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Crowdwork for young people: Risks and opportunities

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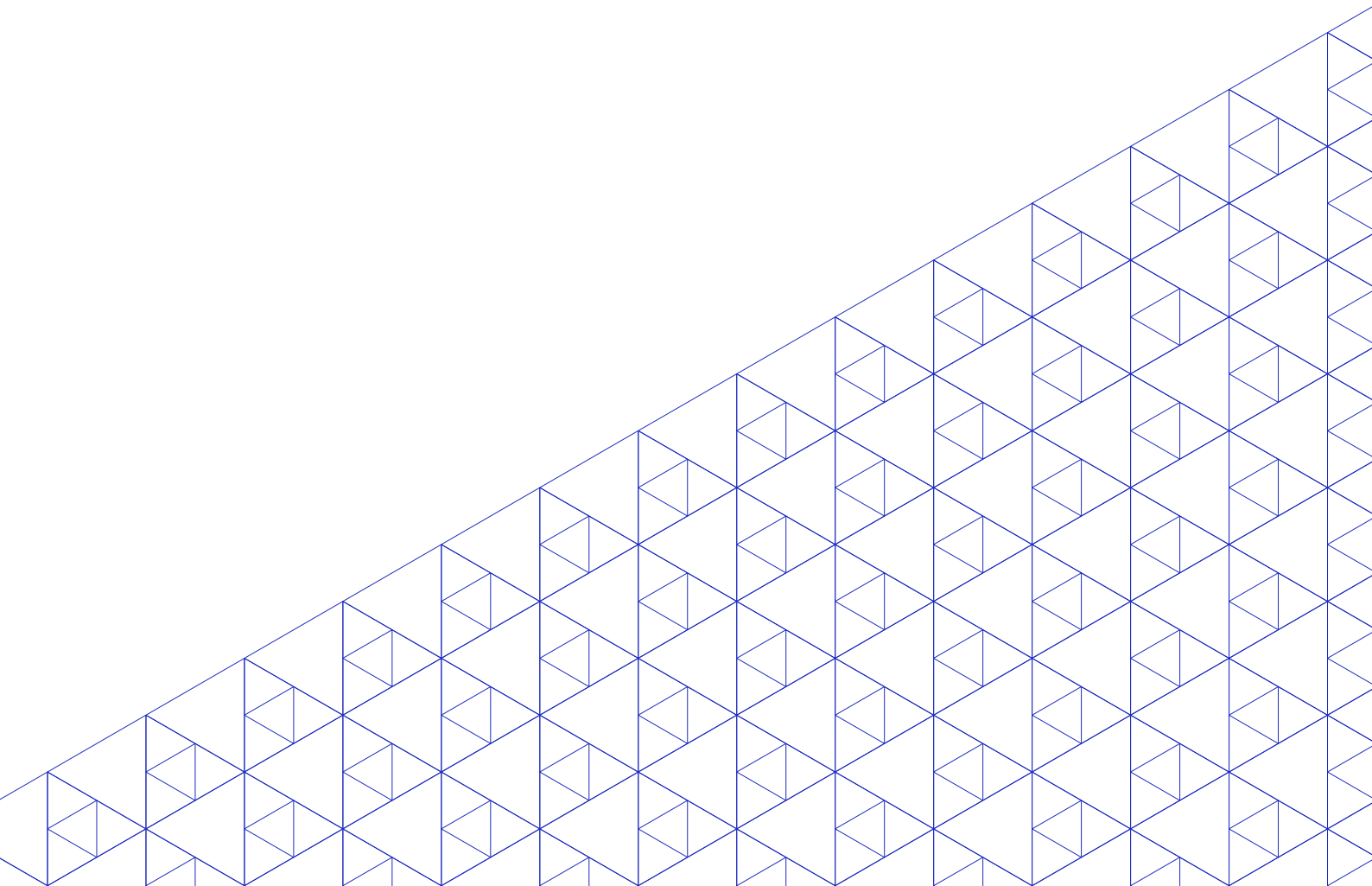
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Risks and opportunities

Authors / Niall O'Higgins, Luis Pinedo Caro





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Abstract

In recent years, crowdworking has emerged as a small but rapidly growing source of employment and income principally for young(er) people. Here, we build on previous work in identifying the determinants of crowdworkers' earnings. We focus on the reasons why young crowdworkers earn significantly higher hourly wages than their older counterparts. We show that this is due to the higher returns to experience accruing to younger crowd-workers. Educational attainment does not explain this age-based differential, as education is a negligible factor in determining crowdworkers' earnings. We also analyse why young women earn around 20% less than their male counterparts despite blind hiring. We confirm that this is partly explained by constraints on working time faced by women with children. The analysis also shows that 'freely chosen' crowd work - as opposed to, young people crowd-working because of a lack of alternative employment opportunities - is conducive to higher levels of job satisfaction. Moreover, young crowdworkers in middle income countries earn less than their counterparts in high income countries but report higher levels of job satisfaction. This is entirely attributable to the lower quality of their options outside of crowdwork.

Keywords: Crowdsourcing platforms, global labour markets, job satisfaction, youth employment. **J.E.L. Classification:** J-20, J-41, F-41.

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► Introduction

The internet has transformed many aspects of our lives including the way we communicate, the way we learn and the way people meet each other. Jobs have been no exception, with the internet modifying how people work and the jobs they perform. Some of these newly created jobs are part of the so-called “gig economy” and can be found on crowdsourcing platforms, online labour markets where employers and workers from all nationalities meet.¹

The COVID-19 pandemic has accelerated an already growing trend, with companies exploiting the potential of a digital labour force and workers affected by curfews and lockdowns seeing online gigs as an opportunity to earn a living. In this context, the contribution of this paper, focused on working conditions on crowdsourcing platforms, is timelier than ever. The objective of this research can be bluntly summarized in the following question: “Can we foresee a future crowd workplace in which we would want our children to participate?” (Kittur et al. 2013, 1). Two indicators of working conditions are investigated in this paper, earnings and job satisfaction, which we have obtained from an International Labour Office (ILO) survey of crowdworkers.

Crowdsourcing platforms allow employers to post online tenders for small tasks which job seekers may accept. The advantage to employers is clear; instead of hiring an employee and bearing the risk that the person will not be needed or will not perform to the agreed standard, companies hire workers for a project or task, using piece-rate rewards that are only paid if the work is of the desired quality. If the work does not meet the employer’s expectations, they may choose to not pay the worker but keep the work. Moreover, workers in these platforms operate as own-account workers independently of how frequently they work for the same employer.² This characteristic has lead authors like Berg (2016) or de Stefano (2016) to argue that crowdworking increases the number of workers excluded from fundamental rights.

However, crowdworking also has significant potentially positive attributes for workers. For instance, it allows for remote labour market access that is relatively discrimination free. This helps workers that suffer from discrimination in their local labour markets or whose circumstances require them to work from home. These, and other features, like self-management and the diversity of the tasks posted may have important beneficial implications for workers’ lives. Furthermore, crowdsourcing platforms provide access to relatively high paying tasks to people from developing countries, as emphasized by Thies et al. (2011) or Taeiagh (2017). Indeed, we present evidence showing that crowdsourcing platforms remunerate at internationally determined prices which are higher than many countries’ minimum or even average hourly wages. This means that workers from developing nations can, in principle, benefit significantly from crowdwork. The participation of workers from poor countries is, nevertheless, low; in spite of initiatives like mClerk, a platform for mobile crowdsourcing.³ Lack of reliable connectivity and access to computers still pose significant entry barriers to workers in lower-income countries.

Despite the game-changing implications of crowdsourcing platforms’ earnings for workers in developing countries, the determinants of crowdwork earnings have seldom been explored. Literature on the topic has usually been more focused on the implications of crowdsourcing for employers. Examples of this employer-focused literature are to be found in research dealing with informational asymmetries between workers and employers and how it gives rise to a principal-agent problem. Research on cheating workers, malicious behaviour, and validation mechanisms for employers can be found in Difallah et al. (2012), Gadiraju et al. (2015) and Hirth et al. (2013). On the contrary, research on crowdwork earnings, either empirical or theoretical, is rather limited. An example of the former is Adams & Berg (2017), who, with the same ILO survey

¹ See Käsä & Lehdonvirta (2016), who use an *Online Labor Index* -OLI- to measure the utilization of online labour platforms.

² See, for instance, Felstiner (2011) for a review of how labour law affects crowdsourcing platforms or Baudry and Chassagnon (2016) for the types of contracts used in the context of crowdworking.

³ See Gupta et al. (2012) for more information on this platform.

analysed here, used earnings from crowdsourcing platforms to estimate the gender-pay-gap of crowdworkers. At the theoretical level we find Horton & Chilton (2010), who calibrate the average hourly earnings for workers using the Amazon Mechanical Turk (AMT) platform.

The second contribution of this paper concerns the determinants of job satisfaction of workers using crowdsourcing platforms. This area has been investigated by Brawley et al. (2016) for workers registered on the AMT platform. Their study focused on the interactions between crowdworkers and the platforms they utilize. They conclude that some of the traditional determinants of job satisfaction do not apply to online platforms. In part, this is a direct consequence of the very nature of the micro-jobs: specifically, the freedom not to engage with unfair employers. Given the apparent freedom of choice it is hard to think crowdworkers would be deeply dissatisfied because the tasks and terms of work, in principle, are chosen by the crowdworkers themselves. The analysis presented here proposes a different approach, one that assesses the reasons for doing crowdwork (i.e. the circumstances of the person) as a determinant of crowdworkers' satisfaction. In this regard, "freely chosen" crowdwork -as opposed to crowdwork being done due to the lack of available jobs- is found to increase workers satisfaction.

We focus on young people because they will be the ones who will benefit (or suffer) the most from crowdworking, but also because they tend to be more technologically savvy than adults. This technological aptitude makes them more likely to take full advantage of crowdsourcing platforms. Analysis confirms that young crowdworkers learn how to use online platforms faster and more efficiently than adults. This is, in turn, reflected in a positive youth/adult hourly wage differential in crowdwork. For young people, wages increase rapidly with experience in online tasks. In addition, due to young people's poorer outside options, they find crowdwork more rewarding in terms of fairness of pay. Last but not least, young people are also more satisfied crowdworkers -other things being equal - than adults. This makes them ideal candidates to, in principle, be the main beneficiaries of crowdwork.

In what follows, after first describing the data used in the analysis, Section 2 analyses the determinants of crowdworkers' earnings, whilst Section 3 focuses on the factors determining job satisfaction for workers on crowdsourcing platforms. Section 4 draws together some conclusions based upon the analyses.

► 1 Crowdwork and earnings

Data and descriptive statistics

This paper uses data from a global crowdwork survey carried out by the International Labour Office in November, 2015. The survey was taken by 999 respondents from 47 countries via either the Amazon Mechanical Turk (AMT) or Crowdfunder.⁴

The information gathered by the ILO survey includes basic socio-demographic information (age, primary language, country of residence, educational attainment), questions about crowdwork employment (reasons for doing crowdwork, hours worked, earnings, tenure, skill mismatch) and some questions about other types of employment held by the respondent. It should be noted that the variable educational attainment is measured in terms of the highest qualification obtained rather than by years of schooling and that the various reasons for doing crowdwork are not mutually exclusive.

Of particular importance is the existence of a measure of wages (reported in 2015 US\$) and hours worked, both reported on a weekly basis. There are two measures of hours worked, the first one only counts the hours of work actually paid (i.e., the time a person would spend filling out a survey if that were the given task). The second one also includes the time spent in searching for tasks, reviewing clients and other unpaid duties related to the job. Throughout the paper we use the latter measure when calculating the hourly wage so that crowdwork earnings can be compared with wages from salaried employment. For example, if an employee were to be paid US\$ 100 for 8 hours and a crowdworker US\$ 100 for 1 hour of work that requires 7 of preparation, it would not be accurate to say the crowdworker earns 8 times more. The hourly wage is calculated by taking weekly wages and dividing that figure by the total number of hours devoted to crowdworking tasks.

Table 1 provides mean values of the variables used in the analysis in Sections 3 and 4. In addition, Appendix A provides the same statistics by age group and by the purchasing power of a dollar in the crowdworkers' countries of residence. The average hourly wage shown in Table 1 is strongly influenced by the large number of American 'Turkers' in the sample; these workers earn, on average, US\$ 5.09 per hour, much higher than the US\$ 1.95 per hour that workers from other countries earn. It is important to note that the variable AMT appearing in Table 1 denotes the crowdsourcing platform used by the respondent to fill in the survey, i.e. it is a binary variable since workers took the survey either in AMT or Crowdfunder. Moreover, it does not preclude that a person is active on both platforms or indeed also on other platforms, although such incidence is rare in the dataset.

Statistics on job satisfaction are restricted to three rating categories, "neutral", "satisfied" and "very satisfied." The original question also allowed respondents to answer "dissatisfied" (6.6%) and very "dissatisfied" (0.9%) but due to their low prevalence they are put together with those who answered "neutral" (17.3%). The low prevalence of dissatisfied crowdworkers is not particularly surprising. As observed above, the amount of choice workers have, starting with whether to do crowdwork altogether or not, but also (and in contrast to other jobs) the choice over the number of hours spent working, the tasks performed and the timing of working hours points to why crowdworkers tend to not be dissatisfied.

⁴ The ILO actually carried out two crowdwork surveys. Only the data from the first of these surveys is used for this research. The original sample consisted of 1,167 individuals; 7 individuals younger than 20 years old and 15 older than 65 years old were dropped in order to have a cleaner picture regarding age groups. The remaining difference is due to listwise deletion; It should be noted that the survey respondents were not randomly drawn, and the survey cannot be said to be representative of crowdworkers worldwide; Respondents took the survey in one of the two mentioned platforms, but workers can be (and are) enrolled in other crowdsourcing platforms.

► Table 1. Descriptive statistics, mean value of each variable

Variable	Other regions	USA	Variable	Other regions	USA
Hourly wage	3.74	4.09	Main job	0.42	0.33
Weekly hours	33.28	30.93	English	0.79	0.65
Age	36.46	33.24	AMT	0.81	0.68
Tenure			Under-qualified	0.25	0.22
<6 months	0.27	0.23	Over-qualified	0.33	0.38
6-12 months	0.19	0.21	Reason for crowdworking		
>12 months	0.54	0.55	No employment available	0.14	0.15
Education			Only able to work at home	0.23	0.12
High school or less	0.11	0.14	Prefers working at home	0.47	0.41
Post-secondary	0.37	0.29	Pay is better	0.08	0.13
Tertiary	0.52	0.57	Complement a second job	0.47	0.51
Job satisfaction			Cash while at school	0.07	0.10
Neutral/dissatisfied	0.25	0.25	Leisure	0.24	0.31
Satisfied	0.57	0.53	It is fun	0.41	0.46
Very satisfied	0.18	0.22	Other	0.13	0.06
N° of obs.	414	585	N° of obs.	414	585

Crowdworkers are highly educated compared to their compatriots. For example, more than 90% of Indian crowdworkers, aged 20-65, have a tertiary educational qualification, compared to 11% countrywide.⁵ The divergence in educational attainment is particularly noticeable for crowdworkers from developing countries (see Appendix A). This signals that there are restrictions in access to crowdworking platforms, perhaps due to computers being relatively expensive or because of lack of reliable internet connectivity. At the same time, this is also suggestive of where future crowdworkers might come from. If computers keep getting cheaper and reliable Internet connections become a reality in more developing countries, people with more means, particularly in Africa, will have the potential to become crowdworkers.⁶

The reasons given for starting crowdwork by those surveyed range from a lack of other job opportunities to crowdwork being somewhere close to a hobby. These reasons can plausibly be thought of in terms of individual constraints, either at the personal level (e.g. family choices) or at the regional level (i.e. job market tightness, locally prevailing wages, etc.). Seen in this way, it is not surprising that crowdworkers living in richer countries -where alternative salaries are higher - are more likely to use crowdwork as a second job, rather than as their major source of income. Similarly, the proportion of young people (51%) using crowd-sourcing platforms as the primary source of income is higher than for adults (28%). In poor countries, close to 30% of people surveyed chose crowdwork because they earn more than in other available jobs. This is practically non-existent in rich countries. (see Appendix A).

Overall, gender differences in the descriptive statistics are minor. One of the few exceptions concerns the proportion of women who chose crowdwork because they had to work at home, which is significantly higher than the corresponding proportion of males. Women in the sample are also slightly older (2.5 years more) and work longer hours (3 hours more).

⁵ Employment-Unemployment 2011-2012 microdata and authors' own calculations.

⁶ With some start-ups offering notable efforts, see, for instance, BRCK (www.brck.com).

Finally, the survey we gathered data from does not represent newbies to online platforms but rather seasoned crowdworkers. The majority of respondents reported having more than one year of experience in crowdworking. However, this statistic might have been influenced by the selection rule for survey participants; only those who, at the time of the survey, had completed at least 500 tasks in AMT or were deemed as a “Quality Worker” by Crowdfunder could participate.

Wages in crowdsourcing platforms

The press has repeatedly noted that crowdwork earnings are extremely low.⁷ The research literature on crowdsourcing analyses whether a minimum wage should be imposed or directly wonders why workers do it at all.⁸ In this section we use global information on crowdworkers’ earnings contained in the ILO-SOC dataset to, precisely, find out whether or not the bad reputation crowdsourcing platforms have earned is justified. We do so by first testing whether the “law of one price” holds in crowdsourcing markets and, thus, whether we can speak in terms of a unified global labour market. This test is simple but at the same time powerful; unified pricing means that the utility from crowdworkers’ earnings depends exclusively on the cost of living in the workers’ residence country, thus disproportionately benefitting those living in developing countries.

Young people are another group that might find crowdsourcing platforms rather attractive. This is primarily due to the relatively poor employment options faced by young people, compared to older workers, in local labour markets. In particular, young people are more likely than adults to be unemployed and face higher degrees of uncertainty regarding their work contracts. Young people also have low expectations regarding present job security. This would make those aged 15-29 more content with the type of work offered by crowdsourcing platforms. (ILO, 2020) In addition, young people seem to have, on average, better problem-solving skills in technology-rich environments, potentially making them more productive than older workers when employed as crowdworkers.⁹ In sum, young people might benefit more than older workers from crowdwork because of their more limited outside options and their higher chance at excelling at this type of job. This also suggests that young people are more likely to report being content with the opportunities provided by crowdsourcing platforms.

Determining the impact of these and other factors – like education- on crowdwork earnings is the aim of the econometric model described in the following subsection.

Econometric model

In order to analyse the determinants of hourly wages in our cross-section of crowdworkers we propose a Mincerian equation whose dependent variable is the natural logarithm of hourly wages. The wage equation model is given by:

$$\ln(w_i) = \beta_0 + X_i\beta + Z_i\delta + \epsilon_i \quad (1)$$

where δ and β are vectors of coefficients, β_0 is the constant term, and X and Z are matrices including observations for the i^{th} individual on job-related and individual characteristics, respectively. Hourly wages are obtained by dividing a crowdworker’s typical weekly earnings during the last year by the typical number of

⁷ See, for instance, Pooler (2014), or Bauwens (2014).

⁸ Mankar et al. (2017) analyses whether a minimum wage should be imposed, Law et al. (2016) explores the role of curiosity, von Ahn (2006) assesses the role of crowdwork as a form of entertainment and Huberman et al. 2009) an altruistic motive.

⁹ Authors’ own calculations from the OECD PIACC.

weekly hours worked during the same time span (including time spent on unpaid work-related duties such as looking for tasks, writing reviews or communicating with clients). Table 2 presents the average wage attained by a number of relevant sub-groups for two regions, the United States of America (USA), and the rest of the world.

With regards to the job-related characteristics, we specifically allowed for crowdworkers to earn a premium based on how long they have been crowdworking. We built three tenure intervals, less than 6 months, 6 to 12 months, and more than 12 months. We included the last two in the regression. We also included a binary variable called AMT to take the value 1 when the worker took the survey on Amazon Mechanical Turk and 0 for when taken on Crowdfunder. On a related issue, we checked whether comments found on the internet about AMT employers discriminating in favour of US crowdworkers have an empirical basis.¹⁰ We did so by allowing for an interaction term, AMT*US, that takes the value 1 when the individual who took the survey in the Amazon Mechanical Turk was based in the United States. We also added a binary variable that takes the value 1 when the person is a native English speaker. We did this to make sure the model does not produce a false positive (higher AMT*US coefficient) in the discrimination test just because US crowdworker almost invariably would possess this skill.

► **Table 2. Crowdwork average hourly earnings, by region**

Variable	Other regions	USA	Variable	Other regions	USA
XR/PPP ratio			English	1.91	5.10
<1.2	1.14	5.09	AMT	2.75	5.13
1.2-2.4	1.68	Na	Tenure length		
>2.4	2.30	Na	<6 months	1.94	4.30
Weekly hours			6-12 months	1.70	4.86
<15	3.11	6.14	>12 months	2.02	5.61
15-30	1.39	5.09	Education		
>30	1.06	4.57	High school or less	1.95	5.20
Age			Post-secondary	1.52	5.14
20-29 years	2.29	5.86	Tertiary	2.05	5.02
30-65 years	1.74	4.69			

Among the individual characteristics included in the matrix *Z*, we find the gender and the age of the person, education level and two macroeconomic variables, the average wage, and the ratio of exchange rate to purchasing power parity conversion factor of the country where the person is based (XR/PPP). Gender is included as a binary variable called *female* that takes the value 1 when the crowdworker is a woman. Educational attainment is divided in three groups, high school or lower, post-secondary or unfinished tertiary, and tertiary education or above, with the last two groups being added to the model. The rationale behind the inclusion of the average wage is to test for the existence of demand side discrimination.

In other words, if the estimated coefficient is positive and statistically significant, we cannot reject the hypothesis that online employers price discriminate against crowdworkers based on their country of origin. Adding the XR/PPP ratio allows us to control for supply side effects that might interfere with the discrimination test just mentioned. Workers living in cheaper places may (through an efficiency wage effect) work

¹⁰ See enigmatic7569 (2015), https://www.reddit.com/r/mturk/comments/2w6i1x/can_a_requester_impose_country_specific_where_it_is_confirmed_the_possibility_of_such_restriction.

harder because they are earning more goods and services than workers in more expensive locations, even if the nominal pay rate is identical. If that were to be the case, not adding the ratio could cause the coefficient on average wages to become positive when it should not, giving our data a false positive variable.

Tenure and age. A second specification based on the model shown in equation (1) incorporates interaction terms between age and tenure (including an option that allows for non-linear effects). This is implemented to test whether younger people are more apt at learning than adults in technological environments. These modelled interactions are a modified version the model from Pinedo Caro et al. (2021), where we allow for greater functional flexibility, including the possibility of non-linear returns to age. That on-the-job learning is a highly relevant feature of these platforms is confirmed by Margaryan (2016) who argues that both, on-line freelancing, and microwork are learning-intensive activities.

Likewise, Barnes et al. (2015) defend a similar argument by emphasizing that crowdworkers have a disposition for, and feel the need to, continuously improve their skills. This specification adds the following line to equation (1):

$$+ \gamma_1 age^2 + \gamma_2 tenure_{6-12m} \times age + \gamma_3 tenure_{6-12m} \times age^2 + \gamma_4 tenure_{+12m} \times age + \gamma_5 tenure_{+12m} \times age^2 \quad (2)$$

where $tenure_{6-12m}$ and $tenure_{+12m}$ are binary variables taking the value 1 when the person has, respectively, spent between 6 to 12 months and more than 12 months crowdworking -with the comparison category being less than 6 months crowdworking.

Gender issues. Finally, we estimate a third specification that investigates two gender-related issues. The first issue deals with whether women have lower quality job opportunities than men in local labour markets. This is done by adding a proxy for ability in the form of a binary variable that takes the value 1 if the person does crowdwork because no other job was available. This proxy is included both on its own as well as being interacted with the female dummy. The coefficient attached to the binary indicator of ability is expected to yield a negative outcome. This is because those who have worse local labour market prospects should, on average, be relatively low ability individuals. If then, the coefficient attached to the interacted 'female' dummy is greater than zero, we could argue that women in crowdwork are, on average, more able than men. This could be the outcome of self-selection due to harsher conditions faced by women in local labour markets.

The second issue deals with the effect of children on earnings when parents decide to work at home. This is modelled as a triple interaction with the help of a binary indicator that becomes active when the person does crowdwork because he/she prefers working from home. The female indicator and a binary variable takes the value 1 if there are children in the house. The coefficient α_5 (see equation 3) would measure the impact of children on their mother's earnings, as well as signalling an unequal distribution of child-bearing duties between genders. To estimate this specification, we add the following expression to equation (1):

$$+ \alpha_1 nojob + \alpha_2 nojob \times female + \alpha_3 home + \alpha_4 home \times female + \alpha_5 home \times female \times children \quad (3)$$

where "nojob" means that the person does crowdwork because he/she could not find other employment and "home" means that the person does crowdwork because he/she prefers to work from home (reasons not mutually exclusive).

Results

The results from estimating all three specifications - Eq. (1) to Eq. (3) - can be found, in their order of appearance, in Table 3. The coefficients can be -roughly- interpreted as the percentage increase in wages when a variable is active/increased marginally because of the log-level modelling.

Decreasing returns to work intensity. A remarkable feature emerging from all specifications is that crowdworkers do not sustain constant hourly wages when they increase their individual labour supply. The work-intensity penalty is plotted in Figure 1, for a realistic range of weekly hours worked, with full-time workers earning up to three times less than part timers.¹¹ Reasons for this phenomenon might have to do with the relative shortage of high-paying tasks or with some characteristic not included in the regression of those working full-time that makes them less efficient.

Salient gender issues. According to the results shown in Table 3, women in crowdwork earn, other things being equal, 23% less than men. In contrast with the typical interpretation of adjusted gender wage gaps, earnings differentials in crowdsourcing platforms can hardly be thought of as being the result of employer-based discrimination. When employers post a task, everyone registered is free to accept it regardless of their gender (i.e., employers do not know who they are hiring ex-ante). In this case, the gender wage gap could be interpreted as women self-selecting themselves into lower paying tasks, perhaps because they have different constraints.

¹¹ This result assumes that part-time workers work 20 hours and full-time workers 40. Since the penalty is roughly 40% for the former and 80% for the latter, for any given earnings, part timers earn three times more per hour (60% vs. 20% of the base earnings) than full time workers.

► Table 3. Log hourly wage regressions

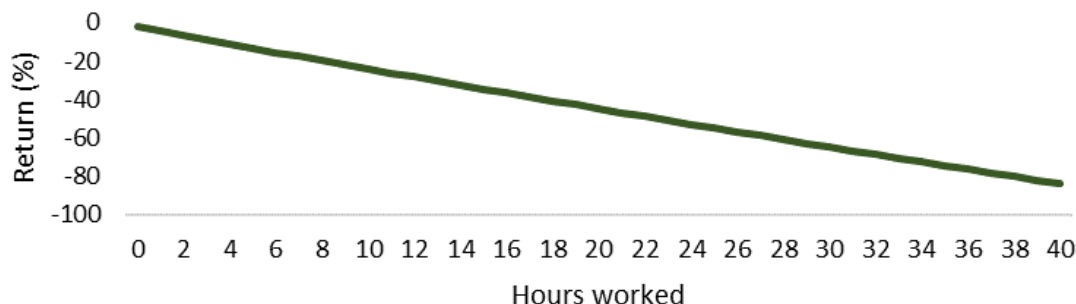
Variable	Specification 1	Specification 2	Specification 3
Weekly hours	-0.02***	-0.02***	-0.02***
Weekly hours ²	0.00003***	0.00003***	0.00004***
Ratio XR-PPP	0.04	-0.04	0.08
US\$ Average wage	-0.00005	-0.00005	-0.00002
Age	-0.01***	0.04	-0.01***
Age ²		-0.0006	
Education (high school or less=0)			
Post-secondary	0.03	-0.03	-0.04
Tertiary	-0.13	-0.13	-0.15*
Tenure (<6 months=0)			
6-12 months	0.08	1.67*	0.09
6-12 months*Age		-0.08*	
6-12 months*Age ²		0.0009	
12+ months	0.21***	1.49**	0.23***
12+ months*Age		-0.07	
12+ months* Age ²		0.0007	
English	0.09	0.09	0.08
Female	-0.23***	-0.23***	-0.22***
AMT	0.01	-0.02	-0.04
AMT*US	1.61***	1.59***	1.62***
No other job			-0.21**
No other job*female			0.11
Prefers home			0.24***
Prefers home*female			0.02
Prefers home*female*children			-0.28***
R ²	0.4985	0.5003	0.5091
Nº of observations	999		

Significance: ***at 1%, ** at 5%, *at 10%.

One of these constraints may well be related to the extra duties women face at home. For instance, male crowdworkers who work at home because they prefer it (variable 'prefers home' in Table 3) earn 24% more. This earnings' premium is unaltered in the case of women without children at home but becomes negative (-4%, which results from subtracting 0.28 to 0.24 in Table 3) when female crowdworkers have children at home. One question remains open though, what is the channel between children and lower earnings? This could happen if, for instance, more rewarding tasks (in terms of hourly earnings) took longer to finish, thus, not allowing someone with other ongoing duties (i.e. childbearing) to take them.

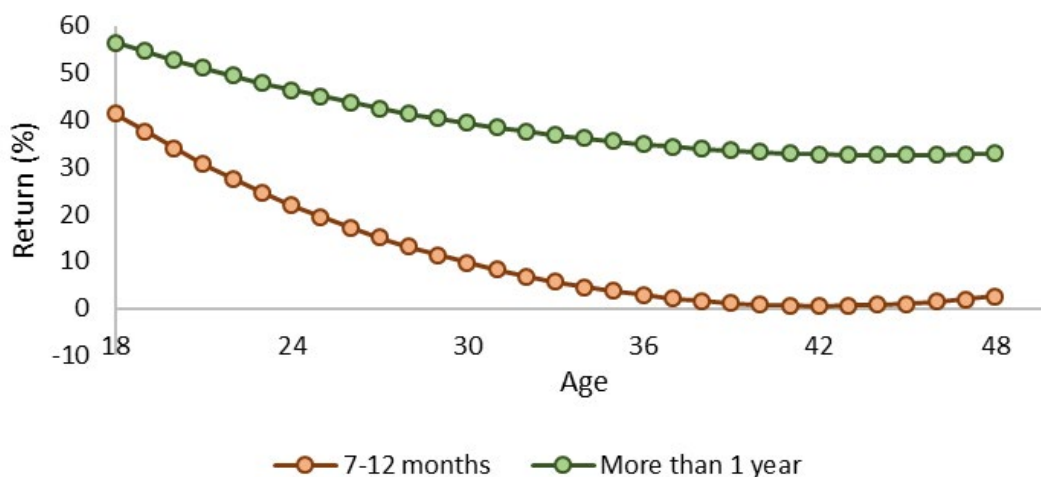
Female crowdworkers, considering the preceding paragraph, might come across as low performers but this is not confirmed by the analysis. The proxy for ability ("no other job") is associated with 21% lower earnings in the case of men, whilst the coefficient on the female interaction term is actually positive albeit not statistically significant. This suggests that women with fewer outside (local) opportunities are, if anything, more able than similarly positioned men. An obvious plausible explanation for this would be the existence of gender discrimination in local labour markets.

► Figure 1: Return to hours worked



Formal education vs. on-the-job learning. None of the coefficients linked to formal education are statistically significant. This suggests that the skills acquired via formal education do not provide any advantage to crowdworkers that is reflected in their earnings. On the contrary, results in Table 3 suggests that the necessary skills to succeed in this market seem to be learned on-the-job. For instance, workers with more than 1 year of experience in crowdworking would expect to earn 21% more than the same worker with less than six months of experience.

► Figure 2: Returns to tenure in crowdwork, by age



Note: The graph shows the return to two levels of tenure, 6-12 months and more than 1 year, in comparison with crowdworkers with less than 6 months of experience in crowdwork whose return is normalized at zero.

The gains from experience, though, are not equally distributed among age groups. The second specification finds that young people can be regarded as being technologically savvy (see Figure 2, Returns to tenure levels by age). According to the marginal effects, younger people are not only faster at learning (shorter distance between the horizontal axis and the 6-12 months of tenure line), but also more effective since their returns are significantly larger than those of older workers for any tenure level.

A global market. The lack of significance of the coefficient attached to the average country wage in all three specifications gives support to the existence of a global market for crowdworkers that shares a unified price. An exception to the law of one price is found in American crowdworkers enrolled on the Amazon

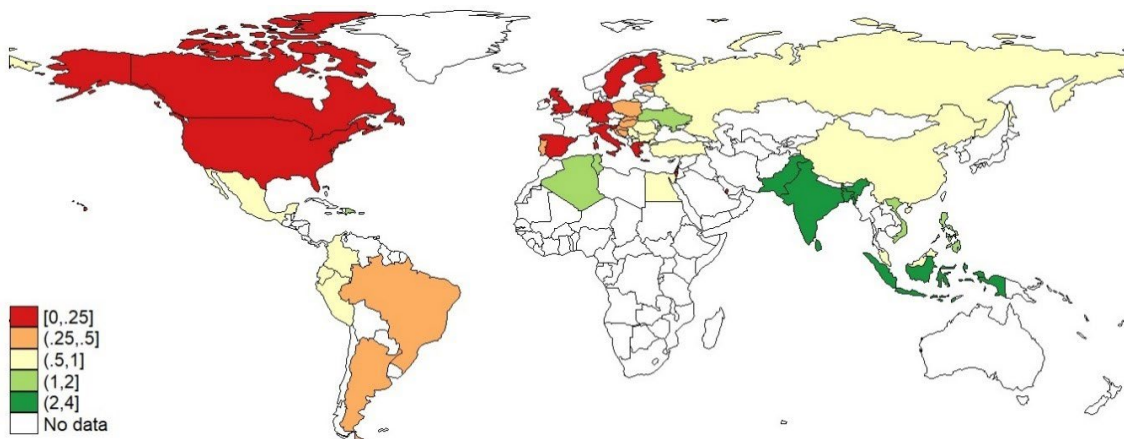
Mechanical Turk platform; these workers earn more than double what other crowdworkers do. This earnings differential and the fact that the average earnings of American AMT crowdworkers is close to the US federal minimum wage that was in force when the survey was taken -US\$ 7.25 in 2015- support the existence of positive discrimination towards American workers on the Mechanical Turk platform.¹²

The main consequence of a global market is the generation of losers and winners, the latter mainly arising in countries with a low cost of living. In order to identify the countries where crowdwork pay is more likely to be found attractive we define the ratio between the full time equivalent average monthly earnings in crowdwork, w_i^c , and the average monthly salary in the country in 2015, w_i^a , as follows:¹³

$$r_{a,i}^c = \frac{w_i^c}{w_i^a} \quad (4)$$

Here, it refers to the country, meaning we calculate the ratio for each of the countries represented in the data. Full time equivalent earnings are calculated by multiplying the average hourly earnings in crowdwork, US\$ 1.95, by the number of hours that constitute a full-time week in each of the 47 countries under analysis.¹⁴¹⁵

► **Figure 3: FTE Monthly average earnings in crowdwork to monthly average salary in the country**



Source: Crowdwork earnings from the ILO-SOC dataset. Average wages from ILO (2016) and the ILO Labour Force Micro Database.

The ratio is plotted in a map (see Figure 3) where the green colour represents countries where crowdwork earnings are higher than the average salary of the country while the yellow/red colours denote the contrary.

According to the map, crowdworking would hardly allow workers in developed countries to earn a living. This is particularly acute in North America and among the richest members of the European Union, where the FTE monthly crowdwork earnings are less than 25% of the country's average wage. In some countries (coloured in yellow and orange) crowdworking earnings would allow full time workers to live and, depending on the workers' personal circumstances (outside options), they might even find crowdwork earnings

¹² Average earnings calculated by dividing the average weekly earnings by the average weekly hours actually worked (not including the time spent on unpaid tasks as was done for the estimated models in Table 3). The average earnings of US AMT crowdworkers using this method are US\$ 6.64 per hour; There is another possibility, that US "turkers" self-select themselves into the high paying tasks, thus increasing their average hourly wage. But, we do not find this sort of self-selection among respondents of other high-income countries, thus, weakening the relevance of this theory.

¹³ See Appendix C for the figures and the sources.

¹⁴ For calculation of fulltime equivalent earning in the case of the US, we use the local average crowdwork earnings. This is because we suspect that the AMT positively discriminates for US-based workers and, thus, the international pay rate does not apply.

¹⁵ Figures obtained from https://en.wikipedia.org/wiki/List_of_minimum_wages_by_country.

attractive. But the true winners of crowdsourcing live in green coloured countries. Crowdworkers in Indonesia, India and Pakistan earn, at least, twice as much as the average employee in their respective countries.

Crowdworking as an opportunity for youth. Young people seem to benefit the most from crowdwork. For instance, some 20-year-old crowdworkers would earn, on average, around 50% more than those their age who were not crowdworkers (see Figure 2). In addition, the benefits that crowdworking offers to young people are amplified in the least developed countries. To exemplify the extent to which workers in developing countries see crowdworking differently we select two questions from the survey, 1) whether the respondent chose crowdworking because the wage paid was higher than his outside option and 2) whether the respondent agrees that rates paid in crowdworking are fair. Crowdworkers' answers to the questions above are tabulated in Table 4 by the Human Development Index of the respondent's country of residence: lower than 0.7, between 0.7 and 0.9 and greater than 0.9. The results are staggering; 39% of young people in developing countries chose crowdwork because the pay rate was higher than in their remaining available options, compared with a mere 9% among young people in developed countries. As expected, the figures for older adults are lower in all levels of development, either because they have higher expectations or because they have better outside options (perhaps due to bigger networks or more years of experience).

Agreement over pay fairness is also widely different among respondents who come from lower- versus higher-income countries. For example, we find that the percentage of young people agreeing pay is fair is 31 percentage points higher among those living in the lowest HDI countries than among those living in the highest HDI countries. Last but not least, Table 4 also shows that crowdworking is better regarded by young people than by adults, irrespective of the degree of development of their country of residence.

► **Table 4: Percentage of respondents who agree that crowdworking pay is fair**

HDI	Pay is better		Pay is fair	
	20-29 years	30-65 years	20-29 years	30-65 years
>0.9	9.09	3.68	31.37	23.74
0.7-0.9	20.00	10.32	52.31	30.00
<0.7	38.89	25.93	62.32	52.57

► 2 Determinants of job satisfaction

Crowdwork is characterized by a high degree of flexibility in when and how a person decides to work. But, it is also characterized by other, not so positive, aspects: lack of promotion opportunities, simple and repetitive tasks (that may lead to perceived over-qualification), relatively low pay and, above everything, an extreme short-termism that demands crowdworkers sign several contracts every day. All of the above-mentioned characteristics have the potential to affect -mostly negatively- crowdworkers' job satisfaction. These factors prompt the question: who can benefit from crowdworking?

A partial answer can be extracted from Section 3, where it is shown that crowdwork pay is constant across countries.¹⁶ Thus, those living in developing countries are more likely to benefit from crowdwork. Despite the importance of monetary earnings for a family's well-being, however, pay is by no means the only determinant of job satisfaction.¹⁷ Indeed, earnings might not even be one of the major determinants of job satisfaction. According to Morgan (2014), monetary compensation comes 8th in a list of 10 determinants of job satisfaction. Regarding crowdworking platforms specifically, a review by Chamorro-Premuzic (2013) reported that earnings are found to have a weak correlation with crowdworkers' job satisfaction, thus, opening the door to further research on the determinants of job satisfaction for this type of worker.

Methodology

We assume the existence of an unobserved latent variable, s_i^* , that reflects the job satisfaction of the i^{th} crowdworker as a continuous measure. Job satisfaction is assumed to be a function of the reasons that made the person take that job among other variables. This idea is expressed as:

$$s_i^* = \mathbf{x}_i' \boldsymbol{\beta} + \epsilon_i \quad \text{for } i \in \{1, \dots, N\}, \quad (5)$$

where \mathbf{x}_i is a row vector containing information on exogenous variables for the i^{th} individual, $\boldsymbol{\beta}$ is a row vector of unknown parameters to be estimated and ϵ_i is a random disturbance term which is assumed to be distributed logistically.

Among the determinants contained in \mathbf{x}_i are two binary variables that control for the existence of over-qualification and under-qualification with respect to the tasks undertook on crowdsourcing platforms. Both variables are self-assessed by the worker, who, when prompted to describe his/her skills, had to choose among "further training is needed," "present skills are suitable" or "I have skills to do more demanding tasks." Those answering the third option are assigned an over-qualified tag while those answering either of the first two options are assigned an under-qualified tag. The reason for adding this variable is to test whether in an environment where formal education does not seem to affect earnings (see Section 3), overqualified persons might develop negative feelings and see their job satisfaction decline.

In addition, we construct a conversion factor based on the ratio of the exchange rate to PPP for the country of residence of the crowdworker.¹⁸ The ratio XR/PPP provides the amount of local goods that a US dollar can buy, representing the international purchasing power of crowdworkers' earnings. This variable adds a

¹⁶ Except for American AMT workers.

¹⁷ See Smith et al. (1969) or Judge et al. (2000) for discussions on other determinants like workers' personality, the nature of the work and promotion opportunities.

¹⁸ Exchange rate between the local currency of the crowdworker's country of residence and the US dollar on January 1, 2021 from xe.com, measured by the amount of local currency necessary to buy a dollar; World Bank, conversion factors referring to 2015, accessed on November 15, 2017.

cross-country component and allows us to test whether living in a cheaper country (holding earnings constant) provides higher job satisfaction. It can also be part of a test (the other part being the nominal hourly pay rate) to ascertain whether workers' satisfaction is linked to either the nominal or the real component of their earnings.

Finally, we allow for the reasons that led crowdworkers to join these platforms as potential determinants of job satisfaction. This is a different approach from the one followed by Brawley and Pury (2016) whose research is focused on the impact that online platforms' characteristics have on crowdworkers' job satisfaction. The rationale and the need for a paper focused on personal, as opposed to platform, characteristics is that the latter do not allow for a precise profiling of the winners and losers of crowdwork. Instead, the reasons for crowdworking tell us more about the kind of people doing these tasks and allow for future policy actions such as offering alternatives to those who are more likely to find themselves dissatisfied.

Job satisfaction measurement. Job satisfaction is originally reported as an ordinal variable with five options ranging from "very dissatisfied" to "very satisfied." Crowdworkers' job satisfaction, s_i , $i \in 1, N$, has a natural ordering and, therefore, an ordered response model is, in principle, deemed as the most appropriate to find the links between this dependent variable and the reasons for doing crowdwork. We propose an ordered Logit model like the one Millán et al. (2017) used in a similar setting to assess the job satisfaction with "false own account workers."

The percentage of respondents falling into each of the categories is shown in Table 5. Due to the low number of respondents in certain groups, those who answered, "very dissatisfied" and "dissatisfied" were grouped together with those who claimed to be "neutral".¹⁹ The new variable has, thus, three options, "very dissatisfied"/ "dissatisfied"/ "neutral" (hereafter referred as "neutral" for brevity), "satisfied" and "very satisfied", respectively denoted by $j \in \{1, 2, 3\}$.

► **Table 5: Percentage of respondents in each of the job satisfaction categories**

	<i>Very dissatisfied</i>	<i>Dissatisfied</i>	<i>Neutral</i>	<i>Satisfied</i>	<i>Very satisfied</i>
<i>Percentage</i>	0.82	6.73	16.83	54.05	21.57

The group-specific percentage of respondents falling into each of the three job satisfaction levels is reported in Table 6. Overall, the percentage of workers falling into each of the satisfaction levels is intuitive. This suggests that choice is positively related to job satisfaction and, thus, is in line with the weak axiom of revealed preference. With respect to the reasons for doing crowdwork, the data shows that the highest proportion of very satisfied workers is found among those who argued that in crowdwork "pay is better" than in other available jobs and among those who find crowdworking "fun." In turn, the highest proportion of neutral (including dissatisfied) crowdworkers is found among those who joined crowdsourcing platforms because "no other employment was available." Among the rest of the variables, it is noteworthy to observe that those over-qualified and in more expensive countries (ratio $XR/PPP < 1.2$) showcase the highest percentages of neutral workers.

¹⁹ Using a four options variable unnecessarily blurs the conclusions due to the small sample size of the "dissatisfied" group.

► Table 6: Summary statistics, job satisfaction by sub-group

Variable	Satisfaction level		
	Neutral/Dis.	Satisfied	Very satisfied
<i>Ratio exchange rate/PPP factor</i>			
<i>Ratio</i> ≤ 1.2	0.30	0.56	0.14
1.2 < <i>Ratio</i> ≤ 2.4	0.14	0.61	0.25
<i>Ratio</i> > 2.4	0.14	0.45	0.40
<i>Women</i>	0.25	0.57	0.18
<i>Men</i>	0.25	0.53	0.22
<i>Under-qualified</i>	0.22	0.58	0.20
<i>Over-qualified</i>	0.29	0.54	0.17
<i>Crowdworking reason (not exclusive)</i>			
<i>No employment available</i>	0.44	0.46	0.10
<i>Only able to work at home</i>	0.26	0.51	0.23
<i>Prefers working from home</i>	0.22	0.56	0.22
<i>Pay is better</i>	0.06	0.43	0.51
<i>Complement a second job</i>	0.23	0.58	0.20
<i>Cash while at school</i>	0.17	0.62	0.21
<i>Leisure</i>	0.16	0.60	0.24
<i>It is fun</i>	0.11	0.59	0.30
<i>Other</i>	0.38	0.51	0.11

Ordered logit. In a setting where the dependent variable has several job satisfaction levels, it is natural to think in terms of thresholds. It should be noted that α_j , associated with these levels, split the observed job satisfaction levels into 2 intervals. Once a crowdworker's latent variable, s_i^* , passes a certain threshold, the person reports a higher satisfaction level. The specific relationship between the latent variable and the observed job satisfaction levels is given by:

$$s_i = \begin{cases} 1 & \text{if } s_i^* > \alpha_1 \\ 2 & \text{if } \alpha_1 < s_i^* \leq \alpha_2 \\ 3 & \text{if } s_i^* > \alpha_2 \end{cases} \quad (6)$$

Given the above stated information the probability that an individual (i) reports a job satisfaction level (j) is given by:

$$\pi_{i,j} \equiv P(s_i = j \mid x_i') = \Delta(\alpha_j - x_i'\beta) - \Delta(\alpha_{j-1} - x_i'\beta) \quad (7)$$

where $\Delta(\bullet)$ represents the standard logistic cumulative distribution function, $\alpha_0 = -\infty$ and $\alpha_3 = +\infty$ and the model is estimated via maximum likelihood.

Parallel lines assumption. Even though there is a natural ordering in job satisfaction, justifying employment of the ordered Logit, this model assumes that the coefficients, β , are the same for all levels of job satisfaction. This is a very strong assumption and there are reasons to suspect that some of the reasons that workers enrol in crowdsourcing platforms may make them just "satisfied" and not "very satisfied." For example, reasons might be framed differently by different subgroups, or reasons might entail mild (as opposed to extreme) reactions.

We carry out a Brant test as well as other Wald tests in order to test the parallel lines assumption. The results from the Brant tests are shown in Table 7. The p-value from the full model (column “All”) accepts that the entire model satisfies the parallel lines assumption. Still, three individual variables’ p-values (in bold) suggest that forcing the coefficients to be identical might not be correct. The source of these problems is better gauged when the test is performed on models for men and women separately; while in the model for the former group all variables satisfy the assumption, in the model for the latter group the parallel lines assumptions suffers a serious drawback. It not only showcases the same problem as the model for all workers does, but also is very close to rejecting the idea that the model meets the parallel lines assumption. The failure of the assumption is also accepted by the Wald tests suggested by Williams (2006), which also flags the same four variables in bold in Table 7.

Although the ordered logit appears to be excessively parsimonious for women, the multinomial logit (which allows each satisfaction level to have its own β) is also deemed too extreme since the majority of the variables are not in conflict with the parallel lines assumption.

► **Table 7: Brant test for the parallel lines assumption**

Indicator	p-value		
	All	Women	Men
Full model	0.276	0.068	0.926
Ratio XR/PPP	0.488	0.995	0.485
Under-qualified	0.112	0.139	0.403
Over-qualified	0.820	0.572	0.923
Age	0.711	0.434	0.505
Female	0.426		
Female*age	0.592		
Hourly pay	0.710	0.621	0.346
Crowdworking reason (not exclusive)			
No employment available	0.757	0.432	0.366
Only able to work at home	0.807	0.490	0.672
Prefers working from home	0.020	0.021	0.498
Pay is better	0.729	0.737	0.541
Complement a second job	0.207	0.435	0.315
Cash while at school	0.143	0.024	0.859
Leisure	0.678	0.549	0.352
It is fun	0.046	0.068	0.361
Other	0.692	0.878	0.616

Notes: P-values lower than 0.1 signal that the variable/model may not satisfy the parallel lines assumption.

In order to take advantage of both modelling options we follow Williams (2016) and employ a partial proportional odds model. This model allows the coefficients to depend on the job satisfaction level as follows:

$$\pi_{i,j} \equiv P(S_i = j \mid x_i') = \Delta(\alpha_j - x_i' \beta_j) - \Delta(\alpha_{j-1} - x_i' \beta_{j-1}) \quad (8)$$

where the parallel lines (constant coefficient) assumption is relaxed in the model for women for three of the potential determinants of job satisfaction, “prefers working from home”, “cash while at school” and “it is fun.” Moreover, because the parallel lines assumptions was only marginally accepted for the variable “under-qualified”, we also relax the assumption for this variable in both models, the one for men and the one for women. Results from both models (the ordered logit and the generalized ordered logit where the

parallel lines assumption is partially relaxed) are presented. The ones from the ordered logit are presented as odd-ratios to understand the direction of change in a simpler way (and which is accurate for most variables). The results from the generalized ordered logit are presented as marginal effects for a deeper analysis of the non-linearities found for some explanatory variables.

In order to determine the marginal effects of the covariates on the probability of achieving a certain satisfaction level we use equation (6) which defines the probability, $\pi_{i,j}$, of achieving the j^{th} level of happiness for the i^{th} individual as:

$$\pi_{i,j} = \frac{e^{x_i' \beta_j}}{\sum_{\tau=1}^3 e^{x_i' \beta_{\tau}}} \quad (9)$$

Then, we take the partial derivative of the probability with respect the k^{th} covariate to compute the individual marginal effect as follows,

$$\frac{\delta \pi_{i,j}}{\delta \pi_{i,k}} = \pi_{i,j} \left(\beta_{i,j} - \sum_{\tau=1}^3 \pi_{i,\tau} \beta_{\tau,k} \right) \quad (10)$$

Finally, the average marginal effect, AME, of the k^{th} covariate on the j^{th} satisfaction level is computed as an arithmetic average.

Results

Table 8 presents odd ratios which are simple and represent a reasonable approximation, however, it makes sense to go further and analyse the variables whose coefficients are marked in bold using the partial proportional odds model since for these variables, the parallel lines assumption is invalidated. Not doing so carries the risk of dismissing the importance of some variables as determinants of job satisfaction when they actually do play a role. Results from the PPO model in the form of marginal effects are shown in Figure 4, for men in graphs (a) and (c), and for women in graphs (b) and (d).

Do reasons underlying the ‘choice’ to crowdwork matter? First of all, the results shown in Table 8 suggest that it is not just the reasons underlying the engagement of individuals in crowdwork that matter for job satisfaction; for instance, the quality of the match between a task’s requirements and a person’s skills and the monetary compensation offered can also actively shape crowdworkers’ job satisfaction. Apart from these aspects of crowdwork, three reasons directly related to the characteristics of the job itself stand out as potential job satisfaction determinants, enjoying the work performed (“it is fun/I enjoy it”), a higher pay with respect to the person’s outside options (“pay is better”) and doing crowdwork because the person could not find any other job (“no employment available”).

► Table 8: Likelihood of reaching a higher job satisfaction tier, ordered logit odd-ratios

Variable	Odd ratios		
	All	Women	Men
Ratio XR/PPP	1.41***	1.61***	1.36***
Hourly pay	1.00	1.03	0.99
Under-qualified	0.88	1.06	0.77
Over-qualified	0.71**	0.73**	0.69*
Age	0.96***	0.98**	0.96***

Variable	Odd ratios		
	All	Women	Men
<i>Female</i>	0.74		
<i>Female*age</i>	1.02		
<i>Crowdworking reason (not exclusive)</i>			
<i>No employment available</i>	0.35***	0.33***	0.36***
<i>Only able to work at home</i>	0.81	0.89	0.70
<i>Prefers working from home</i>	0.93	0.78	1.05
<i>Pay is better</i>	3.40***	5.32***	2.93***
<i>Complement a second job</i>	1.06	1.04	1.09
<i>Cash while at school</i>	0.85	0.79	0.87
<i>Leisure</i>	1.15	0.98	1.21
<i>It is fun</i>	3.01***	3.35***	2.96***
<i>Other</i>	0.60**	0.54*	0.69**
pseudo-R ²	0.1238	0.1339	0.1218
N° of observations	999	414	585

Significance: *** at 1%, ** at 5%, * at 10%.

These three reasons are all related to the person's (lack of) opportunities and attitudes towards work but at the same time they offer different connotations that enrich the analysis. For instance, the link between finding crowdworking fun and the person gaining a higher job satisfaction, although in line with current trends towards a "gamification" culture, it is more likely to be indirect than direct.²⁰ That is to say, fun is rarely the sole objective for doing a job and should not be expected to trigger job satisfaction on its own. The indirect link could be based on the positive attitude showcased by those loving their jobs as explained in Kupka (2012), who argues that happiness at work is a powerful signal for caring, being passionate and being content with one's reality. Caution should be exercised when interpreting the coefficient on "it is fun" for women; according to Figure 4 this factor has a slightly milder effect on women, with "satisfied" being a more likely outcome than "very satisfied."²¹

The second reason that stands out as a job satisfaction determinant is the lack of professional opportunities. From a utility maximization perspective, a reduction in the number of professional options available would normally reduce job satisfaction -or keep it on the same level in the best case. Not having other alternatives has a strong negative correlation with crowdwork "fun" (the reason commented in the previous paragraph) with a correlation at -0.75 and both coefficients being statistically significant.²² This suggests that not having other opportunities has further connotations. Using the example of the previous paragraph, a person who enjoys doing crowdwork ("it is fun") might not be satisfied if, for instance, the job does not fulfil the worker's career expectations.

We also find that workers have higher levels of job satisfaction whenever their crowdwork pay is higher than the one they would attain in their best outside option (the job that would pay the second highest among the worker's available options). This variable has a strong negative correlation with the reason 'no other employment available' which is logical since the less jobs are available the lower the chances the person is able to find one that pays more than crowdwork.

²⁰ See Eyal (2014) for a brief explanation of the "gamification" concept.

²¹ See also Appendix E for a table with the full results from the Partial Proportional Odds Model.

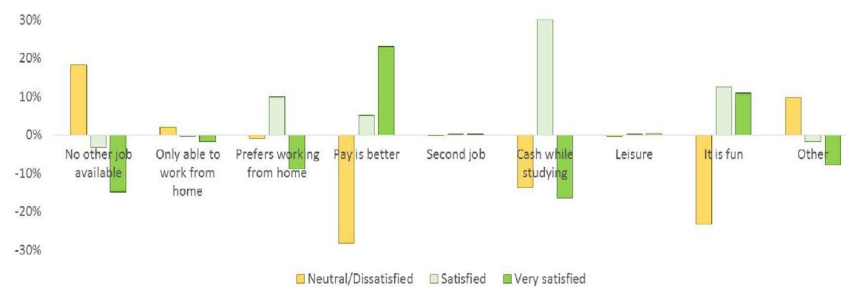
²² Pearson correlation when at least one of the two options was selected.

► Figure 4. Marginal effects on three satisfaction levels

a) Men: Reasons for Crowdfunding



b) Women: Reasons for crowdfunding



c) Men: Other determinants



d) Women: Other determinants



In fact, these two reasons (“no other job available” and “pay is better”) complement each other. The former can be interpreted as the set of choices’ size and the latter as the job satisfaction derived from having chosen the highest paying option.

At last, two reasons for women to do crowdwork that would have been dismissed as unimportant had we only looked at the results from the ordered logit (“prefers working at home” and “cash while going to school”), become statistically significant in Figure 4 (partial proportional odds model). In both cases women

who argued those reasons showcase a milder, yet still positive, reaction in their job satisfaction level. These two, seemingly unrelated reasons, have one thing in common that could explain the milder link with job satisfaction: they reflect situations where the person is constrained (children or other dependents at home or difficulties paying for studies). In these situations, crowdwork, while not ideal, presents itself as a handy way to improve short-term economic challenges.

Skill mismatch. Table 8 provides estimates for the role of skill mismatch on crowdworkers' job satisfaction. On the one hand, we find that over-qualification makes workers more likely to be neutral towards crowdwork. This result is in line with former investigations on this issue and might be related to over-education.²³ On the other hand, under-qualification plays a less clear role in shaping job satisfaction and according to the marginal effects in Figure 4 it has an ambiguous effect, if any.

Monetary compensation. The results from the ordered logit (Table 8) underline the importance of purchasing power as a determinant of job satisfaction. This positive relationship has a direct implication; global labour markets' main beneficiaries are those living in countries where goods and services are cheaper. However, as is commented on in the introduction of this section and in line with other investigations, its impact seems limited. Every unit increase in the XR/PPP ratio only increases the likelihood of workers being more likely to be "very satisfied" by five percentage points (p.p.). The results also allow us to argue in favour of workers' rationality. This statement is backed by two coefficients; first the positive, significant relationship between the amount of goods workers can purchase for every dollar they earn (represented by the XR/PPP ratio) and their level of job satisfaction. Second, the fact that higher nominal earnings do not make workers more likely to reach a higher job satisfaction level.

Age groups. Finally, young people, particularly young men, other things being equal, seem to enjoy, higher levels of job satisfaction. This difference could be explained if, for instance, young people's expectations regarding crowdwork were lower than that of adults. This point is precisely what the ILO Global Employment Trends for Youth 2017 argues with respect to job security, with young people not expecting much in the present.

²³ See Benedict et al. (2009), Hsing-Ming et al. (2016) or Johnson (2000) for analysis on perceived overqualification and job satisfaction respectively focused on executives, teachers, and postal workers; The variable over-qualified has a positive correlation with tertiary education, no correlation with post-secondary education and a negative correlation with secondary education.

► Conclusion

This paper contributes to the existing literature on crowdsourcing platforms by researching which sub-populations are more likely to achieve higher earnings and higher job satisfaction levels. Crowdsourcing is likely to continue growing and the COVID-19 pandemic may have accelerated even further this trend. Many employers have understood that telework is a possibility, and the next likely step would be to outsource some of tasks that can be performed online. Understanding how this growth can benefit its users and what risks need to be prevented should be an important policy issue that this paper aims at addressing.²⁴

In order to do so, we estimate a Mincer equation for crowdworkers' earnings. On this basis, we find evidence that supports the existence of a global crowdsourcing market with a unique price for labour at around US\$ 1.95 an hour. The comparison between the global rate of crowdwork and the hourly wage of employees in lower and lower-middle income countries (US\$ 0.80) explains why some authors find great potential in the development of these platforms for the well-being of workers in developing countries.²⁵

Regarding job satisfaction in crowdsourcing platforms we put the focus on the reasons that led workers to enrol in crowdsourcing platforms rather than, as Brawley and Pury (2016) did, on the characteristics of the platforms themselves. The aim is to produce a more accurate characterization of crowdsourcing platforms' winners and losers. Results from this analysis highlight the role of choice as a determinant of job satisfaction. For example, crowdworkers are much more likely to be very satisfied when the platform pays more than the worker's outside options or when the worker chose to do crowdwork while having other job opportunities.

At last, the results not only confirm the existence of learning in crowdsourcing platforms, as was highlighted in Margaryan (2016), but also detect marked differences in the returns to tenure of young people and their older counterparts, with the former being able to learn faster and more efficiently than the latter. In contrast, this paper finds that formal education plays no role in shaping the earnings of crowdworkers; in fact, we find that a higher educational attainment produces, if at all, lower levels of job satisfaction due to overqualification. It seems that current educational systems do not prepare people for the gig-economy, and the question for policymakers is: whether they should be preparing workers for this new economic model or not?²⁶

²⁴ Crowdsourcing relies on an online labour supply which, in turn, depends on the number of Internet users. Even though improvements in Internet accessibility have brought the number of users from 1% in 1995 to 40% nowadays, the room for growth is notable.

²⁵ Hourly wage comparison obtained from the Labour Force Micro Database, ILO. See Thies et al. (2011) or Taeihagh (2017) for information on these platforms potential impact on workers in developing countries.

²⁶ Although the Kenyan government may have already made a decision, see Miriri (2017).

Appendices

Appendix A – Descriptive statistics

► Table A.1: Descriptive statistics by age group.

Variable	Mean	
	Young	Adult
Hourly wage	4.49	3.65
Weekly hours	31.79	31.96
Age	25.64	39.55
Tenure length	0.29	0.22
< 6 months		
6-12 months	0.20	0.21
+1 year	0.51	0.57
Education	0.13	0.12
High school or less		
Post-secondary	0.37	0.30
Bachelor or above	0.50	0.58
Job satisfaction	0.22	0.26
Neutral/Dissatisfied		
Satisfied	0.52	0.57
Very satisfied	0.26	0.17
Nº of observations	357	642

Variable	Mean	
	Young	Adult
Main job	0.51	0.28
English	0.71	0.71
AMT	0.77	0.72
Under-qualified	0.20	0.25
Over-qualified	0.33	0.37
Reasons for doing crowdwork	0.20	0.12
No employment available		
Only able to work at home	0.20	0.14
Prefers working from home	0.50	0.40
Pay is better	0.17	0.08
Complement a second job	0.41	0.54
Cash while at school	0.19	0.02
Leisure	0.27	0.29
It is fun	0.45	0.44
Other	0.05	0.11
Nº of observations	357	642

Note: Young refers to those aged 20-29 while adults are those aged 30-65.

► Table A.2. Descriptive statistics by country XR/PPP ratio.

Variable	Mean			Variable	Mean		
	<1.2	1.2-2.4	2.4		<1.2	1.2-2.4	>2.4
Hourly wage	4.92	1.68	2.30	Main job	0.36	0.30	0.42
Weekly hours	31.01	31.34	35.65	English	0.96	0.02	0.35
Age	35.41	33.75	32.22	AMT	0.94	0.00	0.59
Tenure				Under-qualified	0.19	0.34	0.31
<6 months	0.26	0.26	0.19	Over-qualified	0.40	0.24	0.29
6-12 months	0.21	0.25	0.13	Reason for crowdworking			
>12 months	0.53	0.49	0.69	No employment available	0.16	0.18	0.07
Education				Only able to work at home	0.15	0.10	0.28
High school or less	0.14	0.17	0.04	Prefers working at home	0.42	0.38	0.52
Post-secondary	0.41	0.22	0.11	Pay is better	0.06	0.14	0.29
Tertiary	0.45	0.61	0.85	Complement a second job	0.56	0.40	0.32
Job satisfaction				Cash while at school	0.09	0.10	0.06
Neutral/dissatisfied	0.30	0.14	0.14	Leisure	0.30	0.26	0.24
Satisfied	0.56	0.61	0.46	It is fun	0.41	0.45	0.55
Very satisfied	0.14	0.25	0.40	Other	0.11	0.02	0.08
Nº of observations	666	152	181	Nº of observations	666	152	181

Appendix B – Ratio exchange rate/PPP conversion factor

► Table B.1: Descriptive statistics, ratio exchange rate/PPP conversion factor.

Country	Ratio XR/PPP	Country	Ratio XR/PPP
<i>Algeria</i>	3.08	<i>Malaysia</i>	2.46
<i>Argentina</i>	1.39	<i>Mexico</i>	1.75
<i>Bangladesh</i>	2.76	<i>Netherlands</i>	1.02
<i>Belgium</i>	1.03	<i>Pakistan</i>	3.46
<i>Bosnia & Herzegovina.</i>	2.33	<i>Peru</i>	1.94
<i>Brazil</i>	1.41	<i>Philippines</i>	2.49
<i>Bulgaria</i>	2.36	<i>Poland</i>	2.01
<i>Canada</i>	0.93	<i>Portugal</i>	1.43
<i>China</i>	1.78	<i>Qatar</i>	1.92
<i>Colombia</i>	1.98	<i>Romania</i>	2.26
<i>Croatia</i>	1.79	<i>Russia</i>	2.52
<i>Dominican Rep.</i>	2.16	<i>Serbia</i>	2.03
<i>Ecuador</i>	1.85	<i>Slovak Republic</i>	1.69
<i>Egypt</i>	2.95	<i>Slovenia</i>	1.43
<i>Estonia</i>	1.56	<i>Spain</i>	1.23
<i>Finland</i>	0.92	<i>Sri Lanka</i>	2.95
<i>Germany</i>	1.07	<i>Sweden</i>	0.87
<i>Greece</i>	1.33	<i>Tunisia</i>	2.81
<i>Hungary</i>	2.00	<i>Turkey</i>	1.87
<i>India</i>	3.70	<i>Ukraine</i>	2.70
<i>Indonesia</i>	3.08	<i>United Kingdom</i>	0.92
<i>Israel</i>	1.02	<i>United States</i>	1.00
<i>Italy</i>	1.13	<i>Viet Nam</i>	2.82
<i>Macedonia</i>	2.64		

Note: The acronym 'XR' refers to the exchange rate between the local currency of the crowdworker's country of residence and US\$ 1 as of 1st January 2015. In turn, 'PPP' refers to the purchasing power parity conversion factor. Source: Exchange rates from XE.com, historical exchange rates. PPP conversion factors from the World Bank.

Appendix C - Average and lowest/minimum wages.

► Table C.1: Descriptive statistics, monthly average and lowest/minimum wages, US\$ 2015.

Country	Ave. wage	Min. wage	Country	Ave. wage	Min. wage
<i>Algeria</i>	332	204	<i>Malaysia</i>	660	257
<i>Argentina</i>	1,001	659	<i>Mexico</i>	446	117
<i>Bangladesh</i>	113	19	<i>Netherlands</i>	2,881	1,817
<i>Belgium</i>	3,738	1,813	<i>Pakistan</i>	149	129
<i>Bosnia & Herzegovina.</i>	797	251	<i>Peru</i>	481	285
<i>Brazil</i>	818	220	<i>Philippines</i>	226	133
<i>Bulgaria</i>	553	222	<i>Poland</i>	1,101	505
<i>Canada</i>	3,550	1,554	<i>Portugal</i>	1,285	713
<i>China</i>	527	137	<i>Qatar</i>	2,953	206
<i>Colombia</i>	448	270	<i>Romania</i>	635	263
<i>Croatia</i>	1,272	479	<i>Russia</i>	560	99
<i>Dominican Rep.</i>	346	177	<i>Serbia</i>	609	282
<i>Ecuador</i>	606	413	<i>Slovak Republic</i>	989	460
<i>Egypt</i>	493	168	<i>Slovenia</i>	2,073	957
<i>Estonia</i>	1,288	471	<i>Spain</i>	2,301	915
<i>Finland</i>	4,039	1,413	<i>Sri Lanka</i>	163	50
<i>Germany</i>	3,292	1,742	<i>Sweden</i>	4,099	1,876
<i>Greece</i>	1,562	827	<i>Tunisia</i>	292	183
<i>Hungary</i>	947	401	<i>Turkey</i>	712	514
<i>India</i>	172	66	<i>Ukraine</i>	265	87
<i>Indonesia</i>	166	100	<i>United Kingdom</i>	3,430	1,723
<i>Israel</i>	2,402	1,193	<i>United States</i>	3,744	1,256
<i>Italy</i>	2,629	1,467	<i>Viet Nam</i>	218	145
<i>Macedonia</i>	636	259			

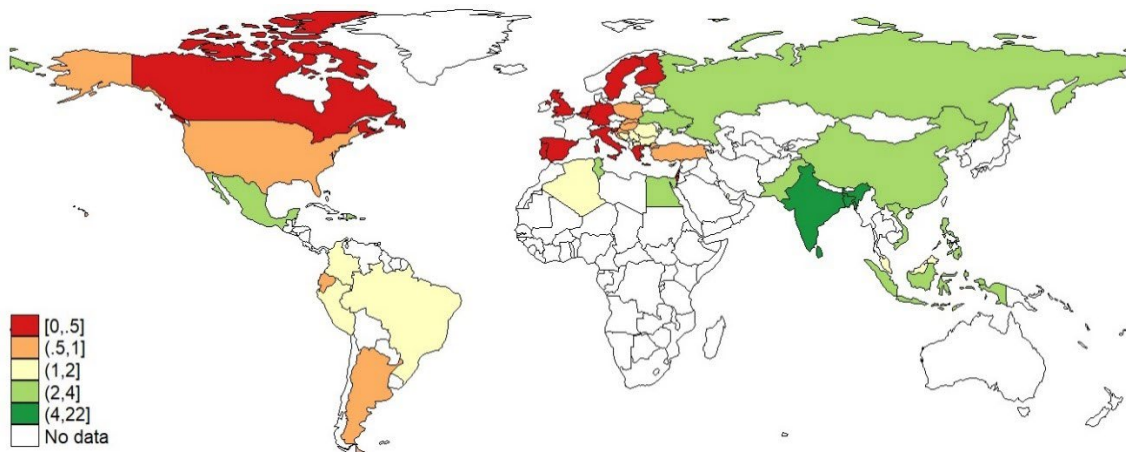
Source: Average wages from ILO (2017) and calculated from the ILO Labour Force Micro Database. Lowest/minimum wages from Wikipedia and other media.

Appendix D - World map, ratio of crowdwork earnings to minimum wage.

This world map shows the ratio between the global FTE crowdworking earnings, w_i^c , calculated as is explained in Section 3, and the 2015 monthly lowest/minimum wage in USD²⁷ w_i^m , for each of the countries. Sometimes, no statutory minimum wage exists in a given country; in those cases we relied upon the lowest sectoral collectively bargained minimum wages. In some other instances the statutory minimum wage varies by region (and within region, by area, like in China); in those cases, we used the lowest among the full list of statutory minimum wages.

It is also important to note, when interpreting the map, that the crowdworkers in the dataset are not the kind of workers who earn a minimum wage; most of them are highly educated and, especially in lower-income countries, they probably belong to relatively well-off families. Therefore, this map is better interpreted as the comparison between crowdwork earnings and crowdworkers' outside option if access to these platforms were universal, in sum, a hypothetical scenario.

► Figure 5: FTE average monthly earnings in crowdwork to lowest/minimum wage in the country



Source: List of minimum wages by country from the Wikipedia and other online sources are used for retrieving minimum/lowest wages. see Appendix C for the full list of lowest/minimum wages. The website xe.com is used to retrieve the exchange rates.

²⁷ Exchange rates between US\$ and the local currency from xe.com are used.

Appendix E - Generalized ordered logit estimates

► **Table E.1: Odd-ratios from a generalized ordered logit on crowdworkers' job satisfaction. Baseline: very satisfied.**

Variable	Women		Men	
	Neutral	Satisfied	Neutral	Satisfied
Ratio XR/PPP		1.63***		1.36***
Hourly wage	1.03			0.99
Under-qualified	0.81		0.66	
Over-qualified	0.72			0.70*
Age		0.98**		0.96***
Crowdworking reason				
No employment available		0.30***		0.35***
Only able to work at home	0.87			0.70
Prefers working from home	0.48**			1.05
Pay is better		6.52***		2.96***
Complement a second job	1.01			1.09
Cash while at school	0.26*			0.89
Leisure	1.02			1.21
It is fun	4.73***	2.43***		2.96***
Other		0.69		0.70
Pseudo-R2	0.1565		0.1225	
N° of observations	414		585	

Significance: *** at 1%, ** at 5%, * at 10%.

References

- Adams, A. and J. Berg. 2017. "When Home Affects Pay: An Analysis of the Gender Pay Gap Among Crowdworkers." *SSRN.com*.
- Barnes, S.-A., A. Green, and M. de Hoyos. 2015. "Crowdsourcing and Work: Individual Factors and Circumstances Influencing Employability." *New Technology, Work and Employment* 30 (1): 16–31.
- Baudry, B. and V. Chassagnon. 2016. "L'arbitrage entre le salariat et le travail indépendant au prisme des théories de la firme. une analyse économique des pratiques de crowdworking." *Revue de l'OFCE* 149 (5): 167-189.
- Bauwens, M. February 21st, 2014. "The Hyper-exploitation of Crowdworking, Mechanical Turk and Amazon". *P2P Foundation Blog*.
- Brawley, A. M. and C. L. S. Pury. 2016. "Work Experiences on MTurk: Job Satisfaction, Turnover, and Information Sharing." *Computers in Human Behavior* 54: 531-546
- Benedict, J. N., S. G. Devi, and A. Velayudhan. 2009. "Perceived Overqualification, Job Satisfaction, Somatization, and Job Stress of MNC Executives." *Journal of the Indian Academy of Applied Psychology*, 35 (2): 282–289.
- Berg, J. 2016. "Income Security in the On-demand Economy: Findings and Policy Lessons from a Survey of Crowdworkers." ILO Working Paper, Conditions of Work and Employment Series, no 74.
- Brawley, A. M. and C. L. Pury. 2016. "Work Experiences on MTurk: Job Satisfaction, Turnover and Information Sharing." *Computers in Human Behavior* 54 (2016), 531–546.
- Chamorro-Premuzic, T. 2013. "Does Money Really Affect Motivation?: A Review of the Research," *Harvard Business Review*, April 10, 2013.
- de Stefano, V. 2016. "The Rise of the 'Just-in-Time Workforce': On-demand Work, Crowdwork and Labour Protection in the 'Gig-economy.'" *Comparative Labor Law & Policy Journal*, 37 (3): 471-504. .
- Difallah, D. E., G. Demartini, and P. Cudré-Mauroux. 2012. "Mechanical Cheat: Spamming Schemes and Adversarial Techniques on Crowdsourcing Platforms." In *Proceedings of the First International Workshop on Crowdsourcing Web Search*, Lyon, France, April 17, 2012. *CrowdSearch*: 842: 26-30.
- enigmatic7569. "Can a Requester Impose Country-Specific Restrictions for Workers?" *Reddit*, February 17, 2015.
- Eyal, N. 2014. "The Pros and Cons of a Gamified Work Culture." *Fast Company*, September 5, 2014.
- Felstiner, A. 2011. "Working the crowd: Employment and labour law in the crowdsourcing industry." *Berkeley Journal of Employment & Labor Law*, 32 (1).
- Gadiraju, U., R. Kawase, S. Dietze, and G. Demartini, 2015. "Understanding Malicious Behaviour in Crowdsourcing Platforms: The Case of Online Surveys" In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. April 18 -23, 2014. Seoul, Rep. of Korea. New York, NY: Association for Computing Machinery

Gupta, A., W. Thies, E. Cutrell, and R. Balakrishnan. 2012. [“mClerk: Enabling Mobile Crowdsourcing in Developing Regions.”](#) In *Proceedings of the Conference on Human Factors in Computing Systems (CHI 2012)*, May 5-12, 2012, Austin, Texas, 1843–1852. New York, NY: Association for Computing Machinery

Hirth, M., T. Hoßfeld, and P. Tran-Gia. 2013. [“Analyzing costs and accuracy of validation mechanisms for crowdsourcing platforms.”](#) *Mathematical and Computer Modelling* 57(11-12): 2918–2932.

Horton, J. and L. Chilton. 2010. [“The Labor Economics of Paid Crowdsourcing”](#) In *Proceedings of the 11th ACM conference on Electronic commerce (EC '10)*, June 7 - 11, 2010, Cambridge Massachusetts, 209–218. New York, NY: Association for Computing Machinery

Hsing-Ming, L., C. Mei-Ju, and W. Ho-Tang. 2016. [“The Measurement of Perceived Overqualification and the Relationships Among Perceived Overqualification, Psychological Empowerment and Job Satisfaction of Private Kindergarten Teachers”](#). *European Journal of Research in Social Sciences*, 4 (8).

Huberman, B. A., D. M. Romero, and F. Wu. 2009. [“Crowdsourcing, Attention and Productivity.”](#) *Journal of Information Science* 35 (6): 758–765.

ILO (International Labour Organization). 2016. [Global Wage Report 2016/17: Wage Inequality in the Workplace](#), Geneva.

ILO. 2017. [Global Employment Trends for Youth 2017: Paths to a Better Working Future](#), Geneva.

ILO. 2020 [Global Employment Trends for Youth 2020: Technology and the Future of Jobs](#) Geneva.

Johnson, G. J. and W. R. Johnson. 2000. [“Perceived Overqualification and Dimensions of Job Satisfaction: A Longitudinal Analysis.”](#) *The Journal of Psychology*, 134 (5): 537–555.

Judge, T. A., J. E. Bono, and E.A. Lock. 2000 [“Personality and Job Satisfaction: The Mediating Role of Job Characteristics”](#) *Journal of Applied Psychology*, 85 (2): 237–249.

Kässi, O. and V. Lehdonvirta. 2016. [“Online Labour Index: Measuring the Online Gig Economy for Policy and Research”](#), Munich Personal RePEc Archive Paper no 74943

Kittur, A., J. V. Nickerson, M. S. Bernstein, E. M. Gerber, A. Shaw, J. Zimmerman, M. Lease, and J.J. Horton. 2013. [“The future of crowd work.”](#) In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work, San Antonio, Texas. February 23 - 27, 2013*, 1301-1318. New York, NY: Association for Computing Machinery

Kupka, A. 2012. [“Why You Need To Love Your Job,”](#) *Forbes*, January 26, 2012,

Law, E., M. Yin, J. Goh, K. Chen, M.A. Terry, and K. Z. Gajos. 2016. [“Curiosity Killed the Cat, but Makes Crowdwork Better.”](#) *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San José, California. May 7-12, 2016*, 4098-4110. New York, NY: Association for Computing Machinery

Manker, A, R. J. Shah., M. Lease. 2017 [“Design Activism for Minimum Wage Crowd Work”](#) *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*, Denver, Colorado. May 6 – 11, 2017. New York, NY: Association for Computing Machinery

Margaryan, A. 2016. [“Understanding Crowdworkers’ Learning Practices.”](#) *Internet, Policy and Politics 2016 Conference*, University of Oxford, UK. September 22-23, 2016.

Millán, A., J. M. Millá, and C. Román. 2017. [“Are False Own-Account Workers Less Job Satisfied Than True Ones?”](#) *Applied Economic Letters*, 25 (13): 945–950.

Miriri, D. 2017. "Kenya Targets 1 Million Digital Jobs for Youths in a Year." Reuters January 20, 2017.

Morgan, J. 2014. "The Top 10 Factors For On-The-Job Employee Happiness," *Forbes*, December 15th, 2014.

Pinedo Caro, L., N. O'Higgins, and J. Berg. 2021. "Young People and the Gig-economy." In *Is the Future Ready for Youth? Youth Employment Policies for Evolving Labour Markets*, edited by S. Dasgupta and J. Chacaltana. 38-52. ILO: Geneva.

Pooler, M. 2014. "Crowdworkers Form Their Own Digital Networks." *Financial Times*, November 3rd, 2014.

Smith, P. C., L. M. Kendall, and C.L Hulin. 1969. *The Measurement of Satisfaction in Work and Retirement: A Strategy for the Study of Attitudes*. Oxford, England: Rand McNally.

Taeihagh, A. 2017. "Crowdsourcing, Sharing Economies and Development." *Journal of Developing Societies*, 33(2): 1912–1922.

Thies, W., Ratan, A., and Davis, J. 2011. "Paid Crowdsourcing as a Vehicle for Global Development." in Proceedings of the ACM CHI Workshop on Crowdsourcing and Human Computing, May, 1-4.

von Ahn, L. 2006. "Games with a Purpose" *Computer* 39 (6): 96–98.

Williams, R. 2006. "Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables." *The Stata Journal*, 6 (1): 58–82.

Williams, R. 2016. "Understanding and Interpreting Generalized Ordered Logit Models." *The Journal of Mathematical Sociology*, 40 (1): 7–20.

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