Workers in the crowd: the labour market impact of the online platform economy*

Michele Cantarella[†,1] and Chiara Strozzi[2]

[1]University of Modena and Reggio Emilia and European Central Bank
[2]University of Modena and Reggio Emilia and IZA

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Abstract

In this paper, we compare wages and labour market conditions between individuals engaged in online platform work and in traditional occupations by exploiting individual-level survey data on crowdworkers belonging to the largest micro-task marketplaces, focusing on evidence from the United States and Europe. To match similar individuals, survey responses of crowdworkers from the US and EU have been harmonised with the American Working Conditions Survey (AWCS) and the European Working Conditions Survey (EWCS). Our findings indicate that traditional workers retain a significant premium in their earnings with respect to online platform workers, and that those differences are not explained by the observed and unobserved ability of individuals. This holds true also taking into account similar levels of routine intensity and abstractness in their jobs, as well as the time spent working. Moreover, labour force in crowdworking arrangements appears to suffer from high levels of under-utilisation, with crowdworkers being more likely to be found wanting for more work than comparable individuals.

Keywords: *crowdwork, online platform economy, micro-tasks, routine intensity, labour market conditions*

JEL codes: J31, J42, F66

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†Corresponding author. Email: michele.cantarella@unimore.it.

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, 2016, Harris and 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 online micro-task labour markets, within what is described as the gig, on-demand, or platform-based economy (Degryse, 2016, Prassl and Risak, 2015).

These workers are usually 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 analysed in a number of recent descriptive studies (e.g. Berg et al., 2018, Berg, 2015, Difallah et al., 2018, Hara et al., 2018, Pesole et al., 2018) showing how these workers suffer from the erosion of fundamental labour rights, the loss of social protections and difficulties in exercising collective action. However, it would be a mistake to assume, solely based on the evidence from these descriptive studies, that this deterioration of working condition is to be fully attributed to a platform effect, as it could be argued that the characteristics of crowdworkers are intrinsically different from the characteristics of workers in traditional 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 possibility 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 inter-mediated by digital platforms' (European Parliament, 2017, European Parliament resolution of 19 January 2017 on a European Pillar of Social Rights).

and poor working conditions.[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 micro-tasks crowdworkers. We focus on the evidence from the United States and Europe, aiming to answer to the following questions: Are individuals involved in online micro-task service outsourcing intrinsically different from traditional salaried workers involved in comparable occupations, and are there differences between micro-task crowdworkers from the US and from Europe? Is it possible to estimate the real impact of micro-task crowdwork on wages and working conditions of platform workers? We focus on the supply side of these labour markets and intend to measure how much individual characteristics influences those differences in outcomes.

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. As our aim is to provide an unbiased comparison of earnings and working conditions of platform workers and traditional workers, we supplement data from general working conditions surveys with responses from specific surveys on online workers, creating two groups of 'traditional' and 'crowd' workers, and analysing variations in outcomes conditionally on participation into crowdwork markets.

For both the US and Europe, the crowdwork group includes information on workers from different 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 general surveys on working conditions in the US and the EU (namely, the American Working Conditions Survey, and the European Working Conditions Survey).

Our findings indicate that earnings in crowdwork are mostly indifferent to skills, and that crowdworkers earn about 70% less than traditional workers with comparable ability, while working only a few hours less per week. 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 by matching different surveys. Moreover, in contrast with most studies on the online platform economy, which aim their attention at specific regional settings, we focus on both the United States and Europe simultaneously.

The rest 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 describes the data used

[3] On the contrary, individuals participating in online freelancing marketplaces (such as UpWork) are involved in job projects which are usually larger in scope and can enjoy more favourable conditions.

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. The Appendix is dedicated to additional descriptive statistics and regressions.

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. 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 work and transcends traditional 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 majority of online platforms explicitly deny the existence of any employment relationship between the parties, individuals in crowdwork are generally characterised as independent contractors, performing their work in a discontinuous or intermittent basis.

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 and Risak, 2015) and, because of this, it has also been defined as "crowdsourcing".[5] By requiring platforms as intermediate actors, crowdwork manages to reduce most transaction costs, thus allowing for a flexible and potentially global workforce to enter the labour market and maximise the use of under-utilised assets such as human capital.[6]

Crowdwork arrangements may vary greatly: skill requirements for outsourced jobs may range from high to low and, while tasks with high routine intensity and low abstract content

[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]This term which was first used by Jeff Howe in the article "The Rise of Crowdsourcing", Wired Magazine, 14, 2006.

[6]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.

are prevalent – as, for example, most tasks in Amazon Mechanical Turk (AMT), Clickworker and Figure-Eight – complex and even creative activities are also present. 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 and Krueger, 2015). The short and repetitive tasks offered in AMT, as in the many other platforms, often include: image/video processing, translation, data verification, information gathering and processing, audio and visual editing, amongst many others.[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, information technology and economics. Until recently, the body of research on the economics of crowdsourcing has been, so far, remarkably thin, compared to other areas of study: a glaring lacuna, considering the growing size of the platform economy.

As suggested by Hara et al. (2018), this scarcity of literature is mostly attributable to the absence of publicly available data on crowdwork platforms and their workers. Nonetheless, as discussed by Horton et al. (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 and Chilton (2010) offer one the first attempts to obtain empirical evidence on reservation wages in crowd employment from an experimental framework.

Several additional descriptive studies have been provided. Harris and 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) and FEPS (Huws et al., 2017), have contributed to the literature with a thorough overview of the demographics of crowdsourcing. Hara et al. (2018) document wage and working time amongst AMT crowdworkers, discussing the necessity of including the time spent searching for tasks in working time indicators, while a recent paper from Difallah et al. (2018) summarises the main take-aways from a longitudinal survey on AMT workers.[8]

Another important contribution on the analysis of the platform economy in US comes from Katz and Krueger (2018), 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,

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

[8] 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/

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 (see Harris and Krueger, 2015).

Crowdwork can be considered as another form of service outsourcing. Some – 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 and 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.

A few recent works, however, have focused on a number of supply and demand factors which contribute to the deterioration of earnings in online labour markets. Dube et al. (2018) address monopsony in online labour markets, finding that their peculiar structure allows platforms to impose a considerable markup on workers' productivity, leading up to a 20% contraption in their earnings. Looking at the supply of online workforce, 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. Negative spill-over effects from crowdwork markets may be less obvious, but cannot be excluded. Focusing on on-demand labour platforms, Berger et al. (2018) explore the effect of introduction of Uber across taxi drivers, finding a negative association with their hourly earnings. Finally, the effects of digital labour markets on high skilled service flows are investigated in Horton et al. (2017), who focus on the UpWork freelancing platform.

While these studies all improve our understanding of important factors contributing to wage deterioration of online platform workers, none of these contributions focuses on the issue of self-selection into crowdsourcing, leaving the effect of individual ability unmeasured. We believe that a complete picture on working conditions in online crowdsourcing can only be achieved by comparison with other forms of work, and measuring how much individual characteristics of online platform workers contribute to these conditions, a task which we intend to pursue with this paper.

4 Data

The identification of crowdworkers in existing general working conditions surveys is not trivial. The European Working Conditions Survey (EWCS) (European Foundation For The Improvement Of Living And Working Conditions, 2017) and the American Working Conditions Survey (AWCS) (Maestas et al., 2017) both contain comparable information on wages, job quality and skills but, in both instances, it is often not possible 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 as a serious source of bias. Also, due to the current size of the platform economy, platform workers, even if correctly identified, will naturally be under-represented in general surveys.

Dedicated surveys on crowdworkers can assist with bridging this gap. 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, Difallah et al., 2018) or web plug-ins (e.g. Hara et al., 2018) – 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, only data sources which maximised comparability, while retaining a satisfactory pool of observations and key variables, were selected.

4.1 Crowdworkers and traditional workers

Our crowdwork sample uses 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, a group of 'traditional' workers was constructed using data from the American Working Conditions Survey and from the European Working Conditions Survey. We harmonise the ILO Survey on Crowdworkers with these general working conditions surveys in our attempt to put these new forms of work into a comparative and global perspective.

The dataset from Berg (2015) and Berg et al. (2018) consists of two consecutive surveys conducted on major online micro-task platforms[9] in 2015 and 2017 and covers crowdworkers from both the United States and Europe, along with other countries. 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 of the survey, we extracted a group of 1,393 US crowdworkers and 1,000 European[10] 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

[9]In detail: Amazon Mechanical Turk (US, EU), Crowdflower (EU), Clickworker (EU), Microworkers (EU) and Prolific Academic (EU).

[10]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).

household size. The survey also includes items which allowed us to identify whether crowdwork constituted the respondent's main source of income.[11] 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) in a single cross-section.

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

Table 1: Differences across crowdworkers and traditional workers in the US and EU

	US			EU		
	Traditional	Crowdwork	diff.	Traditional	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)	

Notes: Mean-comparison t-tests across crowdworkers (ILO data) and traditional workers (AWCS and EWCS data) from the US and EU. Standard errors in parentheses. Summary statistics and t-test are calculated from weighted US and EU reference samples. The sample is restricted to employed and self-employed individuals in working age. †: adjusted for time spent in unpaid activities.

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

We used information from the EWCS and AWCS to construct a baseline group for traditional workers. 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).[12] Similarly, a sample of 32,429 employed working-age individuals from the EU28 area was extracted from the EWCS, weighted, and paired as a group of traditional workers to the data on European crowdworkers. All data was finally aggregated into a single dataset, providing a shared set of common variables and adjusting earnings for inflation and purchasing power parity.

Summary statistics for all relevant variables are reported in Tables A.1, A.2 and A.3 in the Appendix. Weighted mean comparison t-tests for a number of key dimensions across the crowdwork and traditional work groups are shown in Table 1 (United States: n = 3,339 and Europe: n = 33,281). Mean comparison t-tests between the two groups, restricted to the employed working age population, reveal differences in earnings, age, education and marital status across forms of work. While earnings, as expected, appear to be lower for online platform workers, their demographic composition also shows significant differences with traditional workers from both the US and the EU, with the typical crowdworker being more likely to be younger, single and more educated overall. These 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 1 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 (US: -76.58%, EU: -61.39%). Also, while hourly earnings between crowdworkers in the two regions average at similar levels, the hourly rate of pay among platform workers in the EU is subject to much higher variability, presumably

[12] For most our estimates, we decided not to narrow our sample of traditional workers based on the respondent's profession. While an analysis of earnings and outcomes across comparable tasks (for example, in terms of routine intensity, as suggested in Autor and Dorn, 2013 and Ottaviano et al., 2013) will not be disregarded, our 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 group of traditional workers to individuals in occupations with comparable routine and abstract task-intensity in Table 3, so to provide a more complete picture of the crowdworking phenomenon: the results included in said table, for all the aforementioned reasons, are included for descriptive purposes and should be intended void of any causal interpretation.

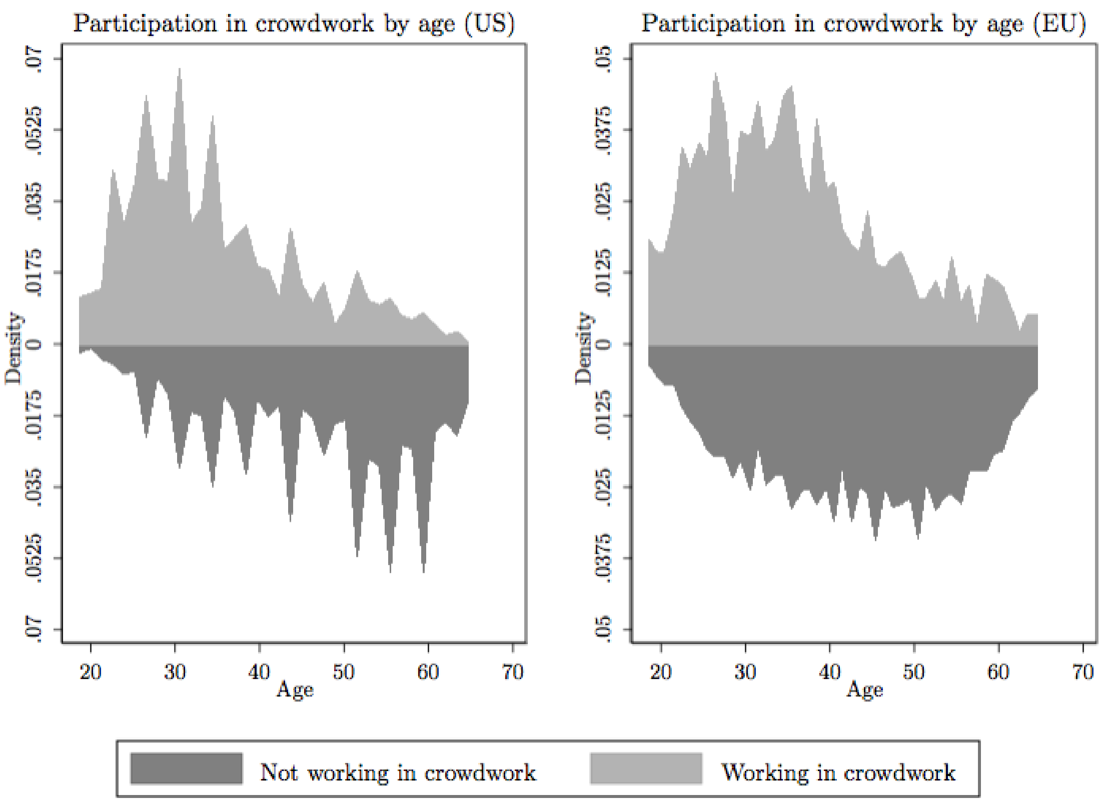

Figure 1: Participation in crowdsourcing versus traditional occupations by age

*N*otes: 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.

because of differences in the platforms. 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.

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 re-coding, for the sake of harmonisation. Keeping the changes at a minimal level, the final coding sometimes differs across the US and European samples. In many cases, the changes have been negligible, but will nonetheless be reported when needed.[13]

Hourly nominal earnings have been selected as our key variable of interest. Given that crowdworkers do not have fixed working hours, and considering how some individuals already in employment may work on online labour platforms in their free time to gain access an auxiliary source of income, hourly rate of pay will not suffer from distortions caused by the number of hours worked per week, allowing for a comparison between platform and traditional workers. This does not imply that hourly earnings are indifferent to crowdwork being the main – or only – source of income for the respondent, a variable for which we will also control.

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 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.[14]

Additionally, 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,[15] 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

[13]This is the case for education, where achievements were grouped to the closest common title, while other similar adjustments were made to marital status.

[14]While the ILO survey reports weekly earnings, AWCS reports yearly earnings, and EWCS lets the respondent to choose the measure he/she is most comfortable with. Hourly rate was then computed by dividing weekly nominal earnings by weekly working hours.

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

on earnings have been widely documented,[16] while gender pay gaps have also been studied thoroughly.[17] 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 for children or disabled/elderly relatives. The implications of this variable for our 2SLS model will be discussed later.

5 Model specification

We estimate the effect of working in online platforms on labour market outcomes comparing earnings and working conditions between platform and 'traditional' workers, which we treat as two distinct groups. In our case, the first group is composed by crowdworkers interviewed in the ILO survey, while the second group includes workers from the AWCS and EWCS surveys. From this point of view, our approach has drawn inspiration from LaLonde (1986), while our identification strategy is not dissimilar from previous studies on part-time employment which instrumented hours of work through household size and fertility (such as Ermisch and Wright, 1993, and Hotchkiss, 1991).

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 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).

Simple descriptive analyses may then 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 characteristics which make them qualitatively different from traditional 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 initially compare outcomes across types of workers, controlling for observable characteristics with an OLS model, and later offer further controls for unobservable skills by adopting an instrumental variable approach. For our instrumental variable model, we choose the following specification:

(1) $Y_i = \alpha_2 + \hat{T}_i\lambda + X_i^{'}\gamma_2 + F_i\varphi_2 + e_{2i}$

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

[16]See, e.g., Angrist and Krueger (1991) and Card and Krueger (1992).
[17]E.g., Blau and Kahn (2003) and, Altonji and Blank (1999).

where i refers to each individual, Y is the set of our outcome variables (natural logarithm of hourly earnings and of hourly earnings adjusted for unpaid activities), while X is a vector of k–2 controls, and F is a dummy which indicates whether the respondent is female.[18] The full set of controls in the X vector are age, age squared, number of people in household, main earner (i.e. if an individual is the main earner in the household), main source of income (i.e. if the reported earnings refers to the individual's main source of income), education level, marital status and state/country of residence.

In the first stage regression (2), working in crowdwork T (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 T (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 crowdwork T is really assigned exogenously conditionally on Z, then the coefficient on λ will not suffer from selection bias.

5.1 Instrumental variable identification

A number of exogenous variables, such as age or health condition, are significantly correlated with crowdwork (age: -0.1643***; poor health: 0.0193***).[19] Their adoption as instrumental variables, however, would potentially 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 third instrument: time spent in caregiving at home. This variable is 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 extra income to these individuals, given their circumstances.

Both the ILO and the AWCS-EWCS 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.

[18]The need for this specification, with the gender dummy appearing outside the X vector, will be explained in subsection 5.1, as the coefficient φ_2 will be used to adjust split-sample estimates to the whole population.

[19]Sidak-adjusted pairwise correlations. Survey question: : "Do you have any illness or health problem which has lasted, or is expected to last, for 6/12 months or more?".

Indeed, according to this study, caregivers working at least 15 hours per week have declared that this activity significantly affected their work life.[20]

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 subsidised child care. It is then not unreasonable to expect labour market policies to similarly influence participation in crowdwork.

While the connections between crowdsourcing and caregiving are theoretically plausible and empirically proven, the choice of this instrument, however, can raise concerns with regards to its endogeneity and to the risk of violation of the exclusion restriction. These concerns, however, can be overcome, as discussed below.

5.2 Gender bias in caregiving

Caregiving 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 (US+EU) correlation coefficient of 0.1920*** to 0.2502*** for the female population. This differential may support prior evidence on men's caregiving being a complex phenomenon influenced by endogenous socio-economic determinants,[21], uncovering a potential obstacle in our identification strategy. Indeed, while a number of studies finds caregiving to be exogenous to the female population (see, as discussed later Ciani, 2012, and Schmitz and Westphal, 2017), the effect on the male population is less unambiguous.

Nonetheless, we trust that these complications can be overcome 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 discrimination based on the sex of the worker, due to the relative anonymity that service providers enjoy on the platform:[22] clients are, indeed, usually unable to ascertain the gender of online service providers. Should this assumption hold, all differences between genders will

[20]For details about the Gallup-Healthways Well-Being Index, see https://www.gallup.com/175196/gallup-healthways-index-methodology.aspx. For the Gallup evidence about the relevant threshold levels for caregiving, see https://news.gallup.com/poll/148640/one-six-american-workers-act-as-caregivers.aspx.

[21]See, for example, Gerstel and Gallagher (2001).

[22]As found in Adams, Abi and Berg, Janine, (2017) "When Home Affects Pay: An Analysis of the Gender Pay Gap Among Crowdworkers"

then be linked to common structural trends across traditional and platform forms of work 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. In other words, if the interaction term between gender and crowdwork yields a zero effect on earnings, said interaction can be added to the instrument pool without expecting violations of the exclusion restriction.

Additionally, 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. Given that earnings are estimated by a log wage equation, the non significance of interaction effect (which we will denote as ζ, omitting, from now on, the second-stage index from equation 2) allows the non-interacted gender effect to be fully absorbed by the constant term in the split sample estimate, leading, after controlling for all observables, to:

(3) $\lambda \approx \lambda_f + \zeta$

meaning that λ_f, the effect of platform work on the female population as predicted by our model will approximate the full sample coefficient λ minus the interaction term ζ. If this interaction term is not statistically different from zero, λ_f will also closely approximate the baseline effect of platform work on the selected dependent variable. As our 2SLS estimation will be based on the full US-EU sample,[23] 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 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.

Split sample instrumental variable models – or TS2SLS – have already been explored in the past by Angrist and Krueger (1995) and Inoue and Solon (2010), who 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.

5.3 Potential earnings and violations of the exclusion restriction

The chosen instrumental variable – caregiving – could also pose as a threat to our identification strategy in terms of violations of the exclusion restriction. Indeed, it is reasonable to believe

[23]Since our chosen instrument affects participation in crowdwork but is not intended to randomise regional assignment, differential effects across countries become a second-order priority. Hence controls for specific regional differences are sufficient for the estimation of these effects, with the 2SLS estimation benefiting from the increase in sample size for all groups.

that the amount of time a worker spends in caregiving is endogenous to the wage he/she could earn in the market. While this condition should clearly affect working hours and – by extension – total earnings (as documented in Wakabayashi and Donato, 2005, and Earle and Heymann, 2012), the effects on hourly earnings are less obvious. If the wage is high enough, individuals could, in fact, purchase care for either a child or a relative and, in such a case, transition to caregiving will be biased towards lower salaries.

To properly account for this endogenous variation, we would need to have access to a measure of unobserved potential earnings, i.e., the hourly salary a worker would earn before being engaged in caregiving. In case potential earnings are available, it holds that:

(4) $E[Y_{1,0}|Y_{0,0},T] - E[Y_{1,c}|Y_{0,c},T] = \xi.$

This means that the expected value of earnings of workers in caregiving $E[Y_{1,c}]$ would equal the expected value of earnings of individuals not in caregiving $E[Y_{1,0}]$, minus the caregiving bias ξ, once we control for occupation T (traditional or crowdwork) and unobserved potential earnings Y_0. This, of course, implies that $Y_{0,0} = Y_{0,c}$, meaning that, all else being equal, potential earnings are indifferent to caregiving.

However, we are only able to observe effective earnings. While we cannot observe potential earnings, we can nonetheless proxy for them through our set of controls X, which we believe can correctly predict them. In this is the case, Y_0 can then be replaced by our set of controls X. This will also allow us to filter out other endogenous aspects of caregiving linked, for example, with household size and marital status.

As it will be discussed later, our findings – see Table 6 below – suggest that hourly earnings are unaffected by caregiving after controlling for other observables. This implies that not only this bias is absent, but also, as long as there is no reason to suspect ξ to be positive, that the chosen set of controls correctly proxies for potential earnings as in equation 4.

In other words, while access to caregiving is most probably related to the inability to purchase formal care, we believe our set of control to correctly predict potential earnings and appease concerns concerning the violation of the exclusion restriction, given that the effect of caregiving on the hourly rate of pay appears null after controlling for these these variables.

Evidence from the literature provides support to these findings, as Ciani (2012) shows that caregiving, while affecting labour market participation, can be, in most cases, assumed as exogenous. Similarly, Leigh (2010) finds a direct effect on participation, while observing no impact on hourly wages, while Schmitz and Westphal (2017) also find female caregiving to be related to a decrease in probability in working full time, with no short-term effect on hourly wages.

Another potential concern comes from the fact that caregiving could influence skills, and thus the returns to them. However, when potential earnings are properly controlled for, caregiving is likely unable to influence ability. Caregiving could affect the opportunity to work more, not the relative skills of an individual – or how much the labour market rewards these skills.

The test presented in Table 6 is comparable to the zero-first stage test presented in Bound and Jaeger (2000), Altonji et al. (2005), and Angrist et al. (2010). Essentially, as we also present results from the effect of caregiving splitting the sample conditionally on the work type (crowdwork or traditional work), we are testing the effect of the instruments on samples where there is no first stage, as assignment into online working arrangements is undefined. Accordingly, individuals in caregiving who retain their status in traditional occupations should earn a lower hourly salary than comparable workers if transition to caregiving is only linked to the ability to purchase formal care, and cannot be properly controlled for by the other observables. This, however, does not happen, and suggests that the choice of caregiving as an instrument does not violate the exclusion restriction. As caregiving influences participation in crowdwork, crowdworkers in caregiving can, however, earn more than crowdworkers not in caregiving: in this case, the zero coefficient identified by those equations will then suggest, anticipating our final interpretation, that earnings in crowdwork are indifferent to individual ability.

While these are convincing arguments with regards the validity of caregiving as an instrument for hourly earnings, similar reasonings, however, prevent the use of the same instrument for the estimation of the effects of crowdwork on other outcomes. Indeed, as the crowdwork 'complier' group[24] will include individuals spending a significant amount of time in caregiving, we can expect the 2SLS estimates of working hours and weekly earnings to suffer from a downward bias, as will be discussed in the next section.

6 Discussion of results

Columns (1) to (3) from Table 2 present initial OLS results, using a sample of US crowdworkers from the ILO survey and regular workers from the AWCS. The dependent variable is hourly earnings and additional controls are added with each specification, with an initial sample including a total of 3,128 workers.[25] The coefficient for the dummy variable for working in crowdwork will denote the earnings differential between occupations.

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 respondent is the main contributor to the household's income and whether crowdwork is his/her main source of income. We also take into account a set of control dummies for the different US and EU28 states of residence (with a total of 79 states)

[24]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.

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

Table 2: OLS estimates of the effect of online platform work on earnings in the US and EU

VARIABLES	(1) US OLS	(2) OLS	(3) OLS	(4) EU OLS	(5) OLS	(6) OLS	(7) US+EU 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

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. The effect of the female dummy also remains negative and significant, confirming the presence of a gender pay gap in all labour markets. 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),[26] 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

[26]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.

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 and, as discussed earlier, provide support to our identification strategy.

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 magnitude 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.[27] Most importantly, the $Crowdwork \times Female$ interaction turns again not significant, 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. 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.

We also test for the presence of differential returns to observable skills in crowdwork by interacting crowdwork with education and maintaining the same specification from Table 2. The results suggest that disparities between traditional and platform workers persist and increase with the level of education. Most importantly, crowdwork arrangements appear to offer almost no return to observable skills, as the negative interaction coefficients mostly cancel out the returns to education in traditional occupations (Table B.1, Appendix).

Table 3 presents the results of our OLS regressions where we take into account the degree of routine intensity and abstractness of the tasks performed, with reference to both the traditional work and crowdwork samples. It is worth pointing out that, while occupation could be considered a poor choice for a control and, by inducing bias in the estimates, 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

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

Table 3: OLS estimates of the effect of online platform work on earnings in the US and EU

VARIABLES	(1) US OLS routine tasks	(2) OLS abstract tasks	(3) OLS a+r tasks	(4) EU OLS routine tasks	(5) OLS abstract tasks	(6) OLS a+r tasks	(7) US+EU OLS routine tasks	(8) OLS abstract tasks	(9) OLS 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 × 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 × 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

Notes: 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

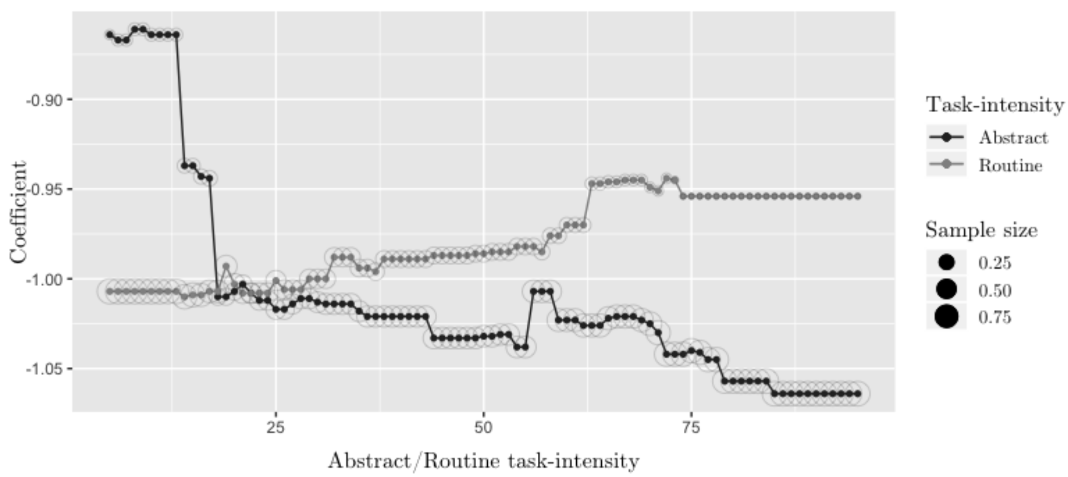

Figure 2: Estimated OLS coefficients from varying task-intensity splits (US+EU)

*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.

enhance our ability to explore the actual wage premium of traditional workers with respect to platform workers.

To this aim, we break down the two groups of workers finding regions of common support based on the degree of routine task intensity, abstractness, and a combination of the two indicators. We assign routine and abstract task intensity scores to individuals in the traditional occupations using the indicators from Autor and 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 and Autor (2011), and then averaging the scores after re-weighting each task by its relative frequency. Finally, we restrict the group of traditional workers to those observations whose routine and non-routine task intensity falls within the range of scores obtained in the crowdwork 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 crowdworkers and traditional workers, we provide a further robustness check in Figure 2, 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 3 (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 maximum abstract intensity of traditional occupations is lowered, the more the effect of crowdwork on earnings is reduced. A similar decrease is found when we raise the minimum routine content for regular occupations. Nevertheless, our previous interpretation is not invalidated: these contractions in the effect of crowdwork on earnings remain 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 minimum 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 4. 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), Table 4 – 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), Table 4, 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 occupations (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

Table 4: OLS estimates of the effect of online platform work on working hours in the US and EU

	(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 × *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 × *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

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, possibly linked to a scarcity in demand.

These results are consistent with the interpretation of Katz and Krueger (2018), who find slack in online platform work to be mostly involuntary and linked to economic reasons. Also, 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 and 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.

We now turn turn to out IV estimates for the effect of platform work on hourly earnings, which are displayed in Table 5, together with OLS estimates for both the full sample and a female-only sample.[28] 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 endogenous caregiving in the male sub-sample. 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). Complete first stage regressions are shown in Appendix B.

As discussed earlier, while the exogeneity of the instrument on the male population can be disputed, the literature points at caregiving being exogenous to the female population, implying that, if randomisation is achieved though this channel, the -0.918 coefficient could be considered close to an unbiased parameter of the effect of crowdwork on the earnings of the

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

TABLE 5: 2SLS ESTIMATES OF THE EFFECT OF ONLINE PLATFORM WORK ON EARNINGS IN THE US AND EU

	(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

Notes: 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

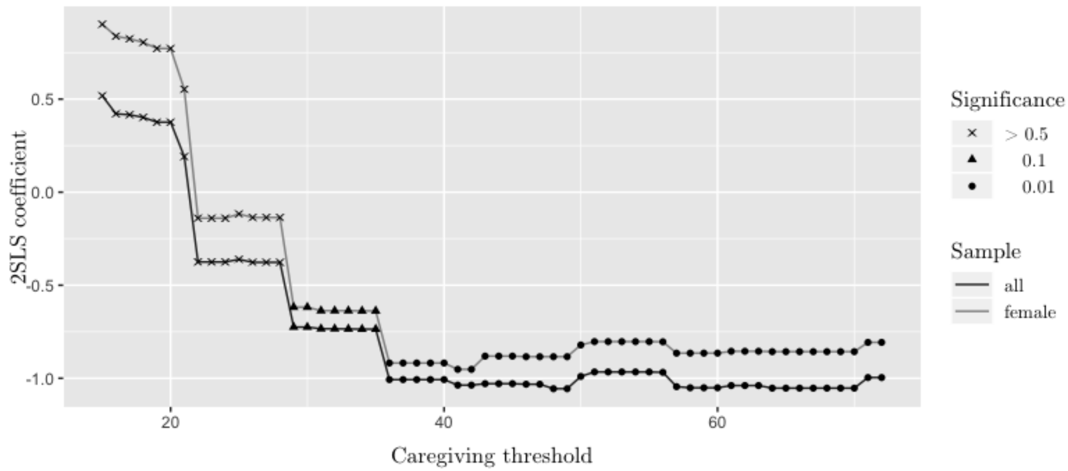

FIGURE 3: ESTIMATED 2SLS COEFFICIENTS FROM VARYING FULL-TIME CAREGIVING THRESHOLDS (US+EU)

*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 6: EFFECT OF CAREGIVING ON HOURLY EARNINGS (US+EU)

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Female only		
	C+T	T	C	C+T	T	C
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"(crowdwork and traditional work samples), "C" (crowdwork sample), "T" (traditional work sample). Notes: State clustered standard errors in parentheses. Dependent variable: natural logarithm of hourly PPP adjusted nominal earnings (US dollars). The dummy caregiving is first set at the 15h and then at 40h threshold, and the sample is reduced to the traditional work (AWCS+EWCS) groups in (2) and to the crowdwork (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.

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

whole population, given that these online labour platforms do not seem to generate further gender gaps in earnings. After generalising the split-sample estimates as in equation (3), we obtain a baseline reduction in earnings of 60.07%, raising our confidence in the results from the previous full sample specification. This interpretation holds even if we assume presence of gender based self-selection into the crowdworker population: should this hypothesis be true, then only full sample 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 two groups of platform and traditional workers, Figure 3 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. In this case, our interpretations from Table 4 should then be understood as not robust to unobserved heterogeneity, and alternative instruments should be considered for this specific analysis.

Caregiving certainly influences weekly earnings though two distinct channels: first, as more time is allocated to caregiving, the total number of maximum weekly working hours is reduced; secondly, this activity may also generate costs for the caregiver which influence how much he or she will necessitate to earn each week. As argued earlier, our focus on hourly earnings allows us to filter most of these issues out under the assumption that, in a static setting such as in our cross-section, platform workers are unable to individually influence their hourly salary, which is only determined by how efficiently they work. However, the less obvious implication stemming from this reasoning, as also discussed in Section 5, is that these caregiving costs may lead to a lowering of the reservation wage, which in turn could also affect participation in online labour markets and raise concerns with regards to violations of the exclusion restriction.

While this mechanism is expected and motivates our identification strategy by providing a theoretical justification for transition into crowdwork for individuals in caregiving, whether ability is linked to the level of prior and posterior reservation wages is, instead, a source of concern. In other terms, if individuals previously outside of the workforce are entering the labour force because of caregiving and are only able to join crowdworking arrangements

TABLE 7: 2SLS ESTIMATES OF THE EFFECT OF ONLINE PLATFORM WORK ON NET HOURLY EARNINGS, ADJUSTED FOR UNPAID TASKS, IN THE US AND 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 × *Female*	-0.002		-0.084		-0.032			
	(0.068)		(0.052)		(0.059)			
EU × *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
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

because of their ability, then self-selection into online labour markets cannot be excluded, and estimated will suffer from bias. At the same time, caregiving may not affect may not affect participation in crowdwork for individuals who already have access to other forms of income or who can purchase formal care.

Following from this reasoning, a final test for our instrument is provided in Table 6, where hourly earnings are regressed over the instrument and the full set of control covariates across partitions of our sample.[29] The analysis is performed for different specifications including, first, the 15 hours and, then, the 40 hours care-giving threshold, effectively showing reduced form estimates for the instrumental variable model. If heterogenous ability factors which we cannot already control for affect reservation wages and, in turn, participation in crowdwork, then we should see differential effects of caregiving in our reduced form estimates across the two groups of workers: non-caregivers in traditional occupations should earn more, on average, than their counterparts in caregiving, and caregivers who crowdwork should similarly earn less than other crowdworkers not in caregiving.

Our results, however, tell us a different story, indicating that our covariate selection already controls for these effects relatively well. While caregiving, under the 15 hours threshold, appears to have a negative and slightly significant effect on earnings in our full sample of female workers, these effects are rendered insignificant when performing the same regressions over the crowdwork and traditional work groups, indicating that the negative sign of that initial coefficient is entirely linked to the first-stage relationship between caregiving and crowdwork. Most importantly, when caregiving is set at its 40 hours, no significant effect on hourly earnings is found in any of the specifications presented in the Table.

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). As the income bias described in section 5.2 is accounted for, the exogenous variation left by the caregiving instrument will yield the income-indifferent individual propensity to assist a relative needing for care.

Last but not least, we model hourly earnings again while accounting for time spent in unpaid activities in Table 7. As a consequence, hourly earnings – columns (1), (3) and (5) – fall well below our previous estimates, displaying a coefficient of -1.323 (-73.3%), with the prediction moving to -70.6% when instrumenting participation in crowdwork in column (7). Comparable results also apply to the female population (columns 2, 4, 6, and 8), where IV estimates point at a 0.68% reduction in the hourly rate of pay.

[29]This analysis can be seen as an extension of the zero first-stage test for the validity of the exclusion restriction presented in Bound and Jaeger (2000), Altonji et al. (2005), and Angrist et al. (2010).

7 Robustness checks

7.1 Instrumental variable specification

In this section we perform robustness checks for our 2SLS model. The choice of caregiving in the female population as an instrument for participation in crowdwork calls indeed 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 the participation in crowdwork but not the duration of crowdwork arrangements. Differences in 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 spent 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 8 for time spent in the current occupation, a control that was previously excluded from the final model due to its – obvious – correlation with participation in crowdwork.

In the final models from Tables 5 and 7, 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 8, where we run the same final IV specification from Table 5, adding dummies for years spent in current occupation along with all prior covariates in columns (1) and (5).[30] In the subsequent 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 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 model. The trade-off is that, the more we reduce our sample size, the more our estimates lose in precision.

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

Table 8: 2SLS estimates of the effect of online platform work on hourly earnings in the US and 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

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 generalising for split-sample trends, as in equation (3), we can reasonably argue that working in crowdwork generates a negative effect on earnings ranging between 67.2 and 55.02% less than for comparable workers after controlling for time spent in current occupation.

Finally, as mentioned earlier, it could be argued that the inability to distinguish between different forms of caregiving may pose as a source of bias. Indeed, differences between surveys have led to the inability to disentangle caring for children from caring for elderly or disabled relatives. Evidence from studies such as Kremer and Chen (2002) suggests that fertility may be influenced by a number of social drivers. While we believe that our controls are able to filter these influences out,[31] 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 9, adopting the same approach used for the robustness checks in Table 8. The reductions in the "complier" group for crowdworkers leave to an increase in the variability of our estimates which 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 8, they surely suffer from some level of overestimation. In any case, these results do not contradict our previous findings.

7.2 Model specification

All robustness checks we previously presented rely on the correct specification of the IV estimator. In this section, instead, we address the concerns related to this approach by relying on an alternative specification for the estimation of the effects of crowdwork on earnings.

An interesting result from our IV estimates is that first-stage regressions produce comfortably high R-squared statistics, meaning that our set of observables adequately predicts assignment into platform work. If we have a correct specification for the probability to work in online labour platforms, then a binomial model can be used to compute propensity scores, which can be used to re-weight observations across the two groups of workers. Re-weighting

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

Table 9: 2SLS estimates of the effect of online platform work on hourly earnings in the US and EU

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US+EU				US+EU			
	Caregiving (Elderly only, 40h)				Caregiving (Elderly only, 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

Notes: State clustered standard errors in parentheses. Dependent variable: natural logarithm of hourly nominal earnings (US dollars). Control sample restricted to employed and 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

Table 10: Effect of online platform work on earnings in the US and EU

	(1) Coeff.	(2) Std.Err.	(3) z-score	(4) n
	Earnings (natural log)			
ATE				
Working in crowdwork	-0.877	0.294	-2.985	43,643
ATT				
Working in crowdwork	-0.928	0.316	-2.936	2,380
	Earnings†(natural log)			
ATE				
Working in crowdwork	-1.191	0.306	-3.886	43,643
ATT				
Working in crowdwork	-1.192	0.328	-3.629	2,380

*N*otes: IPWRA estimator of the average treatment effect (ATE) and average treatment effect on the treated (ATT) of online platform work on earnings. †: adjusted for time spent in unpaid activities. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

can be achieved through inverse probability weighting (first proposed by Rosenbaum, 1987; see Austin, 2011, for a methodological review of uses of propensity scores in quasi-experimental settings), where new weights are produced by assigning each observation the inverse of the conditional probability of its treatment status.

This means that, in our case, individuals in crowdwork will receive a weight equal to $1/p_i$, while traditional workers will be weighted $1/(1-p_i)$, where p_i indicates the propensity score; in other words, it indicates each individual probability $P(T = 1|X)$ to be working in crowdsourcing, given a set of covariates X. The differences of inverse propensity scores weighted averages will yield the effect of platform work, under the caveat that the underlying propensity score model is correct.

To overcome this issue, an inverse-probability-weighted regression adjustment (IPWRA), first covered by Robins et al. (1994) and further developed in Wooldridge (2007) is proposed, where inverse probability weighting is combined with regression adjustments in order to produce a doubly robust estimator. In IPWRAs, regression models are fit on inverse probability weighted observations according to their treatment status (meaning that the model is fit on two separate treatment and control samples), and the parameters from these models are used to predict counter-factual outcomes on an individual level, for all observations. The difference in means between treatment and control predicted outcomes will then yield the ATE.

The IPWRA estimator ensures that, as long as one of the two models, one for predicting assignment, and the other one for modelling outcome, is correct, then the results will not suffer from bias. We then use a binomial logistic model to calculate propensity scores,[32] and then assign the new weights to each observation so that a log-normal model for earnings can be fit across the two groups of workers, using the same covariate specification from Table 2, column 7 (omitting, for obvious reasons, the "Working in crowdwork" dummy). The results from our test can be found in Table 10.

Our estimates show that, after controlling for these different models, working in crowdwork still produces a statistically significant -69.62% reduction on earnings (adjusted for unpaid tasks). Extending our double robust approach to the estimation of the ATT, we find the effect on the treated to be close to -70% as well (with comparable statistical significance). These results are remarkably similar to the ones obtained by our previous instrumental variable approach (and OLS, by extension), and reinforce our finding that working conditions in crowdwork are generally unaffected by the characteristics of individuals working in these arrangements.

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 assemble data from different sources, harmonising responses from an online survey on crowdworkers with observations from two general surveys on workers' conditions in the US and EU, and then comparing outcomes across forms of work. 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 our contribution, we focused on the effects of individual ability on earnings in the platform economy, finding that most of the differences between platform workers and traditional workers are unexplained by individual characteristics. As we show that the effect of crowdsourcing on earnings is even larger as it could be expected from simple differences in means, our estimates cast a dark shadow over platform work: crowdsourcers earn 70.6% to 68.1% 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, suggest crowdworkers to belong to 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 hold for US and EU platform workers, the

[32] Covariates list: Female, Female*EU, Age, Age squared, No. of people in household, Main earner in household, Married or living with a partner, Health condition and Education controls.

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 specific skills and creative input from service providers, are offered, such as in the case of 'macro-task' freelance marketplaces like UpWork.

The observed disparities should then be attributed to factors other than individual ability. We were able to rule out the possibility that most of these differences are 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. competition from equally skilled but cheaper labour from other countries within the same platform;
2. scarcity and heterogeneity in demand for these kind of activities;
3. lack of labour rights and minimum standards stemming from the status of independent contractors.

In the first case, the earnings effect of platform work can be attributed to excess supply: indeed, the influx of "digital immigrants" may lead to an increase in labour supply and infra-task competition, lowering remunerations due to the low complementarity of these workers. Indeed, Borchert et al. (2018) have found that unemployment shocks, leading to increased participation in online markets, can have a positive effect on wage elasticities in crowdwork.

In the second case, it could be argued either that firms and clients are mostly uninformed about the possibility of outsourcing through online platforms, or that the sample of clients which employs online labour is intrinsically different in its nature from other firms employing traditional workers, generating scarcity in demand. While panel data are necessary to study these effects, the lack of particular differences between crowdworkers in 2015 and 2017 – in the ILO quasi-panel – indicates that, so far, the demand for these services has seen little growth. Also, while Katz and Krueger (2018) estimate a general rise in participation in the platform economy between 2005 and 2015 (from 10.7 to 15.8% in the US), evidence from Farrell and Greig (2017) could support the claim that these markets have, overall, reached their peak in 2016. Still, persistence of slack and factor under-utilisation in these markets is indicative of the presence of a mismatch between supply and demand which, if not found to change over the next years, could be described as a structural condition of crowdsourcing as a consequence of the nature of its clients.

In the third and final case, the monopsonistic nature of platforms, linked with the general lack of labour standards, enables the imposition of a heavy markup over online workers, allowing clients to operate at prices well below the market's marginal costs. These considerations are consistent with the results of Dube et al. (2018). As our results refer to year 2015, the influence of these factors could change in the future, in parallel with the evolution of the platform economy. In any case, 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 of these factors from the others.

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A - Summary statistics

Table A.1: Descriptive statistics on US workers employed in traditional occupations, AWCS 2015

	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 for workers in traditional occupations from the US (AWCS 2015). Sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home.

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

Table A.2: Descriptive statistics on EU workers employed in traditional occupations, EWCS 2015

	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

Notes: Weighted summary statistics for workers in traditional occupations from the EU (EWCS 2015), EU member states only. Control sample restricted to employed and self-employed individuals in working age, excluding freelancers working from home. Earnings are adjusted for purchasing power parity.

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

Table A.3: Descriptive statistics, US and EU crowdworkers, ILO (2015, 2017)

	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 for crowdworkers from the US and EU (ILO), pooled 2015 and 2017 survey waves. Earnings are deflated to the 2015 reference period (local currency) and then adjusted for purchasing power parity. †: adjusted for time spent in unpaid activities.

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

B - Returns to observable skills and first stage IV regressions

Table B.1: Returns to education in crowdwork in US and EU

	(1)	(2)	(3)
	US	EU	US+EU
VARIABLES	OLS	OLS	OLS
Working in crowdwork	-0.558	-0.837***	-0.806***
	(0.486)	(0.135)	(0.135)
Crowdwork × High school diploma	-0.260	-0.062	-0.056
	(0.472)	(0.113)	(0.115)
Crowdwork × Technical/associate degree	-0.370	-0.455***	-0.217*
	(0.474)	(0.107)	(0.117)
Crowdwork × Bachelor's degree	-0.674	-0.425***	-0.355***
	(0.473)	(0.139)	(0.120)
Crowdwork × Master's degree	-1.102**	-0.402***	-0.510***
	(0.490)	(0.116)	(0.133)
Crowdwork × Higher	-1.202**	-0.852***	-0.859***
	(0.534)	(0.165)	(0.162)
High school diploma	0.313	0.111***	0.109***
	(0.226)	(0.025)	(0.028)
Technical/associate degree	0.493**	0.264***	0.267***
	(0.207)	(0.034)	(0.035)
Bachelor's degree	0.758***	0.399***	0.413***
	(0.221)	(0.027)	(0.031)
Master's degree	0.998***	0.505***	0.520***
	(0.225)	(0.023)	(0.026)
Higher	1.111***	0.731***	0.754***
	(0.229)	(0.067)	(0.063)
Observations	3,217	27,676	30,893
Adjusted R-squared	0.408	0.380	0.382
Control covariates	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

Table B.2: 2SLS First and Second Stage coefficients of the effect of online platform work on earnings in the US and EU (Table 5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US+EU	US+EU	US+EU	US+EU	US+EU	US+EU	US+EU	US+EU
	Caregiving (15h)				Caregiving (40h)			
VARIABLES	First Stage full sample	Second Stage full sample	First Stage female only	Second Stage female only	First Stage full sample	Second Stage full sample	First Stage female only	Second Stage female only
Female	0.042***	-0.284***			0.027**	-0.213***		
	(0.012)	(0.059)			(0.012)	(0.049)		
$EU \times Female$	-0.040***	0.207***			-0.024*	0.146***		
	(0.012)	(0.053)			(0.013)	(0.048)		
Age	-0.004***	0.020***	-0.002*	0.018***	-0.004***	0.014***	-0.003**	0.016***
	(0.001)	(0.003)	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(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)	(0.000)	(0.000)	(0.000)	(0.000)
No. of people in household	0.001	-0.006	-0.001	-0.010	0.000	-0.004	-0.002	-0.009
	(0.001)	(0.005)	(0.002)	(0.008)	(0.001)	(0.006)	(0.002)	(0.008)
Main earner in household	0.021***	0.122***	0.024***	0.075**	0.022***	0.154***	0.026***	0.120***
	(0.006)	(0.024)	(0.006)	(0.031)	(0.006)	(0.016)	(0.006)	(0.019)
Main source of income	-0.873***	1.503*	-0.849***	1.818*	-0.866***	0.171	-0.835***	0.271
	(0.029)	(0.894)	(0.038)	(0.975)	(0.030)	(0.227)	(0.039)	(0.211)
Married or living with a partner	-0.004*	0.121***	0.011*	0.081***	-0.005**	0.115***	0.011*	0.102***
	(0.002)	(0.011)	(0.006)	(0.020)	(0.002)	(0.011)	(0.006)	(0.018)
Caregiving	-0.006		0.017**		0.044*		0.123***	
	(0.004)		(0.008)		(0.023)		(0.026)	
$Caregiving \times Female$	0.024***				0.077**			
	(0.008)				0.077**			
Working in crowdwork		0.518		0.902		-1.007***		-0.918***
		(1.060)		(1.158)		(0.247)		(0.236)
Observations	30,893	30,893	15,921	15,921	30,893	30,893	15,921	15,921
Adjusted R-squared	0.737	0.151	0.710	0.051	0.742	0.255	0.720	0.231
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test		18.33		23.35		47.20		90.36
First Stage R^2		0.738		0.712		0.742		0.722

Notes: 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