Technological Change and the Gender Pay Gap: Evidence from an U.S. Online Labour Market

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Extended Abstract

Women still earn less than men in most countries. For instance, in the United States, full-time employed females earn roughly 80% of what is earned by full-time employed males (Goldin, 2021). The gender wage gap has persisted in most countries even though women tend to acquire similar or higher levels of education than men in almost all high- and middle-income countries (Schofer & Meyer, 2005; Van Bavel et al., 2018). Recent technological advances might help to narrow this gap. A growing number of people find and perform work via online labour platforms. Online labor breaks down work into smaller pieces - so-called "gigs" - which increases worker substitutability (Cook et al., 2021). This new form of labour could help women overcome what Goldin (2014) coined the "job-flexibility penalty": imperfect substitution between workers can result in a convex hours-earnings relationship. In other words, women earn less per hour than men because they tend to work fewer hours and have more disruption in their labour force participation. The flexibility of online labour could help to break this logic and reduce the gender pay gap.

This paper describes and explains the gender pay gap in online freelancing - one important sub-field of the platform economy. We use the granularity of our data to improve the understanding of the causal mechanisms driving gender pay disparities, thus providing results that can be useful beyond the specificity of our dataset. Our sample consists of 45,953 projects posted between the years 2015 to 2022 on one of the leading online freelancing platforms and completed by U.S.-based freelancers. The data offers a unique combination of both skills and job application behaviour.

Datasets used for estimating gender pay gaps, such as the census, typically lack detailed information on skills. In contrast, our online freelancing data contains detailed information on worker skills. This enables us to study whether differences in worker skills drive differences in earnings, going beyond broadly descriptive education levels, and capturing differences in specific fields of education or in past work experience. To efficiently use this data in our analysis, we develop a way to compress the high-dimensional binary skill data into a one-dimensional continuous representation. Conceptually, this parsimonious measure represents the estimated market value of each combination of worker skills. In practice, we train a machine learning model on skill requirements and hourly wages of job postings to predict the value of workers' skill sets. We use this *value of skill sets* to account for differences in worker-level capabilities beyond formal education.

We then investigate whether unobserved differences in skills and differences in job-seeking behaviour could drive gender pay disparities. For instance, women might systematically target jobs with lower skill demands, lower work-time demands, or more flexible working hours. This way, the gender gap could be rooted in the types of jobs and firms men and women apply for (Fluchtmann et al., 2021). In addition to lacking skill information, public use data sets typically lack information on job application behaviour. To understand the impact of application

behaviour on the gender pay gap, we use the machine learning model from the previous stage to calculate the estimated value of each job based on their skill requirements. We use this value to investigate what types of jobs workers applied to and whether they were successful. Finally, we also measure if the application behaviour of men and women differs along other essential job characteristics. These include the part-time vs full-time status of the job, the contract duration, and the employer's budget.

According to our preliminary results, the raw gender gap in hourly wages conditional on worker-level controls is 32%. Controlling for the value of worker skills accounts for over 50% of the gender gap in hourly wages. Controlling for past application behavior accounts for the entire remainder of the gender gap. Given the unregulated nature of platform labour, it is surprising that we find no evidence of direct gender-based discrimination. Even if our data shows a substantial gender pay gap in hourly wages, we can fully explain it by two factors: differences in skills and the types of jobs the workers apply to. Consequently, we find no evidence of *direct* wage discrimination against women.

The descriptive visualizations below provide additional insights. Figure 1 illustrates the considerable raw pay gap between male and female freelancers. However, split by type of occupation, this gap narrows in most cases (Figure 2). What drives the gender pay gap is that female freelancers are strongly overrepresented in low-paying occupations (Figure 3). According to our analysis, women bring different skills to the platform and apply to different types of jobs.

References

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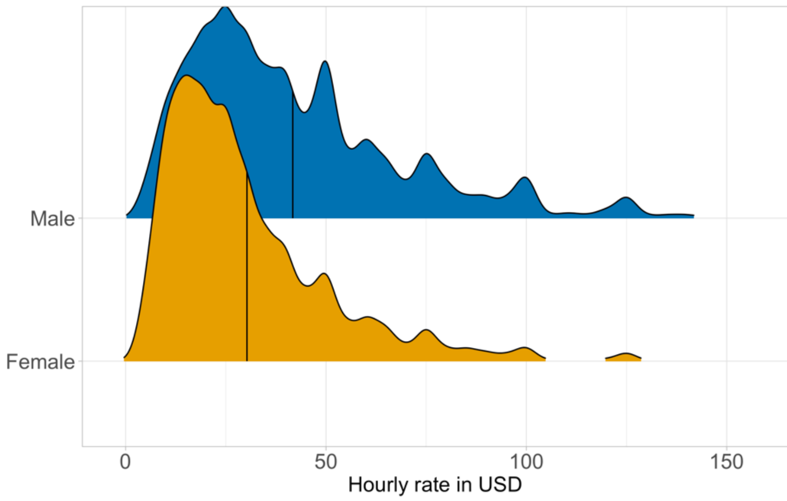

Figure 1: *The distribution of hourly wages in USD by gender. The black vertical line represents the median. Overall, the median hourly wage is 30 USD. The median hourly wage of male workers is 35 USD. Female workers have a median hourly wage of 25 USD.*

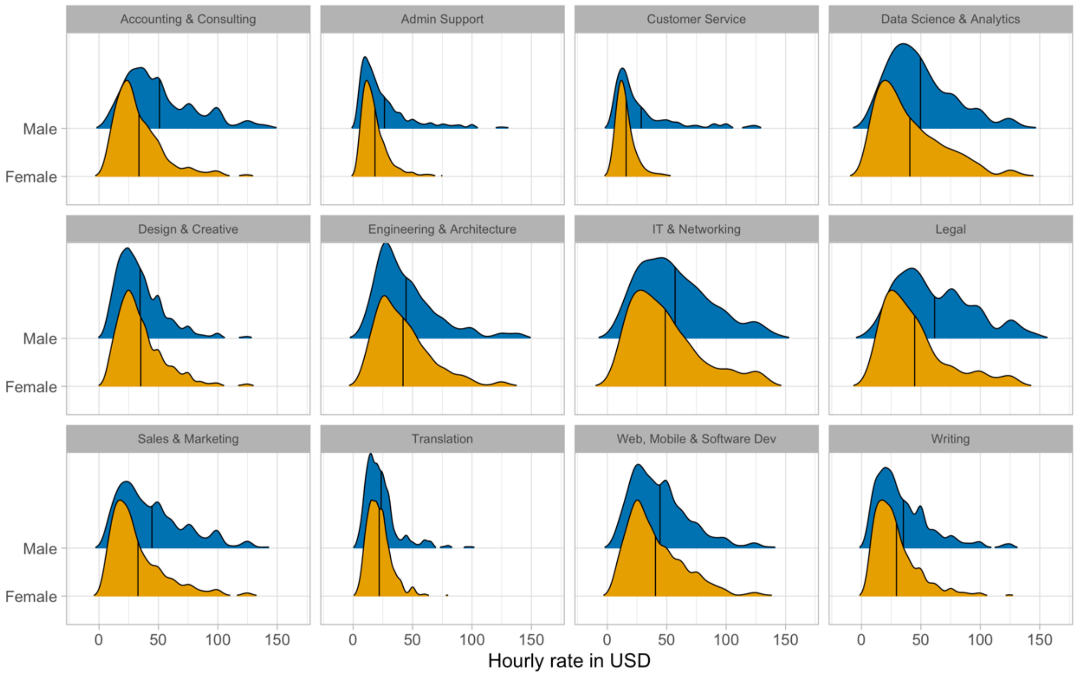

Figure 2: *The distribution of hourly wages in USD by gender and by occupation. The black vertical line represents the median. The gender pay gap differs by occupation but tends to be narrower than the overall gap. More importantly, the median wage differs significantly by occupation. And men and women do not work in the same occupations (see Figure 3).*

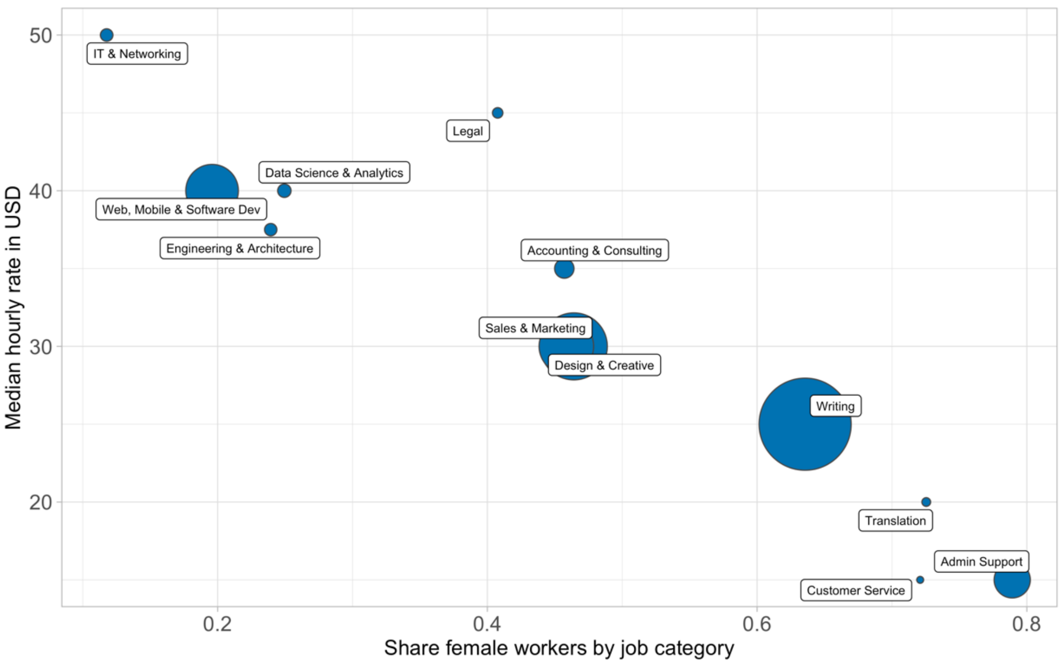

Figure 3: *The share of female freelancers in each occupation is plotted against the median hourly wage in that occupation. The size of the points represents the market share of the occupations. The largest occupations are Writing, Design & Creative and Web, Mobile & Software Development. There is a clear and strong negative correlation between the median hourly wage and the share of female freelancers. For example, IT & Networking has a median hourly wage of about 50 USD but a share of female freelancers of less than 10%. In contrast, Admin support has a median hourly wage of about 10 USD and a share of female freelancers of almost 80%.*