Good gigs if you get them: analysis of working schedules and wages of platform workers in India*

Otto Kässi
Etla Economic Research
otto.kassi@etla.fi

Elvis Melia
University of Duisburg-Essen
elvis.melia@uni-due.de

March 2023

We utilise transaction-level data from a leading online labour platform spanning the years 2018-2019 to examine the workload and earnings of online platform freelancers in India. Based on approximately 115,000 projects completed by 28,000 workers for clients primarily based in the Global North, our findings indicate that the platform labour market outcomes are unevenly distributed. Around two-thirds of the workers in our data were unable to secure any jobs, and even the workers who secured jobs, usually work only a few hours per week. On the other hand, conditional on working, the hourly and weekly earnings of workers are relatively high, even after taking into account platform fees. Our findings indicate that the main reason for the economic

* Funding from Deutsche Geschellschaft für Internationale Zusammenarbeit (GIZ) is gratefully acknowledged. Comments from Jann Lay and Tevin Tefese during the writing process greatly improved the final paper. Usual disclaimers apply.

precarity of online workers is the availability of jobs, while the typical wages are around five to six times higher than the average hourly wage of a new graduate.

1 Introduction

The platform labour economy has shown a double-digit growth rate for years (Kässi & Lehdonvirta, 2018), and the major leading labour platform companies are reporting multi-billion-dollar sales. Various online labour platforms enable workers to serve many clients remotely from their homes at varying hours.

While platform labour can afford workers a high degree of flexibility and autonomy (Wood et al., 2019), many authors have noted that platform workers often report very low earnngs. One explanation for this offered in the literature is that workers are exposed to global competition, which pushes their wages down (Braesemann et al., 2022; Graham et al., 2017) and that the platforms are designed to tilt market power towards the clients (Kingsley et al., 2015). Indeed, there is an ongoing policy debate on fair compensation for platform labour. The hourly wages of workers from the global north countries are often below average in their home countries (Hara et al., 2018). Whilst workers from the global south might be able to earn wages higher than the national average in their own countries (Berg and Rani, 2021), they still face stiff competition from peers and seldom secure full-time employment (Graham et al., 2017).

This paper aims to provide descriptive evidence on the working hours and incomes of Indian platform workers.[1] Our research question is: can platform work provide a steady income stream for workers? To answer this question, we study platform workers' working schedules and weekly and hourly wages in India.[2]

We concentrate solely on Indian workers. While limiting attention to a single country will arguably weaken the external validity of our findings to other countries, this restriction is justifiable. First,

---

[1] There is an on-going legal debate on whether online workers should be classified as self-employed workers or not. Throughout this paper, we use the terms worker or freelancer to refer to the workers and clients to refer to the employers on the platform. This naming is used for consistency with the literature and is not an indication of our views on the legal status of workers.

[2] We collected our data from one of the largest online labour platforms, which did not wish to be identified.

the societal effects of growing platform labour are strongly shaped by the educational institutions, internet infrastructure, and the working conditions prevailing in the traditional labour markets (Braesemann et al., 2021), which implies that the results from one country might not generalise well to other locations.

Second, India is the leading provider of remote platform workers. Roughly one-quarter of the global platform labour workforce on English language platforms resides in India. Moreover, Indians are involved in all types of platform work ranging from relatively low-skill microwork to highly complex software development tasks (Stephany et al., 2021). Consequently, we are more likely to capture the full spectrum of potential labour market outcomes in a place like India than in a smaller and more homogeneous country.

The existing descriptive evidence on the wages of platform workers is varied in both methods and results. A large share of the existing data is collected using surveys (e.g., Wood et al., 2019; Rani & Furrer, 2019; ILO 2021b, and Difallah et al., 2015). While the survey data can provide valuable insights into various facets of the jobs that platform workers do, the representativeness of surveys is often unclear. There are two reasons for this. First, many surveys are based on convenience samples. Moreover, because it is often technically infeasible to collect background information on the non-surveyed platform workers, it is not possible to weigh the responses to match the underlying populations.

Another prominent source of wage data is various technical data collection methods. These include data collected using voluntarily installed browser extensions (e.g., Hara et al. 2018) and data collected by programmatically harvesting data from worker profiles (e.g. Beereport et al. 2015; Barzilay & Ben-David, 2016; Kässi & Lehdonvirta, 2022), or obtained via a research collaboration with platform operators (e.g. Gomez-Herrera & Müller-Langer, 2019, Agrawal, et al. 2016). While technical data collection usually allows for much larger data sets than surveys, the representativeness of these samples remains unclear. The data resulting from research collaborations with platforms are less likely to suffer from bias due to unrepresentativeness.

Only a handful of the above papers strictly concentrate on wages and earnings. Instead, their emphasis is on the effect of specific policies or platform design features on wages and earnings of workers. Consequently, in the literature, there exists much more information on the average wages of platform workers compared to working times and schedules. Moreover, many papers that concentrate on wages use data from microwork platforms such as Amazon Mturk (see Hornuf & Vrankar, 2022). To what extent these results generalise to other platforms where more high-skill work is transacted remains unclear.

A shortcoming shared by many of the studies listed above is that they fail to differentiate between working time and non-work time. Consequently, it is unclear whether the income measures capture only work or also when some workers are not working but are applying for jobs. By conventional definition, these workers would be unemployed.

In addition to job search, platform workers spend often spend considerable amounts of time doing other types of unpaid work (e.g., Howson et al., 2022). For instance, they might revise their work for free. While a well-crafted survey can capture this type of unpaid work, and also differentiate it from job search, this is rare in practise. Non-survey data sources mostly fail to capture this type of unpaid work.

The contribution of this paper is twofold. First, our data allows us to differentiate between work- and non-work time and thus calculate weekly and hourly wages for working time without relying on self-reported income measures. Second, our data consists of the universe of active Indian workers on the platform, so our results are not biased by non-response. Our data is from a leading online labour platform, where most projects are relatively high-skill instead of microwork. This gives new insights into a less studied facet of online platform labour.

The rest of this paper is structured as follows. Section 2 outlines how our data is collected. Sections 3 and 4 describe our main empirical results. In Section 3, we study the workload of Indian workers. In Section 4, we study wages and earnings. We describe the average hourly wages, project values, and weekly earnings of the workers and how these compare to workers' wages in the traditional offline labour markets. In Section 5, we contextualise our results and discuss the robustness of the results for possible omitted features in the data. Section 6 concludes.

2 Data and descriptive statistics

We start this section by describing how the transaction data is generated on the labour platform and the steps involved in collecting our sample of online workers. After that, we describe two features of the data – the types of tasks the Indian workers do and their clients' home countries –

that are not directly linked to workload and wages but are important when contextualising the main results we present in the following sections.

2.1 Data collection and sample sizes

We collected the data from the API of one of the largest online labour platforms, which did not wish to be identified. Before turning to details, we briefly present a typical contracting workflow within the platform. Clients looking to hire a worker for a particular task typically start the process by posting a vacancy on the site. The vacancy includes the expected contract duration, preferred worker characteristics such as experience level, and the contract type (either a fixed sum contract or an hourly pay rate).

After the vacancy is posted, it is visible to registered workers who can apply for the position by submitting private bids. The interview and wage negotiation phases also take place on the platform. Besides facilitating matching, the labour platform offers various other affordances to both workers and clients. For instance, the platform offers payroll management, monitoring, project management, and dispute resolution tools. It also provides workers with protection against client non-payment.

The platform in question hosts projects in various categories ranging from virtual assistance to graphic design and from writing to programming. The minimum hourly wage for the jobs transacted on the platform is \$3. Thus, most microwork is priced out of the platform in question.

To better contextualise the wages on the platform in question, it is helpful to compare them to those on the most prominent microwork platform, Mturk. Hara et al. (2018) developed a browser plugin for calculating average hourly wages for Mturk workers. They found that the median hourly wage is around \$2, and the median value of a single task is usually under \$0.50.

The platform allows for two alternative ways of pricing contracts: fixed sum or hourly rate. Under hourly contracts, workers are monitored by semi-regular screenshots of workers' screens and keystroke logging. As a trade-off, clients must compensate workers for their time, regardless of the job quality, in exchange for this level of monitoring. In contrast, fixed fee contracts do not allow for easy monitoring of workers, but they do allow for payment withholding if the client deems the output of low quality. Since the workers are not monitored under fixed-sum contracts, their work hours are not reported in our data. Consequently, we are able to calculate hourly wages and working hours for the hourly rate projects. Roughly 50% of the tasks are fixed prices.

Our data was collected in the following way. In the context of the Online Labour Index project (Kässi & Lehdonvirta, 2018), we used the platform search API to collect information on the daily new public project postings during 2018-2019. In total, there were 597,974 filled job postings during these years.

We also collected further information on whether the project had been filled, the realised value and hourly wage, and the eventually hired worker. At this point, we exclude all project-worker pairs where the worker was not based in India.

Sample sizes are described in Table 1. Our data consists of almost 600,000 completed projects by 167,000 workers. Indian workers completed 19% of the. 17% of the workers in our data are Indians.

Our data might miss some observations for three specific reasons. First, we failed to capture projects where a job was filled without a public job posting. These are not included in our data.Second, we will miss projects that are first created public and later set as private. Third, if a client or worker has either deactivated their account or set it private between the time of project posting and data collection, the corresponding projects will be excluded from our data.

Table 1: Sample sizes

Projects in 2018-2019 completed	597,974
Projects in 2018-2019 completed by Indians	114,495
Number of workers	166,959
Number of Indian workers	27,649

2.2 Occupations

The platform in question has around 100 distinct categories for the job. We have mapped the job categories into six mutually exclusive descriptive categories to ease interpretation. The grouping is based on Kässi & Lehdonvirta (2018), who combined qualitative and quantitative data from various platforms and developed a classification of six mutually exclusive categories for posts. These categories are summarised in Table 2.

The Clerical and data entry category typically includes microwork or human intelligence work vacancies that involve tasks such as data entry and image classification. These tasks usually only require basic computer literacy and numeracy skills. On the other hand, occupations in the professional services category usually require formal education and knowledge about local institutions. Sales and marketing support tasks are mainly related to online advertising and are separated from the other two categories as they form a significant portion of online freelancing. Writing, software development and technology, and creative and multimedia categories are self-explanatory.

However, due to limitations in the available data, we do not distinguish between professional occupations, associate professional occupations, and clerical occupations. Nonetheless, we note that the importance of formal educational qualifications is relatively low in online gig labour markets compared to traditional labour markets (Herrman et al., 2023).

It is important to note that our occupation classification has some limitations. For example, a website design vacancy that includes both graphical design and programming could be classified as either a Design and creative vacancy or a Software development and technology vacancy. This caveat is not unique to our classification and is present in all studies examining discrete occupational groups.

Table 2: Classification of occupation types on the platform

Occupation class	Examples of projects
Professional services	Accounting
	Consulting

	Financial planning
	Legal services
	Human resources
	Project management
Clerical and data entry	Customer service
	Data entry
	Transcription
	Tech support
	Web research
	Virtual assistant
Creative and multimedia	Animation
	Architecture
	Audio
	Logo design
	Photography
	Presentations
	Video production
	Voice acting
Sales and marketing support	Ad posting
	Lead generation
	Search engine optimisation
Software development and technology	Data science
	Game development
	Mobile development
	QA and testing
	Server maintenance
	Software development
	Web development
	Web scraping
Writing and translation	Academic writing
	Article writing
	Copywriting
	Creative writing
	Technical writing

Translation

Figure 1 presents the occupation shares of Indian workers. We present the shares in the number of projects (green bars) and the wage bill (light yellow bars). Software Development and Technology dominates both project postings and wage bill. Sales and Marketing and Design and Creative have a share of roughly ten per cent, while Writing, Clerical and Business Development have a share of roughly 5 per cent.

Comparison between wage bill and project shares reveals that the wage bill share of Software Development jobs is even higher than the project share (over 70%). In contrast, both Design and Creative and Writing and Translation jobs have a wage bill share much smaller than the project share. This implies that the average project values in Software Development and Technology are larger than average. At the same time, the average project values in Writing and translation and Design and creative are smaller than average.

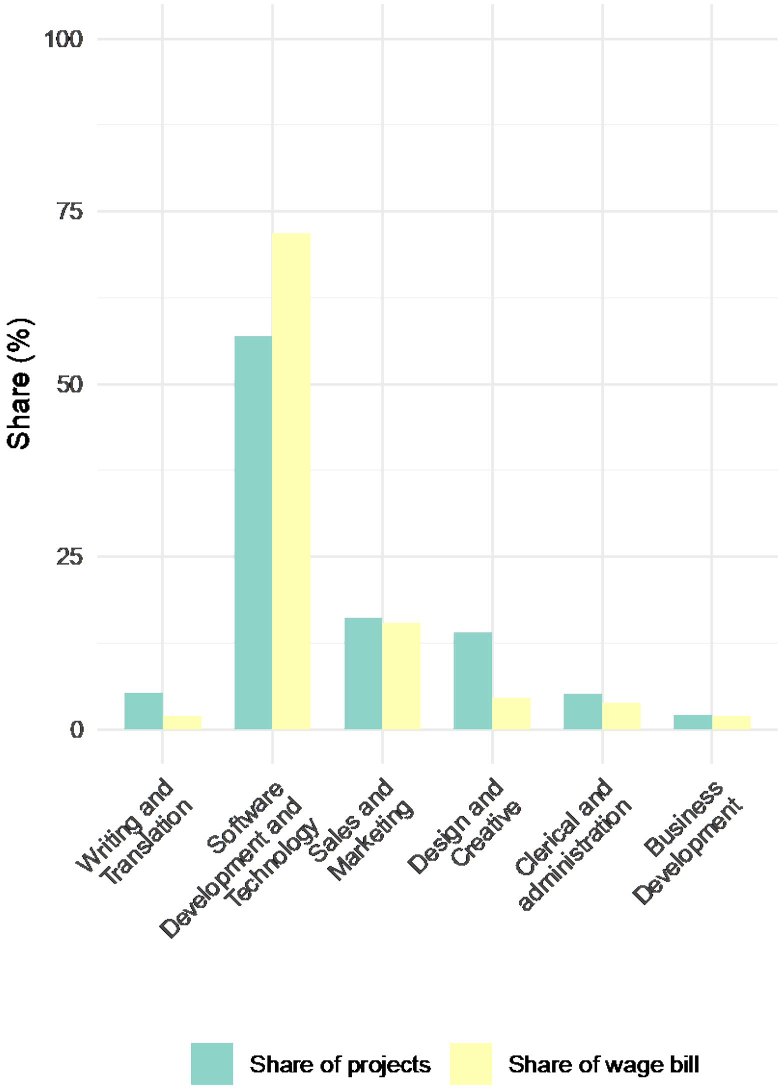


Figure 1: Types of jobs done by Indians. The green bars correspond to completed projects, and the yellow bars correspond to the wage bill. Both distributions add up to 100%.

2.3 Client home countries

We now describe the distribution of clients' home countries for whom the Indians work. The top 10 countries in terms of projects and the wage bill are plotted in Figure 2. Our data indicate that in the platform labour market, workers in the Global South primarily undertake tasks for clients in the Global North. Around 45% of the completed projects are done for clients based in the United States. However, the US share is even more significant regarding the wage bill, closer to 60%. Other prominent client countries include Australia, the United Kingdom, and Canada. Of the top-5 employer countries, the only global south country is India. It is noteworthy that while the share of projects posted by Indians is on par with Australia, the United Kingdom, and Canada, the wage bill share of India is considerably smaller than that of the other countries. This implies that the average value of an Indian client's project is much smaller than that of other employer countries. The findings suggest that the main reason for platform offshoring to India is wage arbitrage. I.e., employers use the platform to find workers whose wage requirements are lower than in their home countries.

It might seem unexpected that a lower-middle-income country like India would be so prominent in the hiring market. However, according to Lehdonvirta et al. (2015), people who win contracts occasionally employ other online workers to complete the task in their stead, acting as project managers. Moreover, since India has its own advanced IT sector, there also is domestic demand for occasional platform labour.

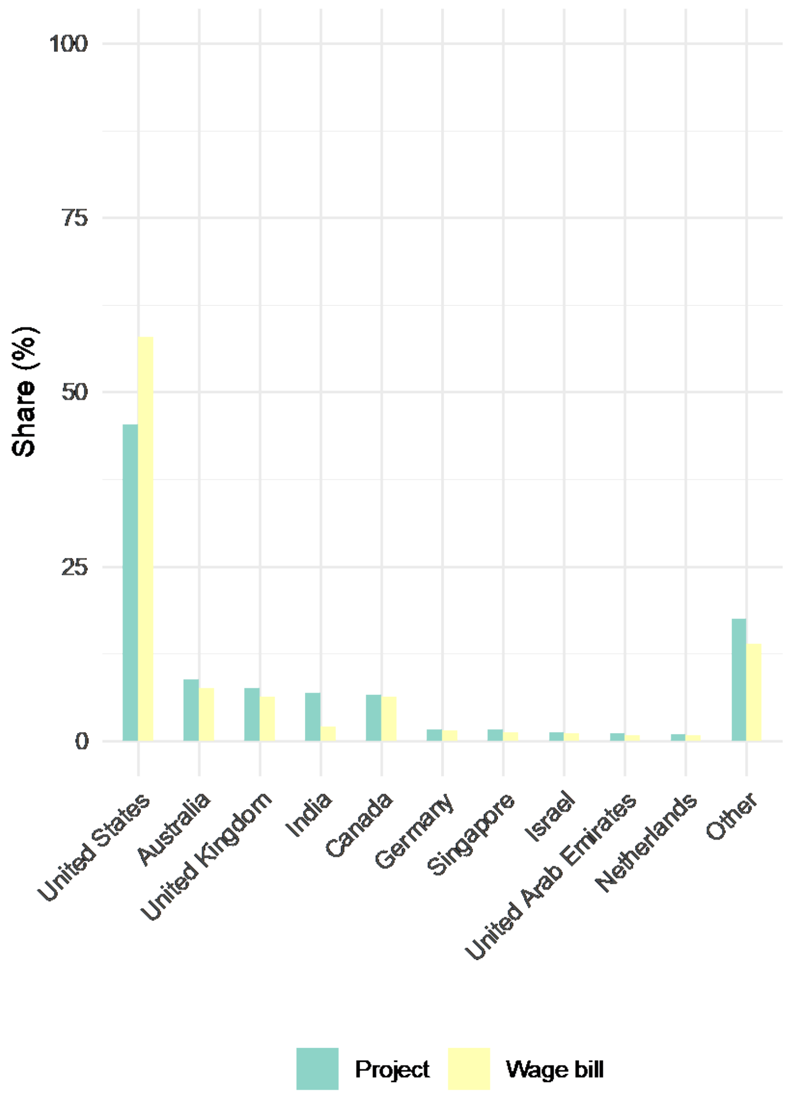


Figure 2: Top 10 client countries for Indian online workers. The green bars correspond to completed projects, and the yellow bars correspond to the wage bill. Both distributions add up to 100%.

3 Workload of Indian workers

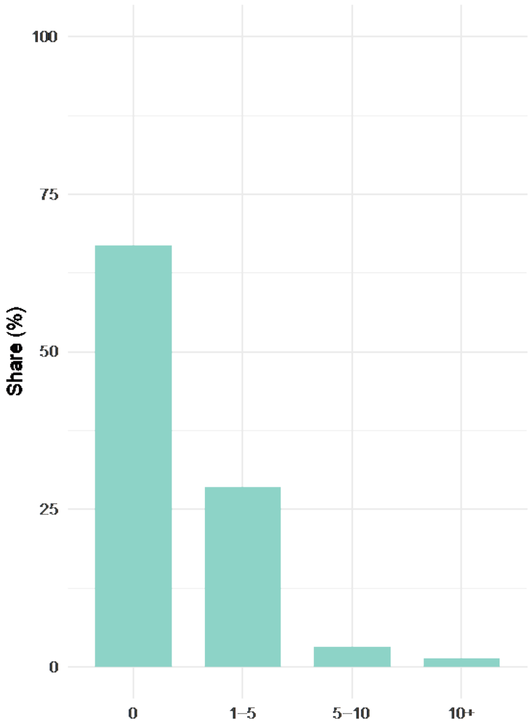
We will now examine online workers' working hours, beginning with examining the distribution of completed projects throughout the year, then moving on to analysing the number of working weeks, and finally, focusing on the number of working hours.

The distribution of completed projects per year is plotted in Figures 3a and 3b for 2018 and 2019, respectively. The sampling frame outlined in Section 2.1 excludes the workers who have not worked. However, according to Kässi et al. (2021), this share is often substantial. To approximate this in this section, we also include Indian workers who had applied for jobs in 2018 or 2019 but did not complete any projects in those years. It is worth noting that the share of workers who applied but did not get any jobs is most likely an understatement because it is more likely that the workers who failed to get any jobs have later deactivated their accounts.

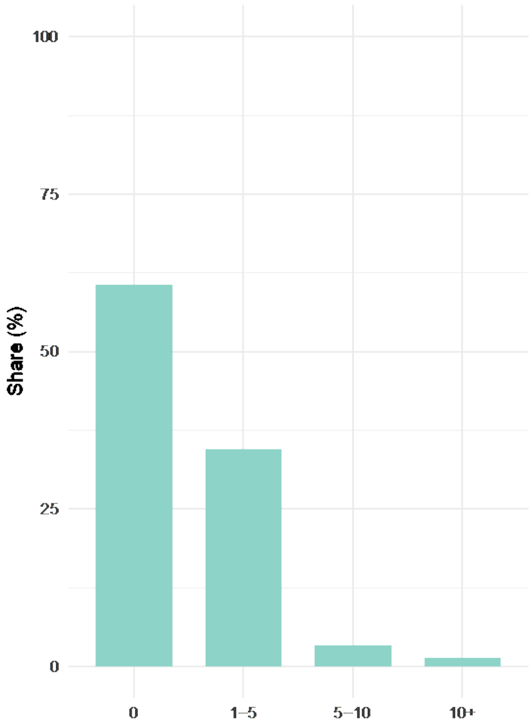
Both Figures 3a and 3b paint a consistent picture. In 2018 and 2019, roughly two-thirds of the Indian workers who applied for jobs did not work at all despite applying for jobs. One explanation could be that the clients are uncertain if the workers' skills match their needs. An alternative explanation could be that there is not enough demand to cover the labour supply on the market. Moreover, while the registration process on the platform is time-consuming by design to discourage workers who are not serious about online employment, it is still possible that some of the registered workers have only applied to a few jobs and have become discouraged after that and consequently never break into the labour market.

Figure 4 plots the distribution of completed projects for the subsample with completed projects. The median project count across all categories is between 1 and 3 per year. 90% of workers have completed fewer than six projects. For visualisation purposes, we have excluded the top 1% of the completed project distribution from the graph. The top 1% of the workers have completed up to 238 projects in a year.

It is difficult to disentangle whether the differences in median project counts across occupation types are due to differences in demand or supply. Nonetheless, according to the findings of Braesemann et al. (2022), fewer demanding jobs tend to attract more applications. This might explain why the project count in the Clerical and administration is the lowest.



(a) 2018



(b) 2019

Figure 3: Distribution of projects by workers in 2018 (panel (a)) and 2019 (panel (b)). Group 0 corresponds to workers who applied for at least one job but did not work on any projects.

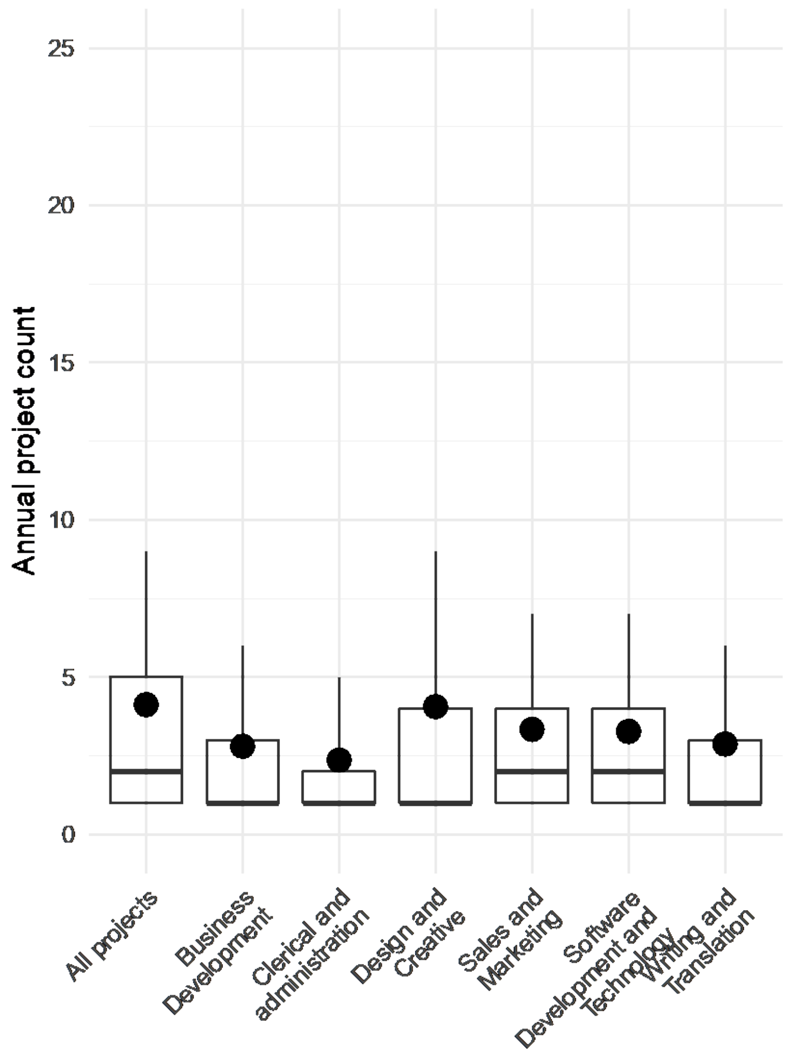


Figure 4: Distribution of projects by workers in 2018 and 2019. In each of the box-and-whiskers plots, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution. Note: for visualisation purposes, 1% of the distribution is excluded.

3.1 Distribution of working weeks

This section inspects the workload of the workers who work. We measure this by counting how many weeks per year the workers are involved in an ongoing project. This is sometimes inaccurate since a project may remain open when the worker has delivered the required project outputs, but the client has yet to accept them. Consequently, the weeks of employment distribution plots the weeks in which a worker was linked to an active project per year instead of the weeks where the worker worked on an active project per year. The latter may be a smaller number than the former.

With this caveat in mind, Figure 5 plots the working week distribution. The median working weeks range from 5-6 for Business development, Clerical and administration, and Design and creative categories, to 11 in the Sales and marketing and Software development and technology categories. In other words, depending on the occupation, a typical worker is only involved in platform work between one in 5 and one in 10 weeks of the year. The corresponding means are always considerably higher than the medians, which indicates that the distributions of working weeks are skewed to the right. This implies that there is a non-trivial minority of workers who work a lot more than that.

A worker may work in different categories and be able to work more. In these cases, the category medians might understate the total working weeks of these workers. Nonetheless, generally, Kässi & Lehdonvirta (2022) show that workers tend to specialise. I.e., they primarily work within one category. Moreover, according to Figure 5, the median of total working weeks across categories does not exceed 10, which suggests that working across categories does not skew the category medians upward.

Moreover, Figure 5 shows that the workers in the Design and Creative category work the least, with three-quarters of the workers working on less than 20 weeks of the year. On the other hand, the workers in Sales and Marketing and Software Development and Technology work the most. Three-quarters of Sales and Marketing workers work less than 29 weeks, and three-quarters of Software Development and Technology workers work less than 26 weeks of the year.

Figures 1 and 5 show that while the workers work least on Design and Creative, the number of jobs in this category is the second largest, led only by Software Development and Technology. This implies that Graphic Design jobs are relatively numerous but also short.

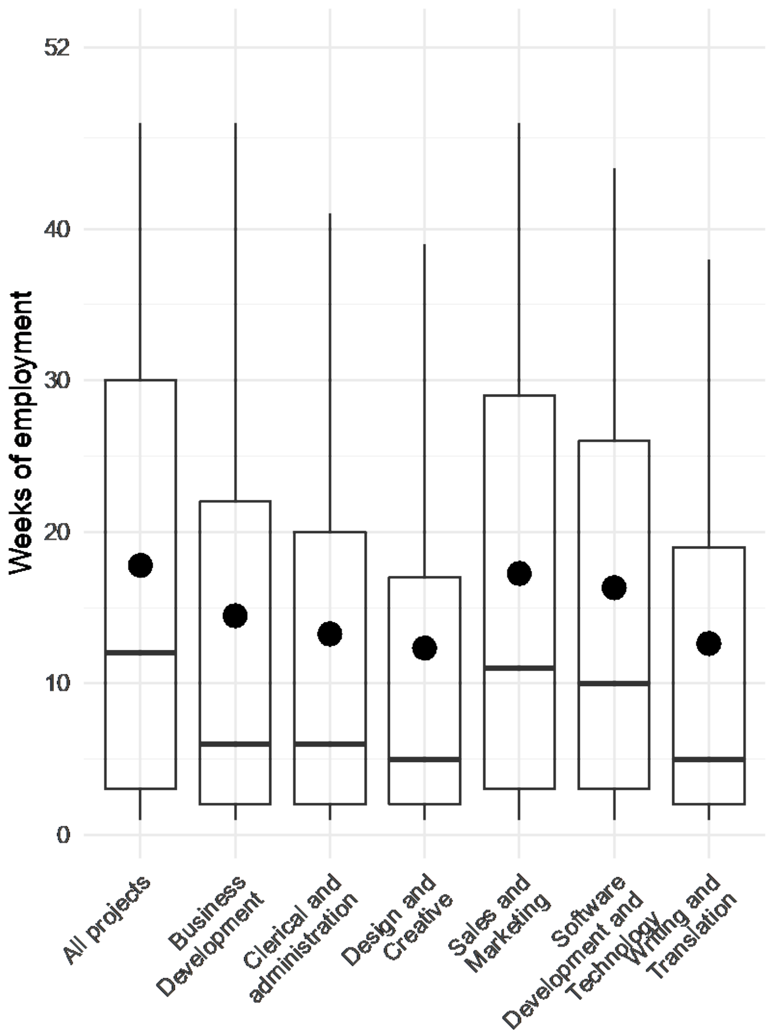


Figure 5: Distribution of working weeks of Indian workers by occupation. In each of the box-and-whiskers plots, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution.

3.2 weekly working hours

Figure 6 plots the distribution of average weekly working hours for working weeks. As noted in Section 3, we only observe the working hours for the hourly projects. Moreover, since we only observe the start and end dates of the project, but not the exact times when workers clock their working hours, we calculate weekly working hours by dividing total hours by the project duration in weeks.

Thus, it is likely that weekly working hours are underestimated either because we fail to capture the working hours worked on flat price projects or because the start and end dates of the project might be measured with error. With these caveats in mind, our findings indicate that typical weekly working hours are relatively low, with medians ranging from two to five. The averages are higher, between four and twelve hours per week. While the median weekly working hours are relatively small, the top 10% work very long hours.

The workers specialising in Design and Creative jobs have the shortest work weeks, with a median of 2 hours, while 75% work under 6 hours. On the other hand, workers in Sales and marketing have a median working week length of 5 hours, with 75% of workers working under 16 hours.

Again, this finding highlights that the availability of work is the limiting factor for typical freelancers. While survey data might indicate that many workers work long hours, our data suggest that most of this time is spent applying for jobs rather than working.

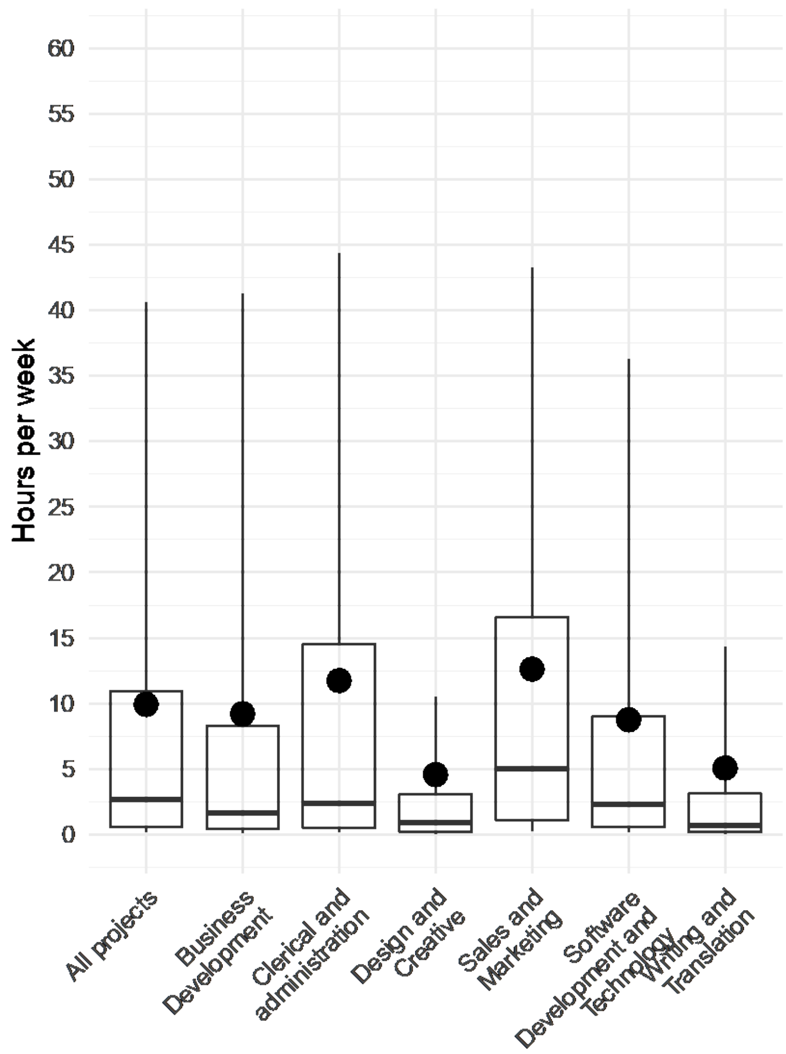


Figure 6: Distribution of average weekly working hours of Indian workers by occupation. In each box-and-whiskers plot, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. Working hour distributions are winsorised at 60 hours per week (the 99th percentile of the data). The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution.

4 Incomes of Indian platform workers

4.1 Distribution of project values

We will now examine the income of Indian workers on platforms, using various metrics to evaluate their earnings. The most straightforward one is the distribution of project values among workers. We plot this distribution in Figure 7.

The median value for all projects is USD 180, while the average is USD 870. Across categories, the lowest-value projects are in Design and Creative (median USD 70 and mean USD 270), while the highest-value projects are in Software Development and Technology (median USD 200 and mean USD 980).

Figure 7 also highlights that the project values are highly skewed to the right (the highest value of the project is over USD 100,000). Thus, the averages are extremely sensitive to individual outliers. Figure 7 excludes the top 1% of observations to better capture the project values' distribution.

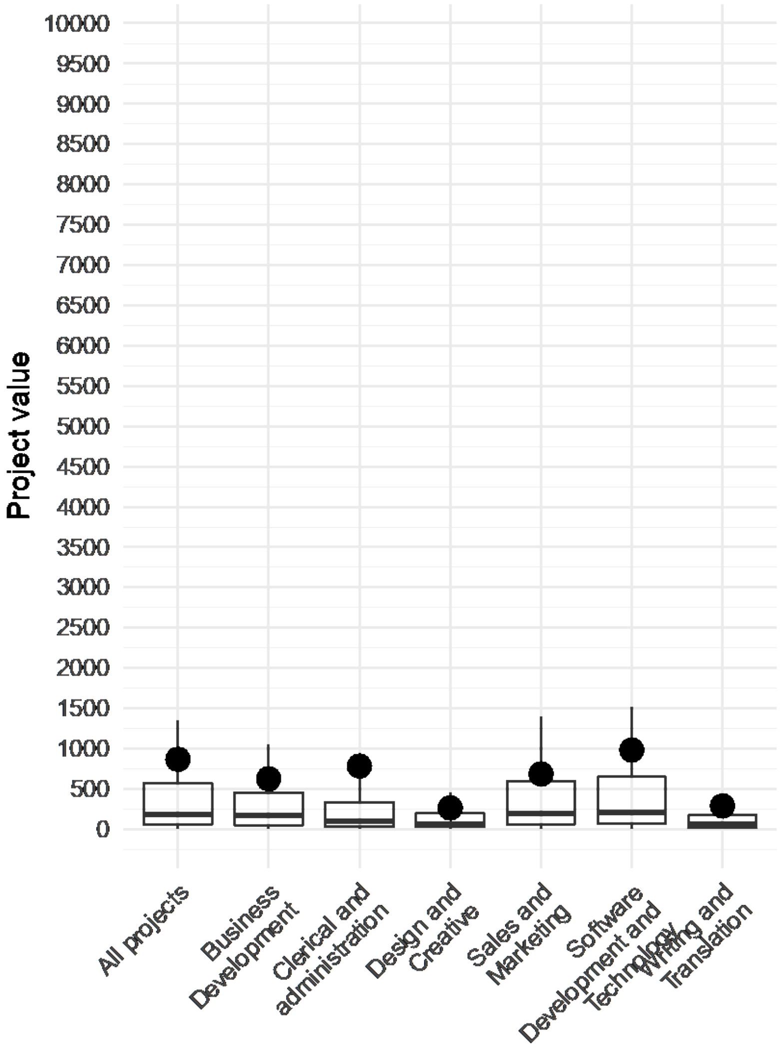


Figure 7: Distribution of average project values of Indian workers by occupation. In each box-and-whiskers plot, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution. For visualisation purposes, 1% of the distribution is excluded from the graph.

4.2 Distribution of weekly wages

Figures 8 (a) and (b) plot the weekly wages of Indian online workers. In Figure 8 (a), we have excluded the top 1% of the weekly wage distribution from the graphs. In Figure 8 (b), we only show the mean and the median for each occupation.

To get a better benchmark for online workers' wages, we include the 'typical' weekly wages based on different sources. Unfortunately, we do not have access to an authoritative source such as a Labour Force Survey for the wage data. Instead, we opt for two proxy measures. First is the weekly salary of recent college graduates in India in December 2022, according to a survey by Indeed.com converted to USD using the mid-market average exchange rate of December 2019. Second, we use the average Indian monthly wage from 2018 as reported by the ILO Global Wage Survey data (ILO 2021, Appendix I). We convert this number into weekly wages by dividing the monthly wage by four and further convert the number into USD using the 2018 average mid-market exchange rates.

According to Indeed, the average weekly wage of new graduates in December 2022 is 58.30 USD, and the average wage of Indians, according to ILO Global Wage Survey, is 49.00 USD. Both measures have their advantages and drawbacks. The Indeed measure is more comparable in that recent graduates are likely more similar to online workers, at least in the sense that online workers work in white-collar occupations similar to those advertised on Indeed.

One downside for the Indeed data, on the other hand, is that the periods (December 2022 vs 2018–2019) are slightly less comparable. Moreover, Indeed does not provide details on how their average wage measure for new graduates is calculated. Thus, the representativeness of the data underlying the Indeed wage measures is not entirely clear.

The ILO wage measure, on the other hand, covers both blue-collar and white-collar workers. Both measures cover only the formal labour market. In a country with a large informal labour market, such as India, the average wages in the informal sector are likely much lower. Thus, the prevailing wage rates across formal and informal sectors combined, are likely lower than the formal sector only.

According to Figure 8 (a), the median weekly wage is 230 USD across all projects. The smallest weekly median wages are in Design and Creative (USD 80), while the largest are in Software Development and Technology (USD 250). The distribution is highly skewed, where the top earners can make more than USD 10,000 per week.

Due to the scale, the average offline wages are not visible in Figure 8 (a). Therefore, Figure 8 (b) only shows the mean and the median for each distribution. It is apparent that, regardless of the weekly wages measure, the average offline wages are much lower than the typical weekly wages of platform workers. Even in the lowest-paying categories (Design and Creative and Writing and Translation), the median wages are slightly larger than the corresponding weekly wages from offline work.

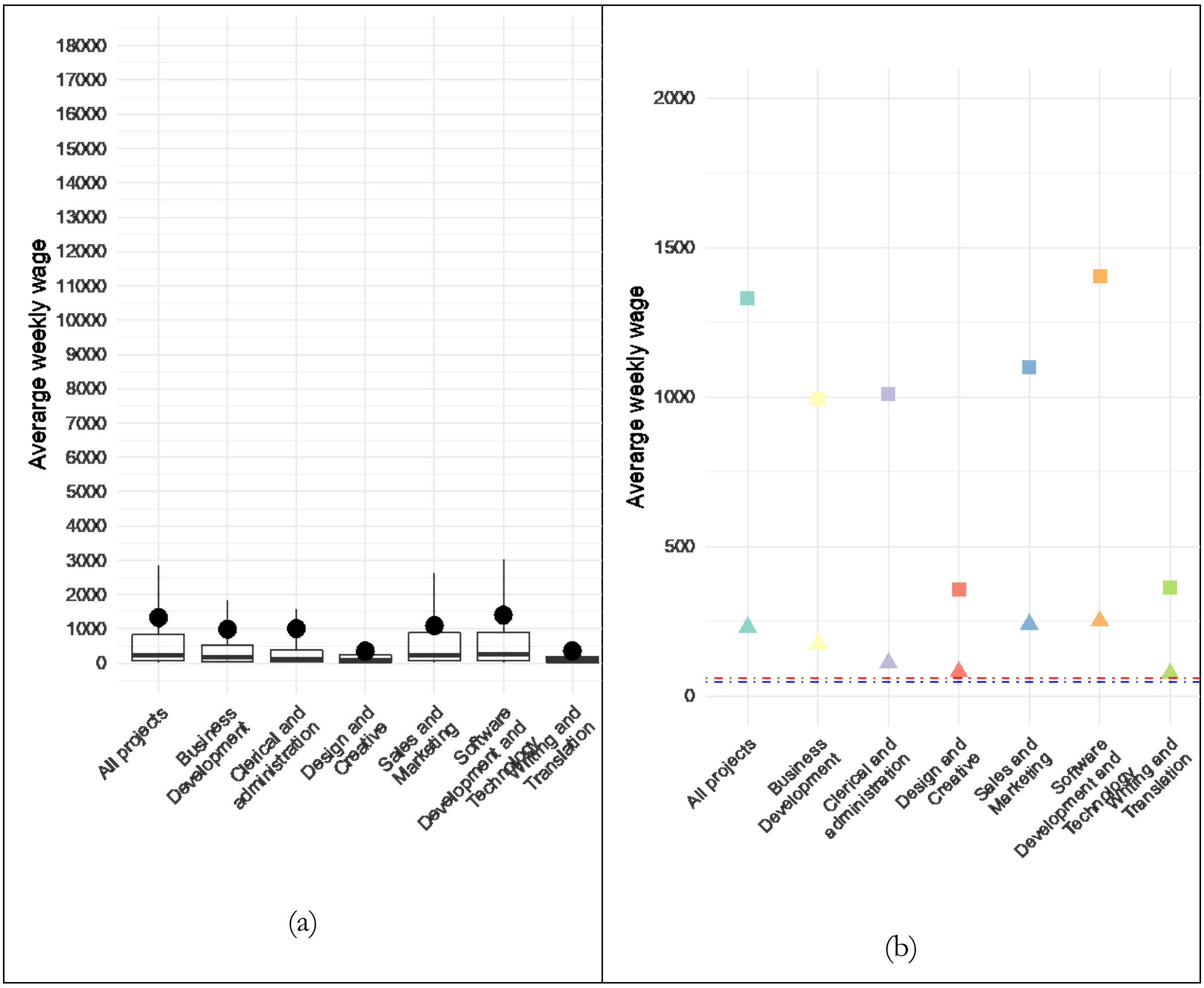


Figure 8: Distribution of average weekly wages of Indian workers by occupation. In each of the box-and-whiskers plots, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution. In panel (a), the top 1% of the distribution is excluded from the graph. Panel (b) shows the means (squares) and medians (triangles) for each occupation. In panel (b), the red dashed line

corresponds to the average weekly wage of new college graduates based on data from Indeed.com. The blue dashed line corresponds to the average weekly wage according to ILO (2021a)

4.3 Hourly wages

We finally turn to study average hourly wages by the worker. This information is only available for hourly-priced projects, as in the previous section. We plot this information in Figure 9. The figure also shows the average hourly wages based on data from Indeed.com.

The median hourly wages of Indians range from USD 7 to USD 13. This is more than an average hourly wage of a new graduate, as reported by Indeed.com, which is roughly USD 1.8.

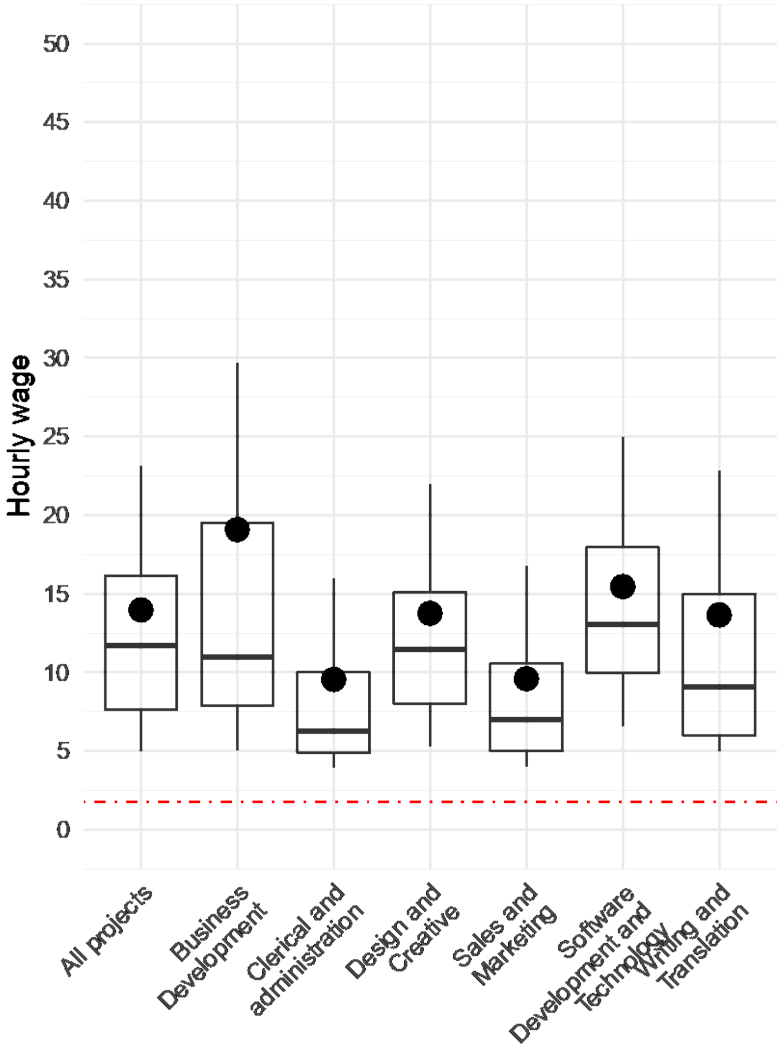


Figure 9: Distribution of average hourly wages of Indian workers by occupation. In each of the box-and-whiskers plots, 75% of the observations are inside the box, and 90% of the observations are inside the whiskers. The top decile of the observations is denoted as light grey symbols. The horizontal lines correspond to medians, and the black dots correspond to the means of each distribution. The red dashed line corresponds to the average weekly wage of new college graduates based on data from Indeed.com.

5 Discussion

This paper uses platform transaction data to describe the working hours and wages of Indian platform workers. In general, online labour tends to pay well for the majority of workers. Moreover, weekly and hourly wages for close to most online workers are higher than comparable average wages in the traditional labour market.

That said, the high wages are conditional on workers getting jobs. Our data shows that over two-thirds of workers who apply for jobs fail to land any jobs. This happens despite various algorithmic and other practices introduced by the platform to improve matching and balancing labour supply with the demand. Among other things, most labour platforms have relatively strict entry requirements. This means that only workers whose skills are deemed to be in demand are allowed to register as workers (and thus get included in our data). Moreover, the workers face the risk of deactivation if they are considered to be providing poor-quality work. Additionally, virtually all platforms have various digital tools, such as recommendation algorithms (Horton, 2017), digital skill tests (Kässi & Lehdonvirta, 2022), and reputation systems (Gandini et al., 2016), built to facilitate matching between workers and clients. Nonetheless, even with these policies, the "unemployment rate" among Indians in our data is almost 70%.

Previous research suggests that information frictions related to skills are at least a partial explanation. For example, Pallais (2014) reports on a field experiment in which she randomly hired inexperienced workers and provided feedback on their performance. These workers earned considerably more from their subsequent projects than the control group, who received no feedback. Since the field experiment only altered the information that the clients observed on the workers, this suggests that the workers face uncertainty about the quality of work that the workers can provide, and lacking feedback is a barrier to entry.

While Pallais' results imply that information frictions partially explain the difficulty of landing the first job, the estimated effect sizes are far too small to explain the large share of workers without any work experience.

Some authors (e.g., Braesemann et al., 2022) have noted that the fierce competition in online labour markets tends to push wages down. While this argument is valid, we also note that in online labour markets, the platforms' fees are based on the wage bill of jobs transacted on the platform. Therefore, it is in the interest of the platforms to increase the wage bill for each completed task. If anything, the wages paid in the labour market are expected to be higher than in a less regulated environment. For instance, most platforms have introduced a minimum hourly wage (Horton, 2017).

The workers pay a part of the platforms' service fees. In traditional labour markets, it is usually illegal for an employment agency to charge fees from a worker, but this is relatively common in platform labour. Recent empirical evidence also suggests that workers cannot offset higher fees by charging their clients higher rates (Gomez-Herrera, 2022). Typical platform fees range from 10% to 30%.

Transaction data also misses unpaid work. Given the intense competition for jobs, many workers need to spend considerable time looking for jobs, writing job applications and negotiating the details of their contracts. Our finding of very high median weekly wages suggests that a large share of the unpaid work is related to job search. According to conventional definitions, workers looking for jobs would count as unemployed. While the existing survey evidence suggests that, on average, the share of unpaid work ranges from 25-30% (see ILO 2021), it is likely that a large share of the unpaid work is related to job search. Differentiating job search from other unpaid work activities such as non-payment of completed work, and coerced free revisions of tasks would be important in understanding the causes of non-paid work. It should also be noted that for most workers – those who fail to land any jobs – the share of unpaid work is 100%.

Under the assumption that platform fees are 30%, and workers spend 30% of their time doing unpaid work, we can adjust the hourly wages by a factor of 0.49 (0.7 * 0.7). Even after this adjustment, most hourly wages are far above the average wages of recent college graduates depicted in Figure 9.

That said, especially new platform workers often have difficulties assessing the amount of unpaid work and platform costs that are part of doing platform work (e.g. Maffie, 2022). This underestimation is one central factor leading to lower work satisfaction.

Throughout the paper, we have assumed that a worker id is associated with precisely one worker. While the platforms tend to put considerable effort into verifying workers' identities, it still might be the case that, instead of individual workers, especially in the highest earning accounts, companies employ multiple workers operating under a single user's name. The highly unequal distribution of work opportunities among workers makes re-outsourcing lucrative from workers' perspectives. However, quantitative information on the extent and impact of re-outsourcing remains slim and inconsistent. The small number of surveys that try to measure this reviewed in Kässi et al. (2021) re-outsourcing is relatively rare. Roughly between one-fifth and one-quarter of accounts are shared by multiple workers. At the same time, Melia (2020) uses qualitative data on Kenyan platform workers to show that due to fierce competition and unequal distribution of work between workers, there might be ten or more workers working under a single worker account. Likely, the level of re-outsourcing varies greatly across online work tasks and geographies.

6 Conclusions

This paper uses transaction-level data from a leading online labour platform to study whether platform work provides continuous employment or mostly one-off gigs for Indians. According to our findings, most Indians face an insurmountable hurdle in landing any jobs on the market. Over two-thirds of workers fail to get any jobs despite applying.

Even the minority of workers who get jobs tend to only work on a handful of projects yearly. The median number of platform work weeks is slightly over 10. This means that for over four-fifths of a year, the workers tend to get their income from other sources, and the income from platform labour is only a supplementary source of income.

Conditional on working, working on the platform pays relatively well. Both median weekly and hourly wages are over five times larger than our best estimate for the corresponding numbers in the traditional labour market. Our measure of wages is based on the hours billed from the client, which likely is an overestimate for the take-home pay. There are several reasons for this. First, our measure fails to account for platform fees, unpaid work time, and the fact that several workers might be working under the same account. If we account for these factors using estimates from the literature, our estimates still suggest that platform workers are paid rather well if they manage to land a job.

Our findings also highlight that separately accounting for intensive (probability of working) and extensive (earnings) margins of online labour participation are essential if one tries to understand the labour market outcomes of platform workers. Not accounting for intensive and extensive margins separately directly impacts the conclusions on possible regulation of platform work. Our data suggest that since the main reason for the low total earnings of workers is the availability of work and not hourly wages, mandating a living wage standard for platform workers would do very little to help the most vulnerable workers. On the other hand, a regulation limiting the maximum weekly hours of workers might be more efficient in redistributing work more evenly across the workforce. A possible practical problem here is that many of the most active worker accounts might be agencies that aggregate the work of multiple individuals.

It is worth highlighting that wage and availability of work are but two facets of job quality. Even if the work pays relatively well for those who can get jobs, many online labour platforms still have various policies in place that are risky from the worker's point of view. For instance, non-payment for work is common (Howson et al., 2022), and workers' accounts can often be deactivated without justification, sometimes even without even a previous warning.

Our research has a takeaway for platform labour scholars regarding data collection. A large share of research on platform labour utilises surveys, which is often the only viable way of collecting data on workers. Nonetheless, our findings highlight that the sampling frame and questions should be designed in a way that both intensive and extensive margins are captured. Averaging the wages of working and non-working freelancers hides a large part of the heterogeneous outcomes of platform workers. Moreover, given the highly skewed nature of the labour market outcomes of platform workers, concentrating on average wages likely misses some information on the labour market outcomes of platform workers.

Researchers often collect survey by hiring workers to answer survey questions. In that case, the high-earning freelancers may be systematically under-sampled due to their higher opportunity cost of answering. This systematically biases the earnings measures downwards. Transaction-level digital trace data, such as the data set used in this paper, thus has obvious strengths over surveys. That said, the main shortcoming of digital trace data is that it systematically misses non-platform work. Combining survey and digital trace data for the same workers could be a valuable way forward.

In summary, the evidence presented in this paper corroborates a long series of papers showing that economic insecurity of platform workers is considerable. Our findings indicate that the insecurity is largely driven by sporadic and unpredictable working schedules rather than low wages. Consequently, the opportunities for continuous employment from platform work remain small for the vast majority of workers.

References

Agrawal, A., Lacetera, N., & Lyons, E. (2016). Does standardised information in online markets disproportionately benefit job applicants from less developed countries?. *Journal of international Economics*, *103*, 1-12.

Beerepoot, N., & Lambregts, B. (2015). Competition in online job marketplaces: towards a global labour market for outsourcing services?. *Global Networks*, *15*(2), 236-255.

Barzilay, A. R., & Ben-David, A. (2016). Platform inequality: Gender in the gig-economy. *Seton Hall L. Rev.*, *47*, 393.

Gandini, A., Pais, I., & Beraldo, D. (2016). Reputation and trust on online labour markets: the reputation economy of Elance. *Work Organisation, Labour and Globalisation*, *10*(1), 27-43.

Graham, M., Hjorth, I., & Lehdonvirta, V. (2017). Digital labour and development: impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transfer: European review of labour and research*, 23(2), 135-162.

Gomez Herrera, E., & Müller-Langer, F. (2019). Is there a gender wage gap in online labor markets? Evidence from over 250,000 projects and 2.5 million wage bill proposals.

Gomez-Herrera, E. (2022). Do Workers Bear the Burden of Fee Increases on Online Labor Platforms? Unpublished working paper.

Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C., & Bigham, J. P. (2018, April). A data-driven analysis of workers' earnings on Amazon Mechanical Turk. In *Proceedings of the 2018 CHI conference on human factors in computing systems* (pp. 1-14).

Hornuf, L., & Vrankar, D. (2022). Hourly Wages in Crowdworking: A Meta-Analysis. https://www.cesifo.org/en/publications/2022/working-paper/hourly-wages-crowdworking-meta-analysis

Herrmann, A. M., Zaal, P. M., Chappin, M. M., Schemmann, B., & Lühmann, A. (2023). "We don't need no (higher) education"-How the gig economy challenges the education-income paradigm. *Technological Forecasting and Social Change*, *186*, 122136.

Horton, J. J. (2017). The effects of algorithmic labor market recommendations: Evidence from a field experiment. *Journal of Labor Economics*, 35(2), 345-385.

Horton, J. J. (2017). Price floors and employer preferences: Evidence from a minimum wage experiment. Available at SSRN 2898827.

Howson, K., Johnston, H., Cole, M., Ferrari, F., Ustek-Spilda, F., & Graham, M. (2022). Unpaid labour and territorial extraction in digital value networks. *Global Networks*.

International Labour Organisation (2021a). *Global Wage Report 2020-21*. Geneva: International Labour Organisation.

International Labour Organisation (2021b). *World employment and social outlook: the role of digital labour platforms in transforming the world of wor*k. Geneva: International Labour Organisation.

Maffie, M. D. (2023). Becoming a pirate: Independence as an alternative to exit in the gig economy. *British Journal of Industrial Relations*, *61*(1), 46-67.

Kingsley, S. C., Gray, M. L., & Suri, S. (2015). Accounting for market frictions and power asymmetries in online labor markets. *Policy & Internet*, 7(4), 383-400.

Kässi, O., Lehdonvirta, V. and Stephany, F. (2021) How many online workers are there in the world? A data-driven assessment [version 4; peer review: 4 approved]. *Open Res Europe 1:53* (https://doi.org/10.12688/openreseurope.13639.4)

Kässi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological forecasting and social change*, 137, 241-248.

Kässi, O., & Lehdonvirta, V. (2022). Do Microcredentials Help New Workers Enter the Market? Evidence from an Online Labor Platform. *Journal of Human Resources* (forthcoming).

Lehdonvirta, V., Hjorth, I., Graham, M., & Barnard, H. (2015, August). Online labour markets and the persistence of personal networks: evidence from workers in Southeast Asia. In American Sociological Association Annual Meeting (Vol. 8, pp. 23-45).

Melia, E. (2020). *African jobs in the digital era: Export options with a focus on online labour* (No. 3/2020). IDOS Discussion Paper, German Institute of Development and Sustainability.

Pallais, A. (2014). Inefficient hiring in entry-level labor markets. *American Economic Review*, 104(11), 3565-99.

Rani, U., & Furrer, M. (2019). On-demand digital economy: Can experience ensure work and income security for microtask workers?. *Jahrbücher für Nationalökonomie und Statistik*, *239*(3), 565-597.

Stephany, F., Kässi, O., Rani, U., & Lehdonvirta, V. (2022). Online Labour Index 2020: New ways to measure the world's remote freelancing market. *Big Data & Society* 8.

Silberman, S. (2018). Rights for platform workers, IG Metall crowdsourcing project discussion paper, IG Metall. Frankfurt.

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 33(1), 56-75.