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Platform Work and Economic Insecurity: Evidence from Italian Survey Data

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2021/13 April 2021
ISSN(ONLINE) 2284-0400

Platform Work and Economic Insecurity: Evidence from Italian Survey Data

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Abstract

The emergence of the platform economy has served as a defining feature of increasing fragmented labour markets in modern economies. Recent research on platform work, however, has struggled to quantify the socio-economic conditions of platform workers relative to other occupation groups. Moreover, it remains unclear if the socio-economic disadvantages that platform workers are likely to face are primarily channeled through lower incomes or their more precarious working conditions. This study uses representative survey data of platform workers in Italy to investigate their size, composition, and socio-economic conditions relative to individuals in other occupations. Our findings reveal that platform workers tend to be students and of younger age, but are diverse with respect to sex, educational attainment, and native-born status. We find that platform workers face greater economic insecurity relative to all other occupation classes. Strikingly, they also feature a rate of economic insecurity that is not significantly different from that of unemployed adults. Moreover, we find that the higher levels of insecurity are not primarily channeled through lower incomes; instead, higher rates of insecurity persist even when taking family incomes into account, suggesting that the precarity and volatility of platform work matter as much as income differences in shaping economic disadvantage. Results hold under analyses that account for selection into platform work. Our findings carry important consequences for understandings of the intensity and sources of socio-economic disadvantage of individuals engaged in platform work.

Keywords: platform work, non-standard work, economic insecurity
JEL classification: J40, J80, J81

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1 Introduction

The emergence of the platform economy has served as a defining feature of increasing fragmented labour markets in modern economies. New forms of platform-based work – from Amazon Mechanical Turk crowdworkers to Deliveroo food carriers – have become more prevalent, albeit at varying growth rates, across high-income countries in recent years. Moreover, early evidence suggests that the COVID-19 pandemic has accelerated the expansion of platform work (Eurofound, 2020). Recent research on platform work has offered mixed evidence as to the whether workers in such jobs prefer the flexibility that the jobs tend to offer (Berg et al., 2018), the characteristics of adults who enter platform work (Pesole et al., 2018), and whether such workers tend to face adverse socio-economic consequences relative to unemployed adults or workers in other lower-pay jobs (Drahokoupil and Piasna, 2017). Several limitations in these prior studies, however, have prevented a more thorough accounting of the demographic characteristics and socio-economic conditions of platform workers.

First, existing sources of survey data have struggled to distinguish platform workers from other survey respondents (O'Farrell and Montagnier, 2020). Contemporary occupation and industry codes used in large-scale surveys such as the EU Labor Force Survey, for example, do not feature unique labeling schemes for platform jobs. In turn, the data are ill-equipped to identify the characteristics of platform workers. Several studies have turned to non-probability sampling techniques instead, though with limitations related to representativeness and selection. As a result, the available empirical evidence concerning the size and composition of platform work is still relatively small (notable exceptions are, among others, Berg et al., 2018; Pesole et al., 2018) and affected by the lack of higher-quality survey or administrative data (for a discussion on the empirical limitations of the analysis on labor platforms, see Riso, 2019).

Second, studies have convincingly demonstrated that workers in platform jobs face more precarious working conditions, tend to have lower incomes, and face more uncertainty relative to other types of jobs (for a thorough review, see Bogliacino et al., 2019b). Less clear, however, is how the socio-economic conditions of platform workers compare to workers in other low-pay jobs and unemployed individuals. Put differently, if we imagine a spectrum of economic insecurity ranging from that of permanent employees of high-pay occupations to unemployed individuals, toward which side of the spectrum should we place platform workers? It may be that the conditions of platform workers fall halfway in between the stably-employed and the unemployed; alternatively, it could be that socio-economic conditions of platform workers mirror those of the unemployed. The distinction is critical for understanding whether such jobs offer a pathway toward improved socio-economic conditions for jobless workers, or whether the jobs do little to advance beyond the conditions in unemployment. Relatedly, more research is needed on whether the disadvantages that platform workers face is primarily due to lower incomes or other characteristics of their employment (e.g. less consistent hours, less autonomy, reduced access to social insurance, etc.). If platform workers face more economic insecurity, but this were not channeled through the incomes associated with platform work, then such findings would suggest that increasing incomes alone, without attention to other dimensions of job quality, may be insufficient to increase well-being.

Single-country studies are common in the literature on economic insecurity and the platform economy; most of these studies focus exclusively on the United States (e.g., Hall and Krueger (2018); Katz and Krueger (2019)). This study also focuses on a single country, but shifts the focus to Italy due to its high-quality, representative survey data featuring the characteristics and socio-economic conditions of platform workers. Specifically, this study employs the ad-hoc "Gig Economy" module of the Survey on Labour Participation and Unemployment (PLUS - *Participation, Labour, Unemployment, Survey*) conducted by the National Institute for the Analysis of Public Policies (INAPP). We focus specifically on adults who offer works and services through intermediate platforms ("platform work", hereafter). Unique from many of the non-probability studies specifically targeting platform workers (e.g., Huws (2017)), our data source also includes workers in standard occupations (and the jobless), allowing us to make direct, within-sample comparisons of platform workers to a representative sample of other individuals.

This study's findings produce three major contributions to the literature on the platform economy. First, we provide updated and detailed evidence concerning size and composition of platform work in Italy (data from 2018). We find that platform workers in Italy tend to be students and younger, but notable differences in sex, education, and native-born status do not emerge. Second, we assess the extent to which platform workers receive lower incomes relative to the rest of the Italian workforce, confirming that platform workers tend to be concentrated in the bottom half of the income distribution. Third, we investigate levels of economic insecurity among platforms workers relative to other occupation classes. Strikingly, we find that platform workers face greater economic insecurity relative to all other occupation classes and feature a rate of economic insecurity that is not significantly different from that of unemployed adults. Moreover, we find that the higher levels of insecurity are not primarily channeled through lower incomes; instead, higher rates of insecurity persist even when taking family incomes into account, suggesting that the precarity and volatility of platform work matter as much as, or more than, income differences in shaping economic disadvantage.

2 Prior Research on Platform Work

Consistent with prior research (e.g. Bogliacino et al. (2019b)) this study broadly defines "platform work" as jobs that involve service-based tasks coordinated through a digital platform (phone application or website) through which customers can place requests. Common examples are Uber drivers or Deliveroo food carriers.[1] Platform work has expanded across higher-

[1] In our definition of platform work, we include both online, often referred to as 'crowd-workers' (a typical example is that of those performing tasks via online platforms as 'Amazon Mechanical Turk), and offline platform

and lower-income countries alike in the past decade (for a thorough review, see, among others, Kenney and Zysman, 2016, 2019). In turn, social scientists have dedicated increasing attention to these new forms of employment. Scholars have demonstrated that platform work entails a reconfiguration of work and workplace arrangements with the potential to affect many segments of the service sector (e.g., the disruptive change in the taxi business following the advent of Uber) challenging, within a significantly short amount of time, their technological, organizational and competitive set-up (Prassl and Risak, 2015; Parker et al., 2016; Huws, 2017; Riso, 2019; Bogliacino et al., 2019b). Scholars have also investigated the socio-economic consequences of the rise of platform work, identifying the lack of adequate rights and social protection for platform workers, combined with their low pay and precarious working conditions, as factors that increase labour market inequalities (Prassl and Risak, 2015).

Below, we distill central findings from prior research related to platform workers. First, we review the analyses focusing on the size and composition of labor platforms in different countries. In doing so, we highlight the key socio-economic implications related to the growth of labor platforms, particularly those related to platform workers' income and working conditions. Second, we synthesize the previous empirical evidence on labor platforms in Italy. We then put forth our three primary research questions.

2.1 Size, characteristics and socio-economic conditions of platform work

Prior investigations of the size of platform work have offered competing accounts on how prevalent this type of work is in modern labour markets. Initial estimates in the U.S., for example, suggested that around only 0.5 percent of the labour market was engaged in platform work in 2015 Katz and Krueger (2019). In contrast, the U.S. Bureau of Labor Statistics (BLS) estimated in its Contingent Worker Supplement in 2017 that the size of the platform economy was twice as high (around 1 percent) (BLS, 2018), comparable to estimates from other web surveys Berg et al. (2018). Still, Robles and McGee (2016) find yet higher estimates. Relying on the Survey of Enterprising and Informal Work Activities (EIWA), the authors find that 4.3 percent of the U.S. engaged in platform work (which they define as 'being engaged in any sort of online or offline informal work activities in the previous six months'), notably higher than prior estimates in part, perhaps, due their broader definition.

Estimates from the European Union likewise produce heterogeneous findings. The European Commission's COLLEEM web-survey (Pesole et al., 2018; Brancati et al., 2020) measures service provision via digital platforms and is administered to respondents resident in 14 European countries. Respondents are asked whether they have ever gained income from different online sources, among which there are two corresponding to labour service platforms.The COLLEEM survey provides a wide range of estimations concerning size and characteristics of platform

workers (e.g., Uber drivers), referred to as 'gig-workers'. For a discussion on this point, see De Stefano (2015) work according to the relevance that the income earned via platforms has for the survey's respondents. The last COLLEEM wave (Brancati et al., 2020), providing information on the diffusion of digital platforms in Europe for the year 2018[2], reports that about the 1.4% of European internet users earn at least 50% of their income providing services on platforms. In turn, those declaring to provide services via platforms only occasionally are a slightly larger fraction, about the 4.1%. As for the characteristics of platform work, it emerges that those working on platforms are relatively younger, more educated, and more likely to live in a larger household and have dependent children. A similar picture emerges by looking at the first wave, based on data collected in 2017 (Pesole et al., 2018). According the narrower measure adopted to define platform work (i.e. workers relying on digital platforms as their main source of income), platform workers amount, on average, at the 2% of the respondents. The highest share of platform workers is detected in the UK (4%), the Netherlands (3%), and Germany (2.3%); in Sweden, Spain, Portugal, Italy and France the share of platform workers is around the 2%; while lower rates, between 0.6% and 0.2% are reported in countries as Lithuania, Romania, Croatia, Hungary, Slovakia and Finland.

Work from Huws et al. (2017), in contrast, suggests that platform work may be more widespread in Europe than identified in Pesole et al. (2018). Estimating the share of working age population that has ever provided (paid) services via platforms (both as main or secondary activity), the authors find rates of 9% for Netherlands and the UK, 10% for Sweden, 12% for Germany, 18% for Switzerland, 19% for Austria and 22% for Italy. Importantly, though, their estimates suggest that only a half of the respondents provide services via platforms frequently (i.e. at least weekly).

Though levels of platform work are disputed, there is little doubt about the direction of the trends. Hall and Krueger (2018), for example, focus on a paradigmatic case: Uber. Between 2012 and 2015, Uber drivers in the US increased from 0 to approximately 460,000.[3] Moreover, scholars have demonstrated that platform workers tend to face more precarity and economic uncertainty. Legally, platform workers are mostly classified as independent contractor depriving them of most social protection instruments (e.g., sick and maternity pay) and exposes them to significant employment and income risks. The lack of social protection is associated to higher occupational health and safety risks to which platform workers are exposed as compared to standard workers. Similarly, the lack of a proper occupational status minimises the chances for platform workers' unionization and collective bargaining risking to deprive them from the protection against discrimination, since many jurisdiction reserve these fundamental rights to employees (Drahokoupil and Piasna, 2017; Gyulavári, 2020; De Stefano, 2015; Adams-Prassl, 2019; De Stefano and Aloisi, 2019; Griesbach et al., 2019). However, such concerns were countered by arguments referring to the occasional and limited nature of the phenomenon, the

[2]The COLLEEM 2018 gathered a total of 38.022 responses from internet users aged between 16 and 74 years old in 16 EU Member States: Croatia, Czech Republic, Finland, France, Germany, Hungary, Ireland, Italy, Lithuania, the Netherlands, Portugal, Spain, Sweden, Slovakia, Romania, and the United Kingdom.

[3]At present, Uber claims to have more than 3.9 million drivers operating in 63 countries.

prevalence of groups, such as youngsters or university students, not to be accounted for as real workers but rather as individuals temporary seeking for some additional income and not for an actual job (for a discussion on this point see, among others, De Stefano and Aloisi, 2019).[4]

As detailed in the introduction, however, challenges remain with respect to comparing the socio-economic conditions of platform workers to a representative sample of non-platform workers. The available empirical evidence on the size and conditions of the platform economy face concerns of representativeness and selection effects (Bogliacino et al., 2019b; Kenney and Zysman, 2019). This may in part contribute to the largely divergent estimates of the share of platform workers in the studies noted above. Equally concerning, however, is the lack of sufficient understanding of how the economic insecurity of platform workers compares to other service-sector jobs or even jobless individuals.

2.2 Platform Work in Italy

This study focuses specifically on platform in Italy for two primary reasons. The first is practical: Italy features high-quality, representative survey data on the characteristics and socio-economic conditions of workers in platform jobs. We elaborate more on the data in the subsequent section.

Second, Italy marks a useful case in which to study the characteristics of platform work. As in many other high-income countries, platform work in Italy has quickly expanded throughout the past decade, especially in the sectors of food delivery, intermediating supply, tourism, real estate, and retail (Guarascio and Sacchi, 2018; Guarascio, 2018). Italy is also facing socio-economic challenges shared in many other high-income countries: labour markets are increasingly polarized and composed of precarious jobs, union membership is declining while non-standard work is rising, and the threats of offshoring and automation have raised the risk of unemployment for those with low-skill and low wages (Cirillo et al., 2017). The rise of platform thus threatens to exacerbate social inequality within Italy, a concern present within many high-income countries where platform work is expanding.

As in many other high-income countries, labour platforms in Italy that provide off-line services (for example, food-delivery platforms) tend to "outsource" a large part of their tasks relying on individuals classified as "partners" or contractors. As a result, the 'direct' employment base of these companies tends to be small, mostly including high-skill workers largely employed in tasks related to management, marketing and maintenance of the technological

[4] The lack of labor rights and recognition of worker status to those working via platforms is also related to the inappropriate use of the term 'sharing economy' to, at least initially, define many digital platforms. The idea is that the latter are just a neutral intermediary providing a free space wherein individuals are able to match their needs and share their assets, including working time. According to this view, the platform mediated match occurs in such a free and flexible way that cannot be accounted for as a standard economic relationship. However, as underlined by authors as Codagnone and Martens (2016) and De Stefano and Aloisi (2019), the for profit nature of the large majority of platforms and the degree of control and hetero-direction they exert on those working for them make the former normal for-profit businesses; and the latter comparable to standard employees.

infrastructure, while the task providers do not formally count as employees (Guarascio and Sacchi, 2018).

As discussed before, the Pesole et al. (2018) study estimates that around 2 percent of Italians are engaged in platform work. The National Social Security Institute (INPS) instead finds, using a web-survey, that about the 0.5% of the working population uses platform work for their primary source of income (INPS, 2018). If one considers also those working for a platform occasionally or as a second job, the share rises to the 2%.

The INPS Report also provides some insight into the socio-economic conditions of platform workers, focusing specifically on two of the major food-delivery platforms that are active in Italy, Deliveroo and Foodora.[5] The latter are analyzed relying on internal report and on an ad-hoc web-survey. Those working for Deliveroo and Foodora are hired as independent contractors[6] thus lacking protection against social risks (i.e. sick and maternity pay) and having comparatively lower pension contributions vis-a-vis standard workers. On average, both platforms declare that, during the year 2016, they employed around 2.000 'riders'. This value is significantly higher than the one provided by Guarascio and Sacchi (2018) who relied on administrative and balance sheet data to carry out their analyses. This discrepancy testifies the difficulty of adequately tracking and quantifying platform workers when relying on official data sources. According to the platforms' statements, only 20% of their riders work more than 20 hours per week earning an average of 12 Euros per hour. On the other hand, INPS (2018) reports that for the 35% of those declaring to work for a digital platform it represents the primary income source while for the remaining part platform income represents an additional source on top of the primary one. In terms of employment status, more than the 50% of those working for Foodora say that they would prefer to have a standard labor contract so to have a greater stability in their employment relationship.

2.3 Research Questions

Overall, the available evidence on the size, composition, and socio-economic conditions of platform workers in Europe and Italy particularly is influenced by the absence of high-quality, representative survey data and within-sample comparisons to other types of workers. Given these limitations, we propose three research questions to improve the field's understanding of workers in the platform economy. First, we ask, (RQ1) what are the demographic characteristics of platform workers in Italy? In using high-quality, representative survey data, we can directly compare the characteristics of platform workers to other workers across Italy.

Second, we ask, (RQ2) to what extent do platform workers face income disadvantages relative to the rest of the workforce? Specifically, we seek to understand how the incomes of platform workers compare to other occupations, independent of the basic demographic char-

[5]Indeed, in 2018 the Italian branch of Foodora has been acquired by the Spanish platform Glovo.

[6]The contractual types that are adopted, respectively, by Deliverro and Foodora are the 'lavoro autonomo occasionale' and the 'collaborazione coordinata and continuativa'.

acteristics of workers. In doing so, we can provide useful evidence related to the extent of economic disadvantage that platform workers face.

Importantly, though, earnings are only one measure of disadvantage. Thus, we also ask, (RQ3) to what extent are platform workers exposed to greater economic uncertainty relative to the rest of the workforce? And to what extent is this disadvantage channeled through the earnings disadvantages posited in RQ2? If incomes are lower for platform workers relative to others, we can likely expect their level of economic insecurity to be greater. However, the instability and precariousness of platform work may act independently (i.e. not channeled through income alone) to affect the economic insecurity of platform workers relative to others. Investigating these effects, we can understand how the socio-economic conditions of platform workers compare to workers in other occupations and to jobless individuals.

3 Data and Methods

3.1 Data source

The empirical investigation relies on the VIII *Participation, Labour, Unemployment, Survey* (hereafter PLUS) developed and administered by the National Institute for the Analysis of Public Policies (INAPP). The main aim of the PLUS survey is to provide reliable estimates of labour market characteristics that other surveys only marginally explore. In doing so, the survey is able to provide more direct evidence on aspects such as non-standard work. The survey has been released in the first half of 2019 and collected in 2018 on a sample of 45,000 interviewees. Individuals were contacted through a dynamic computer-assisted telephone interviewing (CATI). One of the key characteristics of the PLUS survey is the absence of proxy interviews: only survey respondents are included, in order to reduce the extent of measurement errors and partial non-responses. The questionnaire was submitted to a sample of residents between 18 and 74 years old. The sample design is stratified over the Italian population: strata are defined by region (20 administrative regions), type of city (metropolitan/non-metropolitan), age (five classes), sex and the employment status of the individual (employed, unemployed, student, retired, other inactive). The reference population is derived from the annual averages of the ISTAT Labour Force Survey and weights are provided in order to account for the probability of attrition based on surveyed characteristics [7]

The VIII wave of the INAPP-PLUS survey includes an ad-hoc module on the "Gig economy"[8] collecting information on individuals participating in several ways to digital platforms by: (i) selling on-line goods and/or services; (ii) offering works and services through platforms intermediating work; (iii) providing lucrative sharing (leasing) of real estate (so called capital

[7]Both descriptive statistics and estimates have been weighted applying survey weights.

[8]Despite its name, the module includes information on both online and offline platform work as well as on individuals relying on platforms to rent and sell their own goods.

platform). This study focuses on digital labour markets and specifically on those individuals that have declared in 2018 to offer their own work in exchange of money through platforms. More specifically, we focus on online (e.g., performing online activities such as completing surveys or data entry) and offline platforms workers (e.g., individuals working for food-delivery, cleaning or Uber-type platforms), the latter being the component of platform work that has grown the most in Italy and about which more information is available.

The dataset features a rich set of demographic and employment information. In addition to measuring demographic characteristics such as age, sex, citizenship status, education, and family structure, we can measure an individual's health status, net monthly earnings from employment and net monthly family income (inclusive of taxes and transfers). The data also feature one question directly related to economic insecurity. The prompt for this question asks whether the respondent had to postpone medical treatment for financial reasons in the past year. The likelihood of postponing medical treatment may, of course, be dependent on whether a given individual actually faces health challenges. Given that we can also measure an individual's health status in the dataset, however, we interpret the conditional likelihood of posting medical treatment for financial reasons (while accounting for health) as an appropriate proxy for economic insecurity.

3.2 Methods

Our methodological approach relies on three steps. First, we will present broad descriptive findings related to each of our RQs. Second, we will use a series of Probit regression models to understand the conditional association of platform work with demographic characteristics of individuals in such jobs (RQ1) and the incomes and economic insecurity associated with such jobs (RQs 2 and 3). Third, we will apply a propensity score matching estimate to assess the robustness of our results when accounting for possible selection into platform work. We discuss the second and third steps here.

Our regression estimates follow Equations (1) and (2). In Equation (1), we estimate a Probit model that identifies the conditional likelihood that an individual i with a vector of demographic characteristics (M_i, W_i, H_i) participates in platform work (PW_i).

$$Prob(PW_i) = \alpha + \gamma M_i + \delta W_i + \lambda H_i + \epsilon_i \tag{1}$$

In Equation (2), we estimate the extent to which participation in platform work is associated with economic insecurity. The latter is measured through a dichotomous variable taking value of 1 if the individual declares to have postponed medical treatment due to financial concerns during the last year, a proxy widely used in the literature to proxy income vulnerability and incapacity to deal with financial shocks.[9] Equation (2) includes a dummy variable, (PW_i), that

[9] On the relation between households' financial fragility and consumer behavior, in particular decisions with respect to cutting back health care usage (see Lusardi et al. (2011); Schneider and Harknett (2019).

indicates whether the individual i has engaged in platform work in the past year. Thus, β_1 is the coefficient of interest and informs us about the conditional association of platform work and economic insecurity.

$$Prob(Y_i) = \alpha + \beta_1 PW_i + \gamma M_i + \delta W_i + \lambda H_i + \theta F_i + \epsilon_i \quad (2)$$

Both models include a wide set of controls referring to: (i) individual characteristics (M_i) such as age measured in age classes (18-24, 25-29, 30-39, 40-49, 50-64, more than 64), gender, nationality, family status (single or in a couple); (ii) socio-economic features (W_i) such as education (primary, high school, university or post-university background), living with people with disabilities, living with children, living in large cities (more than 250 thousands inhabitants) and (iii) a set of controls (H_i) referring to average household income and employment status (being employed versus inactive, unemployed, retired or student).

In equation (2) we include the same set of controls as equation (1) (M_i, W_i, H_i), but also add two more variables capturing whether the individual has health problems and the number of earners in the household (F_i), both potentially influencing our economic insecurity indicator (the need to postpone medical treatments for financial reasons).

In order to account for heterogeneity of drivers for platform participation and heterogeneity of effects with respect to inability to deal with unexpected expenses, we estimate equation (1) and (2) on the whole population of PLUS survey - residents in Italy (18-74 years old) - and on the sub-population of employed. In the latter case, we include as further controls: (i) the type of employment contract (permanent employee with respect to other type of contracts) and (ii) the net work income (in logarithm).

One may be concerned that selection effects into platform work bias the estimates from Equations (1) and (2). Put differently, if we find a conditional relationship between platform work and economic insecurity, this may be due to positive selection into platform work among the economically insecure, rather than platform work being the source of economic insecurity. Thus, we also implement propensity score matching (PSM) that attempts to account for selection effects.[10] More formally, Y being our variable of interest (inability to deal with unexpected expenses) and D the dummy for the platform status, equal to one for platform workers ($D = 1$) and zero otherwise, we can define - using standard notation from Rubin (1974), Rubin (1977) - Y^0 to be the outcome (inability to deal with unexpected expenses) in absence of platform participation, and Y^1 as the outcome under participation, therefore we can call 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 (inability to deal with unexpected expenses) as a result of platform participation for those who are currently platform workers. However, we can not directly observe income fragility of platform workers in absence of treatment (i.e. lack

[10]Due to the non random assignment to treatment, the estimations in equation 2 can be biased because the difference in (Y_i^1, Y_i^0) might be correlated with platform status, meaning that income fragile individuals are more likely to work on digital labour markets.

of platform status). Therefore, we resort to propensity score matching (Rosenbaum and Rubin, 1983) which entails forming matched sets of treated (platform) and untreated subjects (non platform workers) who share similar characteristics. More in detail, PSM matches each (treated) individual working on a platform with the most similar individual belonging to the (control) group of non-platform workers (untreated). Each pair is identified on the basis of the propensity scores yielded by a probit regression, which predicts the probability of working on a platform conditioned on a set of observable characteristics. After the matching, the statistical significance of the difference between the proportion of subjects experiencing inability to deal with unexpected expenses in each of the two groups (treated - platform w. - vs. untreated - non platform w.) in the matched sample can be tested. This difference represents the Average Treatment Effect on the Treated (ATET) (Austin, 2011).

Therefore, we first create a propensity score selecting the main variables that can affect participation to digital labour markets as well as income status ensuring an adequate balance of propensity score across treatment (platform) and comparison (non-platform w.) groups. Second, we evaluate to which extent the two groups of platform and non-platform workers sharing similar values of propensity score differ with respect to our outcome of interest.

4 Findings

4.1 Descriptive Findings

We first present descriptive findings related to the size and characteristics of platform work in Italy (RQ1). In 2018, about the 0.5 percent of all residents of Italy, around 213.000 individuals, claim to provide online or offline services via digital platforms. Remarkably enough, in contrast to those relying on digital platforms to rent or sell products online, platform workers are more likely to rely on platforms as their primary source of income (i.e. according to the PLUS survey, more than 60% of people selling products online and renting properties are already employed, whereas less than 40% of platform workers have another formal occupation); and to face more precarious working conditions (Codagnone et al., 2018) as compared to the rest of the workforce (see the following evidence).

Table 4.1 provides summary statistics related the composition of platform workers relative to non-platform workers. Relative to individuals not working on a platform (left panel of Table 2), those who are in platform work are around twice as likely to be between the age of 18 and 24 (18.9 percent of platform workers compared to 9.6 percent of all others), three times as likely to be between age 25-29 (25.6 percent to 7.3 percent), and slightly more likely to be between age 30-49. In contrast, platform workers are much less likely to be between the ages of 50-64.

We now provide descriptive evidence on income differences among platform workers and non-platform workers (related to RQ2). Figure 1 presents the share of workers in each monthly household income bin, that is how platform workers and non-platform workers are distributed

Table 1: Descriptive statistics by platform status (sample weights applied)

	Working on a platform		Not working on a platform		Difference (Rob.St. Errors)		
	Mean	Sd	Mean	Sd	Coeff	Sd	
Age class (18 - 24)	0,189	0,392	0,096	0,295	0,093	0,034	**
Age class (25 -29)	0,256	0,437	0,073	0,260	0,183	0,046	***
Age class (30 - 39)	0,205	0,405	0,167	0,373	0,038	0,034	
Age class (40 - 49)	0,242	0,429	0,218	0,413	0,024	0,042	
Age class (50 - 64)	0,092	0,289	0,297	0,457	-0,206	0,022	***
Women	0,456	0,499	0,507	0,500	-0,051	0,047	
Living in a couple	0,313	0,465	0,551	0,497	-0,238	0,051	***
Living with children	0,267	0,444	0,237	0,425	0,030	0,052	
Italian	0,976	0,154	0,979	0,144	-0,003	0,010	
Living with people with disabilities	0,093	0,291	0,073	0,261	0,019	0,017	
Elementary school	0,374	0,485	0,426	0,494	-0,052	0,052	
High school	0,468	0,500	0,411	0,492	0,057	0,046	
Degree and post-graduated studies	0,158	0,366	0,163	0,369	-0,005	0,023	
Net work income (log)	1,545	2,904	2,919	3,532	-1,374	0,242	***
Permanent contract	0,263	0,442	0,619	0,486	-0,356	0,051	***
Living in large cities (>250.000)	0,171	0,377	0,131	0,337	0,040	0,028	
Number of earners in the household	1,598	0,803	1,715	0,819	-0,117	0,067	
Bad health	0,027	0,163	0,020	0,138	0,008	0,014	
Living in a property	0,818	0,387	0,884	0,321	-0,066	0,035	
Employed	0,393	0,490	0,529	0,499	-0,136	0,046	**
Unemployed	0,238	0,427	0,105	0,307	0,133	0,033	***
Retired	0,018	0,134	0,134	0,341	-0,116	0,010	***
Inactive	0,179	0,384	0,172	0,377	0,007	0,048	
Student	0,171	0,377	0,059	0,237	0,112	0,031	***
Less than 1000€	0,153	0,360	0,105	0,307	0,048	0,031	
Family income 1001-1500€	0,233	0,424	0,186	0,389	0,047	0,039	
Family income 1501-2000€	0,146	0,354	0,178	0,383	-0,032	0,027	
Family income 2001-3000€	0,254	0,436	0,202	0,401	0,052	0,051	
Family income 3001-5000€	0,058	0,233	0,114	0,317	-0,056	0,013	***
Family income More than 5000€	0,039	0,194	0,030	0,172	0,008	0,012	
Don't know - don't want to answer	0,118	0,323	0,185	0,388	-0,067	0,025	**
N observations	222		44778		45000		

according to their average monthly net household income. The blue bars represent the distribution of non-platform workers among household income bin; the red bars represent the same distribution for platform workers. The left panel provides results for the entire population of 18-74 year old individuals, while the right panel provides results specifically for the population of working adults (the sample is restricted to those that self-declare to work).

The top row demonstrates that platform workers have a higher likelihood to live in households whose monthly income is less than 1,000 EUR per month relative to non-platform workers. Among all platform workers between ages 18 to 74, 15.3 percent have monthly (household) incomes below this level, compared to 10.5 percent of non-platform workers. Among the working-age population, 9.9 percent of platform workers live in a household whose income is below 1,000 EUR per month, compared to 6.2 percent of non-platform workers. The over-representation of platform workers persists throughout the bottom half of the income distribution. Specifically, platform workers are more likely to have (household) incomes below 3,000 EUR/month relative to non-platform workers, and are much less likely to have incomes between 3,000-5,000 EUR/month or more than 5,000 EUR/month relative to non-platform workers. Among the working-age population, more than half of platform workers live in a household whose average net income is below 2,000 EUR/month, our estimates suggest. In contrast, an estimated 38 percent of non-platform workers are below this benchmark.[11]

[11] On average platform workers live in households composed by a lower number of earners see Fig. 7 in the Appendix.

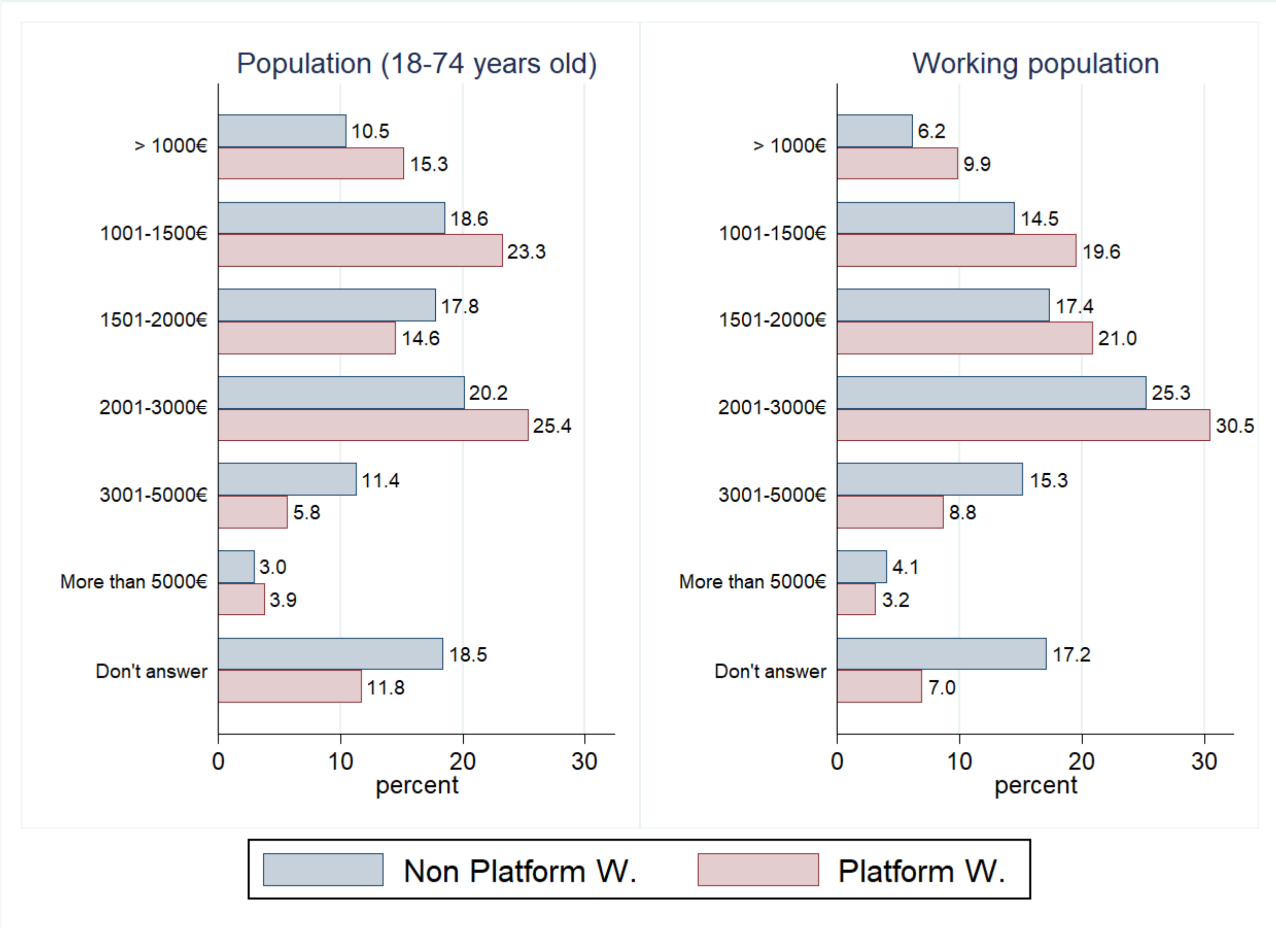

Figure 1: Mean Monthly Family Incomes among Platform and non-Platform Workers

We now turn to descriptive evidence of economic insecurity among platform workers relative to others (related to RQ3). Figure 2 provides the unconditional means of insecurity among the full 18-74 year-old population (left panel) and the working population (right panel). Among the 18-74 year old group, an estimated 35.6 percent of platform workers report that they had to postpone medical treatment for financial reasons. Among platform workers who are currently employed (right panel), the rate is 32.6 percent. In contrast, an estimated 22.7 percent of non-platform workers in the 18-74 year-old group report having to postpone medical treatment for financial reasons, and 19.1 percent among the working population.

Put simply, platform workers face rates of economic insecurity (defined narrowly here as postpone medical treatment for financial reasons) that are more than 10 percentage points higher than all other individuals. In all, around one-third of platform workers face economic insecurity in Italy.

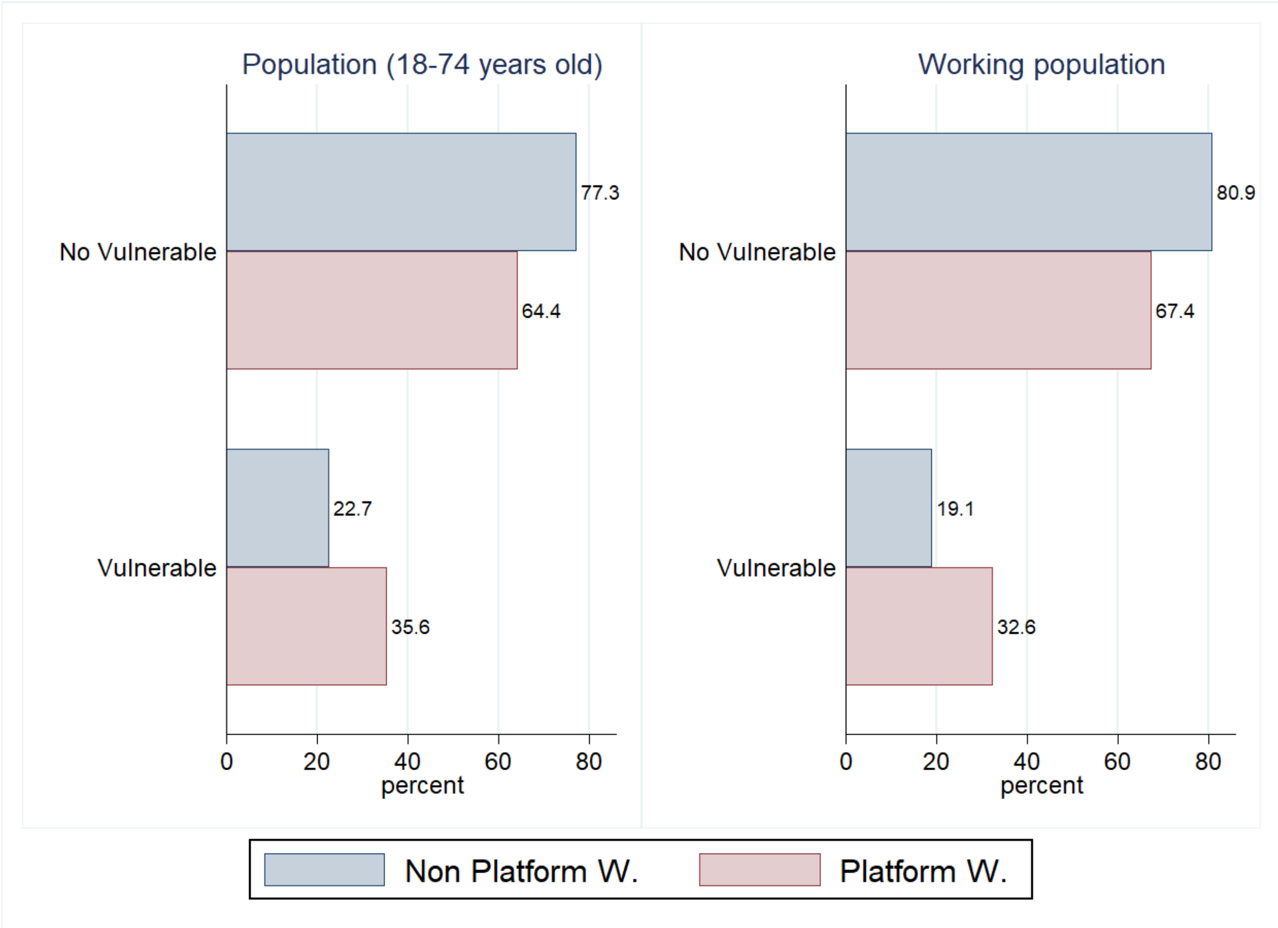

Figure 2: Had you to postpone medical treatment for financial reasons?

To further disaggregate rates of economic insecurity across sub-populations, Figure 3 presents unconditional means across several broad (and mutually exclusive) occupation classifications ranging from Managers to Elementary Occupations (ISCO 1 digit major groups). Here, we also include platform workers and unemployed adults as their own respective categories. The findings show large heterogeneity in the extent to which individuals in different groups report postponing medical treatment for financial reasons, that is our proxy for income vulnerability.

Mangers, professionals, technicians, and members of the armed forces face the lowest rates of economic insecurity (between 14.3 percent and 16.4 percent). Meanwhile, clerks, craft workers, and machine operators make up a middle group with means ranging from 17 percent to 19.6 percent. Behind them are sales workers and elementary occupations (23.4 and 27.9 percent, respectively). Platform workers and unemployed adults feature much higher rates of economic insecurity; in fact, there is very little difference between the rates for platform workers (35.6 percent) and for the unemployed (38 percent).

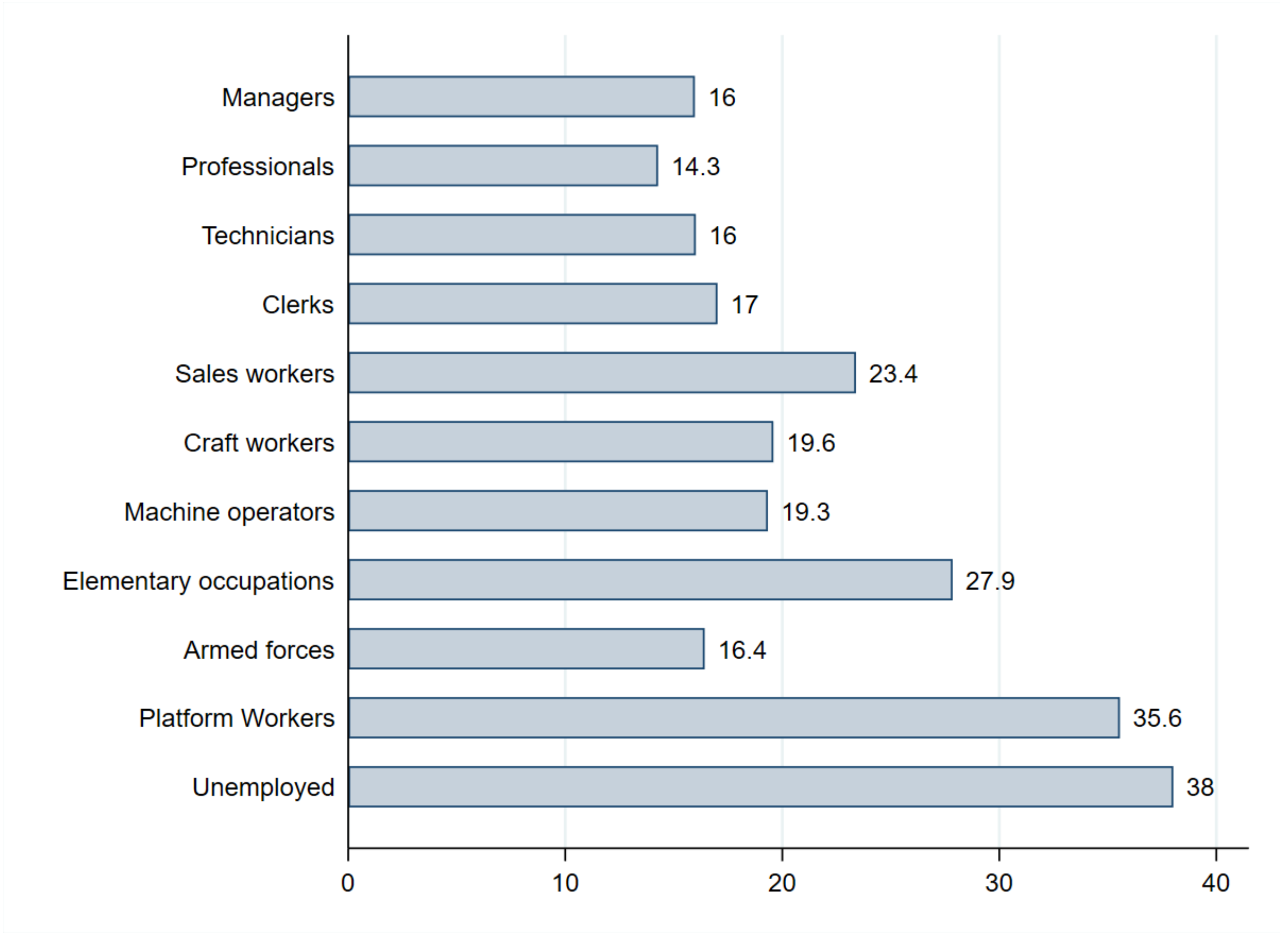

Figure 3: Econonomic Insecurity by Occupation Classification (percent)

Earlier, we posed the question of where in the occupation distribution platform workers tend to fall with respect to economic insecurity. These descriptive patterns suggest that they belong well at the bottom of the distribution; not only is insecurity more widespread among platform workers relative to all other occupations, but the level of insecurity is essentially no different than that of unemployed adults.

There may, of course, be many factors influencing these descriptive patterns. Differences in age, education, or health status between platform workers and workers in other types of jobs may contribute to the higher relative rates of insecurity among platform workers. Similarly, selection effects into platform work may bias our findings. To test these possibilities, we now turn toward our econometric analysis.

4.2 Estimation Results

Table 2 presents results from Equation 1 and displays the marginal likelihoods of working in a platform job. Models (1) and (2) look at the full population of 18-74 year old adults, while Models (3) and (4) only look at the employed population. Among the full population, Table 3 largely corroborates what the descriptive statistics suggested: younger adults (25-29 year olds) have a higher likelihood of participating in platform work. Moreover, adults who live alone or who live in a large city are more likely to participate in platform work. In Model (1), there is no statistically significant difference in the likelihood of participating in platform work by sex, nationality, or education. These findings suggest that platform work is not simply restricted to lower-educated men or non-native residents.[12]

When taking family income and self-reported labour market status into account (M2), the findings are mostly stable; however, the conditional likelihood of women participating in platform work does become negative and statistically significant, suggesting that men are slightly more likely to participate in platform work when family income is taken into account. Again, the results suggest that individuals with family incomes higher than 3,000 EUR/month are less likely to participate in platform work. Moreover, the findings demonstrate that students are particularly likely to participate in platform work.[13]

Similar patterns emerge when focusing specifically on working adults in Models (3) and (4). Among working adults, the 25-29 year old age group is again particularly likely to participate in platform work, as are adults living in large cities. Perhaps unsurprisingly, individuals who have permanent jobs and higher earnings from employment (”net work income”) are also less likely to participate in platform work.

In answering RQ1, our results reveal that the composition of platform workers in Italy is a heterogeneous group with respect to sex, education, and native-born status, but is skewed toward younger workers (often students) in high-cost cities in families with lower incomes. In answering RQ2, our results confirm that platform workers in Italy tend to earn less than workers in other jobs, as also demonstrated in Figure 1.

Table 3 returns to the association of platform work and economic insecurity as part of RQ3. Specifically, the results show the marginal effects from Equation 2. Recall that the outcome variable is a binary indicator of whether the respondent had to postpone medical treatment for financial reasons. Models (1) and (2) again look at the full population of 18-74 years old, while Models (3) and (4) only include workers. Our primary coefficient of interest is whether the individual is engaged in platform work.

Model (1) includes the demographic characteristics but excludes family income. The results suggest that working in a platform job is associated with a 9.9 percentage point increase in the likelihood of economic insecurity. The remaining characteristics in the model suggest that the likelihood of economic insecurity is also higher for individuals with poorer health, who live with children, who are not Italian, who are women, and who are unemployed or low-educated.

Model (2) brings in family income. If the economic insecurity were driven primarily though family income, the coefficient on platform work may be reduced to zero. Strikingly, though, the association of platform work and economic insecurity is hardly changed. Platform workers

[12]Notice that, as a consequence of the Sars-Cov-2 pandemic the size of the platform economy increased and its composition may also have changed. This is particularly true with regard to the share of non-native residents working for platforms. With new data available, further investigation in this regard will be needed.

[13]This evidence is partly in line with the findings of Brancati et al. (2020)

Table 2: Marginal effects of probability to work on a digital labour market

	(1)	(2)	(3)	(4)
	All population (15-74 years old)		Only workers (self-declared)	
	b/se	b/se	b/se	b/se
Age class (18 - 24)	0,011***	0,009***	0,007**	0,007**
	(0,00)	(0,00)	(0,00)	(0,00)
Age class (25 -29)	0,015***	0,014***	0,011***	0,011***
	(0,00)	(0,00)	(0,00)	(0,00)
Age class (30 - 39)	0,009***	0,009***	0,007**	0,007**
	(0,00)	(0,00)	(0,00)	(0,00)
Age class (40 - 49)	0,009***	0,009***	0,008***	0,008***
	(0,00)	(0,00)	(0,00)	(0,00)
Age class (50 - 64)	0,004	0,004*	0,004	0,004
	(0,00)	(0,00)	(0,00)	(0,00)
Women	-0,001	-0,002*	-0,001	-0,001
	(0,00)	(0,00)	(0,00)	(0,00)
Living in a couple	-0,002**	-0,002*	-0,002	-0,002
	(0,00)	(0,00)	(0,00)	(0,00)
Living with children	0,002	0,002	0,001	0,001
	(0,00)	(0,00)	(0,00)	(0,00)
Italian	0,001	0,001	-0,001	-0,001
	(0,00)	(0,00)	(0,00)	(0,00)
Living with people with disabilities	0,003**	0,002*	0,003	0,002
	(0,00)	(0,00)	(0,00)	(0,00)
High school	-0,001	-0,000	-0,001	-0,001
	(0,00)	(0,00)	(0,00)	(0,00)
Degree and Post-grad studies	-0,002	-0,000	-0,001	-0,000
	(0,00)	(0,00)	(0,00)	(0,00)
Living in large cities (>250.000)	0,002*	0,002*	0,003*	0,003**
	(0,00)	(0,00)	(0,00)	(0,00)
Family income 1001-1500 €		-0,000		0,000
		(0,00)		(0,00)
Family income 1501-2000 €		-0,002		0,001
		(0,00)		(0,00)
Family income 2001-3000 €		0,001		0,001
		(0,00)		(0,00)
Family income 3001-5000 €		-0,003***		-0,002
		(0,00)		(0,00)
Family income More than 5000 €		-0,000		-0,002
		(0,00)		(0,00)
Don't know - don't want to answer		-0,003***		-0,004*
		(0,00)		(0,00)
Unemployed		0.005***	0.007**	0.007**
		(0.00)	(0.00)	(0.00)
Retired		0.001	0.013*	0.012*
		(0.00)	(0.01)	(0.01)
Inactive		0.004	0.011*	0.011*
		(0.00)	(0.01)	(0.01)
Student		0.006***	0.010**	0.009**
		(0.00)	(0.01)	(0.01)
Net work income (log)			-0.000	-0.000
			(0.00)	(0.00)
Permanent job			-0.003*	-0.003*
			(0.00)	(0.00)
N	45000	45000	21359	21359
Wald chi2(24)	107,61	168,83	290,21	337,58
Prob>chi2	0,0000	0,0000	0,0000	0,0000
Pseudo R2	0,0654	0,0873	0,0901	0,1047

Significance level: * p<0.10, ** p<0.05, *** p<0.01
Base categories: More than 64 years old; Elementary and no title of education; Less than 1000 euro

remain 9 percentage points more likely to face economic insecurity after accounting for income and all other characteristics. Thus, the low incomes associated with platform work are not the only factor driving insecurity; instead, the volatility of income within the job, the uncertain scheduling, and precarious working conditions more generally may each contribute to greater uncertainty.

Looking exclusively among the employed population (excluding the retired, inactive, and jobless) in Models (3) and (4) renders similar findings. In Model (3), working in a platform job is associated with a 9.4 percentage point increase in the likelihood of economic insecurity. Even after taking family income into account in Model (4), we find that platform work is associated with an 8.5 percentage point increase in the likelihood of insecurity. Thus, even among workers, the negative economic effects associated with platform work appear to extent well beyond income.

Table 4 now expands the results to look at the relative likelihood of insecurity by broad occupation groups. Similar to Figure 3, we include the unemployed as their own category. Our broader aim is to understand where in the occupation distribution platform workers are placed with respect to their level of economic insecurity. In Table 5, platform work is the reference occupation group (excluded from the models) and all occupation categories are exclusive; thus, the coefficients for each occupation group reflect the relative likelihood of economic insecurity for that group relative to platform workers.

Model (1) presents results without family income controls. Notably, all occupation groups from Managers through Armed Forces feature negative and statistically significant coefficients, suggesting that each of these occupation groups faces a lower likelihood of economic insecurity relative to platform workers (independent of age, sex, health, family structure, and so on). Managers, for example, face a conditional likelihood of insecurity that is 22.6 percentage points lower than that of platform workers. Strikingly, the coefficient for unemployed adults is also negative, though statistically insignificant. Thus, the most we can conclude is that there is no statistically significant difference in the conditional likelihood of economic insecurity for platform workers relative to unemployed adults.

Model (2) again brings family income into consideration. As before, accounting for family income slightly reduces the magnitude of most the occupation coefficients, but all remain negative and statistically significant. The unemployed coefficient remains negative but insignificant. Thus, even after taking family income into account, platform work is associated with levels of economic insecurity comparable to the effect of being unemployed.

Figure 4 presents the results visually and summarizes the key findings. The coefficients and their confidence intervals are plotted for each occupation grouping in relation to platform workers. Whether accounting for family income or not, all occupation groups feature a 10 percentage point or greater advantage over platform workers with respect to the likelihood of economic insecurity. As Figure 4 visualizes, however, there is little differences for the unemployed and platform workers.

Table 3: Marginal effects of inability to deal with unexpected expenses

	(1)	(2)	(3)	(4)
	All population (15-74 years old)		Only workers (self-declared)	
	b/se	b/se	b/se	b/se
Working on a platform	0,099**	0,093**	0,094*	0,085*
	(0,04)	(0,04)	(0,04)	(0,05)
Number of earners in the household	-0,035***	-0,003	-0,041***	-0,003
	(0,00)	(0,00)	(0,01)	(0,01)
Bad health	the num	0,133***	0,150***	0,130***
	(0,02)	(0,02)	(0,03)	(0,03)
Living in a property	-0,113***	-0,096***	-0,105***	-0,090***
	(0,01)	(0,01)	(0,01)	(0,01)
Living with children	0,031***	0,037***	0,027**	0,034***
	(0,01)	(0,01)	(0,01)	(0,01)
Living with people with disabilities	0,066***	0,066***	0,071***	0,068***
	(0,01)	(0,01)	(0,01)	(0,01)
Italian	-0,037*	-0,025	-0,025	-0,003
	(0,02)	(0,02)	(0,03)	(0,02)
Age class (18 - 24)	-0,138***	-0,113***	-0,062*	-0,071**
	(0,02)	(0,02)	(0,03)	(0,03)
Age class (25 -29)	-0,029*	-0,016	0,037	0,027
	(0,02)	(0,02)	(0,02)	(0,02)
Age class (30 - 39)	-0,005	0,001	0,045*	0,026
	(0,01)	(0,01)	(0,02)	(0,02)
Age class (40 - 49)	0,007	0,015	0,045*	0,030
	(0,01)	(0,01)	(0,02)	(0,02)
Age class (50 - 64)	0,012	0,021**	0,051**	0,039**
	(0,01)	(0,01)	(0,02)	(0,02)
Women	0,069***	0,060***	0,074***	0,064***
	(0,01)	(0,01)	(0,01)	(0,01)
Living in a couple	0,011	0,032***	0,012	0,033***
	(0,01)	(0,01)	(0,01)	(0,01)
Employed	-0,019	-0,023		
	(0,02)	(0,02)		
Unemployed	0,121***	0,096***		
	(0,02)	(0,02)		
Retired	-0,051*	-0,058**		
	(0,02)	(0,02)		
Inactive	0,037*	0,015		
	(0,02)	(0,02)		
Living in large cities (¿250.000)	0,012*	0,015**	0,019**	0,022**
	(0,01)	(0,01)	(0,01)	(0,01)
High school	-0,058***	-0,034***	-0,071***	-0,047***
	(0,01)	(0,01)	(0,01)	(0,01)
Degree and post-graduated studies	-0,127***	-0,085***	-0,137***	-0,093***
	(0,01)	(0,01)	(0,01)	(0,01)
Net work income (log)			0,002	0,000
			(0,00)	(0,00)
Permanent contract			-0,055***	-0,040***
			(0,01)	(0,01)
Family income 1001-1500€		-0,072***		-0,080**
		(0,01)		(0,02)
Family income 1501-2000€		-0,141***		-0,163***
		(0,01)		(0,02)
Family income 2001-3000€		-0,186***		-0,200***
		(0,01)		(0,02)
Family income 3001-5000€		-0,242***		-0,257***
		(0,01)		(0,02)
Family income More than 5000€		-0,275***		-0,307***
		(0,02)		(0,02)
Don't know - don't want to answer		-0,170***		-0,220***
		(0,01)		(0,02)
N	45000	45000	21359	21359
Wald chi2(24)	2349,28	2791,97	643,84	935,03
Prob¿chi2	0,0000	0,0000	0,0000	0,0000
Pseudo R2	0,0822	0,1027	0,0549	0,0813

Significance level: * p¡0.10, ** p¡0.05, *** p¡0.01
Base categories: More than 64 years old; Elementary and no title of education; Less than 1000 euros

Table 4: Marginal effects of inability to deal with unexpected expenses (II)

	(1)	(2)
	All population (15-74 years old)	
	b/se	b/se
Managers	-0.226***	-0.191***
	(0.05)	(0.05)
Professionals	-0.217***	-0.179***
	(0.05)	(0.05)
Technicians	-0.220***	-0.185***
	(0.05)	(0.05)
Clerks	-0.229***	-0.200***
	(0.05)	(0.05)
Sales workers	-0.188***	-0.174***
	(0.05)	(0.05)
Craft workers	-0.213***	-0.195***
	(0.05)	(0.05)
Machine operators	-0.208***	-0.185***
	(0.05)	(0.05)
Elementary occupations	-0.162**	-0.160**
	(0.05)	(0.05)
Armed forces	-0.223**	-0.185**
	(0.07)	(0.07)
Unemployed	**-0.054**	**-0.050**
	(0.05)	**(0.05)**
Family income 1001-1500 €		-0.061***
		(0.02)
Family income 1501-2000 €		-0.132***
		(0.02)
Family income 2001-3000 €		-0.177***
		(0.02)
Family income 3001-5000 €		-0.229***
		(0.02)
Family income More than 5000 €		-0.281***
		(0.02)
Other controls	Yes	Yes
Number of obs	26,403	26,403
Wald chi2(35)	1547.69	1865.67
Prob>chi2	0.0000	0.0000
Pseudo R2	0.0826	0.1036
* p¡0.05, ** p¡0.01,	p¡0.001	

Significance level: * p<0.10, ** p<0.05, *** p<0.01
Base categories: Platform Workers; More than 64 years old; Elementary and no title of education; Less than 1000 euros

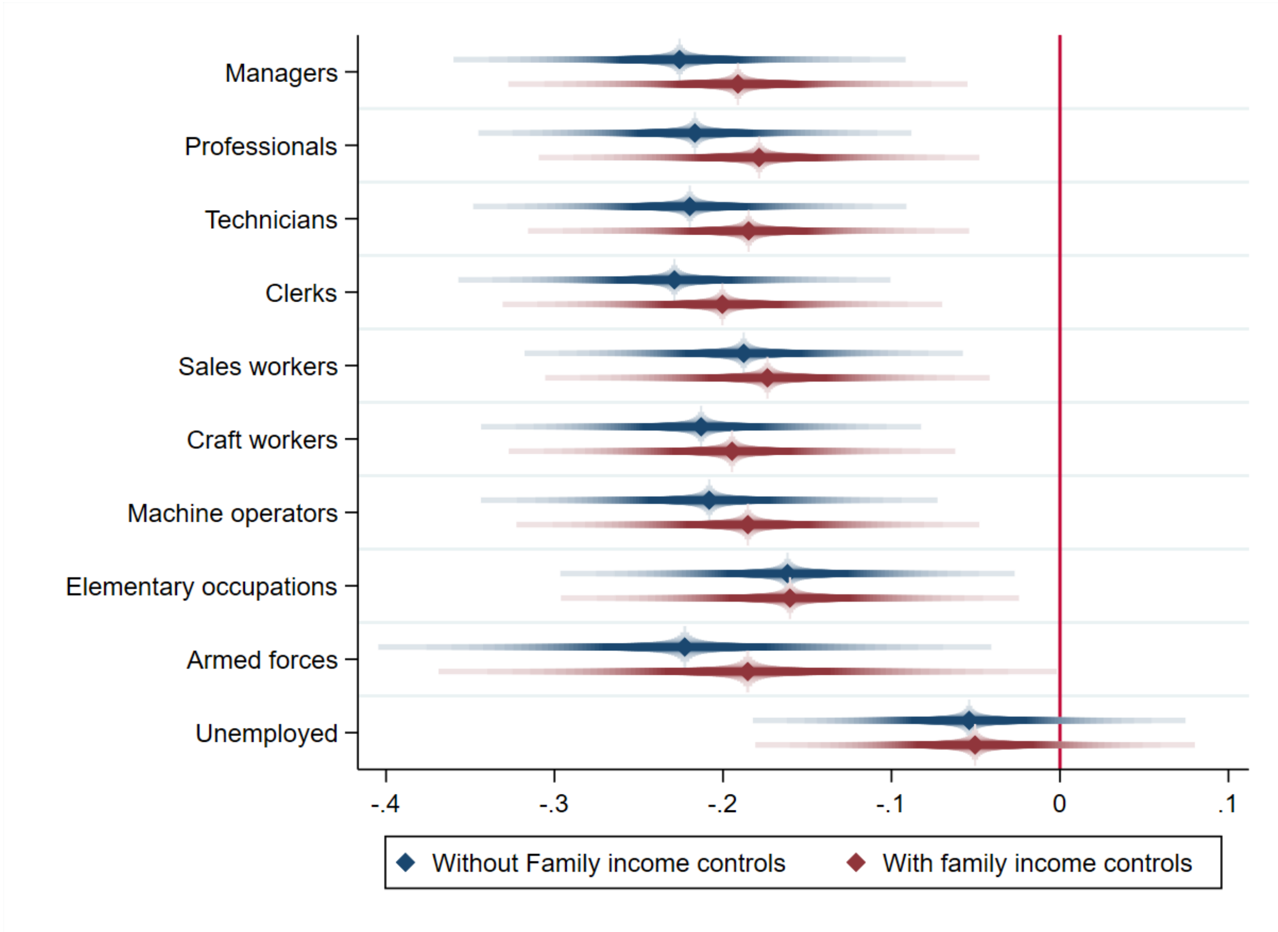

Figure 4: Marginal effects of income vulnerability with respect to Platform Workers

4.2.1 Robustness check: propensity score matching

Despite our main results being robust to the inclusion of a large set of controls, concerns may be raised about a potential 'selection bias'. That is, individuals who are relatively worse off (e.g., long-term unemployed, low-income individuals, etc.) may be more inclined to offer their services on platforms as way to increase their income (see the discussion in the Methods section). In order to partly control for some of the selection-related endogeneity, we implement a propensity score matching (PSM) model testing the robustness of the income vulnerability-platform work relationship. As already argued, the PSM allows controlling for the potential presence of confounding factors (other elements affecting both income vulnerability and the individual decision to work through digital labour markets) by comparing individuals that are as similar as possible with respect to a selected set of characteristics (Becker and Ichino, 2002).

The estimation is based on two steps. In our case, the first step entails the estimation of the propensity score, that is the probability to perform platform work conditioned on a set of selected covariates (gender, age classes, marital status, living in households with disabled people, living in large cities, being employed).[14] The second step implies the estimation of the

[14]We had to restrict the number of covariates with respect to those included in eq. 1 and eq. 2 in order to

"average treatment effect on the treated", that is the average difference in outcome (inability to deal with unexpected expenses) as a result of platform participation for those who are currently platform workers. [15]

Table 5 shows the results of treatment effects estimation performed through inverse-probability weighting for the outcome model (income fragility). The Abadie-Imbens standard error calculation is performed automatically.

Table 5: Average treatment effects on the treated (ATET) (inverse-probability weighting)

	Inability to deal with unexpected expenses	Coef.	Rob Std. Err.	z	P>z	[95% Conf.	Interval]
ATET							
	Working on a platform (1 vs 0)	0,1643	0,0309	5,31	0,000	0,1036	0,2250
PO mean							
	Working on a platform 0	0,2050	0,0073	27,91	0,000	0,1906	0,2194

Table 5 confirms main results shown in Table 3. Working on a platform increases the probability of income fragility. The result of ATET (Average Treatment Effects on the Treated) - i.e. the mean differences between treated and untreated individuals after the matching - indicates that platform workers have a higher probability of income fragility than non-platform workers. The chance of facing income vulnerability of platform workers is about 16 percentage points higher than that of non-platform workers.[16] Table 5 also shows that the baseline incidence of income fragility in the population of non-platform workers is estimated to be about 20% (potential-outcome means: POmean).

Overall the PSM exercise highlights that platform workers are exposed to greater economic uncertainty relative to the rest of the workforce (RQ3). This is verified when we match individuals having similar characteristics in terms of age, gender, employment status, marital status, place of living and type of households and only differing with respect to their work on the platform.

Lastly, repeating the PSM on the same set of covariates plus the inclusion of a dummy taking value of one if the individual lives in a household whose income is below 1,500 EUR per month and zero otherwise, we estimate an average treatment effects on the treated of 0.14. The

guarantee balance of propensity score across treatment and comparison groups.

[15]See Fig. 6 in the Appendix for the distribution of the pscore on treated and controls and Tab.6 for descriptive statistics of covariates for the two groups before matching. Furthermore, we test the balance of covariates after matching by implementing the test proposed in Imai and Ratkovic (2014) and we cannot reject the null that IPW model/weights balance covariates.

[16]Very similar results have been obtained by performing one-to-one matching without replacement, kernel matching, and a matching within the radius of 5% combined with different techniques to impose common support over the set of covariates such as minmax and trimming (Caliendo and Kopeinig, 2008). Minimax 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 is the lowest (Bogliacino et al., 2019a). Results in Tab.7 in the Appendix show that platform workers face a higher probability of income vulnerability ranging between 14 and 17 percentage points.

chance of facing income vulnerability of platform workers is thus 14 percentage points higher than that of non-platform workers, even once we control for family income. This last step further highlights that platform workers are exposed to greater economic uncertainty relative to the rest of the workforce and that this disadvantage is not exclusively channeled through lower earnings.

5 Discussion

Well before the onset of the COVID-19 pandemic, many European labor markets were becoming increasingly fragmented (Green and Livanos, 2017). The declining share of workers with permanent contrasts, insurances against job loss or adverse health, and standard employment protections has widened the gaps between labour market insiders and outsiders (Picot and Menéndez, 2019). The rise of platform work across advanced economies throughout the past decade has prompted further concern about the socio-economic conditions of these labour market outsiders. Scholars have, in turn, investigated the size, composition, and working conditions of individuals in platform work. Given that standard labour force surveys have struggled to identify adults engaged in platform work, many scholars have turned to web-based and/or non-probability sampling techniques to specifically target individuals engaged in platform work (O'Farrell and Montagnier, 2020). While these surveys have proved useful, they carry their own set of limitations related to selection effects, representativeness, and inability to make within-sample comparisons of socio-economic well-being across a broad range of occupation groups. This study, in contrast, employs representative survey data from Italy to provide a more detailed comparison of the economic insecurity of platform workers relative to others in 2018.

Our findings produce three broad conclusions with several implications for the broader literature on the platform economy and socio-economic well-being among employed adults. First, our findings corroborate evidence from INPS (2018) that platform work remains relatively small in Italy. Around 0.5 percent of Italians between the ages of 18 and 76 provided work or direct services (e.g. food delivery, taxi rides, or similar) through a platform or phone application in 2018. Platform workers tend to be students and of younger age, but are more diverse with respect to sex, educational attainment, and native-born status. Platform workers are also more prevalent in cities, where demand for their services is higher and more concentrated.

We find that platform workers face greater economic insecurity relative to all other occupation classes. Despite the salience of platform work and the rise of such occupations throughout recent years, such jobs do remain a relatively small part of the overall labour market, and our data suggest that the occupations remain relatively diverse with respect to education, sex, and citizenship status.

Second, we are able to quantify the relative income disadvantages of individuals engaged in platform work in Italy. Specifically, we find that about 15% of platform workers have net family incomes below 1,000 euros per month; in contrast, this percentage falls to 10% for non-platform workers.

Third, and most important, we find that economic insecurity among platform workers is greater than in all other occupation groups and, strikingly, is not significantly different from that of unemployed adults. Moreover, we find that the higher levels of insecurity are not primarily channeled through lower incomes; instead, higher rates of insecurity persist even when taking family incomes into account, suggesting that the precarity and volatility of platform work matter as much as, or more than, income differences in shaping economic disadvantage. Our findings hold under propensity score matching techniques that attempt to account for selection into platform work.

Our findings carry important consequences for our understandings of the intensity and source of socio-economic challenges of individuals engaged in platform work. While it is generally understood that platform workers face more disadvantage, our study is able to quantify the levels of these disparities in one high-income country and, equally important, identify that disparities in economic insecurity are not solely a product of having lower incomes. Instead, it appears likely that the less-regular working hours, reduced autonomy, and reduced access to social protections contribute as much, if not more, to economic insecurity than the lower incomes associated with platform jobs. 'Digital workers' are not entitled to benefit from existing social protection schemes (Collier et al., 2017; Codagnone et al., 2018). These findings correspond with evidence from the broader labour market literature regarding the role of scheduling practices and intra-year earnings volatility in shaping economic hardship, independent of the level of monthly or annual income (among recent works on the US labour market, see Schneider and Harknett (2020); Finnigan and Meagher (2019)). In turn, our findings suggest that efforts to raise earnings of platform workers is only one step toward reducing their socio-economic disparities relative to the rest of the labour market. Instead, providing more security and predictably may be necessary to close the gaps in economic insecurity.

Our study does have limitations. First, like many in the labour market literature, we focus on a single country. Often in single-country studies, scholars investigate conditions in the United States; we instead focus on Italy due to its higher-quality, representative survey data inclusive of platform workers. As with all single-country studies, however, external validity is not assured. Though Italy shares many high-level features with other advanced economies, variation in demographic composition and national welfare state and labour market institutions may lead to better (or worse) working conditions for platform workers in other countries. Second, our data only feature one measure of economic insecurity (whether an individual delays medical care due to financial difficulties). Given that we can directly control for health status, the indicator should serve as a reliable measure of economic uncertainty. Nonetheless, future work would benefit from a broader suite of economic insecurity measures. Still, our study finds that whether focusing on net earnings, net family income, or economic insecurity, workers engaged in platform work tend to be at the bottom of the occupational distribution and with conditions comparable to the unemployed.

Future work would benefit from the use of longitudinal panel data to investigate whether our findings hold when evaluating changes in employment status among the same individuals over time. Moreover, advancing from single-country to cross-country comparisons may provide more insight how national welfare state and labour market institutions affect patterns of well-being among platform workers. Additionally, the integration of indicators relating to platform work into broader, cross-national surveys, such as the EU Labour Force Survey, would more readily enable reliable, cross-national comparisons.

Nonetheless, our evidence reveals that the levels of economic insecurity among platform workers remain high in Italy, and that the insecurity is not driven solely through income disparities. Insofar as the platform economy continues to expand, our findings portend widen disparities between labour market insiders and outsiders.

References

Adams-Prassl, J. (2019): "What if your boss was an algorithm? Economic Incentives, Legal Challenges, and the Rise of Artificial Intelligence at Work," *Comp. Lab. L. & Pol'y J.*, 41, 123.

Austin, P. C. (2011): "An introduction to propensity score methods for reducing the effects of confounding in observational studies," *Multivariate behavioral research*, 46, 399–424.

Becker, S. O. and A. Ichino (2002): "Estimation of average treatment effects based on propensity scores," *The stata journal*, 2, 358–377.

Berg, J., M. Furrer, E. Harmon, U. Rani, and M. S. Silberman (2018): "Digital labour platforms and the future of work," *Towards Decent Work in the Online World. Rapport de l'OIT.*

BLS (2018): "Electronically mediated work: new questions in the Contingent Worker Supplement," *Monthly Labor Review*, 1–32.

Bogliacino, F., V. Cirillo, C. Codagnone, M. Fana, F. Lupiáñez-Villanueva, and G. A. Veltri (2019a): "Shaping individual preferences for social protection: the case of platform workers," Tech. rep., LEM Working Paper Series.

Bogliacino, F., C. Codagnone, V. Cirillo, D. Guarascio, et al. (2019b): "Quantity and quality of work in the platform economy," *Handbook of Labor, Human Resources and Population Economics.*

Brancati, M. C. U., A. Pesole, E. Férnandéz-Macías, et al. (2020): "New evidence on platform workers in Europe: Results from the second COLLEEM survey," Tech. rep., Joint Research Centre (Seville site).

Caliendo, M. and S. Kopeinig (2008): "Some practical guidance for the implementation of propensity score matching," *Journal of economic surveys*, 22, 31–72.

Cirillo, V., M. Fana, and D. Guarascio (2017): "Labour market reforms in Italy: evaluating the effects of the Jobs Act," *Economia Politica*, 34, 211–232.

Codagnone, C., F. Lupiáñez-Villanueva, P. Tornese, G. Gaskell, G. A. Veltri, J. Vila, Y. Franco, S. Vitiello, A. Theben, P. Ortoleva, et al. (2018): *Behavioural study on the effects of an extension of access to social protection for People in all forms of employment*, Publications Office of the European Union.

Codagnone, C. and B. Martens (2016): "Scoping the sharing economy: Origins, definitions, impact and regulatory issues," *Cristiano Codagnone and Bertin Martens (2016). Scoping the Sharing Economy: Origins, Definitions, Impact and Regulatory Issues. Institute for Prospective Technological Studies Digital Economy Working Paper*, 1.

Collier, R. B., V. Dubal, and C. Carter (2017): "Labor platforms and gig work: the failure to regulate," .

De Stefano, V. (2015): "The rise of the just-in-time workforce: On-demand work, crowdwork, and labor protection in the gig-economy," *Comp. Lab. L. & Pol'y J.*, 37, 471.

De Stefano, V. and A. Aloisi (2019): "Fundamental labour rights, platform work and human rights protection of non-standard workers," in *Research handbook on labour, business and human rights law*, Edward Elgar Publishing.

Drahokoupil, J. and A. Piasna (2017): "Work in the platform economy: Beyond lower transaction costs," *Intereconomics*, 52, 335–340.

Eurofound (2020): "Living, working and COVID-19," Tech. rep., Publications Office of the European Union, Luxembourg.

Finnigan, R. and K. D. Meagher (2019): "Past due: combinations of utility and housing hardship in the United States," *Sociological Perspectives*, 62, 96–119.

Green, A. and I. Livanos (2017): "Involuntary non-standard employment in Europe," *European Urban and Regional Studies*, 24, 175–192.

Griesbach, K., A. Reich, L. Elliott-Negri, and R. Milkman (2019): "Algorithmic control in platform food delivery work," *Socius*, 5, 2378023119870041.

Guarascio, D. (2018): "Report sull'economia delle piattaforme digitali in Europa e in Italia," .

Guarascio, D. and S. Sacchi (2018): "Digital platforms in Italy; an analysis of economic and employment trends," *INAPP policy brief*, 8.

Gyulavári, T. (2020): "Collective rights of platform workers: the role of EU law," *Maastricht Journal of European and Comparative Law*, 27, 406–424.

Hall, J. V. and A. B. Krueger (2018): "An analysis of the labor market for Uber's driver-partners in the United States," *Ilr Review*, 71, 705–732.

Huws, U. (2017): "Where did online platforms come from? The virtualization of work organization and the new policy challenges it raises," in *Policy implications of virtual work*, Springer, 29–48.

Huws, U., N. Spencer, D. S. Syrdal, and K. Holts (2017): "Work in the European gig economy: Research results from the UK, Sweden, Germany, Austria, the Netherlands, Switzerland and Italy," .

Imai, K. and M. Ratkovic (2014): "Covariate balancing propensity score," *Journal of the Royal Statistical Society: Series B: Statistical Methodology*, 243–263.

INPS (2018): "XVII RAPPORTO ANNUALE," Tech. rep., Istituto Nazionale per la Previdenza Sociale.

Katz, L. F. and A. B. Krueger (2019): "Understanding trends in alternative work arrangements in the United States," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 5, 132–146.

Kenney, M. and J. Zysman (2016): "The rise of the platform economy," *Issues in science and technology*, 32, 61.

——— (2019): "Work and value creation in the platform economy," in *Work and Labor in the Digital Age*, Emerald Publishing Limited.

Lusardi, A., D. Schneider, P. Tufano, A. Morse, and K. M. Pence (2011): "Financially Fragile Households: Evidence and Implications/Comments and Discussion," *Brookings Papers on Economic Activity*, 83.

O'Farrell, R. and P. Montagnier (2020): "Measuring digital platform-mediated workers," *New Technology, Work and Employment*, 35, 130–144.

Parker, G. G., M. W. Van Alstyne, and S. P. Choudary (2016): *Platform revolution: How networked markets are transforming the economy and how to make them work for you*, WW Norton & Company.

Pesole, A., M. Brancati, E. Fernández-Macías, F. Biagi, and I. González Vázquez (2018): "Platform workers in Europe," *Luxembourg: Publications Office of the European Union.*

Picot, G. and I. Menéndez (2019): "Political parties and non-standard employment: an analysis of France, Germany, Italy and Spain," *Socio-Economic Review*, 17, 899–919.

Prassl, J. and M. Risak (2015): "Uber, taskrabbit, and co.: Platforms as employers-rethinking the legal analysis of crowdwork," *Comp. Lab. L. & Pol'y J.*, 37, 619.

Riso, S. (2019): "Mapping the contours of the platform economy," Tech. rep., Eurofound Working Paper. Dublin: European Foundation for the Improvement of ....

Robles, B. J. and M. McGee (2016): "Exploring online and offline informal work: findings from the Enterprising and Informal Work Activities (EIWA) survey," .

Rosenbaum, P. R. and D. B. Rubin (1983): "The central role of the propensity score in observational studies for causal effects," *Biometrika*, 70, 41–55.

Rubin, D. B. (1974): "Estimating causal effects of treatments in randomized and nonrandomized studies." *Journal of educational Psychology*, 66, 688.

——— (1977): "Assignment to treatment group on the basis of a covariate," *Journal of educational Statistics*, 2, 1–26.

Schneider, D. and K. Harknett (2019): "Consequences of routine work-schedule instability for worker health and well-being," *American Sociological Review*, 84, 82–114.

——— (2020): "Hard Times: Routine Schedule Unpredictability and Material Hardship among Service Sector Workers," *Social Forces*, 99.

A Appendix

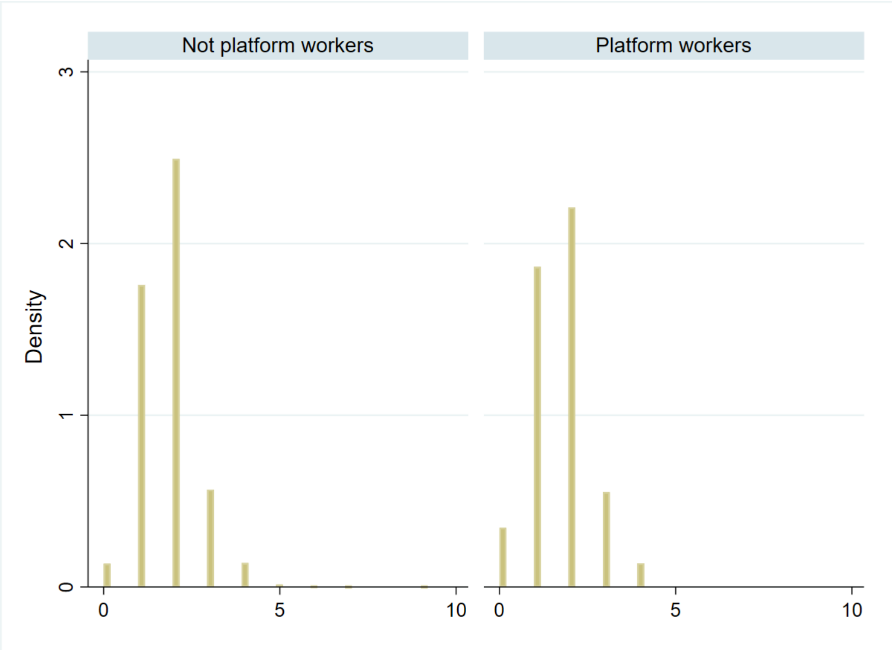

Figure 5: Average number of earners per household

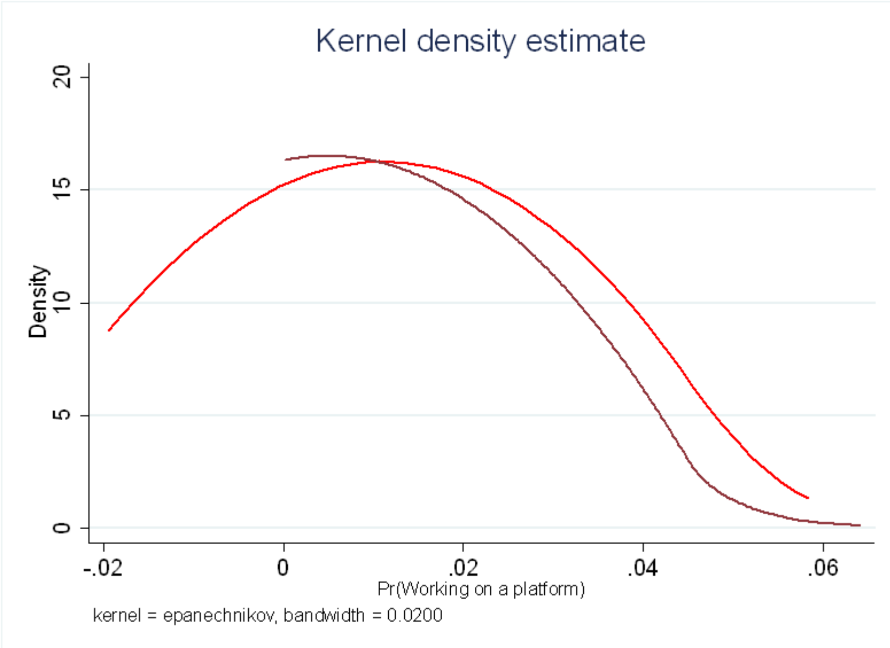

Figure 6: Distribution of the propensity score before matching

Table 6: Summary statistics of covariates for matched samples (common support) weighted by the propensity score

	Non platform workers			Platform workers		
Variables	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Age class (18 - 24)	42,098	0,0831	0,2761	222	0,0820	0,2750
Age class (25 -29)	42,098	0,1030	0,3040	222	0,1176	0,3228
Age class (30 - 39)	42,098	0,1589	0,3656	222	0,1388	0,3465
Age class (40 - 49)	42,098	0,1837	0,3872	222	0,1844	0,3887
Age class (50 - 64)	42,098	0,3357	0,4722	222	0,3152	0,4656
Living in a couple	42,098	0,5480	0,4976	222	0,5407	0,4994
Living with people with disabilities	42,098	0,0815	0,2736	222	0,0589	0,2359
Living in large cities (¿250.000)	42,098	0,1526	0,3596	222	0,1793	0,3845
Women	42,098	0,5285	0,4991	222	0,5029	0,5011
Employed	42,098	0,4595	0,498	222	0,4030	0,4916

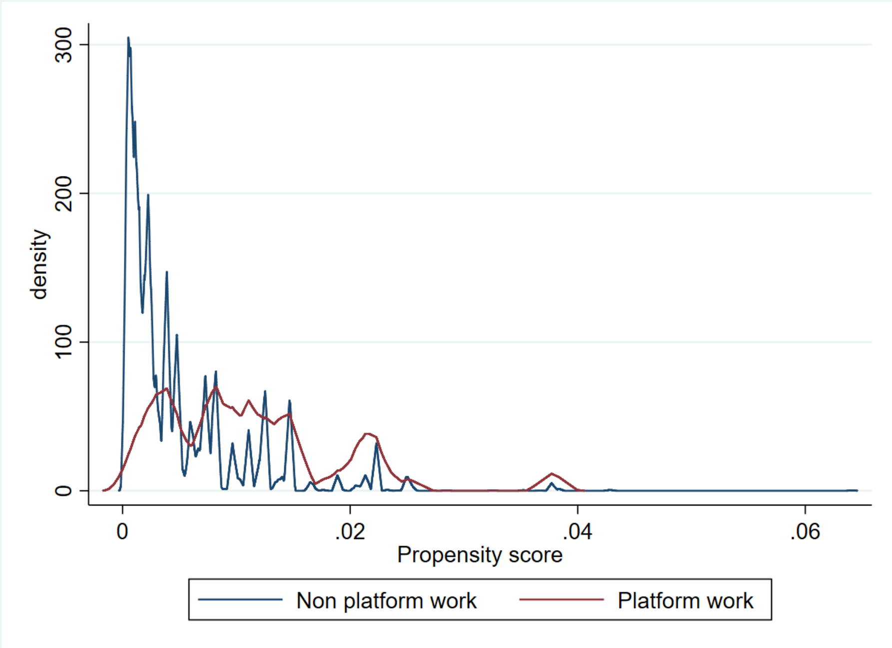

Figure 7: Distribution of the propensity score after matching

Table 7: Treatment-effects estimation (Outcome model: propensity-score matching; Treatment model: probit)

Propensity score matching (common non replacement)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3694	0,2207	**0,1486**	0,0428	3,47

Propensity score matching (common non replacement with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3791	0,2227	**0,1564**	0,0441	3,55

Propensity score matching (common non replacement kernel)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3694	0,2207	**0,1486**	0,0428	3,47

Propensity score matching (common non replacement kernel with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3791	0,2227	**0,1564**	0,0441	3,55

Propensity score matching (common non replacement radius caliper)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3694	0,2026	**0,1668**	0,0325	5,13

Propensity score matching (common non replacement radius caliper with trimming)						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Inability to deal with unexpected expenses	Unmatched	0,3694	0,2026	0,1668	0,0271	6,16
	ATT	0,3791	0,2026	**0,1766**	0,0335	5,27