Diginomics Working Paper

Research Group Diginomics
Digitalization - Economy - Society

Hourly Wages in Crowdworking: A Meta-Analysis

Lars Hornuf, Daniel Vrankar

January 2022

No. 0007

Universität Bremen

Impressum:

Diginomics Working Paper

ISSN: 2701-6307

Published by:
Universität Bremen, Diginomics Research Group, Max-von-Laue-Straße 1, 28359 Bremen, Germany

Editor:
Prof. Dr. Lars Hornuf
Phone: +49(0)421 218 66820
E-mail: hornuf@uni-bremen.de

https://www.uni-bremen.de/graduiertengruppe-diginomics/forschung/diginomics-working-paper

Hourly Wages in Crowdworking: A Meta-Analysis

Lars Hornuf

University of Bremen, Faculty of Business Studies and Economics, Max-von-Laue-Straße 1, 28359 Bremen, Germany
hornuf@uni-bremen.de

Daniel Vrankar

University of Bremen, Faculty of Business Studies and Economics, Max-von-Laue-Straße 1, 28359 Bremen, Germany
vrankar@uni-bremen.de

Abstract

In the past decade, crowdworking on online labor market platforms has become the main source of income for a growing number of people worldwide. This development has led to increasing political and scientific interest in the wages that people can earn on such platforms. In this article, we extend the literature based on a single platform, region, or category of crowdworking by conducting a meta-analysis of the prevalent hourly wages. After a systematic and rigorous literature search, we consider 20 primary empirical studies, including 104 wages and 76,282 data points from 22 platforms, eight different countries, and a time span of 12 years. We find that, on average, microwork results in an hourly wage of less than $6. This wage is significantly lower than the mean wage of online freelancers, which is roughly three times higher. We find that hourly wages accounting for unpaid work, such as searching for tasks and communicating with requesters, tend to be significantly lower than wages not considering unpaid work. Legislators and researchers evaluating wages in crowdworking should be aware of this bias when assessing hourly wages, given that the majority of the literature does not account for the effect of unpaid work time on crowdworking wages. To foster the comparability of different research results, we suggest that scholars consider a wage malus to account for unpaid work. Finally, we find that hourly wages collected through surveys tend to be lower than wages collected via browser plugins or other technical data collection methods.

This version January 20, 2022

Keywords Crowdworking, Crowdsourcing, Meta-analysis, Hourly wage, Remuneration, Gig-economy

1. Introduction

After years of annual double-digit growth, crowdworking has become a multi-billion-dollar industry, offering work to millions of people (Kaganer et al. 2013; Aloisi 2015; Kuek et al. 2015; ILO 2018; Kässi and Lehdonvirta 2018; Durward et al. 2020). Crowdworking enables the near instant worldwide matching of workers and requesters on so-called online labor market platforms (Shafiei Gol et al. 2018). At first glance, this outgrowth of the digital economy provides considerable advantages for workers and requesting companies. Workers are attracted by low entry barriers, high flexibility in working hours and location, and high autonomy in choosing their specific tasks (Hara et al. 2018; Shafiei Gol et al. 2018). These factors should in turn boosts social mobility, particularly in developing countries and for people with disabilities and other minorities (Kittur et al. 2013; Adams and Berg 2017). Requesters, which often come from developed countries, profit from remunerations far below the minimum wage in their respective jurisdiction.

The remuneration in crowdworking often causes frustration due to underpayment on the worker side, regardless of the workers' location (Whiting et al. 2019). Workers from developed countries are dissatisfied with hourly wages far below the national average. Workers from developing countries can earn wages above the national average but are often frustrated knowing that their work would be better paid in the requester's country (Berg et al. 2018). Although intrinsic motivators such as self-growth or enjoyment (Berg 2016; Shafiei Gol et al. 2018) should not be neglected as an explanation for why people participate in online labor, especially new crowdworkers mainly focus on financial remuneration (Brewster et al. 2019), which aligns with crowdwork being the main income for almost two-thirds of crowdworkers (Rani et al. 2021).

Examining the hourly wage of crowdworkers is therefore highly relevant, as evidence by the growing number of studies examining the remuneration on online labor market platforms during the last years. Most of these studies, however, focus on one platform (Beerepoot and Lambregts 2015; Hara et al. 2019) or one region (Dunn 2017; Serfling 2018; Bayudan-Dacuycuy and Kryz Baje 2021) and base their analysis on only one method of data collection (Hara et al. 2018; Wood et al. 2019a). By conducting a meta-analysis, we overcome many of these limitations and increase the transparency in the hourly wages crowdworkers earn.

We contribute to extant literature in at least two ways. First, we estimate average hourly wages for microtasks and online freelancing using a comprehensive dataset of hourly wages in crowdworking. Second, we highlight methodical differences when reporting wages without considering unpaid work, and we report hourly wage differences that exist among various categories of crowdworking. We also distinguish between the different methods of data collection and interpretations of calculated wages in crowdworking. In particular, we shed light on different systematic biases in the literature.

The structure of this article is as follows: Section 2 gives an overview of the relevant literature and develops the hypotheses. In section 3, we describe the data and methods, after which we report the results in section 4. In section 5, we discuss the limitations of our approach and connect our results with the current policy debate. Section 6 concludes the article.

2. Literature Review and Hypotheses

With the emergence of online labor market platforms, the remuneration of crowdworkers has attracted increasing attention from the scientific community (Ipeirotis 2010; Paolacci et al. 2010; Brawley and Pury 2016; Pongratz and Bormann 2017; Khovanskaya et al. 2019), trade unions (Drahokoupil and Fabo 2016; Leimeister et al. 2016; DGB 2021), and both governmental and non-governmental agencies (Dengler and Matthes 2015; Bertschek et al. 2016; De Groen et al. 2016; Greef et al. 2017; Maier and Viete 2017; Serfling 2018). Initial research has mostly focused on the requester side of online labor market platforms and, for example, determined the reservation wage of crowdworkers (Horton and Chilton 2010). That changed as increasingly more authors voiced concerns about low wages and the exploitation of workers (Nickerson 2013; Pallais 2014) and tried to increase wage transparency for workers and legislators. When investigating wages in crowdworking, researchers face at least three challenges.

The first challenge pertains to the term "crowdworking" itself, because it describes a rather diverse and broad set of work, including different platforms with different payment structures. On some platforms, such as Upwork, workers and requesters can directly and immediately negotiate an individual hourly wage. By contrast, workers on Amazon Mechanical Turk (MTurk) are paid for the completion of each task, and on contest platforms such as 99designs, only the best idea are remunerated (Rani et al. 2021). Everyone whose submission was determined not to be the best or one of the best leaves the competition empty-handed. Thus, a simple comparison of earnings between the different categories of crowdworking has only limited value because on some platforms, users may work many hours without being remunerated, while on other platforms, they are paid for every task. We therefore decided to separate crowdwork into *microtasks* and *online freelancing* (De Stefano 2015; Kuek et al.

2015). While some researchers add a third category for *contest-based crowdwork* (e.g., design competitions), we include it in the category of online freelancing. This is because wages in contest-based crowdwork can only be determined if a contract with an hourly pay was concluded after winning the contest, effectively turning the worker into an online freelancer (Nickerson 2013; Schmidt 2016; Berg et al. 2018; Rani and Furrer 2021).

The work classified as microtasks often involves assignments that take only seconds or, at most, a few minutes to complete and require only little prior knowledge and rudimentary education (Gao et al. 2015; Schmidt 2017; Durward et al. 2020). Tasks range from data entry and transcription to image recognition. The most notable platforms are MTurk and Appen (Rani et al. 2021). It is precisely this category of crowdwork that some scholars view as an extreme form of Taylorism (Kittur et al. 2013; Aloisi 2015), defined as the partitioning of a large, intellectually demanding task into many small tasks, each of which can be completed with minimal mental effort.

Online freelancing involves assignments that can take hours, days, and even weeks and need specialized skills, such as programming knowledge, the comprehension of multiple languages, or legal expertise (Beerepoot and Lambregts 2015). Exemplary tasks involve designing a logo, developing a small program, or acting as customer support for a requester's product. As a result, a disproportionate number of workers on online freelancing platforms have earned at least a bachelor's degree (Ross et al. 2010; Bertschek et al. 2016; Rani et al. 2021). The mismatch between the average education of the general population and the people who work as online freelancers is especially high in developing countries (Berg et al. 2018; Braesemann et al. 2021). The most popular site for such work is Upwork, followed by Freelancer.com, and PeoplePerHour (Kässi and Lehdonvirta 2018). As the name of the last platform suggests, online freelancers often deliberately negotiate hourly wages. Clearly defined hourly wages help online freelancers to be more aware of their hourly remuneration than microtask workers, who often have difficulties adding up the remuneration of many small tasks without the help of additional tools such as browser plugins. Online freelancers can therefore more easily distinguish between tasks that result in low and high wages. Because of this difference in payment structure and especially owing to the broader skill set required to complete online freelancing tasks, we posit the following:

Hypothesis 1: In crowdworking research, the hourly wages of online freelancers are higher than those of workers completing microtasks.

In addition to different forms of crowdworking, empirical studies often use different definitions of work time, which makes it difficult to calculate and compare hourly wages. This poses the second challenge when analyzing hourly wages in crowdworking research. In her seminal article, Berg (2016) includes unpaid work in her calculations of hourly wages. She notes that "looking for tasks, earning qualifications, researching requesters through online forums, communicating with requesters or clients and leaving reviews, as well as unpaid/rejected tasks/tasks ultimately not submitted" (p. 49), take up a major part of the overall work time of crowdworkers. While some authors assume half of all work to be unpaid (Berg et al. 2018), others assume around one-third of the work time to be dedicated to unsalaried work (Rani and Furrer 2021). Given the nature of the respective assignments, online freelancers are likely to spend significantly more time doing unpaid work than people working on microtasks, which also results from the higher need for communication between freelancers and the requester. Online freelancers, for example, often negotiate terms and discuss details of the commissioned work (Rani and Furrer 2021), which are often specified in standard contracts for microtasks. While most research considering paid and unpaid work compares the remuneration only for one specific dataset, we compare both types of wages over different studies and datasets. Thus, we posit the following:

Hypothesis 2: In crowdworking research, hourly wages only accounting for paid work are higher than wages that also consider unpaid work.

Another distinction between studies covering wages in crowdworking is the method of data collection. This leads to the third challenge in comparing crowdworking wages. In particular, the literature employs two methods to gather data on wages: *surveys* (e.g., Barzilay and Ben-David 2017; Wood et al. 2019a) and *technical data collection methods* (e.g., Ipeirotis 2010; Hara et al. 2018). Surveys are often the only way to collect information about wages, because most platforms do not offer an easy way to extract wages and information about unpaid work. An exception is MTurk, on which hourly wages can be estimated via browser plugins (Hara et al. 2018; Saito et al. 2019). After a worker has installed one of the available plugins, the plugin tracks the completion time per task, the reward per task, and the acceptance rate, among other statistics, and allows the estimation of an hourly wage (Callison-Burch 2014; Hara et al. 2018). The respective hourly wage is then displayed to the worker and thus helps her or him keep an eye on productivity. Some plugins even offer the possibility of rating the individual requester after the completion of each task. All ratings are then aggregated and displayed to other workers using the same plugin, potentially warning workers about tasks that are considered unfair or are not feasible (Irani and Silberman 2013). The plugins themselves are often programmed by researchers who make them available to workers free of charge and allow other researchers to then analyze the respective data.

On other platforms, researchers are dependent on the willingness of online labor platforms to participate in research projects and to share primary data on wages and other information on unpaid work (Agrawal et al. 2015; Barzilay and Ben-David 2017; Dunn 2017). Wages that rely on technical data collection methods, regardless of whether the wages are estimated by the researchers themselves or are provided by the platform, frequently do not entail information on unpaid work. For the estimation of an hourly wage, the remuneration for completing a task is therefore often simply divided by the duration of the task ($Time_{Finished} - Time_{Accepted}$). The resulting pay per minute is then scaled up to one hour (Ipeirotis 2010), which neglects various components of unpaid work as compared with a survey. Although it might be argued that workers misrepresent and overstate their hourly wages when taking part in a survey to maintain a positive self-image (Mazar et al. 2008), recent research shows that crowdworkers are well aware of their often low hourly remuneration (D'Cruz and Noronha 2016; Whiting et al. 2019) and could also want to draw attention to their precarious working conditions. We therefore suspect a systematic bias resulting from the choice of data collection method. Thus:

Hypothesis 3: In crowdworking research, technically measured hourly wages are higher than hourly wages reported through a survey.

3. Data and Method

3.1. Data

Fig. 1 provides a flow diagram of the process of searching, screening, and including or excluding studies in the meta-analysis. In line with the guidelines for Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), we used and slightly modified the template of Liberati et al. (2009). As a first step in our meta-analysis, we conducted a systematic and rigorous literature search from July 2020 to March 2021 to identify suitable studies and hourly wages. Initial keywords were extracted from *ex ante* known articles that analyze hourly wages in crowdworking. With keyword combinations such as “crowdwork per hour,” “crowdsource remuneration,” “crowdwork earnings,” and “crowdwork hourly,” we then manually searched the databases ScienceDirect, Scopus, Business Source Premier, and

ProQuest,[1] which led to the identification of 399 potentially relevant studies and articles. In a second step, we considered the first 50 search results on Google Scholar for all the keywords, which resulted in 380 additional studies found during the systematic literature search. We judged studies as potentially relevant if they were published in a journal, as a report of a trade union, by a government authority or non-governmental organization, or as a conference paper. Of the 779 potentially relevant studies, 669 were irrelevant, because they did not report a crowdworking wage in any form. Consequently, we checked the remaining 110 studies for eligibility and searched their respective reference lists, to minimize the risk of missing an important observation.

Figure 1 about here

To be included in the meta-analysis, publications needed to meet two criteria. First, a relevant study had to state an hourly wage or allow the calculation of an hourly wage on the basis of primary data collected by the respective authors of the study. If, for example, the average weekly wage and the average weekly work hours were reported, we calculated the hourly wage and included the study in the meta-analysis. Second, a study must have specified the number of data points on which the reported wage was based. For 67 studies, the reported wages were collected by other researchers and not by the respective authors. Eight studies stated prizes for crowd innovation contests without giving any information on the work time spent for winning the contest.

One study mixed survey responses from online freelancers with responses from freelancers working on *location-based* platforms (Rani and Furrer 2021) such as Uber or Lieferando and therefore was excluded. Four studies stated hourly wages the authors paid in experiments on online labor market platforms. These studies did not have the goal to collect primary data on crowdworking wages, and therefore we did not include them in the meta-analysis. We contacted

[1] The full list of keyword combination included “crowdwork per hour,” “crowdwork hourly,” “crowdwork wage,” “crowdwork remuneration,” “crowdwork earned,” “crowdwork earnings,” “crowdwork pay,” “crowdwork $,” “crowdwork dollar,” “crowdwork USD,” “crowdwork €,” “crowdwork EUR,” “crowdwork ¥,” “crowdwork yen,” “crowdwork £,” “crowdwork pound,” “crowdsource per hour,” “crowdsource hourly,” “crowdsource wage,” “crowdsource remuneration,” “crowdsource earned,” “crowdsource earnings,” “crowdsource pay,” “crowdsource $,” “crowdsource dollar,” “crowdsource USD,” “crowdsource €,” “crowdsource EUR,” “crowdsource ¥,” “crowdsource yen,” “crowdsource £,” “crowdsource pound,” “Crowdsource Pfund,” “Crowdwork Entlohnung,” “Crowdwork Mindestlohn,” “Crowdwork Stundenlohn,” “Crowdwork Einkommen,” “Crowdwork Vergütung,” “Crowdsource Entlohnung,” “Crowdsource Mindestlohn,” “Crowdsource Stundenlohn,” “Crowdsource Einkommen,” and “Crowdsource Vergütung.”

four authors of four studies to obtain additional statistics and, in the end, considered three of the studies.

Ross et al. (2010) is one of the most-cited articles analyzing wages in crowdworking (List and Momeni 2021; Newlands and Lutz 2021; Zhang et al. 2021), even though one of the authors stated in 2015 that the article should no longer be cited because the statistics are no longer up to date.[2] Because of the significance of Ross et al. (2010) in the literature analyzing wages in crowdworking and the adjustments we make in our empirical analysis to account for the data collection period, we deliberately included their observations; however, we discuss the consequences of not including that study in subsection 3.3. Finally, we calculated 10 hourly wages from other statistics in the respective article. Five observations initially measured in euros were converted into U.S. dollars, with the exchange rate at the time of data collection of the respective study.

Overall, 20 primary studies were eligible for inclusion in the meta-analysis, in which we made 104 *observations* of hourly wages. Observations are the average hourly wages reported in a given study for a sample of crowdworkers. The 104 average hourly wages that represent the observations are based on 76,282 data points. Each data point represents either the response to a survey question about the wage of a crowdworker or a wage collected via a data collection method on the respective platform. Unless explicitly stated, we count observations from surveys as considering unpaid work in the wage calculation. We decided to include multiple observations per study in our dataset if, for example, a study included paid and unpaid wages of the same workers. We used this approach to prevent the loss of additional information (Bijmolt and Pieters 2001); however, we did not conduct any tests with overlapping information from the same study when testing our hypotheses. The sample includes between one and 22 hourly wages per study, while the mean was five hourly wages per study. The average number of data points per study was 874 and varied between 14 and 12,326 data points. We account for the variance in data points per study in a weighting procedure, which we describe in more detail in subsection 3.3. Table 1 provides an overview of the included studies and the regions and platforms they respectively cover.

We cannot assume that the number of data points are identical to the number of individual crowdworkers for three reasons. First, crowdworkers often work on multiple platforms (Serfling 2018), which allows them to answer surveys on these platforms and potentially results

[2] See authors' comment at https://dl.acm.org/doi/10.1145/1753846.1753873 (Accessed: Jan 10, 2022).

in two separate data points for one crowdworker. Second, even crowdworkers who only perform tasks on one platform could potentially answer several of the included surveys, as the surveys were conducted by different researchers and at different points in time, which could again result in multiple data points per worker. Arguably, given the large number of crowdworkers on a platform such as MTurk, it seems rather unlikely that one crowdworker would undertake the same task of filling out a survey twice. Third, technical data collection methods often estimate the hourly wage by determining the wage per task and not per worker. Because workers often complete multiple tasks on one platform, the number of observed tasks is not equal to the number of observed workers.

Our meta-analysis includes at a minimum 15,580 unique workers. This figure is the result of adding up data points from different studies but considering only the study with the most underlying data points in the respective country, which hardly includes the same respondents. Two studies in our sample use the same dataset from a 2017 International Labour Organization survey (Berg et al. 2018; Rani and Furrer 2019). Moreover, Hara et al. (2018) and Hara et al. (2019) use identical primary data sources for their studies. We included all these studies in our meta-analysis because they offer different insights into the same datasets. For example, Berg et al. (2018) make a distinction between the mean wage of American and Indian workers on MTurk, and Rani and Furrer (2019) provide the mean wage for the entire Asian region. As a general rule, when calculating mean hourly wages in our meta-analysis and testing our hypotheses, we made sure to only included observations based on different primary datasets. If we confronted multiple observations from the same dataset (e.g., Hara et al. 2018; Hara et al. 2019), we used the observation with the most underlying data points to account for overrepresentation bias (Revelli and Viviani 2015).

In total, we obtained hourly wages for workers from eight different countries,[3] working on 22 of the most common online labor market platforms[4] (Kässi and Lehdonvirta 2018), over a sample period of 12 years, from 2009 to 2021. We obtain roughly three-quarters of the observations through technical data collection methods, and approximately one-fifth of all observations account for unpaid work. Therefore, to best of our knowledge, our meta-analysis uses the most comprehensive dataset of hourly wages in crowdworking in the literature.

[3] China, Germany, India, Italy, Philippines, Serbia, Ukraine, and United States.

[4] Advego.ru, MTurk, Clickworker, CoContest, Crowd Guru, CrowdFlower, EPWK, fl.ru, Freelance.ru, Freelance.ua, Free-lance.ua, Freelancehunt.com, Freelancer.com, Kabanchik.ua, k68, Microworkers, Prolific, Upwork.com, Weblancer.net, ZBJ, 680, and 99designs.

Table 1 about here

3.2. Variables

Table 2 provides an overview of the variables we use in our empirical study. The variable *Hourly Wage* is the variable of interest and measures the hourly wage of crowdworkers in U.S. dollars as reported in a specific study. To test our hypotheses, we treat *Hourly Wage* as our quasi-effect size. To make meaningful comparisons between wages measured at different points in time, we adjusted *Hourly Wage* for the year the data was collected in the respective study to the year 2021. *Hourly Wage 2021* represents the hourly wage as reported in a specific study adjusted over time using the inflation rate of the respective country where the data was collected. If no inflation statistics for the specific country or region were available, we considered the international inflation rate (International Monetary Fund 2021). To calculate and weight the mean hourly wages for a specific category of crowdwork and to make the respective statistical adjustments (for more details, see subsection 3.3.), we obtained the number of data points (*Data Points*) and the standard deviation (*Wage Std. Dev.*) for *Hourly Wage* and *Hourly Wage 2021*. For 11 hourly wages, we needed to calculate the number of data points per observation, for example, from a confidence interval or by percentages. For 85 hourly wages, we were able to obtain or calculate the standard deviation.

To investigate Hypothesis 1, we create the dummy variable *Freelancing*, which equals 1 if the hourly wage results from online freelancing and 0 if the hourly wage results from microtasks. The categorization is based on whether the platform was previously assigned to one of the two categories in the studies (e.g., Berg et al. 2018; Schmidt 2016) and whether the platform itself states that it is active in the domain of online freelancing or microtasks. To examine the effect of unpaid work as outlined in Hypothesis 2, we create the dummy variable *Involves Unpaid Work*, which equals 1 if the reported hourly wage in a study considers unpaid work and 0 otherwise. For Hypothesis 3, we define the dummy variable *Data Collection Method*, which equals 1 if the hourly wage was estimated through a technical data collection method and 0 if the authors used a survey.

Table 2 about here

3.3. Method

To test our hypotheses, we define four groups of hourly wages present in empirical crowdworking studies: the hourly wages of online freelancers, the hourly wages of online freelancers considering unpaid work, the hourly wages of workers conducting microtasks, and the hourly wages of workers conducting microtasks considering unpaid work. Thus, we can calculate average hourly wages for two categories of crowdwork, while considering the effect of studies that account only for paid work and those that also account for unpaid work. We then calculate the mean and standard deviation for each group and test our hypotheses by comparing the means of the respective groups. We use a two-sample t-test for unequal variances and Satterthwaite's (1946) formula as an approximation for the needed degrees of freedom. As sample sizes, we use the respective number of hourly wages per group. To analyze the impact of the inclusion of Ross et al. (2010) on our results, we calculate all hourly wages, including data points with and without the hourly wages that can be obtained from that study.

More precisely, to test Hypothesis 1, the dummy variable of interest is *Freelancing*. We therefore separate our dataset into observations of online freelancers and observations of workers completing microtasks. We further assess the effect of hourly wages earned by online freelancers and workers completing microtasks conditional on whether the studies only account for paid work or also consider unpaid work. In the same way, we test Hypothesis 2, in which the dummy variable of interest is *Involves Unpaid Work,* and Hypothesis 3, in which the dummy variable of interest is *Data Collection Method*. Unfortunately, we do not have sufficient observations to conduct a conditional analysis similar to Hypothesis 1. To identify potential causes of bias resulting in the under- or overestimation of mean hourly wages, we analyze the composition of each group regarding the dummy variables not tested. Ideally the sample would be divided almost equally with regard to the variables not tested in the respective hypotheses. For example, when testing Hypothesis 2, we want the category of *Involves Unpaid Work* to be equally distributed regarding the data collection by survey methods and technical data collection methods. We address this issue in more detail when discussing the methodological limitations of our results in subsection 5.1.

To account for the sophistication of the respective studies and the precision with which the hourly wages are measured, we treat *Hourly Wage* as our quasi-effect size and calculate weighted means of hourly wages. First, we weight hourly wages by the number of data points (*Data Points*) in the respective study to account for the sophistication of the particular study. Second, we weight our observations by the inverted variance of an average hourly wage that was reported in the respective study ($\frac{1}{Wage\ Std.Dev.^2}$) to account for various degrees of precision of the hourly wages.[5] These two weights are commonly used in meta-analyses (Schmidt and Hunter 2015; Lee et al. 2016) and allow us to give greater weight to observations based on many data points and observations with a small variance, which presumably provides more consistent estimates of the true hourly wage in the crowdworking population.

We then respectively calculate the weighted mean of the hourly wages as $\bar{x} = \frac{\sum w_i * x_i}{\sum w_i}$, where w_i is the weight corresponding to observation x_i in our sample of hourly wages. In what follows, we use the abbreviations *n-weighted-mean*, or hourly wages weighted for the number of observations, and *v-weighted-mean*, or hourly wages weighted for the inverted variance, to distinguish the two ways of calculating hourly wages in our sample. We calculate the variance of the n-weighted mean as $v_n = \frac{n}{(n-1)\sum w_i} \sum w_i (x_i - \bar{x})^2$, where n is the number of data points, w_i is the weight corresponding to observation x_i, and $\bar{x}$ is the n-weighted-mean. We calculate the variance of the v-weighted mean as $v = se^2 n = \frac{1}{\sum w_i} n$, where se is the standard error of the v-weighted mean and $\sum w_i$ the sum of all weights used to calculate the v-weighted-mean. In line with prior meta-analyses in the field of crowdworking (Spindeldreher and Schlagwein 2016), we only calculate the mean of *Hourly Wage* if observations from at least five independent studies are available.

4. Results

4.1. Descriptive Statistics

Table 3 provides summary statistics for the variables of interest. We report statistics for the complete dataset and independently for the online freelancer and the microtask subsamples. The observations from these two categories of crowdworking are almost balanced in our sample (online freelancer: 51; microtask: 53). The evidence further shows that other variables are balanced as well. For example, we find that around half the hourly wages were obtained through a survey, while the other half were obtained through technical data collection methods. However, the observations of hourly wages of online freelancers are mainly acquired through technical methods, while workers performing microtasks are often evaluated via surveys. While

[5] Note that most studies report the standard deviation of the hourly wage, which we then converted to the variance.

around one-third of all observations account for unpaid work, only one-fifth of the hourly wages of online freelancers account for unpaid work.

Table 3 about here

The maximum hourly wage recorded in our sample is \$77.93 (\$85.11 when adjusted for 2021), and the minimum hourly wage is \$1.30 (\$1.48 when adjusted for 2021). While one hourly wage was based on 734 data points, hourly wages of microtasks were based on almost twice as many data points as hourly wages in online freelancing. The higher number of data points per hourly wage is a plausible explanation for the lower standard deviation in the microtasks subsample. Nevertheless, the broader spectrum of tasks in the category of online freelancing also requires a broader skill set, which is an alternative explanation for the higher standard deviation in this crowdworking category. The wide range of hourly wages and respective standard deviations shows how heterogeneous crowdworking is and thus highlights the importance of distinguishing between different categories of crowdwork and data collection methods, when investigating hourly wages.

Fig. 2 shows the distribution of the hourly wages per year, separately for online freelancing and workers completing microtasks. Circles indicate one observation—namely, an average hourly wage reported in the respective study. The larger the circles, the higher the number of data points on which the wage is based. Notably, most observations fall in the year 2016, while we could not find observations for 2011, 2013, and 2019. The figure again shows the broad range of reported hourly wages.

Figure 2 about here

4.2. Mean Hourly Wages

Table 4 reports the mean hourly wages for online freelancers and workers completing microtasks, respectively, for the studies considering only paid work and those considering paid and unpaid work. We separate our findings into four panels, depending on whether we adjust the mean hourly wage for the number of data points in a study, the precision with which an hourly wage is measured, and whether we adjusted the hourly wage for the year 2021 or not. In case of a v-weighted hourly wage for online freelancers, when considering unpaid work ([4b] and [4c]), we could only find two independent studies, though we can report five different observations. In line with our inclusion criteria, we therefore did not calculate a v-weighted mean hourly wage for freelancers accounting for unpaid work.

Table 4 about here

Fig. 3 gives an overview of the estimated hourly wages. We find that the mean hourly wage of workers completing microtasks ranges from \$3.24 to \$5.48 per hour, depending on the respective adjustment method. The calculated mean hourly wage of online freelancers in our meta-analysis ranges from \$10.38 to \$20.81 per hour. Our observations suggest that the wages of freelancers always exceed those of workers completing microtasks, even when we adjust the wages for the year 2021 and use different weighting methods. We also find that the v-weighted means are always lower than their n-weighted counterparts. The difference between the n- and v-weighted mean is especially high for online freelancers, which can be partly attributed to the observations stemming from the studies of Barzilay and Ben-David (2017) and Dunn (2017). Both studies report relatively high wages, but also very high standard deviations, even though their hourly wage estimations are based on thousands of data points. As a result, the hourly wages from these studies are weighted more heavily for the n-weighted mean than for the v-weighted mean. This example highlights the importance of using both the number of underlying data points and the inverted variance as weights to estimate the true hourly wage in crowdworking, even though the number of underlying data points is heavily correlated with the resulting variance. We also find that the inclusion of Ross et al. (2010) lowers the mean hourly wage of workers completing microtasks by \$0.43 (\$0.34 when adjusted for 2021). Given the relevance of this study, we test our hypotheses with and without the observations from Ross et al. (2010).

Figure 3 about here

4.3. Hypotheses Testing

Table 5 reports the results of the hypotheses tests. As outlined in subsection 4.1., we separate the results into four groups, depending on the weighting method and whether we adjust the data for the year of data collection or not.

Table 5

We test Hypothesis 1, which states that the hourly wages of online freelancers are higher than those of workers completing microtasks, respectively, in lines (1), (2), and (2a) in Panels A–D of Table 5. In line (1), we first test the mean hourly wage of online freelancers and workers completing microtasks not considering unpaid work. We then consider the effect of unpaid work in line (2) and, in the end, consider the inclusion of Ross et al. (2010) in line (2a). We observe that hourly wages of online freelances are always higher than those of workers completing microtasks. This result is statistically significant at the 1% level, even when we adjust our wages for the year 2021 or when calculating n- or v-weighted means. When adjusting the n-weighted mean for the year 2021, we find the highest difference with on average $15.33 lower hourly wages for workers completing microtasks in comparison with online freelancers. When considering unpaid work in lines (2) and (2a), we find that the wage difference decreases but remains negative in all four panels. We therefore conclude that the mean hourly wage of freelancers exceeds that of workers completing microtasks, even when considering unpaid work. This is in line with Hypothesis 1 and the reality that online freelancers are often better educated than workers completing microtasks (Kuek et al. 2015; Dunn 2017) and therefore are more likely to work in high-paying fields such as programming or design (Leimeister et al. 2016). However, these more complex tasks require a significantly larger share of unpaid work, which becomes evident in the decreasing wage differences when accounting for unpaid work.

To test Hypothesis 2, we compare hourly wages considering only paid work with those also considering unpaid work. Lines (3) and (3a) in Panels A–D of Table 5 report the results. We also investigate whether including the three observations from Ross et al. (2010) affects our findings. We find that all wage differences are in the expected direction and are statistically significant at conventional statistical levels. A positive wage difference indicates that the estimated hourly wage is higher if unpaid work is not accounted for. We thus find support for Hypothesis 2 that hourly wages only accounting for paid work are higher than wages that also consider unpaid work, which is also in line with previous research (e.g., Berg 2016; Berg et al. 2018; Rani et al. 2021).

In lines (4) and (4a) in Panels A–D of Table 5, we test Hypothesis 3, which states that technically measured hourly wages are higher than hourly wages reported through a survey. We again investigate the effect of including the observations stemming from Ross et al. (2010) in line (4a). We find statistically significant wage differences when using n-weighted means (Panels A and C), which show higher wages for studies using technical data collection methods. This finding supports Hypothesis 3. However, when we use v-weighted means, the difference in hourly wages decreases (Panels B and D) and is no longer statistically significant at conventional levels in Panel B. This finding is likely due to the observations in Barzilay and Ben-David (2017) and Dunn (2017). As described in subsection 4.1., the technically estimated hourly wages in the two studies were measured with high standard deviations, which is why they were weighted more lightly for the v-weighted mean, which led to the decrease in the wage difference in Panels B and D.[6] In summary, we find empirical support for Hypothesis 3, though the statistical significance decreases when using v-weighted means.

5. Discussion

5.1. Methodological Limitations

For a meta-analysis, it is essential to check the sample of effect sizes for the occurrence of publication bias. A common method for discovering a publication bias are funnel plots (Elvik 1998; Ahmed et al. 2012). Funnel plots are two dimensional graphs in which the abscissa displays the effect size and the ordinate gives the sample size of the respective study. Every study included in the meta-analysis is marked in the funnel plot, with a distribution similar to a funnel expected if no or hardly any publication bias is present in the respective sample. Meta-analyses suffering from publication bias produce skewed distributions.

For our analysis, funnel plots are not an adequate method to investigate publication bias, because we do not calculate effect sizes such as Hedges *g* or Cohen's *d*, but rather calculate average hourly wages as a quasi-effect size (Song et al. 2000). This is because most articles using hourly wages in crowdworking do not estimate regressions, which would yield coefficients that could be converted to standard effect sizes in a meta-analysis. Not using the standard effect sizes has two implications. First, we do not expect a symmetric distribution of hourly wages, which we would expect when measuring effect sizes. Previous research has shown that the distribution of wages on crowdworking platforms is right skewed (Berg 2016; Adams and Berg 2017; Kaplan et al. 2018). In other words, the majority of online freelancers and workers completing microtasks earn only very small wages, while few earn wages that are many times higher than the average hourly crowdworking wage. We found that the distribution

[6] When excluding the observations from Barzilay and Ben-David (2017) and Dunn (2017), we find that all mean differences between wages estimated via surveys and through technical estimation methods lose their statistical significance. With one exception, however, the mean differences remain negative, which implies that technically estimated wages are higher than wages estimated via surveys.

of hourly wages in our data sample was right skewed as well, which indicates that we observe a representative distribution.

Second, it is questionable whether the common reason for publication bias regarding effect sizes can be transferred to the estimation of hourly wages. Publication bias frequently occurs when only statistically significant results are published, while research resulting in statistically non-significant results remains unpublished (Bozarth and Roberts 1972). In our case, the risk of not reporting non-significant results should be minimal, because most studies in the domain of crowdworking do not conduct tests for statistical differences in wages. Moreover, depending on the category of crowdwork, the range of measured wages is rather broad, which also lowers the risk of authors omitting wages because they are considered *too extreme* in comparison with other studies. Finally, we tried to avoid publication bias by also including reported hourly wages from sources other than academic journals, such as studies from trade unions, government authorities, and non-governmental organizations.

To prevent systematic biases in estimating hourly wages in crowdworking stemming from a single study, we set the criterion that at least five independent studies must be available for calculating an hourly wage (Spindeldreher and Schlagwein 2016). We also considered the impact of including observations from Ross et al. (2010) separately for each hourly wage we calculated. While we find that the respective hourly wages were to some extent influenced by including Ross et al. (2010), the testing of our hypotheses yielded similar results with and without the observations from Ross et al. (2010).

As described in subsection 3.3., it would have been desirable if the statistical composition of the groups we compare had been equal. To examine the effect of potential imbalances in the underlying characteristics, we investigate the distribution of observations with regard to the other variables of interest, for each of the mean comparisons displayed in Table 5. For the comparison in line (1), we expect no systematic under- or overestimation of the hourly wage, because we find a similar composition across all panels for the untested variable *Data Collection Method*. For the comparisons in lines (2) and (2a), we find that the group used for estimating the mean hourly wage of online freelancers, considering unpaid work, consisted only of data points obtained via technical data collection methods. For microtasks, considering unpaid work, a significant share of all data points was obtained via surveys. An imbalance in the data collection method also occurred for the comparison in line (3). Regarding the comparison in line (4), we find strong disparity in the number of observations accounting for unpaid work, when using v-weighted means (Panels B and D). Of the observations used to calculate a v-weighted mean hourly wage for data collected via technical data collection methods, only around 2% of the hourly wages account for unpaid work. By contrast, we find that of the observations used to measure a v-weighted mean for wages estimated via surveys, around two-thirds accounted for unpaid work. Because not considering unpaid work increases the mean hourly wage, we thus suspect an overestimation of the mean difference regarding the data collection method in line (4) in Panels B and D.

Furthermore, we tracked and evaluated the regions in which the hourly wages were observed. When analyzing our data, we find that almost two-thirds of the wages stating a specific location were collected from workers in North America. Unfortunately, we could not find enough observations from Europe or Africa to make a valid comparison between the different regions. Nevertheless, it should be noted that the mean hourly wage strongly depends on the location of the worker. Reasons include different levels of experience and the assignment of high-paid tasks typically to American citizens only (Lehdonvirta et al. 2019). Workers from developing countries are also more willing to participate in low-paid work than workers from developed countries (Berg et al. 2018).

5.2. Contribution to Current Policy Debates

Finally, we relate the contribution of our meta-analysis to the current policy debate and three different discourses in the field of crowdworking, which were originally identified by Greef et al. (2017). First, scholars have observed discourse about the general *transformation of work*, from location-based work to online web-based platforms (Rani et al. 2021). Second, they have identified discourse on *growth and competition*, which evaluates the future potential of online labor markets, but also the already-fierce competition between workers for wages and completion times on crowdworking platforms. The third discourse centers on the issue *of social security and the participation of workers* in shaping the future of their work environment. Here, discourse involves how and in what form agencies such as trade unions can condemn but also change poor working conditions, such as the lack of social security (Johnston and Land-Kazlauskas 2019).

Our study contributes to the general discourse about the transformation of work, especially in the field of the ever-increasing information asymmetry in crowdworking (Agrawal et al. 2015; Aloisi 2015). While online labor platforms monitor workers in ways often unthinkable in traditional labor environments (Wood et al. 2019b), the workers themselves are left with third-party browser plugins, to track their remuneration and performance. In most cases, legislators and trade unions do not have access to these kinds of technically obtained data and therefore must use surveys to monitor hourly wages and other important key figures of work (Serfling 2018). Data collection is also complicated by the presumption that only a fraction of crowdworkers pay income tax and thus disclose information about their remuneration through other means (Wood et al. 2019b). Some scholars therefore suggest granting legislators access to anonymized transaction data from online labor platforms, to help policy makers regulate the crowdworking market (Heeks 2017; European Commission 2021). We contribute to this debate by increasing the transparency in mean hourly wages, based on multiple studies and data collection methods. Regarding the data collection method, researchers should be aware of how different methods can affect their results. We find large differences between hourly wages estimated via surveys and technical data collection methods. Future research should also consider the effect of unpaid work on estimated hourly wages, for example, in the form of a malus subtracted from the estimated hourly wage that only accounts for paid work. As we show in our study, the effects of unpaid work are significant and should not be neglected.

With the mean hourly wages reported in our study, we also contribute to the discussion on the organizational transformation of the relationship between online labor market platforms and crowdworkers. Because of the low wages paid to workers completing microtasks, research often argues that these workers are overdue for legal classification as salaried employees (Berg 2016), as the dependency between workers and platforms is partly comparable to dependent employees (Preis 2016; Leist et al. 2017). Under current laws, however, the classification of crowdworkers into the common categories of labor law is difficult and controversial (see, e.g., *Otey v. CrowdFlowder, Inc. (2013))*. In addition to these problems, regulating and monitoring the crowdworking market is difficult for legislators because of the transnational nature of the markets, the heterogeneity in platforms, and the differing dependencies between workers and platforms (Greef et al. 2017; Serfling 2018). In our study, we deal with this heterogeneity by analyzing the specific area of online crowdworking, which allows us to make meaningful distinctions between two categories of crowdwork. In these different categories, we find significant wage differences, which again highlights the importance of a precise definition of the investigated category of crowdworking in future research.

We also contribute to the second discourse focusing on the growth and development of online labor markets, which is strongly connected with the call for additional research in the field of crowdworking (Greef et al. 2017; Maier and Viete 2017). As others have shown before us, the main motivation for people to participate in crowdwork is remuneration (Berg 2016; Brewster et al. 2019). With the novel dataset used in this study, we aggregate information on the main motivator of crowdworkers and contribute to existing efforts to extend database on online crowdworking.

Our findings are especially relevant to the debate on the social security and participation of crowdworkers in decision-making processes regarding the platforms on which they work (Preis 2016). In most countries and on the majority of platforms, neither social security nor options for participation exist. Many researchers have therefore criticized the working conditions in crowdworking, with some even describing them as precarious (Kittur et al. 2013; Schriner and Oerther 2014; Hara et al. 2018; Whiting et al. 2019). As workers are mostly not employed by the platforms, but labeled "contractors" or "freelancers," online labor market platforms are not responsible for paid leave, maximum working hours, or mandatory breaks (Barzilay and Ben-David 2017). While factors such as power asymmetries, or the lack of communication between workers on one side and platforms and requesters on the other side, also contribute to the poor working conditions, the main criticism is on low wages (Berg 2016; Schmidt 2016; Pongratz and Bormann 2017).

Because of unclear governance mechanisms and information asymmetries, platforms are particularly prone to contribute to precarious work conditions (Cutolo and Kenney 2019; Gegenhuber et al. 2021). In this case, trade unions can act not only as strong negotiators on behalf of the workers, as in traditional labor markets, but also as an institution that could facilitate the necessary communication and exchange between workers (Johnston and Land-Kazlauskas 2019). With our meta-analysis, we substantiate this criticism of low wages, at least in the area of microtasks, for which we consistently find mean hourly wages of under \$6 per hour. Given this mean wage and the lack of health insurance for the majority of workers, it is clear why many workers have called for better or even any social benefits (Wood et al. 2019b). In online freelancing, however, we calculate mean hourly wages, which are much higher than those for workers completing microtasks, with calculated mean wages up to \$20.81 per hour.

It is also important to note that these wages should not be considered only from a Western and industrialized country perspective (Elbanna and Idowu 2021). When considering the prices of particular goods at different locations, it is understandable why an hourly wage of \$1–\$2 is more attractive to a Kenyan than a U.S. citizen (Kuek et al. 2015; De Groen and Maselli 2016; Bayudan-Dacuycuy and Kryz Baje 2021). Regarding the concept of purchasing power parity, Beerepoot and Lambregt (2015) determined higher relative wages for online workers from India and the Philippines in comparison with U.S. workers. In recent years, platforms' governance has also improved, such as the introduction of a minimum hourly wage on oDesk (now Upwork)

(Heeks 2017). In principle, the advantages of crowdworking should not be neglected. For example, the high degree of spatial and temporal flexibility when completing work as a crowdworker is one of the greatest advantages of crowdwork (Brandt et al. 2016; D'Cruz and Noronha 2016; Berg et al. 2018). Thus, crowdworking could potentially facilitate the participation of people with disabilities or individuals with care obligations in the labor market (Adams and Berg 2017; Hara et al. 2019).

6. Conclusion

This meta-analysis investigates 104 mean hourly wages in crowdwork that were reported in 20 different studies. We extend the literature by estimating the mean hourly wages for different subcategories of crowdworking, while also considering the method of data collection and the effect of unpaid work. Our investigation of mean hourly wages is not limited to a single platform, region, or data collection method, which further raises transparency for workers, researchers, and legislators (De Groen et al. 2016; Litman et al. 2020; Wong et al. 2020). Our results, to our knowledge, are based on the most comprehensive dataset on hourly wages in crowdworking in recent literature. We show that working on microtasks results in wages ranging from \$3.27 to \$5.48 per hour on average, even when adjusting the data to the year 2021. Online freelancers earn \$10.38 to \$20.81 per hour on average, which is significantly more than workers completing microtasks. This finding is in line with existing literature.

We found empirical support for our hypothesis that hourly wages collected through surveys tend to be lower than wages collected via technical data collection methods. However, this finding could be due to the possibility that some studies are outliers from the rule. Future experimental research should test the influence of data collection methods that might result in self-reporting bias in crowdworking wages. For example, researchers could monitor crowdworkers' hourly wages through a plugin and then ask them about their earnings. Quantifying the potential difference between the different methods of data collection is especially important when evaluating the wages of online freelancers, as the unpaid portion of the work is likely to be higher and could be underestimated. Policy makers should be aware that the use of surveys instead of technical data collection methods could change the estimation of wages. In recent literature, the method of data collection strongly depends on the willingness of the specific crowdworking platform to share its data with researchers (Agrawal et al. 2015; Bertschek et al. 2016; Barzilay and Ben-David 2017). If an online freelancing platform decides not to share its data or only shares out-of-date data, surveys become the only option to investigate the current wages of workers. Surveys could also turn out to be the only viable option to examine wages on contest platforms, a field in which estimates of hourly wages are sparse (De Groen and Maselli 2016).

As we found a significant difference in wages accounting and not accounting for unpaid work, we suggest that researchers investigating hourly wages in crowdworking in the future always report an hourly wage that also accounts for unpaid work. Because most researchers assume that one-third to one-half of the work time is unpaid, a wage malus that does take unpaid work into account should be around 25% and 33% (Berg et al. 2018; Rani et al. 2021). Such a wage malus for hourly wages that does not consider unpaid components would make hourly wages from different crowdworking studies more comparable. Furthermore, we encourage researchers to assess crowdworkers from countries other than the United States. Undertaking a broader comparison of wages between different regions and considering the prices of goods and services at different locations might provide a more refined picture of crowdworking as a new online labor market.

References

Adams, A. and Berg, J. (2017) 'When Home Affects Pay: An Analysis of the Gender Pay Gap Among Crowdworkers', *SSRN Electronic Journal*. doi: 10.2139/ssrn.3048711

Agrawal, A., Horton, J., Lacetera, N. and Lyons, E. (2015) 'Digitization and the Contract Labor Market: A Research Agenda', in Goldfarb, A., Greenstein, S.M. and Tucker, C. (eds.) *Economic analysis of the digital economy.* (National Bureau of Economic Research conference report). Chicago: The University of Chicago Press.

Ahmed, I., Sutton, A.J. and Riley, R.D. (2012) 'Assessment of publication bias, selection bias, and unavailable data in meta-analyses using individual participant data: a database survey', *BMJ (Clinical Research Ed.)*, 344, d7762. doi: 10.1136/bmj.d7762

Aloisi, A. (2015) 'Commoditized Workers The Rising of On-Demand Work, A Case Study Research on a Set of Online Platforms and Apps', *SSRN Electronic Journal*. doi: 10.2139/ssrn.2637485

Barzilay, A.R. and Ben-David, A. (2017) 'Platform Inequality: Gender in the Gig-Economy', *Seton Hall Law Review*, 47(393). doi: 10.2139/ssrn.2995906

Bayudan-Dacuycuy, C. and Kryz Baje, L. (2021) 'Decent Work in Crowdwork: Gendered Takeaways from an Online Survey in the Philippines', *PDIS: Discussion Paper Series* (2021-11). Available at: https://think-asia.org/handle/11540/13316 (Accessed: Oct 14, 2021).

Beerepoot, N. and Lambregts, B. (2015) 'Competition in online job marketplaces: towards a global labour market for outsourcing services?' *Global Networks*, 15(2), pp. 236–255. doi: 10.1111/glob.12051

Berg, J. (2016) 'Income Security in the On-Demand Economy: Findings and Policy Lessons from a Survey of Crowdworkers', *Comparative Labor Law & Policy Journal*, 37(3).

Berg, J., Furrer, M., Harmon, E., Rani, U. and Silbermann, M.S. (2018) *Digital labour platforms and the future of work, Torwards decent work in the online world*: ILO. Available at: https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_645337.pdf (Accessed: Oct 28, 2021).

Bertschek, I., Ohnemus, J. and Viete, S. (2016) 'Forschungsbericht 462: Befragung zum sozioökonomischen Hintergrund und zu den Motiven von Crowdworkern: Endbericht'. Available at: https://www.ssoar.info/ssoar/handle/document/47092 (Accessed: Dec 2, 2021).

Bijmolt, T.H. and Pieters, R.G. (2001) ‘Meta-Analysis in Marketing when Studies Contain Multiple Measurements’, *Marketing Letters*, 12(2), pp. 157–169. doi: 10.1023/A:1011117103381

Bozarth, J.D. and Roberts, R.R. (1972) ‘Signifying significant significance’, *American Psychologist*, 27(8), pp. 774–775. doi: 10.1037/h0038034

Braesemann, F., Stephany, F., Teutloff, O., Kässi, O., Graham, M. and Lehdonvirta, V. (2021) ‘The polarisation of remote work’, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3919655

Brandt, A., Polom, L. and Danneberg, M. (2016) ‘Gute digitale Arbeit: Auswirkungen der Digitalisierung im Dienstleistungsbereich : Studie im Auftrag der Vereinten Dienstleistungsgewerkschaft (ver.di) Landesbezirk Niedersachsen-Bremen und der Friedrich-Ebert-Stiftung’. Available at: http://library.fes.de/pdf-files/wiso/12786.pdf (Accessed: Oct 9, 2021).

Brawley, A.M. and Pury, C.L. (2016) ‘Work experiences on MTurk: Job satisfaction, turnover, and information sharing’, *Computers in Human Behavior*, 54, pp. 531–546. doi: 10.1016/j.chb.2015.08.031

Brewster, S., Fitzpatrick, G., Cox, A. and Kostakos, V. (2019) *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems. CHI ‘19: CHI Conference on Human Factors in Computing Systems*. Glasgow Scotland Uk, 5 April - 5 September: ACM.

Callison-Burch, C. (2014) ‘Crowd-Workers: Aggregating Information Across Turkers to Help Them Find Higher Paying Work’, *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, 2, pp. 8–9. Available at: https://ojs.aaai.org/index.php/HCOMP/article/view/13198 (Accessed: Oct 17, 2021).

Cutolo, D. and Kenney, M. (2019) ‘The Emergence of Platform-Dependent Entrepreneurs: Power Asymmetries, Risk, and Uncertainty’, *Academy of Management Perspectives*, 35(4). doi: 10.5465/amp.2019.0103

D’Cruz, P. and Noronha, E. (2016) ‘Positives outweighing negatives: the experiences of Indian crowdsourced workers’, *Work Organisation, Labour and Globalisation*, 10(1). doi: 10.13169/workorgalaboglob.10.1.0044

De Groen, W.P. and Maselli, I. (2016) ‘The Impact of the Collaborative Economy on the Labour Market’, *CEPS Special Report* (138). Available at: https://www.semanticscholar.org/paper/The-Impact-of-the-Collaborative-Economy-on-the-Groen-Maselli/07f0c2b016de0f8ee6655457e076b3db7cfa06e1 (Accessed: Oct 27, 2021).

De Groen, W.P., Maselli, I. and Fabo, B. (2016) *The Digital Market for Loca Services: A one night stand for workers? An example from the on demand economy*: CEPS Publications Office.

De Stefano, V. (2015) 'The Rise of the 'Just-in-Time Workforce': On-Demand Work, Crowd Work and Labour Protection in the 'Gig-Economy'', *Comparative Labor Law & Policy Journal, Forthcoming Bocconi Legal Studies Research Paper*, (2682602). doi: 10.2139/ssrn.2682602

Dengler, K. and Matthes, B. (2015) *Folgen der Digitalisierung für die Arbeitswelt: Substituierbarkeitspotenziale von Berufen in Deutschland* (IAB-Forschungsbericht 11/2015).

DGB (2021) *DGB-Position zur Plattformarbeit*.

Drahokoupil, J. and Fabo, B. (2016) *The platform economy and the disruption of the employment relationship* (ETUI Policy Brief 5).

Dunn, M. (2017) 'Digital Work: New Opportunities or Lost Wages?' *American Journal of Management*, 17(4). doi: 10.5465/ambpp.2016.11689abstract

Durward, D., Blohm, I. and Leimeister, J.M. (2020) 'The Nature of Crowd Work and its Effects on Individuals' Work Perception', *Journal of Management Information Systems*, 37(1), pp. 66–95. doi: 10.1080/07421222.2019.1705506

Elbanna, A. and Idowu, A. (2021) 'Crowdwork, digital liminality and the enactment of culturally recognised alternatives to Western precarity: beyond epistemological terra nullius', *European Journal of Information Systems*, pp. 1–17. doi: 10.1080/0960085X.2021.1981779

Elvik, R. (1998) 'Evaluating the statistical conclusion validity of weighted mean results in meta-analysis by analysing funnel graph diagrams', *Accident Analysis & Prevention*, 30(2), pp. 255–266. doi: 10.1016/S0001-4575(97)00076-6

European Commission (2021) *Commission proposals to improve the working conditions of people working through digital labour platforms* [Press release]. 9 December. Available at: https://ec.europa.eu/commission/presscorner/detail/en/ip_21_6605.

Gao, Y., Chen, Y. and Liu, K.J.R. (2015) 'On Cost-Effective Incentive Mechanisms in Microtask Crowdsourcing', *IEEE Transactions on Computational Intelligence and AI in Games*, 7(1), pp. 3–15. doi: 10.1109/TCIAIG.2014.2298361

Gegenhuber, T., Schüßler, E., Reischauer, G. and Thäter, L. (2021) 'Building Collective Institutional Infrastructures for Decent Platform Work: The Development of a Crowdwork Agreement in Germany', *Research in the Sociology of Organizations*.

Greef, S., Schroeder, W., Akel, A., Berzel, A., D'Antonio, O., Kiepe, L., Schreiter, B. and Sperling, H.J. (2017) 'Forschungsbericht 500: Plattformökonomie und Crowdworking: Eine Analyse der Strategien und Positionen zentraler Akteure'. Available at: https://www.ssoar.info/ssoar/bitstream/document/55503/1/ssoar-2017-greef_et_al-Plattformokonomie_und_Crowdworking_Eine_Analyse.pdf (Accessed: Oct 12, 2021).

Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C. and Bigham, J.P. (2018) 'A Data-Driven Analysis of Workers' Earnings on Amazon Mechanical Turk', *Engage with CHI: CHI 2018 : Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems : April 21 -26, 2018, Montréal, QC, Canada, CHI '18: CHI Conference on Human Factors in Computing Systems*, Montreal QC Canada, 04.21.2018-04.26.2018: ACM, pp. 1–14. doi: 10.1145/3173574.3174023

Hara, K., Adams, A., Milland, K., Savage, S., Hanrahan, B.V., Bigham, J.P. and Callison-Burch, C. (2019) 'Worker Demographics and Earnings on Amazon Mechanical Turk', *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems, CHI '19: CHI Conference on Human Factors in Computing Systems*, Glasgow Scotland Uk, 5 April - 5 September: ACM, pp. 1–6. doi: 10.1145/3290607.3312970

Heeks, R. (2017) *Decent Work and the Digital Gig Economy: A Developing Country Perspective on Employment Impacts and Standards in Online Outsourcing, Crowdwork, Etc*.

Horton, J.J. and Chilton, L.B. (2010) 'The labor economics of paid crowdsourcing', *Proceedings of the 11th ACM conference on Electronic commerce, the 11th ACM conference.* ACM Special Interest Group on Electronic Commerce, Cambridge, Massachusetts, USA, 6/7/2010 - 6/11/2010. New York, NY: ACM, p. 209. doi: 10.1145/1807342.1807376

ILO (2018) 'Job quality in the platform economy', *Issue Brief No. 5 for the 2nd meeting of the Global Commission on the Future of Work 15-17 February*. Available at: https://www.ilo.org/wcmsp5/groups/public/---dgreports/---cabinet/documents/publication/wcms_618167.pdf (Accessed: Dec 31, 2021).

International Monetary Fund (2021) *World Economic Outlook Database, April 2021,* 4 October. Available at: https://www.imf.org/en/Publications/WEO/weo-database/2021/April (Accessed: Oct 4, 2021).

Ipeirotis, P.G. (2010) 'Analyzing the Amazon Mechanical Turk marketplace', *XRDS: Crossroads, The ACM Magazine for Students*, 17(2), pp. 16–21. doi: 10.1145/1869086.1869094

Irani, L.C. and Silberman, M.S. (2013) ‘Turkopticon: interrupting worker invisibility in amazon mechanical turk’, *CHI 2013: Changing perspectives; the 31st Annual CHI Conference on Human Factors in Computing Systems, conference proceedings, 27 April - 2 May 2013, Paris, France, CHI ‘13: CHI Conference on Human Factors in Computing Systems.* Association for Computing Machinery; CHI 2013; Annual CHI Conference on Human Factors in Computing Systems, Paris France, 27 04 2013 02 05 2013. New York, NY: ACM, pp. 611–620. doi: 10.1145/2470654.2470742

Johnston, H. and Land-Kazlauskas, C. (2019) ‘Organizing on-demand representation, voice, and collective bargaining in the gig economy’, *Conditions of Work and Employment*, 94. Available at: https://ideas.repec.org/p/ilo/ilowps/994981993502676.html (Accessed: Dec 8, 2021).

Kaganer, E., Carmel, E., Hirschheim, R. and Olsen, T. (2013) ‘Managing the Human Cloud’, *MIT Sloan Management Review*, 54(2).

Kaplan, T., Saito, S., Hara, K. and Bigham, J.P. (2018) ‘Striving to Earn More: A Survey of Work Strategies and Tool Use Among Crowd Workers’, *Sixth AAAI Conference on Human Computation and Crowdsourcing*, Zürich Switzerland, 7 May - 7 August.

Kässi, O. and Lehdonvirta, V. (2018) ‘Online labour index: Measuring the online gig economy for policy and research’, *Technological Forecasting and Social Change*, 137, pp. 241–248. doi: 10.1016/j.techfore.2018.07.056

Khovanskaya, V., Dombrowski, L., Rzeszotarski, J. and Sengers, P. (2019) ‘The Tools of Management’, *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW), pp. 1–22. doi: 10.1145/3359310

Kittur, A., Nickerson, J.V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., Lease, M. and Horton, J. (2013) ‘The future of crowd work’, *Proceedings of the 2013 conference on Computer supported cooperative work, the 2013 conference.* ACM Special Interest Group on Computer-Human Interaction, San Antonio, Texas, USA, 2/23/2013 - 2/27/2013. New York, NY: ACM, p. 1301. doi: 10.1145/2441776.2441923

Kuek, S.C., Paradi-Guilford, C., Fayomi, T., Imaizumi, S., Ipeirotis, P., Pina, P. and Singh, M. (2015) *The Global Opportunity in Online Outsourcing*. Available at: https://openknowledge.worldbank.org/handle/10986/22284/22284 (Accessed: Oct 29, 2021).

Lee, C.H., Cook, S., Lee, J.S. and Han, B. (2016) 'Comparison of Two Meta-Analysis Methods: Inverse-Variance-Weighted Average and Weighted Sum of Z-Scores', *Genomics & Informatics*, 14(4), pp. 173–180. doi: 10.5808/GI.2016.14.4.173

Lehdonvirta, V., Kässi, O., Hjorth, I., Barnard, H. and Graham, M. (2019) 'The Global Platform Economy: A New Offshoring Institution Enabling Emerging-Economy Microproviders', *Journal of Management*, 45(2), pp. 567–599. doi: 10.1177/0149206318786781

Leimeister, J.M., Durward, D. and Zogaj, S. (2016) *Crowd Worker in Deutschland: Eine empirische Studie zum Arbeitsumfeld auf externen Crowdsourcing-Plattformen*. (Study / Hans-Böckler-Stiftung Reihe Praxiswissen Betriebsvereinbarungen). Düsseldorf: Hans-Böckler-Stiftung. Available at: http://hdl.handle.net/10419/146407 (Accessed: Dec 9, 2021).

Leist, D., Hießl, C. and Schlachter, M. (2017) 'Forschungsbericht 499: Plattformökonomie - Eine Literaturauswertung'. Available at: https://www.bmas.de/SharedDocs/Downloads/DE/Publikationen/Forschungsberichte/fb499-plattformoekonomie-eine-literaturauswertung.pdf?__blob=publicationFile&v=1 (Accessed: Dec 17, 2021).

Liberati, A., Altman, D.G., Tetzlaff, J., Mulrow, C., Gøtzsche, P.C., Ioannidis, J.P.A., Clarke, M., Devereaux, P.J., Kleijnen, J. and Moher, D. (2009) 'The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration', *PLoS Medicine*, 6(7), e1000100. doi: 10.1371/journal.pmed.1000100

List, J.A. and Momeni, F. (2021) 'When Corporate Social Responsibility Backfires: Evidence from a Natural Field Experiment', *Management Science*, 67(1), pp. 8–21. doi: 10.1287/mnsc.2019.3540

Litman, L., Robinson, J., Rosen, Z., Rosenzweig, C., Waxman, J. and Bates, L.M. (2020) 'The persistence of pay inequality: The gender pay gap in an anonymous online labor market', *PLOS ONE*, 15(2). doi: 10.1371/journal.pone.0229383

Maier, M.F. and Viete, S. (2017) 'Forschungsbericht 498: Plattformbasierte Erwerbsarbeit: Stand der empirischen Forschung'. Available at: https://d-nb.info/1192198085/34 (Accessed: Oct 3, 2021).

Mazar, N., Amir, O. and Ariely, D. (2008) 'The Dishonesty of Honest People: A Theory of Self-Concept Maintenance', *Journal of Marketing Research*, 45(6), pp. 633–644. doi: 10.1509/jmkr.45.6.633

N.D. Cal. (2013) 'Otey v. CrowdFlowder, Inc., Case No. 12-cv-05524-JST', 27 August.

Newlands, G. and Lutz, C. (2021) ‘Crowdwork and the mobile underclass: Barriers to participation in India and the United States’, *New Media & Society*, 23(6), pp. 1341–1361. doi: 10.1177/1461444820901847

Nickerson, J.V. (2013) ‘Crowd Work and Collective Learning’, in Littlejohn, A. and Margaryan, A. (eds.) *Technology-Enhanced Professional Learning: Processes, Practices, and Tools.* (Advancing Technology Enhanced Learning).

Pallais, A. (2014) ‘Inefficient Hiring in Entry-Level Labor Markets’, *American Economic Review*, 104(11), pp. 3565–3599. doi: 10.1257/aer.104.11.3565

Paolacci, G., Chandler, J.J. and Ipeirotis, P.G. (2010) ‘Running Experiments on Amazon Mechanical Turk’, *Judgment and Decision Making*, 5(5).

Pongratz, H.J. and Bormann, S. (2017) ‘Online-Arbeit auf Internet-Plattformen: empirische Befunde zum ‚Crowdworking‘ in Deutschland’, *AIS-Studien*, 10(2), pp. 151–181. doi: 10.21241/SSOAR.64850

Preis, U. (2016) ‘Forschungsbericht 490: Sozialversicherungsrechtliche Einordnung neuer Beschäftigungsformen mit Schwerpunkt Plattform- bzw. Gig-Ökonomie’. Available at: https://www.bmas.de/SharedDocs/Downloads/DE/Publikationen/Forschungsberichte/fb499-plattformoekonomie-eine-literaturauswertung.pdf?__blob=publicationFile&v=1 (Accessed: Dec 18, 2021).

Rani, U., Dhir, K.R., Furrer, M., Gőbel, N., Moraiti, A., Cooney, S. and MC Manus, Alberto Coddou (2021) *World Employment and Social Outlook - The role of digital labour platforms in transforming the world of work*: ILO. Available at: https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_771749.pdf (Accessed: Dec 27, 2021).

Rani, U. and Furrer, M. (2019) ‘On-Demand Digital Economy: Can Experience Ensure Work and Income Security for Microtask Workers?’ *Jahrbücher für Nationalökonomie und Statistik*, 239(3), pp. 565–597. doi: 10.1515/jbnst-2018-0019

Rani, U. and Furrer, M. (2021) ‘Digital labour platforms and new forms of flexible work in developing countries: Algorithmic management of work and workers’, *Competition & Change*, 25(2), pp. 212–236. doi: 10.1177/1024529420905187

Revelli, C. and Viviani, J.-L. (2015) ‘Financial performance of socially responsible investing (SRI): what have we learned? A meta-analysis’, *Business Ethics: A European Review*, 24(2), pp. 158–185. doi: 10.1111/beer.12076

Ross, J., Irani, L., Silberman, M.S., Zaldivar, A. and Tomlinson, B. (2010) 'Who are the crowdworkers?' *CHI '10 Extended Abstracts on Human Factors in Computing Systems, CHI '10: CHI Conference on Human Factors in Computing Systems.* ACM Special Interest Group on Computer-Human Interaction, Atlanta Georgia USA, 10 04 2010 15 04 2010. New York, NY: ACM, pp. 2863–2872. doi: 10.1145/1753846.1753873

Saito, S., Chiang, C.-W., Savage, S., Nakano, T., Kobayashi, T. and Bigham, J.P. (2019) 'TurkScanner: Predicting the Hourly Wage of Microtasks', *The World Wide Web Conference on - WWW '19, The World Wide Web Conference*, San Francisco, CA, USA, 5/13/2019 - 5/17/2019. New York, New York, USA: ACM Press, pp. 3187–3193. doi: 10.1145/3308558.3313716

Satterthwaite, F.E. (1946) 'An Approximate Distribution of Estimates of Variance Components', *Biometrics Bulletin*, 2(6), p. 110. doi: 10.2307/3002019

Schmidt, F.A. (2016) *Arbeitsmärkte in der Plattformökonomie - zur Funktionsweise und den Herausforderungen von Crowdwork und Gigwork*: Friedrich-Ebert-Stiftung. Available at: https://library.fes.de/pdf-files/wiso/12826.pdf (Accessed: Dec 5, 2021).

Schmidt, F.A. (2017) 'Conclusion: Towards an Ethics of Creative Crowdwork', in Schmidt, F.A. (ed.) *Crowd design: From tools for empowerment to platform capitalism.* (Board of international research in design): Birkhäuser, pp. 211–236.

Schmidt, F.L. and Hunter, J.E. (2015) *Methods of meta-analysis: Correcting error and bias in research findings*: SAGE.

Schriner, A. and Oerther, D. (2014) 'No Really, (Crowd) Work is the Silver Bullet', *Procedia Engineering*, 78, pp. 224–228. doi: 10.1016/j.proeng.2014.07.060

Serfling, O. (2018) *Crowdworking Monitor No. 1.* Available at: https://www.bmas.de/SharedDocs/Downloads/DE/Meldungen/2018/crowdworking-monitor.pdf?__blob=publicationFile&v=1 (Accessed: Oct 19, 2021).

Shafiei Gol, E., Stein, M.-K. and Avital, M. (2018) 'Why Take the Risk? Motivations of Highly Skilled Workers to Participate in Crowdworking Platforms', *Proceedings of the Thirty Ninth International Conference on Information Systems, ICIS 2018*, San Francisco, CA, USA, 13-16 December: Association for Information Systems (AIS). Available at: https://aisel.aisnet.org/icis2018/crowd/Presentations/7 (Accessed: Oct 17, 2021).

Song, Eastwood, Gilbody, Duley and Sutton (2000) 'Publication and related biases', *Health Technology Assessment*, 4(10). doi: 10.3310/hta4100

Spindeldreher, K. and Schlagwein, D. (2016) 'What Drives the Crowd? A Meta-Analysis of the Motivation of Participants in Crowdsourcing', *Pacific Asia Conference on Information Systems: PACIS 2016*, Chiayi, Taiwan, 27.06.2016-1-07.2016.

Whiting, M.E., Hugh, G. and Bernstein, M.S. (2019) 'Fair Work: Crowd Work Minimum Wage with One Line of Code', *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, Stevenson, Washington USA, 10.28.2019-10.30.2019, pp. 197–206. Available at: https://ojs.aaai.org//index.php/HCOMP/article/view/5283.

Wong, S.I., Fieseler, C. and Kost, D. (2020) 'Digital labourers' proactivity and the venture for meaningful work: Fruitful or fruitless?' *Journal of Occupational and Organizational Psychology*, 93(4), pp. 887–911. doi: 10.1111/joop.12317

Wood, A.J., Graham, M., Lehdonvirta, V. and Hjorth, I. (2019a) 'Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy', *Work, Employment and Society*, 33(1), pp. 56–75. doi: 10.1177/0950017018785616

Wood, A.J., Graham, M., Lehdonvirta, V. and Hjorth, I. (2019b) 'Networked but Commodified: The (Dis)Embeddedness of Digital Labour in the Gig Economy', *Sociology*, 53(5), pp. 931–950. doi: 10.1177/0038038519828906

Zhang, R., McNeese, N.J., Freeman, G. and Musick, G. (2021) '"An Ideal Human": Expectations of AI Teammates in Human-AI Teaming', in Lampe, C., Nichols, J., Karahalios, K., Fitzpatrick, G., Lee, U., Monroy-Hernandez, A. and Stuerzlinger, W. (eds.) *Proceedings of the ACM on Human-Computer Interaction,* 4th edn. (Issue CSCW3): Association for Computing Machinery.

Table 1 Included studies

Study	Country/region	Platform	Wages	No. of data points	
				Paid	Unpaid
Bayudan-Dacuycuy and Kryz Baje (2020)	Philippines	-	$4.60	-	381
Beerepoot and Lambregts (2015)	US	oDesk[a]	$3.11-$26.66	925	-
Berg (2016)	US, India, International	MTurk, CrowdFlower,[b] Prolific, Microworkers	$1.90-$7.60	1056	1056
Berg et al. (2018)	US, India, International	MTurk, CrowdFlower,[b] Prolific, Microworkers	$2 -$8.50	2020	2022[c]
De Groen et al. (2016)	Italy, Serbia	CoContest	$3.50-$10.30	156	156
Dunn (2017)	US	"One of the largest online platforms for work"	$10.64-$15.29	12932	-
Hara et al. (2018)	International	MTurk	$3.13-$3.48	2666	5332
Hara et al. (2019)	US, India	MTurk	$2.48-$3.47	1113	- [d]
Ipeirotis (2010)	International	MTurk	$4.80	5147	-
Kaplan et al. (2018)	US	MTurk	$4.73-$5.12	-	720
Leimeister et al. (2016)	Germany	"Microtask, marketplace, design, testing"	$5.94-$15.45	-	248
Litman et al. (2020)	International	MTurk	$4.59-$4.87	22272	-
Pallais 2014	International	oDesk	$2.11-$2.20	3767	-
Rani and Furrer (2021)	Africa, Asia, Latin America,	MTurk, CrowdFlower,[b] Clickworker, Prolific, Microworkers	$1.30-$5.80	1350	1350 [c]
Rani et al. (2021)	China, Ukraine, International	[e]	$2.70-$11.20	1983	1988
Barzilay and Ben-David (2017)	US	Upwork	$17.26-$58.96	4324	-
Ross et al. (2010)	International	MTurk	$1.67-$1.92	-	1823 [f]
Saito et al. (2019)	International	MTurk	$9.15	83	-
Wong et al. (2020)	International	MTurk, Clickworker	$5.56	801	-
Wood et al. (2019)	Africa, Asia	"On one of two leading platforms"	$3.66-$4.41	-	611
				∑ 60595	∑ 15687

[a] The two crowdworking platforms Elance and oDesk merged in 2013 and resulted in a new platform called Upwork.
[b] CrowdFlower was acquired by Appen in 2020.
[c] Dataset is from the ILO 2017 survey.
[d] Dataset is from Hara et al. (2018).
[e] Freelancer, Upwork, 99designs, 680, EPWK, k68, ZBJ, Advego.ru, MTurk, fl.ru, Free-lance.ua, Freelance.ru, Freelance.ua, Freelancehunt.com, Freelancer.com, Kabanchik.ua, Upwork.com, Weblancer.net and Other
[f] Authors state that their data are out of date and should no longer be used.

Table 2 Definition of variables

Variable	Definition
Data Collection Method[a]	Dummy variable that equals 1 if the data points of the respective observation were obtained through technical data collection methods (e.g., a browser plugin) and 0 if the authors conducted a survey.
Freelancing[a]	Dummy variable that equals 1 if the respective hourly wage results from online freelancing and 0 if the observation results from microtasks.
Involves Unpaid Work[a]	Dummy variable that equals 1 if the respective observation considers unpaid work and 0 otherwise.
Hourly Wage	The average hourly wage in U.S. dollars that was observed in a given study. Observations in currencies other than U.S. dollars were converted with the exchange rate at the time the data in the study were collected.
Hourly Wage 2021	Inflation-adjusted hourly wage. If the observation was not assigned to a specific region or country, the international inflation rate was used. (Source for inflation rates: International Monetary Fund)
Data Points	Number of data points on which the hourly wages in a study are based. A data point can be the answer to a survey question or the calculated hourly wage of a specific task that was obtained through technical data collection methods.
Wage Std. Dev.	Standard deviation of Hourly Wage and Hourly Wage 2021 that is reported in a given study or was obtained from the authors of the study.

[a] Indicates a dummy variable.

Table 3 Summary statistics

	Full dataset					Subsample online freelancer (n = 51)		Subsample microtask (n = 53)	
Variable	M	SD	Min	Median	Max	M	SD	M	SD
Data Collection Method	0.46	0.50	0	0	1	0.71	0.46	0.23	0.42
Freelancing	0.49	0.50	0	0	1	--	--	--	--
Involves Unpaid Work	0.35	0.48	0	0	1	0.20	0.40	0.49	0.50
Hourly Wage	12.50	14.79	1.30	4.84	77.93	21.56	16.75	3.78	2.33
Hourly Wage 2021	13.92	16.11	1.48	5.69	85.11	23.87	18.17	4.35	2.47
Data Points	733.48	1754.97	14	252	12326	537.10	1039.65	922.45	2233.18
Wage Std. Dev.	12.52	13.58	0.71	5.74	71.04	19.19	15.04	5.53	6.89

For the complete dataset, we could measure standard deviations for only 86 of the 105 observations. For the subsample Online Freelancer, we could measure standard deviations for only 44 of the 51 observations. For the subsample Microtask, we could measure standard deviations for only 42 of the 53 observations. The means reported in this table are unweighted.

Table 4 Mean hourly wages				
Group	Mean	SD	No. of data points	No. of observations
(4a) n-weighted				
Freelancer	$18.72	$13.15	24087	41
Freelancer considering unpaid work	$4.19	$2.16	3305	10
Microtask	$4.60	$0.86	35395	23
Microtask considering unpaid work	$3.75	$1.48	6183	13
Including Ross et al. (2010)	$3.32	$1.52	8006	16
(4b) v-weighted				
Freelancer	$10.38	$7.89	20320	39
Freelancer considering unpaid work	[a]		2144	5
Microtask	$4.34	$2.04	29447	21
Microtask considering unpaid work	$3.27	$3.21	6104	11
(4c) n-weighted, adjusted 2021				
Freelancer	$20.81	$14.29	24087	41
Freelancer considering unpaid work	$4.56	$2.35	3305	10
Microtask	$5.48	$1.11	35395	23
Microtask considering unpaid work	$4.27	$1.52	6183	13
Including Ross et al. (2010)	$3.93	$1.48	8006	16
(4d) v-weighted, adjusted 2021				
Freelancer	$12.04	$7.89	20320	39
Freelancer considering unpaid work	[a]		2144	5
Microtask	$4.97	$2.04	29447	21
Microtask considering unpaid work	$3.72	$3.21	6104	11

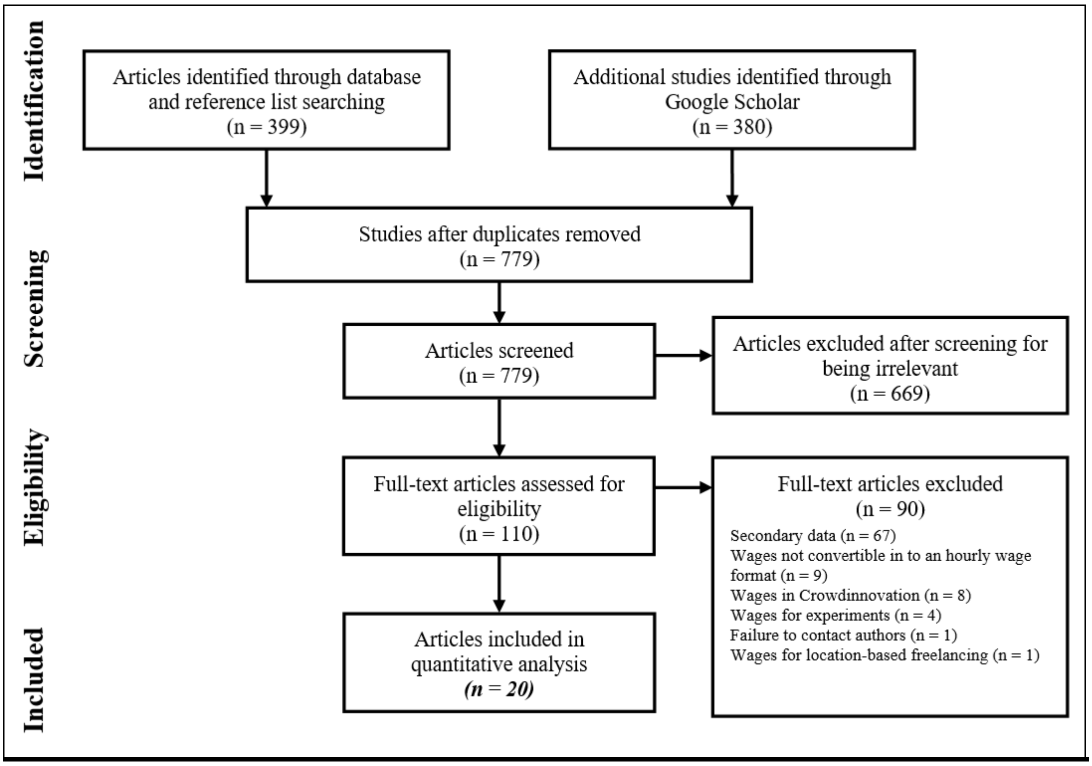
[a] Less than five independent data points.

Table 5 Comparison of means

Comparison	Mean	Difference	No. of data points	No. of observations
Panel A: Comparison of n-weighted means				
(1) Freelancing paid/Microtask paid	$18.72	-$14.12***	24087/35395	41/23
(2) Freelancing unpaid/Microtask unpaid	$4.19	-$0.44	3305/6138	10/13
(2a) Including Ross et al. (2010)	$4.19	-$0.87	3305/8006	10/16
(3) Involves unpaid work/Paid work	$3.90	$6.58***	9488/58132	23/56
(3a) Including Ross et al. (2010)	$3.58	$6.90***	11311/58132	26/56
(4) Technical/Survey	$11.05	-$6.40***	52476/12838	42/37
(4a) Including Ross et al. (2010)	$11.05	-$6.75***	52476/14661	42/40
Panel B: Comparison of v-weighted means				
(1) Freelancing paid/Microtask paid	$10.38	-$6.04 ***	20320/29447	39/21
(2) Freelancing unpaid/Microtask unpaid	[a]		2144/6104	5/11
(3) Involves unpaid work/Paid work	$3.30	$2.14**	8248/48417	16/52
(4) Technical/Survey	$5.51	-$1.78*	43652/10797	39/29
Panel C: Comparison of n-weighted means, adjusted 2021				
(1) Freelancing paid/Microtask paid	$20.81	-$15.33***	24087/35395	41/23
(2) Freelancing unpaid/Microtask unpaid	$4.56	-$0.29	3305/6138	10/13
(2a) Including Ross et al. (2010)	$4.56	-$0.63	3305/8006	10/16
(3) Involves unpaid work/Paid work	$4.37	-$7.5***	11311/58132	23/56
(3a) Including Ross et al. (2010)	$4.12	-$7.75***		26/56
(4) Technical/Survey	$12.54	-$7.74***	52476/12838	42/37
(4a) Including Ross et al. (2010)	$12.54	-$7.07***	52476/14661	42/40
Panel D: Comparison of v-weighted means, adjusted 2021				
(1) Freelancing paid/Microtask paid	$12.04	-$7.07***	20320/29447	39/21
(2) Freelancing unpaid/Microtask unpaid	[a]		2144/6104	5/11
(3) Involves unpaid work/Paid work	$3.69	$2.54 ***	8248/48417	16/52
(4) Technical/Survey	$6.33	-$2.15***	43652/10797	39/29

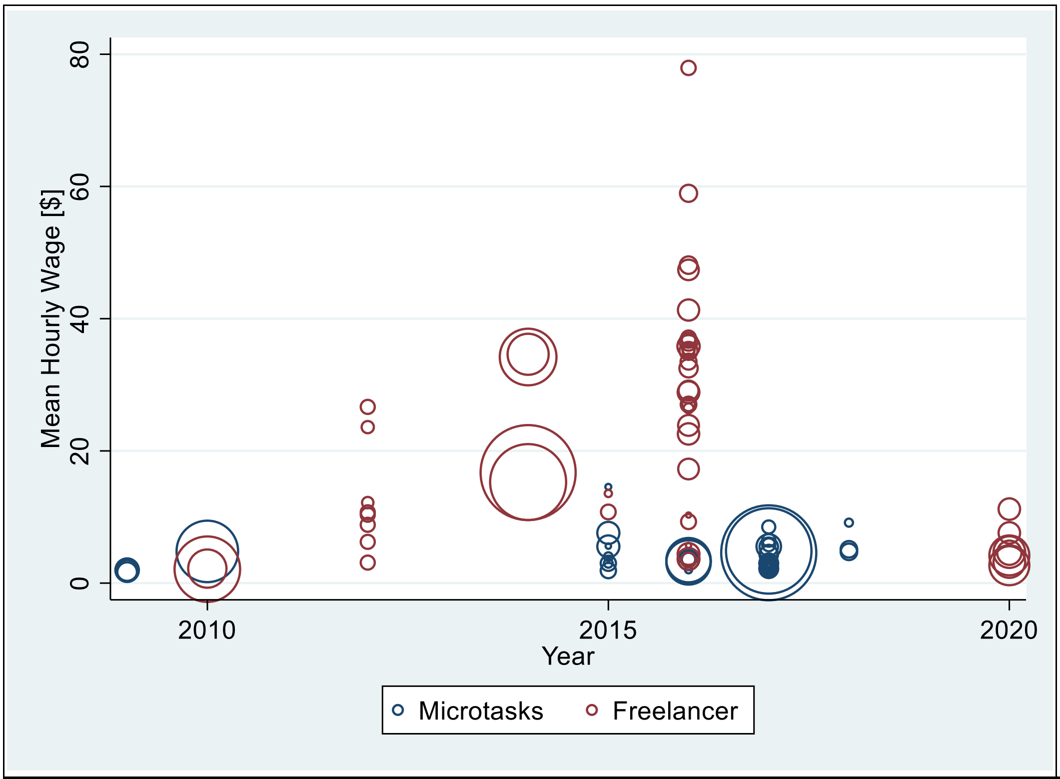
[a] Less than five independent data points
* *p* < .10%, ** *p* < .05, *** *p* < .01.

Fig. 1 PRISMA flow diagram



This flow diagram reports how the 20 primary studies in the meta-analysis were selected for inclusion. It is based on the template of Liberati et al. (2009).

Fig. 2 Scatterplot of wages from 20 primary studies



The size of each circle represents the number of observations relative to the other observations.

Fig. 3 Comparison of calculated mean hourly wages

Excluding Ross et al. (2010) | Including Ross et al. (2010)

Based on year of data collection

Adjusted to the year 2021