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Shaping individual preferences for social protection: the case of platform workers

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Shaping individual preferences for social protection:

the case of platform workers[1]

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Abstract

Workers who perform their occupations through platforms are becoming an increasing share of the labour force. The debate is polarized between those arguing for platforms as an instrument to increase flexibility and labor force participation, and those who see it as a further mechanism to increase Non Standard Work (NSW). This debate is policy relevant because in either case, platform participation is associated to a difference in terms of willingness to contribute to the social security system. Nevertheless, the evidence is scant because we lack reliable data sources. In this contribution, we use a dedicated survey to estimate Willingness to Pay (WTP) for social security and estimate the causal impact of platform participation using a selection on observable strategy.

We found that platform workers are less disposed to contribute to social security, although perception of accessibility and adequacy are not affected. Results are robust to specifications and multiple hypotheses testing.

JEL Classifications: J32; J40; C21

Keywords: employment; preferences; work; economic behavior

1. Introduction

The XXI century has witnessed a profound reshaping of the European labor market. Although it started in the 1990s, the ongoing process of flexibilisation has been accelerating, increasing the proportion of non-standard employment (part-time, temporary contracts and self-employment). The increasing penetration of digital innovation has introduced a new actor, platforms, with consequences on both employment and industrial relations (Pesole et al. 2018; Eurofound, 2018a). Among non-standard type of work (NSW), "gig" (or crowd) workers not only represent a step further in the process of outsourcing and lengthening of the value chain, but also a new forms of work organization as occupations are replaced by tasks. Using Eurofound's definition, platform work "is a form of employment that uses an online platform to enable organisations or individuals to access other organisations or individuals to solve problems or to provide services in exchange for payment" (Eurofund, 2018b). The saliency of work in the day-to-day experience contributes to shape preferences. Among those, we can include the perception of entitlements to social protection (e.g. social rights), and the willingness to contribute to it. Social rights have been at the forefront of the current policy debate. In fact, the combination of new contracts with simpler firing procedure, product of labor market reforms and digital innovation, and the fiscal consolidation implemented as a result of the 2008 financial crisis proved to be a daunting obstacle to guarantee access to social rights (see among others Heyes 2013, Herman 2014, Moreira et al. 2015). Does work on the platform determine different perceptions regarding social rights? The answer to this question is complicated by the obvious fact that people self select into platform, sometimes for lack of opportunities elsewhere, sometimes to guarantee flexibility in the working arrangements.

Social protection became a policy issue, although there is currently no consensus on how to face it or solve it. The European Social Insurance Platform - a platform for transnational dialogue and exchange of best practices between national social security institutions in Europe- does not claim for a comprehensive reform of social protection, at least regarding digital platforms for work, while some Member States have already enacted specific legislation (Eurofound, 2018) and there is a proliferation of court sentences. For example, the Labor Inspectorate of Valencia stated that the workers of digital delivery companies are employees and not self-employed, therefore the platform was asked to pay due and unpaid social security contributions (Gomez, M.,2017). A similar sentence has been adopted by the Labor Inspectorate of Barcelona in July 2018. In Italy, the first sentence on a Foodora trial established that riders were not employees, however the sentence has been rejected during the appeal declaring

that those workers are entitled to the same economic treatment, including social protection, as employees in the same sector (transport and logistics). Other European cases can be found in the Eurofound repository of platform economy. However, court sentences spread around continents, like in Belo Horizonte, Brazil, and the one against Lyft in the US.

In general, those arguing in favor of gig workers as "self-employed" posit that platforms provides a channel to increase labor participation by those segments which are excluded from formal labor market (immigrants) or need special flexibility (women) and claim that extending social contribution and social protection would hurt the workers by inducing companies to suppress those jobs. Those arguing that platforms have a pervasive and intrusive planning of labor, suggest that the work relation is closer to subordination and require to extend fully the entitlements to social security. At the moment, the demand for social security is not well documented, because we lack reliable data, either because of the novelty of the phenomenon, or for lack of homogeneity in definitions. The debate is also plagued by *passions and interests* (Codagnone et al. 2016; Codagnone et al. 2019), as rhetoric replaces evidence based reasoning.

In this article, we aim at filling this gap. We try to identify the impact of the participation on the platform on the workers' demand for social protection, measured as the self-reported willingness to pay for it. Our empirical evidence is based on an original ad-hoc sample of European working-age adults collected by Codagnone et al. (2018).

The empirical strategy is to control for selection using observables. The survey questionnaire allows to control for a rich set of household and individual characteristics. We provide both OLS and matching estimation. The results suggest that belonging to a platform decreases the demand of social protection.

In the second part we explore mechanisms that may explain this phenomenon. We explore both preference traits such as risk and time preferences, and financial pressures. Apparently, none of these mechanisms that have been posited account for the change in willingness to pay.

The rest of the paper is organized as follows. In section 2 we discuss the main findings emerging from empirical literature on platform workers, in section 3 we present the data and some descriptive statistics. In section 4 we discuss the empirical strategy and the results. In the last section, we draw some conclusions.

2. Platform workers and social protection

Digital labour markets are defined as markets where labour-intensive services are traded on platforms that match employers and consumers with suppliers. The activity of digital labour market is one of the channels of diffusion of NSW that includes part-time work, temporary work and self-employment. NSW accounts on average 33% of total employment across OECD countries with wide ranging differences among countries - as low as 20% in Eastern Europe to up to 46% in the Netherlands (OECD, 2015). Among non-standard forms of work, involuntary part-time is the one which strongly increased from 22.4% of all part-time work to 29% between 2007 and 2015. Temporary contracts and self-employment increased in earlier decades till the onset of the recession in 2007, while part-time work continues to grow even during the recession. Still, those trends show high heterogeneity across countries. Similarly, in Europe the incidence of self-employment without employees changes towards self-employed that work for only one client (from 1.5% in 2010 to 3% in 2015), mostly in health and social care activities. This pattern seems to depict a shift of the employment relations from dependent to non-standard forms usually framed as self-employment activities. NSW is characterized not only by more unstable contract durations but also by lower entitlement to social protection schemes. Major differences apply between part-time and fixed-term workers and self-employed. The former are usually covered by social protection although less than full time standard workers, while self-employed are often excluded *a priori* since they are not covered by the specific employment law and regulation but rather by civil and commercial ones (Buschoff and Protsch 2008). Furthermore, the choice to hire a dependent self-employment rather than a different type of non-standard employee seems to be strategically driven by social security costs (Eichhorst et al. 2013). Overall, the reforming process occurred since the crisis did not reduce this form of segmentation, but rather deepened the reduction in social security for atypical workers instead of integrating them into a system of imperfect but at least universal flexicurity system (Heyes 2011).

Other forms of employment emerging after the crisis involve those related to the digital economy and in particular to platforms. We stress that a precise estimation of the magnitude of this phenomenon is still missing. We first start from the US. Katz and Krueger (2016) take advantage of a random sample to examine workers who identify customers through an online intermediary. Focusing on Google searches for terms related to online intermediaries, Harris and Krueger (2015) estimate that 0.4% of the employed work with online intermediaries; Farrell and Greig (2016) estimate it around 0.6% for US, looking at the frequency of bank deposits from online work platforms.

Using the Survey of Enterprising and Informal Work Activities (EIWA), Robles and McGee (2016) estimate a 4.3% rate of participation to platform work among all adult population in the previous six months. In Europe, a more recent survey aiming to be representative of all internet users between 16 and 74 years old in selected European countries (COLLEEM - COLLaborative Economy and EMployment) indicates that on average 10% of the adult population has used at least once online platforms for the provision of some type of labour services (Pesole et al. 2018). However, considering only "main platform workers" defined as those who earn 50% or more of their income via platforms and/or work via platforms more than 20 hours a week, authors account for about 2% of the adult population (Pesole et al., 2018). A strong heterogeneity emerges across European countries in terms of workers participation to digital platforms: the UK has the highest incidence of platform work, followed by Germany, the Netherlands, Spain, Portugal, and Italy. For the United Kingdom, CIPD (2017) interviewed a nationally representative sample of 5,000 employed people in the UK asking about their use of online platforms in the previous 12 months. The authors estimate that almost 4% of UK employed people can be classified as "gig workers". However, according to the same study, only 25% of this 4% work for digital platforms; 58% of the "gig workers" are permanent employees engaging in the "gig economy" to supplement their income. According to Huws et al. (2016), crowd work in the UK, Sweden, Germany, Austria and the Netherlands accounts for 5-9% of total employment, for half of them participation to digital platform accounts for no more than 10% of income. However, platform work accounts for more than half of household income for almost 2.4% in Austria, 2.6% in Germany, 1.7% in the Netherlands and 2.8% in both the UK and Sweden. Relying on an online survey in the US, UK, France, Sweden, Germany and Spain in 2016, Bugin et al. (2016) estimates that about 20%-30% of the working-age population were independent-earners and half of them used platform work as a complementary source of income. Online platforms were used by 3%-4.5% of the working-age population. Putting together this evidence, Eurofound (2018) states that the share of working-age population participating to digital platforms could be conservatively estimated in 0.5%.

Moving to the characteristics of platforms workers, it is usually highlighted that workers whose primary activity depends on digital platforms are a small fraction of all workers taking part to digital labour markets. Indeed, this should be taken into account when focusing on characteristics of digital platform workers and motivation for working in the gig economy. According to the evidence from the COLLEEM survey, the typical European platform worker is a young male, with tertiary education; whereas the proportion of women decreases as the

intensity of platform work increases. Looking at social protection, most studies highlight that the main issue is whether people working via digital platforms are employees or not, which implies a different degree of control that the platform exerts on the execution of the work and on the entitlements in terms of social security. Non-standard employment contracts do not have thresholds related to contribution, working hours and earnings. The self-employed lack the legal entitlements, face difficulties in meeting the eligibility threshold, and have a poor contribution record (Eurofound, 2018). As it clearly emerges from the COLLEEM survey, the employment status of platform workers is a controversial issue because on average in Europe 75.7% of platform workers claimed to be an employee (68.1%) or self-employed (7.6%). The fact that platform workers usually have a regular job (first/main job) as employees or self-employed revealed whether they are potentially covered by standard employment legislation, but digital workers can have a misleading perception concerning their employment status - Pesole et al. (2018) declared that the labour market status of platform workers remains unclear. Furthermore, the implications of digital labour platforms for work and employment are ambivalent (Pesole et al., 2018), since there may be a trade off between the possibility of an increase of labour market participation for more vulnerable groups (women, young, migrants, etc.) and weakening of working conditions, hampering representation and *voice,* and slashing social protection. The latter occurs because digital labour is not recognized as a dependent work and its classification in terms of employment status is fuzzy. Hiring platform workers as independent workers is an "attempts to remove the platforms from the responsibility of providing standard labour protections designated in labour law or collective bargaining agreements, including social protection benefits" as stressed by Berg et al. (2018).

Indeed, as digital labour markets concern labour issues, they have been the source of most of the legal disputes, and the rhetoric is very much entangled with some of the hypotheses of the economic and social science literature (see Codagnone et al. 2018 for a more extensive review). These stereotyped arguments include, among others, the idea that individuals work in these markets i) for pin-money or out of other non-monetary motivations; ii) that these are stepping stones toward better employment or entrepreneurship; iii) that they bring back to work the unemployed or underemployed (including students, stay at home parents, retirees), and iv) that they bring about a flat world online meritocracy making labour markets in general more efficient. However, the spread of digital labour markets can lead to new forms of precarisation, exploitation (Wood et al. 2018), and in most cases deprivation of any labour related rights and social protection. For example, Melián-González and Bulchand-

Gidumal's study (2018) claim that over the distribution of earnings from platform, even the income of the worker at the 75th percentile is not enough to make a living. Similarly, based on a survey involving Amazon Mechanical Turk and Crowdflower platforms, Berg (2016) stresses the poor income achievement of crowd workers both in the US and in India. Another pivotal issue is social protection coverage, which is spreading both at the country and European level. In 2018, within the European Social Pillar Rights framework, the European Commission launched a Council Recommendation on social protection accessibility -fixing minimum standard- to all workers regardless of the type of work (European Commission 2018). Still, the discussion is far from settled at the country level given the still ongoing debate on the status of platform work (Schoukens et al. 2018). With regards to coverage, few studies investigate the actual contribution to public or private protection schemes as a measure of the willingness to pay to get coverage. According to Berg (2016), only the 8.1% of workers economically dependent from platform work in the US report making regular contributions to a private retirement scheme and only 9.4% contribute to social security. As for India, the same study shows that only 13.7% per cent of crowdworkers contribute to a private fund. According to Berg et al. (2018) results from two ILO surveys conducted in 2015 and 2017 show that only the 16% of individuals economically dependent from platform work are covered by a retirement plan; this is strikingly in contrast with respect to the 44% reported by those who can rely on a different main source of income.

3. Data and Descriptive statistics

3.1 The data

Data used for the analysis are drawn from the ad-hoc survey collected for the European Commission initiative on extending social protection across different forms of employment (Codagnone et al. 2018). The data gather information on socio-economic characteristics, employment status, entitlement to social protection schemes, and the subjective attitude towards social protection. In fact, the questionnaire elicits the willingness to pay to have access to social security schemes. The sample includes 8,000 working-age adults in 10 European countries (800 per each of the 10 countries: France, Germany, Italy, Netherlands, Poland, Portugal, Romania Slovakia, Spain, Sweden) and is representative of the online population in each country, stratified as follows: a) 40% in open ended

full or part-time work; b) 40% in NSW (temporary part or full time contract and self-employed); 20% unemployed or looking for a job). The sample is therefore a three-strata sample including people in unemployment, standard employment and non-standard and self-employment.

The sampling strategy was designed to capture people in NSW (including self-employed) and to a lesser extent employer. For the purpose of having a sample capturing NSW, a non-proportional stratified random sample design was proposed, where the strata were defined by the different segments of employment in each country. Moreover, to increase representativeness of the sample, the design established quotas by gender and age, as additional blocking variables (see Codagnone et al, 2018 for additional details). This strategy allowed to produce information that (1) is representative for the population in each country and (2) pays special attention to the accuracy of the results in the segment of non-standard employment and self-employment.

Table 1 Descriptive statistics

	No Labour Platforms Workers				Labour Platforms Workers			
	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum
Willingness to pay	0.27	0.242	0	1	0.29	0.264	0	1
Accessibility	0.47	0.461	0	1	0.48	0.462	0	1
Adequacy	0.57	0.667	0	1	0.57	0.667	0	1
Share of workers with an open-ended contract	0.38	0	0	1	0.39	0	0	1
Share of self-employed	0.15	0	0	1	0.38	0	0	1
Age	41.12	40	16	80	40.80	40	18	66
Male	0.53	1	0	1	0.62	1	0	1
Partner works	0.46	0	0	1	0.49	0	0	1
Having a second job	0.12	0	0	1	0.29	0	0	1
0-11 years of education	0.132	0	0	1	0.077	0	0	1
12 years of education (high school diploma)	0.353	0	0	1	0.234	0	0	1
Some years of university (not completed)	0.130	0	0	1	0.142	0	0	1
University degree (BA, BS)	0.215	0	0	1	0.271	0	0	1
Post-graduate degree	0.171	0	0	1	0.277	0	0	1
Married or living with a partner, with children	0.390	0	0	1	0.426	0	0	1
Married or living with a partner, without children	0.187	0	0	1	0.156	0	0	1
Single with children	0.082	0	0	1	0.092	0	0	1
Single without children	0.341	0	0	1	0.326	0	0	1
In a rented dwelling I/we share with other people	0.410	0	0	1	0.410	0	0	1
In a dwelling that I/we own	0.436	0	0	1	0.466	0	0	1
With parents	0.154	0	0	1	0.124	0	0	1
Total work income (very low)	0.382	0	0	1	0.298	0	0	1
Total work income(low)	0.180	0	0	1	0.165	0	0	1
Total work inncome (medium)	0.168	0	0	1	0.202	0	0	1
Total work income (high)	0.270	0	0	1	0.335	0	0	1
Total household income (very low)	0.294	0	0	1	0.248	0	0	1
Total household income(low)	0.141	0	0	1	0.117	0	0	1
Total household inncome (medium)	0.147	0	0	1	0.156	0	0	1
Total household income (high)	0.418	0	0	1	0.479	0	0	1

3.2 Descriptive statistics

In Table 1 we report basic descriptive statistics, distinguishing between platform workers and others. Building on Codagnone et al. (2018), we consider as digital labour market those where (1) services of various nature are produced using preponderantly the labour factor (as opposed to renting property or a car); (2) where labour (i.e. the produced services) is exchanged for money; (3) where the matching is digitally mediated and administered although performance and delivery of labour can be electronically transmitted or physical; (4) where the allocation of labour and money is determined by a collection of buyers and sellers operating within a price system. Since we

are interested in the preferences toward social protection schemes of those working for the platform economy and/or selling goods, individuals using them to rent goods or services are excluded from the sample.

Within the population interviewed (8000 individuals), 1893 reported that they generate income from digital platforms (all kind of platforms), accounting for the 23% of the total sample. They are distributed among standard employment forms (30%), non-standard employment (52.6%) and unemployment (16.7%). We focus on the employment status of those participating to the platform, the motivations, and on perspectives on social protection. Those participating into the platform economy as "workers" or business units can be classified into two main groups: individuals whose main job is classified as an open-ended contract (both full time or part time) and self-employed.

While the share of individuals with an open-ended contract is similar between the two groups (0.38 for non-platform workers and 0.39 for the others), a significant difference emerges in terms of employment status: almost two out of five platforms' workers are self-employed against the 15% of non-platforms' workers. This difference brings several considerations to the front. First, social protection schemes across countries apply only to dependent workers and do not cover self-employers, therefore attitude towards them and the willingness to pay may differ accordingly. Second, the possibility to hold a job through platforms may be driven by employment status as long as digital intermediaries may serve self-employed, like free lancers to acquire new customers/clients, so they are considered mechanisms enabling their economic possibilities on the market. Finally, the choice to sell work services through the digital market could compensate lower work intensity and/or higher variability in labour income.

These hypotheses seem to be supported if we look at Table 1. In fact, as shown in the table, platforms workers tend to belong more frequently to higher income classes and are on average less willing to pay for social security although they are mainly self-employed. In particular, the share of platforms workers belonging to the highest income group is 33% against the 27% of those not working through platforms. On the opposite, the share of platforms workers belonging to the lowest class is 29% compared to 38% of non-platforms ones. The same holds if we look at the overall household income, with the share of platforms workers belonging to the richest groups being higher than that of non platforms workers. Platforms workers tend to be more educated. In particular, almost one out three holds a post-graduate degree against less than one tenth for non platforms workers. Finally,

on average age does not differ between the two groups although the maximum age for non platforms workers is substantially higher, 80 years old against 66.

Turning to the outcome variable, we defined the willingness to pay for social security by means of a principal component analysis putting together answers to all questions in the survey referring to willingness to pay.[3] The questions are the following ones: "Would you choose enrolling in voluntary social protection schemes, and if yes, what percentage of your current gross annual income would you be willing to pay to enroll in such schemes?" and is asked separately for benefits related with *unemployment, old age, maternity/paternity, sickness, invalidity, Accidents/occupational diseases*. For each item, the respondent might answer: 1 (no interest), 2 (yes up to 5%), 3 (yes from 5% to 15%), 4 (15% to max 25%). The scale of the answers has been re-codified in a continuous variable taking values from zero –highest willingness to pay- to 1 – lowest level. From the summary table emerges that on average non platform workers are more willing to contribute to social security although the difference is on average small; this is also true if we look at the median of such variable.

The same procedure has been applied to recode answers to the questions on the degree of accessibility to social security schemes.[4] In this case the lower the value the lower the degree of accessibility and we do not find at the summary level any difference between the two groups. Finally, when asked the perceived adequacy to social security the worker is entitled to, unconditional distributions across groups do not display significant differences[5].

[3] We calculate the Kaiser-Meyer-Olkin Measure of Sampling Adequacy. The result is 0.8469. KMO values between 0.8 and 1 indicate the sampling is adequate. The eigenvalue associated to the first component is 3.058, explaining 50% of total variability.

[4] The Kaiser-Olkin Measure of Sampling Adequacy is 0.8536 for accessibility. The eigenvalue associated to the first component is 3.643, explaining 60% of total variability.

[5]The demand for adequacy of social protection is the following one: "Do you think that in general the social protection you have access to provide adequate support for various situations such as becoming unemployed, covering old age pension, maternity/paternity leave, sickness leave, disability leave?" and the answer can assume values according to a scale from 1 to 4, where 1 stays for "very adequate" to 4 "Not at all adequate". Also, this variable has been standardized in order to range from 0 to 1.

4 The empirical strategy: Model and Results

Define Y to be our variable of interest, and D to be the dummy for the platform status, equal to one for platform workers and zero otherwise. Using standard notation from the Rubin Causal Model (Rubin, 1974; 1977; 1991; Angrist and Pischke, 2009), one can define Y^0 to be the outcome in absence of platform participation, and Y^1 as the counterfactual under participation. In this section, we will use the standard convention of calling treatment the participation to platform and control the lack thereof.

We are interested in $E[Y^1 - Y^0|D = 1]$, i.e. the average difference in outcome as a result of platform participation for those who are currently platform workers.

Using the dichotomous status of D, which is either one or zero, for the individual *i,* we get:

$$Y_i = D_i Y_i^1 + (1 - D_i)Y_i^0 = Y_i^0 + D_i\left(Y_i^1 - Y_i^0\right) = \alpha + \beta D_i + \varepsilon_i \quad [1]$$

Where α, β are respectively the average outcome variable under no participation, and the average impact of participation.

Given non random assignment to treatment, an estimation by OLS of [1] would not converge to β, because difference in (Y_i^1, Y_i^0) are systematically correlated with platform status. We condition on a set of observables that explain self selection into platform (X). In other words, we assume that:

$$E[Y_i|X, D = 1] - E[Y_i|X, D = 0] = E[Y_i^1|X] - E[Y_i^0|X] = E[Y_i^1 - Y_i^0|X] \quad [2]$$

This is normally defined as the Conditional Independence Assumption (CIA), which states that once we consider a certain value of a vector of covariates, the assignment to the platform is as good as random.

Define δ_X as the last term in [2], the average effect of platform participation on those who participated can be calculated as $E[\delta_X|D = 1]$. This can be interpreted as the weighted average of the impact of platform participation for those who participated across all the cells defined by the values of X.

The literature proposes different estimators of $E[\delta_X|D = 1]$. In the end, it is a matter of defining a weighting function for the estimated impact in each cell defined by the covariates. A regression estimator weights according to the variance of assignment to treatment (platform participation) in each cell, while matching methods weight according to the probability of assignment conditioned on the covariates.

We will perform both, using OLS and a number of matching estimators. The general form of the matching estimator is the following:

$$\widehat{\delta_{X|D=1}} = \sum_{i \in T} \omega_i \left(y_i - \sum_{j \in C} \omega_{ij}\, y_i \right)$$

where T is the set of indicators for treated units, and C is the set of indicators for control units, ω is a weighting function and *y* is the outcome of interest.

Covariates include socio-demographics characteristics (age, sex and education), household characteristics (marital status, partner work), occupational characteristics (having a second job, having an open-ended contract, being self-employed) individual and household income group, and a set of fixed effect for country and sector.

In using matching, practical problems are usually related with how we match ex post treated and control observation, and how we impose the common support over the set of covariates (Caliendo and Kopeining, 2008). For the latter, we use the minmax and a trimming: minmax simply drops all treated observation whose propensity score is higher than the maximum or lower than the minimum of that estimated on the controls; trimming exclude a percentage of treated observation for which the propensity score density of observation is the lowest.

For the former, we perform one-to-one matching without replacement, kernel matching, and a matching within the radius of 5%. We report the six combinations between the matching method, and technique used to impose the common support.

Our main dependent variable is the willingness to pay for social security, scaled from higher to lower WTP.

4.1 Results

In Table 2 below we report the main results. There is a significantly lower WTP for social security by platform workers. In Appendix A1, we report the estimation for perception of adequacy and accessibility of social protection. For those alternative outcome variables, we found no significant impact of platform participation.

In Table 2, second column, we estimate the standard error using Romano and Wolf stepdown estimator for multiple hypotheses testing (Romano and Wolf, 2005a; 2005b; 2016), including adequacy, WTP, and accessibility as dependent variables. The results for WTP are robust to multiple hypotheses testing.

In Table 3, we report the matching estimators. Regardless of the matching method, or technique to impose the common support, the results are very robust and stable. In Appendix, Table A2 we report the results for the other dependent variables, showing no significant difference.

Given that the standard deviation of WTP is 0.305, the effect size of platform participation is 9.8% of a standard deviation.

Notice that the average difference between platform and not platform worker is actually lower when we do not condition on unobservables, increasing from 2.3 to 3% in matching. In OLS regression, estimated coefficient from regression without control returns 2.3%, increasing to 3% after controlling for observables. If we follow the logic of Oster (2017) and infer the effect of selection on unobservables from the selection on observables, we would conclude that the impact on WTP is significantly bounded away from zero, even if the CIA in [2] does not hold.[6]

Another potential objection concerns the quality of the controls. In the set of covariates in Table 2 and 3, we include also income variables. Income variables are potentially affected by the treatment and thus may bias the estimation (Angrist and Pischke, 2009; Duflo et al. 2008). Our answer to this objection is twofold: the variables themselves are measured as discrete level, thus less likely to be causally affected by the treatment; moreover, even after removing them the results do not change (Table A3 in Appendix).

[6] This technique corrects for the estimation of the asymptotic bias due to omitted variables. It is usually implemented assuming a set of scenarios for how much would the R-squared explain in the case in which the unobservables would be included within the regressors. The overall logic is that if the selection on observables explain x% of the difference between treated and untreated and provided that the observables and unobservables have a similar importance (in a mathematically precise sense), one could estimate the true asymptotic treatment effect (see for example Bogliacino et al. 2018). In this case the exercise is pointless because controlling for selection would actually increase the estimated impact.

Table 2 OLS estimation of the impact of platform participation on WTP.

	Willingness to Pay	Willingness to Pay
	(OLS)	(OLS with adjusted p-values for multiple hypothesis testing)
Working on a Platform economy (only doing work)	0.0233**	0.0356***
	(2.74)	(4.66)
Open ended contract	-0.0490***	-0.0547***
	(-8.73)	(-8.79)
Sefl-employed	0.0114	0.00905
	(1.26)	(1.18)
Male	0.0172***	0.0177**
	(3.66)	(3.28)
Age	-0.00319*	-0.00383*
	(-2.12)	(-2.44)
Age squared	0.0000496**	0.0000542**
	(2.83)	(2.95)
High-school diploma	0.00680	-0.00413
	(0.81)	(-0.45)
Some years of University	0.00686	0.0113
	(0.73)	(1.03)
University degree	0.0000853	-0.0149
	(0.01)	(-1.45)
Post-graduate degree	-0.00726	-0.0265*
	(-0.88)	(-2.52)
Married or living with a partner, without children	0.0118	0.0125
	(1.38)	(1.69)
Single with children	-0.0134	-0.0216
	(-1.23)	(-1.82)
Single without children	0.000600	-0.0133
	(0.06)	(-1.34)
Partner work	0.0000754	-0.00453
	(0.01)	(-0.50)
Own property	-0.0152*	0.0000796
	(-2.55)	(0.01)
Living with parents	0.0180*	0.0271**
	(1.98)	(2.97)
Medium-low total annual income	-0.0327**	-0.0309**
	(-3.00)	(-2.85)
Medium-high total annual income	-0.0358**	-0.0286**
	(-3.27)	(-2.71)
High total annual income	-0.0436***	-0.0380***
	(-4.11)	(-3.50)
Medium-low total household income	0.0103	0.00934
	(0.92)	(0.77)
Medium-high total household income	-0.00335	-0.0141
	(-0.27)	(-1.23)
High total household income	-0.0254	-0.0353**
	(-1.90)	(-3.02)
Having a second job	0.0229**	0.0258***
	(3.04)	(3.56)
Sector and country dummies	0.337***	0.397***
Constant	(9.40)	(10.60)
N	6919	6976

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 3 Propensity Score Matching estimation of the impact of platform participation on WTP

Propensity score matching (common non replacement)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290677315	0.264780783	0.025896532	0.010481329	2.47

Propensity score matching (common non replacement with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290786374	0.26360883	0.027177545	0.010736092	2.53

Propensity score matching (common non replacement kernel)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290677315	0.264780783	0.025896532	0.010481329	2.47

Propensity score matching (common non replacement kernel with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290786374	0.26360883	0.027177545	0.010736092	2.53

Propensity score matching (common non replacement radius caliper)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290677315	0.26609751	0.024579804	0.008640708	2.84

Propensity score matching (common non replacement radius caliper with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Willingness to pay	Unmatched	0.291781231	0.268063835	0.023717396	0.007705611	3.08
	ATT	0.290786374	0.26594502	0.024841354	0.008708	2.85

4.2 Testing for causal mechanisms

Why would platform participation reduce the WTP for social security? There are two main explanations: on the one hand, platform participation is a sort of "last resource" to face financial difficulties, and thus WTP is simply determined by the budget constraint (Marvit, 2014; Uddin, 2012; Zittrain, 2009). Alternatively, platform workers are workers whose behavioral traits made them more rewarded by labour flexibility and do not want the side effect of social security protection (Hall and Krueger, 2018).

To assess this alternative explanation, we follow a diff-in-diff strategy (Card, 1990; Card and Krueger, 1994), where we include an additional control and we interact it with the platform dummy. For the former explanation, we use a variable from the questionnaire which explicitly asks about financial weakness ("Do you consider your financial situation weak?"). For the latter explanation, we use a variable that captures present bias in intertemporal preferences (Loewenstein and Prelec, 1992), and two measures of risk aversion (Pfeifer, 2008). These variables are constructed in the following way. Present bias is constructed from the questions: "When I make plans, I am confident I can make them work"; "Life is very stressful these days"; "It is not worth planning ahead as the future is so uncertain"; "I like to plan ahead carefully", all measured with a Likert scale from one to four. The variable is built through a principal component analysis, retaining the first component (eigenvalue of 1.46, explaining 36.66% of the variability) and rescaling from zero to one. The first measure of risk aversion is taken from the answer to the following question: "Suppose you are given a ticket that pays 100 euros if the flip of a coin is head, 0 otherwise. What is the minimum amount you would sell it for?", where a risk averse is a person which is declaring less than 50. The second measure is taken from the question "How do you see yourself: are you a person who is generally willing to take risks or do you try to avoid taking risks?", which is elicited through a Likert scale from 0 to 10, and we introduce a median split.

The coefficient of the interaction should be interpreted as shifting from risk loving to risk aversion in platform workers, with respect to the same shift in non platform worker (equivalently for financially sound and financially weak).

The results are reported in Table 4 below. Notice that both financial weakness and a measure of risk averse are significant and the sign comes out as expected: risk averse are more willing to pay for social security, and workers with financial constrains are less disposed to pay. However, the interaction effect is never significant. This implies that both explanations do a poor job in trying to account for the existing empirical evidence.

From Table 2 above, we can see that those workers with an open ended contract are more willing to pay for social security. Nevertheless, the nature of the contract is not an explanation either. In Appendix, Table A4, we report the estimation with an interaction effect with the dummy for open ended contract, and it doesn't come out significant.

It is possible that platform effect is quite heterogeneous, with *riders* or workers in the logistic sectors, which have been in the spotlight (both for their court appeals in Italy, UK, Spain, US – see above- and their collective actions,

mainly strikes, as the joint French strike of Ubereas, Foodora and Deliveroo riders in France during the Football World Cup or the New Years' Eve Strike in Amsterdam, Utrecht and Haarlem at the end of 2017, as reported by Bhagwat, 2018) as symbol of exploitation, coexist with professionals and freelancers whose search for clients benefits from platforms (Freelancers Union & Elance-oDesk, 2014; Freelancers Union & Upwork, 2015; MBO Partners, 2015). For the former, poor income and poor job quality makes them unwilling to contribute, whereas the latter are simply less willing to sacrifice their current status through what they perceive as paying taxes.

If this would be an explanation, then we should find that, on platform, low income and financially weak should be less willing to pay than either only low income or only financially weak. Similarly, on platform, high income and risk loving should be less willing to contribute than just risk lovers or high income. This is a triple difference strategy (Miguel and Kremer, 2004). Results are included in Table 5 below.

Table 4 Testing for causal mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Willingness to Pay								
Working on a Platform economy	0.0226**	0.0292*	0.0235***	0.0307**	0.0234**	0.0187	0.0230**	0.0216*	0.0225**
	(2.98)	(2.06)	(3.40)	(2.85)	(2.63)	(1.84)	(2.75)	(2.56)	(2.84)
Financially weak	0.0231***	0.0244***							0.0227***
	(3.89)	(4.02)							(3.70)
Platform * Financially weak		-0.00949							
		(-0.51)							
presentbias			0.00588	0.00817					0.00362
			(1.08)	(1.32)					(0.70)
Platform * Presentbias				-0.0164					
				(-1.03)					
Risk_Adverse					0.00452	0.00173			0.00599
					(0.72)	(0.26)			(0.91)
Platform* Risk Adverse						0.0220			
						(1.21)			
Risk Adverse (II)							-0.0122*	-0.0128*	-0.0128**
							(-2.22)	(-2.12)	(-2.68)
Platform * Risk Adverse								0.00467	
								(0.29)	
Open ended contract	-0.0468***	-0.0468***	-0.0488***	-0.0488***	-0.0490***	-0.0490***	-0.0489***	-0.0489***	-0.0466***
	(-7.46)	(-7.69)	(-8.26)	(-7.69)	(-7.33)	(-7.70)	(-7.57)	(-8.01)	(-6.71)
Sefl-employed	0.0138	0.0139	0.0118	0.0118	0.0113	0.0113	0.0109	0.0110	0.0133
	(1.76)	(1.59)	(1.43)	(1.46)	(1.33)	(1.33)	(1.33)	(1.49)	(1.46)
Male	0.0178**	0.0177***	0.0174**	0.0173**	0.0175***	0.0174**	0.0160**	0.0159**	0.0169**
	(3.16)	(3.34)	(3.28)	(3.03)	(3.50)	(2.98)	(2.84)	(3.01)	(3.04)
Age	-0.00356*	-0.00357*	-0.00331*	-0.00333*	-0.00319	-0.00320*	-0.00315	-0.00315*	-0.00360*
	(-2.17)	(-2.29)	(-2.16)	(-2.24)	(-1.76)	(-2.38)	(-1.80)	(-2.05)	(-2.25)
Age squared	0.0000538**	0.0000540**	0.0000509**	0.0000511**	0.0000496*	0.0000498**	0.0000494*	0.0000495**	0.0000544**
	(2.93)	(2.95)	(2.81)	(2.98)	(2.34)	(3.05)	(2.37)	(2.80)	(2.91)
High-school diploma	0.00734	0.00739	0.00706	0.00722	0.00684	0.00673	0.00663	0.00664	0.00737
	(0.76)	(0.75)	(0.85)	(0.90)	(0.80)	(0.68)	(0.78)	(0.76)	(0.83)
Some years of University	0.00729	0.00729	0.00739	0.00749	0.00691	0.00694	0.00656	0.00654	0.00735
	(0.60)	(0.61)	(0.67)	(0.78)	(0.65)	(0.60)	(0.63)	(0.59)	(0.61)
University degree	0.00116	0.00113	0.000764	0.000873	0.0000959	-0.0000838	-0.000179	-0.000237	0.00130
	(0.12)	(0.11)	(0.07)	(0.10)	(0.01)	(-0.01)	(-0.02)	(-0.03)	(0.13)
Post-graduate degree	-0.00600	-0.00592	-0.00655	-0.00639	-0.00727	-0.00740	-0.00739	-0.00741	-0.00573
	(-0.61)	(-0.51)	(-0.66)	(-0.69)	(-0.74)	(-0.65)	(-0.75)	(-0.79)	(-0.55)
Married or living with a partner, without children	0.0116	0.0116	0.0119	0.0119	0.0117	0.0116	0.0122	0.0122	0.0120
	(1.40)	(1.71)	(1.45)	(1.41)	(1.55)	(1.71)	(1.43)	(1.56)	(1.72)
Single with children	-0.0148	-0.0147	-0.0139	-0.0140	-0.0133	-0.0131	-0.0134	-0.0135	-0.0152
	(-1.28)	(-1.31)	(-1.32)	(-1.21)	(-1.10)	(-1.11)	(-1.13)	(-1.04)	(-1.37)
Single without children	0.000641	0.000768	0.000462	0.000655	0.000635	0.000692	0.000605	0.000583	0.000608
	(0.06)	(0.08)	(0.05)	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Partner work	0.000155	0.000219	-0.000123	-0.0000652	0.000141	0.000206	-0.000346	-0.000358	-0.000323
	(0.02)	(0.02)	(-0.01)	(-0.01)	(0.02)	(0.02)	(-0.03)	(-0.04)	(-0.04)
Own property	-0.0136*	-0.0136*	-0.0148*	-0.0146**	-0.0153*	-0.0153*	-0.0149*	-0.0148*	-0.0130*
	(-2.06)	(-2.20)	(-2.34)	(-2.58)	(-2.37)	(-2.53)	(-2.11)	(-2.25)	(-2.24)
Living with parents	0.0177	0.0178*	0.0180	0.0180	0.0180	0.0181*	0.0184	0.0184	0.0181
	(1.69)	(1.97)	(1.95)	(1.66)	(1.85)	(2.10)	(1.71)	(1.84)	(1.95)
Medium-low total annual income	-0.0321**	-0.0321*	-0.0327***	-0.0326*	-0.0328**	-0.0327**	-0.0332**	-0.0333***	-0.0327**
	(-2.92)	(-2.57)	(-3.31)	(-2.58)	(-3.02)	(-3.05)	(-3.24)	(-3.39)	(-2.94)
Medium-high total annual income	-0.0339**	-0.0339**	-0.0357**	-0.0356***	-0.0357**	-0.0358***	-0.0366***	-0.0366***	-0.0345**
	(-2.98)	(-2.80)	(-3.17)	(-3.39)	(-3.22)	(-3.36)	(-3.54)	(-3.44)	(-3.22)
High total annual income	-0.0399***	-0.0400***	-0.0434***	-0.0433***	-0.0434***	-0.0435***	-0.0446***	-0.0446***	-0.0406***
	(-3.44)	(-3.39)	(-3.70)	(-3.73)	(-3.68)	(-3.83)	(-3.97)	(-4.03)	(-3.47)
Medium-low total household income	0.0114	0.0114	0.0105	0.0107	0.0104	0.0104	0.0101	0.0101	0.0113
	(0.94)	(0.85)	(1.03)	(0.89)	(0.82)	(0.76)	(0.86)	(0.82)	(0.91)
Medium-high total household income	-0.00250	-0.00241	-0.00314	-0.00314	-0.00339	-0.00317	-0.00351	-0.00351	-0.00260
	(-0.21)	(-0.20)	(-0.24)	(-0.25)	(-0.27)	(-0.27)	(-0.32)	(-0.33)	(-0.23)
High total household income	-0.0215	-0.0214	-0.0247	-0.0248*	-0.0254*	-0.0252	-0.0259*	-0.0258*	-0.0218
	(-1.63)	(-1.73)	(-1.87)	(-2.16)	(-2.09)	(-1.88)	(-2.09)	(-2.13)	(-1.82)
Having a second job	0.0223**	0.0222**	0.0228***	0.0229**	0.0229***	0.0230**	0.0222**	0.0221**	0.0214**
	(2.73)	(2.78)	(3.62)	(2.79)	(3.38)	(2.77)	(2.61)	(2.94)	(3.05)
Sector and country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.323***	0.322***	0.336***	0.335***	0.336***	0.336***	0.343***	0.343***	0.327***
	(8.33)	(8.87)	(9.08)	(9.94)	(8.00)	(10.23)	(9.17)	(8.39)	(8.29)
N	6919	6919	6919	6919	6919	6919	6919	6919	6919

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 5 Testing for causal mechanisms and interactions

	Willingness to Pay	Willingness to Pay
	(OLS)	(OLS)
Working on a Platform economy	0.0292	0.0204
	(1.72)	(1.80)
Financially weak	0.0278***	
	(3.34)	
Working Platform*financiallyweak*middle Low income	-0.0116	
	(-0.36)	
Working Platform*financiallyweak	-0.00443	
	(-0.20)	
Working on a Platform economy* Middle low income	0.00223	
	(0.08)	
Financially weak*middle low income	-0.00831	
	(-0.62)	
Risk Adverse		-0.0130*
		(-2.22)
Working on Platform *Risk adverse		0.00295
		(0.15)
Risk adverse* Self-employed*Working on Platform		0.00615
		(0.17)
Risk adverse*Self-employed		0.00106
		(0.06)
Self-employed*Working on Platforms		0.00422
		(0.20)
Open ended contract	-0.0469***	-0.0488***
	(-8.20)	(-7.18)
Sefl-employed	0.0137	0.00938
	(1.67)	(0.90)
Male	0.0178***	0.0159**
	(3.33)	(2.59)
Age	-0.00353*	-0.00318
	(-2.31)	(-1.86)
Age squared	0.0000536**	0.0000497*
	(3.02)	(2.52)
High-school diploma	0.00745	0.00668
	(0.93)	(0.73)
Some years of University	0.00729	0.00650
	(0.69)	(0.54)
University degree	0.00116	-0.000131
	(0.12)	(-0.01)
Post-graduate degree	-0.00579	-0.00736
	(-0.54)	(-0.68)
Married or living with a partner, without children	0.0118	0.0122
	(1.66)	(1.45)
Single with children	-0.0145	-0.0135
	(-1.32)	(-1.05)
Single without children	0.000963	0.000553
	(0.10)	(0.06)
Partner work	0.000353	-0.000364
	(0.04)	(-0.04)
Own property	-0.0135*	-0.0148*
	(-2.04)	(-2.32)
Living with parents	0.0179*	0.0184*
	(1.97)	(2.03)
Medium-low total annual income	-0.0334**	-0.0334**
	(-2.98)	(-2.98)
Medium-high total annual income	-0.0367**	-0.0367**
	(-3.14)	(-3.14)
High total annual income	-0.0447***	-0.0447***
	(-3.63)	(-3.63)
Medium-low total household income	0.0100	0.0100
	(0.86)	(0.86)
Medium-high total household income	-0.00354	-0.00354
	(-0.25)	(-0.25)
High total household income	-0.0258	-0.0258
	(-1.72)	(-1.72)
Having a second job	0.0220**	0.0220**
	(3.06)	(3.06)
Sector and country dummies	Yes	Yes
Constant	0.326***	0.344***
	(9.01)	(8.21)
N	6919	6919
* p<0.05, ** p<0.01, *** p<0.001		

5. Conclusions

The aim of this work is to shed light on the relationship between the employment status of the platform workers and the demand for social protection adequacy taking into account both individual, household and job characteristics. We exploit an ad-hoc sample of workers, from a survey design to investigate the demand for social protection by NSW. The questionnaire covers a large array of socio-demographic and economic topics, and investigates explicitly perception of adequacy, accessibility and willingness to pay for social security.

We try to identify the impact of platform participation on those perceptions. Since participation is not randomly assigned, we control for a large set of observables characteristics and explore a variety of methods.

We found a significant effect of platform participation on the willingness to pay for social security. In particular, platform workers are significantly less willing to contribute. We explore a number of mechanisms. Some scholars argue that platform participation is a sort of "last resource" to face financial difficulties. Others, that platform workers are self employed rewarded by labour flexibility. Neither explanation is explaining the stylized facts. The nature of the contract is not the main explanation, according to the data, and heterogeneity is not a main driver of the evidence, even though this explanation may be downplayed by the nature of the data.

In fact, our major limitation is the lack of details linking the actual occupation as platform worker, i.e. riders versus freelance professionals, a difference that could help exploiting the heterogeneity of platform workers and their attitude toward social welfare systems. Another limitation is the impossibility to disentangle those workers actually performing work services and those getting rewards as online survey respondents.

We close by suggesting that the right policy mix should consider the heterogeneity of these workers. On the one hand, there are clearly situations in which the condition of dependency requires the full recognition of the subordination, and the extension of the required extension. For freelances and independent workers, the "old style" extension of benefits may be a poor strategy.

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Appendix

Tab. A1 OLS on platform workers defined as those doing work for business or individuals

	OLS		OLS with adjusted p-values for multiple hypothesis testing	
	Accessibility	Adequacy	Accessibility	Adequacy
Working on a Platform economy (only doing work)	0.00284	-0.00249	-0.00276	-0.0125
	(0.41)	(-0.27)	(-0.37)	(-1.44)
Open ended contrat	-0.0493***	-0.0771***	-0.0518***	-0.0708***
	(-8.58)	(-11.29)	(-8.61)	(-9.92)
Sefl-employed	0.0360***	0.0566***	0.0356***	0.0498***
	(4.49)	(5.77)	(4.66)	(5.57)
Male	-0.00202	-0.0206**	0.00530	-0.0240***
	(-0.41)	(-2.92)	(1.00)	(-3.83)
Age	0.00140	0.0126***	0.00536***	0.0130***
	(0.86)	(6.15)	(3.50)	(7.14)
Age squared	-0.00000446	-0.000115***	-0.0000529**	-0.000120***
	(-0.23)	(-4.72)	(-2.95)	(-5.65)
High-school diploma	0.0209*	0.00962	0.0205*	0.0138
	(2.43)	(0.90)	(2.32)	(1.31)
Some years of University	0.00685	0.0178	-0.00288	0.0242
	(0.69)	(1.34)	(-0.27)	(1.93)
University degree	-0.00229	-0.00323	-0.00573	0.00762
	(-0.22)	(-0.26)	(-0.58)	(0.66)
Post-graduate degree	0.00845	0.00213	0.00730	0.0183
	(0.82)	(0.16)	(0.73)	(1.53)
Married or living with a partner, without children	0.0270**	0.0257**	0.0296***	0.0299***
	(3.24)	(2.76)	(4.10)	(3.49)
Single with children	-0.0121	0.0167	-0.00683	0.00359
	(-1.12)	(1.31)	(-0.60)	(0.26)
Single without children	-0.00888	0.0148	-0.00225	0.00973
	(-0.87)	(1.23)	(-0.23)	(0.83)
Partner work	-0.0202*	-0.00450	-0.0153	-0.0180
	(-2.30)	(-0.45)	(-1.73)	(-1.68)
Own property	-0.0118*	-0.0156*	0.000222	-0.0337***
	(-2.08)	(-2.55)	(0.04)	(-4.94)
Living with parents	0.0152	0.0149	0.0372***	0.00687
	(1.70)	(1.45)	(4.20)	(0.65)
Medium-low total annual income	-0.0300**	-0.0407***	-0.0421***	-0.0203
	(-2.92)	(-3.47)	(-3.93)	(-1.64)
Medium-high total annual income	-0.0391***	-0.0475***	-0.0355***	-0.0315*
	(-3.84)	(-3.78)	(-3.32)	(-2.51)
High total annual income	-0.0455***	-0.0488***	-0.0463***	-0.0561***
	(-4.26)	(-3.86)	(-4.24)	(-4.41)
Medium-low total household income	-0.00397	0.0256*	0.0146	0.00425
	(-0.32)	(1.98)	(1.22)	(0.31)
Medium-high total household income	-0.00584	-0.00865	-0.00883	-0.0181
	(-0.50)	(-0.63)	(-0.77)	(-1.33)
High total household income	-0.0194	-0.00517	-0.0153	0.00150
	(-1.54)	(-0.38)	(-1.29)	(0.11)
Having a second job	-0.00447	-0.0160	-0.0148*	-0.0172*
	(-0.66)	(-1.63)	(-2.07)	(-2.07)
Sector and country dummies	Yes	Yes	Yes	Yes
Constant	0.480***	0.287***	0.384***	0.279***
N	(13.60)	(5.26)	(10.51)	(6.42)
	6919	6919	6932	6949

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Tab. A2 Propensity Score Matching on platform workers defined as those doing work for business or individuals

Propensity score matching (common non replacement)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.47340088	0.47507726	-0.00167638	0.0099682	-0.17
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12
	ATT	0.56194389	0.56776182	-0.00581793	0.01182725	-0.49

Propensity score matching (common non replacement with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.46915317	0.47073575	-0.00158258	0.01008179	-0.16
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12
	ATT	0.55674903	0.5621196	-0.00537057	0.01208561	-0.44

Propensity score matching (common non replacement kernel)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.47340088	0.47507726	-0.00167638	0.0099682	-0.17
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12
	ATT	0.56194389	0.56776182	-0.00581793	0.01182725	-0.49

Propensity score matching (common non replacement kernel with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.46915317	0.47073575	-0.00158258	0.01008179	-0.16
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12
	ATT	0.55674903	0.5621196	-0.00537057	0.01208561	-0.44

Propensity score matching (common non replacement radius caliper)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.47340088	0.47217998	0.0012209	0.0081372	0.15
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12
	ATT	0.56194389	0.56792049	-0.0059766	0.00970909	-0.62

Propensity score matching (common non replacement radius caliper with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Accessibility	Unmatched	0.47422107	0.46760193	0.00661914	0.00738478	0.9
	ATT	0.46915317	0.46921388	-6.0712E-05	0.00811837	-0.01
Adequacy	Unmatched	0.56258505	0.56361903	-0.00103398	0.00897998	-0.12

ATT	0.55674903	0.56345318	-0.00670415	0.00970865	-0.69

Tab A3. OLS and OLS with correction without income variables

	Willingness to Pay	Willingness to Pay
	(OLS)	(OLS with adjusted p-values for multiple hypothesis testing)
Working on a Platform economy (only doing work)	0.0234**	0.0129
	(2.74)	(1.76)
Open ended contract	-0.0651***	-0.0650***
	(-11.79)	(-11.65)
Sefl-employed	-0.00235	-0.00698
	(-0.27)	(-0.96)
Male	0.00728	0.00820
	(1.39)	(1.62)
Age	-0.00242	-0.00125
	(-1.59)	(-0.85)
Age squared	0.0000397*	0.0000273
	(2.17)	(1.58)
High-school diploma	-0.00216	0.00628
	(-0.24)	(0.74)
Some years of University	0.000751	0.0167
	(0.07)	(1.63)
University degree	-0.0132	-0.0125
	(-1.29)	(-1.33)
Post-graduate degree	-0.0249*	-0.0101
	(-2.45)	(-1.05)
Married or living with a partner, without children	0.0179**	0.0197**
	(2.69)	(2.86)
Single with children	-0.00984	-0.00713
	(-0.89)	(-0.62)
Single without children	0.0110	0.00883
	(1.17)	(0.94)
Partner work	-0.0115	0.00127
	(-1.26)	(0.15)
Own property	-0.0198***	-0.0284***
	(-3.47)	(-5.09)
Living with parents	0.0134	0.0255**
	(1.41)	(3.11)
Having a second job	0.0188*	0.0232***
	(2.50)	(3.35)
Sector and country dummies	0.312***	0.285***
Constant	(9.35)	(8.23)
N	8000	8000
t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001		

Tab A4. Difference in Difference analysis with the type of contract

	Willingness to Pay
	(OLS)
Working on a Platform economy (only doing work)	0.0224
	(1.87)
Open ended contract	-0.0493***
	(-7.82)
Open ended contract*Working on a Platform	0.00227
	(0.15)
Sefl-employed	0.0116
	(1.43)
Male	0.0172**
	(2.67)
Age	-0.00318
	(-1.90)
Age squared	0.0000495*
	(2.49)
High-school diploma	0.00683
	(0.85)
Some years of University	0.00691
	(0.67)
University degree	0.0000754
	(0.01)
Post-graduate degree	-0.00725
	(-0.71)
Married or living with a partner, without children	0.0118
	(1.37)
Single with children	-0.0133
	(-1.17)
Single without children	0.000639
	(0.07)
Partner work	0.0000755
	(0.01)
Own property	-0.0152*
	(-2.57)
Living with parents	0.0180
	(1.87)
Medium-low total annual income	-0.0327**
	(-3.16)
Medium-high total annual income	-0.0358**
	(-3.27)
High total annual income	-0.0436***
	(-4.31)

Medium-low total household income	0.0103
	(0.77)
Medium-high total household income	-0.00332
	(-0.27)
High total household income	-0.0254*
	(-1.98)
Having a second job	0.0229**
	(2.73)
Sector and country dummies	Yes
Constant	0.337***
	(8.56)
N	6919