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## Gender Differences in Preference for Non-pecuniary Benefits in the Labour Market. Experimental Evidence from an Online Freelancing Platform.*

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**Abstract**

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***Study Pre-Registration***: The trial was registered prior to data collection.
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# 1 Introduction

Do women value non-pecuniary job attributes more than men? The answer to this question has important implications. First, the value men and women attach to various non-pecuniary benefits could explain part of the gender wage gap (Petrongolo, 2019). Women may have higher valuations for non-pecuniary benefits like flexibility because of social norms around who should shoulder the responsibility of household work. Flexibility might allow women to balance household and wage work (Sullivan, 2019).[1] Men and women may sort into different jobs based on non-pecuniary benefits, and firms may make lower wage offers to employees that demand expensive non-pecuniary benefits (Penner et al., 2022). Second, limited provision of these non-pecuniary benefits may cause women to stay out of the labor market. Female labor force participation in many developing countries, particularly in Asia, remains low even after accounting for the level of economic development. One explanation could be that frictions in the labor market often lead to limited provisions of non-pecuniary benefits that women prefer (Gupta, 1993; Macpherson and Hirsch, 1995; DeLeire and Levy, 2004; Grazier and Sloane, 2008; Kleinjans, 2009; Borker, 2018). Third, the increase in the use of internet technology, the rise of the gig economy, and the changes because of COVID-19 have led to increased provision of flexibility, opening up new debates around flexible working arrangements. A key question is whether firms must provide flexible working arrangements to attract better employees or to retain existing ones? The answer depends on how strong the preference for flexible working arrangements is. Gender differences in these preferences will have implications for the composition and diversity of the workforce. Thus, firms and policy-makers interested in an optimal response to these changes must therefore understand gender differences in preferences for these work arrangements (Cook et al., 2021; Gottlieb et al., 2021).[2]

Despite the far-reaching implications, answering the question is empirically challenging. We only observe the gender distribution of employees and the final package of pecuniary and non-pecuniary benefits that employees receive in equilibrium. Besides preferences for non-pecuniary benefits, several observed and unobserved demand- and supply-side factors play a role in determining the equilibrium. For example, in equilibrium, we may observe a higher proportion of women in flexible, low-paying desk jobs compared to less flexible, high-paying construction jobs. However, this sorting could also be a result of higher productivity of men in jobs that require physical

[1] That said, a large literature has documented gender differences in various attributes, like competitiveness, risk preference, and willingness to negotiate, that are relevant to wage determination (Croson and Gneezy, 2009; Azmat and Petrongolo, 2014; Exley and Kessler, 2019). However, the exact sources of these differences are often unknown. These differences can result from social norms, like the difference in competitiveness between matrilineal and patrilineal societies, or have evolutionary roots. Gender differences in preference for flexibility could also be a product of social norms or have other roots. In this study, we remain agnostic to the sources of these differences.

[2] Some studies argue that increased flexibility 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.

strength. An empirically observed association between certain non-pecuniary benefits and female employee shares across firms, industries, or sectors of the economy, therefore, does not necessarily imply that women prefer these benefits. Another complication in identifying a preference for a particular non-pecuniary benefit from observable real-world job choices is that jobs typically vary along several dimensions of non-pecuniary benefits. Jobs that provide greater workplace flexibility may also have lower travel requirements and could also be safer workplaces. It is, therefore, even more challenging to infer a preference for a specific non-pecuniary benefit from observed choices (Wiswall and Zafar, 2018; Wasserman, 2019; Adams-Prassl, 2020; He et al., 2021; Mas and Pallais, 2017).

In this paper, we address these empirical challenges by using a randomized audit study that focuses on a specific non-pecuniary benefit - the flexibility in choosing work hours during the day. We conduct our experiment on a major online freelance labor market platform. We post four otherwise identical job advertisements for each of 80 distinct tasks that vary only in their flexibility and the fee offered.[3] Flexible jobs allow the freelancer to choose any two-hour window during the day on a pre-specified date to complete the task. Inflexible jobs require the work to be completed within a pre-specified two-hour period of our choosing on the pre-specified date. The jobs also differ in the fee offered, a "high-wage" job posting offers a lump-sum one-time payment of USD 40 and a "low-wage" job posting offers a lump-sum one-time payment of USD 30. Thus, we have 320 job postings for 80 distinct tasks.[4] 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 our job postings within each task vary only along the dimension of flexibility or wage offered, we can attribute any difference between male and female application responses to a difference in the value attached to these dimensions of pecuniary and non-pecuniary benefits.

We believe that the context of online freelance labor markets is particularly relevant for answering this question. First, the online freelance market generates sizable levels of employment. Estimates suggest that there are 14 million active online workers. A substantial amount of the recent growth has come from developing countries of South Asia (Stephany et al., 2021).[5] Second, online labor markets are likely to become more important in the near future. Firms have made investments to adapt to remote working during the pandemic. These investments may have created new knowledge (possibly in management skills) in dealing with online remote working. The fixed

[3] These tasks cover a wide range of activities, like proofreading, writing, and coding.

[4] The four jobs corresponding to a 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 eighty tasks across days of the week and across user accounts. The order in which we posted the four jobs within a task was also random. Each job posting was open for a day, after which we hired one applicant at random to do the job and paid the promised wage.

[5] For example, the share of India in the online labor market has grown from 25 percent in 2017 to 33 percent in 2021 (Stephany et al., 2021).

nature of these investments along with the new knowledge is likely to create incentives for firms to work in an online remote environment, particularly by hiring online freelancers (Umar et al., 2021).[6] Third, despite the recent growth, participation of women in online labor markets continue to lag behind. Data from Online Labor Observatory shows that only 39 percent of the workers are female (Stephany et al., 2021). In addition, there are significant differences across countries and occupations. In the US, 41 percent of workers are females while only 28 percent of all online workers in India are females.

The results from the experiment suggest a gender difference in preference for flexibility. Flexible jobs attract a higher number of applications from both men and women. However, compared to inflexible jobs, flexible jobs lead to a 24 percent rise in the number of female applicants as opposed to a 12 percent 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 2 percent rise in the proportion of female applicants. Women are also more likely to put more effort into getting flexible jobs. Compared to inflexible jobs, women are more likely to make an application before men and include their previous work samples in the application for flexible jobs. Our results also suggest that the valuation for flexibility is sufficiently high, such that only a 10 USD increase in wage will not attract the same set of workers that value flexibility.

We contribute to the literature on gender and non-pecuniary benefits. A large literature has highlighted the importance of non-pecuniary benefits particularly for women (Goldin and Katz, 2011; Flabbi and Moro, 2012; Goldin, 2014; Sullivan and To, 2014; Bronson, 2014; Lavetti and Schmutte, 2016; Sorkin, 2018). However, most papers face the key challenge of empirically disentangling the role of preferences from other unobserved workers' firm and job level characteristics[7]. In addition, many papers in the literature face the data challenge of identifying the role of a specific non-pecuniary benefit. In this paper, we overcome these challenges by using an experiment that allows us to causally identify the role of preferences and at the same time we focus on a specific non-pecuniary benefit.

Recent literature has used experiments that elicit stated preferences (and willingness to pay) for various job characteristics (Wiswall and Zafar, 2018; Maestas et al., 2018; Mas and Pallais, 2017). These papers broadly find women have a higher willingness to pay for non-pecuniary job benefits. Wiswall and Zafar (2018) uses a sample of students from a top US university and finds that women are willing to give up higher salaries for job stability and job flexibility. Maestas et al. (2018) uses the American Working Conditions Survey and finds that women have a higher preference for jobs

[6]For a more detailed discussion, please see Harvard Business School (2020)

[7]For a literature review on this topic covering studies from several disciplines see Chung and Van der Lippe (2020)

with less physical work and more paid leaves. These papers validate the stated preferences by looking at real job attributes and find that the stated preferences match the actual job characteristics of the respondents. Though stated preferences match with real job attributes, we do not observe the set of jobs that the respondents are choosing in the real labor market. Thus, at least partially the concern remains that the stated preferences are not incentive-compatible. Our experiment adds to this by focusing on the revealed preferences of workers for flexibility. In this, our paper is most closely related to He et al. (2021). They conducted a field experiment using a Chinese job board and found that married females have a stronger preference for flexible jobs than married males. We add to the findings of He et al. (2021), by focusing on the worldwide online freelance labor market and on applications from a range of $80$ distinct job types that vary across several dimensions including being male or female-dominated.

Our paper also contributes to a large literature that investigates differences in preferences between men and women, particularly its implication on the labor market (Croson and Gneezy, 2009; Azmat and Petrongolo, 2014; Exley and Kessler, 2019). Broadly, the literature documents using both field and lab experiments that there are significant gender differences in various attributes like risk preferences and competitiveness that have an impact on labor market outcomes. We add to that literature by documenting gender differences in preferences for flexibility in jobs. Finally, our paper also adds to a recent and growing multidisciplinary literature that focuses on various aspects of the gig economy and the online freelance labor market (Stanton and Thomas, 2016, 2020; Cook et al., 2021; Stanton and Thomas, 2021). In general, the literature notes limited data availability on online freelance workers. We add to the literature by collecting a rich set of data on applicants and their applications. In addition, we also focus on the role of flexibility that may limit the participation of women in online labor markets.[8]

## 2 Conceptual Framework

We begin a simple conceptual framework to help interpret the results from the experiment. Consider 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 that the hired freelancer must work. In the flexible jobs, the applicants can choose to work any two-hour window during the day. Let us denote the set of possible time slots by $S = (1, 2, 3, ...., n)$.

[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. While workers have the option to choose between jobs, these strict deadlines limit the ability of workers to allocate their work flexibly within the day. This lack of flexibility in allocating the job within the day can be one factor that limits female labor force participation in the online labor market, both in the intensive and the extensive margin. 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 largely remains empirically unverified, a gap that this paper seeks to address.

Workers have an opportunity cost of working during these time slots. These opportunity costs capture the pecuniary costs of working, like forgone wages from alternative occupations, and non-pecuniary costs like 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 with $i \in I$, 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 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 fee $w$ to be done during time slot $\bar{s}$, if

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

However, if the same job with a fee $w$ 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 fee $w$b 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 fee $w$, the share of all applicants who will apply for the job will be given by:

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

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

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 $w_H = 40$ for 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 $5.99$ 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 using $F^F(c_{i\tilde{s}})$ 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

The experiment was conducted with ethical approval from the University of Western Australia [File # 021/ET000599]. We conducted our experiment on one of the largest online freelance labor market platform that attract clients and freelancers from around the world. The process of matching a freelancer with a client starts with a client posting a description of their job and a fee that they will pay a freelancer to complete it. The client may invite specific freelancers to apply for the job

[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.

or post the job for any freelancer who may be interested. Candidates apply with a cover letter, their proposed wage (a counteroffer), and other details, like past experience with similar work, that may indicate their competence and interest in the job. The client can then choose one or more freelancers to perform the task. Next, the client sends the chosen freelancer a contract specifying the agreed number of hours, a fee or an hourly wage, and a deadline for the work to be completed by. At this stage, the chosen freelancer can accept the contract, renegotiate with the client, or reject the offer.

Our experiment entails posting several jobs on this platform as clients and studying the responses we receive from the freelancers. Specifically, we post four variations ('jobs') of 80 distinct ***tasks*** that cover a wide range of activities. Our job advertisements resemble job advertisements typically posted on the platform. With 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 they provide in choosing work hours. A 'high-flexibility' (or just 'flexible') job allowed the applicant to choose any two-hour window during the day on a pre-specified date to complete the task. A 'low-flexibility' (or just 'inflexible') job required the applicant to start the job at a specified time (8 AM in their local time) on a pre-specified date and finish it within two hours. High-wage jobs offered 40 USD for two hours of work while low-wage jobs offered 30 USD. 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 two-hour work window in the case of low-flexibility jobs or outside the chosen two-hour window in the case of high-flexibility jobs. We take several steps to make sure that applicants understand these requirements before applying. First, the job postings contained information like the skills required and the expected time it might 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 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 screening question that requires the applicant to respond with the specified two-hour window (in case of low flexible jobs) or enter their chosen two-hour window (in case of high flexible jobs) before they can start the application. This made the requirements around work hours more salient. It is important to note that both the flexible and the inflexible job postings required the task to be completed in two hours. Thus, all four job variants for a task required the same skill set and the same amount of time commitment. The only difference was the flexibility in choosing the work hours or the wage.

We use five different accounts for posting and hiring freelancers for the 320 jobs. We randomly allocate 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, as much as possible, at the same time of the day, but in different weeks. This was in an attempt to keep other observed and unobserved factors the same across job postings within a task. All job postings were kept open for $24$ hours. Once a job posting was closed, we randomly hired an applicant to complete the jobs and paid them the promised wage. The order of posting of the four jobs within a task was random for each task. The title, the skills required, and other attributes were kept the same across the four job postings within a task. Table A2 provides an example. All the jobs required the job to be completed two days after the posting. For example, a high-flexibility job posted on Monday required the applicant to complete the job on Wednesday at a chosen time of their convenience. The jobs were posted on all days of the week for four weeks between November 2021 to December 2021.

The data we use for our analysis are the number of applications and information from the applicant profiles and applications. Applicants do not state their gender on their profile or the application.[11] 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 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 into male, female, or gender-uncertain groups using their profile pictures.[12]

[11]We could, in principle, have asked applicants to report their gender at the time of responding to the posting. However, applicants could have seen it as a signal of gender discrimination. Such a perverse signal might disincentivize women applicants. Another reason we avoided explicitly asking for their gender is because job postings on this platform rarely ask applicants to report their gender. Doing so would have made our postings stand out, and might have impacted the response rates.

[12]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 a task, any person-specific bias is likely to impact both flexible and inflexible jobs in the same manner. We could have used an algorithm to infer gender from the names of the applicants (Blevins and Mullen, 2015). Though algorithms that predict gender from names work well for Western countries like the US and the UK, they are not as accurate for predicting gender from names of applicants from such a wide range of countries that we observe in our experiment. In addition, the accuracy of such algorithms depends on the sample size they are trained on. Since we had a manageable number of applicants, we believe that manual classification is less prone to error than other methods. However, one possibility is that there may be an unconscious bias on our part in inferring gender. We had two external research assistants reclassify the applicants for seventy-two jobs, chosen randomly, into *male*, *female*, and *gender unclear* categories. Of the $2,824$ applicants they categorized, only $45$ applicants ($1.6\%$) had a gender different from what was initially entered. Moreover, this mismatch was not different across inflexible and flexible jobs.

## 4 Empirical Specification

Our experiment was pre-registered with the American Economic Association registry. The primary aim of our empirical exercise was to understand the causal effect of flexibility in choosing work hours on the number of applications. For this, we estimated the following specification:

$$Y_j = \alpha + \beta \text{ Flexible}_j + X_j + \epsilon_j \tag{1}$$

where $Y_j$ is one of the following dependent variables of interest for job posting $j$: total number of all applicants, male applicants, female applicants, and the share of female applicants.$Flexible_j$ takes a value of '1' if the job posting allows the freelancers to choose their work hours, '0' otherwise. $X_j$ denotes task fixed effects. $\epsilon_j^s$ is the error term.

The main coefficient of interest is $\beta$. Since, for every flexible job posting, we also have an otherwise identical job posting that only differs in the flexibility of choosing work hours, $\beta$ captures the causal effect of flexibility on labor supply. Because of our interest in understanding the gender difference in demand for flexibility, we compare the estimates of $\beta$ across male and female applicants. A higher $\beta$ (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 wage and flexibility, we estimated the causal effects of each type of job posting.

$$Y_j = \alpha^s + \beta_1^s \text{ HWLF}_j + \beta_2^s \text{ LWHF}_j + \beta_3^s \text{ HWHF}_j + X_j + \epsilon_j^s \tag{2}$$

where $Y_j$ is one of the following dependent variables of interest for job posting $j$: total number of all applicants, male applicants, female applicants, and the share of female applicants. $HWLF_j$ is an indicator variable that denotes jobs that have a high wage but no greater flexibility than a low-wage-low-flexibility job. $LWHF_j$ and $HWHF_j$ denote low-wage-high-flexibility and high-wage-low-flexibility jobs, respectively. $X_j$ denotes task fixed effects. $\epsilon_j^s$ is the error term. Since we have two wage offers and both flexible and inflexible jobs for each of the wage offers, we can compare the marginal effects of flexibility at higher and lower wages. The marginal effect of flexibility at lower wages is given by $\beta_2^s$ and the marginal effect of flexibility at higher wages is given by $\beta_3^s - \beta_2^s$. 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 ($\beta_1^s$) with the response to the provision of flexibility ($\beta_2^s$).

## 5 Results

Table 1 presents a summary of the characteristics of applicants to our job postings. As the results show, women form only one-third of all applicants. This is despite our job postings covering a wide range of tasks (80 distinct tasks) that include both female-dominated tasks, like translation and proofreading, and male-dominated tasks, like financial consulting and coding. The Online Labour Observatory at the University of Oxford tracks projects across major online labour market platforms (including our platform) from across the world. Their estimate suggests that women form 39 percent of all workforce in online labour markets (Stephany et al., 2021). In Figure A1, we compare the country-wise distribution of our applicants and the data from the Online Labour Observatory. As the figure indicates, the distribution of country profiles in our data closely matches that of the Online Labour Observatory. Both these comparisons indicate that our sample from the experiment is representative of the gender composition and country profiles of online labour markets. Other takeaways 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.

Does flexibility lead to more job applications? Table 2 reports the findings for our primary outcome of interest - number of applications. As Column 1 shows, jobs that offer flexibility attract more applications compared to a job with no flexibility. On average, flexible jobs received 5.99 more applicants than inflexible jobs. Comparing this effect with the average number of applications per job, this is about a 15.8 percent increase in the number of applications.

Is the effect of flexibility different across genders? Column 2 and 3 of Table 2 presents the effect of an increase in flexibility on the number of male and female applications, respectively. Compared to inflexible flexible jobs, flexible jobs attract 2.92 more male applicants and 3.03 more female applicants. While the estimated effect magnitudes are similar for males and females, the percentage change with respect to the mean is significantly larger for females. Only a third of all applicants are 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. Thus, of the pool of workers on the platform, a larger proportion of women respond to flexibility than men. One can interpret this as elasticity of labor supply with respect to flexibility being twice as high for women than for men. Our results complement the recent findings from a study of the gender wage gap in online labour markets by Adams-Prassl (2020). The study finds that women in online freelance labour markets earn less because they need schedule flexibility (taking breaks between tasks) because of childcare responsibilities. Our results add to that by showing that women are more likely to select into jobs that allow such schedule flexibility.

Does flexibility in jobs lead to a more gender diverse workforce? Since women have higher

**Table 1:** Summary Statistics

| | Females | | Males | | Difference |
|---|---|---|---|---|---|
| | N | Mean | N | Mean | in means |
| | All jobs | | | | |
| Counteroffer | 4019 | 34.68 | 8021 | 33.92 | 0.77*** |
| Fee offered - Counteroffer | 4019 | 0.84 | 8021 | 1.39 | -0.55*** |
| Underbid | 4028 | 0.12 | 8054 | 0.16 | -0.04*** |
| Overbid | 4028 | 0.02 | 8054 | 0.02 | 0 |
| Position percentile | 4028 | 52.2 | 8054 | 50.89 | 1.31** |
| Cover letter length | 3844 | 416.81 | 7796 | 398.13 | 18.67** |
| Share provided a work sample | 4028 | 0.17 | 8054 | 0.17 | 0 |
| Total prior contracts | 4028 | 5.49 | 8054 | 7.19 | -1.7** |
| Total prior contracted hours | 4028 | 15.3 | 8054 | 14.29 | 1.01* |
| Total prior earnings | 4028 | 925.16 | 8054 | 893.79 | 31.37 |
| | Inflexible jobs | | | | |
| Counteroffer | 1766 | 34.84 | 3775 | 34.02 | 0.82*** |
| Fee offered - Counteroffer | 1766 | 0.91 | 3775 | 1.31 | -0.4** |
| Underbid | 1769 | 0.11 | 3796 | 0.15 | -0.04*** |
| Overbid | 1769 | 0.01 | 3796 | 0.02 | -0.01** |
| Position percentile | 1769 | 52.65 | 3796 | 50.89 | 1.76** |
| Cover letter length | 1603 | 430.22 | 3561 | 398.61 | 31.62** |
| Share provided a work sample | 1769 | 0.15 | 3796 | 0.16 | -0.01 |
| Total prior contracts | 1769 | 5.34 | 3796 | 8.34 | -3** |
| Total prior contracted hours | 1769 | 16.79 | 3796 | 14.93 | 1.87 |
| Total prior earnings | 1769 | 1070.95 | 3796 | 1053.68 | 17.27 |
| | Flexible jobs | | | | |
| Counteroffer | 2253 | 34.56 | 4246 | 33.82 | 0.74*** |
| Fee offered - Counteroffer | 2253 | 0.79 | 4246 | 1.46 | -0.67*** |
| Underbid | 2259 | 0.12 | 4258 | 0.16 | -0.04*** |
| Overbid | 2259 | 0.02 | 4258 | 0.02 | 0 |
| Position percentile | 2259 | 51.85 | 4258 | 50.89 | 0.96 |
| Cover letter length | 2241 | 407.21 | 4235 | 397.74 | 9.47 |
| Share provided a work sample | 2259 | 0.18 | 4258 | 0.17 | 0.01 |
| Total prior contracts | 2259 | 5.6 | 4258 | 6.17 | -0.57 |
| Total prior contracted hours | 2259 | 14.13 | 4258 | 13.73 | 0.4 |
| Total prior earnings | 2259 | 810.99 | 4258 | 751.24 | 59.76 |

*Sources*: Authors' calculation based on data collected from the experiment.
*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 fee offered and the counteroffer made by an applicant implies that the freelancer's counteroffer was higher (lower) than the proposed fee. 'Underbid' is an indicator variable that takes the value '1' when fee offered - counteroffer $> 0$, '0' otherwise. 'Overbid' takes the value '1' when fee 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 | 5.99*** | 2.92*** | 3.03*** | 1.48* |
| | (1.44) | (0.90) | (0.74) | (0.80) |
| Task FE | ✓ | ✓ | ✓ | ✓ |
| p-value [$\beta^{male} = \beta^{female}$] | | | | 0.96 |
| Mean of DV | 37.87 | 25.25 | 12.54 | 28.26 |
| Control mean of DV | 34.78 | 23.73 | 10.99 | 27.31 |
| R-squared | 0.94 | 0.94 | 0.92 | 0.89 |
| Observations | 319 | 319 | 319 | 319 |

*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1. 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.

elasticity with respect to flexibility than men, flexible jobs can lead to a more gender-diverse workforce. Our results from Table 2 and Table 3 suggest that is indeed the case. Column $4$ of Table 2 suggests that flexible jobs lead 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.[13] Column $4$ of Table 3 reports similar results. High-flexibility jobs lead to a $3$ percentage point rise in the proportion of female applicants, a $10.6$ percent rise over the average share of women applicants. Flexible jobs increase the gender diversity of the application pool. These results have implications for employers and policymakers interested in improving gender diversity in the online labor market.

How does the effect of flexibility compare at higher and lower wages? Table 3 presents the findings. Compared to men, the effects of flexibility are higher for women at all wages. Next, the effects of flexibility for men are 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 is slightly higher at lower wages, but the difference between the effect sizes at the two wages is statistically insignificant ($\beta_3^{female} - \beta_1^{female} = 2.37$ at the higher wage and $\beta_2^{female} = 3.66$ at the lower wage). A related question is whether

[13] 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 weigh 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 services that are not traded as frequently. Our results are qualitatively similar even if we do not weigh the observations.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Applicants | | | |
| VARIABLES | Total | # Male | # Female | % Female |
| High-wage, low-flexibility job | 6.39*** | 3.10** | 3.29*** | 3.46*** |
| | (1.97) | (1.24) | (1.02) | (1.15) |
| Low-wage, high-flexibility job | 6.63*** | 2.92** | 3.66*** | 2.99** |
| | (1.98) | (1.25) | (1.03) | (1.16) |
| High-wage, high-flexibility job | 11.70*** | 5.99*** | 5.66*** | 3.70*** |
| | (1.97) | (1.24) | (1.02) | (1.12) |
| Task FE | ✓ | ✓ | ✓ | ✓ |
| p-value [$\beta_1 = \beta_2$] | 0.90 | 0.88 | 0.72 | 0.67 |
| p-value [$\beta_1 + \beta_2 = \beta_3$] | 0.64 | 0.99 | 0.38 | 0.08 |
| p-value [$\beta_1^{male} = \beta_1^{female}$] | | | | 0.95 |
| p-value [$\beta_2^{male} = \beta_2^{female}$] | | | | 0.78 |
| p-value [$\beta_3^{male} = \beta_3^{female}$] | | | | 0.91 |
| Mean of DV | 37.88 | 25.25 | 12.54 | 28.26 |
| Control mean of DV | 31.59 | 22.18 | 9.35 | 26.73 |
| R-squared | 0.94 | 0.94 | 0.92 | 0.90 |
| Observations | 319 | 319 | 319 | 319 |

*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Of the 320 jobs posted, one did not have any applicants. A high-wage, low-flexibility job offered a fixed fee 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 fee 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.

there are 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 have a similar willingness to trade off higher wages and flexibility. Providing flexibility has a similar effect on the number of male applicants as a $10$ USD rise in the fee offered ($\beta_1^{male} = 3.10$, $\beta_2^{male} = 2.92$). Similarly, providing flexibility also has a similar effect as a $10$ USD rise in wages ($\beta_1^{female} = 3.29$, $\beta_2^{female} = 3.66$) on women. In percentage terms, this translates into a $12.3$ percent increase in the number of male applicants because of a ten-dollar increase in the fee as opposed to an $11.6$ percent rise in response to flexibility. For women, a similar $10$ USD rise in wages leads to a $26.2$ percent rise in the number of female applications as opposed to a $29.2$ percent rise in applications when offered flexibility. Thus, for both men and women, a $10$ USD rise in wages attracts the same number of applicants as the provision of more flexibility. How do we make sense of these results? One possibility is that, for both men and women, there is sufficient heterogeneity in preference for pecuniary and non-pecuniary benefits, and applicants are reluctant to substitute one for the other. Some applicants might have strong preferences for flexibility. They might apply to both high- and low-wage jobs as long as they are flexible. Thus, the marginal effects of flexibility could be the same at high and low wages. However, a similar number of applicants might apply only to high-wage jobs regardless of flexibility. In such a scenario, we will find that the gender difference in the trade-off between higher wages and flexibility to be the same.

Do women put more effort into getting selected for these 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 at how quickly applicants apply to our job advertisement. For this, we rank all applicants by their position in the application queue. Since all job advertisements were open for applications for the same amount of time, we can compare the proportion of female applicants among "early" applicants across flexible and inflexible jobs.[14] Table 4 reports the effect of providing flexibility on the proportion of female applicants among "early" applicants. We find a higher proportion of women among the earliest $25$ and $50$ percentile of applicants. As indicated by the p-value for $\beta = 1.48$, the effect at the $25^{th}$ percentile is significantly higher than the effect of flexibility on the overall share of female applicants ($1.48$) reported in Table 2. The changes in the share of women among the earliest 10 or 75 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 making quicker applications than men.[15]

[14]Please note that the applicants were not aware that the job application would close exactly twenty-four hours after posting. The job posting did not mention any deadline for application. However, the job posting mentioned the specific date on which the job needed to be done. While the date of the job is an implicit deadline, we closed the job posting before the job date.

[15]It is important to emphasize that we do not observe the exact time of these applications. 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

**Table 4:** 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 | 0.99 | 4.69*** | 2.27** | 1.46 |
| | (2.30) | (1.50) | (1.06) | (0.94) |
| Task FE | ✓ | ✓ | ✓ | ✓ |
| p-value[$\beta = 1.48$] | 0.83 | 0.03 | 0.46 | 0.98 |
| Mean of DV | 21.07 | 24.98 | 26.53 | 26.97 |
| Control mean of DV | 21.55 | 23.42 | 25.40 | 26.13 |
| R-squared | 0.56 | 0.74 | 0.82 | 0.86 |
| Observations | 319 | 319 | 319 | 319 |

*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 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 weighed by the number of total applicants in each job.

**Table 5:** Cover letter length and work samples

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Cover letter length | | | Work sample provided | | |
| | All applicants | Males | Females | All applicants | Males | Females |
| Flexible job | -11.29 | -2.52 | -29.62* | 0.01* | 0.01 | 0.03** |
| | (8.59) | (10.27) | (15.81) | (0.01) | (0.01) | (0.01) |
| Task FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| p-value [$\beta^{male} = \beta^{female}$] | | | 0.18 | | | 0.18 |
| Mean of DV | 404.30 | 398.13 | 417.78 | 0.17 | 0.17 | 0.17 |
| Control mean of DV | 408.42 | 398.61 | 430.80 | 0.16 | 0.16 | 0.15 |
| R-squared | 0.03 | 0.04 | 0.05 | 0.08 | 0.09 | 0.08 |
| Observations | 11,640 | 7,796 | 3,817 | 12,082 | 8,054 | 4,000 |

*Sources*: Authors' calculation based on data collected from the experiment.
*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. '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.

Second, we look at whether the applicants attached a previous work sample with their applications to indicate the ability or expertise to complete the job and the length of the cover letter they wrote as a part of their application. Attaching a previous work sample takes effort and time and also indicates the willingness of the applicants to signal their quality to the employer. The length of the cover letter may also signal effort. The findings, reported in Table 5, 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 for flexible job applications, indicating their 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 applications. The impact on cover letter length 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 making the letter more concise and precise. However, it is important to note that the results may also reflect differences in the composition of applicants rather than their effort. It is possible that marginal applicants to flexible jobs are of higher quality and thus provide a better application package.

One proxy of quality is experience. Experienced women might prefer showcasing their past

respond faster.

**Table 6:** Flexibility and applicant experience

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Total prior contracts | | | Total prior contracted hours | | | Total prior earning | | |
| | All | Male | Female | All | Male | Female | All | Male | Female |
| Flexible job | -1.39** | -2.09*** | 0.14 | -2.01 | -1.49 | -3.39 | -277.07** | -288.05** | -287.27 |
| | (0.62) | (0.80) | (0.94) | (1.40) | (1.71) | (2.46) | (112.07) | (136.16) | (199.50) |
| Task FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| p-value [$\beta^m = \beta^f$] | | | 0.08 | | | 0.54 | | | 1.00 |
| Mean of DV | 6.62 | 7.19 | 5.51 | 14.63 | 14.29 | 15.19 | 904.25 | 893.79 | 930.52 |
| Control mean of DV | 7.39 | 8.34 | 5.37 | 15.52 | 14.92 | 16.89 | 1059.17 | 1053.68 | 1077.02 |
| R-squared | 0.03 | 0.03 | 0.05 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.05 |
| Observations | 12,082 | 8,054 | 4,000 | 12,082 | 8,054 | 4,000 | 12,082 | 8,054 | 4,000 |

*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1. 'Total prior contracts' is the number of contracts an applicant had completed on the platform by the time of their application for our advertised job. 'Total prior contracted hours' and 'Total prior earning', similarly, capture the number of hours they had worked on job contracts and the earnings they had had through the platform. 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.

work as evidence of ability than writing longer cover letters, which is essentially cheap talk. We cannot entirely rule out this possibility. However, in Table 6, we show that women applicants to flexible jobs are no more experienced, as measured by the number of prior jobs, hours worked, and earnings from the platform, than female applicants to inflexible jobs. That said, it is possible that these candidates have other unobserved experience, like working outside the platform, which might allow them to have work samples but may not show up as experience on the platform.

Third, we look at counteroffers made by applicants. Although we specified the fee in 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 understand that counteroffers do not affect effort. Instead, it could be driven by several other factors, like willingness to negotiate and reservation wages. We report our findings on counteroffers made by applicants in Table 7. As the results indicate, less than two percent of the candidates overbid and around 14 percent of candidates underbid. One interesting pattern that emerges is men are much more likely to underbid than women. We further explore this in Table A3. As the results in Column (1) indicate, women indeed are less likely to underbid. The results show that this translates into a 29 percent reduction over the average. One explanation for men underbidding more than women could be that male applicants may have a lower reservation wage, on average. Unfortunately, we do not observe reservation wages. In the columns that follow, we control for other task, job, and applicant characteristics as well as our

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

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Fee offered - Counteroffer | | | Underbid | | | Overbid | | |
| | All | Male | Female | All | Male | Female | All | Male | Female |
| Flexible job | 0.05 | 0.14 | -0.11 | 0.01** | 0.01* | 0.02 | 0.00 | -0.00 | 0.01*** |
| | (0.11) | (0.14) | (0.16) | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) |
| Task FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| p-value [$\beta^m = \beta^f$] | | | 0.24 | | | 0.82 | | | 0.02 |
| Mean of DV | 1.21 | 1.39 | 0.84 | 0.14 | 0.16 | 0.12 | 0.02 | 0.02 | 0.02 |
| Control mean of DV | 1.18 | 1.31 | 0.91 | 0.14 | 0.15 | 0.11 | 0.02 | 0.02 | 0.01 |
| R-squared | 0.02 | 0.03 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.04 |
| Observations | 12,040 | 8,021 | 4,019 | 12,082 | 8,054 | 4,028 | 12,082 | 8,054 | 4,028 |

*Notes*: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1. A negative (positive) difference between the fee offered and the counteroffer implies that the freelancer's counteroffer was higher (lower) than the proposed fee. 'Underbid' is an indicator variable that takes the value '1' when fee offered - counteroffer $>$ 0, '0' otherwise. 'Overbid' takes the value '1' when fee 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.

crude measures of effort to proxy for their reservation wage. As the results indicate, 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 that involves underbidding. 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 a negotiation, a setting similar to ours. Our results provide a new insight from online labour markets - men are also more likely to undercut wages to secure a job. The negotiation, therefore, can happen in either direction. That said, we cannot comment on the reasons behind the gender differences in willingness to negotiate. This is distinct from the results in Table 7 that indicate that there is no difference in underbidding behavior in response to flexible jobs for either men or women.

**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 | 2.42*** | 1.10** | 1.29*** | 2.77* | 3.66*** | 1.90*** | 1.75*** | 0.45 |
| | (0.78) | (0.53) | (0.39) | (1.54) | (0.94) | (0.58) | (0.49) | (1.09) |
| Observations | 307 | 307 | 307 | 307 | 315 | 315 | 315 | 315 |
| R-squared | 0.94 | 0.92 | 0.92 | 0.69 | 0.91 | 0.91 | 0.88 | 0.84 |
| 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 |
| p-value [$\beta^{male} = \beta^{female}$] | | | | 0.84 | | | | 0.91 |
| ***Panel B*** | Applicants from low-FLFP countries | | | | Applicants from high-FLFP countries | | | |
| Flexible job | 3.02*** | 1.67*** | 1.35*** | 1.20 | 3.15*** | 1.40*** | 1.71*** | 2.47* |
| | (0.84) | (0.61) | (0.36) | (1.20) | (0.89) | (0.50) | (0.56) | (1.45) |
| Observations | 311 | 311 | 311 | 311 | 311 | 311 | 311 | 311 |
| R-squared | 0.93 | 0.94 | 0.87 | 0.76 | 0.92 | 0.89 | 0.91 | 0.78 |
| 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 |
| p-value [$\beta^{male} = \beta^{female}$] | | | | 0.85 | | | | 0.79 |
| ***Panel C*** | Applicants from low-GDP pc countries | | | | Applicants from high-GDP pc countries | | | |
| Flexible job | 4.31*** | 2.07*** | 2.21*** | 1.54 | 1.79*** | 0.92*** | 0.86*** | 2.99 |
| | (1.14) | (0.74) | (0.57) | (0.94) | (0.51) | (0.35) | (0.30) | (2.13) |
| Observations | 316 | 316 | 316 | 316 | 292 | 292 | 292 | 292 |
| R-squared | 0.94 | 0.94 | 0.92 | 0.85 | 0.89 | 0.83 | 0.89 | 0.67 |
| 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 |
| p-value [$\beta^{male} = \beta^{female}$] | | | | 0.94 | | | | 0.93 |
| ***Panel D*** | Applicants from Asia | | | | Applicants from outside Asia | | | |
| Flexible job | 3.55*** | 1.77*** | 1.76*** | 0.83 | 2.52*** | 1.20*** | 1.29*** | 3.63** |
| | (1.01) | (0.67) | (0.49) | (1.42) | (0.71) | (0.45) | (0.41) | (1.56) |
| Observations | 311 | 311 | 311 | 311 | 313 | 313 | 313 | 313 |
| R-squared | 0.94 | 0.94 | 0.91 | 0.72 | 0.93 | 0.91 | 0.91 | 0.73 |
| Task FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Mean of DV | 21.57 | 15.04 | 6.49 | 26.51 | 16.59 | 10.38 | 6.17 | 30.16 |
| Control mean of DV | 19.74 | 14.10 | 5.60 | 26.30 | 15.21 | 9.70 | 5.48 | 27.64 |
| p-value [$\beta^{male} = \beta^{female}$] | | | | 0.99 | | | | 0.92 |

*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.

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. In Table 8, we study the difference in the effect of flexibility between countries with high and low fertility rates. 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 those women who have 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, we report the effect of allowing flexibility in choosing work hours separately for countries that have high fertility and low fertility. We do not find any significant difference in effect for women (relative to the mean) across countries with high and low fertility. The elasticity of response is the same for both high and low-fertility countries. 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 much by the number of children. For example, the time commitment to cook food or to take a child to school could be a fixed cost and thus could be the same regardless of the number of children. However, it is important to keep in mind such country-level averages are coarse measures and our results can reflect the coarseness of the measure rather than any mechanism.

Does lack of flexibility limit female labour force participation? Though our results cannot directly speak to it, a comparison of the effect of flexibility between countries that have low and high female labour force participation rates can provide some insights into that question. In Panel B of Table 8, we present the results separately for countries with high and low female labour force participation rates. The effect of flexibility (relative to the mean) is higher for women in low-female labour force participation countries. The results for men do not differ across these countries. One possibility is that the demand of flexible jobs is higher in these countries and a limited availability of such jobs leads to low female labour force participation. When we post such jobs, we find a large response. That said, 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 labour 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, either for men or for women. It is important to keep in mind per capita GDP is a good predictor of many observables like the availability of other 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 that the difference in preference for flexibility is unlikely to be explained by factors for which per capita GDP serves as a good proxy. That said, it is worth pointing out that per capita GDP is a very coarse measure of the social conditions that our applicants may face. Finally, we do not find that the effects vary between Asian and non-Asian countries. This suggests that our results are not entirely driven by countries like India, Pakistan and Bangladesh that have a large participation in the online labour market.

## 6 Discussion and Conclusion

In this paper, we asked, do workers value non-pecuniary benefits like flexibility and are there gender differences in that valuation? We argued that the answer to this question has important implications. In light of the ever evolving nature of the work place, it important for firms to know the demand for various non-pecuniary benefits. In addition, any potential gender difference in valuation of these non-pecuniary benefits has important implications in explaining gender inequalities in the labour market. For example, lack of supply of non-pecuniary benefits like flexibility can be a potential reason that limits participation of women in the labour market in developing countries.

However, we argued that despite the importance of this question, several empirical challenges make answering this question difficult. Studies that use observational data cannot causally disentangle the 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 separate out the effect of one non-pecuniary benefit like flexibility in choosing the work time. Though studies that use stated preferences overcome these problems, stated preferences are often not incentive-compatible.

In this paper, we overcome these challenges by using an audit experiment. We posted matched pair of jobs on a major online freelance labour market platform that only differed in the flexibility (of the work time) offered. Since these jobs are identical on all other attributes, except for flexibility, any difference in applications to these jobs is a result of preference for flexibility. We find that flexible jobs attract more applications. Though flexible jobs attract a higher number of applications from both men and women, the effects are twice as large for women in percentage terms. Flexible jobs lead 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.

That said, it is important to interpret our results in the context of the limitations of the nature of the experiment. First, though our results are internally valid, we cannot speak to how our results would hold in a general population that includes the brick-and-mortar labour market. The effects can go either way. It is possible that workers in freelance labour markets prefer flexibility more than workers in the brick-and-mortar labour market and we are overestimating the demand for flexibility. Yet, it is also possible that since freelance labour markets already offer so much flexibility, the marginal valuation for flexibility is lower in this market. Moreover, since the contracts in the freelance labour market are short-term, workers may care less about flexibility. Yet, on the other hand, since the contracts are short-term, the benefits from giving up flexibility are also less. Second, our results do not fully speak to the underlying reason behind the gender difference in demand for flexibility. It is possible that women prefer flexibility because of an extra burden for household work and any changes in the structure of intra-household bargaining will lead to a change in such preferences for flexibility. Though we explore some directions, our results on this question are inconclusive. Thus, we remain agnostic on the sources of gender differences in preferences for flexibility. Finally, we are only referring to a specific type of flexibility and the preferences for other types of flexibility may be quite different. For example, our experiment does not speak to the gender differences in preference for work from home.

Our experiment and the results still carry significant relevance for policymakers interested in increasing female labour force participation. The preference for non-pecuniary benefits like flexibility is a somewhat ignored aspect in the policy discussions that aim to increase female labour force participation. Mostly, these discussions focus on issues like skill development, access to finance, social norms and networks, education, and organization of the family. However, the limited availability of non-pecuniary benefits like flexibility is often an important barrier to participation in labour markets. A strong preference for non-pecuniary benefits like flexibility and a limited supply of these benefits in the labour market may explain low female labour force participation.

This mechanism can potentially explain some of the empirical facts that we observe from labour markets in developing countries. For example, we observe that despite a rise in education and reported bargaining power of women in India, fewer women are participating in the labour market. One explanation could be that as income levels are rising, women's preference for flexibility is getting stronger and they are withdrawing from the labour market because there are a limited number of jobs that provide the desired set of non-pecuniary benefits. Wage labour in agriculture or other low-skilled service sector, like as a housemaid may be a last resort in the face of financial distress with limited supply elasticity. As income levels rose, women may be trading off pecuniary returns for flexibility, thus withdrawing from the labour market. Similarly, a strong preference for non-pecuniary benefits may also explain the observation that though access to micro-credit causes a modest rise in income and consumption, we observe large shifts from wage labour to self-employment. Women are potentially using access to credit to choose jobs that provide non-pecuniary benefits, like running a business from the proximity of home, that they value.

What can policymakers do in such settings? Assuming that firms are aware of these differences in preferences but find it costly to provide these non-pecuniary benefits, policymakers could provide incentives like 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 labour market. Firms that are unaware of worker preferences may invest in providing more non-pecuniary benefits. Thus, we believe that our results contribute significantly to the policy discussions on encouraging female labour force participation.

# References

Adams-Prassl, A. (2020). The gender wage gap on an online labour market: The cost of interruptions. CEPR Press Discussion Paper No. 14294. URL: https://cepr.org/publications/dp14294.

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

Blevins, C. and L. Mullen (2015). Jane, John... Leslie? A historical method for algorithmic gender prediction. *DHQ: Digital Humanities Quarterly 9*(3), 2–2.

Borker, G. (2018). Safety first: Perceived risk of street harassment and educational choices of women. Job Market Paper, Department of Economics, Brown University. URL: https://data2x.org/wp-content/uploads/2019/11/PerceivedRiskStreetHarassmentandEdChoicesofWomen_Borker.pdf. [Retrieved: 2021-03-14].

Bronson, M. A. (2014). Degrees are forever: Marriage, educational investment, and life-cycle labor decisions of men and women. Unpublished manuscript. URL: https://cowles.yale.edu/sites/default/files/files/conf/2014/st_bronson.pdf. [Retrieved: 2021-10-12].

Chung, H. (2019). 'Women's work penalty' in access to flexible working arrangements across Europe. *European Journal of Industrial Relations 25*(1), 23–40.

Chung, H. and T. Van der Lippe (2020). Flexible working, work–life balance, and gender equality: Introduction. *Social Indicators Research 151*(2), 365–381.

Cook, C., R. Diamond, J. V. Hall, J. A. List, and P. Oyer (2021). The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers. *The Review of Economic Studies 88*(5), 2210–2238.

Croson, R. and U. Gneezy (2009). Gender differences in preferences. *Journal of Economic literature 47*(2), 448–74.

DeLeire, T. and H. Levy (2004). Worker sorting and the risk of death on the job. *Journal of Labor Economics 22*(4), 925–953.

Exley, C. L. and J. B. Kessler (2019). The gender gap in self-promotion. Technical Report, National Bureau of Economic Research. URL: https://www.nber.org/system/files/working_papers/w26345/w26345.pdf. [Retrieved: 2021-10-12].

Flabbi, L. and A. Moro (2012). The effect of job flexibility on female labor market outcomes: Estimates from a search and bargaining model. *Journal of Econometrics 168*(1), 81–95.

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

Goldin, C. and L. F. Katz (2011). The cost of workplace flexibility for high-powered professionals. *The Annals of the American Academy of Political and Social Science 638*(1), 45–67.

Gottlieb, C., J. Grobovšek, M. Poschke, and F. Saltiel (2021). Working from home in developing countries. *European Economic Review 133*, 103679.

Grazier, S. and P. J. Sloane (2008). Accident risk, gender, family status and occupational choice in the UK. *Labour Economics 15*(5), 938–957.

Gupta, N. D. (1993). Probabilities of job choice and employer selection and male-female occupational differences. *American Economic Review 83*(2), 57–61.

Harvard Business School (2020). The gig is up. The Harvard Gazette. URL: https://news.harvard.edu/gazette/story/2020/11/during-covid-19-remote-freelance-work-is-on-the-rise/.

He, H., D. Neumark, and Q. Weng (2021). Do workers value flexible jobs? A field experiment. *Journal of Labor Economics 39*(3), 709–738.

Hernandez-Arenaz, I. and N. Iriberri (2019). A review of gender differences in negotiation. Oxford Research Encyclopedia of Economics and Finance. URL: https://oxfordre.com/economics/view/10.1093/acrefore/9780190625979.001.0001/acrefore-9780190625979-e-464. [Retrieved: 2023-01-12].

Kleinjans, K. J. (2009). Do gender differences in preferences for competition matter for occupational expectations? *Journal of Economic Psychology 30*(5), 701–710.

Lavetti, K. and I. M. Schmutte (2016). Estimating compensating wage differentials with endogenous job mobility. Working Paper. URL: https://www.bc.edu/content/dam/bc1/schools/mcas/economics/pdf/seminars/CDEM_v21.pdf. [Retrieved: 2022-01-06].

Leibbrandt, A. and J. A. List (2015). Do women avoid salary negotiations? evidence from a large-scale natural field experiment. *Management Science 61*(9), 2016–2024.

Lott, Y. and H. Chung (2016). Gender discrepancies in the outcomes of schedule control on overtime hours and income in germany. *European Sociological Review 32*(6), 752–765.

Macpherson, D. A. and B. T. Hirsch (1995). Wages and gender composition: Why do women's jobs pay less? *Journal of Labor Economics 13*(3), 426–471.

Maestas, N., K. J. Mullen, D. Powell, T. Von Wachter, and J. B. Wenger (2018). The value of working conditions in the united states and implications for the structure of wages. Technical Report, National Bureau of Economic Research. URL: https://www.nber.org/system/files/working_papers/w25204/w25204.pdf. [Retrieved: 2021-10-12].

Mas, A. and A. Pallais (2017). Valuing alternative work arrangements. *American Economic Review 107*(12), 3722–3759.

Penner, A. M., T. Petersen, A. S. Hermansen, A. Rainey, I. Boza, M. M. Elvira, O. Godechot, M. Hällsten, L. F. Henriksen, F. Hou, et al. (2022). Within-job gender pay inequality in 15 countries. *Nature Human Behaviour (E-pub, ahead of print)*, 1–6.

Petrongolo, B. (2019). The gender gap in employment and wages. *Nature Human Behaviour 3*(4), 316–318.

Sorkin, I. (2018). Ranking firms using revealed preference. *The Quarterly Journal of Economics 133*(3), 1331–1393.

Stanton, C. T. and C. Thomas (2016). Landing the first job: The value of intermediaries in online hiring. *The Review of Economic Studies 83*(2), 810–854.

Stanton, C. T. and C. Thomas (2020). The gig economy beyond local services and transportation. CESifo Forum. Munich: ifo Institut-Leibniz-Institut für Wirtschaftsforschung. URL: https://www.econstor.eu/bitstream/10419/226410/1/CESifo-Forum-2020-03-p21-26.pdf. [Retrieved: 2021-10-12].

Stanton, C. T. and C. Thomas (2021). Who benefits from online gig economy platforms? Technical Report, National Bureau of Economic Research. URL: https://www.nber.org/system/files/working_papers/w29477/w29477.pdf. [Retrieved: 2021-10-12].

Stephany, F., O. Kässi, U. Rani, and V. Lehdonvirta (2021). Online labour index 2020: New ways to measure the world's remote freelancing market. *Big Data & Society 8*(2), 20539517211043240.

Sullivan, O. (2019). Gender inequality in work-family balance. *Nature Human Behaviour 3*(3), 201–203.

Sullivan, P. and T. To (2014). Search and non-wage job characteristics. *Journal of Human Resources 49*(2), 472–507.

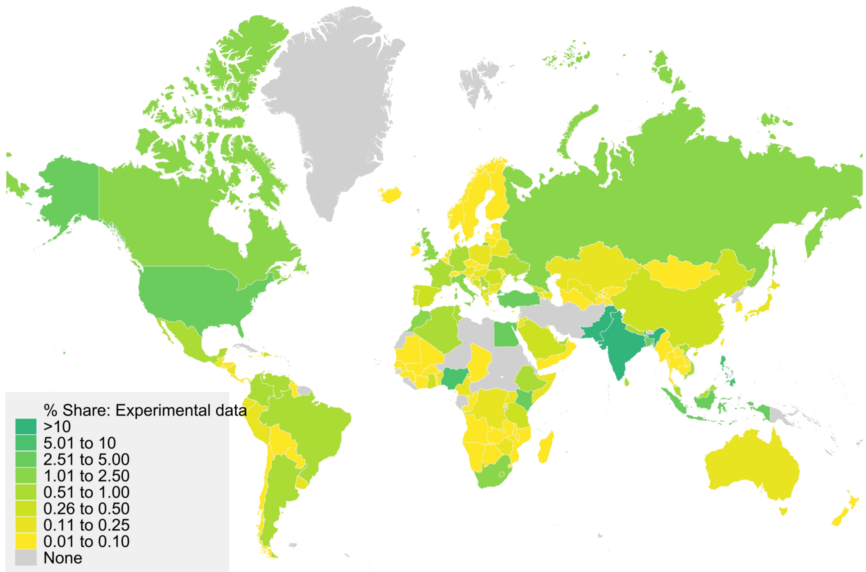
Umar, M., Y. Xu, and S. S. Mirza (2021). The impact of COVID-19 on gig economy. *Economic Research-Ekonomska Istraživanja 34*(1), 2284–2296.

Wasserman, M. (2019). Hours constraints, occupational choice, and gender: Evidence from medical residents. Working Paper. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3371100.

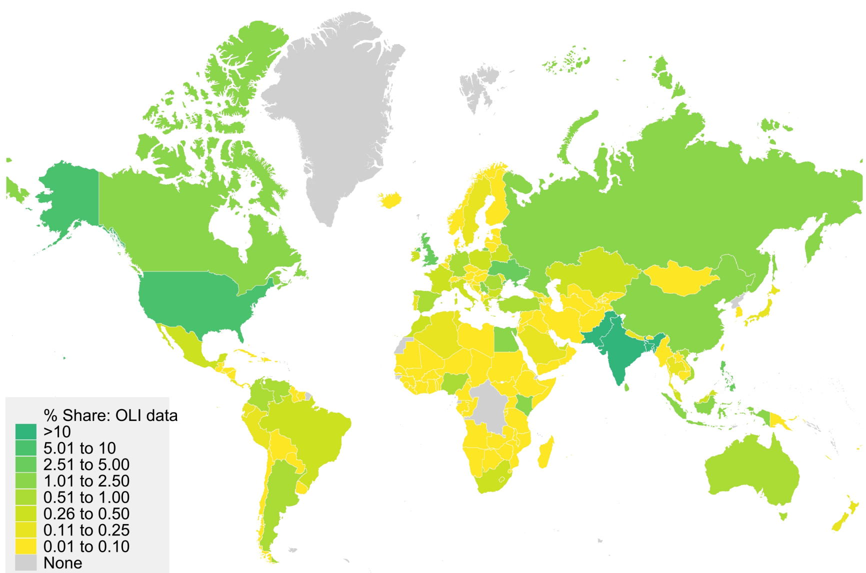
Wiswall, M. and B. Zafar (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics 133*(1), 457–507.

# Supplementary Material

**Figure A1:** Country-wise share of online workers



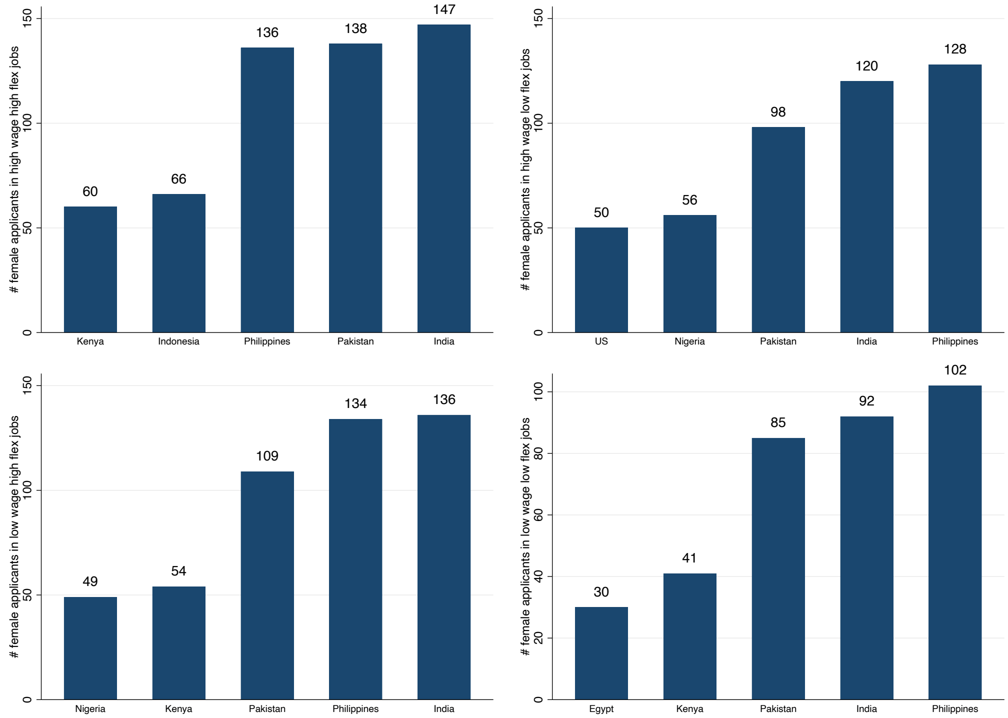

**(a)** Experimental data




**(b)** Online Labour Index

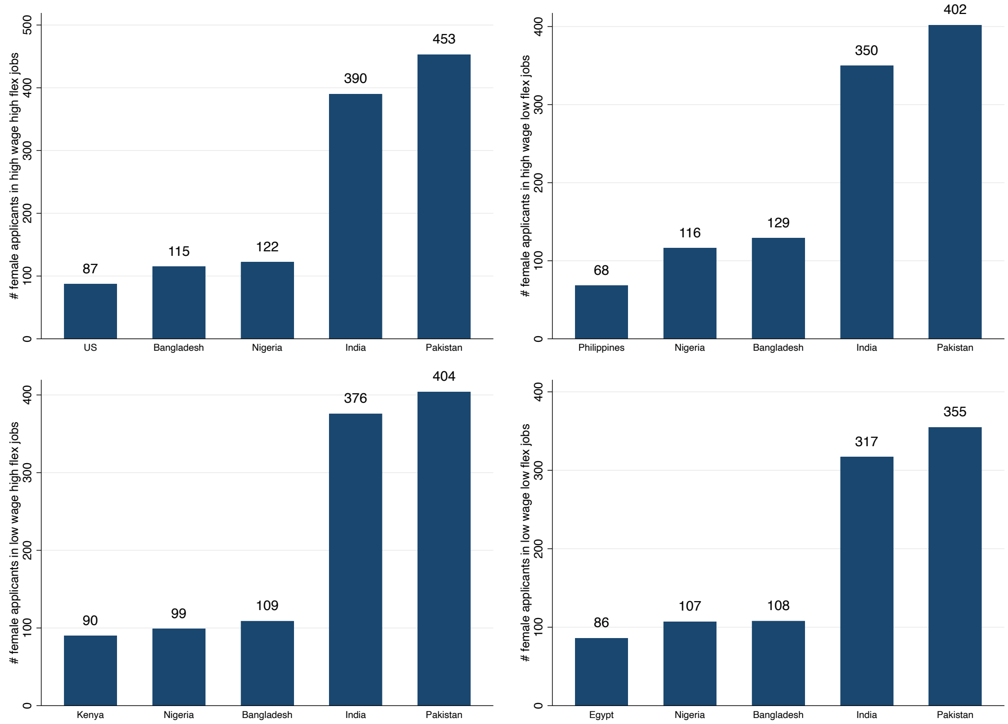
*Sources*: Authors' calculation based on data collected from the experiment and information from Online Labour Index.
*Notes*: Sub-figure A1a plots the share of applicants from the top nine countries with the highest number of applicants across all jobs in our experiment. Sub-figure A1b plots the share of top nine countries in total online freelancing work across all such freelancing platforms calculated by tracking the number of projects and tasks across platforms in real time

**Figure A2:** Wage, flexibility, and country of origin of female applicants




*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: The figures report the number of female applicants from the top five countries with the highest number of female applicants.

**Figure A3:** Wage, flexibility, and country of origin of male applicants




*Sources*: Authors' calculation based on data collected from the experiment.
*Notes*: The figures report the number of male applicants from the top five countries with the highest number of male applicants.

**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 | Stocks trading advice | RB | Thursday |

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

| |
|---|
| **Low-wage, low flexibility job ad** |
| Dear freelancer,<br><br>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.<br><br>I am willing to pay USD 30 for the job.<br>Fee: $30.00 Fixed-price<br>Level: Entry level<br>Project Type: One-time project<br>Skills and Expertise: Arabic<br><br>Screening question:<br>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,<br><br>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.<br><br>I am willing to pay USD 40 for the job.<br>Fee: $40.00 Fixed-price<br>Level: Entry level<br>Project Type: One-time project<br>Skills and Expertise: Arabic<br><br>Screening question:<br>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 bidding

| | (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 | 0.14 | 0.14 | 0.14 | 0.14 | 0.13 |
| R-squared | 0.00 | 0.02 | 0.02 | 0.05 | 0.05 |
| Observations | 12,056 | 12,056 | 12,056 | 12,010 | 11,585 |

*Notes*: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 'Underbid' is an indicator variable that takes value '1' when fee 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 completed 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 varibles 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 two more variables - whether the applicant provided a work sample with their application and how long their cover letter was.