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Abstract

Is it possible to estimate the real impact of micro-task crowdwork on wages and working conditions of platform workers? Do workers involved in micro-task outsourcing differ in their characteristics from traditional salaried workers of similar ability? Are micro-task crowdworkers similar or different in the United States and in Europe? In this paper, we address these questions by comparing wages and working conditions across online-platform workers and traditional workers in a quasi-experimental approach which exploits caregiving as an instrument for participation in crowdwork. We find evidence that, when controlling for workers' observed and unobserved ability, traditional workers retain a significant premium in their earnings with respect to platform workers, though this effect is not as large as descriptive statistics may hint. Moreover, labour force in crowdworking arrangements appears to suffer from high levels of under-utilisation, relegating crowdworkers into a new category of idle workers whose human capital is neither fully utilised nor adequately compensated.

Keywords: *crowdwork, platform economy, micro-tasks, digitalisation, working conditions.*

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1 Introduction

Among the 'mega-trends' which characterise the future of work, the growth of the online platform economy has been steady and fast in the recent years and has been contributing to the changing nature of work (OECD, 2017, Harris & Krueger, 2015).[1] Technological progress and digitalisation are at the basis of its current development. Due to the overall exponential growth of internet facilities, indeed, recent years have shown an increasing number of workers participating in what is described as the 'gig', 'on-demand', or 'platform-based' economy (Degryse, 2016, Prassl & Risak, 2015). These workers are called 'crowdworkers', where crowdwork is defined as an 'employment form that uses an online platform to enable organisations or individuals to access an indefinite and unknown group of other organisations or individuals to solve specific problems or to provide specific services or products in exchange for payment' (Eurofound, 2015).

The economic conditions of crowdworkers have been widely reported in a number of descriptive studies (e.g. Berg et al., 2018, Berg, 2015, Difallah et al., 2018, Hara et al., 2017, De Groen et al., 2017): it arises that these workers appear to suffer from the erosion of fundamental labour rights, the loss of social protections and difficulties in exercising collective actions. It would be a mistake, however, to assume that platform work has a causal effect on working conditions solely based on the evidence of these descriptive studies, as it could be argued that the characteristics of crowdwork are intrinsically different from traditional salaried professions. More definitive answers are needed, especially in light of the 2030 Agenda for Sustainable Development and the goals of the United Nations and the European Parliament in terms of decent work and social rights.[2]

Given the likelihood that the online platform economy will further expand in the coming years, it is crucial for governments and social partners to take an active role in designing labour market institutions (e.g. minimum wages, employment protection, health and safety regulations) that can ensure labour and social rights for this type of workers. This is especially urgent for platform workers involved in the so-called micro-tasks (a series of small tasks which together comprise a large unified project and can be performed independently over the Internet in a short period of time), which are more exposed to risks concerning low pay, precariousness

[1] According to the OECD (2016), the online platform economy is the economic activity which enables transactions - partly or fully online - of goods, services and information.

[2] During the UN General Assembly in September 2015, the four pillars of the Decent Work Agenda – employment creation, social protection, rights at work, and social dialogue – became part of the new UN 2030 Agenda for Sustainable Development (United Nations, 2015, Transforming our world: the 2030 Agenda for Sustainable Development). At the same time, the European Parliament resolution of 19 January 2017 recognised the need to set a European Pillar of Social Rights also for 'atypical or non-standard forms of employment, such as temporary work, involuntary part-time work, casual work, seasonal work, on-demand work, dependent self-employment or work intermediated by digital platforms' (European Parliament, 2017, European Parliament resolution of 19 January 2017 on a European Pillar of Social Rights).

and poor working conditions (Prpić et al., 2015).[3]

In light of these critical issues, in this paper we analyse a large fraction of the available evidence on earning and working conditions of crowdworkers involved in micro-tasks. Our focus is on the evidence from the United States and Europe and our main goal is to answer to the following questions: Do crowdworkers involved in micro-tasks differ in their characteristics from traditional salaried workers involved in similar occupations? Are micro-task crowdworkers from the US similar or different from crowdworkers from Europe? Is it possible to estimate the real impact of micro-task crowdwork on wages and working conditions of platform workers? Is incidence of labour market slack in crowdwork higher than that in traditional forms of salaried employment?

Our contribution is based on an empirical analysis of cross-sectional data collected from three different surveys and harmonised in order to obtain the greatest degree of comparability. The approach we adopt is quasi-experimental, in line with the 'Treatment Effect' literature (see Angrist & Pischke, 2011): the aim is to provide an unbiased comparison of earnings and working conditions of platform workers and 'traditional' workers across control and treatment groups, where variations in outcomes are analysed conditionally on a binary 'treatment' variable indicating participation into crowdwork. For both US and Europe the treatment groups include information on crowdworkers from a number of online platforms – namely, Amazon Mechanical Turk (AMT), Crowdflower, Clickworker, Microworkers and Prolific Academic – coming from two dedicated surveys distributed by the International Labour Organization, while the control groups include information from available extended surveys on American and European workers' conditions (American Working Conditions Survey, European Working Conditions Survey).

Our findings indicate that, overall, crowdworkers earn about 70.6% less than 'traditional' workers with comparable ability, while working only a few hours less per week. Similar figures are obtained for the European and American samples separately. Also, platform workers appear to be uninterested in looking for other forms of occupation, while still expressing the desire to work more than what they currently do. These results suggest that most crowdworkers are similar to a form of idle workforce, which is excluded from traditional employment and is still under-utilised. To the best of our knowledge, this is one of the first attempts to provide an unbiased comparison of platform and traditional workers in terms of earnings and working conditions in a quasi-experimental design. Moreover, contrarily to most other studies on the online platform economy, which concentrate on US crowdworkers, we here focus on both United States and Europe.

The remaining of the paper is organised as follows. Section 2 outlines the online micro-task labour market, Section 3 is dedicated to a review of the literature, Section 4 (together with the

[3] As opposed to individuals participating in online freelancing marketplaces (such as UpWork), where conditions are generally more favourable and projects are usually larger in scope.

Appendix) describes the data used for our empirical analysis, Section 5 outlines our empirical specification and Sections 6 and 7 show our results and robustness checks. Finally, in Section 8 we discuss our conclusions.

2 The online micro-task labour market

Phenomena such as crowdwork do not exist in a vacuum, but are fostered and facilitated by wider socio-economic trends, and the development of 'virtual work' can surely be identified as one of these. The term virtual work has been used by many authors to describe all of the various forms of work characterised by the execution of work through the Internet, computers, or other IT-based tools (Valenduc & Vendramin, 2016). However, not all digital jobs are necessarily a novelty *per se*, and not all new jobs are digital. While new forms of employment have surfaced, pre-existing ones have acquired a new role and relevance, thanks to the influence of new technologies.[4]

Crowd employment is one of these new forms of employment and transcends traditional employment arrangements by de facto requiring a tripartite relationship in which an intermediary agent - the platform - manages workers - or, rather, service providers - not only by matching them with clients but also controlling pay levels, providing ratings and generally exercising many other functions that affect workers directly. Within the platform, through an open call, client companies can offer online tasks, which are performed by contractors in exchange for remuneration (see, e.g., Eurofound, 2015). Because the the majority of online platforms explicitly deny the existence of any employment relationship between the parties, individuals in crowd employment arrangements are generally characterised as independent contractors, performing their work in a discontinuous or intermittent basis.

Amazon Mechanical Turk easily stands as a prime example of a crowdwork platform, being widely recognised as one of the most popular ones (see Harris & Krueger, 2015). The short and repetitive tasks offered in the platform often include: image/video processing, translation, data verification, information gathering and processing, audio and visual editing, amongst many others.[5] Crowdwork arrangements may, however, vary greatly: skill requirements for outsourced jobs may range from high to low and, while tasks with low abstract content are prevalent – as, for example, most tasks in Amazon Mechanical Turk (AMT), Clickworker and Figure-Eight – complex and even creative activities are also present.

Crowd employment can then be identified as a phenomenon that essentially entails a new, and substantially cheaper, way of outsourcing tasks to a large pool of workers through IT-based platforms (Prassl & Risak, 2015) and, because of this, it has also been defined as "crowd-

[4]Eurofound (2015) has identified nine distinct new forms of employment: employee sharing, job sharing, interim management, casual work, ICT-based mobile work, voucher-based work, portfolio work, crowd employment and collaborative employment.

[5]As described in AMT website: https://www.mturk.com/ (last accessed: 19th September 2018).

sourcing".[6] By requiring platforms as intermediate actors, crowdwork manages to virtually nullify most transaction costs, thus allowing for a flexible and 'extremely scalable' workforce (De Stefano, 2015) to enter the labour market and maximise the use of under-utilised assets such as human capital.[7]

3 Literature review

Tackling the issues related to micro-task crowdsourcing has proven to be a multifaceted effort which, so far, has seen the intervention of different disciplines such as law (see, for example, Prassl & Risak, 2015, De Stefano, 2015), information technology and economics. Compared to other areas of study, the body of research on the economics of crowdsourcing has been, so far, remarkably thin: a glaring lacuna, considering the growing size of the platform economy. As suggested by Hara et al. (2017), this scarcity of literature is mostly attributable to the absence of publicly available data on crowdwork platforms and their workers, in addition to a variety of methodological issues concerning the type of data to analyse and the empirical approach to be used.[8] Nonetheless, as discussed by Horton et al. (2011), Mason & Suri (2011), Paolacci et al. (2010) and Berinsky et al. (2012), crowdwork platforms potentially present themselves as an ideal environment for empirical studies, in particular those based on experimental research. In this regard, Horton & Chilton (2010) offer one the first attempts to obtain empirical evidence on reservation wages in crowd employment from an experimental framework. Another overview of experimental methods in the field of online economy is provided by Prpic & Shukla (2016), who also produce a definition of crowd capital.[9] Other contributions focus instead on the demand side of these markets, concentrating on task pricing and worker productivity optimisation (e.g. Mason & Watts, 2009, Singer & Mittal, 2011).

Several additional descriptive studies have been provided. Harris & Krueger (2015) document the development of the platform economy and call for the recognition of an independent worker status, while other studies, receiving support from international institutions such as ILO (Berg, 2015 and Berg et al., 2018), CEPS (De Groen et al., 2017), and FEPS (Huws et al., 2017), have contributed to the literature with a thorough overview of the demographics of crowdsourcing. Hara et al. (2017) document wage and working time amongst AMT crowdworkers, discussing the necessity of including the time spent searching for tasks in working

[6] A term which was first used by Jeff Howe in his article 'The Rise of Crowdsourcing', Wired Magazine, 14.

[7] The ability to provide services online significantly enlarges the scope of crowdwork markets, thus enabling services to be provided globally, as opposed to the local focus of the services offered by work-on-demand platforms (such as Uber, Foodora, or Taskrabbit), which are characterised by the physical and tangible nature of the tasks being offered.

[8] Most of these issues will be explicitly reviewed in the Sections 4 and 5.

[9] Crowd capital is here defined as the 'potential outcome of IT-mediated crowd engagement', which 'like the other forms of capital in the literature, (social capital, financial capital, human capital etc.), [...] requires investment (for example in crowd capability dimensions), and potentially leads to literal or figurative dividends for the organisation'.

time indicators, while a recent paper from Difallah et al. (2018) summarises the main takeaways from a longitudinal survey on AMT whose data has been published in the *mturk tracker* website, curated by Ipeirotis (2010).[10]

Another important contribution on the analysis of the platform economy in US comes from Katz & Krueger (2016), where the two economists, in the context of studying the evolution of all alternative work arrangements from 2005 to 2015, estimate that, out of all occupations, 0.5% involve the direct selling of activities and services mediated by an online intermediary – a figure that can proxy the size of the so called gig-economy[11] (see Harris & Krueger, 2015).

Crowdwork can be considered as another form of service outsourcing, as such other contributions should be taken into consideration. There is an ample body of literature on service outsourcing and its labour market effects, mostly dedicated to analysing whether aggregate labour demand is affected by complementarities or substitution effects. Amiti et al. (2005) and Amiti & Wei (2009) offer evidence on the impact of service offshoring in the UK and US, predicting no significant effects on aggregate employment. In contrast, Görg & Hanley (2005) find negative employment effects for both material and service outsourcing. Other scholars – such as Degryse (2016) – suggest that crowd employment could be equated to a form of digital migration and, in this regard, Ottaviano et al. (2013) offer a valuable study of the labour market effects of migration and task offshoring. Proxying substitutability through routine intensity of tasks – a concept originally introduced by Autor & Dorn (2013) which spurred a novel body of literature focusing on the task-based approach to labour markets – Ottaviano et al. (2013) find that service outsourcing, while having no effect on employment, has changed the task composition of native workers. The relationship between unemployment and micro-task labour markets was further explored in Borchert et al. (2018), where labour demand shocks have been found to affect temporary participation in online labour markets.

Finally, the effects of digital labour markets on high skilled service flows are instead investigated in Horton et al. (2017), where the focus is on the UpWork freelancing platform.

4 Data

Finding appropriate sources of information for our analysis has proved to be a rather demanding task. The first difficulty has been the identification of crowdworkers in existing large-scale survey data on workers and working conditions. The European Working Conditions Survey (EWCS) and the American Working Conditions Survey (AWCS) both contain comparable

[10]The survey contains data on country, gender, age, income from AMT, time spent on AMT, marital status, household income and household size of Mechanical Turk workers, and can be accessed at the address: http://demographics.mturk-tracker.com/

[11]The term 'gig economy' is the umbrella term that has been most frequently used by the literature to analyse work-on-demand and crowdwork, emphasising the temporary nature of the work relationship undergoing between 'clients' and 'service providers' (see Degryse, 2016 and Prassl & Risak, 2015).

data on wages, job quality and skills but, in these cases, it is arduous to disentangle platform workers from any freelancer working from home. As micro-task crowdsourcers tend to perform specific, routine intensive activities, we expect that equating them to any freelancer working from home will likely pose a serious source of bias. While growing, the size of the platform economy is still minor, so platform workers will naturally be under-represented in general surveys.

Dedicated surveys on crowdworkers have been very useful in this regard.[12] However, while there is currently plenty of information on work on digital platforms – acquired either through online questionnaires (e.g. Berg, 2015, Berg et al., 2018, Huws et al., 2017, Ipeirotis, 2010) or web plug-ins (e.g. Hara et al., 2017) – the methodologies behind the collection of this data often differ significantly, with the resulting surveys varying not only in their sample sizes but also in terms of item comparability. With the aim to provide a reliable empirical analysis of the effects of crowdwork on labour market conditions in United States and in Europe, our initial efforts have focused on ascertaining which datasets would have allowed us to maximise the comparability of our results while retaining a satisfactory pool of observations and key variables.

After careful consideration, the information on online platform workers collected by the ILO Surveys on Crowdworkers (Berg, 2015, and Berg et al., 2018) has been used to build our treatment groups, which have then been paired with the AWCS and EWCS data, used as controls. By harmonizing the ILO survey on crowdworkers with these general working conditions surveys from the EU and the US, we believe we are making a step forward in putting these new forms of work into a comparative and global perspective.

4.1 Treatment and control groups

In order to build our treatment sample, we extracted information on European and US crowdworkers from the two rounds of the ILO survey on Crowdworkers (Berg, 2015 and Berg et al., 2018). Thanks to the similarities in terms of the relevant variables of analysis, our control groups were constructed using data from the American Working Conditions Survey and from the European Working Conditions Survey.

The dataset from Berg (2015) and Berg et al. (2018) consists of two consecutive surveys conducted on a number of online platforms[13] between 2015 and 2017 and covers crowdworkers from both the United States and Europe. The 2015 round of the survey provides cross-sectional data on earnings, demographics and working quality indicators for 1,167 crowdworkers from all over the world. The 2017 round similarly provides this information for a much larger number of workers (n = 2350), while also supplying a number of crucial variables that can be used to reconstruct the task composition of online platform work. Using information from both rounds

[12]See Berg, 2015, Berg et al., 2018, Huws et al. 2017, Difallah et al., 2018, Peer et al., 2017.

[13]In detail: Amazon Mechanical Turk , Crowdflower, Clickworker, Microworkers and Prolific Academic.

Table I

Mean-comparison t-tests across type of workers

	US			EU		
	Control	Crowdwork	diff.	Control	Crowdwork	diff.
Hourly nominal earnings (USD)	30,774	7,208	-23.566***	17,058	6,585	-10.473***
	(207,851)	(7,483)		(91,886)	(28,970)	
Hourly nominal earnings (USD)†	30,774	5,433	-25.341***	17,058	3,901	-13.157***
	(207,851)	(5,079)		(91,886)	(18,574)	
Weekly working hours	39,056	21,180	-17.876***	37,176	14,697	-22.479***
	(11,655)	(20,511)		(11,901)	(24,137)	
Weekly working hours†	39,056	28,266	-10.789***	37,176	19,903	-17.273***
	(11,655)	(26,422)		(11,901)	(32,601)	
Age	41,024	35,027	-5.997***	42,207	35,543	-6.663***
	(12,615)	(10,934)		(11,390)	(11,137)	
Female	0,463	0,476	0.013	0,478	0,426	-0.051***
	(0,499)	(0,500)		(0,500)	(0,495)	
Married or living with a partner	0,516	0,434	-0.082***	0,697	0,493	-0.204***
	(0,500)	(0,496)		(0,459)	(0,500)	
No. of people in household	3,063	2,665	-0.398***	2,882	2,819	-0.063
	(1,672)	(1,429)		(1,268)	(1,260)	
Main earner in household	0,603	0,789	0.186***	0,595	0,815	0.220***
	(0,489)	(0,408)		(0,491)	(0,389)	
Educ.: no high school diploma	0,064	0,009	-0.055***	0,161	0,052	-0.109***
	(0,244)	(0,092)		(0,367)	(0,222)	
Educ.: high school diploma	0,502	0,374	-0.128***	0,448	0,309	-0.139***
	(0,500)	(0,484)		(0,497)	(0,462)	
Educ.: technical/associate	0,097	0,157	0.061***	0,147	0,102	-0.045***
	(0,296)	(0,364)		(0,354)	(0,303)	
Educ.: bachelor's degree	0,208	0,348	0.141***	0,127	0,322	0.195***
	(0,406)	(0,477)		(0,333)	(0,468)	
Educ.: master's degree	0,094	0,097	0.003	0,108	0,165	0.056***
	(0,292)	(0,296)		(0,311)	(0,371)	
Educ.: higher	0,036	0,015	-0.021***	0,009	0,051	0.042***
	(0,185)	(0,122)		(0,092)	(0,219)	
Health: Very Good	0,132	0,244	0.112***	0,261	0,257	-0.003
	(0,338)	(0,429)		(0,439)	(0,437)	
Health: Good	0,407	0,534	0.128***	0,532	0,523	-0.008
	(0,491)	(0,499)		(0,499)	(0,500)	
Health: Fair	0,345	0,180	-0.165***	0,185	0,178	-0.007
	(0,475)	(0,384)		(0,389)	(0,383)	
Health: Poor	0,099	0,037	-0.062***	0,020	0,033	0.013**
	(0,299)	(0,190)		(0,140)	(0,178)	
Health: Very Poor	0,018	0,005	-0.013	0,002	0,008	0.006*
	(0,132)	(0,071)		(0,048)	(0,090)	
Caregiving (15h/week)	0,149	0,207	0.058***	0,170	0,112	-0.058***
	(0,356)	(0,405)		(0,375)	(0,315)	
Caregiving (40h/week)	0,082	0,207	0.124***	0,020	0,112	0.092***
	(0,275)	(0,405)		(0,139)	(0,315)	

*N*otes: Standard errors in parentheses. Summary statistics and t-test are calculated from our weighted US and EU reference samples, formed by our control (AWCS and EWCS data) and treatment (ILO data) groups. The sample is restricted to employed and self-employed individuals in working age. †: adjusted for time spent in unpaid activities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of the survey, we extracted a treatment group of 1,393 US crowdworkers and 1,000 European[14] crowdworkers, where dimensions such as earnings, working hours, work quality and proxies for labour utilisation were all recorded along with demographical characteristics including gender, age, education, health condition, marital status and household size. Pivotally, this survey also includes items which allowed us to identify whether crowdwork constituted the respondent's main source of income.[15] Thanks to the design of the ILO survey, its contents have been easily harmonised with data from the 2015 rounds of the European Working Conditions Survey (EWCS) and the American Working Conditions Survey (AWCS).

As outlined earlier, we used information from the EWCS and AWCS to construct our control groups. The AWCS surveys a sample of 3,109 individuals from the US, sharing several dimensions in common with the ILO data. Raked post-stratification weights conforming to the Current Population Survey (CPS) target population are already provided with the survey, and we restricted our sample to employed working age population (n = 1,946).[16] Similarly, a control group of 32,429 employed working-age individuals from the EU28 area was extracted from the EWCS, weighted, and paired as a control group to the data on European crowdworkers. All data was finally aggregated on a single dataset, providing a shared set of common variables and adjusting – when needed – all earnings for inflation and purchasing power parity.

Weighted mean comparison t-tests for a number of key dimensions across the treatment and control groups are shown in Table I (United States: n = 3,339 and Europe: n = 33,281). From these analysis, some apparent differences between crowdworkers and active working population in Unites States and Europe emerge. Mean comparison t-tests between control and treatment groups, restricted to the employed working age population, reveal that demographical differences in salaries, age, education and marital status across forms of work. Summary statistics for all the variables in the samples are reported in Tables A.1, A.2 and A.3 in the Appendix.

While earnings, as expected, appear to be lower for online platform workers, their demographical composition also shows significant differences with both control groups, with the typical crowdworker being more likely to be younger, single and more educated overall. These

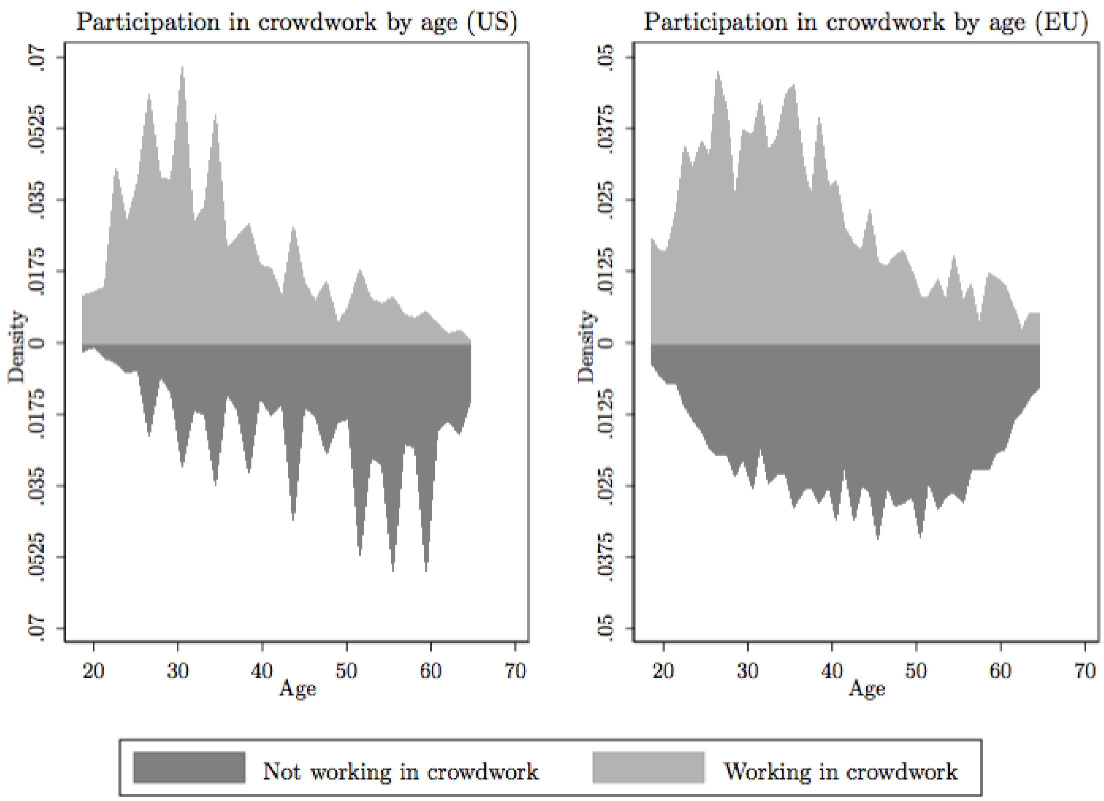
[14]The European data include 852 observations from the European Member States, and 148 observations from EWCS guest countries (Norway, Switzerland, Albania, the former Yugoslav Republic of Macedonia, Montenegro, Serbia and Turkey).

[15]Further details on the sampling methodology followed in the ILO surveys are available in Berg et al. (2018).

[16]For most our estimates,we decided not to narrow our control group based on the profession of these workers. While an analysis of earnings and outcomes across comparable tasks (for example, in terms of routine intensity, as suggested in Autor & Dorn, 2013 and Ottaviano et al., 2013) will not be disregarded, our causal estimates focus on comparing workers while controlling for their ability, disregarding any bias-inducing factor – such in the case of occupations – that could affect our estimates. For similar reasons, a small number of individuals, which have been reporting to do freelancing work from home as their main occupation, has been omitted from the estimations. This being considered, we restrict our control group to workers in occupations with comparable routine and abstract task-intensity in Table III, so to provide a more complete picture of the crowdworking phenomenon: the results included in said table, for all the aforementioned resons, are included for descriptive purposes and should be intended void of any causal interpretation.

Figure I

Participation in crowdsourcing versus traditional occupations by age



Notes: The figure shows the probability density functions of age by type of work across the US and European samples. Control sample is restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

differences are likely explained by the younger relative age of platform workers, being years of schooling and marital status obviously correlated with age. Notably, Figure I pictures participation in crowdsourcing conditional on age for both forms of work, showing how platform workers tend to occupy those younger age cohorts where individuals are more likely to be excluded from traditional forms of employment. This age differential affects the likeliness of not being married or having children, explaining the higher propensity of being the main earner in the household and the smaller household size amongst crowdworkers. The condition of caring for children or disabled relatives, as will be discussed later, also appears more common to platform workers.

Looking at each region, differences in earnings also appear to be much more pronounced in the United States than in Europe, where the differential with traditional occupations increases from 10.47 USD in EU to 23.56 USD in US. Similarly, European crowdworkers, on average, appear to work fairly less than their US counterparts. Other disparities emerge in terms of gender (where a male majority is statistically significant in EU), health status and education: controlling for these differences in a regression setting may help explain the gap between earnings and working hours differentials.

4.2 Selected labour market indicators and controls

In order to compare crowdworkers and traditional salaried workers, we selected a number of key labour market indicators. With our data being extracted from different sources, a number of variables have been subjected to recoding for the sake of harmonisation. Keeping the changes in variability minimal, the final coding sometimes differs across our US and European samples. In many cases, the changes have been negligible, but will nonetheless be reported when needed.

Hourly and weekly nominal earnings have been selected as our variables of most interest, being, without doubt, a fundamental dimension of working conditions. In all groups, we are able to control whether crowdsourcing is the main source of income for the respondent: we expect weekly earnings to be altered by this condition, while hourly earnings should remain unaffected.

Another crucial dimension of interest is weekly working hours. Thanks to the ILO survey, we were able to estimate how much time crowdworkers spend on the platform between paid and unpaid tasks. This also allowed us to investigate the differential in our earnings estimates between crowdworkers and traditional workers when accounting for unpaid working hours. In all instances, availability of weekly working hours proved essential for computing hourly earnings, as all surveys do not report the hourly rate of pay, but rather weekly, monthly or yearly absolute earnings.[17]

[17] While the ILO survey reports weekly earnings, AWCS reports yearly earnings, and EWCS lets the re-

We were also able to conduct our analysis on a different set of dependent variables other than earnings, allowing us to paint a more nuanced picture of the crowdworking phenomenon. Along with indicators of skill use and job satisfaction, the EWCS, AWCS and ILO surveys contain items for identifying if the surveyed individuals would like to work more than what they currently do or whether they are currently looking for another occupation,[18] serving as proxies for labour use in the platform. This enabled us to identify involuntary crowdwork as a dimension that goes beyond standard employment statistics.

In our analysis we consider a number of controls. We first control for age, gender and education and, from there, we add other predictors. In the literature, returns to education on earnings have been widely documented,[19] while gender pay gaps have also been studied thoroughly.[20] We can also expect marital status and the number of people living in the household to affect earnings and working conditions in general. Finally, we control for state specific effects and for whether the respondent is the main earner of his household. Another fundamental variable in our analysis is caregiving, indicating whether the respondent has been involved in full-time caring (either as a 15 or 40 hour commitment) for children or disabled/elderly relatives. The implications of this variable for our 2SLS model will be discussed later.

Some of these variables were subject to harmonisation between the surveys. This is the case for education, where achievements were grouped to the closest common title, while other similar adjustments were made to marital status.

5 Model specification

Inspired by the Treatment Effect literature (Angrist & Pischke, 2011), we estimate the effect of working in online platforms on labour market outcomes in a quasi-experimental framework, where we compare earnings and working conditions of platform and 'traditional' workers across control and treatment groups. From this point of view, our approach has been certainly inspired by LaLonde (1986) and is not dissimilar from previous studies in part-time employment which instrument hours of work through household size and fertility (Ermisch & Wright, 1993, Hotchkiss, 1991, and Blank, 1998). In our case, the treatment group is composed by crowdworkers interviewed in the ILO survey, while the control group includes workers from the AWCS and EWCS surveys.

As platform workers are usually paid by task, and not by hour, hourly earnings are determined first by the demand for those specific skills and characteristics over which clients

spondent to choose the measure he/she is most comfortable with. Hourly rate was then computed by dividing weekly nominal earnings by weekly working hours.

[18]This last item was however only recorded in the AWCS and ILO.

[19]See, for example, Angrist & Krueger (1991) and Card & Krueger (1992).

[20]See Arulampalam et al. (2007), Blau & Kahn (2003), Altonji & Blank (1999) and Azmat & Petrongolo (2014).

can discriminate upon (factors which we can mostly control for with our set of observable covariates) and, on the supply side, by the ability of each individual worker to complete these tasks efficiently (which is mostly unobserved).

A simple comparison of the average outcomes between control and treatment groups is then not sufficient for answering our research question. Descriptive analyses or ordinarily least squares may produce biased results, potentially overestimating the effect of the platform economy on wages and working conditions. Indeed, it could be argued that individuals in crowdsourcing arrangements possess unobserved characteristics which make them qualitatively different from more traditional salaried workers, thus leading to a problem of self-selection into online labour markets. To account for this potential selection bias and offer a more appropriate comparison between the different outcomes, we adopt an instrumental variable approach. We choose the following instrumental variable two stages least squares specification:

(1) $Y_i = \alpha_2 + \hat{P}_i\lambda + X_i^{'}\gamma_2 + F_i\varphi_2 + e_{2i}$

(2) $P_i = \alpha_1 + Z_i\phi + X_i^{'}\gamma_1 + F_i\varphi_1 + e_{1i}$

where i refers to each individual, Y is the set of our outcome variables (hourly earnings, working hours - including hourly earnings and working hours when controlling for unpaid tasks, indicators for skill match and for labour force use[21]), X is a vector of *k–2* controls[22] and F is a dummy which indicates whether the respondent is female.[23]

In the first stage regression (2), the treatment P (a dummy which equals 1 when crowdwork is the individual's main paid activity) is regressed on our chosen instrument Z plus the same controls we use in the second stage regression (1). Using the predicted value of P (the estimated linear probability of working in the platform) in (1), we obtain the impact of crowdwork on our desired outcome through the coefficient λ. In case the treatment P is really assigned exogenously conditionally on Z, then the coefficient on λ will not suffer from selection bias (Angrist, 2006).

5.1 Instrumental variable identification

Drawing from the demographical evidence from the studies mentioned above (see Section 3) a number of instruments have been considered for our analysis. Not all candidates for instrumentation, however, could be used, due to differences between surveys. We nonetheless considered and tested different types of potential instruments.

[21]With dummies indicating whether the respondents believes to her skills to be adequate (on inadequate) for her current occupation, and dummies indicating whether said person is currently looking for another occupation and if it would like to work more.

[22]In our final model the controls are: age, age squared, number of people in household, main earner, main source of income, education, marital status, health status and state controls.

[23]The need for this specification, with the gender dummy appearing outside the X vector, will be explained in subsection 4.1, as the coefficient φ_2 will be used to adjust split sample estimates to the whole population.

Initially, we looked at exogenous variables such as age or having a debilitating health condition, which are both significantly correlated with crowdwork (age: -0.1643***; poor health: 0.0193***).[24] However, we discarded those variables as we believe their adoption would lead to a violation of the exclusion restriction, biasing our estimates downwardly: younger workers typically earn less than older individuals, while workers in poor health may take longer times to complete their work activities, leading to a reduction in hourly earnings.

We then considered an alternative instrument: time spent in caregiving at home. This variable is potentially a good instrument since it is exogenous and potentially highly correlated with crowdwork. The underlying reasoning is that people may be more involved in crowdwork if they are compelled to stay at home to look after children or elderly relatives: this type of work, indeed, can be a reasonable source of income for them, given their circumstances. The choice of this instrument, however, imposes a few restrictions on the analysis, which are outlined below.

Both the treatment dataset by ILO and the AWCS and EWCS control datasets capture time spent in caregiving at home, although in different ways. While caregiving appears as a dummy in the ILO dataset (where the respondent is asked whether this activity constituted a full-time commitment before entering crowdwork), it is treated as a continuous variable in the AWCS and EWCS (where the respondent is asked how many hours per week/per day has been engaged in these activities). We harmonised the two variables by identifying both a 40 and 15 hours-per-week effort as a full-time caring activity, following the findings from the Gallup-Healthways Well-Being Survey (Cynkar & Mendes, 2011). Indeed, according to the Gallup Survey, caregivers working at least 15 hours per week have declared that this activity significantly affected their worklife.

As shown earlier in Table I, caregiving appears to be highly correlated with crowdwork in our US sample (estimated correlations: caregiving 15h=0.0521***; caregiving 40h=0.1698***). This relationship is similar in Europe where caregiving also reveals itself as a significant predictor of platform work, but only at higher thresholds (caregiving 40h=0.0933***). These differences hint at the possibility of welfare-biased differential effects of caregiving, as caregivers may have access to more labour law safeguards in Europe than in US, reducing the need for auxiliary earnings from crowdwork. Evidence from Germany (Bick, 2016), indicates that a large fraction of working mothers in part-time would work full-time if they had greater access to subsidized child care. It is then not unreasonable to expect labour market policies to similarly influence participation in crowdwork.

At the same time, caregiving also appears to be consistently correlated with the gender of the respondent: females are over-represented among crowdworkers who are caregivers, with the correlation between being in caregiving (40h) and crowdwork raising from a full sample

[24] Sidak-adjusted pairwise correlations across all treatment and control groups. Survey question: : 'Do you have any illness or health problem which has lasted, or is expected to last, for 6/12 months or more?'

(US+EU) correlation coefficient of 0.1920*** to 0.2502*** for the female population. This finding supports previous evidence that men's caregiving is a variable phenomenon mainly layered by societal roles, putting its exogeneity into question,[25] and uncovering a serious source of bias in the instrumental variables estimates, where the exclusion restriction is violated if gender is found to be correlated with the dependent variable.

Nonetheless, we trust that these issues can be mitigated by assuming that platform work has no intrinsic effect on gender-dependant outcomes, arguing that, after controlling for individual's characteristics and ability, crowdwork arrangements do not tend to reinforce discriminations based on the sex of the worker, due to the relative anonymity that service providers enjoy on the platform (as found in Adams & Berg, 2017): clients are, indeed, usually unable to ascertain the gender of online service providers. Should this assumption hold, all differences between genders will then be linked to common structural trends across control and treatment groups which can be identified linearly, and the interaction between gender and the selected instrument can be added to the instrument pool in the first stage of the estimation process. As a final check, the 2SLS estimates that can be drawn from the pool of female workers can be also said to hold for the rest of the sample, after adjusting for structural linear effects. This adjustment can be done following this simple formula:

(3) $exp(\hat{\phi}) - 1 = exp(\lambda_f) * exp(\varphi_2) - 1$

where λ_f will be the effect of platform work on the female population as predicted by our instrument, φ_2 the linear common gender effect predicted in the full sample model, and $exp(\hat{\phi})-1$ will indicate the baseline effect of platform work on the selected dependent variable. As our 2SLS estimation will be based on the full US-EU sample,[26] region-specific differential gender effects can also be isolated by the coefficient of the interaction between gender and the regional dummy, and then applied to the final estimates using a similar procedure, if needed.

In first part of our empirical analysis we will show that the coefficient of the interaction term between crowdwork and gender is not statistically different from zero when controlling for other observables, allowing us to generalise the common structural term predicted with φ_2.

Split sample instrumental variable models – or TS2SLS – have already been explored in the past by Angrist & Krueger (1995) and Inoue & Solon (2010), to address those events when the instrument and the outcome are not measured in the same sample. In our case, however, the two subsamples – male and female – are not homogeneous. It is vital, then, to assume the differences between the two subsamples to be linear and, most importantly, to assume the structural relations within them to remain the same.[27]

[25] See, for example, Marks et al. (2002) and Gerstel & Gallagher (2001).

[26] As our selected instrument affects partecipation in crowdwork, but is not intended to randomise regional assignment, differential effects across countries become a second-order priority. Hence controls for specific regional difference are sufficient for the estimation of these effects, all with the 2SLS estimation benefitting from the increased sample size of both treatment and control groups.

[27] As argued by Zhao Q. & D. (2017) in a similar context.

As long as these assumptions are reasonable, we only need to worry about the causal channel between caregiving and our outcome variables on the female population. Evidence from the literature on female caregiving finds that working hours – and, by extension – total earnings are affected by this condition (see Wakabayashi & Donato, 2005, and Earle & Heymann, 2012) but, to the best of our knowledge, there is no mention of hourly earnings.[28] We believe that, with the inclusion of our observable controls, we are able to filter out the endogenous effects of caregiving – due to its relationships with household size and marital status especially. In any case, we do not believe caregiving to be able to influence ability in any way: it is reasonable to assume that caregiving affects the opportunity to work more, not the relative skills of an individual – and how much the labour market rewards these skills.

A similar reasoning prevents the use of this instrument for the estimation of the effect of crowdwork on some of the other working dimensions, such as working hours. As the crowdwork 'complier' group[29] is made out of individuals spending a significant amount of time in caregiving, we can expect 2SLS estimates of working hours and weekly earnings to inevitably suffer from a downward bias, as will be discussed in the next section. In such a case, we will then mostly rely on OLS to obtain more reasonable – yet still biased – estimates of these dimensions.

6 Results

Columns (1) to (3) from Table II present the results of our OLS regressions using the US sample of crowdworkers from the ILO survey and the controls from the AWCS. The dependent variable is hourly earnings and the table shows different regressions with an increasing number of controls, with an initial sample including a total of 3,128 workers.[30] Our key variable of interest is the dummy for working in crowdwork: the dummy identifies all interviewed US crowdworkers. Additional key controls are: gender, age (and its squared term), number of people in the household, marital status (whether the respondent is married or lives with a partner), and two dummies indicating whether the respondant is the main contributor to the household's income and whether crowdwork is her main source of income. We also take into account a set of controls for the different US and EU28 states of residence (with a total of 79 states) and for the level of education (distinguishing among six different education levels). Standard errors are also robust to clustering on the level of the federal or member state.

As shown in the table, the effect of crowdwork on earnings is always negative and significant, confirming the results from the descriptive analyses of previous studies where earnings

[28] Our findings – see Table VI below – similarly suggest that hourly earnings are not significantly affected by caregiving after controlling for other observables.

[29] We here define as 'compliers' all individuals in caregiving who participate in crowdwork arrangements and all individuals not in caregiving who stay in traditional forms of work.

[30] Observations with missing values are excluded from the estimation.

Table II

OLS estimates of the effect of online platform work on earnings in US & EU

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	US			EU			US+EU
VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Working in crowdwork	-1.032***	-1.010***	-1.012***	-1.198***	-1.116***	-1.067***	-1.007***
	(0.036)	(0.043)	(0.055)	(0.072)	(0.043)	(0.049)	(0.043)
Female	-0.245***	-0.179***	-0.181***	-0.127***	-0.074***	-0.071***	-0.195***
	(0.042)	(0.040)	(0.061)	(0.010)	(0.009)	(0.010)	(0.061)
$Crowdwork \times Female$			0.004			-0.103*	-0.043
			(0.069)			(0.051)	(0.054)
$EU \times Female$							0.129**
							(0.059)
Age	0.052***	0.030**	0.030**	0.023***	0.011***	0.011***	0.014***
	(0.010)	(0.014)	(0.014)	(0.004)	(0.004)	(0.004)	(0.003)
Age squared	-0.001***	-0.000*	-0.000*	-0.000***	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household		-0.032**	-0.032**		0.002	0.002	-0.004
		(0.013)	(0.013)		(0.007)	(0.007)	(0.006)
Married or living with a partner		0.252***	0.252***		0.099***	0.100***	0.115***
		(0.036)	(0.038)		(0.010)	(0.010)	(0.011)
Main earner in household		0.348***	0.348***		0.137***	0.137***	0.155***
		(0.050)	(0.050)		(0.013)	(0.013)	(0.014)
Main source of income		0.147***	0.146***		0.127*	0.133*	0.156***
		(0.042)	(0.042)		(0.066)	(0.068)	(0.043)
Observations	3,218	3,217	3,217	27,758	27,676	27,676	30,893
Adjusted R-squared	0.361	0.389	0.389	0.367	0.377	0.377	0.378
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*N*otes: State clustered standard errors in parentheses. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

*p<.05; **p<.01; ***p<.001

from micro-tasks are well below national averages (as found in Berg, 2015 and Hara et al., 2017). The effect of the female dummy is also always negative and significant, confirming a gender pay gap in the labour market. In the third column we present our full specification: all the relevant regressors, controls and interactions are included. The regression shows that crowdwork has a negative and significant effect (indicating a 63.6% reduction in earnings),[31] while both dummies for being the main earner in the family and for the surveyed occupation being the respondent's main job are positive and significant. Controlling for all other observables, the interaction term between gender and crowdwork is not statistically different from zero, while, most notably, the coefficient on gender alone retains its magnitude and significance, showing a negative linear effect on earnings (-16.5%) and no notable variation between specification (2) and (3), where the interaction is introduced. This finding provides support to our hypothesis that crowdwork platforms do not generate any intrinsic gender discriminatory effect other than reaffirming common structural gaps.

Columns (4) to (6) present the estimates for the effect of crowdwork on hourly earnings on the European sample. Here the initial number of complete observations is 27,578, referring to the total number of EU28 workers included in the ILO and EWCS sample. The sign and magnititude of the crowdwork coefficient is always negative and significant and, after controlling for all covariates in column (6), the effect is now much closer to our estimate for the US sample, equalling to a 65.5% reduction in hourly earnings. The effect of the gender dummy is also negative and significant, this time indicating a smaller reduction in earnings (-6.8%). A negative gender effect can also be found across european crowdworkers, albeit with a 5% statistical significance.

A significative improvement in our estimates is offered in column (7), where a full sample (US+EU) specification is presented. The difference in general region-specific gender effects is isolated by the coefficient of the $EU \times Female$ interaction term, whose positive effect counteracts the negative sign of the $Female$ term, now referring to the baseline US sample.[32] Most importantly, the $Crowdwork \times Female$ interaction turns not significant again, as its effect seems to be recaptured by the regional gender effects, confirming that crowdwork platforms do not generate any intrinsic gender discrimination on earnings.[33] Finally, the effect of crowdwork on PPP-adjusted net hourly earnings is estimated up to a 63.5% reduction. Also, in all instances, the negative effect of working in digital labour market is slightly reduced when crowdwork is the main source of income.

Table III presents the results of our OLS regressions taking into account the degree of routine intensity and abstractness of the tasks performed, with reference to both the treatment

[31]Given the magnitude of the effect of crowdwork on earnings, it should be noted that log normal interpretations might be incorrect since the parameters are far above the 0.1 threshold and must then be exponentiated.

[32]The regional dummy for EU (not significant, as its effects are fully captured by the state controls) is omitted from the table.

[33]This finding confirms the results in Adams & Berg (2017).

Table III

OLS estimates of the effect of online platform work on earnings in US & EU

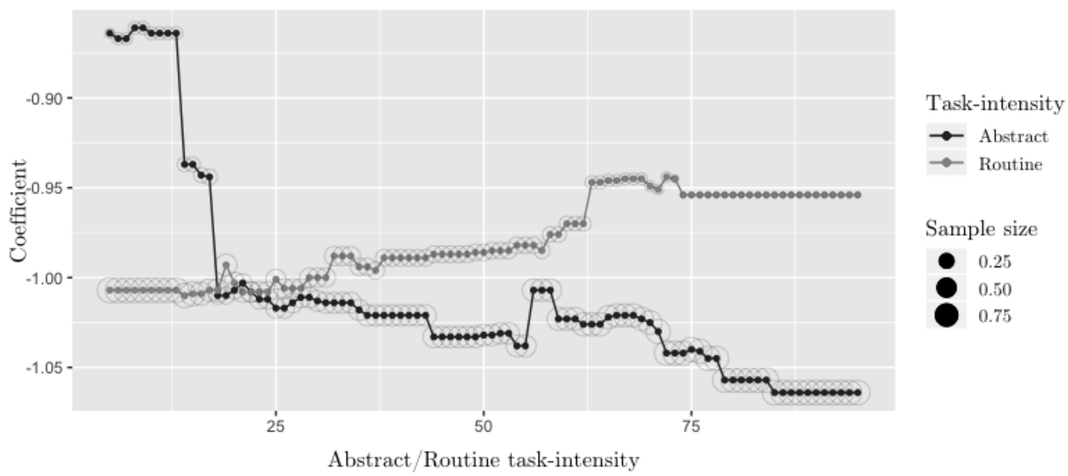
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	US			EU			US+EU		
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
VARIABLES	routine tasks	abstract tasks	a+r tasks	routine tasks	abstract tasks	a+r tasks	routine tasks	abstract tasks	a+r tasks
Working in crowdwork	-1.377***	-1.276***	-1.183***	-1.093***	-1.025***	-1.045***	-1.117***	-1.032***	-1.043***
	(0.105)	(0.163)	(0.150)	(0.050)	(0.052)	(0.048)	(0.046)	(0.054)	(0.057)
Female	-0.305**	-0.637**	-0.331	-0.074***	-0.082***	-0.087***	-0.157**	-0.197***	-0.135**
	(0.115)	(0.269)	(0.345)	(0.015)	(0.016)	(0.014)	(0.062)	(0.073)	(0.056)
$Crowdwork \times Female$	0.124	0.454	0.145	-0.098*	-0.088	-0.082*	-0.068	-0.036	-0.076*
	(0.117)	(0.279)	(0.350)	(0.049)	(0.054)	(0.046)	(0.048)	(0.065)	(0.045)
$EU \times Female$							0.082	0.112*	0.047
							(0.060)	(0.064)	(0.053)
Age	0.015	0.016	0.011	0.011**	0.009**	0.012***	0.011**	0.010***	0.012***
	(0.011)	(0.011)	(0.011)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Age squared	-0.000*	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	-0.063***	-0.057***	-0.049***	0.007	-0.001	0.003	-0.001	-0.005	-0.004
	(0.012)	(0.012)	(0.009)	(0.010)	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)
Married or living with a partner	0.093**	0.092	0.070	0.080***	0.107***	0.103***	0.086***	0.109***	0.108***
	(0.044)	(0.061)	(0.051)	(0.017)	(0.015)	(0.017)	(0.016)	(0.014)	(0.016)
Main earner in household	0.036	0.009	-0.028	0.127***	0.113***	0.117***	0.125***	0.110***	0.111***
	(0.061)	(0.079)	(0.076)	(0.019)	(0.019)	(0.020)	(0.017)	(0.018)	(0.019)
Main source of income	0.065	0.053	0.041	0.120*	0.117*	0.102	0.120***	0.113***	0.097**
	(0.046)	(0.044)	(0.044)	(0.069)	(0.063)	(0.067)	(0.039)	(0.037)	(0.038)
Observations	1,658	1,484	1,415	15,006	20,341	11,107	16,664	21,825	12,522
Adjusted R-squared	0.377	0.178	0.132	0.422	0.373	0.426	0.434	0.376	0.427
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*N*otes: State clustered standard errors in parentheses. Control sample restricted to occupations whose routine and abstract task content is comparable to the 5th and 95th percentile of crowdwork occupations by their routine and abstract task content.

*p<.05; **p<.01; ***p<.001

Figure II

Estimated OLS coefficients from varying task-intensity splits (US+EU)



*N*otes: OLS coefficients for the 'Working in crowdwork' dummy after restricting the control sample (US+EU) by increasing routine task-intensity and decreasing abstract task-intensity. Sample sizes from each estimation are reported as a percentage of the full control sample. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

and the control samples. It is worth pointing out that, while occupation could be considered a 'bad control' and, by inducing bias in the estimates (as discussed in Angrist et al., 2011), certainly cannot be used in the 2SLS estimation stage unless a different instrument is chosen, it is however true that an analysis which focuses only on the individuals who perform similar occupations can enhance our ability to explore the actual wage premium of traditional workers with respect to platform workers. To this aim, we split our treatment and control samples for both United States and Europe according to the degree of routine task intensity, abstractness, and a combination of the two indicators. We assign routine and abstract task intensity score to individuals in the control group using the indicators from Autor & Dorn (2013), where each occupation is given a score based on O*NET task measures. We then compute, using a similar methodology, the same scores from the ILO sample, disaggregating each observation into the five most common tasks, and assigning each task a score based on the routine and non-routine cognitive O*NET measures, as reported in Acemoglu & Autor (2011), and then averaging the scores after reweighting each task by its relative frequency. Finally, we restrict the control groups to those observations whose routine and non-routine task intensity falls within the range of scores obtained in the treatment sample. Our results show that the coefficients do not diverge excessively from our initial results, displaying a negative – and slightly stronger – effect on earnings for platform workers, in all the regressions considered (US, EU, US+EU), indicating that the routine and abstract content of micro-task jobs might not capture the reduction in earnings from traditional professions in any way.

As we cannot ascertain the full comparability of the routine and abstract task-intensity scores between controls and treatment, we provide a further robustness check in Figure II, where we restrict the control sample by decreasing abstract and increasing routine task-intensity scores, and estimate the 'Working in crowdwork' coefficient (y-axis) using the same least squares specifications from Table III (columns 7 and 8). The x-axis indicates the minimum abstract task-intensity and the maximum routine task-intensity score used for the sample split. The figure suggests that, the more the abstract intensity of control occupations is lowered, the more the effect of crowdwork on earnings is reduced. A similar decrease is made evident when we set a higher routine content for control occupations. Nevertheless, our previous interpretation is not invalidated: these contractions in the effect of crowdwork on earnings are very minimal, as we consider that the coefficient fully maintains its sign and significancy, and that the estimated effect ranges from 57.8 to 65.5% only when performing splits on abstract intensity, and from 63.5 to 61.5% when increasing the minumum routine content. The great majority of the earnings differential between platform and traditional work remains then unexplained by the abstract and routine task-intensity of crowdsourcing.

OLS estimates for working hours indicators are shown in Table IV. When investigating time spent on the platform, the estimates appear particularly sensitive to the way working hours are computed. In particular, in columns (1), (4) and (7) we find that, on average, when only paid activities are considered, working in crowdwork reduces the number of weekly working hours by 16 hours, also indicating a 7 hours differential between US and the EU platform workers. When crowdwork is also the main source of income, these figures are further reduced, and all crowdworkers appear to be working circa 7 hours less than traditional workers, all else being equal.

If, however, the indicator is adjusted for the time spent in unpaid tasks – as in columns (2), (5) and (8) – the magnitude of the coefficient changes again, showing a 9 hours increase in working hours across the US and the EU. For individuals whose main occupation is crowdwork, the differential with the control is reduced even more, to the point that, on average, US crowdworkers appear to be working even more than comparable workers. Significant disparities with the European sample remain, indicating that, for EU workers, there is no discernible difference in working hours between platform and traditional workers when crowdwork consists in the main source of income of an individual.

Moving to factor utilisation, we are presented with some intriguing figures. In (3), (6) and (9), our OLS model suggest that most platform workers would like to work more than they currently do in either crowdwork or in other forms of employment, suggesting a degree of factor under-utilisation. While not shown in the table, we also found out that these figures are halved when respondents are asked whether they would prefer to work in non-crowdwork occu-

Table IV

OLS estimates of the effect of online platform work on job quality in US

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	US			EU			US+EU		
	Work Hours	Work Hours†	More work	Work Hours	Work Hours†	More work	Work Hours	Work Hours†	More work
VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Working in crowdwork	-13.792***	-3.009*	0.537***	-21.180***	-15.064***	0.299***	-16.268***	-7.208***	0.452***
	(1.207)	(1.742)	(0.037)	(1.992)	(2.815)	(0.051)	(1.546)	(2.308)	(0.042)
Female	-3.985***	-3.842***	-0.020	-5.516***	-5.521***	-0.001	-4.661***	-4.757***	0.011
	(0.719)	(0.747)	(0.039)	(0.564)	(0.566)	(0.014)	(0.806)	(0.893)	(0.045)
$Crowdwork \times Female$	3.340**	3.170**	0.093**	5.989***	7.578***	0.013	4.686***	5.384***	0.050
	(1.330)	(1.557)	(0.042)	(2.067)	(2.307)	(0.040)	(1.361)	(1.562)	(0.040)
$EU \times Female$							-0.771	-0.662	-0.015
							(0.885)	(0.978)	(0.042)
Age	0.934***	1.150***	-0.011**	0.614***	0.632***	0.000	0.664***	0.714***	-0.001
	(0.267)	(0.332)	(0.005)	(0.111)	(0.111)	(0.003)	(0.107)	(0.113)	(0.003)
Age squared	-0.011***	-0.013***	0.000*	-0.007***	-0.008***	0.000	-0.008***	-0.008***	0.000
	(0.003)	(0.004)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
No. of people in household	-0.345**	-0.408*	0.024**	-0.267*	-0.267*	0.011**	-0.301**	-0.327**	0.013**
	(0.164)	(0.207)	(0.009)	(0.146)	(0.146)	(0.005)	(0.125)	(0.127)	(0.005)
Married or living with a partner	0.775	-0.115	-0.137***	1.565***	1.558***	-0.017	1.487***	1.391***	-0.026
	(0.881)	(1.012)	(0.025)	(0.226)	(0.225)	(0.016)	(0.235)	(0.264)	(0.016)
Main earner in household	5.000***	4.985***	-0.126***	3.701***	3.694***	0.028**	3.828***	3.815***	0.017
	(0.950)	(1.038)	(0.023)	(0.682)	(0.665)	(0.011)	(0.621)	(0.612)	(0.012)
Main source of income	10.423***	15.656***	0.025	5.376***	7.252***	0.048*	9.234***	13.581***	0.101***
	(1.051)	(1.654)	(0.020)	(1.872)	(2.104)	(0.026)	(0.996)	(1.491)	(0.022)
Observations	3,217	3,197	3,216	27,676	27,649	27,129	30,893	30,846	30,345
Adjusted R-squared	0.303	0.168	0.371	0.218	0.175	0.075	0.242	0.173	0.100
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*N*otes: State clustered standard errors in parentheses. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home. †: adjusted for time spent in unpaid activities

*p<.05; **p<.01; ***p<.001

pations (even when crowdwork is the main source of income). These findings partially confute the perception of platform work as a temporary form of occupation for the underemployed, configuring it as a rather stable condition with unremarkable mobility towards other forms of employment – for many, at least. However, even if not actively looking for a job, this status presents some uncanny similarities to the ones of involuntary part-timers or inactive persons with labour force attachment, where individuals would like to work more but are unable or too discouraged to look for other forms of employment, and, for that, crowdwork could be found to be related to slack in the labour market. The idiosyncratic relationship between working nearly as many hours as traditional workers while still desiring to work more, alongside with the largely low earnings, may corroborate the findings from Horton & Chilton (2010), if we inductively assume that platform workers are usually unable to meet their earnings targets. It should be noted, however, that while these remarks could reflect the condition of many online workers, crowdwork could still represent a convenient source of auxiliary income for many others.

Our IV estimates for hourly earnings are displayed in Table V, together with the OLS estimates from both the full sample and a female-only sample. [34] In the 2SLS regressions the estimates for the full sample and the female sample show both weak predictive power when instrumenting caregiving with a 15 hours weekly threshold (columns 3 and 4): while the first stage displays a high R-squared, the crowdwork coefficient is never statistically different from zero and the instrument always fails to pass the F score test for excluded instruments.

The 40 hours threshold generates instead much more reasonable coefficients for working in crowdwork (columns 5 and 6), predicting a general and statistically significant reduction (-63.46%; coeff.: -1.007) in hourly earnings. While very close to our OLS estimates, it could be argued that these estimates still suffer from bias due to the interaction between caregiving and gender (even if this interaction is included in the instrument pool). Restricting our study to the female population, working on crowdwork platforms reduces earnings by 60.07% (column 6, coeff: -0.918) over working age women, all else being equal. This is well below the -1.05 (-65.18%) log points that the least squares model would predict over the female sample (column 2). In both cases, anyway, all instruments pass the F score tests for excluded instruments, with the first-stage partial R^2 also yielding remarkable results (see Bound et al., 1995).

As argued earlier, while we cannot confidently attest the exogeneity of the instrument on the male population, we still believe that caregiving is exogenous to the female population, implying that, if randomisation is achieved though its channel, the -0.918 coefficient could be considered close to an unbiased parameter of the effect of crowdwork on the earnings of the whole population after accounting for the linear gender estimates, with women still earning circa 20% less than men in both control and treatment groups. After adjusting for the rest of

[34]In the former, caregiving and the its interaction with gender is instrumented; in the latter, only caregiving is.

Table V

2SLS estimates of the effect of online platform work on earnings in US and Europe

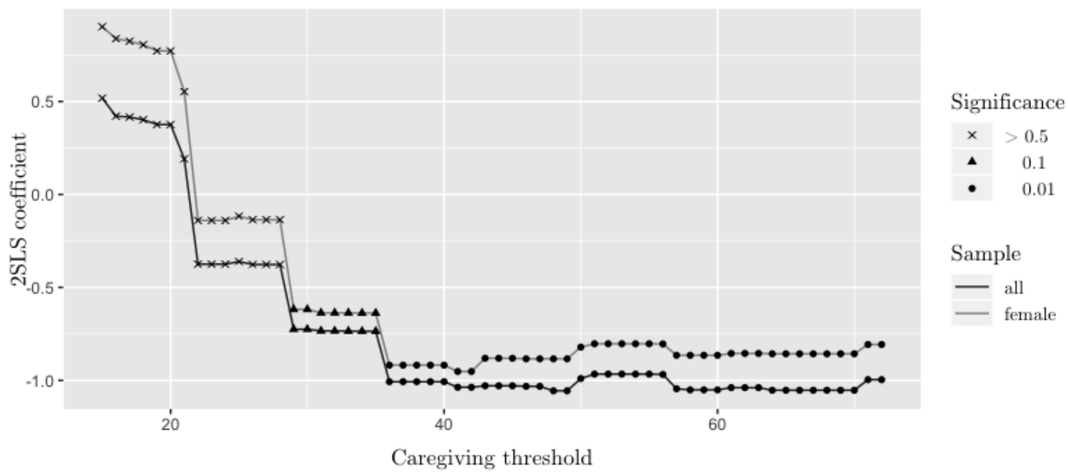
	(1)	(2)	(3)	(4)	(5)	(6)
	US+EU	US+EU	US+EU	US+EU	US+EU	US+EU
			Caregiving (15h)		Caregiving (40h)	
	OLS	OLS	2SLS	2SLS	2SLS	2SLS
VARIABLES	full sample	female only	full sample	female only	full sample	female only
Working in crowdwork	-1.028***	-1.055***	0.518	0.902	-1.007***	-0.918***
	(0.041)	(0.056)	(1.060)	(1.158)	(0.247)	(0.236)
Female	-0.212***		-0.284***		-0.213***	
	(0.045)		(0.059)		(0.049)	
$EU \times Female$	0.145***	1.348***	0.207***		0.146***	
	(0.046)	(0.089)	(0.053)		(0.048)	
Age	0.014***	0.015***	0.020***	0.018***	0.014***	0.016***
	(0.003)	(0.006)	(0.003)	(0.006)	(0.004)	(0.005)
Age squared	-0.000**	-0.000*	-0.000***	-0.000**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	-0.004	-0.009	-0.006	-0.010	-0.004	-0.009
	(0.006)	(0.008)	(0.005)	(0.008)	(0.006)	(0.008)
Married or living with a partner	0.115***	0.104***	0.121***	0.081***	0.115***	0.102***
	(0.011)	(0.018)	(0.011)	(0.020)	(0.011)	(0.018)
Main earner in household	0.155***	0.124***	0.122***	0.075**	0.154***	0.120***
	(0.014)	(0.017)	(0.024)	(0.031)	(0.016)	(0.019)
Main source of income	0.153***	0.156***	1.503*	1.818*	0.171	0.271
	(0.042)	(0.057)	(0.894)	(0.975)	(0.227)	(0.211)
Observations	30,893	15,921	30,893	15,921	30,893	15,921
Adjusted R-squared	0.378	0.366	0.151	0.051	0.255	0.231
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes
F-Test			3.968	4.657	12.40	23.25
First Stage R^2			0.738	0.712	0.742	0.722

*N*otes: State clustered standard errors in parentheses. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

*p<.05; **p<.01; ***p<.001

Figure III

Estimated 2SLS coefficients from varying full-time caregiving thresholds (US+EU)



*N*otes: Second-stage coefficients for the 'Working in crowdwork' dummy instrumented through a caregiving instrument with increasing weekly hours threshold. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

Table VI

Effect of caregiving on hourly earnings (US+EU)

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Female only		
	C+T	C	T	C+T	C	T
VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS
Caregiving (15h)	0.008	0.005	0.032	0.033*	0.026	0.116
	(0.012)	(0.012)	(0.060)	(0.019)	(0.020)	(0.076)
Caregiving (40h)	-0.015	-0.009	0.032	0.017	-0.011	0.116
	(0.030)	(0.029)	(0.060)	(0.032)	(0.030)	(0.076)
Observations	30,893	28,699	2,194	15,921	14,921	1,000
Control covariates	Yes	Yes	Yes	Yes	Yes	Yes

*N*otes: "C+T"(control and treatment samples), "C" (control sample), "T" (treatment sample). Notes: State clustered standard errors in parentheses. Dependent variable: natural logarithm of hourly PPP adjusted nominal earnings (US dollars). The dummy caregiving is set at the 15h and 40h threshold, and the sample is reduced to the control (AWCS+EWCS) groups in (2) and to the treatment (ILO) group in (3). Covariate list: age, age squared, number of people in household, main earner, main source of income, education, marital status, health status and state controls the sample using equation (3), we obtain a baseline reduction in earnings of 67.7%, rasing our confidence in the results from the previous full sample specification. This interpretation holds even if we assume that there is some sort of gender based self-selection into the crowdworker population: should this hypothesis be true, then only our interacted OLS estimates would be biased. Since, however, we are now interested in the effect of earnings, irrespective of gender, this estimate could be considered appropriate for both men and women if the sample conforms to the target population.

In order to achieve a better understanding of the variability of the 2SLS estimates as the instrument changes its threshold, and to reduce the conceptual differences between the definitions of full time caregiving between the control and treatment groups, Figure III plots the selected threshold against the estimated effect of working in crowdwork, together with their significance level. It is evident from the figure that, with caregiving becoming a significant predictor of crowdwork at its 36 hours per week threshold, the estimated coefficients also follow a more reliable pattern with little variation in their sign and statistical significance. Most importantly, full and split sample estimates conform to very similar trends, providing evidence that our instrument choice adequately controls for gendered bias in caregiving.

We do not report 2SLS estimates for working hours. The reason is that the condition of caregiving may prevent crowdworkers from working more or from pursuing other sources of income, whereas the desire to work more may be biased by the complications associated with the transition to caregiving – as reported in Marks et al. (2002). In this case, our interpretations from Table IV should then be understood as neither final or conclusive, and alternative instruments should be considered for this specific analysis.

Some final checks for our instrument are provided in Table VI, where hourly earnings are regressed over the instrument and the full set of control covariates across partitions of our sample.[35] While caregiving appears to have a negative and sligthly significant effect on earnings in our full sample of female workers, these effects are rendered insignificant when performing the same regressions over the control and treatment groups, indicating that the negative sign of that initial coefficient is entirely linked to the first-stage relationship between caregiving and crowdwork. Notably, in no case the caregiving coefficient reaches any level of statistical significance once modelling the same regressions on the full sample (men and women). In any case, while these checks and the first-stage tests give us a good confidence in our results, it could be argued that our model may still suffer from some form of bias, due to the inability to distinguish between different forms of caregiving – a problem which will be addressed in the next section.[36]

Last but not least, we model hourly earnings again while accounting for time spent in unpaid activities in Table VII. As a consequence, hourly earnings – columns (1), (3) and (5)

[35]This analysis is similar to the one presented in Madestam et al. (2013).

[36]We here refer to our inability to disentangle caring for children from caring for elderly or disabled relatives.

Table VII

2SLS estimates of the effect of online platform work on net hourly earnings, adjusted for unpaid tasks, in US & EU

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US		EU		US+EU		US+EU	
							Caregiving (40h)	
	OLS	OLS	OLS	OLS	OLS	OLS	2SLS	2SLS
VARIABLES	full sample	female only	full sample	female only	full sample	female only	full sample	female only
Working in crowdwork	-1.271***	-1.271***	-1.455***	-1.514***	-1.323***	-1.359***	-1.224***	-1.144***
	(0.051)	(0.060)	(0.069)	(0.043)	(0.046)	(0.053)	(0.255)	(0.250)
Female	-0.182***		-0.071***		-0.205***		-0.224***	
	(0.061)		(0.010)		(0.062)		(0.048)	
$Crowdwork \times Female$	-0.002		-0.084		-0.032			
	(0.068)		(0.052)		(0.059)			
$EU \times Female$					0.140**	-0.248***	0.157***	
					(0.059)	(0.038)	(0.047)	
Age	0.029**	0.057***	0.011***	0.009*	0.014***	0.015***	0.014***	0.016***
	(0.014)	(0.015)	(0.004)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)
Age squared	-0.000*	-0.001***	-0.000	-0.000	-0.000**	-0.000*	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	-0.028**	-0.048***	0.002	0.001	-0.004	-0.008	-0.004	-0.008
	(0.013)	(0.017)	(0.007)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)
Married or living with a partner	0.258***	0.270***	0.100***	0.083***	0.117***	0.105***	0.118***	0.102***
	(0.039)	(0.068)	(0.010)	(0.016)	(0.011)	(0.018)	(0.011)	(0.018)
Main earner in household	0.359***	0.272***	0.137***	0.112***	0.155***	0.123***	0.153***	0.118***
	(0.049)	(0.077)	(0.013)	(0.016)	(0.014)	(0.017)	(0.016)	(0.019)
Main source of income	0.084*	0.070	0.095	0.127*	0.119***	0.119*	0.217	0.302
	(0.046)	(0.074)	(0.074)	(0.064)	(0.044)	(0.061)	(0.229)	(0.220)
Observations	3,200	1,696	27,653	14,206	30,853	15,902	30,853	15,902
Adjusted R-squared	0.465	0.476	0.420	0.399	0.428	0.414	0.315	0.287
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health status controls							Yes	Yes
F-Test							12.29	22.99
First Stage R^2							0.742	0.722

*N*otes: State clustered standard errors in parentheses. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home. †: adjusted for time spent in unpaid activities

*p<.05; **p<.01; ***p<.001

– fall well below our previous estimates, displaying a coefficient of -1.323 (-73.3%), with the prediction moving to -70.6% when instrumenting our treatment in column (7). Comparable results also apply to the female population (columns 2, 4, 6, and 8).

7 Robustness checks

In this section we perform robustness checks for our findings. The choice of caregiving in the female population as an instrument for participation in crowdwork calls for a number of robustness checks, as it could be argued that the effect of caregiving on participation in crowdwork may change with time, or that caregiving affects participation but not the duration of crowdwork arrangements. Differences in control and treatment survey items may then cause issues with identification of caregivers when these individuals have been working on the platform for a long time.

While the EWCS and AWCS surveys inquire how much time does the respondent currently spend in caregiving, the ILO survey records whether the respondent was engaged in full-time caregiving right before starting to work on the platform. The design of the ILO survey then allows us to maintain the causal channel between caregiving and platform work (back when they started working online), while the controls enable us to identify whether comparable individuals in the complier group are still employed in traditional forms of work. This approach, however, imposes that, if caregiving is an exogenous determinant of crowdworking, we should reasonably assume that crowdworkers who entered this form of employment due to caregiving are still engaged in this activity. To account for these issues, we control in Table VIII for time spent in the current occupation, a control that was previously excluded from the final model due to its – obvious – collinear relationship with our outcome and treatment variables.

In the final model of Table VII, we made the assumption that most crowdworkers have not been engaged in this form of employment for a long time and the ones acting as caregivers when starting platform work are still engaged as such, based on the finding that 75.51% of crowdworkers have not been engaged in this form of employment for more than two years. We now relax this assumption in Table VIII, where we run the same final IV specifications from Table V, adding dummies for years spent in current occupation along with the previously chosen controls in columns (1) and (5).[37] In the following specifications – columns (2) to (4) and (5) to (8) – we perform a similar analysis by restricting the sample to people who have been working for less than 4 years, 2 years and finally 1 year. By comparing workers that have been working in their current occupation for similar time, the more we reduce the years they have been spending in their current occupation, the more our assumption that these workers are still in caregiving is made more reasonable: in this way, we believe to be able to filter out the effects of time spent in a given occupation through the first stage of the 2SLS

[37]The results are reported for both the 15h and 40h caregiving thresholds.

Table VIII

2SLS estimates of the effect of online platform work on hourly earnings in US & EU

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US+EU				US+EU			
		Caregiving (40h)				Caregiving (40h)		
	2SLS				2SLS			
VARIABLES	full sample	<= 4	<= 2	<= 1	female only	<= 4	<= 2	<= 1
Working in crowdwork	-1.101***	-1.036***	-1.116***	-1.005***	-0.854***	-0.799***	-0.865***	-0.826***
	(0.230)	(0.227)	(0.269)	(0.227)	(0.236)	(0.229)	(0.267)	(0.236)
Female	-0.082***	-0.077***	-0.087***	-0.096***				
	(0.011)	(0.017)	(0.023)	(0.022)				
Age	0.007*	0.015***	0.012**	0.019**	0.007	0.017*	0.013	0.031***
	(0.004)	(0.006)	(0.006)	(0.009)	(0.006)	(0.010)	(0.013)	(0.012)
Age squared	-0.000	-0.000**	-0.000	-0.000**	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	-0.004	-0.022***	-0.025***	-0.018	-0.007	-0.032***	-0.043***	-0.025**
	(0.006)	(0.007)	(0.008)	(0.013)	(0.008)	(0.008)	(0.008)	(0.012)
Main earner in household	0.143***	0.127***	0.110***	0.102***	0.113***	0.084***	0.050	0.040
	(0.015)	(0.016)	(0.019)	(0.031)	(0.018)	(0.026)	(0.033)	(0.039)
Main source of income	0.028	0.059	-0.013	0.066	0.266	0.267	0.180	0.217
	(0.208)	(0.183)	(0.211)	(0.160)	(0.208)	(0.182)	(0.199)	(0.173)
Married or living with a partner	0.100***	0.087***	0.088***	0.097***	0.089***	0.075**	0.075**	0.065**
	(0.010)	(0.014)	(0.017)	(0.025)	(0.018)	(0.032)	(0.036)	(0.032)
Observations	30,673	12,763	8,848	4,104	15,805	6,589	4,570	2,110
Adjusted R-squared	0.265				0.243			
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years in occupation controls	Yes	No	No	No	Yes	No	No	No
F-Test	13.58	20.72	20.93	42.21	24.39	36.14	37.74	61.96
First Stage R^2	0.742	0.747	0.752	0.759	0.722	0.735	0.744	0.768

*N*otes: State clustered standard errors in parentheses. Dependent variable: natural logarithm of hourly nominal earnings (US dollars). Control sample restricted to employedand self-employed American individuals in working age excluding freelancers working from home. From columns (2) to (4) and (7) to (9), the sample is restricted to individuals who have been working in their current occupation for less than 4 years, 2 years and finally 1 year.

*p<.05; **p<.01; ***p<.001

model. The trade-off is that, the more we reduce our sample size, the more our estimates lose in precision. Nevertheless, the interpretation of our results stays relatively unchanged, with the coefficients retaining their signs and significance. The magnitude of our coefficient for platform work, however, seems somewhat sensible to the sample reduction: in any case, it never overestimates the coefficient of the OLS model, while remaining relatively stable after individuals with more than 5 years of employment have been accounted for. After adjusting for gender specific linear trends, as in equation (3), we can reasonably argue that working in crowdwork generates a negative effect on earnings sitting between 67.2 and 58.35% less than for comparable workers after controlling for time spent in current occupation.

Finally, as mentioned earlier, our econometric model may also raise a number of concerns with regards to the exogeneity of our instrument. Evidence from a number of studies – such as Kremer & Chen (2002) and D'Addio & Mira D'Ercole (2005) – suggests that fertility may be influenced by a number of social drivers. While we believe that our controls are sufficiently apt at filtering these influences out,[38] we here intend to relax this assumption and treat fertility as endogenous. Even if, as discussed, conflicting survey designs prevent us from fully separating individuals caring for children from the ones caring for disabled or elderly relatives, we can nonetheless identify individuals in caregiving who, at the same time, do not have kids – and, therefore, are most surely not caring for children. We then switch our instrument with the new one ('Caring for elderly or disabled relatives only') and present our results in Table IX, adopting the same approach used for the robustness checks in Table VIII. The reductions in the 'complier' treatment group leave to an increase in the variability of our estimates which this time appear particularly sensible to the reduction in sample size. Since this time we are only able to compare individuals with no children, some kind of bias can still be expected: in fact, while our estimates maintain their sign and do not diverge too much from our results in Table VIII, they surely suffer from some level of overestimation. In any case, these results do not contradict our previous findings.

8 Conclusions

In this paper we have provided an empirical analysis of the effect of crowdwork on working conditions in both the United States and Europe. We use a quasi-experimental design and we assemble data from different sources, coming from online surveys on crowdworkers, web plugins and commonly used extensive surveys on workers' conditions in the US and Europe. To the best of our knowledge, this is one of the first attempts to provide an unbiased comparison of platform and traditional workers in terms of earnings and working conditions. While we show that the effect of crowdsourcing on earnings is not as large as it could be expected from

[38] In particular, we believe that controls for education, marital status and household size can adequately capture these endogenous variations.

Table IX

2SLS estimates of the effect of online platform work on hourly earnings in US & EU

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US+EU				US+EU			
		Caregiving (40h)				Caregiving (40h)		
	2SLS				2SLS			
VARIABLES	full sample	<= 4	<= 2	<= 1	female only	<= 4	<= 2	<= 1
Working in crowdwork	-1.772***	-1.299**	-1.393*	-1.192**	-1.354***	-0.994**	-1.178	-1.114
	(0.567)	(0.506)	(0.844)	(0.496)	(0.483)	(0.453)	(0.793)	(0.939)
Female	-0.075***	-0.073***	-0.081***	-0.093***				
	(0.012)	(0.018)	(0.026)	(0.021)				
Age	0.006	0.014**	0.012**	0.019*	0.007	0.017*	0.013	0.031***
	(0.004)	(0.006)	(0.006)	(0.010)	(0.006)	(0.010)	(0.014)	(0.012)
Age squared	-0.000	-0.000**	-0.000	-0.000*	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	-0.003	-0.021***	-0.024***	-0.017	-0.007	-0.031***	-0.041***	-0.023*
	(0.006)	(0.007)	(0.009)	(0.013)	(0.008)	(0.008)	(0.010)	(0.013)
Main earner in household	0.160***	0.140***	0.126***	0.115***	0.126***	0.094***	0.071	0.060
	(0.020)	(0.027)	(0.046)	(0.044)	(0.021)	(0.033)	(0.060)	(0.072)
Main source of income	-0.547	-0.157	-0.241	-0.080	-0.151	0.112	-0.068	0.002
	(0.503)	(0.438)	(0.701)	(0.392)	(0.431)	(0.390)	(0.634)	(0.709)
Married or living with a partner	0.100***	0.087***	0.090***	0.099***	0.096***	0.080**	0.087*	0.078
	(0.011)	(0.014)	(0.019)	(0.026)	(0.019)	(0.035)	(0.050)	(0.056)
Observations	30,673	12,763	8,848	4,104	15,805	6,589	4,570	2,110
Adjusted R-squared	0.238				0.238			
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years in occupation controls	Yes	No	No	No	Yes	No	No	No
F-Test	12.68	10.62	6.485	14.79	24.68	22.05	13.35	14.34
First Stage R^2	0.740	0.742	0.745	0.752	0.716	0.725	0.729	0.751

*N*otes: State clustered standard errors in parentheses. Dependent variable: natural logarithm of hourly nominal earnings (US dollars). Control sample restricted to employedand self-employed American individuals in working age excluding freelancers working from home. From columns (2) to (4) and (7) to (9), the sample is restricted to individuals who have been working in their current occupation for less than 4 years, 2 years and finally 1 year.

*p<.05; **p<.01; ***p<.001

descriptive statistics, our estimates still cast a dark light over platform work: crowdsourcers still earn 70.6% less than comparable workers in terms of ability, while spending nearly as much time working in the platform as their counterparts do in traditional occupations. Most importantly, labour force in crowdworking arrangements appears to be highly under-utilised, with all crowdworkers being more likely to be left wanting for more work than comparable individuals. All these findings, along with the fact that these individuals do not appear to be looking for other jobs more than 'traditional' workers, relegate crowdworkers into a new category of idle workers whose human capital is not being fully utilised nor adequately compensated.

It should be noted that while these results mostly hold for US and EU platform workers, the external validity of our estimates is threatened by the nature of crowdwork platforms themselves and, while our conclusions may be extended to routine-task intensive platforms such as Crowdflower or Clickworker, our analysis may not hold in other contexts where more diversified tasks, requiring more creative input from service providers, are offered, such as in the case of UpWork.[39]

Finally, it should be highlighted that we have here only compared the effects of crowdwork between similar workers in terms of their ability and their personal characteristics, but we have not delved into the causes of the differences in earnings and job quality between crowdworkers and traditional workers. We were able to exclude that most of these differences were caused by the routine and abstract content of online platform jobs, as workers with comparable routine and abstract tasks still retain most of their salary premium, indicating that the relative simplicity and repetitiveness of these tasks does not necessarily lead to a sizeable decrease in earnings. This leads us to believe that this effect could be better explained by the following factors:

1. the competition from equally skilled but cheaper labour from other countries within the same platform;
2. the lack of labour rights and minimum standards stemming from the status of independent contractors.

In the first case, the influx of 'digital immigrants' may lead to an increase in labour supply and infra-task competition, lowering remunerations. In the second case, the monopsonistic nature of platforms enables them to impose a heavy markup over their workers, while allowing clients to operate at prices well below the market's marginal costs. We believe that the poor working conditions crowdsourcers have to live with are the result of an interplay between these elements, and it is up to future research to test each of these hypotheses individually, disentangling the effect of each one of them from the other.

[39]Though a case could be made that Upwork and similar freelance marketplaces (as defined in Berg et al., 2018) are inherently different from the crowdwork arragements we studied.

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Appendix - Summary statistics

Table A.1

Descriptive statistics, US traditional occupations controls (AWCS 2015)

	(1)							
	count	mean	sd	min	p5	p50	p95	max
Hourly nominal earnings (USD)	1847	30.77	207.9	0	2.301	17.58	58.81	10547.9
Weekly working hours	1910	39.06	11.65	0	20	40	60	112
Age	1941	41.02	12.61	18	21	41	61	64
Female	1941	0.463	0.499	0	0	0	1	1
Married or living with a partner	1941	0.516	0.500	0	0	1	1	1
No. of people in household	1941	3.063	1.672	1	1	3	6	12
Main earner in household	1891	0.603	0.489	0	0	1	1	1
Educ.: no high school diploma	1941	0.0638	0.244	0	0	0	1	1
Educ.: high school diploma	1941	0.502	0.500	0	0	1	1	1
Educ.: technical/associate	1941	0.0966	0.296	0	0	0	1	1
Educ.: bachelor's degree	1941	0.208	0.406	0	0	0	1	1
Educ.: master's degree	1941	0.0944	0.292	0	0	0	1	1
Educ.: higher	1941	0.0356	0.185	0	0	0	0	1
Health: Very Good	1891	0.132	0.338	0	0	0	1	1
Health: Good	1891	0.407	0.491	0	0	0	1	1
Health: Fair	1891	0.345	0.475	0	0	0	1	1
Health: Poor	1891	0.0991	0.299	0	0	0	1	1
Health: Very Poor	1891	0.0176	0.132	0	0	0	0	1
Caregiving (15h/week)	1941	0.149	0.356	0	0	0	1	1
Caregiving (40h/week)	1941	0.0824	0.275	0	0	0	1	1

*N*otes: Weighted summary statistics. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

Table A.2

Descriptive statistics, EU traditional occupations controls (EWCS 2015)

	(1)							
	count	mean	sd	min	p5	p50	p95	max
Hourly nominal earnings (USD)	26991	17.06	91.89	0.00319	3.935	11.83	29.77	5687.8
Weekly working hours	31650	37.18	11.90	1	15	40	55	126
Age	32429	42.21	11.39	15	23	43	60	64
Female	32429	0.478	0.500	0	0	0	1	1
Married or living with a partner	32429	0.697	0.459	0	0	1	1	1
No. of people in household	32312	2.882	1.268	1	1	3	5	10
Main earner in household	32429	0.595	0.491	0	0	1	1	1
Educ.: no high school diploma	32316	0.161	0.367	0	0	0	1	1
Educ.: high school diploma	32316	0.448	0.497	0	0	0	1	1
Educ.: technical/associate	32316	0.147	0.354	0	0	0	1	1
Educ.: bachelor's degree	32316	0.127	0.333	0	0	0	1	1
Educ.: master's degree	32316	0.108	0.311	0	0	0	1	1
Educ.: higher	32316	0.00856	0.0921	0	0	0	0	1
Health: Very Good	32400	0.261	0.439	0	0	0	1	1
Health: Good	32400	0.532	0.499	0	0	1	1	1
Health: Fair	32400	0.185	0.389	0	0	0	1	1
Health: Poor	32400	0.0201	0.140	0	0	0	0	1
Health: Very Poor	32400	0.00228	0.0477	0	0	0	0	1
Caregiving (15h/week)	32429	0.170	0.375	0	0	0	1	1
Caregiving (40h/week)	32429	0.0197	0.139	0	0	0	0	1

*N*otes: Weighted summary statistics. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home. Earnings are adjusted for purchasing power parity

Table A.3

Descriptive statistics, US+EU crowdwork treatment (ILO 2015, 2017)

	(1)							
	count	mean	sd	min	p5	p50	p95	max
Hourly nominal earnings (USD)	2341	7.166	18.72	0.0489	0.568	4.888	17.39	568.4
Hourly nominal earnings (USD)†	2302	4.697	11.72	0	0.300	3.125	12	357.1
Weekly working hours	2369	19.36	23.69	0	2	13	50	168
Weekly working hours†	2320	26.03	30.56	0	2	18	70	336
Age	2393	35.03	10.93	18	21	33	57	83
Female	2393	0.448	0.497	0	0	0	1	1
Married or living with a partner	2393	0.455	0.498	0	0	0	1	1
No. of people in household	2393	2.768	1.377	1	1	3	5	10
Main earner in household	2393	0.806	0.396	0	0	1	1	1
Educ.: no high school diploma	2391	0.0247	0.155	0	0	0	0	1
Educ.: high school diploma	2391	0.356	0.479	0	0	0	1	1
Educ.: technical/associate	2391	0.132	0.339	0	0	0	1	1
Educ.: bachelor's degree	2391	0.334	0.472	0	0	0	1	1
Educ.: master's degree	2391	0.125	0.330	0	0	0	1	1
Educ.: higher	2391	0.0284	0.166	0	0	0	0	1
Health: Very Good	2392	0.258	0.437	0	0	0	1	1
Health: Good	2392	0.528	0.499	0	0	1	1	1
Health: Fair	2392	0.174	0.379	0	0	0	1	1
Health: Poor	2392	0.0347	0.183	0	0	0	0	1
Health: Very Poor	2392	0.00585	0.0763	0	0	0	0	1
Caregiving (15h/week)	2393	0.166	0.372	0	0	0	1	1
Caregiving (40h/week)	2393	0.166	0.372	0	0	0	1	1

*N*otes: Summary statistics. Earnings are deflated to the reference period (local currency) and then adjusted for purchasing power parity. †: adjusted for time spent in unpaid activities