is no uncertainty about the potential realization of these opportunity costs. Workers can fully and correctly predict these opportunity costs. We index workers by $i \in I$, where I is the universe of freelancers on the platform who see our advertisement. Let us denote the opportunity cost of working during time slot $s \in S$ for worker i by c_{is}.

For simplicity, we assume that the application costs are zero (or minimal) and workers apply to all jobs that they will take up if offered. This is not an unrealistic assumption in our context. The workers usually add minor details (like a short cover letter) to their existing profile on the platform to make an application. There are also no interviews for these jobs.[9] Worker i will apply for an inflexible job offering a wage w to be done during

[8] A crucial aspect of the online freelance labor market is that it allows workers to choose jobs that best match their constraints and requirements. This affords workers greater flexibility in choosing their work schedule. However, a significant number of online jobs come with strict deadlines (see Table A4). While workers have the option to choose between jobs, these strict deadlines limit the ability of workers to allocate their work flexibly between different times on the same day. This lack of flexibility can be one factor that limits female labor force participation in the online labor market, both at the intensive and the extensive margins. Moreover, if women value flexibility in online jobs, they may be willing to accept lower wages for greater flexibility. However, women's preference for job flexibility in the online labor market has, largely, remained empirically unverified, a gap that this study seeks to address.

[9] However, there are some limits to the monthly number of unsuccessful applications a worker can make on the platform for free.

time slot $\bar{s}$ if

$$w - c_{i\bar{s}} > 0.$$

However, if the same job with a wage w allows the worker to choose their work hours $\tilde{s} \in S$, then a worker i will apply if

$$w - c_{i\tilde{s}} > 0,$$

where $c_{i\tilde{s}} = min(c_{i1}, c_{i2}, c_{i3}, ..., c_{in})$.

Now, let us assume that the distribution of $c_{i\tilde{s}}$ across individuals has a probability density function $f(c_{i\tilde{s}})$ and a cumulative distribution function $F(c_{i\tilde{s}})$. Next, assume the distribution of $c_{i\bar{s}}$ is given by the probability density function $g(c_{i\bar{s}})$ and a cumulative distribution function $G(c_{i\bar{s}})$. For a job that offers a wage w but no flexibility in choosing work hours, the share of all applicants applying for the job will be given by:

$$G(w) = \int_0^w g(c_{i\bar{\bar{s}}}) dc_{i\bar{\bar{s}}}$$

Similarly, for flexible jobs with a wage w, the share of all applicants who will apply for the job will be given by:

$$F(w) = \int_0^w f(c_{i\tilde{\tilde{s}}}) dc_{i\tilde{\tilde{s}}}.$$

Based on our findings from Tables 2 and 3, we have

$$F(w) < G(w), \;\; \forall\, w \in \{w_L, w_H\},$$

where $w_L = 30$ and $w_H = 40$ in our experiment. This implies that there must be at least one individual i such that

$$c_{i\tilde{s}} < c_{i\bar{s}} \leq w.$$

Or, $F(.)$ first-order stochastically dominates $G(.)$. The estimated effect of flexibility in Table 2 is proportional to $G(w) - F(w)$. In other words, the coefficient of 5.98 is proportional to the share of all applicants for whom $c_{i\tilde{s}} < c_{i\bar{s}}$. The higher (lower) the number of applicants with $c_{i\tilde{s}} < c_{i\bar{s}}$, the higher (lower) will be the estimated effect of flexibility.

Next, let us differentiate the distribution of $c_{i\tilde{s}}$ and $c_{i\bar{s}}$ for males and females. For males, let us denote the cumulative distribution functions by $F^M(c_{i\tilde{s}})$ and $G^M(c_{i\bar{s}})$. For females, we denote them by $F^F(c_{i\tilde{s}})$ and $G^F(c_{i\bar{s}})$. To construct a mapping that will help us compare the effects of flexibility across the two genders, let us assume $F^M(c_{i\tilde{s}}) = F^F(c_{i\tilde{s}})$. That is, the distribution of minimum opportunity cost for the two genders is the same.[10] A larger effect of flexibility (in percentage terms) on women, as we observe in Tables 2 and 3, implies:

$$G^F(w) < G^M(w) < F^M(w) = F^F(w), \ \ \forall w \in \{w_L, w_H\}.$$

In other words, our findings of a higher percentage effect of flexibility on females than males imply

$$c_{i\tilde{s}} < c_{i\bar{s}} \leq w$$

is true for a larger share of female applicants than male applicants. This means that the opportunity cost of working during the 8 to 10 am slot is, on average, higher for females than for males.

3 Experimental Design and Data Collection

We conducted our experiment on one of the largest online freelance labor market platforms that attracts clients and freelancers from around the world. Typically, a client posts a description of their job requirements and a fee that they are offering for the job. The client may invite specific freelancers to apply for the job or post the job publicly for any freelancer who may be interested. Interested freelancers apply for the job. Usually, an application includes a cover letter, their proposed wage (a counteroffer), and other details, such as past experience that may indicate their competence and interest in the job. The client can then chooses one or more freelancers to perform the job. This involves the client sending the selected freelancer a contract specifying the agreed number of hours, a fixed or an hourly fee, and a deadline for the work to be completed by. At this stage, the chosen freelancer can accept the contract, renegotiate, or reject the offer.

Our experiment entails posting several jobs on this platform as clients and studying the

[10]This simplifying assumption is not entirely implausible. Consider a scenario where all females and males have at least one two-hour window in the entire day when their opportunity cost of working on the platform is counting stars during the daytime, which they all value equally and, unfortunately, minimally.

responses we receive from the freelancers. Specifically, we post four variations ('jobs') of 80 distinct ***tasks*** (see Table A1) that cover a wide range of typical jobs on this platform. Our job advertisements resemble the job advertisements posted on the platform. Since there are four variations for each of the 80 tasks, the experiment consists of 320 ***job postings***. The jobs vary in terms of the fee offered and the flexibility that they provide in choosing work hours during the day. The "high-wage" jobs offered USD 40 for the two hours of work (USD 20 per hour) while the "low-wage" jobs offered USD 30 for the two hours. We choose these wage points keeping in mind the distribution of wage offering on the platform. Figure A2 plots the cumulative distribution function of hourly wage offers (from clients) from over 60000 jobs in the same job categories that we have posted. The "low-wage" jobs (15 USD per hour) corresponds to around 25^{th} percentile of the wage offer distribution and the "high-wage" jobs (20 USD per hour) corresponds to the median wage.

A "high-flexibility" (or just "flexible") job in this experiment allowed the applicant to choose any two-hour window during the day on a pre-specified date to complete the task. In choosing the fixed work hour requirement of the "low-flexibility" jobs, we wanted to mimic the real-world job requirements. Using the American Community Survey, we found that around 60% of the workers arrive at work between 6AM and 10AM, with the largest fraction of workers arriving between 7AM and 8AM (See Figure A3).[11]. This suggests that most workplaces have work hours that start between 6AM and 10AM. Thus, the policy relevant question is to study elasticity of labor supply to jobs that allow flexibility of schedule (start time) that is different from the typical start time in workplaces. Based on this observation, the "low-flexibility" (or just "inflexible") job in our experiment required the applicant to start the job at 8 AM in their local time on a pre-specified date and finish it within two hours. Thus, the four types of jobs were 1) **Low**-wage, **low**-flexibility, 2) **High**-wage, **low**-flexibility 3) **Low**-wage, **high**-flexibility 4) **High**-wage, **high**-flexibility.

It was important to ensure the freelancers understood that they could not work outside the specified (low-flex) or chosen (high-flex) two-hour work window. We took several steps to make sure that applicants understood these requirements before applying. First, the job postings contained information about expectations, such as the skill requirements and the time it would take to complete the job, but did not reveal any details that would have allowed the applicants to work on the job in advance. The job postings specified that

[11] Women arrive marginally later than men. See Figure A4

the details required to finish the job would be shared at the start of the specified or chosen two-hour window. Second, for each job posting, we added a mandatory screening question. As a response to this question, each applicant was required to enter the pre-specified two-hour (in the case of a low flexible job) or their chosen two-hour (in the case of a high flexible job) work window before they could start the application. This ensured that the work hour requirements were salient. Finally, the text of the job advertisement clearly specified the work hour requirements (see example in Table A2).[12] It is important to note that both the flexible and the inflexible job postings required the task to be completed within two hours. Thus, all four job variants for a task required the same skill set and the same amount of time commitment. The only differences were the flexibility in choosing work hours or the fee.

We used five different client accounts for posting the adverstisements and hiring freelancers for the 320 jobs. We randomly allocated each of the 80 tasks to one of the five accounts and to one of the days of the week. All four jobs for a task were posted from the same account on the same day of the week and, to the extent possible, at the same time of the day, but in different weeks. This was to ensure that the four job postings for a task appeared the same across all other observed and unobserved dimensions. We closed the job ads 24 hours after the job posting, at which point we hired a random applicant from with the pool of applicants to complete the job. The chosen applicant was paid the promised wage. The order of posting of the four jobs for a task was random for each task. The title, the skills required, and other attributes were the same across the four job postings for a task. Table A2 provides an example. All jobs were to be performed two days after the posting. For example, a high-flexibility job posted on a Monday required the applicant to complete the job on a Wednesday at their chosen time. The also holds for the low flexible job except it required that the job to be completed at the pre-specified time on a Wednesday. The job postings did not mention that these jobs were a part of an experiment. The applicants, therefore, applied to these jobs in a naturally occurring setting that they would have otherwise faced, not knowing the experimental purpose, making this a natural field experiment (Al-Ubaydli and List 2012, 2015). The jobs were posted on all days of the week for four weeks in November and December 2021.

[12]A few flexible jon postings (18 tasks) offered the freelancer the option of choosing from five two-hours contiguous slots beginning at 8 am. However, the job text was the same within task across the flexible postings (high-wage and low-wage).

The data we use for our analysis are the number of applications as well as the information from the applicant profiles and applications. Applicants do not state their gender on their profile or the application.[13] We infer the gender of the applicant from the profile picture used in the profile. The platform verifies the identity of the freelancer against identity documents, like a passport, driver's license, or national ID, to ensure that the money goes into the correct freelancer's account and no freelancer can operate more than one account on the platform. The platform withholds payments until the name and photograph of the freelancer on the platform match their identity documents. This makes the pictures a reliable source of information. We manually classify applicants as male, female, or gender uncertain, using their profile pictures.[14]

The setting of an online labor market such as ours offers several advantages for studying preference for work hour flexibility. First, in regular jobs, choosing to apply for flexible hours may be confounded by other considerations apart from a preference for such jobs. There may be benefits of signaling availability (or showcasing the work to the manager) for promotions and other career concerns. Moreover, regular jobs often require commuting, and sorting into flexible jobs could in fact be an aversion to commute at specified times of the day. Such aspects are absent in our setting. Further, inflexibility in work is quite common in online freelance jobs. To illustrate this, we extracted the job text for over 64,000 jobs posted on the platform. These jobs were in the same job categories in which we posted our experiment job ads. Table A4 presents our finding on how common it is for job ads to feature certain keywords (like time/day and deadline) that could potentially imply some

[13] We could, in principle, have asked applicants to report their gender at the time of responding to the posting. However, applicants could have seen this as a signal of gender discrimination. Such a perverse signal might have disincentivized women applicants. Another reason we avoided any questions or requirements around gender is because job postings on the platform rarely ask applicants to report their gender. Doing so would have made our postings stand out, and might have affected the response rates.

[14] Members of the research team manually classified the gender of the applicant. Since the same person classified applicants for all jobs (flexible, inflexible, high wage, low wage) within each task, any person-specific bias is likely to similarly affect both flexible and inflexible jobs. One could have used an algorithm to infer the gender from the names of the applicants (Blevins and Mullen 2015). While such algorithms work well for names from Western countries, such as the US and the UK, they are not as accurate at predicting gender from names of applicants from a range of countries as wide as the one that we observed in our experiment. In addition, the accuracy of such algorithms depends on the size of the sample they are trained on. Since we had a manageable number of applicants, we believe that manual classification is less prone to errors than other methods. To rule out the possibility that the research team may have had unconscious bias when inferring gender, we had two external research assistants reclassify the applicants for 72 jobs, chosen randomly, as *male*, *female*, and *gender unclear*. Of the $2,824$ applicants they categorized, only 45 applicants (1.6%) were classified as having a gender different from what was initially entered. Moreover, this mismatch was not different for inflexible jobs and flexible jobs.

inflexibility in work hours.[15] At least 20 percent of job postings had some mention of a time/day, 27 percent had a mention of some form of deadline, and 29 percent has mention of some meeting requirements. The numbers are similar in both fixed payment and hourly payment jobs, indicating freelancers often come across job-descriptions that have some inflexibility in work hours. Second, freelancers from around the world actively look for jobs in these online labor markets. Our sample consisted of applicants from over 150 countries. In Figure A5, we document the distribution of our applicants across countries of the world. Figure A6 repeats the exercise using data from Online Labour Index (Stephany et al. 2021), the largest source of public data on the gig economy compiled by the Online Labour Observatory (OLI).[16] The comparison of the country of work distribution that we observe in our sample is quite close to the distribution observed in all online freelance labour markets as compiled by the OLI. As our applicants come from a range of diverse cultural and institutional contexts, this setting allows us to draw more general conclusions. Third, our setting allows us to examine applicants from a range of distinct tasks that vary significantly in the skill set required. The skills one chooses to acquire and the preference for flexibility could be correlated. Since the jobs in our experiment require diverse skills, this allows us to draw more general inferences about the preference for flexibility.

It is equally important to acknowledge some limitations of our experimental setting for providing externally valid (outside the setting of online labour markets) conclusions (List 2020). A key unknown in this setting is the relation between preference for flexibility and the decision to sort into this market. One possibility is that the inherent flexibility (shorter contract, ability to do multiple jobs at the same time, online work from home) of jobs in online labor markets attracts workers who have a higher preference for all kinds of flexibility, including flexible work. If that were the case, our estimates of elasticity for flexibility may be an over-estimate of such an elasticity for the larger population of workers from across the world. If so, our estimates could be interpreted as an upper bound of the population estimate of the elasticity of labor supply from flexibility. Further, the relation between preference for flexibility and the decision to sort into this market could also vary across gender. For example, if tech-savvy females (compared to males) are more likely to chose online work because of discrimination (or other supply side constraints) in the

[15]We acknowledge that the inflexibility that these keywords imply may not all be of the type of inflexibility that we offered.

[16]The Online Labour Observatory is a collaborative network of researchers and policy makers at the International Labour Organisation and the Oxford Internet Institute at the University of Oxford.

brick-mortar labour market, and tech-savvy individuals like flexibility more than others, our results may also be an over-estimate of the gender difference in response to flexibility. [17]

Yet, since online labour markets already offer several other types of flexibility, the marginal benefit of flexibility in choosing work hours that we offer could also be lower. If that is true, the elasticity of labour supply to flexible work hours that we measure would be lower than what we would observe in other settings. Further, the benefits (and the costs) of flexible working hours for a one-time two-hour job are likely to be different from flexible work hours in a full-time job. One one hand, this benefit could mean more for a one-time two-hour job if the cost of re-adjusting the schedule is high in the short run. In that case, the demand for flexibility would be higher in one-time jobs. On the other hand, if cost of adjusting one's schedule is low for a one-time job compared to a full-time daily job, the demand for flexibility would be lower in one-time jobs compared to full time jobs.

It is also important to point out that our experiment can only speak about one kind of flexibility - the flexibility in choosing work hours. There are several other types of flexibility in the labour market, like some choice in the nature of the work performed, the nature of the contract (freelance vs fixed wage), and the location of work. Our experimental setting (freelance labour market) provides these types of flexibility to all applicants and then studies the demand of flexible working hours. The experimental setting and the results does not allow us to infer the relationship between the flexibility that we provide and the demand and the willingness to pay for these other kinds of flexibility (Adams-Prassl et al. 2023).

Finally, it is important to point out a few challenges that our experimental design poses for inferring elasticity (and gender differences in elasticity) of labour supply to flexible working hours. One possibility is that workers may infer other unobserved employer characteristics (like politeness) from flexible job offers and female workers may prefer those unobserved employer characteristics more than male workers, explaining the gender difference in applications. We cannot rule out this possibility. However, the policy relevant question from an employer's perspective is the effect of offering flexibility. Our experiment

[17] However, this challenge is not unique to our setting. Any experiment that focuses on any sector (doctors, tech-workers, call-center workers) would face a similar challenge as entry into every sector is driven by individual characteristics that may be related to preference for flexibility.

captures this effect and can be thought of as estimating an Intent-to-Treat effect. Another concern is that for the purposes of this experiment, we close the job for applications 24 hours after the posting. One possibility is that women take more time to respond to inflexible applications (perhaps they need time to find an alternative arrangement for household work), generating the gender difference in the response that we observe. We cannot rule out this possibility. However, a large amount of applications to jobs on this platform occurs in the first 24 hours, partly addressing this concern.

4 Empirical Specification

The primary aim of our empirical exercise is to understand the causal effect of flexibility in choosing work hours on the number of applications. For this, we estimate the following specification:

$$Y_{jt} = \alpha + \beta \ \text{Flexible}_{jt} + \gamma_t + \epsilon_{jt} \tag{1}$$

where subscript t denotes task, each with four matched jobs j. Y_{jt} is one of the following dependent variables of interest for job posting j within task t: the number of all applicants, of male applicants, of female applicants, and the share of female applicants. $Flexible_{jt}$ takes a value of '1' if the job posting allows the freelancers to choose their work hours, '0' otherwise. γ_j denotes task fixed effects. ϵ_{jt} is the error term.

The main coefficient of interest is β. For every flexible job posting, we also have an otherwise identical job posting that only differs in the flexibility of choosing the work hours, β captures the causal effect of flexibility on the labor supply. Because of our interest in understanding the gender difference in demand for flexibility, we estimate β separately for male and female applicants. A higher β (as a percentage of the average number of male or female applicants) will indicate a higher elasticity of labor supply in response to flexibility.

To compare the marginal effects of flexibility between high and low wages and the trade-off between wages and flexibility, we estimated the effects of each type of job posting.

$$Y_{jt} = \alpha + \beta_1 \ \text{HWLF}_{jt} + \beta_2 \ \text{LWHF}_{jt} + \beta_3 \ \text{HWHF}_{jt} + \gamma_t + \epsilon_{jt} \tag{2}$$

where Y_{jt} is one of the following dependent variables of interest for job posting j within task t: the total number of all applicants, of male applicants, of female applicants, and the share of female applicants. $HWLF_{jt}$ is an dummy variable indicating that a job has a high wage but no greater flexibility than a low-wage-low-flexibility job. $LWHF_{jt}$ and $HWHF_j$ indicate a low-wage but high degree of flexibility and a high wage as well as a high degree of flexibility, respectively. γ_t denotes task fixed effects. ϵ^s_{jt} is the error term. Since we have two wage offers and difference in flexibility within each wage offer, we can compare the marginal effects of flexibility of at higher and lower wages. The marginal effect of flexibility at lower wages is given by β^s_2 and the marginal effect of flexibility at higher wages is given by $\beta^s_3 - \beta^s_2$. We can also infer the willingness to trade off flexibility and wage. To do this, we will need to compare the response to an increase in wage (β^s_1) with the response to the provision of flexibility (β^s_2).

5 Results

Table 1 presents a summary of the characteristics of the applicants to our job postings. Women make up only one-third of all applicants. This is despite the fact that our job postings covered a wide range of tasks (80 distinct tasks) that included both female-dominated tasks, such as translation and proofreading, and male-dominated tasks, such as financial consulting and coding. The Online Labor Observatory at the University of Oxford tracks projects across major online labor market platforms (including our platform) from across the world. Their estimates suggest that women make up 39 percent of the whole of the workforce in online labor markets (Stephany et al. 2021). As discussed above, we also compare the country-wise distribution of our applicants with the distribution information from the Online Labor Observatory in Figure A5 and Figure A6. We find that the distribution of country profiles in our data closely matches that from the Online Labor Observatory. Both these comparisons indicate that our sample from the experiment is representative of the gender composition and country profiles of online labor markets. Some other takeaways from the summary statistics are that female applicants (i) are less likely to make a counteroffer that is lower than the offered wage, (ii) write marginally longer cover letters and, (iii) are less experienced.

Did allowing freelancers the flexibility to set their work hours lead to more job applications? Table 2 reports the findings for our primary outcome of interest, the number of applications. As Column 1 shows, jobs that offered flexibility attracted more applications compared to jobs that did not. On average, flexible jobs received 5.98 more applicants than inflexible jobs. Comparing this effect of flexibility to the average number of applications per job, this is about a 15.8 percent increase in the number of applications.

Was the effect of flexibility different across gender? Columns 2 and 3 of Table 2 present the effect of offering flexibility on the number of male and female applications, respectively. Compared to inflexible jobs, flexible jobs attracted 2.92 more male applicants and 3.01 more female applicants. While the estimated effect magnitudes are similar for males and females, the percentage change (estimated effect relative to the average number of applicants per job) is significantly larger for females. Only one-third of all applicants were women. Compared to the average number of female applicants, an increase of three applicants translates to a 24 percent rise in the number of female applicants. For males, it translates to a 12 percent increase.[18] Thus, of the pool of workers on the platform, a larger proportion of women respond to flexibility than men. We interpret this as the flexibility-elasticity of the labor supply being twice as high for women than for men. Adams-Prassl (2020) finds that women in online freelance labor markets earn less because they need to flexible schedules (breaks between tasks) to balance childcare responsibilities. Our experimental findings of a more widespread preference for flexibility among women than men complements Adams-Prassl (2020).

Did flexibility in choosing work hours lead to a more gender-diverse workforce? Since women had higher flexibility-elasticity compared to men, flexible jobs could have led to a more gender-diverse workforce. Our results from Table 2 and Table 3 suggest that this was indeed the case. Column 4 of Table 2 suggests that flexible jobs led to a 1.5 percentage point rise in the share of female applicants, amounting to a 5 percent improvement over the average share of women applicants.[19] Column 4 of Table 3 reports similar results.

[18]Our results are robust to including a control for high-wage job and estimating the semi-elasticies instead of the slope. See Table A8, Table A9 and Table A10. In addition, Table A10 shows that using a poisson pseudo maximum likelihood (PPML) to account for zero applications does not affect the findings. We did not pre-specify the PPML specification in our pre-analysis plan because we did not anticipate zero applications.

[19]For the columns where the dependent variable is *% Female*, there is a slight difference between the specification we included in our pre-analysis plan and the specification we use. Specifically, we weight these regressions by the total number of applicants in each of these jobs. This is because the jobs for which we receive a high number of applications/applicants, like proofreading and translation, are the typical services traded on the platform. An increase in the share of females in these jobs, therefore, implies a higher increase in the absolute number of female applicants than an equal increase in the share of females in jobs providing

High-flexibility jobs led to a 3 percentage points rise in the proportion of female applicants (at a lower wage), a 10.4 percent rise over the average share of women applicants. These results have implications for employers and policymakers interested in improving gender diversity in the online labor market. Using changes in the maximum work limit in medical residencies in the US, Wasserman (2019) shows that, relative to men, female participation increases in sub-fields that limit the maximum work time. Our results complement this finding. Drawing experimental data from a wide range of fields, we find that schedule flexibility, like the flexibility to limit the number of working hours, narrows the gender gap in participation.

How did the effect of flexibility compare at higher and lower wages? Table 3 presents the findings. Compared to men, the effects of flexibility were higher for women at all wages. Next, the effects of flexibility for men were similar at lower and higher wages ($\beta_2^{male} = 2.92$ compared to $\beta_3^{male} - \beta_1^{male} = 2.89$). For women, the effect of flexibility was slightly higher at lower wages, but the difference between the sizes of the effects at the two wages is statistically insignificant ($\beta_3^{female} - \beta_1^{female} = 2.38$ at the higher wage and $\beta_2^{female} = 3.63$ at the lower wage). A related question is whether there were gender differences in willingness to trade off higher wages for flexibility. To answer this question, we compare the change in the number of applicants in response to higher flexibility as opposed to higher wages. The results in Table 3 show that both men and women had a similar willingness to trade off higher wages and flexibility. For males, the effect of providing flexibility in choosing work hours and 10 USD rise in the fee offered was similar ($\beta_1^{male} = 3.06$, $\beta_2^{male} = 2.92$). For women too, providing flexibility and a higher fee had similar effects ($\beta_1^{female} = 3.25$, $\beta_2^{female} = 3.63$). In percentage terms, this translates into a 12.2 percent increase in the number of male applicants in response to a ten-dollar increase in the wage as opposed to an 11.6 percent rise in response to flexibility. For women, a similar 10 USD rise in wages led to a 26 percent rise in the number of female applications and a 29 percent rise in applications when offered flexibility. What might generate these findings? One potential situation that can give rise to these findings is when there is sufficient heterogeneity, among both males and females, in preference for pecuniary and non-pecuniary benefits, and applicants are reluctant to substitute one for the other. For example, if some applicants have strong preferences for flexibility and apply to both high- and low-wage jobs as long as they are flexible, and similar share of applicants apply only

services that are not traded as frequently. Our results are qualitatively similar even if we do not weight the observations.

to high-wage jobs regardless of flexibility, we will find no gender difference in the trade-off between higher wages and flexibility.

Did flexible jobs attract better candidates? Given the varied nature of the tasks, it is not possible to systematically measure productivity in this experiment. We use applicant self-reported hourly rate as a proxy of productivity and find that flexible jobs attracted potentially more productive female applicants.[20] Freelancers typically mention an hourly fee that they charge for the jobs they perform on the platform. This rate is non-binding and freelancers can accept or make a counteroffer to the fee offered by the job in their application. Freelancers do not have an incentive to over-report this fee because clients sometimes invite freelancers to apply for a job and may use the self-reported free to screen candidates. This provides candidates an incentive to not over-report their hourly fee. The self-reported hourly fee can be interpreted as the outside option, where a higher fee reflects higher productivity. In Table A5, we find a strong positive association between the self-reported hourly fee (as well as if the hourly fee is higher than the fee we offered) and freelancers' job success rate on the platform for a sub-sample of applicants for whom we have job-success rate. As reported in Table 4 (and in Table A6 for the job-success rate sub-sample), female applicants' self-reported hourly fee rate was 5 percent higher in flexible jobs than inflexible jobs. Flexible jobs were also 12.5 percent more likely to attract female applicants that have hourly fee higher than the hourly fee that we offered. We do not find similar results for males. In Table A7, we compare the effect of flexibility with the effect of a higher fee on the quality of applicants. Compared to low-wage, inflexible jobs, an increase in flexibility (but not wage) attracts better female, but not male, candidates and this effects is statistically insignificant. However, an increase in wage without any chance in flexibility attracts higher-quality male, but not female, candidates. This implies that high flexibility draws better quality female candidates than a higher wage, and the reverse is true for males.

Do women put more effort into applications flexible jobs? While we do not have a direct measure of effort, we look at several indirect measures that indicate effort and willingness to get these jobs. First, we examine how quickly applicants apply to our job advertisement. For this, we rank all applicants by their position in the applicant queue. Since all job advertisements were open for applications for the same amount of time, we can compare

[20] This outcome variable was not pre-specified in the pre-analysis plan.

the proportion of female applicants among "early" applicants across flexible and inflexible jobs.[21] Table 5 reports the effect of providing flexibility on the proportion of female applicants among "early" applicants. For flexible jobs, we find a higher proportion of women among the earliest 25^{th} and 50^{th} percentiles of applicants. Note that the effect at the 25^{th} percentile is significantly higher than the effect of flexibility on the overall share of female applicants (1.47) reported in Table 2. The changes in the share of women among the earliest 10^{th} and 75^{th} percentiles are statistically indistinguishable from the overall increase in the share of female applicants. This suggests that women are not only more responsive to flexible jobs on the extensive margin, but they also respond by applying more quickly than men.[22]

Second, we look at whether the applicant attached a previous work sample with their application to indicate their ability or expertise to complete the job, and the length of their cover letter written as a part of their application. Attaching a work sample takes effort and time and also indicates the willingness of the applicant to signal their quality to the employer. The length of the cover letter may also signal effort. The findings, reported in Table 6, show that compared to an inflexible job, men are no more likely to attach a work sample or write longer cover letters in response to a flexible job. Women, in comparison, are more likely to attach a work sample when applying for a flexible job, indicating an increased effort. Women also write shorter cover letters for applications to flexible jobs. The results seem to suggest that women put more effort into some dimensions of the application. The effect on the length of the cover letter is not straightforward to interpret. Perhaps women partially offset the increased effort required for attaching samples by writing shorter cover letters. Or, they spend more time writing more concise and precise letters. However, it is important to note that the results may also reflect differences in the composition of applicants rather than their efforts. It is possible that marginal applicants to flexible jobs are of higher quality and thus provide a better application package.

Third, we look at counteroffers made by applicants. Although we specified the fee in

[21] Please note that the applicants were not aware that the job application would close exactly 24 hours after posting. The job posting did not mention any deadline for applying. However, it mentioned the specific date on which the work had to be performed. While the date of the job is an implicit deadline, we closed the job posting before that date.

[22] It is important to emphasize that we do not observe the exact time of these applications. We only observe applicants ordered by the time of the application. Thus, it is possible that both men and women take longer (in absolute terms) to apply for these flexible jobs. But, relative to men, women respond faster.

the job posting, applicants could still make a counteroffer in their applications. If applicants have a high valuation of flexible jobs, they may attempt to undercut other applicants by making lower counteroffers. However, it is important to note that counteroffers do not affect the job requirements that appear as non-negotiable in the job posting. We report our findings on counteroffers made by applicants in Table 7. Less than two percent of the candidates overbid and around 14 percent of candidates underbid. One interesting pattern that emerges is men were more likely to underbid than women. We further explore this in Table A3. As per Column (1), women were four percentage points, or 29 percent, less likely to underbid. In the columns that follow, we control for other characteristics of the task, job, and the applicant. The association between gender and underbidding persists, suggesting that the gender difference in underbidding is potentially a reflection of a lower willingness to negotiate even if it involves lowering the asking fee. A large literature has documented that men are more likely to negotiate wage offers than women (see Hernandez-Arenaz and Iriberri (2019) for a review of the literature). For example, Leibbrandt and List (2015) finds that women are less willing to negotiate if the job postings do not explicitly mention the possibility of negotiation, which is the case in our setting. Our results provide a new insight from online labor markets: men are more likely to negotiate in either direction, including *undercutting* wages to secure a job. Dreber et al. (2022) finds that men and women differ on what constitutes a reasonable request of salary. Since our jobs explicitly mention the fee, women might be more inclined to see this is the reference point for a reasonable fee than men. However, we cannot rule out other reasons like social costs, confidence, self-evaluation of relative quality as an explanation behind less frequent under-cutting by women. This is distinct from the results in Table 7, which indicate that there was no difference in underbidding behavior in response to flexible jobs across men and women.

A key question is why women prefer flexibility? Our experiment does not allow us to directly provide an answer to this question. However, understanding the differences in effects across countries may provide an insight to this question.[23] One reason why women might prefer flexibility could be that it allows them to manage time-sensitive childcare responsibilities. If so, the value of flexibility is likely to be higher for women with more children. We do not know the number of children our applicants have. However, a coarse proxy is the average fertility rate of the country of the applicant. In Panel A of Table 8, we

[23]This heterogeneity analysis was not pre-specified in the pre-analysis plan.

study the difference in the effect of flexibility across countries with high and low fertility rates. We do not find any significant differences in effect for women (relative to the mean) across countries with high and low fertility. For men, the elasticity is slightly higher in low-fertility countries. How do we explain these results? One possibility is that the time commitments for childcare responsibilities are fixed costs and do not vary by the number of children. For example, the time commitment to cook or to take children to school may not vary significantly by the number of children. However, it is important to keep in mind that such country-level averages are coarse measures and our results could reflect this coarseness more than any mechanism.

Does lack of flexibility limit female labor force participation? Again, our results cannot directly speak to this, a comparison of the effect of flexibility on applicants from countries with low and high female labor force participation rates can provide some insights. In Panel B of Table 8, we present the results separately for countries with high and low female labor force participation rates. The effect of flexibility (relative to the mean) is higher for women in low female labor force participation countries. The results for men do not differ across these countries. This could indicate a higher demand for flexible jobs in these countries and that the limited availability of such jobs is one of the drivers or low female labor force participation. As a result, when flexible jobs become available, the response is large. But it is important to bear in mind that all of our applicants are existing workers on the platform and the reasons for their high response to flexibility may be different from the reasons that stop women from participating in the labor market at the extensive margin.

In Panels C and D of Table 8, we present additional cross-country differences in the effect of flexibility. We find that the effect of flexibility does not vary across poor and rich countries, as measured by per capita GDP, for either genders. Per capita GDP is a good predictor of many observable country characteristics, like the availability of regular jobs, social welfare, and gender norms. Though this does not provide us with a specific mechanism that explains the preference for flexibility, it does suggest the idea that differences in preferences for flexibility are unlikely to be explained by factors for which per capita GDP serves as a good proxy. It is also worth pointing out that per capita GDP is a coarse measure of the social conditions that our applicants may face. Lastly, we do any differences in the effect of flexibility across Asian and non-Asian countries. This suggests that our results are not entirely driven by countries like India, Pakistan and Bangladesh, which have a large participation in the online labor market.

6 Discussion and Conclusion

Our study inquires whether workers value non-pecuniary benefits like flexibility and does this valuation differ by gender? The answer to this question has important implications. In light of the ever-evolving nature of the workplace, it is important for firms to know the demand for various non-pecuniary benefits. In addition, any potential gender difference in the valuation of these non-pecuniary benefits could help explain gender inequalities in the labor market and design policies to counteract them.

Despite its importance, there are several empirical challenges that make it a difficult question to answer. Observational data does not allow disentangling preference for various non-pecuniary benefits from other worker-, job-, and firm-specific unobserved factors. In addition, several non-pecuniary benefits are offered at the same time, making it challenging to isolate the effect of a specific non-pecuniary benefit, such as flexibility in choosing the work time. Though studies that use stated preferences overcome these problems, stated preferences are often not incentive-compatible.

We overcome these challenges using an experiment. We posted matched pairs of jobs on a major online freelance labor market platform that differed only in the flexibility in choosing work hours. Since these jobs were identical along all attributes except flexibility, any difference in the number of applications for these jobs must have been a result of a preference for flexibility. We find that flexible jobs attracted more applications. While true for men and women, the percentage effects were twice as large for women. Flexible jobs led to a 24 percent rise in the number of female applicants and a 12 percent rise in the number of male applicants. Overall, the results suggest that indeed workers value flexibility and the demand is higher for women than for men.

It is important to interpret our results keeping in view the limitations the experiment. First, while our results are internally valid, we cannot speak to whether they would hold in a general population that includes the brick-and-mortar labor market. It is possible that workers in freelance labor markets prefer flexibility more than workers in the brick-and-mortar labor market and the experiment overstates the demand for flexibility. It is also possible that since freelance labor markets already offer a high degree of flexibility, the marginal valuation for flexibility is lower in this market. Again, since the contracts in the freelance labor market are short-term, workers may care less about flexibility. On the other hand, since the contracts are short-term, the benefits from giving up flexibility are also less. Second, our results cannot speak to the underlying reason behind the gender difference in the demand for flexibility. It is likely that women prefer flexibility to satisfy the demands on their time, which may be driven by norms, social environment, and other legal and cultural institutions. Though we explore some of these avenues, our findings on this question are inconclusive. Thus, we remain agnostic about the sources of gender differences in preferences for flexibility. Finally, we finds pertain to a specific type of flexibility and the preferences for other types of flexibility may be different. For example, our experiment does not speak to the gender differences in the preference for work from home.

Our experiment and the findings carry important implications for policies aimed at increasing female labor force participation. The preference for non-pecuniary benefits, such as flexibility, is somewhat ignored in policy discussions that aim to increase female labor force participation. These discussions tend to focus on issues like the development of skills, access to finance, social norms and networks, education, and the organization of the family. Our findings suggest that limited availability of non-pecuniary benefits, like flexibility, could important barrier to participation in the labor market and policies, moving forward, should aim to address it.

If the lack of flexibility is indeed an explanation, what can policymakers do? Assuming that firms are aware of these differences in preferences but find it costly to provide these non-pecuniary benefits, policymakers could provide incentives, such as tax breaks or cheap credit, to firms that provide benefits like flexible working hours. Further, innovations in technology that reduce search costs and promote the gig economy may open up possibilities for jobs that provide flexibility and thus encourage the participation of women in the labor market. For firms that are unaware of worker preferences and want to hire more females, mere information about these preference may motivate them to invest in providing more non-pecuniary benefits.

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Table 1: Summary Statistics

	Females		Males		Difference
	N	Mean	N	Mean	in means
	All jobs				
Counteroffer	4011	34.68	8005	33.91	0.77***
Wage offered − Counteroffer	4011	0.84	8005	1.39	-0.55***
Underbid	4020	0.12	8036	0.16	-0.04***
Overbid	4020	0.02	8036	0.02	0.00
Position percentile	4020	52.33	8036	50.98	1.35**
Cover letter length	3836	417.18	7780	398.31	18.87
Share providing a work sample	4020	0.17	8036	0.17	0.00
Total prior contracts	4020	5.50	8036	7.20	-1.70**
Total prior contracted hours	4020	15.32	8036	14.31	1.01*
Total prior earnings	4020	926.88	8036	895.51	31.37
	Inflexible jobs				
Counteroffer	1763	34.83	3768	34.02	0.81***
Wage offered − Counteroffer	1763	0.91	3768	1.31	-0.41**
Underbid	1766	0.11	3787	0.15	-0.04***
Overbid	1766	0.01	3787	0.02	-0.01**
Position percentile	1766	52.79	3787	50.97	1.83**
Cover letter length	1600	430.67	3554	398.8	31.86**
Share providing a work sample	1766	0.15	3787	0.16	-0.01
Total prior contracts	1766	5.34	3787	8.34	-3.00**
Total prior contracted hours	1766	16.79	3787	14.92	1.87
Total prior earnings	1766	1072.48	3787	1055.6	16.88
	Flexible jobs				
Counteroffer	2248	34.56	4237	33.82	0.74***
Wage offered − Counteroffer	2248	0.79	4237	1.46	-0.68***
Underbid	2254	0.12	4249	0.16	-0.04***
Overbid	2254	0.02	4249	0.02	0.01
Position percentile	2254	51.97	4249	50.98	0.98
Cover letter length	2236	407.53	4226	397.89	9.64
Share providing a work sample	2254	0.18	4249	0.17	0.01
Total prior contracts	2254	5.61	4249	6.18	-0.57
Total prior contracted hours	2254	14.16	4249	13.76	0.41
Total prior earnings	2254	812.79	4249	752.83	59.97

Notes: ***, **, and * indicate that the difference in the means of a variable between the two groups, male and female applicants, is significant at 1%. 5%, and 10%, respectively. Position percentile is the application's chronological position, in percentile terms, among all applications for the job, with the first percentile indicating that it was the first application received for the job. A negative (positive) difference between the wage offered and the counteroffer made by an applicant implies that the freelancer's counteroffer was higher (lower) than the proposed wage. 'Underbid' is an indicator variable that takes the value '1' when wage offered − counteroffer > 0, '0' otherwise. 'Overbid' takes the value '1' when wage offered − counteroffer < 0, '0' otherwise.

Table 2: The Impact of Flexibility on the Number of Applicants

	(1)	(2)	(3)	(4)
	Applicants			
	Total	# Male	# Female	% Female
Flexible Job	5.98***	2.92***	3.01***	1.47*
	(1.44)	(0.90)	(0.74)	(0.80)
Task FE	✓	✓	✓	✓
Mean of DV	37.79	25.19	12.51	28.29
Control mean of DV	34.71	23.67	10.98	27.37
Observations	319	319	319	319

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. Of the 320 jobs posted, one did not have any applicants. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date.

Table 3: The Impact of Wage and Flexibility on the Number of Applicants

	(1)	(2)	(3)	(4)
	Applicants			
	Total	# Male	# Female	% Female
High-wage, low-flexibility	6.31***	3.06***	3.25***	3.42***
	(1.96)	(1.18)	(1.05)	(1.10)
Low-wage, high-flexibility	6.60***	2.92**	3.63***	2.95***
	(1.88)	(1.09)	(1.04)	(1.01)
High-wage, high-flexibility	11.63***	5.95***	5.63***	3.67***
	(1.97)	(1.24)	(1.02)	(1.12)
Task FE	✓	✓	✓	✓
p-value [$H_0 : \beta_1 = \beta_2$]	0.88	0.91	0.71	0.67
p-value [$H_0 : \beta_1 + \beta_2 = \beta_3$]	0.64	0.99	0.38	0.09
Mean of DV	37.79	25.19	12.51	28.29
Control mean of DV	31.55	22.14	9.35	26.80
Observations	319	319	319	319

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. Of the 320 jobs posted, one did not have any applicants. A high-wage, low-flexibility job offered a fixed wage of USD 40 and required the freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. A low-wage, high-flexibility job offered a wage of USD 30 but allowed the freelancers to choose any two-hour window during which they wanted to work on the pre-specified date. A high-wage, high-flexibility job offered USD 40 and allowed the freelancers to choose any two-hour window on the pre-specified date.

Table 4: Association between job characteristics and hourly rate of applicant freelancers

	(1)	(2)	(3)	(4)	(5)	(6)
	Indicator(Hourly rate > Fee offered)			Ln(Hourly rate)		
	All	Male	Female	All	Male	Female
Flexible Job	0.01	-0.00	0.03*	0.01	-0.02	0.05**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
High-wage Job	-0.12***	-0.11***	-0.15***	0.02*	0.04**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Task FE	✓	✓	✓	✓	✓	✓
Mean of DV	0.27	0.28	0.26	2.54	2.54	2.54
Control mean of DV	0.26	0.28	0.24	2.54	2.55	2.50
Observations	12,056	8,036	3,992	11,966	7,978	3,961

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors reported in parentheses. The outcome variable in the first three columns is an dummy variable that indicates whether the rate mentioned on the applicant's public profile is higher than the hourly fee we offered for the job that the freelancer applied for. The dependent variable in the last three columns is the natural log of the hourly rate of the freelancer. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date.

Table 5: The Impact of Flexibility on the Positions of the Freelancers' Applications

	(1)	(2)	(3)	(4)
	% female in the first			
	10	25	50	75
	%iles of application positions			
Flexible Job	0.83	4.61***	2.27**	1.45
	(2.87)	(1.70)	(1.00)	(0.94)
Task FE	✓	✓	✓	✓
p-value [$\mathrm{H}_0 : \beta = 1.47$]	0.78	0.04	0.45	0.98
Mean of DV	21.04	24.99	26.49	27.00
Control mean of DV	21.56	23.45	25.36	26.17
Observations	319	319	319	319

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. The outcome variable is the application's chronological position, in percentile terms, among all applications for the job, with the first percentile indicating that it was the first application received for the job. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. The number of total applicants is more than the sum of male and female applicants because we could not deduce the gender of a few applicants from their profile pictures and names. All job-level observations are weighted by the total number of applicants for each job.

Table 6: Cover Letter Length and Work Samples

	(1)	(2)	(3)	(4)	(5)	(6)
	Cover letter length			Work sample provided		
	All applicants	Males	Females	All applicants	Males	Females
Flexible Job	-11.34	-2.55	-29.79*	0.01*	0.01	0.03**
	(8.72)	(10.48)	(16.02)	(0.01)	(0.01)	(0.01)
Task FE	✓	✓	✓	✓	✓	✓
Mean of DV	404.54	398.31	418.16	0.17	0.17	0.17
Control mean of DV	408.70	398.80	431.25	0.16	0.16	0.15
Observations	11,616	7,780	3,809	12,056	8,036	3,992

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 'Cover letter length' is the number of characters in an applicant's cover letter, including spaces. Robust standard errors reported in parentheses. 'Work sample provided' is an indicator variable that takes a value of '1' if the applicant attached at least one work sample with their application, '0' otherwise. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. The number of total applicants is more than the sum of male and female applicants because we could not deduce the gender of a few applicants from their profile pictures and names.

Table 7: The Impact of Flexibility on the Freelancers' Proposed Bids

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Wage offered − Counteroffer			Underbid			Overbid		
	All	Male	Female	All	Male	Female	All	Male	Female
Flexible Job	0.05	0.14	-0.14	0.01**	0.02**	0.01	0.00	-0.00	0.01***
	(0.11)	(0.14)	(0.17)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	1.21	1.39	0.83	0.14	0.15	0.11	0.02	0.02	0.02
Control mean of DV	1.18	1.31	0.91	0.13	0.15	0.11	0.02	0.02	0.01
Observations	12,016	8,005	3,984	12,016	8,005	3,984	12,016	8,005	3,984

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors reported in parentheses. A negative (positive) difference between the wage offered and the counteroffer implies that the freelancer's counteroffer was higher (lower) than the proposed wage. 'Underbid' is an indicator variable that takes the value '1' when wage offered − counteroffer > 0, '0' otherwise. 'Overbid' takes the value '1' when wage offered − counteroffer < 0, '0' otherwise. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. The number of total applicants is more than the sum of male and female applicants because we could not deduce the gender of a few applicants from their profile pictures and names.

Table 8: Heterogeneity in the Impact of Flexibility

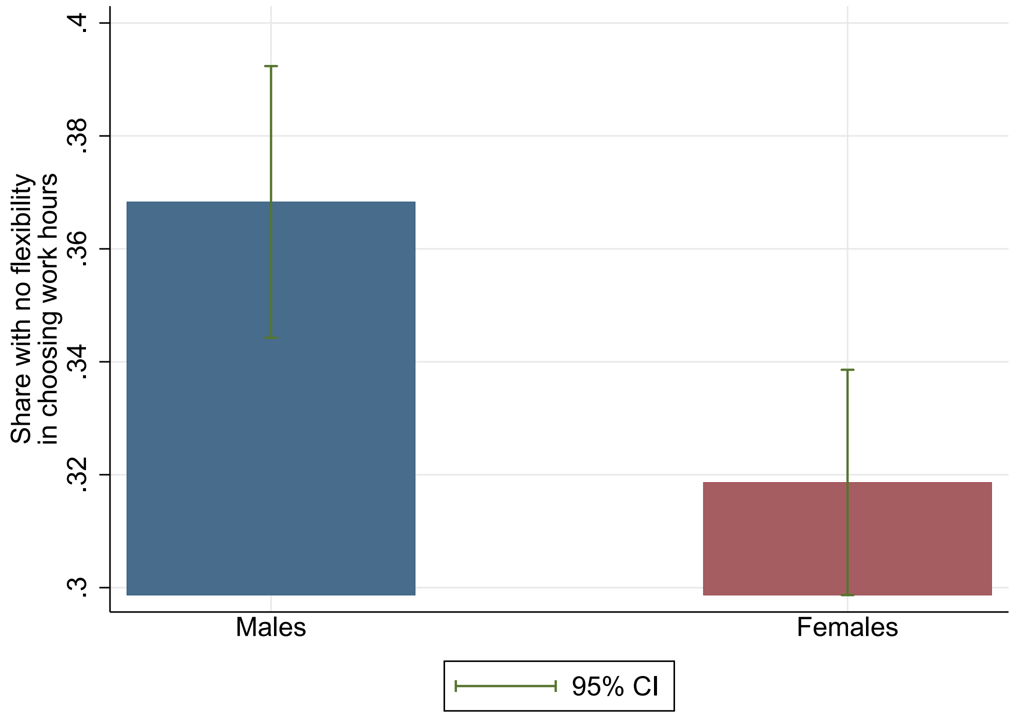
	Applicants							
	Total	# Male	# Female	% Female	Total	# Male	# Female	% Female
Panel A	Applicants from high-TFR countries				Applicants from low-TFR countries			
Flexible job	2.40***	1.08**	1.29***	2.78*	3.66***	1.91***	1.73***	0.43
	(0.78)	(0.53)	(0.39)	(1.54)	(0.94)	(0.58)	(0.49)	(1.09)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	17.06	11.43	5.59	26.65	21.16	14.02	7.09	29.09
Control mean of DV	15.64	10.74	4.88	24.78	19.38	13.10	6.24	29.36
Observations	307	307	307	307	315	315	315	315
Panel B	Applicants from low-FLFP countries				Applicants from high-FLFP countries			
Flexible job	3.02***	1.68***	1.34***	1.17	3.14***	1.38***	1.71***	2.50*
	(0.84)	(0.61)	(0.36)	(1.20)	(0.89)	(0.49)	(0.55)	(1.45)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	19.20	14.47	4.69	22.06	19.07	11.02	8.01	32.56
Control mean of DV	17.65	13.60	4.01	21.49	17.38	10.25	7.10	31.09
Observations	311	311	311	311	311	311	311	311
Panel C	Applicants from low-GDP pc countries				Applicants from high-GDP pc countries			
Flexible job	4.30***	2.06***	2.21***	1.57*	1.78***	0.92***	0.84***	2.92
	(1.14)	(0.74)	(0.56)	(0.93)	(0.51)	(0.35)	(0.29)	(2.13)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	28.70	19.76	8.88	26.57	9.71	5.76	3.92	33.73
Control mean of DV	26.40	18.62	7.74	26.11	8.92	5.36	3.54	31.09
Observations	316	316	316	316	292	292	292	292
Panel D	Applicants from Asia				Applicants from outside Asia			
Flexible job	3.53***	1.76***	1.75***	0.86	2.52***	1.21***	1.28***	3.62**
	(1.01)	(0.67)	(0.48)	(1.42)	(0.71)	(0.45)	(0.41)	(1.56)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	21.52	15.00	6.47	26.53	16.57	10.36	6.16	30.17
Control mean of DV	19.69	14.06	5.59	26.35	15.18	9.68	5.47	27.66
Observations	311	311	311	311	313	313	313	313

Sources: Authors' calculation based on data collected from the experiment and information from the World Development Indicators.

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. Countries are grouped into high- and low-TFR/FLPF/GDP categories by splitting them at the mean value.

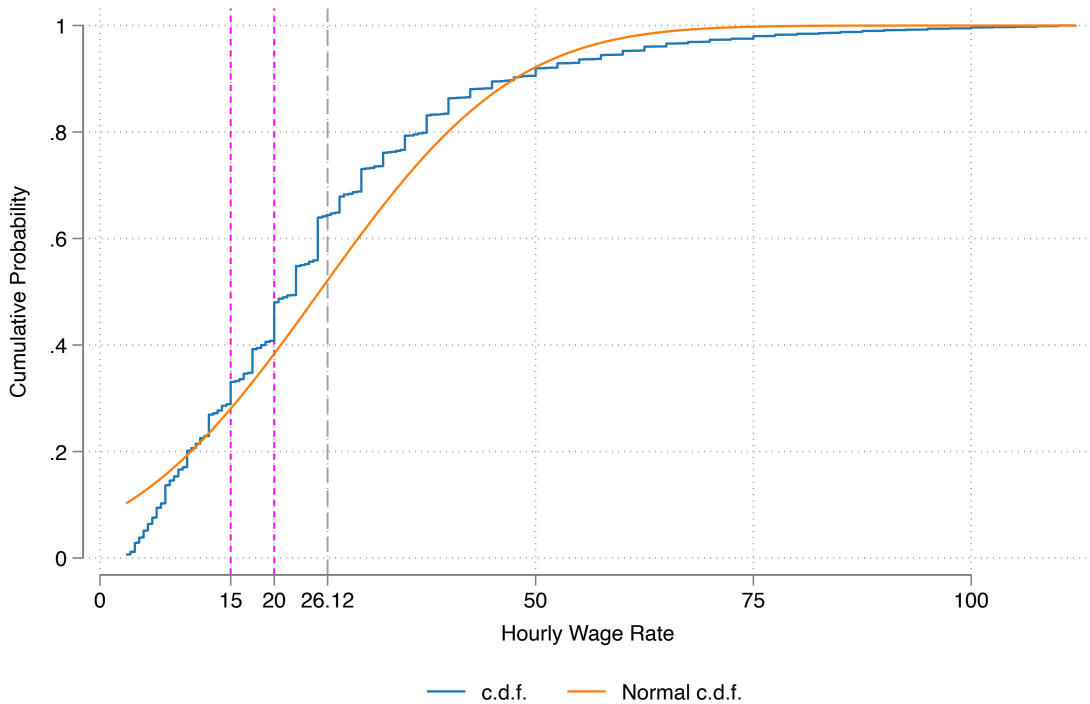
Appendix

Figure A1: Flexible Working Arrangements



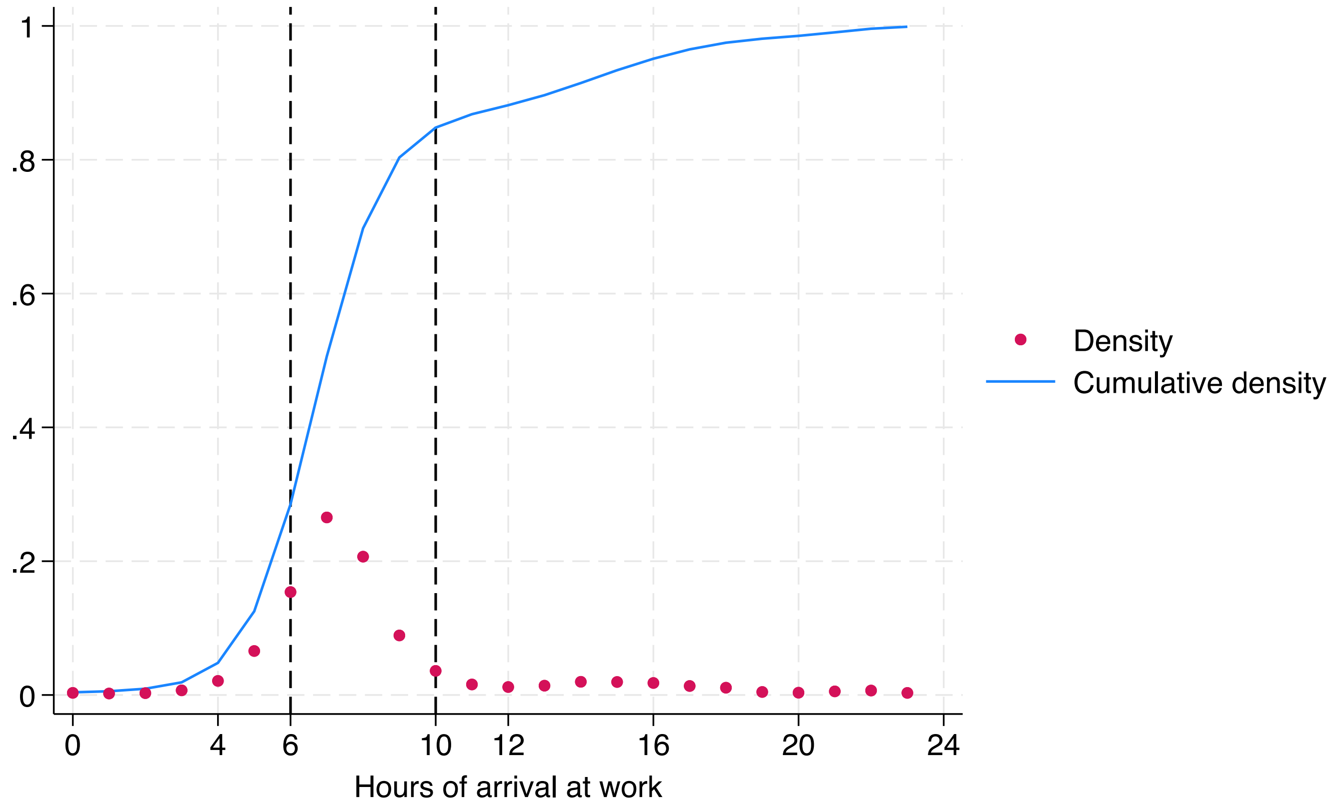
Notes: Authors' calculation based on data from the American Working Conditions Survey.

Figure A2: Distribution of Hourly Wage Rates in the Online Freelance Platform



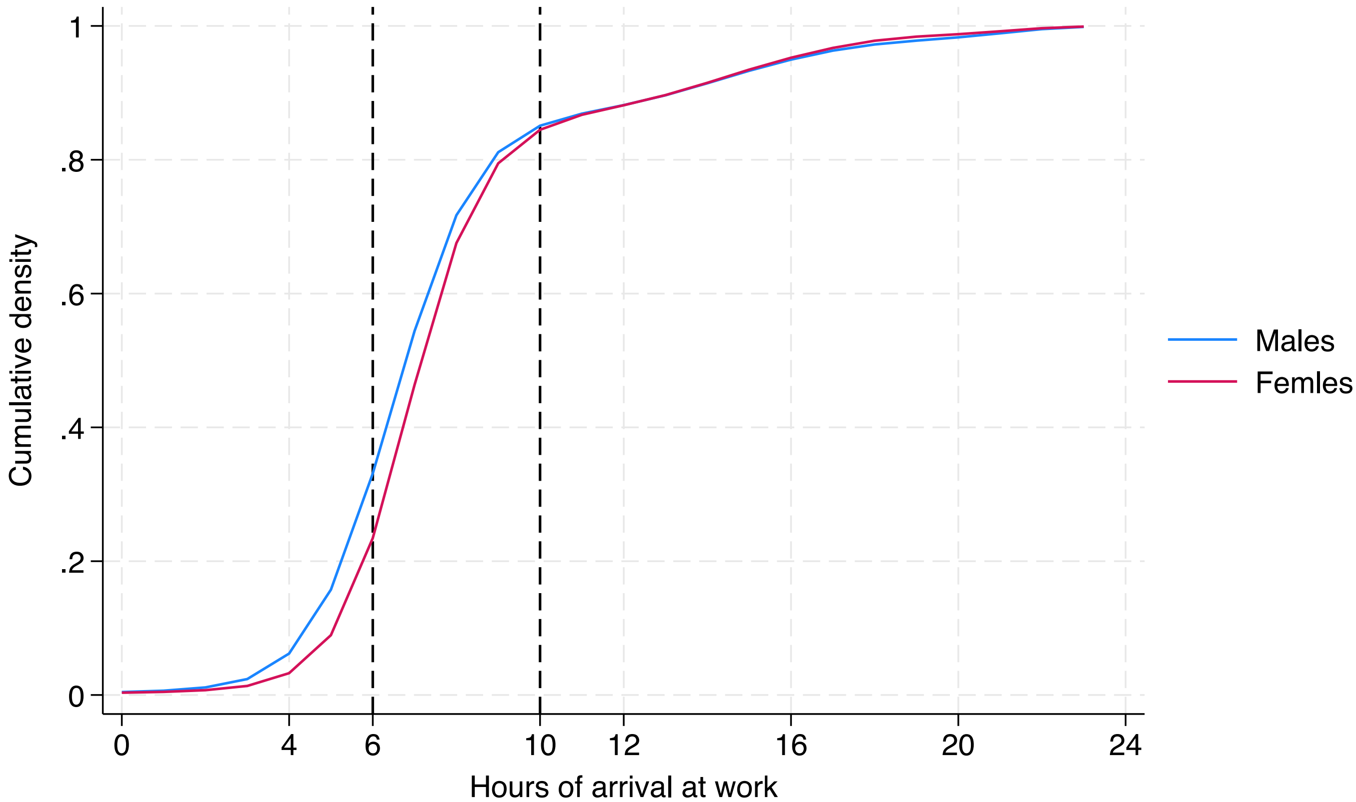
Notes: Authors' calculations based on scraped job postings in the online freelance platform. All job postings in the online freelance platform were scraped encompassing the categories related to the tasks posted for the experiment. 64,726 jobs were available of whom 64.5% were hourly payment jobs with hourly wage rates. Winsorized values of the hourly wage rates at the 99th percentile were used to plot the cumulative distribution. The dashed grey line shows the mean hourly wage rate of USD 26.12. The dotted magenta lines show the low and high hourly wages used in the experiment.

Figure A3: Arrival Time at Office



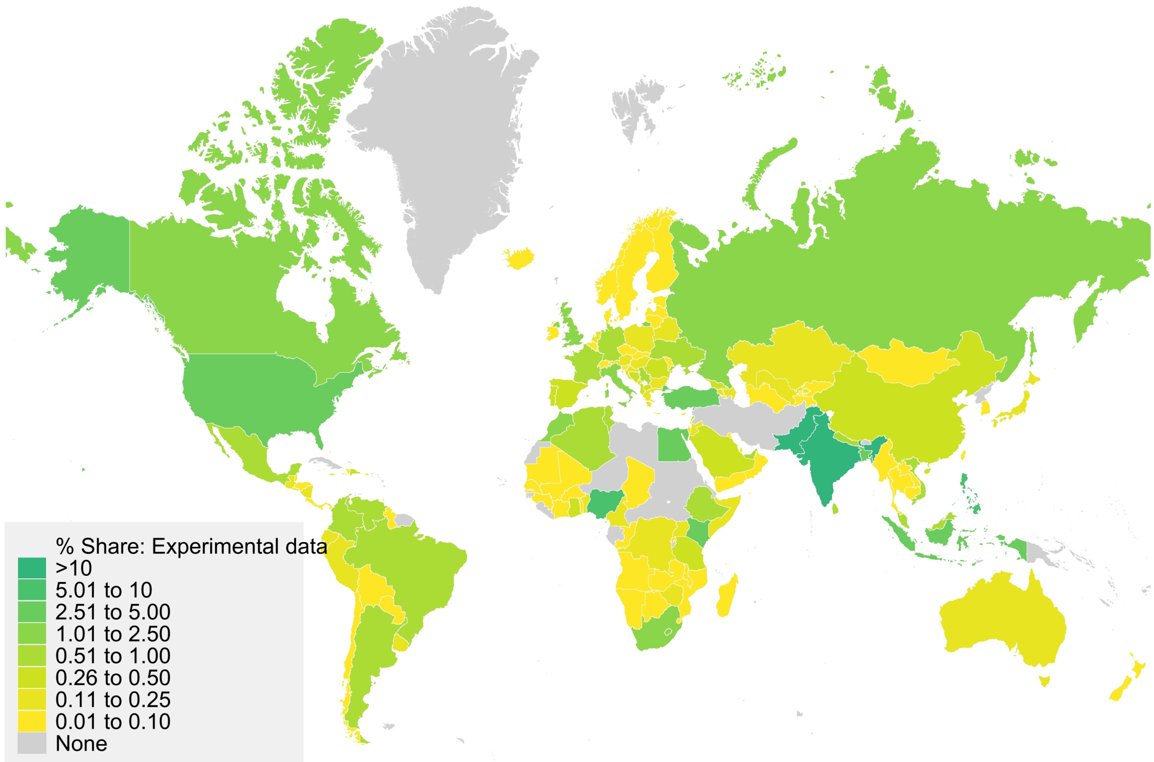
Notes: Authors' calculation based on data from the American Community Survey. Arrival time is approximated at the previous hour, for example arrival at $6:45$ am is counted as arriving at 6 am.

Figure A4: Arrival Time at Office by Gender



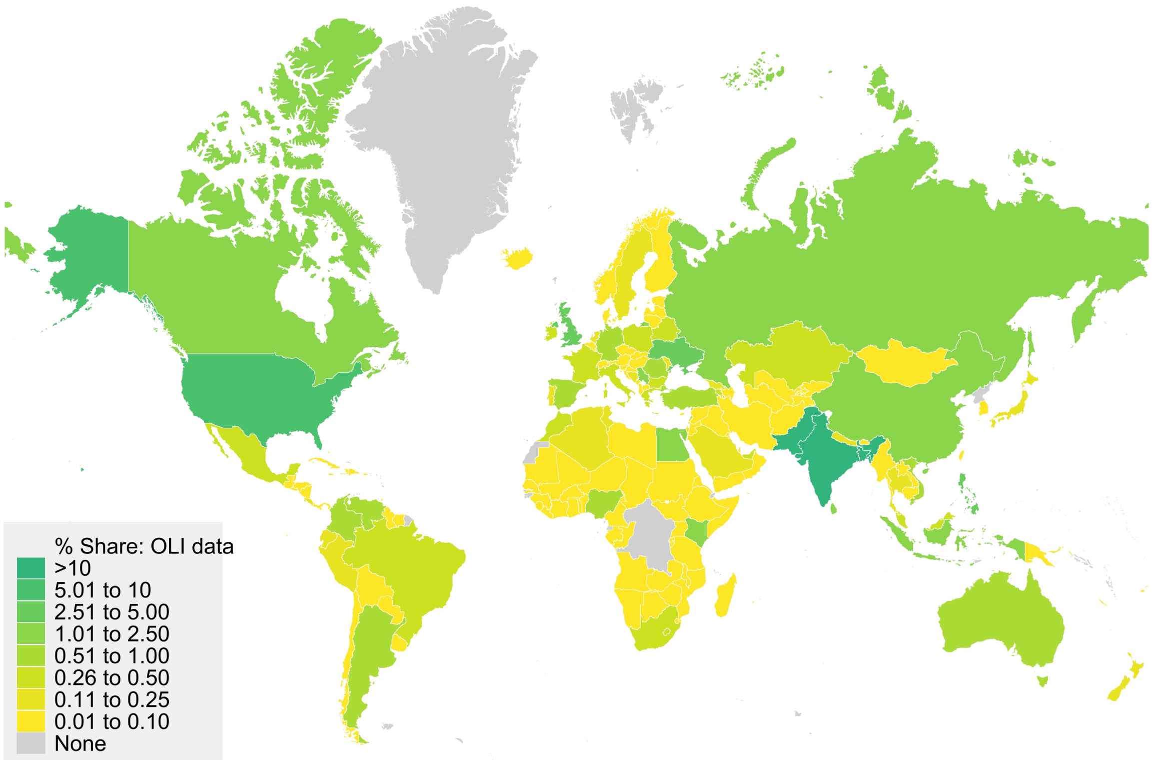
Notes: Authors' calculation based on data from the American Community Survey. Arrival time is approximated at the previous hour, for example arrival at $6:45$ am is counted as arriving at 6 am.

Figure A5: Distribution of Experiment Applicants Across Countries



Notes: Authors' calculation based on data collected from the experiment. The figures report the share of applicants for each country in our data.

Figure A6: Distribution of Online Freelancers Across Countries



Notes: Authors' calculation based on Online Labour Index (OLI) data. The figures report the share of applicants for each country in the Online Labour Index data.

Table A1: Full List of Tasks posted on the platform

Task #	Task	Client	Day
1	Convert json files to Excel	TB	Friday
2	Webscrapping using Python	AF	Saturday
3	Webscrapping using R	RB	Saturday
4	Cloud computing using Azure	NS	Sunday
5	Webscrapping using Ruby	YQ	Friday
6	Webscrapping using Apple Script	AF	Monday
7	Webscrapping using Excel VBA	AF	Sunday
8	Webscrapping using .NET	TB	Sunday
9	Python + Selenium framework	YQ	Tuesday
10	Economics tutor	RB	Wednesday
11	Cloud computing using AWS	NS	Sunday
12	Photoshop	TB	Monday
13	Audio editing	AF	Friday
14	Piano lesson	NS	Saturday
15	Spanish tutor	AF	Friday
16	Archival research (Newspapers)	TB	Monday
17	Geo-spatial coding	TB	Friday
18	Cartoon sketches	NS	Wednesday
19	Zoom webinar	YQ	Tuesday
20	Stata analysis	AF	Saturday
21	SAS analysis	TB	Wednesday
22	SPSS analysis	AF	Tuesday
23	R analysis	AF	Friday
24	Transcription	RB	Saturday
25	Website building	YQ	Saturday
26	Cover Art logo	AF	Tuesday
27	Editor for Canva workbook	RB	Tuesday
28	Email client	YQ	Wednesday
29	Push notifications	RB	Monday
30	CAD Drawing	RB	Thursday
31	Journal article summary - Pol Science	NS	Thursday

32	Music	NS	Monday
33	Food recipe	AF	Thursday
34	Digital comics art	YQ	Wednesday
35	Microsoft Access	YQ	Wednesday
36	Fabric art	RB	Sunday
37	Game experience	YQ	Sunday
38	Medical billing consultancy	NS	Wednesday
39	Web of Science literature review	TB	Saturday
40	CV/Cover Letter	YQ	Tuesday
41	Biology tutor	NS	Sunday
42	UI/UX developer	NS	Wednesday
43	Proof reading a research article	TB	Friday
44	Translation English to French	RB	Wednesday
45	Translation English to German	RB	Sunday
46	Telegram bot	NS	Monday
47	Sheet music and guitar tutor	AF	Thursday
48	Flutter developer	AF	Friday
49	Translation English to Hindi	RB	Tuesday
50	PDF to Word table conversion	NS	Wednesday
51	Instagram and Facebook ads monetization	AF	Tuesday
52	Translation English to Spanish	NS	Tuesday
53	Translation English to Punjabi	YQ	Saturday
54	Help with Matlab code	TB	Tuesday
55	Online yoga instructor	TB	Saturday
56	Translation English to Italian	AF	Thursday
57	YouTube script writer	YQ	Friday
58	Data entry in Access and Excel	YQ	Friday
59	Translation Arabic to English	TB	Thursday
60	Contract writing	YQ	Monday
61	Interior decoration	YQ	Sunday
62	Podcast manager	NS	Friday
63	Classical Literature tutor	RB	Wednesday
64	Accounting	TB	Friday
65	Brochure design	NS	Saturday

66	Tutorial on blockchain	TB	Saturday
67	Instagram page optimization	NS	Thursday
68	Voice-over artist	TB	Sunday
69	Sync voice over and music to video	RB	Monday
70	Translation English to Indonesian	AF	Monday
71	Full Stack developer	AF	Monday
72	Photo Editing	RB	Saturday
73	YouTube video editing	NS	Monday
74	SQL queries on employee database	TB	Thursday
75	Webscrapping using Java	NS	Sunday
76	Architecture	NS	Tuesday
77	Virtual assistant for Ebay product listing	RB	Thursday
78	Facebook group bot	RB	Sunday
79	Machine Learning tutorial	TB	Thursday
80	Stock trading advice	RB	Thursday

Table A2: Example job advertisements for the *Translation Arabic to English* task

Low-wage, low flexibility job ad
Dear freelancer, I am looking for someone who can help me translate some text material from Arabic to English. Good knowledge of Arabic is required. The job can be done within two hours. I need it done on [redacted]. You must meet me at 8 am your local time. I will share the text at the beginning of our meeting. I am willing to pay USD 30 for the job. Fee: $30.00 Fixed-price Level: Entry level Project Type: One-time project Skills and Expertise: Arabic Screening question: Can you please respond with the meeting time I have specified in the post? I will not consider you for the job if you do not respond correctly.
High-wage, low flexibility job ad
Dear freelancer, I am looking for someone who can help me translate some text material from Arabic to English. Good knowledge of Arabic is required. The job can be done within two hours. I need it done on [redacted]. You must meet me at 8 am your local time. I will share the text at the beginning of our meeting. I am willing to pay USD 40 for the job. Fee: $40.00 Fixed-price Level: Entry level Project Type: One-time project Skills and Expertise: Arabic Screening question: Can you please respond with the meeting time I have specified in the post? I will not consider you for the job if you do not respond correctly.

Table A2 (cont.): Example job advertisements for the *Translation Arabic to English* task

Low-wage, high flexibility job ad
Dear freelancer, I am looking for someone who can help me translate some text material from Arabic to English. Good knowledge of Arabic is required. The job can be done within two hours. I need it done on [redacted]. You can choose any two-hour window during the day. I will share the text at the beginning of our meeting. I am willing to pay USD 30 for the job. Fee: $30.00 Fixed-price Level: Entry level Project Type: One-time project Skills and Expertise: Arabic Screening question: Can you please respond with the time slot you prefer on [redacted]? I will not consider you for the job if you do not respond with a preferred time slot.
High-wage, high flexibility job ad
Dear freelancer, I am looking for someone who can help me translate some text material from Arabic to English. Good knowledge of Arabic is required. The job can be done within two hours. I need it done on [redacted]. You can choose any two-hour window during the day. I will share the text at the beginning of our meeting. I am willing to pay USD 40 for the job. Fee: $40.00 Fixed-price Level: Entry level Project Type: One-time project Skills and Expertise: Arabic Screening question: Can you please respond with the time slot you prefer on [redacted]? I will not consider you for the job if you do not respond with a preferred time slot.

Table A3: Gender differences in underbidding

	(1)	(2)	(3)	(4)	(5)
			Underbid		
Female Applicant	-0.04***	-0.05***	-0.05***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls	None	Task FE	Set 1	Set 2	Set 3
Mean of DV	0.14	0.14	0.14	0.14	0.14
Control mean of DV	0.13	0.13	0.13	0.13	0.13
Observations	12,016	12,016	12,016	11,972	11,548

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors reported in parentheses. 'Underbid' is an indicator variable that takes the value '1' when wage offered $-$ counteroffer > 0, '0' otherwise. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date. The number of total applicants is more than the sum of male and female applicants because we could not deduce the gender of a few applicants from their profile pictures and names. Set 1 consist of job level controls, like the level of flexibility and wage offered, and fixed effect for the client making the post as well as Task FE. Set 2 has all variables from Set 1 plus applicant-level predetermined controls: their prior jobs on the platform, contract hours, and earnings as well as their official country location. Set 3 consists of three more variables: whether the applicant provided a work sample with their application, log of self reported hourly wage, and how long their cover letter was.

Table A4: Description of online freelance platform job advertisements

Hourly Payment Jobs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Job Advert Contained Specific Work:				Job Duration:			
	Sample Size	Hourly Rate (in USD)	Time/Day	Deadline	Time/Day & Deadline	Meeting	< 1 months	$1-3$ months	$3-6$ months	> 6 months
Full Sample	41,749	26.12	0.20	0.27	0.37	0.29	0.38	0.26	0.11	0.25
Creative and Multimedia	15,621	26.13	0.18	0.25	0.35	0.44	0.45	0.22	0.10	0.23
Professional Services	7,009	28.10	0.23	0.28	0.39	0.18	0.37	0.23	0.11	0.28
Sales and Marketing	367	17.29	0.17	0.27	0.36	0.20	0.32	0.23	0.14	0.30
Software Dev. and Tech.	14,903	25.72	0.21	0.27	0.38	0.19	0.28	0.33	0.12	0.27
Writing and Translation	3,750	23.37	0.20	0.29	0.37	0.23	0.49	0.21	0.10	0.20

Fixed Payment Jobs

	(1)	(2)	(3)	(4)	(5)	(6)
			Job Advert Contained Specific Work:			
	Sample Size	Fixed Pay (in USD)	Time/Day	Deadline	Time/Day & Deadline	Meeting
Full Sample	22,977	552.99	0.19	0.28	0.37	0.31
Creative and Multimedia	10,519	344.15	0.19	0.28	0.39	0.48
Professional Services	2,811	644.46	0.20	0.29	0.38	0.18
Sales and Marketing	132	608.12	0.16	0.29	0.35	0.20
Software Dev. and Tech.	7,285	870.16	0.18	0.27	0.36	0.15
Writing and Translation	2,223	361.10	0.18	0.27	0.35	0.23

Notes: All job postings in the online freelance platform were scraped encompassing the categories related to the tasks posted for the experiment. 64,726 jobs were available of whom 64.5% were hourly payment jobs and the remaining 35.5% were fixed payment jobs. The average hourly wage rate for hourly payment jobs and the average fixed payment amount for fixed payment jobs are reported in column 2 (winsorized at the 99th percentile). The description of the job adverts were then analysed to find the share of jobs that specified the time/day(s) when the work was to be done (column 3), the job deadline only (column 4), both the time/day(s) when the work was to be done and the job deadline (column 5) and if the job description requested video meeting(s) with the applicant (column 6). Additionally, the hour payment jobs also specified the duration of work (in discrete categories) which is reported in columns 7-10.

Table A5: Association between hourly rate and job success rate of applications

	(1)	(2)	(3)	(4)	(5)	(6)
	Job Success Rate					
	All	Male	Female	All	Male	Female
Indicator(Hourly rate > Fee offered)	3.28***	3.78***	3.02***			
	(0.65)	(0.87)	(1.01)			
Ln(Hourly rate)				2.24***	2.40***	2.27***
				(0.57)	(0.71)	(1.15)
Task FE	✓	✓	✓	✓	✓	✓
Mean of DV	91.70	90.94	93.55	91.70	90.94	93.55
Control mean of DV	91.89	91.20	93.72	91.89	91.20	93.72
Observations	1,475	1,038	427	1,475	1,038	427

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. The dependent variable in all specifications is the job success rate of the applicant in all jobs completed on the platform visible on their public profile. The main explanatory variable in the first three columns is an dummy variable that indicates whether the rate mentioned on the applicant's public profile is higher than the hourly fee we offered for the job that the freelancer applied for. The explanatory variable in the last three columns is the natural log of the hourly rate of the freelancer.

Table A6: Association between job characteristics and hourly rate of applicant freelancers conditional on non-missing job success rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Indicator(Hourly rate > Fee offered)			Ln(Hourly rate)		
	All	Male	Female	All	Male	Female
Flexible Job	0.02	-0.00	0.06	0.01	-0.01	0.06
	(0.02)	(0.03)	(0.05)	(0.03)	(0.04)	(0.06)
High-wage Job	-0.12***	-0.12***	-0.14***	0.05*	0.06	0.04
	(0.02)	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)
Task FE	✓	✓	✓	✓	✓	✓
Mean of DV	0.31	0.32	0.27	2.68	2.69	2.67
Control mean of DV	0.30	0.32	0.23	2.67	2.69	2.63
Observations	1,466	1,038	427	1,466	1,038	427

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. The sample for this analysis is limited to those applicants who have a job success rate visible on their public profile. The outcome variable in the first three columns is an dummy variable that indicates whether the rate mentioned on the applicant's public profile is higher than the hourly fee we offered for the job that the freelancer applied for. The dependent variable in the last three columns is the natural log of the hourly rate of the freelancer. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date.

Table A7: Association between job characteristics and hourly rate of applicant freelancers

	(1)	(2)	(3)	(4)	(5)	(6)
	Indicator(Hourly rate >15 USD)			Ln(Hourly rate)		
	All	Male	Female	All	Male	Female
High wage low flexibility	0.02*	0.04***	-0.01	0.02	0.05**	-0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
Low wage high flexibility	0.01	0.01	0.02	0.01	-0.00	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
High wage high flexibility	0.03**	0.02*	0.03	0.03	0.02	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
Task FE	✓	✓	✓	✓	✓	✓
Mean of DV	0.34	0.35	0.34	2.54	2.54	2.54
Control mean of DV	0.34	0.35	0.31	2.54	2.55	2.50
Observations	12,056	8,036	3,992	11,966	7,978	3,961

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. The outcome variable in the first three columns is an dummy variable that indicates whether the rate mentioned on the applicant's public profile is higher than the hourly fee we offered for the job that the freelancer applied for. The dependent variable in the last three columns is the natural log of the hourly rate of the freelancer. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date, and a high wage job paid 40 USD for two hours. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date and paid 30 USD for two hours.

Table A8: The Impact of Flexibility on the Number of Applicants, conditional on Wage

	(1)	(2)	(3)	(4)
	Applicants			
	Total	# Male	# Female	% Female
Flexible Job	5.96***	2.90***	3.00***	1.50*
	(1.40)	(0.88)	(0.72)	(0.77)
High-wage Job	5.67***	3.05***	2.62***	1.97**
	(1.40)	(0.88)	(0.72)	(0.77)
Task FE	✓	✓	✓	✓
Mean of DV	37.79	25.19	12.51	28.29
Control mean of DV	34.71	23.67	10.98	27.37
Observations	319	319	319	319

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. Of the 320 jobs posted, one did not have any applicants. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date.

Table A9: The Impact of Flexibility on the Log of Number of Applicants

	(1)	(2)	(3)	(4)
	Applicants			
	Ln(applicants)	Ln(male applicants)	Ln(female applicants)	% Female
Flexible Job	0.16***	0.13***	0.26***	1.47*
	(0.04)	(0.05)	(0.07)	(0.82)
Task FE	✓	✓	✓	✓
Mean of DV	3.17	2.81	1.99	28.29
Control mean of DV	3.08	2.74	1.88	27.37
Observations	319	317	274	319

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. Of the 320 jobs posted, one did not have any applicants. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date. The omitted category comprises inflexible jobs that required freelancers to complete the task at a designated time (8 am to 10 am) on a pre-specified date.

Table A10: Difference in the Impact of Flexibility on the Number of Applicants of Different Genders

	(1) Ln(# applicants)	(2) # applicants	(3) Ln(# applicants)	(4) # applicants
Flexible job	0.13***	0.12***		
	(0.05)	(0.03)		
Flexible job × Female	0.13*	0.13**		
	(0.08)	(0.06)		
High-wage, low-flexibility, β_1			0.14**	0.13***
			(0.07)	(0.04)
Low-wage, high-flexibility, β_2			0.13**	0.12***
			(0.06)	(0.04)
High-wage, high-flexibility, β_3			0.27***	0.24***
			(0.06)	(0.04)
High-wage, low-flex × Female, β_4			0.10	0.17**
			(0.12)	(0.08)
Low-wage, high-flex × Female, β_5			0.19*	0.20***
			(0.11)	(0.08)
High-wage, high-flex × Female, β_6			0.18*	0.23***
			(0.11)	(0.07)
Task × Female FE	✓	✓	✓	✓
Specification	OLS	PPML	OLS	PPML
p-value [$\beta_1 = \beta_2$]			0.95	0.90
p-value [$\beta_1 + \beta_2 = \beta_3$]			0.96	0.80
p-value [$H_0 : \beta_4 = \beta_5$]			0.41	0.67
p-value [$H_0 : \beta_4 + \beta_5 = \beta_6$]			0.45	0.19
Mean of DV	2.45	19.06	2.45	19.06
Control mean of DV	2.30	15.94	2.30	15.94
Observations	586	631	586	631

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors reported in parentheses. Of the 320 jobs posted, one did not have any applicants. A flexible job was one where the freelancers could choose any two-hour window during which they wanted to work on the pre-specified date.