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Digital Labour Platforms in Europe: Numbers, Profiles, and Employment Status of Platform Workers

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Abstract

This report explores three issues related to the growing phenomenon of Digital Labour Platforms: firstly, how to measure platform work as a form of employment incorporating elements such as regularity of provision, time allocated and income generated; on this basis, and drawing on a new dedicated survey (COLLEEM), the article quantifies and categorises platform work into sporadic, secondary and main. Secondly, it provides an empirical investigation of the association between individual characteristics, such as gender, age, family composition, education and motivation, and the probability of carrying out particular types of platform work, such as microtasking, creative services, software development, transportation and so on. The analysis highlights substantial heterogeneity in the attributes and motivations of the workers performing different tasks. Finally, it discusses the employment status of platform workers and provides some descriptive statistics suggesting that a large share of platform workers perceive themselves as employees, even though they are in most cases legally considered self-employed.

1   Introduction

Digital labour platforms (DLP) are a new form of coordinating the provision of labour services and arguably one of the most visible results of the latest technological revolution in the world of work. Because they are relatively new, researchers strive to define and measure them, while policy-makers struggle to regulate them. Pesole et *al*. (2018) defines DLP as "digital networks that coordinate labour service transactions in an algorithmic way". De Groen et *al* (2018) provide a longer, more detailed definition of platform work as "an employment form in which organisations or individuals use an online platform to access other organisations or individuals to solve specific problems or to provide specific services in exchange for payment." Berg et *al*. (2018) draws a distinction between "web-based platforms, where work is outsourced through an open call to a geographically dispersed crowd ("crowdwork"), and location-based applications (apps) which allocate work to individuals in a specific geographical area". All these definitions share the underlying notion that DLPs act as intermediaries, hence not as conventional employers; they also imply that the object of each mediation is not a job in the traditional sense, but a single task or service – in this they differ from temporary agencies. Furthermore, they assume that management is carried out by algorithms, that is, step by step sets of instructions to automate the optimal allocation, monitoring and evaluation of jobs.

DLPs have attracted a lot of attention, both from the media and from policy-makers, because of their potential to disrupt labour markets. A priori, the impact of DLPs on employment is ambivalent: if on the one hand they can have a positive effect by increasing participation in the labour market through better matching procedures and more flexible working conditions, on the other, they can have a negative effect by circumventing regulation and lowering the quality of employment. If DLPs are to be considered as mere intermediaries, then it follows that they are not required to guarantee basic employment rights to the people whose services they coordinate, for instance a minimum wage, holiday pay, maternity leave or sick leave, and social security, as well as the right to organise into unions. If the size of the platform economy were to grow, as many predict, and DLPs kept on being considered as merely intermediaries, then a large proportion of the workforce would risk being excluded from employment protection and even some types of welfare provision.

However, DLPs have the potential to affect society not just by improving access to the labour market or damaging working conditions: if we conceive jobs as bundles of tasks, and understand that DLPs allow the unbundling of such tasks into atomized units, then we may conclude that DLPs could shatter the very notion of jobs by reducing them to single tasks. Such a dissolution of jobs would have consequences that go beyond work organization, as jobs are not only contracts for the provision of labour services, but, in Durkheim's words, they are a crucial anchor of "organic solidarity", a system of representations rooted in and reflective of concrete social groups (Lincoln and Guillot 2004).

However, while it is true that, at least in theory, DLPs can disrupt labour markets and the social structures in which they are embedded, their transformative power hinges on how widespread they are today and how widespread they are likely to become in the future. In other words, to assess the potential impact of DLPs, we need precise and reliable estimates of the number of people who spend a significant amount of time and gain substantial income via DLPs, because they are the ones who will be affected by platform regulation or the lack of it. At the same time, when we talk about the impact of DLPs on working conditions, it is imperative to understand whether platform work is just a side gig as it is often claimed, or whether it represents a major source of income. Thus, we need to ascertain the regularity, time allocated and income generated from platform work, as well as the employment status of platform workers, since this will provide information as to whether they have other forms of social protection from other jobs. Finally, to investigate the extent to which the unbundling of tasks is feasible, we need have detailed information of what type of tasks platform workers actually carry out.

In this paper, we address these questions by reviewing the academic and grey literature as well as by conducting an empirical analysis. The analysis draws from a new and unique source of data: the JRC COLLEEM survey carried out in 2017, which aimed to identify platform workers, their characteristics, the nature of their work, and their working conditions (Pesole *et* al. 2018).

The remainder of this paper is organised as follows: section 2 provides a quick review of previous attempts to measure platform work, then proposes a methodology and illustrates it with empirical estimates. Section 3 focuses on the types of tasks performed by platform workers. Section 4 discusses issues related to the employment status of platform workers, and section 5 concludes.

2 Estimating the number of platform workers across Europe

2.1 A quick summary of previous attempts

A few studies have tried to estimate the size of the platform economy in the last couple of years. In general, they follow two alternative approaches: one approach is to infer the size of the DLPs workforce through the use of publically available data, such as company reports, blogs, and so on. This approach often results in very low estimations. For instance, according to McKinsey (2015), approximately 1% of the US population provides services via DLPs; they reached this figure by simply summing up the number of people active on 10 platforms and dividing it by the US working age population. Farrel and Greig (2016) report a very similar figure for the prevalence of platform work in the US, between approximately 0.5% and 1.5%. To derive this figure, the authors calculated the proportion of JPMorgan Chase customers (nearly 6 million people) who received income at least once over the 36 months preceding the study from at least one of 42 online platforms. A study by the European Commission (2017) presents a similar figure, estimating that approximately 1.79% of European workers provide services via online platforms. However, even in this case the estimate is indirect and results from combining Eurostat aggregate data on sectoral employment with information on platforms revenues.

The second main approach found in the literature is to estimate the number of platform workers on the basis of a dedicated survey, generally ad hoc, and directly asking respondents whether they provide services via DLPs (Katz and Krueger, 2016; Robles and McGee, 2016; Flash Eurobarometer, 2016; Bonin; 2017; Huws et al. 2017; Lepanjuuri et al., 2018; Pesole et al., 2018). In this case, respondents who answer positively to a screener question are subsequently asked about frequency of provision, regularity, income earned and so on. Estimates coming from surveys generally yield much higher figures. It should be noted that drawing comparisons between these different studies is not that straightforward, because each one measures the phenomenon in a slightly different way; in addition, there is substantial heterogeneity across countries, so estimates at the aggregate level vary widely.

According to Huws et al (2017) about 2.9% of the people in their sample of seven European countries earned at least 50% of their income from platform work. Lepanjuuri et al. (2018) estimate that approximately 4.4% of people aged 18 over and in the UK did platform work during the previous 12 months. Pesole *et* al (2018) estimate that approximately 2.3% of the respondents in their sample of 14 European member states provide services via platforms as their main job.

Katz and Krueger (2016) estimate that only 0.5% of people aged 18 and over in the US do platform work as a main job. However, it would be hasty to say that DLPs are less widespread in the US than in Europe because the authors adopt a particularly restrictive definition, by only considering people who did platform work in the previous week; in addition, they define platform work as "any gigs, HITs or other small paid jobs […] through an online app, such as TaskRabbit or Uber". Similarly, the estimates for Canada (Statcan, 2017) are particularly low: 0.3%; however, the scope is limited to people who provide services such as "rides" facilitated by online platforms such as Uber or Lyft.

2.2 A conceptual framework to measure platform work as a form of employment

To assess the impact of DLPs on employment and on working conditions we need precise estimates of the number of people doing platform work; in addition we need information on what type of services they provide, how frequently these services are provided, how much money is earned as a result of this provision and so on. Most of the studies carried out until now provide only limited information, and often lack a conceptual framework guiding the analysis.

This section fills a gap in the literature by providing a framework on how to elicit all the necessary information so that an appropriate measure of platform work as a form of employment can be retrieved from the data. It should be noted that, because of the inherent difference between traditional employment and platform work, the latter cannot be quantified using exactly the same indicators and methodology of the European Union Labour Force Survey[1] (EU LFS) - the reference statistical source to assess labour participation in Europe. While the object of the LFS is regular employment, where work activity generally corresponds to a job, the object of a survey aimed at estimating the prevalence of platform work is to assess how many people perform, more or less regularly, atomised tasks via DLPs. The basic LFS question used to ascertain participation in the labour market – whether the respondent did any paid work as employee or self-employed in the 7 days before the interview – assumes that a person who answers "yes" has a job, and therefore carries out work activity with some regularity. However, if a respondent were asked if they did any paid work on a DLP and answered "yes", we would only know that the person has carried out a one-off task, without further indication on how regularly the task was performed.

This has two important corollaries for the purposes of measuring platform work: first of all, the identification of platform work as a form of employment requires that we assess not only whether someone has done some work via platforms on a particular reference period, but also the regularity, intensity and significance of that work; secondly, any measure of the attributes of the work performed or the type of labour relationship should refer to a specific task.

In practical terms, we propose the following principles to measure platform work as a form of employment - assuming that the measurement is implemented through a survey aimed at the working age population.

First of all, it is necessary to identify whether the respondent is part of the platform economy with a screener question. The screener question must include all the elements of the definition of platform worker, i.e. someone who provides services mediated by a DLP and gets paid for it. The question should be worded in such a way as to exclude platforms of a different nature, such as online marketplaces (e.g. eBay) or asset based platforms to rent out accommodation (e.g. Airbnb). Additionally, the following attributes of this work should be measured:

- Locus (online or in-person provision)

- Regularity (how often) over a specific reference period (e.g. last month)

- Time allocated (working hours) in the reference period.

- Income generated (in monetary terms and as a share of total personal income)

Information on the regularity, time allocated and income generated via DLPs, can then be used by the researcher to set thresholds to classify platform work as:

a) Main - equivalent to a regular job: regular, enough hours, enough income (whereby enough means more than a reasonable threshold)

b) Secondary – whereby the employment is somewhat regular, but less the respondents does not work enough hours (below a given threshold) and/or earns enough income through DLPs as to be considered her main job;

c) Sporadic - infrequent and inconsequential in terms of time or income.

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[1]   The European Union Labour Force Survey (EU LFS) is conducted in the 28 Member States of the European Union, 2 candidate countries and 3 countries of the European Free Trade Association (EFTA). The Labour Force Surveys are conducted by the national statistical institutes across Europe and are centrally processed by Eurostat. http://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

Estimates of the size of the platform economy in terms of employment should focus on the categories "secondary" and "main".

Secondly, a survey should identify the characteristics of the work itself by eliciting information on the specific tasks performed over the reference period. If respondents worked on multiple task categories, the time worked in each task category in the reference period should be asked.

More specifically, for the main task category over the reference period, the following information could be collected: number of transactions; number of platforms used; number of clients; income generated; time spent; typical location; and general conditions (physical and psychological risks, social interaction, intrinsic rewards and satisfaction).

2.3 An empirical demonstration to classify platform work as a form of employment

The JRC COLLEEM survey 2017 can be used as a source of data to illustrate how platform work can be measured as a form of employment. The JRC COLLEEM 2017 is an online survey representative of all internet users between 16 and 74 years old in 14 European countries. When compared to data from official statistics, the original sample of the survey appears to underrepresent certain profiles of respondents, therefore calibration weights should be used to present adjusted estimates.[2]

The JRC COLLEEM survey contains a screener question to identify platform workers as the one suggested in section 2.2. It asks whether the respondent has ever gained income from different online sources, among which there are two corresponding to DLPs (online/web-based or in-person): "providing services via online platforms, where you and the client are matched digitally, payment is conducted digitally via the platform and the work is location-independent, web-based" and "providing services via online platforms, where you and the client are matched digitally, and the payment is conducted digitally via the platform, but work is performed on-location (i.e. in-person)". Given that the definition appears to be rather lengthy, examples of typical platforms are provided to help respondents.

The share of the JRC COLLEEM sample that responded positively to either of those questions is reported in the first columns of panel 1 in Table 1. All categories in Table 1 refer to services provided either online or in person without differentiating, since the locus of service provision will be analysed in the next section. Because COLLEEM tends to overestimate the proportion of high frequency internet users, estimates have to be adjusted using information from Eurostat's ICT survey.

Adjusted estimates range from 6.9% in Finland to 12.5% in Spain. However, as we already mentioned, knowing that someone provided services via DLPs at least once in their life-time is not a particularly useful piece of information to infer the size of the platform workforce, therefore in the second column of panel 1, we report the share of people who provided services at least monthly. Predictably, the proportions drop for all countries, but not necessarily evenly or proportionately: for instance, the proportion of people who provide services via DLPs monthly is 4.6 percentage points smaller than the proportion of those who have ever provided services in Portugal, but less than 1 percentage point in the UK. In the second panel, we combine information on regularity, time allocated, and income, as suggested above, to show the proportion of respondents who provide services via DLPs sporadically, as a secondary activity, and as a main job. More specifically, the column "sporadic" identifies people who work between 0 and 10 hours a week on platforms and earn less than 25% of their total income from platform work; the column "Secondary" identifies respondents who earn at least 25% of their income via platforms (but less than 50%) and/or work via platforms between 10 and 20

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2   Calibration weights were computed using raking ratio estimation. Raking consists of adjusting proportions of certain variables in the sample to given population proportions. The survey was adjusted by country and the raking procedure included the following three variables: level of formal education, frequency of internet use and employment status.

hours per week; the column "main" identifies respondents who earn 50% or more of their income via platforms and/or work via platforms more than 20 hours a week. Unsurprisingly, the proportion of people doing platform work as main or secondary activity is significantly lower than the proportion of those who do it sporadically. The UK has the largest proportion of Platform workers who do it as a main job (3.6%), followed by the Netherlands (2.8%) and Spain (2.7%). At the bottom of the ranking we find Finland (0.9%) and Slovakia (0.9%).

Table 1: An estimation of platform work as a form of employment (adjusted for high frequency internet use)

	Panel 1: screener questions		Panel 2: core measures			
	Ever platform work	At least monthly platform work	Sporadic	Secondary	Main	Obs.
Spain	12.5%	10.2%	6.3%	2.6%	2.7%	2,331
UK	12.0%	9.9%	4.3%	3.2%	3.6%	2,320
Portugal	11.5%	7.8%	6.4%	1.8%	2.1%	2,305
Germany	10.6%	8.3%	4.2%	2.5%	2.6%	2,319
Lithuania	10.3%	6.5%	4.0%	1.9%	2.4%	2,308
Netherlands	10.2%	9.0%	4.1%	2.9%	2.8%	2,314
Italy	9.5%	7.5%	4.2%	2.5%	2.4%	2,317
Romania	8.8%	7.0%	4.8%	2.0%	1.4%	2,307
Croatia	7.9%	5.2%	3.7%	1.7%	1.4%	2,300
France	7.6%	6.0%	2.8%	2.3%	1.9%	2,315
Sweden	7.6%	5.5%	3.7%	1.2%	1.7%	2,321
Slovakia	6.9%	5.0%	4.0%	1.1%	0.9%	2,313
Hungary	6.9%	5.2%	2.8%	1.6%	1.8%	2,309
Finland	6.5%	4.6%	3.4%	1.3%	0.9%	2,310
Total	10.5%	8.0%	4.8%	2.3%	2.3%	32,389

Source: authors' elaborations using COLLEEM 2017; weighted data. To adjust for high frequency internet use, we calculated the share of daily and weekly internet users by country in COLLEEM, divided it by the share of daily and weekly internet users by country in the ICT survey in 2017 (isoc_ci_ifp_fu) and applied it to the estimates of platform workers in COLLEEM. Note: results are slightly different from Pesole et al (2018) because in this paper we use 2017 ICT survey data as opposed to 2016.

As previously mentioned, the information on regularity, time allocated and income generated by platform work should be collected by keeping in mind that the unit of analysis is the task, or at least a task-type.

The next section discusses how tasks in DLPs can be classified within a typology defined, among other things, by locus (online or in-person provision) and skills required.

3 What do platform workers actually do? A look at the type of tasks carried out

Labour services provided via DLPs can be broadly characterised as services performed online or via web and services performed in person or on location. This basic categorisation can be broken down further; for instance, Eurofound (2018) sketches a classification of platforms which takes into account skills required, scale of the task, selection process, and the form of matching as well as the locus of provision. However, combining all these elements would result in 120 combinations, so the authors focused on a smaller subset of 27. De Groen, Maselli and Fabo (2016) provide a much simpler classification resulting in four groups which combine skill (high/low) and locus of provision (in person/online). The JRC COLLEEM 2017 survey elicits information on types of task, which implicitly combines information on locus and skill level; Pesole et al (2018) use the information on tasks provided by COLLEEM to classify platform workers into three categories: professional, non-professional and on-location. The classification was used mainly to look at potential skill mismatch within each broader category.

For the purposes of this section, we will analyse the 10 different task types in the COLLEEM survey without grouping them into smaller sets, so as to exploit even minor differences.

The 10 tasks types defined by the COLLEEM survey are the following[3]:

- Online clerical and data-entry tasks (e.g. customer services, data entry, transcription, and similar);

- Online professional services (e.g. accounting, legal, project management and similar)

- Online creative and multimedia work (e.g. animation, graphic design, photo editing and similar)

- Online sales and marketing support work (e.g. lead generation, posting ads, social media management, search engine optimisation and similar)

- Online software development and technology work (e.g. data science, game development, mobile development and similar)

- Online writing and translation work (e.g. article writing, copywriting, proofreading, translation and similar)

- Online micro tasks (e.g. object classification, tagging, content review, website feedback and similar)

- Interactive services (e.g. language teaching, interactive online lessons, interactive consultations and similar)

- Transportation and delivery services (e.g., driving, food delivery, moving services and similar)

- On-location services (e.g. housekeeping, beauty services, on-location photography services and similar)

Respondents could choose one or more tasks; it must be noted that in many cases there is not a one-one association between a specific DLP and a type of task. For instance, a person who provides services via "Freelancer" may be carrying out online clerical and data-entry tasks, as well as online professional or creative services.

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[3] The survey also contains information on an 11th type of task, called on-location ancillary services, (e.g. housekeeping, cleaning) specifically to short-term rental accommodation (i.e. apartments listed on Airbnb and similar); however, the authors of the survey claim that it was put there just as control, and therefore we can disregard it.

Pesole et al. (2018) report that nearly 40% of the respondents who have ever provided services via DLPs carry out only one type of task; 23% claim to have carried out two types of task; 16.2% three; while the remaining 20% claim to have performed four or more types of tasks. This illustrates the problem of studying platform work as if it were a regular form of employment: whereas in the regular labour market it can be assumed that anyone employed can easily answer questions referring to their main job, people providing services via DLPs are likely to carry out many different tasks, linked to different characteristics and working conditions, and therefore may struggle to answer a generic question on the nature or conditions of their work. In theory, the problem could be overcome by asking the question on working conditions and characteristics only to those respondents who carry out just one type of task; however, this would result in a significant loss of information.

As per the relationship between the type of work carried out and the frequency or regularity with which it is done, one would expect to find significant differences between the categories identified in the previous section. Figure 1 shows the share of respondents who provide services sporadically, as a secondary activity and as a main job for each type of task, with the task types ordered according to the proportion of platform workers who performs them overall (number in red).

The category "sporadic" is almost always the dominant one, except among respondents who carry out professional tasks, which are more often likely to do it as a main job. Relatively medium skilled task types, such as translation, micro tasks or interactive tasks are the ones in which the proportion of platform workers who do it as a main job is lower.

It is also worth noticing the lack of clear correlation between how widespread a task type is and the proportion of people who do it sporadically, which suggests that the prevalence of a task type is not driven by the presence of people simply trying out.

Figure 1: Regularity of platform work by task type
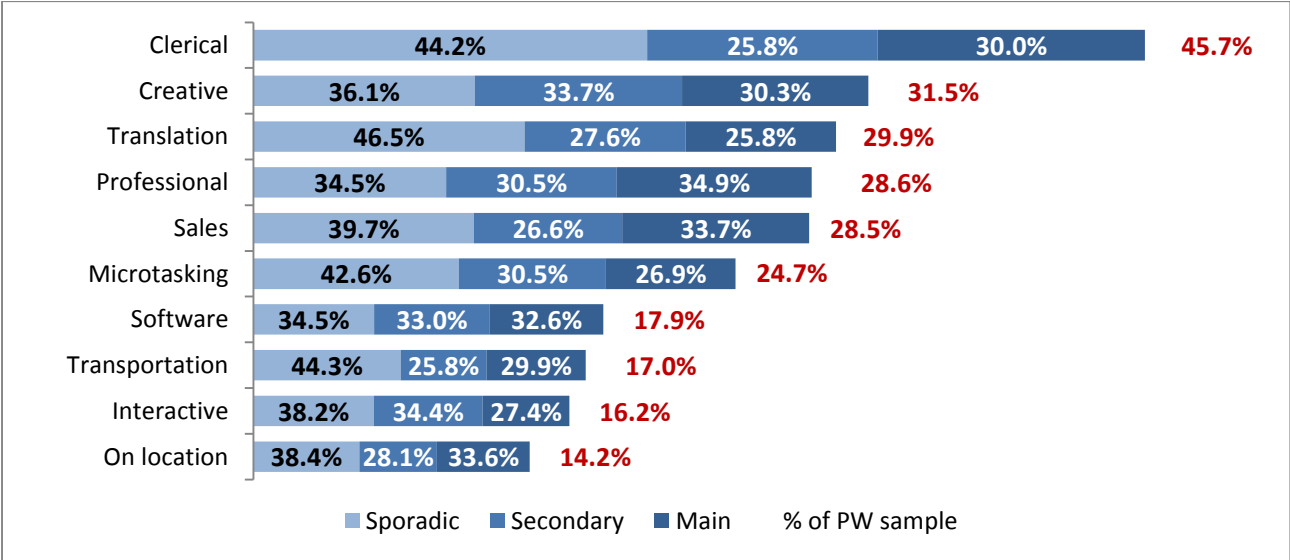
Source: authors' elaborations using COLLEEM 2017; weighted data.

Even in this case, any further analysis of task types should be limited to the sample of platform workers who provide services as a secondary or main activity, because they are likely to be more relevant from a policy perspective.

3.1 Socio-demographic profiling by task type: an empirical analysis

The empirical analysis of COLLEEM conducted by Pesole et al. (2018) revealed that, in general, platform workers tended to be young, highly educated males; when the authors regressed the three broad groups of task types – professional, non-professional and on-location – on the socio-demographic characteristics and country of residence of the workers, they found similar coefficients across all types, except for a higher probability of providing on-location services among the low educated. The study did not however look at the socio-demographic determinants of choosing each specific task type, which is what we are going to do in this section. Besides the usual socio-demographic control variables, such as age, gender, household composition and educational attainment, we add a few indicators relating to motivations provided for working in the platform economy. In a recent study carried out for the British Government, Broughton et al. (2018) report that flexibility of the work – both in terms of hours worked, location and work-life balance, was one of the main reasons for participating in the platform economy, based a series of qualitative interviews. We therefore create a few simple indicators (more details below) to investigate empirically their association with the choice to perform a given task. In addition, we include an indicator representing another typical motivation for working as self-employed which can be applied to platform workers, that is the desire to be one's own boss. Finally, as mentioned above, the sample will be limited to respondents who provide services via platforms either as a main or as a secondary job, hence excluding those who do it sporadically.

Econometric specification:

Let (y_n) be a binary variable equal to 1 if the respondent carries out a specific task type: clerical, creative, professional, translation, interactive services, software development, microtasking, sales, transport and on-location; in this case, the probability of choosing a specific type of task (y_n) can be estimated with a discrete choice model by maximum likelihood.

We run a probit model that includes as a vector of regressors: age, gender (1 = female), education (1 = low education, 2 = medium, and 3=high education), household composition (1 = couple), four indicators related to motivation (binary variables equal to 1 if respondents find important or very important flexibility over workplace, flexibility over hours, work-life balance and being one's own boss), and country level fixed effects, while ε is the error term.

We report average marginal effects, that is, how the probability of carrying out a task changes as the independent variables change in Table 2.

3.2 Results

Estimates in Table 2 show that the sign and coefficient of some of the socio-demographic characteristics associated with platform work vary significantly across tasks, while others remain remarkably similar. For instance, females are 5.0 percentage points less likely to perform creative tasks, 3.9 percentage points less likely to do microtasking, 4.1 percentage points less likely to do transportation and a 14.3 percentage points less likely to do software development; by contrast, they are 6.4 percentage points more likely to engage in translation work via DLPs. Interpreting the coefficient of the age variable is not as straightforward when estimating a probit model, and ideally we would have to look at average marginal effects at representative ages to get a more detailed picture. However, it is still possible to say that while in general age shows a negative correlation with the probability of being a platform worker, Table 2 suggests that the relationship is significant only for some types of tasks, namely clerical, creative, software development, translation and micro-tasking. Being part of a couple raises the probability of doing professional tasks by 5 percentage points and of doing software development by 3.7

percentage points, while has no correlation with the probability of carrying out other tasks. Having children appears to have a positive association with the probability of doing all tasks except for translation, microtasking and on location, which is consistent with the findings of Ipeirotis (2010) on a sample of microtasking workers (Amazon Mechanical Turk). High education appears to be positively correlated with all types of tasks, except for microtasking, transportation and on location; in particular, respondents with a degree are 8.8 percentage points more likely to perform professional tasks than those who have medium education, and 6.3 percentage points more likely to carry out software development tasks. On location tasks are the only ones that appear to be predicted by medium education given that both the coefficient on high education and the coefficient on low education have a negative sign.

The motivation related indicators are significantly associated only with the probability of carrying out a few specific tasks. For instance, flexibility to choose the place of work appears to be positively associated only with the probability of doing software development and interactive tasks, while flexibility over hours worked appears to have the strongest association with translation and microtasking (+6.9 percentage points) followed by creative, clerical and sales tasks.

Respondents who claim that an important motivation to do platform work is that it "offers a type of work that is more compatible with [their] family commitments than standard employment" (indicator=balance) are 6.5 percentage point more likely to do professional tasks than those for whom work life balance is not an issue, 4.0 percentage points more likely to do transportation tasks, but there is no significant association with other tasks. Finally, those who claim that the desire to be their own boss has been an important driver to choose platform work are more likely to carry out creative, translation or on location tasks.

Table 2: Average marginal effects of the probability of choosing a task-type

	(1) clerical	(2) professional	(3) creative	(4) sales	(5) Software	(6) translation	(7) microtasking	(8) interactive	(9) transportation	(10) onlocation
Prob (y=1):	0.445	0.295	0.330	0.288	0.199	0.281	0.240	0.168	0.164	0.139
	AME	AME	AME	AME	AME	AME	AME	AME	AME	AME
Female (d)	0.023	-0.015	-0.050**	0.005	-0.143***	0.065***	-0.039*	0.004	-0.041**	0.003
	(0.024)	(0.022)	(0.022)	(0.021)	(0.019)	(0.021)	(0.020)	(0.018)	(0.018)	(0.016)
Age	-0.002**	0.000	-0.003***	-0.000	-0.002***	-0.001*	-0.002**	-0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Couple (d)	-0.018	0.050**	0.011	0.011	0.037*	-0.033	0.016	-0.016	0.004	0.012
	(0.026)	(0.023)	(0.024)	(0.023)	(0.020)	(0.023)	(0.022)	(0.019)	(0.019)	(0.018)
Children	0.032**	0.035***	0.029**	0.021*	0.029***	0.008	-0.000	0.024***	0.019**	0.007
	(0.012)	(0.011)	(0.012)	(0.011)	(0.010)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Highedu (d)	0.053**	0.088***	0.033	0.056**	0.063***	0.049**	-0.012	0.028	-0.020	-0.032*
	(0.025)	(0.023)	(0.024)	(0.023)	(0.020)	(0.022)	(0.021)	(0.019)	(0.018)	(0.017)
Low educ (d)	-0.073*	0.026	-0.051	0.062	0.002	-0.103**	-0.130***	-0.076**	-0.003	-0.059*
	(0.044)	(0.040)	(0.042)	(0.039)	(0.036)	(0.042)	(0.041)	(0.036)	(0.032)	(0.031)
flexi_time	0.055*	-0.044	0.061**	0.051*	-0.014	0.071**	0.069***	-0.034	-0.002	-0.030
	(0.030)	(0.028)	(0.029)	(0.028)	(0.024)	(0.028)	(0.026)	(0.023)	(0.022)	(0.021)
flexi_place	0.018	0.034	0.016	-0.007	0.074***	-0.025	-0.009	0.057**	-0.010	0.001
	(0.031)	(0.028)	(0.029)	(0.028)	(0.025)	(0.028)	(0.026)	(0.024)	(0.023)	(0.021)
balance	0.017	0.065***	0.015	0.023	0.010	-0.014	-0.028	0.026	0.040**	0.023
	(0.026)	(0.024)	(0.024)	(0.023)	(0.021)	(0.023)	(0.022)	(0.020)	(0.019)	(0.018)
ownboss	0.005	0.011	0.074***	0.029	0.010	0.067***	-0.006	-0.015	-0.017	0.055***
	(0.026)	(0.024)	(0.025)	(0.024)	(0.021)	(0.024)	(0.022)	(0.020)	(0.020)	(0.019)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$P>\chi^2$	0.0000	0.000	0.000	0.0011	0.0000	0.0000	0.0002	0.0085	0.0008	0.0421
Pseudo R^2	0.0236	0.0411	0.0295	0.0214	0.0633	0.0272	0.0243	0.0238	0.0289	0.0215
Observations	1,933	1,933	1,933	1,933	1,933	1,933	1,933	1,933	1,933	1,933

Standard errors in parentheses are robust to heteroscedasticity

*** p<0.01, ** p<0.05, * p<0.1

Most of results are fairly intuitive and appear to be consistent with previous findings. What is remarkable is that by looking at task types separately rather than grouped as in Pesole et al (2018), different determinants emerge. For instance, the coefficient on being female is not significant in any of the regressions when the dependent variable is a group of tasks defined by high-low skill and locus of provision, where in in our analysis we find a significant association with five task types. This can be explained by the fact that creative, software development and translation tasks are grouped in the same category – i.e. professional – however the first two tasks are significantly and negatively associated with being a woman, while the association with the last type of task is positive. Similarly, being highly educated appears to be positively correlated not only with what Pesole et al term professional tasks, but also with some non–professional task types such as clerical or sales services.

Furthermore, some of the measures for motivation to participate in labour platforms appear in line with common knowledge while others seem more counterintuitive: for instance while it seems reasonable that people who are driven by the desire for flexible hours will opt for creative, translation or microtasking, the positive association between those who rate highly being one's own boss and on-location tasks appear less obvious, in the case of, for instance food delivery riders, and more acceptable in the case of ride hailing apps. This leads to the topic explored in the next section, the labour markets status of platform workers.

4 The actual or perceived employment status of platform workers

4.1 Legal issues about the employment status of platform workers

The classification of platform workers, the delineation of the relevant market, and the nature of the services provided by DLPs are some of the complex challenges that the platform economy poses to the legal system. Both Pesole et al (2018) and Huws et al (2017) highlight that the labour market status of platform workers is a challenging issue and arguably one of the most important from a policy perspective. The 2016 Communication of the European Commission on the Collaborative Economy calls for solutions that protect service providers (platform workers) without limiting the innovative potential of the platform economy with onerous regulation (European Commission, 2016). DLPs tend to qualify platform workers as independent contractors - a sub-category of the self-employed.

Even though some platform workers may display characteristics that are typical of independent contractors, others, for example those who carry out transportation or on-location tasks are more reminiscent of employees (De Stefano and Aloisi, 2018).

To fill what they perceived as a gap in employment legislation, Harris and Krueger (2015) proposed to create an intermediary, third category of workers: the Independent Worker, which would be specifically suited for (microtasking) platform workers. According to their proposal, such independent workers would gain rights to organise and bargain collectively and would also gain anti-discrimination protections in the US. However, this proposal would exclude payment for overtime and minimum wage arrangements.

The proliferation of individual lawsuits and grassroots organisations asking for a more accurate classification of platform workers supports the claim that not all platform workers should be classified as self-employed. However, the lack of a unified legal framework often results in uneven court rulings. For instance, in the case of Aaslam Y. & Farrar J. against Uber[4], the US employment tribunal ruled in their favour by agreeing that they were "workers" within the definition in s.230(3)(b) of the Employment Rights Act 1996, and were thus entitled to the minimum wage and holiday pay. However, the tribunal did not settle the issues of the employment status as it did not specify whether the claimants were also employees. Another example in the US is the case of Otey vs. Crowdflower in 2013,[5] where the court identified violations of the Fair Labor Standards Act (FLSA) and ruled in favour of a minimum wage for Crowdflower workers who performed microtasks via Amazon Mechanical Turk.

In France, a ruling of the Conseil des Proud'hommes de Paris in December 2016 has qualified the relation between a private-hire driver ("voiture de transport avec chauffeur") and a transportation DLP (Le Cab) as an employment contract, in light of the exclusivity clause preventing the driver from using other platforms or serving a customer on his own. In addition, the French social security institution has demanded contributions by Uber, therefore qualifying its "partner-drivers" as employees and not self-employed (De Stefano and Aloisi, 2018). In the UK grassroots organisations, such the "Independent Workers Union of Great Britain", have started promoting lawsuits to overturn the improper classification of platform workers and achieving remarkable victories, such as the right to a minimum wage and holiday pay. However, they did not manage to win the right to collective bargaining for on-location platform works who delivered food, as the High Court ruled in favour of the food delivery service app Deliveroo.[6]

In Italy, six platform workers providing on-location services (food delivery) through the DLP "Foodora" filed an employment claim before the Turin Employment Tribunal at the

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[4]   Employment Tribunal, Mr Y Aslam, Mr J Farrar and Others v Uber, Case Numbers: 2202551/2015 & Others, 28 October 2016.

[5]   Otey v. CrowdFlower, Inc., No. 12-cv-05524 JST, 2013 WL 4552493, at *3 (N.D. Cal. Aug. 27, 2013).

[6]   https://www.ft.com/content/51fb5da8-f879-11e8-af46-2022a0b02a6c.

end of 2017 asking that their contracts be reclassified as employment contracts, and therefore their dismissal ruled as unfair. On 11 April 2018 the tribunal ruled in favour of Foodora claiming that "riders" were completely free to accept or refuse any meal delivery requests from the platform, and therefore fit within the category of freelance, not subordinate employment.[7] Similarly, the British High Court judgment backed an earlier ruling by the Central Arbitration Committee (CAC), which found that Deliveroo riders cannot be classed as "workers" because they have the option of asking other riders to take their deliveries.

A recent study focusing on a specific type of on-location platform workers in Italy, specifically those providing services through a food delivery app, investigated the extent to which the characteristics associated with this type of work made it more similar to subordinate employment or self-employment (Giorgiantonio and Rizzica, 2018). The authors claim that to understand the extent to which platform workers should be classified as employee as opposed to self-employed it is necessary to have information on regularity, time allocated and income earned. In other words, only platform workers who provide services as a main job should be classified as employees. Albeit related because of policy implications, the employment status of platform workers is a distinct issue from the classification in terms of regularity, time allocated and income; a worker may be earning all of his or her income by providing professional services via DLPs and yet not fit within the category of employee. Furthermore, as Figure 1 showed, the proportion of platform workers who provide services via DLPs as a main job does not differ exceedingly across task types.

Pesole et al. (2018) tried to address this issue by classifying platform workers according to whether they claimed to have a side gig as self-employed. The authors initially comment on the problem of retrieving information on employment status by directly eliciting from platform workers, since workers themselves may not be aware of what their legal status is. They explain that the fact that many platform workers identify as employees does not imply that they have other employment contracts besides platform work, because they may be simply considering the provision of services via DLPs as subordinate employment. For this reason, Pesole et al. combine information on main employment status and additional self-employment provided by the COLLEEM survey to split the population of platform workers into the following five categories: Self-employed; Employees; Employee + self-employed (platform workers who are employees as main activity, but also self-employed as additional activity); Not employed (unemployed, retirees, students, and homemakers); and Not employed on the main but self-employed on the side (platform workers who claim to be mainly unemployed, retirees, students, and homemakers, but also have additional activity as self-employed).

The authors found that the proportion of platform workers who claimed to have self-employment as secondary activity was substantially higher among those who provided services more regularly. However, the study did not look at how different categories of employment status interacted with the types of tasks that platform workers provided, as we are doing in this section. A priori, we would expect a higher proportion of respondents who identify as self-employed among those who provide typically freelance services, such as creative, translation or software development tasks. Similarly, it would not be surprising to find a high proportion of platform workers providing transportation or on location services who claim to be employees.

4.2 An empirical assessment of the employment status of platform workers

This section builds on the work by Pesole *et* al (2018) and looks at the self-declared employment status of platform workers with a specific focus on task types.

We grouped the employment status of platform workers defined by Pesole *et* al. in four categories by focusing on the main issue, trying to assess whether platform workers consider the provision of services via DLPs as a form of self-employment (either main or on the side).

Table 3 report some simple descriptive statistics of employment status for sporadic, secondary and main platform workers.

Table 3: Employment status of platform workers

	Sporadic	Secondary	Main
Self-employed	7.0%	9.9%	13.8%
Employee	48.0%	38.5%	37.8%
Side-gig as self-employed	27.83	38.52	42.32
Not employed	17.3%	13.1%	6.1%
Observations	1,693	405	376

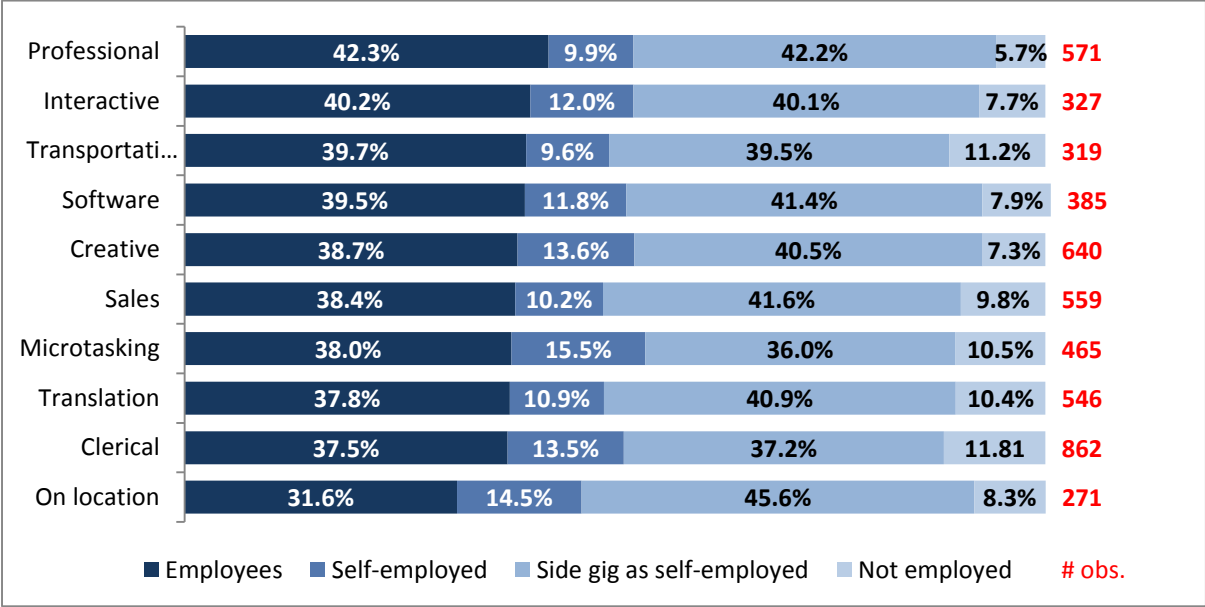*Source: authors' elaborations using COLLEEM 2017; weighted data.*

From Table 3 two things emerge: first of all, the proportion of self-employment as a main and as a side gig increases with the intensity of platform work. Secondly, even among secondary and main platform workers there is still a significant proportion of respondents (approx. 38%) who claim to be an employee. Respondents who claim to be self-employed and provide services via platforms as a secondary or main source of income are likely to consider their work via DLPs as a form of self-employment. Similarly, those who claim to have another main employment status, be it employee, student, retired or other, but also have a side gig as self-employed, probably consider platform work as their side gig. The fact that even allowing for a secondary status as self-employed we still find a substantial proportion of platform workers who claim to be an employee suggest that many of them probably consider their work via platforms as subordinate employment – which would not be entirely surprising, given the aforementioned court cases.

We further investigate whether the relationship between the self-reported employment status of platform workers as employee may depend on the task they perform in Figure 2. The sample is limited to platform workers who provide services as a secondary and main job.

Figure 2 illustrates the relationship between the four categories of employment status and the type of task platform workers carry out (sample limited to secondary and main platform workers). Because the emphasis is placed on respondents who claim to be only employees (with no secondary self-employment), the chart is sorted so that tasks with the highest proportion of only employees are at the top.

Platform workers carrying out professional, interactive or transportation tasks are the ones who report more frequently that they are only employees (42.3%, 40.2%and 39.7% respectively), while those who provide on-location services report being an employee with the lowest frequency (31.6%). In addition, on location platform workers report more frequently that they are self employed, both as a main job (14.5%) and as a side gig (45.6%). The highest proportion of platform workers who claim to be only self-employed occurs among those who carry out microtasking (15.5%) as well as on-location workers (14.5%), while, somewhat predictably, the same is true for a remarkably low proportion of platform workers who provide transportation services (9.6%).

Figure 2: Self-reported employment status by task type – only main and secondary platform workers

Task type	Employees	Self-employed	Side gig as self-employed	Not employed	# obs.
Professional	42.3%	9.9%	42.2%	5.7%	571
Interactive	40.2%	12.0%	40.1%	7.7%	327
Transportati...	39.7%	9.6%	39.5%	11.2%	319
Software	39.5%	11.8%	41.4%	7.9%	385
Creative	38.7%	13.6%	40.5%	7.3%	640
Sales	38.4%	10.2%	41.6%	9.8%	559
Microtasking	38.0%	15.5%	36.0%	10.5%	465
Translation	37.8%	10.9%	40.9%	10.4%	546
Clerical	37.5%	13.5%	37.2%	11.81	862
On location	31.6%	14.5%	45.6%	8.3%	271

Source: authors' elaborations using COLLEEM 2017; weighted data.

5 Discussion and conclusions

This article explored some key issues related to the emerging phenomenon of digital labour platforms: firstly, how to measure platform work as a form of employment incorporating elements such as regularity of provision, time allocated and income generated; secondly, how to investigate the services provided via DLPs, by focusing on task types as the unit of analysis; and finally how to classify the employment status of platform workers, given the current gap in legislation and unevenness in the literature.

Accurate measurement is crucial for understanding the current magnitude and potential growth of the platform economy. This article identified some necessary information to classify platform workers, and therefore be able to produce reliable estimates of the size of the DLP workforce. Ideally, future surveys investigating this subject should include all the basic elements identified in this paper: frequency of provision, time allocated and income generated, as well as characteristics linked to the task performed, such as number of transactions, platform used, time spent carrying out a task, and other general conditions. However, collecting information on regularity, time allocated and income generated via DLPs has implications beyond the need to estimate precisely the size of the platform economy: according to Broughton et al (2018), the experience of platform workers depends heavily on whether they are providing services via DLPs as their main source of income. If this is the case, they are more vulnerable to fluctuations in working time and therefore pay levels, short notice of working schedules, and suffer from a degree of precariousness in terms of a lack of employment rights. In addition, if platform work represents their main source of income, individuals may not have a real choice about which work to accept. By contrast, individuals providing services via platforms as a secondary or sporadic activity in order to top up their income are less vulnerable to fluctuations in the amount of work available and typically have more freedom to choose which jobs to accept and reject. The notion that a worker who provides services via platforms as a main job is not free to reject a job he or she does not want is in complete antithesis with the Foodora or Deliveroo court rulings, which was based on the formal characteristics of the work, rather than the substantial ones.

This highlights the importance to come up with a harmonized way to measure platform work, which is able to disentangle sporadic from main/secondary service provision, and regulate them accordingly. Furthermore, it is imperative to look at task types separately, and gather information directly linked to single tasks carried out rather than platform work in general, given the substantial heterogeneity not only in the intrinsic characteristics of different tasks, but also in the attributes and motivations of the workers performing them.

Finally, our findings suggest that even though a very large proportion of platform workers consider their work through platforms as a form of self-employment (either primary or as side activity) across all different types of tasks, a significant share still perceive themselves as employees, probably because they lack the kind of freedom and control over the work they do that is typically associated with self-employment. For these workers, a clarification of their employment status and a proper protection of their employment rights and entitlements is an urgent necessity.

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