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Gender differences in preferences for non-pecuniary benefits in the labor market: Experimental evidence from an online freelancing platform

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GENDER DIFFERENCES IN PREFERENCES FOR NON-PECUNIARY BENEFITS IN THE LABOR MARKET: EXPERIMENTAL EVIDENCE FROM AN ONLINE FREELANCING PLATFORM

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Abstract

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 though 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. Our findings have important implications for explaining gender differences in labor market outcomes and for firms interested in attracting more women employees.

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

JEL Classification: J22, O14, J16, L86

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, the 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 provision of the non-pecuniary benefits that women prefer (Gupta 1993; Macpherson and Hirsch 1995; DeLeire and Levy 2004; Grazier and Sloane 2008; Kleijnans 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 an 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 the diversity of the workforce. Thus, firms and policy-makers interested in the optimal response to these changes must therefore understand gender difference 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 challeng-

¹That said, a large literature has documented gender differences in various attributes, such as 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 about the sources of these differences.

²Some 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.

ing. 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 result from a higher productivity of men in jobs that require physical strength. An empirically observed association between certain non-pecuniary benefits and shares of female employee 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 located in 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 conducted our experiment on a major online freelance labor market platform. We posted four otherwise identical job advertisements for each of 80 distinct tasks that vary only in their flexibility and the wage offered.³ Flexible jobs (“high-flexibility”) allow the freelancer to choose any two-hour window during the day on a pre-specified date to complete the task. Inflexible jobs (“low-flexibility”) 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 wage offered: a “high-wage” job posting offers a lump-sum onetime payment of USD 40 and a “low-wage” job posting offers a lump-sum onetime 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 the job postings for each specific task varied

³These tasks cover a wide range of activities, such as proofreading, writing, and coding.

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

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 in adapting 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 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, the participation of women in online labor markets continues to lag behind. Data from the 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 the 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 make 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 effort into getting a flexible job. Compared to inflexible jobs, women are more likely to make an application before men and include their previous work sample in the application for a flexible job. Our results also suggests that the valuation of flexibility is sufficiently high: an increase in the wage by only 10 USD will not attract the same set of workers that value flexibility.

⁵For 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).

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

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 to empirically disentangle the role of preferences from other unobserved characteristics of the worker, firm and job level 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 causally identifying the role of preferences and at the same time we focus on a specific non-pecuniary benefit.

The more 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), broadly finding that 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 a higher salary 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 with less physical work and more paid leave. These papers validate the stated preferences by looking at real job attributes, so as to check that the stated preferences of the respondents match the actual job characteristics. Even if the stated preferences match the real job attributes, we do not observe the set of jobs from which 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 conduct a field experiment using a Chinese job board and find that married females have a stronger preference for flexible jobs than do married males. We add to the findings of He et al. (2021) by focusing on the worldwide online freelance labor market and on applications for 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 their implications for the labor market

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

(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, such as risk preferences and competitiveness, that have an impact on labor market outcomes. We add to that literature by documenting gender difference in preferences for flexibility in jobs. Lastly, 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, 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 interpret the results from the experiment. 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 $S = (1, 2, 3, \dots, n)$.

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

⁸A 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 at the intensive and 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 paper seeks to address.

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 wage w to be done during 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 $c_{i\tilde{s}} = \min(c_{i1}, c_{i2}, c_{i3}, \dots, c_{in})$.

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:

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

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

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

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

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

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

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

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

Or, $F(\cdot)$ first-order stochastically dominates $G(\cdot)$. 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 $c_{i\bar{s}} < c_{i\bar{s}}$. The higher (lower) the number of applicants with $c_{i\bar{s}} < c_{i\bar{s}}$, the higher (lower) will be the estimated effect of flexibility.

Next, let us differentiate the distribution of $c_{i\bar{s}}$ and $c_{i\bar{s}}$ for males and females. For males, let us denote the cumulative distribution functions by $F^M(c_{i\bar{s}})$ and $G^M(c_{i\bar{s}})$. For females, we denote them by $F^F(c_{i\bar{s}})$ 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 $F^M(c_{i\bar{s}}) = F^F(c_{i\bar{s}})$. 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:

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

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

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

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 platform, which attracts 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 wage that they will pay a freelancer to complete it. The client may invite specific freelancers

¹⁰This 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.

to apply for the job 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, such as 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 fixed 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*, which cover a wide range of activities. Our job advertisements resemble the 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 wage 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 the 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 the low-flexibility jobs or outside the chosen two-hour window in the case of the high-flexibility jobs. We took several steps to make sure that applicants understood these requirements before applying. First, the job postings contained information such as 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 the case of a low flexible job) or enter their chosen two-hour window (in the case of a high flexible job) before they could start the application. This made the requirements regarding the 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 differences were the flexibility in choosing the work hours or the wage.

We used five different accounts for posting 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, 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 matches 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.¹²

¹¹We 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 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 affected the response rates.

¹²Members of the research team manually classified the gender of the applicant. Since the same person

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:

$$Y_j = \alpha + \beta \text{Flexible}_j + X_j + \epsilon_j \quad (1)$$

where Y_j is one of the following dependent variables of interest for job posting j : the number of all applicants, of male applicants, of 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. ϵ_j^s is the error term.

The main coefficient of interest is β . Since, 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 compare the estimates of β across 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 causal effects of each type of job

classified applicants for all jobs (flexible, inflexible, high wage, low wage) for each task, any person-specific bias is likely to affect both flexible and inflexible jobs in the same manner. We could have used an algorithm to infer the gender from the names of the applicants (Blevins and Mullen 2015). Though algorithms that predict gender from names work well for Western countries such as the US and the UK, they are not as accurate for 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 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 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.

posting.

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

where Y_j is one of the following dependent variables of interest for job posting j : the total number of all applicants, of male applicants, of female applicants, the share of female applicants. HWLF_j is an indicator variable that indicates that a job has a high wage but no greater flexibility than a low-wage-low-flexibility job. LWHF_j respectively, HWHF_j , indicate that the job has a low wage and a high degree of flexibility, respectively, a high wage and a low degree of flexibility. X_j denotes task fixed effects. ϵ_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 of at higher and lower wages. The marginal effect of flexibility at lower wages is given by β_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 (β_1^s) with the response to the provision of flexibility (β_2^s).

5 Results

Table 1 presents a summary of the characteristics of the applicants to our job postings. As the results show, 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 include both female-dominated tasks, such as translation and proofreading, and male-dominated tasks, such as financial consulting and coding. The Online Labour 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 work force in online labor markets (Stephany et al. 2021). Further, we also compare the countrywise distribution of our applicants and the data from the Online Labour Observatory. We find that the distribution of country profiles in our data closely matches that from 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 labor 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.

Table 1: Summary Statistics

	Females		Males		Difference in means
	N	Mean	N	Mean	
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.

Does flexibility 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 offer flexibility attract more applications compared to a job with no flexibility. On average, flexible jobs received 5.98 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.

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

	(1)	(2)	(3)	(4)
	Applicants			
	Total	# Male	# Female	% Female
Flexible Job	5.98*** (1.44)	2.92*** (0.90)	3.01*** (0.74)	1.47* (0.80)
Task FE	✓	✓	✓	✓
p -value [$\beta^{male} = \beta^{female}$]				0.96
Mean of DV	37.79	25.19	12.51	28.29
Control mean of DV	34.71	23.67	10.98	27.37
R -squared	0.94	0.94	0.92	0.89
Observations	319	319	319	319

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.

Is the effect of flexibility different across gender? Columns 2 and 3 of [Table 2](#) present the effect of an increase in flexibility on the number of male and female applications, respectively. Compared to inflexible jobs, flexible jobs attract 2.92 more male applicants and 3.01 more female applicants. While the estimated magnitudes of the effect are similar for males and females, the percentage change with respect to the mean is significantly larger for females. Only one-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 the elasticity of the 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 labor markets by [Adams-Prassl \(2020\)](#). The study finds that women in online freelance labor markets earn less, as they need schedule flexibility (taking breaks between tasks) because of childcare responsibilities. Using experimental evidence, our results add to that by showing that women are more likely to select into jobs that allow such schedule flexibility.

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

VARIABLES	(1)	(2)	(3)	(4)
	Total	# Male	# Female	% Female
High-wage, low-flexibility	6.31*** (1.97)	3.06** (1.24)	3.25*** (1.02)	3.42*** (1.15)
Low-wage, high-flexibility	6.60*** (1.98)	2.92** (1.25)	3.63*** (1.02)	2.95** (1.15)
High-wage, high-flexibility	11.63*** (1.97)	5.95*** (1.24)	5.63*** (1.02)	3.67*** (1.12)
Task FE	✓	✓	✓	✓
p -value [$\beta_1 = \beta_2$]	0.88	0.91	0.71	0.67
p -value [$\beta_1 + \beta_2 = \beta_3$]	0.64	0.99	0.38	0.09
p -value [$\beta_1^{male} = \beta_1^{female}$]				0.95
p -value [$\beta_2^{male} = \beta_2^{female}$]				0.79
p -value [$\beta_3^{male} = \beta_3^{female}$]				0.91
Mean of DV	37.79	25.19	12.51	28.29
Control mean of DV	31.55	22.14	9.35	26.80
R -squared	0.94	0.94	0.92	0.90
Observations	319	319	319	319

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 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.

Does flexibility in jobs lead to a more gender-diverse work force? Since women have higher 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 this 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 points rise in the proportion of female applicants (at a lower wage), a 10.4 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. Using changes in the maximum work limit in medical residencies in the US, Wasserman (2019) shows that, relative to men, the participation of women increases in sub-fields that limit the maximum work time. Our results complement this finding by providing experimental evidence, from a wide range of fields, that schedule flexibility narrows the gender gap in participation.

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 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 are gender differences in willingness to trade off higher wage for flexibility. To answer this question, we compare the change in the number of applicants in response to higher flexibility as opposed to higher wage. 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 an effect on the number of male applicants similar to that of a 10 USD rise in the wage offered ($\beta_1^{male} = 3.06$, $\beta_2^{male} = 2.92$). For women, similarly, providing flexibility also has an effect similar to that of a 10 USD rise in wages ($\beta_1^{female} = 3.25$, $\beta_2^{female} = 3.63$). In percentage terms, this translates into a 12.2 percent increase in the number of male applicants because of a ten-dollar increase in the wage as opposed to a 11.6 percent rise in response to flexibility. For women, a similar 10 USD rise in wages leads to a 26 percent rise in the number of female applications as

¹³For 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 services that are not traded as frequently. Our results are qualitatively similar even if we do not weight the observations.

opposed to a 29 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 the gender difference in the trade-off between higher wages and flexibility to be the same.

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	0.83 (2.29)	4.61*** (1.50)	2.27** (1.06)	1.45 (0.94)
Task FE	✓	✓	✓	✓
p -value[$\beta = 1.47$]	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
R -squared	0.57	0.75	0.82	0.86
Observations	319	319	319	319

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 weighted by the total number of applicants for each job.

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 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 25th and 50th percentiles of applicants. Note that the effect at the 25th 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 10th and 75th 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.¹⁵

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	-11.34 (8.61)	-2.55 (10.29)	-29.79* (15.84)	0.01* (0.01)	0.01 (0.01)	0.03** (0.01)
Task FE	✓	✓	✓	✓	✓	✓
p -value [$\beta^{\text{male}} = \beta^{\text{female}}$]			0.17			0.17
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
R -squared	0.03	0.04	0.05	0.08	0.09	0.08
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. ‘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.

¹⁴Please 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.

¹⁵It 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 to these flexible jobs. But relative to men, women respond faster.

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 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 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 dimension 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 to make the letter more concise and precise. However, it is important to note that the results may also reflect differences in 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.

Table 6: Flexibility and applicant experience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total prior contracts			Total prior contracted hours			Total prior earnings		
	All	Male	Female	All	Male	Female	All	Male	Female
Flexible Job	-1.38** (0.62)	-2.08*** (0.81)	0.14 (0.94)	-1.97 (1.41)	-1.44 (1.71)	-3.35 (2.46)	-277.13** (112.30)	-287.53** (136.47)	-289.85 (199.86)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
$p\text{-value } [\beta^{\text{male}} = \beta^{\text{female}}]$			0.08			0.54			0.99
Mean of DV	6.63	7.20	5.52	14.64	14.31	15.21	905.97	895.51	932.26
Control mean of DV	7.39	8.34	5.37	15.51	14.92	16.88	1060.97	1055.60	1078.57
$R\text{-squared}$	0.03	0.03	0.05	0.02	0.03	0.03	0.03	0.03	0.05
Observations	12,056	8,036	3,992	12,056	8,036	3,992	12,056	8,036	3,992

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 earnings,’ 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.

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

past work as evidence of ability to 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.

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 (0.11)	0.14 (0.14)	-0.14 (0.16)	0.01** (0.01)	0.01* (0.01)	0.01 (0.01)	0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)
Task FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
p -value [$\beta^{male} = \beta^{female}$]			0.19			0.97			0.02
Mean of DV	1.21	1.39	0.83	0.14	0.16	0.11	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	12,016	8,005	3,984	12,056	8,036	3,992	12,056	8,036	3,992

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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.

Third, we look at counteroffers made by applicants. Although we specified the wage 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. But it is important to understand that counteroffers do not affect the effort, as the effort appears non-negotiable in the job posting. 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 the reservation wage. In the columns that follow, we control for other characteristics of the task, job, and applicant, as well as our 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 negotiating, a setting similar to ours. Our results provide a new insight from online labor 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](#), which indicate that there is no difference in underbidding behavior in response to flexible jobs for either men or women.

A key question is why do 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 effect of flexibility between countries of high and low fertility rate. One reason why women might prefer flexibility could be that it allows them to manage time-sensitive child care responsibilities. If so, the value of flexibility is likely to be higher for those women that 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 child care responsibilities are fixed costs and do not vary much by 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

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 labor force participation? Though our results cannot directly speak to this, a comparison of the effect of flexibility between countries that have low and high female labor 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 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. One possibility is that the demand for flexible jobs is higher in these countries and the limited availability of such jobs leads to low female labor 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 labor market at the extensive margin.

In Panels C and D of [Table 8](#), we present additional cross country differences of 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 that per capita GDP is a good predictor of many observables, such as the availability of other jobs, the social welfare, and gender norms. Though this does not provide us 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. 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. Lastly, 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, which have a large participation in the online labor 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

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*** (0.78)	1.08** (0.53)	1.29*** (0.39)	2.78* (1.54)	3.66*** (0.94)	1.91*** (0.58)	1.73*** (0.49)	0.43 (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*** (0.84)	1.68*** (0.61)	1.34*** (0.36)	1.17 (1.20)	3.14*** (0.89)	1.38*** (0.49)	1.71*** (0.55)	2.50* (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	4.30*** (1.14)	2.06*** (0.74)	2.21*** (0.56)	1.57* (0.93)	1.78*** (0.51)	0.92*** (0.35)	0.84*** (0.29)	2.92 (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	3.53*** (1.01)	1.76*** (0.67)	1.75*** (0.48)	0.86 (1.42)	2.52*** (0.71)	1.21*** (0.45)	1.28*** (0.41)	3.62** (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	0.72
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
p-value [$\beta^{male} = \beta^{female}$]				1.00				0.94

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.

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 the valuation of these non-pecuniary benefits has important implications in explaining gender inequalities in the labor market. For example, lack of supply of non-pecuniary benefits like flexibility can be a potential reason that limits the participation of women in the labor market in developing countries.

However, we argued that despite the importance of this question, several empirical challenges makes 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 isolate the effect of one 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.

In this paper, we overcome these challenges by using an audit experiment. We posted matched pairs of jobs on a major online freelance labor market platform, which only differed in the flexibility (of the work time) offered. Since these jobs are identical in all other attributes, except flexibility, any difference in the applications for these jobs are a result of a 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 suggests 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 labor market. The effects can go either way. It is possible that workers in freelance labor markets prefer flexibility more than workers in the brick and mortar labor market and we are overestimating the demand for flexibility. Yet, it is also possible that since freelance labor markets already offer so much flexibility, the marginal valuation for flexibility is lower

in this market. Moreover, since the contracts in the freelance labor 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 the demand for flexibility. It is possible that women prefer flexibility because of an extra burden due to 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 about the sources of gender differences in preferences for flexibility. Lastly, 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 the preference for work from home.

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

If the lack of flexibility is indeed an explanation, what can policy makers do? Assuming that firms are aware of these differences in preferences but find it costly to provide these non-pecuniary benefits, policy makers 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 cost 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. Firms that are unaware of worker preferences may invest in providing more non-pecuniary benefits. Thus, we believe that our result contributes significantly to the policy discussions on encouraging female labor force participation.

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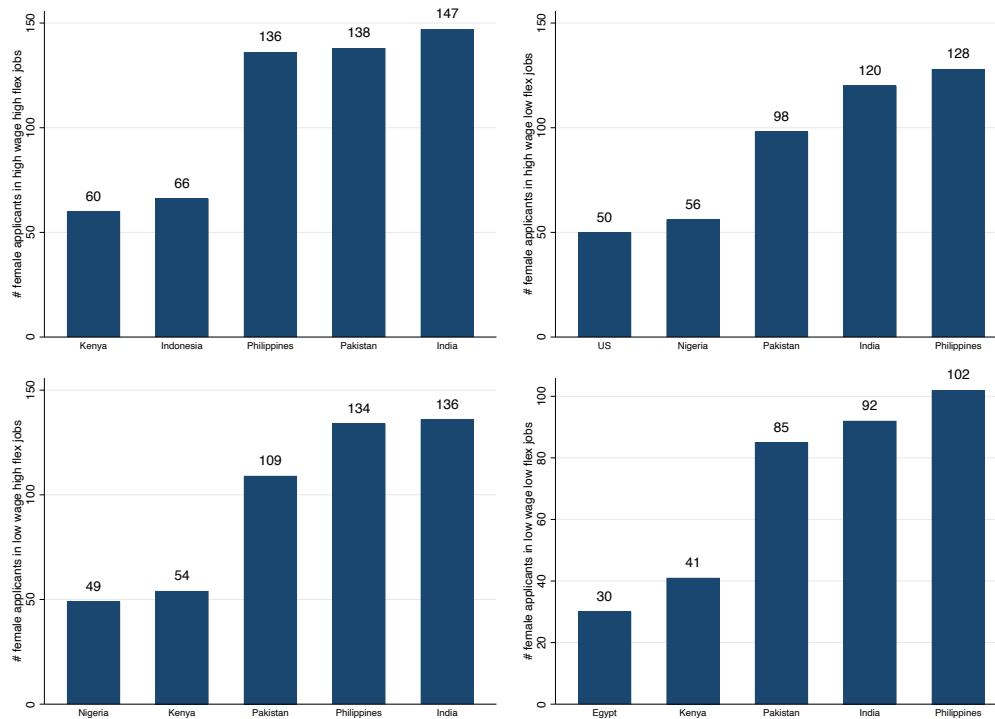
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Supplementary Material

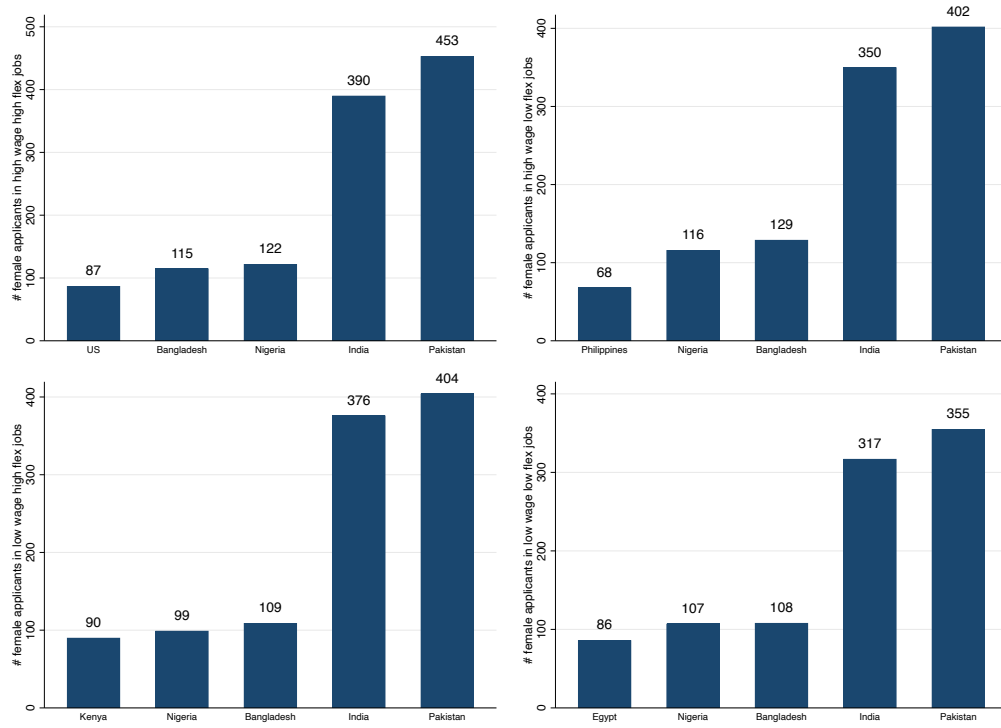
Figure A1: Wage, flexibility, and country of origin of female applicants



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 A2: 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	Stock trading advice	RB	Thursday

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

Low-wage, low flexibility job ad
<p>Dear freelancer,</p> <p>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.</p> <p>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</p> <p>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.</p>
High-wage, low flexibility job ad
<p>Dear freelancer,</p> <p>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.</p> <p>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</p> <p>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.</p>

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

Low-wage, high flexibility job ad
<p>Dear freelancer,</p> <p>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.</p> <p>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</p> <p>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.</p>
High-wage, high flexibility job ad
<p>Dear freelancer,</p> <p>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.</p> <p>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</p> <p>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.</p>

Table A3: Gender differences in bidding

	(1)	(2)	(3)	(4)	(5)
	Underbid				
Female applicant	-0.04*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.04*** (0.01)	-0.04*** (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
<i>R</i> -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 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 two more variables: whether the applicant provided a work sample with their application and how long their cover letter was.