



Article

Labour market digitalization and social class: evidence of mobility and reproduction from a European survey of online platform workers

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Abstract

The type of work we do as adults is significantly influenced by our parents' social class. However, digital technologies are transforming the way labour markets work. Candidates are screened using algorithmic decision-making systems. Skills are validated with online tests and feedback ratings. Communications take place online. Could these transformations undermine the advantages that have accrued to workers with privileged backgrounds or reproduce this privilege through digital divides? We examine this question with survey evidence from the online (remote) platform economy, a labour market segment where these digital transformations have progressed furthest ($N = 1,001$). The results reveal that online platform workers come predominantly from privileged class backgrounds, but we find less evidence of parental class shaping what types of online work they do. We conclude that digital transformations of labour markets may reproduce disparities in *access to work* but attenuate some class-based differences in the *selection of workers* by employers.

Key words: class; labour markets; social mobility; stratification; technological change

JEL classification: J620 job; occupational, and intergenerational mobility; promotion

1. Introduction

The type of work we do as adults is significantly influenced by the social class of our parents. A substantial body of research shows how financial capital, social ties, and cultural resources acquired from parents influence what kinds of jobs their children end up in (Torche 2015; Bukodi and Goldthorpe 2018; Friedman and Laurison 2019; Breen and Müller

2020). However, labour markets are currently undergoing significant transformations associated with the adoption of new digital technologies and the shift toward remote working. Candidates are increasingly screened using data and algorithmic decision-making systems. Skills are validated with online tests and customer feedback ratings. Workplace communications take place over digital media. The purpose of this article is to examine how these digital transformations may be affecting the link between parents' occupational class and their children's occupational attainment.

Research on digital divides has shown that the availability, adoption, and use of new information and communication technologies are marked by disparities that follow established social class divisions (Scheerder *et al.* 2017). People from more privileged backgrounds tend to be able to obtain greater benefits from new digital technologies (van Deursen and Helsper 2015). This suggests that digital transformations in labour markets could be sustaining or even deepening class divides. However, digital transformations could also plausibly be hindering some of the mechanisms through which class reproduction conventionally takes place in labour markets. For example, expensive degrees and cultural signifiers may be less relevant in a quantified, algorithmic, and digitally mediated labour market. In this article, we study the impacts of these digital transformations on class reproduction by analysing an extreme case: the online market for remote freelance labour, in which digital transformations that are only nascent in the broader labour market have already been widely adopted. The market is underpinned by web-based platforms that validate workers' skills using tests and feedback ratings, match workers with employers in part by using algorithmic recommendations, and digitally mediate communications between the parties. If digital transformations are disrupting the link between parental class and children's occupational outcomes, then we should be able to observe it in this online labour market.

Labour platforms are an increasingly popular research context, but researchers are yet to empirically evaluate class and social reproduction in this setting. In this article, we provide initial answers to the following questions: (1) What are the parental class backgrounds of people doing online platform work? (2) Does class origin influence the type of work workers undertake in the online labour market? Our analyses are based on data from the European Centre for the Development of Vocational Training's (Cedefop) CrowdLearn survey. The respondents are 1,001 freelancers who obtained work via four major online labour platforms (Upwork, Fiverr, PeoplePerHour, and Twago) and were resident in six European countries (Finland, Germany, Italy, Romania, Spain, and the UK).

Results reveal that people doing online platform work are somewhat surprisingly disproportionately from privileged parental class backgrounds. We also find some evidence that parental class background predicts which types of work the platform workers are engaged in. First, those doing work categorized as 'Professional Services' are disproportionately from more privileged backgrounds. This disparity is entirely accounted for by differences in educational attainment, suggesting that even in a digitally transformed labour market, parental class background can influence children's job outcomes indirectly through the formal educational system. Secondly, those doing 'Sales and Marketing' work are likewise disproportionately from more privileged backgrounds, an association that cannot be accounted for using available controls. This suggests that even in the digitally transformed labour market, parental class background retains a direct influence on children's likelihood of ending up in sales work, possibly through the kinds of cultural resources valued in sales work. However, we find no links between class origins and other types of online work. We conclude that digital

transformations could be reproducing class divides in access to work while somewhat attenuating the influence of class on the selection of workers by employers.

Our study presents an empirical contribution to the rapidly growing literature on online platform work and ‘gig work’, as the first quantitative analysis of class and social reproduction in this context. The study also presents a theoretical contribution in extending social mobility debates into digitally transformed work and developing initial understandings of mechanisms that may generate social mobility and reproduction in a quantified, algorithmic, and digitally mediated labour market. In this way, we also offer a modest contribution to the broader discussion on digital technologies and inequality.

2. Literature review

2.1 Intergenerational social mobility

Researchers of intergenerational social mobility have long investigated how parental class influences occupational outcomes for the next generation (Torche 2015; Bukodi and Goldthorpe 2018; Friedman and Laurison 2019; Breen and Müller 2020). Intergenerational class reproduction matters because the more life chances are determined by accident of birth rather than merit or effort the less societies live up to the rhetoric of equality of opportunity espoused across the political spectrum. However, debates continue over the extent to which the influence of parental class persists or whether it is attenuating over time. Persistence approaches particularly emphasize the indirect role of education in class reproduction (Bukodi and Goldthorpe 2018; Breen and Müller 2020). Parents in more privileged class positions can secure longer and higher quality educations for their children, improving their chances of attaining jobs in more privileged classes (Goldthorpe 2007). In addition, the direct influence of parents’ social networks and the transmission of particular cultural resources that communicate suitability for roles in particular occupational classes (e.g. forms of speech, modes of self-presentation, consumption of different media) also contribute towards class reproduction (Friedman and Laurison 2019).

In contrast, approaches emphasizing the attenuation of the influence of parental class on the occupational outcomes of the next generation argue that the rapid expansion of educational provision since the mid-20th century has reduced inequalities in educational outcomes between children of different class origins and, by extension, their occupational attainment (Blau and Duncan 1967; Treiman 1970; Bell 1973). In addition, attenuation approaches emphasize the importance that owners and managers must place on the productive efficiency and competitiveness of their firms. Workers must therefore be increasingly selected based on their competence, which is frequently proxied by educational qualifications, rather than via nepotism or cultural matching.

In the next sections, we argue that the attenuation approach is implicit in many discussions concerning the digital transformation of the labour market and that the remote, online platform economy, where these transformations are most advanced, represents a most likely case for such attenuation. However, we also identify reasons why digitalization could fail to attenuate class reproduction, or even deepen it.

2.2 Digital labour market transformations

While researchers of social mobility have debated which theories of class reproduction have proved more accurate, labour markets themselves have continued to change. In particular,

much scholarly attention has been paid to the impacts of technological transformations on labour markets. Many influential studies have examined changes in the demand for different types of skills as a result of the adoption of computers and automation technologies (e.g. [Rumberger and Levin 1985](#); [Di Pietro 2002](#); [Frey and Osbourne 2017](#)). In previous eras, job losses linked to automation were concentrated in low-income, routine-intensive occupations ([Braverman 1974](#); [Goldin and Katz 1998](#); [Bresnahan 1999](#)). However, over the past two decades, technology-induced job losses in Europe and the USA are thought to have taken place predominantly in middle-income manufacturing and clerical jobs ([Goos *et al.* 2009](#); [Autor and Dorn 2013](#)). This is feared to have led to a ‘hollowing out’ of the labour market, in which jobs that sustain the middle class are eliminated ([Goos and Manning 2007](#); [Autor and Dorn 2013](#)).

Yet, besides changes in the skill content of jobs, the adoption of new technologies is also associated with transformations in employment practices—changes not only in the ‘what’ but also in the ‘how’. It is possible to identify at least three such transformations. One is the adoption of telework ([Huws *et al.* 1990](#)) or telecommuting ([Mokhtarian 1991](#)), which refers to workers working remotely from their homes, co-working spaces, or other locations. As home Internet access has improved and office information systems have moved to the cloud, working remotely has gradually become more common ([Dunn 2017](#)). The need for social distancing during the pandemic further accelerated the use of remote working. Digitally mediated remote interaction has also become extremely common in hiring, with the initial interview in many cases being performed via videoconferencing, or even via text-based instant messaging ([Sanchez-Monedero and Dencik 2019](#)).

A second, more recent digital transformation is the adoption of ‘AI’ or digital automation technologies in human resource management, especially in the hiring process ([Guenole *et al.* 2017](#); [Dencik and Stevens 2021](#)). For instance, many employers and labour market intermediaries use algorithmic recommendation systems to identify suitable candidates ([Horton 2017](#)). A widely used example is LinkedIn’s ‘Recommended Candidates’ feature, which automatically identifies potential matches for a job opening from its vast pool of profiles ([Wiggers 2020](#)). Employers also use digital automation in applicant screening ([Cowgill 2017](#)) and some even in initial interviewing through ChatGPT-like automated chatbots ([Sanchez-Monedero and Dencik 2019](#)).

A third related transformation is the use of digital data sources in skills validation and performance evaluation ([Guenole *et al.* 2017](#)). Employers in information technology industries have long used private professional certifications to validate candidates’ skills in addition to, or instead of, degrees and other publicly regulated qualifications ([Painter and Bamfield 2015](#)). More recently, employers have begun to assess candidates’ skills and suitability with automated computer-administered online tests ([Hoffman *et al.* 2018](#); [Dencik and Stevens 2021](#)). Cedefop describes ‘microcredentials’ awarded on the basis of such tests as a new ‘megatrend’ ([Cedefop 2021](#)). Some companies have also begun to use observational data from sources, such as social media, voice analysis, emails, and customer feedback surveys to automatically produce quantitative measures of worker performance that are used in hiring, task assignment, and promotion decisions ([Guenole *et al.* 2017](#); [Levy and Barocas 2018](#); [Sanchez-Monedero and Dencik 2019](#)).

Terms sometimes used to describe these practices include ‘algorithmic management’ ([Wood *et al.* 2019](#)), ‘datafication’ ([Dencik and Stevens 2021](#)), and ‘people analytics’ ([Guenole *et al.* 2017](#)). We will refer to all these changes in employment and hiring

practices associated with the adoption of digital technologies as digital labour market transformations.

2.3 Digital disruptions and divides

What implications do digital labour market transformations have for social mobility, and specifically, for the influence of parental class on occupational attainment? On the one hand, digitalization could be disrupting the operation of the direct and indirect mechanisms that lead to class reproduction. The introduction of telework and remote hiring could mean that family social ties in the worker's local community are becoming less useful for obtaining and holding onto work. The remote nature of the work and restricted social contact between employer and employee could also reduce the influence of class cultural judgements, in sharp contrast with jobs awarded on the basis of face-to-face interviews. The substitution of AI technologies for managerial judgement could likewise be drastically reducing the significance of social ties and cultural resources in hiring decisions. Moreover, the adoption of new digital forms of skill validation and performance measurement could be reducing the relative value of formal educational qualifications as signalling devices, eroding the influence of class origin-induced inequalities in educational attainment. For these reasons, digital labour market transformations could be disrupting the influence of parental class background on occupational outcomes.

On the other hand, a recurring finding in research on 'digital divides' is that people from privileged backgrounds tend to benefit more from digital technologies (Scheerder *et al.* 2017). Digital divides were first identified in the 1990s in access to the Internet. Older and poorer people and those living in rural areas were found to have less access than young, privileged city-dwellers (Räsänen 2006). As access became increasingly widespread in wealthier societies, research in the 2000s and 2010s turned towards inequalities in digital skills and the ways people used digital technologies (Dimaggio *et al.* 2004). It was found that older and poorer Internet users were less skilled and more likely to use digital technologies for entertainment than younger and wealthier users, who were more likely to exploit online educational and commercial opportunities (Scheerder *et al.* 2017). More recently, research has begun to focus on a 'third-level' divide: differences between social groups in the extent to which outcomes from Internet and digital technology use are beneficial (Scheerder *et al.* 2017). Echoing earlier research on divides in access, skills, and usage, researchers in the Netherlands have found that wealthier, more educated people are able to achieve better commercial, social, and informational outcomes in digital media (van Deursen and Helsper 2015).

A newer stream of research on the use of data and algorithmic decision making in government and private organizations also suggests that these technologies can perpetuate and even accentuate inequalities (e.g. O'Neil 2016; Eubanks 2017). System designers tend to transmit their own values and prejudices into technologies. Machine learning systems trained with biased data can continue to perpetuate the bias. Eubanks (2017) argues that poor and working-class people, in particular, have been adversely affected by digital surveillance and algorithmic decision-making systems. This is because they may have to deal with such systems more often, while privileged people may be afforded personal service. Another reason is that poor and working-class people may lack the resources to effectively challenge the systems when they make mistakes. Findings like these should cause us to treat with caution the idea that digital transformations would necessarily reduce the influence of class on labour market outcomes.

2.4 An extreme case: online platform labour

Do digital labour market transformations disrupt class reproduction or not? In this study, we approach this question through an extreme case: the online market for remote freelance labour, in which self-employed workers sell labour remotely to clients through web-based platforms (Bergvall-Kåreborn and Howcroft 2014; Kalleberg and Dunn 2016). Virtually, every kind of labour that can be delivered remotely over the Internet is transacted through these platforms, such as software development, graphic design, database management, customer service, sales lead generation, accounting, and legal work (Kässi and Lehdonvirta, 2018). The entire relationship from screening and matching to contracting, time tracking, billing, payment, and dispute resolution is mediated by the platform company.

Research suggests that such online platform work—also known as online freelancing, online gig work, and crowdwork—is a small but growing form of non-standard employment around the world, including in Europe. According to data from the European Commission Joint Research Centre's second COLLEEM survey, the prevalence of platform-mediated work is slowly rising over time and is now the main source of income for about 1.4% of adults across sixteen EU Member States (Pesole *et al.* 2018; Urzi Brancati *et al.* 2019). This figure includes both local gig economy platforms (e.g. transport and food delivery) and the web-based remote online labour platforms that are the focus of our study. Data collected directly from the largest online labour platforms suggest that the global market almost doubled in size from 2016 to 2021 (Stephany *et al.* 2021). Leading platforms include Upwork, Freelancer, Fiverr, and PeoplePerHour.

Pay and working conditions in this online labour market vary significantly between different types of work. In general, more skilled types of work tend to be better compensated. For instance, the highest-paying category of work on Upwork in 2020 was 'professional services', which includes legal work and architecture (Lehdonvirta 2022). The median hourly rate in this category globally was \$22.50, with some workers charging rates in excess of \$100. In contrast 'data entry keyers' were the lowest-paid online workers, with an average rate close to \$5 (Braesemann *et al.* 2022). Besides low pay, workers undertaking more menial types of online work are also more likely to experience negative job quality characteristics, such as lack of autonomy and task variety (Wood *et al.* 2019). The mobility of workers between categories is limited, so the market is stratified between better and worse jobs.

Who, then, gets the best jobs? The online labour market is an attractive setting for conducting a case study of technology, class, and social reproduction because digital transformations that are only nascent in the broader labour market are already fully operational in this market. From start to finish, all interactions are remote and computer mediated, with hiring interviews being conducted via video calls or instant messaging or omitted in favour of purely document-based selection. Employers find suitable workers (and vice versa) from among the millions of possible matches by using the platforms' algorithmic search and recommendation engines. For instance, Upwork (then called oDesk) is documented to have used a recommendation engine that highlights workers to employers on the basis of a statistical model that considers factors such as the degree of overlap between the worker's skills and the requirements of the employer's job opening (Horton 2017). Upwork also provided workers with automated advice on how much pay they should be asking for, based on a statistical analysis of how much employers have been willing to pay for similar work in the past (Lehdonvirta 2022).

All online labour platforms track worker performance using digital data sources that are translated into metrics and scores that are displayed to prospective employers (Gandini 2019). For instance, Upwork displays a 'Job Success' score for each worker, which is calculated from previous client feedback and other inputs using an undisclosed algorithm (Wood and Lehdonvirta, 2022). Employers can filter out candidates whose score falls below their chosen threshold or choose to include only candidates flagged as 'Top Rated' or 'Rising Star' by the platform's algorithms. Some platforms, such as PeoplePerHour, also utilize automated computer-administered online tests to award badges or 'microcredentials' that validate candidates' skills (Kässi and Lehdonvirta 2022). Even clicks on a particular worker's profile are in some cases recorded and used as a proxy of the employer's interest in them (Horton 2017).

Due to this extremely digitalized nature, the online labour market arguably represents a most-likely case for theories of the attenuation of class reproduction, which posit that economic and technological progress reduces the influence of class origins on occupational attainment. If digital labour market transformations can disrupt the link between parental class and children's occupational outcomes, then we should be able to observe it here. On the other hand, theories of digital divides and algorithmic bias suggest that the most privileged should reap the benefits. Previous research has examined the online workers' demographics (Pesole *et al.* 2018) and found that they are younger than the general population, but otherwise very diverse. No previous research has attempted to link the measures of parental class to online labour market outcomes. We therefore seek to answer two main questions: (1) What are the class origins of online platform workers? and (2) Does class origin influence the type of work workers undertake in the online labour market?

3. Data

3.1 Sampling

Data for the analyses come from Cedefop's CrowdLearn survey of freelancers working on four prominent online labour platforms in six European countries (Finland, Germany, Italy, Romania, Spain, and UK) ($N=1,001$). The survey was collected between April and November 2019 under a contract with the European Union's European Centre for the Development of Vocational Training (Cedefop 2020). Two online labour platforms (Fiverr and PeoplePerHour) collaborated with the project team, randomly sampled their registered workers, and issued invitations and reminders to complete the survey online ($N=465$). The remaining respondents ($N=536$) were sampled from eligible workers on two platforms (Upwork and Twago) by the project team using an equal-quota approach for country and sex.

The sampling procedure does not permit us to straightforwardly assume that results generalize to the population of remote platform freelancers. Questions about representativeness apply at two levels: the choice of platforms and the sampling of workers within the platforms. Upwork and Fiverr are the two largest platforms globally, PeoplePerHour is a significant player in Europe, and Twago has local importance in some European countries and sectors. Together, they command the vast majority of the remote platform-based freelancing market in Europe and globally. When it comes to platform choice, our analyses therefore pertain to the preponderant mainstream of remote platform-based work in Europe.

As for worker sampling, it should be noted that online platform gig work in Europe, from where we draw our sample, tends to be medium/high skilled, whereas in much of the

rest of the world, this work can be very low skilled (e.g. microtasks) (Braesemann *et al.* 2022). On two of the platforms, we were able to draw random samples, which is unprecedented in platform labour research. On the other two platforms, we had to use non-probabilistic quota sampling, which is likely to introduce bias into our results (Lehdonvirta *et al.*, 2021). We mitigate this bias in two ways. In the first analysis, we match our respondents' observed demographic characteristics and educational attainment with the 2018 European Social Survey (ESS). ESS sampling introduces additional uncertainty into our analyses, but the ESS is a high-quality survey that takes representative, random samples of national populations. In the second analysis, we control for observed demographic characteristics, educational attainment, and platform.

While our mitigations cannot address unobserved differences between our sample and the population, we can quite confidently say that our sample is among the most representative ones in a field that tends to rely on fully non-probabilistic samples to reach this hard-to-reach population. Reassuringly, our respondents are similar in age and educational characteristics to the large-scale survey of remote platform workers conducted for the European Union's COLLEEM project (Pesole *et al.* 2018; Supplementary Appendix).

An alternative approach that is sometimes used in platform labour research is to use digital trace data (Lehdonvirta *et al.*, 2021). But this comes with its own problems (Lewis 2015a, b), most notably in that it constrains the available variables. Uniquely, the CrowdLearn survey contains questions concerning the parental class of platform workers, thereby enabling the first-ever assessment of the extent to which remote platform workers' parental backgrounds influence their job outcomes.

3.2 Measures

To assess platform workers' class origins, our survey instrument asked respondents, '*At the time you finished school, which category best matched your mother's/female guardian's main occupation?*'. The question was repeated for fathers/male guardians. Respondents chose from eight categories (with example occupations) based on the European Socio-Economic Classification (Harrison and Rose 2006): Higher Managerial/Professional, Lower Managerial/Professional, Middle-Class Service/Technical, Small Employer, Lower Technical, Lower Service, Unskilled, and Non-Working. In operationalizing the class origins of online workers, we follow the 'dominance' approach favoured in research on social mobility. The dominance approach takes the class of the parent/guardian with the more privileged class position as representative of the class origin of the respondent. This reflects the idea that the resources available to the family will be substantially influenced by the dominant parent. The dominance approach is considered superior to earlier approaches which took only male parents' class into account because of the rapid growth in female labour force participation. Although recent scholarship has begun to draw the dominance approach into question and has suggested that averaging parental socioeconomic status is a superior approach (Thaning and Hällsten 2020), adopting an averaging approach to parental class background was not possible using the categorical data in the survey. Nevertheless, the results of the models below are robust to alternative specifications, which include the non-dominant parental class as a separate independent variable as well as the interaction of the dominant and non-dominant, as recommended by Thaning and Hällsten (2020).

To assess the influence of class origins on the type of work undertaken in the online labour market, the respondents were asked to indicate which category of work they primarily

Table 1. Online work categories and characteristic jobs

Online work category	Characteristic jobs
Clerical and Data Entry	Administrative support, data entry, typing, proofreading
Creative and Multimedia	Animation, graphic design, audio/photo/video editing
Professional Services	Accounting, architecture, business services, consulting, legal, tax
Sales and Marketing Support	Customer service, digital marketing, sales and marketing, social media
Software Development and Technology	Networking, programming, software development, web development
Writing and Translation	Translation, technical writing, blog writing

conducted through the platform. Six categories were used, following the iLabour taxonomy (Table 1) used in previous research on online labour platforms (Kässi and Lehdonvirta, 2018).

4. Analyses

4.1 What are the class origins of online platform workers?

Figure 1 reveals that online platform workers in the sample tend to have privileged origins: having dominant parents in (1) Higher Managerial/Professional, (2) Lower Managerial/Professional, and (3) Middle-Class Service/Technical categories. The pattern is repeated across all countries in the sample (Fig. 2). Workers who had dominant parents in these categories are likely to have benefited from the advantages that accrue to such positions: higher wages, wages that peak later in life, more permanent contracts, and lower risks of unemployment (Goldthorpe and MacKnight 2006; Rose and Harrison 2010; Bukodi and Goldthorpe 2018). These proportions are substantially higher than estimates for dominant parents in the general population in the similarly timed 2018 ESS (Fig. 3, ‘ESS 2018 (Weighted)’), which takes representative, random samples of national populations (Romania was not included in ESS 2018).

However, CrowdLearn workers differ substantially from the general population of workers. For example, differences in the proportion of dominant parents from privileged classes could be due to the fact that CrowdLearn respondents are younger than the general population. Due to the expansion of managerial and professional work in the latter half of the 20th century, younger workers are more likely to have had parents in such roles. To mitigate this, CrowdLearn respondents were matched to ESS respondents using ‘MatchIt’ and ‘Matching’ packages in R (Ho et al. 2007; Sekhon 2011; Diamond and Sekhon 2013). Respondents were matched on age, sex, detailed educational attainment, employment status, immigration background, and country using the ‘genetic’ method, which maximizes the similarity between samples on these covariates using the generalized Mahalanobis distance (Ho et al. 2007). This method produces excellent balance on respondents’ characteristics (Supplementary Appendix Figure A.1 and Table A.2), and results are robust to alternative matching methods (e.g. exact, nearest neighbour). Figure 3 (‘ESS 2018 (Matched)’)

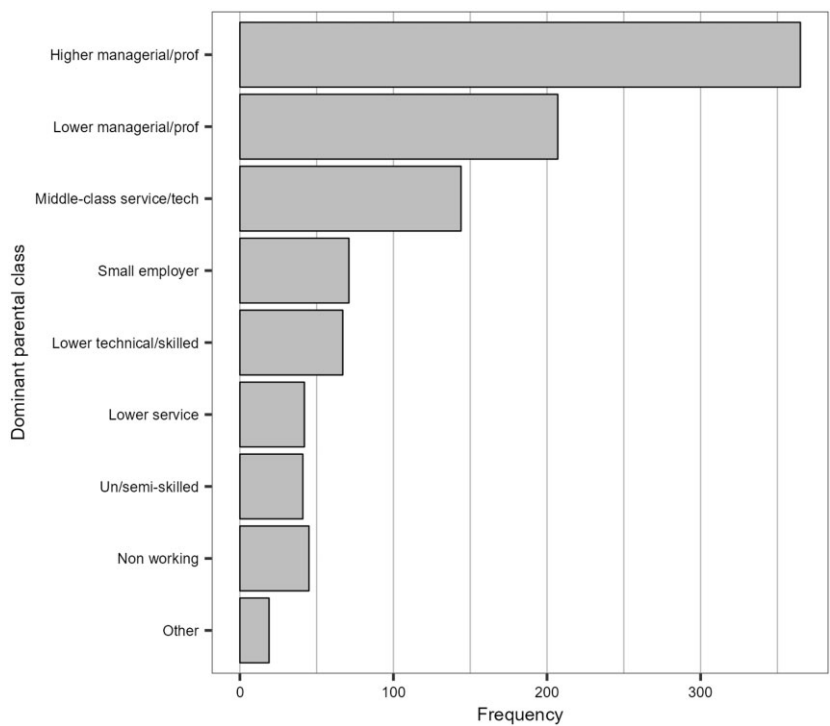


Figure 1. Dominant parental class background.

that, after matching, CrowdLearn respondents were still significantly more likely to have privileged dominant parents than ESS respondents. Evidence from Figs 1–3 therefore reveals a surprising digital divide in access to online platform work. Nevertheless, 28 per cent of the platform workers in the sample came from less privileged backgrounds, that is, categories other than Higher Managerial/Professional, Lower Managerial/Professional, or Middle-Class Service/Technical.

4.2 Does class origin influence the type of work in the online labour market?
To assess whether class origin influences types of work undertaken in the online labour market, we estimated multinomial logistic regression models of the following form:

$$\ln\left(\frac{P(i\text{Labour} = i)}{P(i\text{Labour} = \text{Clerical})}\right) = \beta_{i0} + \beta_{i1}\text{Parental Origins} + \beta_{i2}\text{Education} + \sum_{j=3}^n \beta_{ij}X_{ij} + \varepsilon \tag{1}$$

where $i \in \{\text{Creative and Multimedia; Professional Services; Sales and Marketing Support; Software Development and Technology; Writing and Translation}\}$.
In Equation (1), iLabour stands for the respondent’s primary category of work. A multinomial logistic regression model of this form enables us to estimate the relative odds of a

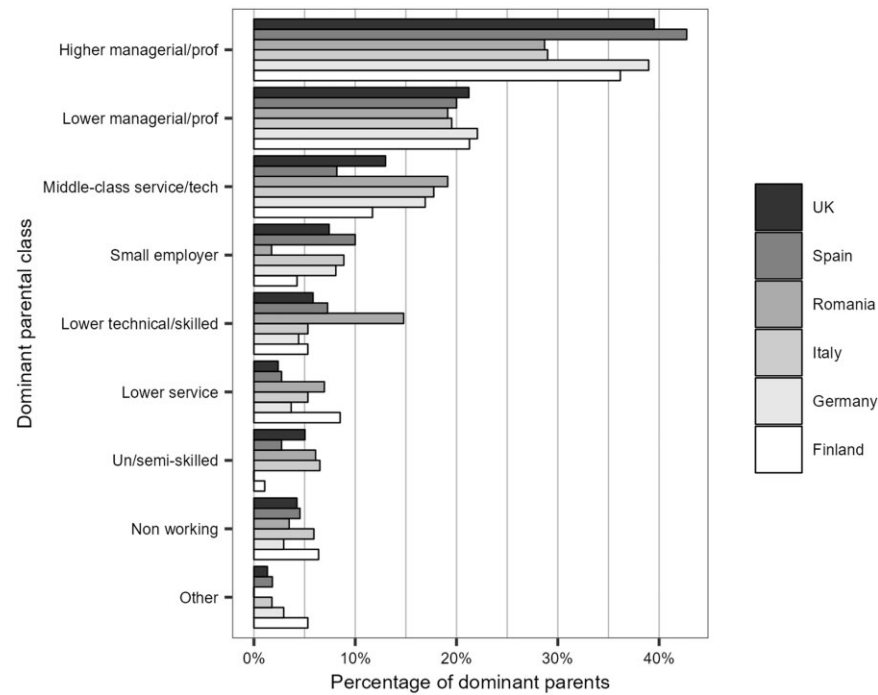


Figure 2. Dominant parental class background by country.

respondent working in five of the categories against a single comparator category. We use ‘Clerical and Data Entry’ as the comparator category. The model is estimated five times, once for each category of work i . Each of the independent variables is therefore associated with five coefficients, which indicate how a one-unit increase in the independent variable is associated with a change in the logged odds of a respondent belonging to category i instead of Clerical and Data Entry.

Parental Origins in Equation (1) is a dummy variable for whether the occupation of a respondent’s dominant parent was categorized as Higher Managerial/Professional, Lower Managerial/Professional, or Middle-Class Service/Technical, that is, more privileged class origins. For the purposes of this analysis, this binary operationalization of class origin captures a significant cleavage in the class structure while facilitating the interpretation of the results. Table 2 shows descriptive statistics for the percentage of ‘privileged’ and ‘non-privileged’ class origin workers in different categories of online work.

In a first stage, the association between *Parental Origins* and the category of online work was estimated in bivariate models. Results in Fig. 4 reveal that, without controls, associations between class origins and online work are significant for only two categories (full results in the Supplementary Appendix). Having a privileged parental origin is not significantly associated with a greater or lesser chance of working in Creative and Multimedia, Software Development and Technology, or Writing and Translation relative to Clerical and Data Entry. Having a privileged parental origin does, however, increase the chance of working in Professional Services and Sales and Marketing Support.

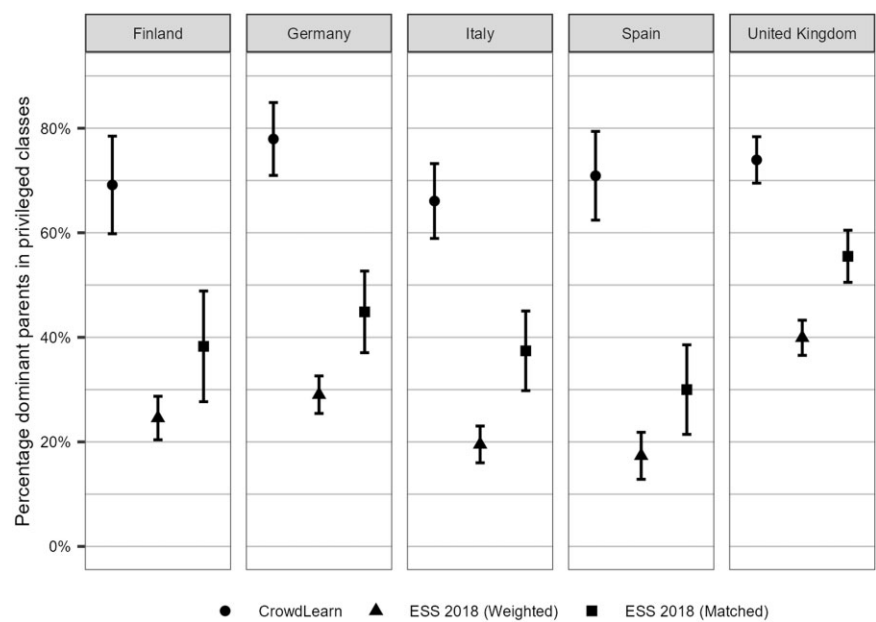


Figure 3. Percentage of dominant parents in higher managerial/professional, lower managerial/professional or middle-class service/technical classes.

Table 2. Category of online work by parental class origin

Category of online work	Privileged origin (%)	Non-privileged origin (%)	Difference
Clerical and Data Entry	8.2	11.8	−3.6
Creative and Multimedia	28.2	28.7	−0.5
Professional Services	9.5	6.8	+2.9
Sales and Marketing Support	11.1	6.8	+4.3
Software Development and Technology	12.1	13.3	−1.2
Writing and Translation	30.9	32.6	−1.7
Total	100	100	

The substantive magnitudes of these two associations are considerable. The horizontal axis in Fig. 4 measures the exponentiated coefficients for *Parental Origins* in models for each online work category. Exponentiating undoes the effect of the natural log operator, $\ln()$, on the left-hand side of Equation (1). The value of the horizontal axis is therefore equivalent to the probability of being in category i divided by the probability of being in Clerical and Data Entry, also known as relative risk. A relative risk of about two, as in the case of Professional Services, can be interpreted as meaning that having a privileged parental origin doubles the probability of working in Professional Services relative to Clerical and Data Entry. A converse interpretation is that the probability of ending up in Clerical and Data

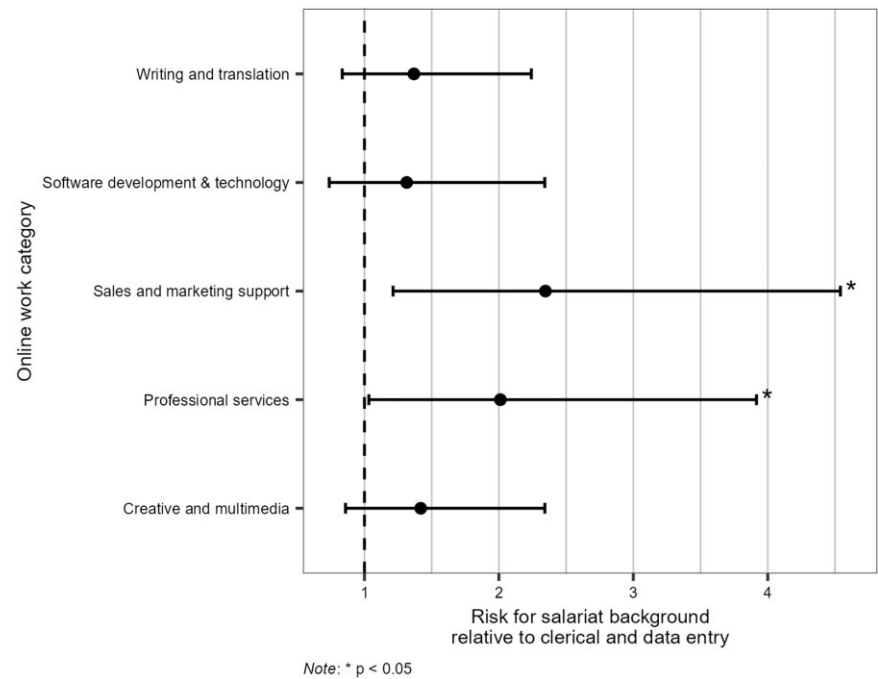


Figure 4. Association between privileged class origin and online work category.

Entry is halved relative to Professional Services. The correct interpretation is likely a mixture of both: privileged origin workers have a lower probability of ending up in Clerical and Data Entry and a higher probability of ending up in Professional Services, as seen in Table 2. The estimated association was of a similar magnitude for Sales and Marketing work.

These two significant bivariate associations could be the result of class origin-induced differences in educational attainment. To examine this possibility, we introduce educational attainment into the model as a dummy variable for whether workers have attained at least an undergraduate degree. Figure 5 ('Education') plots the results of models for Professional Services and Sales and Marketing Support when this education dummy is introduced. The association for Sales and Marketing Support remains significant. However, the association between *Parental Origins* and Professional Services is no longer significant. This suggests that the influence of class origins for this category is mediated by class differentials in educational attainment. This is unsurprising for Professional Services work, which mainly includes occupations that require specific educational qualifications, such as accountancy and legal advice (Table 1). These results are robust to an alternative specification in which educational attainment is operationalized by separate dummy variables for each of the nine categories of educational attainment recorded in the data, from no formal schooling to a doctorate.

In a final stage, control variables X_{ik} were introduced for other factors which could help to explain associations between class origin and category of online work: age, sex, country, platform, and number of jobs completed on the platform. The results are depicted in Fig. 5

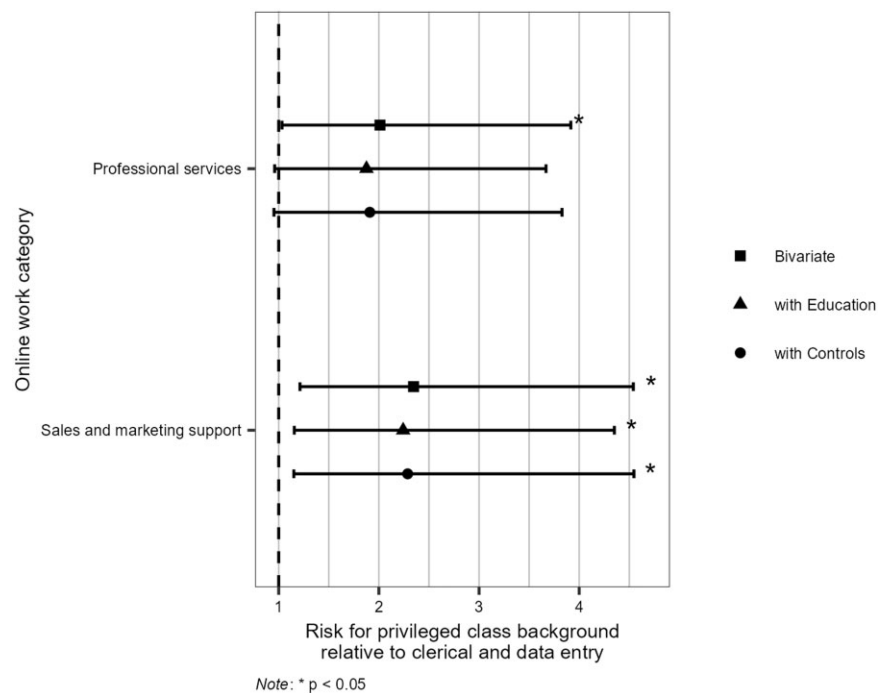


Figure 5. Association between privileged background and online work category with controls.

(‘Controls’). The significant association for Sales and Marketing Support remains even with this full suite of controls. Privileged class origins are therefore directly related to working in Sales and Marketing Support relative to Clerical and Data Entry, assuming that relevant variables have been included in the model. The sample size unfortunately does not permit the estimation of models separately for each country, but the inclusion of country as a control helps to ensure that associations are not driven spuriously by national differences in online work categories and class backgrounds.

5. Discussion

Our results suggest, for the first time, that class origins are strongly associated with the use of online platforms for remote work. Those engaging in remote online platform work are overwhelmingly from privileged class backgrounds: 72 per cent of sampled workers reported having at least one parent in the three most privileged classes. This finding is the first empirical evidence of a divide in the use of platforms for remote work and is consistent with previous research on digital divides which has found that the more privileged are more likely to use digital technologies for commercial opportunities. In addition, this finding is consistent with theories of the persistence of the influence of class origins on occupational attainment rather than theories predicting the attenuation of this relationship. If, as per attenuation theories, technological and economic development were weakening the relationship between class origins and work, then we would not have expected to observe such a strong

link between parental class and the online platform economy, which is at the forefront of technological and economic change.

The causes of this digital work divide are likely to be partly similar to the causes behind earlier digital divides, particularly resource access and skills. Workers with less privileged class origins may not select into online platform work because of the risks and the set-up costs involved. Hardware, software, and reliable Internet access can be expensive. Building an online reputation takes time and may involve long initial periods of low pay or even no pay (Wood *et al.* 2019). Pay tends to be much more volatile than in regular employment, as each online job, or 'gig', is negotiated separately. Workers in countries where English is not the native language face the additional set-up cost of acquiring proficiency in English, the dominant language in the online labour market (Stephany *et al.* 2021). Many platform workers are young (40 per cent of the sample were 30 years of age or younger), and parental support is more likely to help those with more privileged origins to absorb these costs and risks (Goldthorpe 2007).

It may seem surprising that workers from privileged class backgrounds would choose to select online platform work, given widely held beliefs about how social isolation and fragmentary working patterns in precarious occupations are undermining labour standards (Standing 2011; Gandini 2019), of which online platform work is often held up as a prime example (Bergvall-Kåreborn and Howcroft 2014). Privileged workers are likely to have relatively good alternative employment options, so why would they be attracted to online platform work? The result is unlikely to be explained simply by bias in the sample because our sample is relatively high-quality, and even if it were not, when Internet penetration is pervasive, self-selection in non-probabilistic online samples tends to result in privileged people being under-represented rather than overrepresented (Lehdonvirta *et al.* 2021).

Recent qualitative studies suggest a likely answer: more privileged workers with better savings, safety networks, and alternative sources of income can afford to pick and choose their gigs on a platform, whereas less privileged workers who depend on the platform for their day-to-day needs must accept whatever work is offered. This allows privileged platform workers to enjoy positive job quality characteristics, such as good wages, flexibility, autonomy, and task variety, while less privileged workers on the same platform may experience poor wages, unpredictability, loss of control, and repetition (Schor *et al.* 2020). Indeed, the two most commonly reported motivations for choosing platform work among our sample of relatively privileged respondents were being their 'own boss' (48 per cent of respondents) and 'schedule control' (also 48 per cent). These reasons appear similar to why many privileged workers in standard employment are choosing to stick with remote work arrangements in the post-pandemic era. In addition, remote, online platform work may represent a better second-best option than lower-level service or manual occupations for workers from privileged backgrounds who are somehow less competitive at the higher end of traditional labour markets (e.g. due to discrimination on ascribed characteristics).

Yet, despite the predominance of those with privileged class origins, 28 per cent of workers, nevertheless, came from less privileged backgrounds. A second set of analyses suggested, for the first time, that class origins are to a certain extent associated with the types of online work platform workers were engaged in. Workers with more privileged backgrounds were more likely to engage in Professional Services, and Sales and Marketing work, relative to Clerical and Data Entry work. Professional Services work is associated with the best pay and working conditions in the online labour market (Braesemann *et al.* 2022; Lehdonvirta

2022). In other words, class privilege in the occupational sense was reproduced. However, the significance of the association for Professional Services disappeared with the inclusion of a control for education. This implies that the outcome was attributable to differences in education levels due to class of origin. Even if the digitalized labour market itself were class agnostic, stratification into different educational streams takes place before labour market entry, which then influences labour market outcomes, especially in occupations that require specific qualifications, such as legal advice or accountancy.

Sales and Marketing remained significantly associated with privileged class origins, even with a full suite of available controls. This suggests that despite the use of digital technologies to screen and select candidates, privileged class origins still provide workers with resources that attract employers in this category. Considering the forms of interpersonal skills required for sales work, these could be the kinds of embodied cultural resources that are reassuring and persuasive to customers: genteel forms of self-presentation that communicate high social status. Exactly how these resources are signalled by candidates to employers in a highly digitalized labour market remain unclear. Are algorithmic systems applied unevenly as Eubanks (2017) suggests, so that more privileged types of jobs involve a greater degree of traditional human touch in the selection process? Or are algorithmic rankings and recommendations intentionally or inadvertently trained to be sensitive to names, profile photos, and manners of writing or speaking that suggest privilege? This is an interesting area for future research, but those attempting to use digital trace data to address these issues should be aware of the considerable sampling difficulties that are involved (Lewis 2015a, b). Moreover, given that only Sales and Marketing work was associated with privileged class origins after controls were applied, human involvement seems a more likely explanation.

At the same time, we found no evidence of associations between class origins and working in other categories of online work, namely Creative and Multimedia, Software Development and Technology, or Writing and Translation work relative to Clerical and Data Entry work. Our model estimates are likely to be biased downward due to the sample of platform workers being quite select in terms of class background, so this absence of evidence cannot straightforwardly be taken as evidence of absence. Nevertheless, the results suggest that class origins are less important in explaining types of work undertaken within online labour platforms than they are in explaining who uses online labour platforms in the first place.

It is not difficult to see why this might be the case. A wealth of previous research suggests that clients on the platforms avail themselves of the extensive worker job histories, reputation ratings, skill tests, and observational performance metrics provided by the platforms when choosing among candidates, with the consequence that these metrics explain much of the variation in pay and employment between online platform workers, although we were unable to directly assess the influence of these mechanisms here (Pallais 2014; Lin *et al.* 2018; Gandini 2019). Platform algorithms also use such data to automatically recommend workers that match clients' demands (Horton 2017). To the extent that these characteristics are unrelated to class origins, client demand generates little stratification by class origin among those who work on platforms. To assess this, future research should seek to investigate in greater depth the factors that influence client-hiring decisions, an area of the platform economy that remains understudied.

The CrowdLearn survey used in the analyses was collected just before the onset of the Coronavirus disease-2019 pandemic, but other research indicates that the online labour

market has continued to function and grow as companies have adjusted to remote, digitally mediated ways of working (Lehdonvirta 2022; Stephany *et al.* 2020). Moreover, the pandemic has only hastened the diffusion of practices prevalent in the online labour market—including remote work, digital surveillance, and algorithmic management—into the broader labour market (Aloisi and De Stefano 2022), underscoring the potential broader relevance of our results.

6. Conclusions

Labour markets today are undergoing significant transformations associated with the adoption of new digital technologies and the shift to remote work. Candidates are screened using data and algorithmic decision making. Skills are validated with online tests and customer feedback ratings. Workplace communications take place remotely over digital media. There are reasons to speculate that such digital transformations could be disrupting the well-established link between parental class and the kinds of work their children end up doing. On the other hand, digital transformations could introduce digital divides and algorithmic biases that favour those from privileged backgrounds. Online labour platforms offer an extreme case of labour market digitalization in which we should see any such outcomes most clearly today.

We found that online platform workers—those who have succeeded in establishing themselves in the online freelancing market—are disproportionately from privileged class backgrounds. This is the first demonstration of a digital divide in the use of online platforms for work. Our interpretation is that the unequal distribution of parental resources permits or prevents access to the new world of digitally mediated work. However, we found much less evidence of class background shaping types of work undertaken within the online labour market. We argued that this contradiction could result from the operation of worker supply and client demand: (1) workers differentially select into (or away from) online platform work based on class origin, but (2) clients select among platform workers using digital affordances that are not directly connected to class origin.

Overall, our findings suggest that ongoing technological transformations of labour markets are not likely to simply increase or decrease social mobility, but instead may rearrange the points at which mobility and reproduction occur. While digital transformations are likely to reproduce digital divides in *access to work*, they could attenuate some class-based differences in the *selection of workers* by employers. Workers from privileged backgrounds are still likely to have an easier time gaining access to exclusive companies and labour markets; our results, though based on an exploratory study of a special case, point quite strongly in this direction. But, more tentatively, our results permit the interpretation that once workers have gained access, then employers' use of digital mediation, algorithms, and quantification may be blunting some of the traditional advantages that accrue from privileged class backgrounds. Other advantages, such as better access to education before labour market entry, remain unchanged.

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Supplementary data

[Supplementary data](#) is available at *SOCECO Journal* online.

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