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Participation inequality in the gig economy

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ABSTRACT

In theory, the gig economy facilitates flexible, digitally mediated employment arrangements. Why do some people wind up doing gig work while others do not? We focus on how online participation inequalities, and Internet use experiences and skills, shape the composition of online gig workers. Specifically, we analyze a unique survey data set from a national sample of 1512 U.S. adults that includes information about background attributes and behaviors, detailed measures of Internet experiences and skills, as well as questions about whether study participants had completed specific steps necessary to becoming a task worker on two prominent gig economy platforms: Amazon Mechanical Turk and TaskRabbit. We use Bayesian regression to compare four stages of gig economy participation. Workers who participate in the gig economy tend to be younger, more highly educated, and more skilled Internet users. This implies that the gig economy increases labor market stratification and that digital participation inequalities compound labor inequalities.

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online labor markets; digital inequality; online participation; survey research; Bayesian regression; gig economy

Introduction

Online labor markets and the gig economy have had contradictory effects for workers. Various platforms make it possible for millions to enter into flexible, digitally mediated employment arrangements (Gansky, 2012). Yet, the potential benefits of such increased flexibility and convenience to workers often remain unfulfilled. Gig workers face challenges such as low pay, lack of job security, reduced ability to communicate or bargain collectively with employers, and regulatory structures ill-adapted to their needs (Gray & Suri, 2019; Schor, 2020; Woodcock & Graham, 2020). These issues have provoked concerns that the gig economy will create a new global precariat (Gray & Suri, 2019; Schor, 2020).

But even as gig work has become more widespread, explanations of who participates in – or benefits from – such labor remain scarce. Prior studies have revealed differentiated gig economy participation reflecting multiple social, economic, and psychological forces at play (e.g., Gray & Suri, 2019; Hoang et al., 2020; Schor, 2017). Most gig work seems to get done by people with higher socioeconomic status and privilege. What shapes

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these unequal patterns of participation in the gig workforce? This question has drawn far less attention. Stratification in terms of who engages in digitally mediated gig work may exacerbate broader social and economic inequalities. This possibility has become more urgent as the COVID-19 pandemic has pushed even more people into remote and short-term work arrangements.

In this paper, we evaluate the determinants of workforce participation in gig economy platforms. In conceptualizing the gig economy, we follow the broad definition of Woodcock and Graham (2020): 'labor markets that are characterized by independent contracting that happens through, via, and on digital platforms' (p. 3). The jobs, so-called gigs, associated with this economy tend to be narrow and short-term with little commitment from either workers or employers. Gig work requires would-be workers and employers to interact via websites and online platforms. As such, much of what classical Marxian accounts might term the 'labor process' (Marx, 1992/1867), as well as labor relations (job search, hiring, management, etc.), entails online participation. Prior research on Internet use has revealed highly differentiated levels of access and participation (e.g., Gan et al., 2018; Schradie, 2011; Shaw & Hargittai, 2018), including differentiated behaviors and skills related to job-seeking (DiMaggio & Bonikowski, 2008; Peng, 2017; Puckett & Hargittai, 2012). As a result, understanding participation in digitally mediated gig work requires consideration of online stratification.

We investigate how distinct factors may explain the 'pipeline of online participation inequalities' (Shaw & Hargittai, 2018) in online gigs. We analyze a unique survey dataset collected in summer 2016 from a national sample of U.S. adults that includes questions about whether study participants had completed steps necessary to becoming a worker on two widely studied gig economy platforms: Amazon's Mechanical Turk and TaskRabbit. The data allow us to model the relationships between degrees of engagement with gig work and multiple aspects of participants' background as well as online experiences. The results suggest online participation inequalities and socioeconomic inequalities compound each other in online gig work. The implications are striking: even the flexibility and low barriers to entry of the gig economy do not lead to broad participation. Instead, people who already possess important advantages in the labor market are most likely to work gigs.

Background

The gig economy and the future of work

The Internet has enabled numerous labor market innovations, including the expansion of small scale, short-term, and on-demand contracting. This phenomenon, captured in the term 'the gig economy,' encompasses multiple examples referred to in various ways, including online labor, crowd work, crowdsourcing, the sharing economy, and microtasks (Vallas & Schor, 2020). Online and mobile platforms mediate exchanges between gig economy employers and workers. The work itself tends to be broken down into small-scale tasks rather than larger concatenations of responsibilities or goals. Employers range from large corporations to individuals, all of whom use websites to post requests for work, hire contractors, and, in most cases, manage work and payments. Workers either select or are assigned gigs that they complete independently, often with little or no direct interaction with the employer. Depending on the platform, tasks can range from 'human computation' work, such as labeling images or transcribing snippets of audio, to in-person chores, such as painting or cleaning a house (Gray & Suri, 2019).

The gig economy exemplifies longer-term changes in the labor market. Part-time, flexible, and low-skill forms of precarious employment have increased across many countries in recent decades (Kalleberg, 2018). The case of the United States is illustrative. The burdens of economic risk and uncertainty increasingly fall on workers (Kalleberg, 2018), contributing to overall declines in economic mobility (Chetty et al., 2017) and elevated rates of part-time work since the Great Recession (Valletta & van der List, 2015). Shifting family structures, educational inequality, and demand for novel kinds of skills contribute to these patterns (Cherlin, 2014; Deming, 2017). The COVID-19 pandemic and the attendant wave of unemployment has likely reinforced these patterns and the expansion of the gig economy.

For workers, online gigs promise control over the types, places, and times of work (Wood et al., 2019) at a high price. Gig workers lack financial and legal security, benefits, or even basic protections against unfair hiring and firing practices (Gray & Suri, 2019; Schor, 2020; Woodcock & Graham, 2020). This can lead to poor working conditions, especially with an online workforce spanning the globe (e.g., Berg, 2015). Gig workers may put in long and irregular hours under multiple kinds of risk to make anything like a living wage (Gregory, 2020). In many cases, this leads to high levels of stress, exhaustion, and social isolation (Wood et al., 2019).

Despite these well-documented issues, the scale and impact of gig work remains difficult to establish. Neither the firms that operate online gig platforms nor public agencies publish detailed information about workers, contracts, payments, complaints, or the substance of the work being done. Important work attempts to fill these gaps (Kässi & Lehdonvirta, 2018), but the absence of central and public data leaves holes in public understanding and policy debates. While several recent excellent studies shed light on the experiences of workers across multiple gig platforms (we discuss several below), these studies sample among the existing population of gig workers. A different approach is needed to understand the determinants of gig economy participation and requires information about people who do not participate in the gig economy.

The present study focuses on the stratification of participation in online gig labor markets. Our work asks: *What explains who accesses the novel work arrangements presented by the gig economy and who does not?* In particular, we investigate the role of online participation inequalities and Internet use experiences and skills in shaping the composition of online gig workers. We consider how these inequalities may explain both who works in the gig economy as well as who seeks that work in the first place. Studies that consider data only within gig economy sites or only among existing gig workers cannot speak to these concerns. Neither can macro-economic and administrative data sources that, as far as we know, lack measures of gig economy participation.

Online participation inequalities

According to more optimistic accounts, the gig economy provides enhanced labor-market access by removing key barriers to workforce participation (Kittur et al., 2013 give an early summary of these accounts). However, the gig economy also obligates workers to navigate the gig-work process via digital platforms and websites, which introduce obstacles to equity. Understanding gig economy participation therefore entails consideration of online participation inequalities (Hargittai & Jennrich, 2016). Past research into online participation has emphasized the persistence of inequalities, knowledge gaps, and skills divides in terms of who does and does not engage in various types of online activities. More recent work has sought to disaggregate the specific types of skills involved (Hargittai & Micheli, 2019; van Deursen et al., 2017) as well as processes by which people come to engage in online work, collaboration, and knowledge production (Shaw & Hargittai, 2018). Our work applies this latter approach to the study of gig economy platforms.

Individual Internet usage differs widely among those with access to the web (e.g., Haight et al., 2014; Schradie, 2011). Participation gaps arise in terms of content production and platform adoption, where the adoption of gig economy platforms falls into the second category. Rather than considering platform adoption as a binary process, we use Shaw and Hargittai's (2018) pipeline model to disaggregate it over four stages: First, people must have heard of a platform. Then they need to visit the platform. Next (in the case of the sites we analyze here), they need to create an account, after which they can finally participate by performing a task. The first three steps are conditions for this last stage. By collecting data on each stage, we can identify the points at which people leak out of the pipeline.

Participation inequality in the gig economy

Participation inequality in the gig economy has not been studied widely. Several factors, including financial reasons, work flexibility, and skills acquisition (e.g., language learning), attract workers into the gig economy; whereas concerns with unfair/unjust labor practices, unsustainable risks, and poor wages seem to drive gig workers out (Brewer et al., 2016; Dunn, 2020; Schor, 2017). However, these findings reflect the perspectives of people who have already become gig workers. They cannot provide insights into why other people are not gig workers. Put differently, samples of gig economy workers drawn from within gig economy platforms cannot support valid inferences about the determinants of ending up on these platforms, i.e., participation in the gig economy.

Only a few studies analyze gig economy participation using data drawn from more general sampling frames. Hoang et al. (2020) find that gig economy workers are more likely to be male, younger, well-educated, and wealthier compared to those who do not work in the gig economy. Among gig workers, those active on online selling platforms, such as Ebay, are more likely to be male, White, middle-aged, college-educated and have higher incomes than those who work through labor-exchange platforms, such as Amazon Mechanical Turk.

The analysis we pursue investigates the role of individuals' backgrounds as well as their Internet experiences and skills in explaining gig economy platform adoption. Very little prior work has considered the role of Internet use experiences and skills in who does or does not engage in online gig work (one exception is Hargittai & Shaw, 2020). Adding to the factors considered by Hoang et al. (2020), our analysis also takes into account autonomy of Internet use, frequency of use, and skills, all identified as key determinants of digital inequalities (e.g., Dutton & Blank, 2014; Livingstone &

Helsper, 2007; van Deursen et al., 2017). No studies we know of break down the process by which potential workers might end up engaging in gig economy opportunities.

Methods

We analyze survey data from a national sample of U.S. adults (18 and older) collected in summer 2016. The data set is particularly appropriate for examining factors that shape whether people engage (or not) in gig work since it provides detailed measures of respondents' background attributes, Internet experiences, and skills as well as multiple types of engagement with two prominent gig economy platforms: Amazon Mechanical Turk (AMT) and TaskRabbit (TR). AMT and TR exemplify different types of gig economy online labor markets: one entirely remote (AMT) and the other largely in-person (TR). For the purposes of this study, analyzing the pipeline of participation across both allows us to draw inferences that encompass these differences. We briefly introduce the two sites below before providing additional details about the survey measures, data collection, sample, and analysis strategy.

Amazon Mechanical Turk and TaskRabbit

Launched in 2005, AMT facilitates remote microtasks such as the collection and verification of data for machine learning models. The platform enables businesses to outsource large numbers of small and often repetitive tasks to remote contractors for a predetermined monetary reward. AMT workers find gigs through an interface that lists tasks and the associated details, such as pay and allotted time. 'Requesters,' the platform's name for employers, can also be matched with workers through an application programming interface (API), which searches based on qualifications. Workers on AMT tend to be young, highly educated, White, unemployed, and live in urban areas (Gray & Suri, 2019; Hargittai & Shaw, 2020). Their incomes tend to be below average in the U.S. (Difallah et al., 2018; Hargittai & Shaw, 2020). Turnover is high and the entire population renews every year or so (Difallah et al., 2018, p. 142).

TaskRabbit, which launched in 2008 under the name RunMyErrand, is an online marketplace for outsourcing in-person service tasks, such as grocery shopping or moving. The platform displays profiles of 'taskers' (workers) indicating their skills, experiences, and the prices of services they offer. Prospective employers respond to profiles to initiate contracts. Compared to AMT, there is little known about the composition of TR participants. The majority of taskers are White males and more likely to reside in urban areas compared to the average U.S. resident (Hannák et al., 2017). In a qualitative study of TR participants in Chicago, Thebault-Spieker et al. (2017) found that taskers tend to live in middle-income areas and work in high-income areas.

Data collection

We contracted with the independent research organization NORC at the University of Chicago to survey their AmeriSpeak panel, which is designed to be representative of the U.S. adult population (sampling, recruitment, survey administration, and panel composition details appear in NORC, n.d. and NORC, 2021). NORC administered the survey from 25 May to 5 July 2016, collecting 1,512 valid responses, with a response rate of 37.8%.

Measures: dependent variables

Early in the survey, we asked respondents: 'Have you ever heard of the following sites and services?' with Amazon Mechanical Turk and TaskRabbit among the options listed. Only 15% reported having heard of either one. We then asked those who had heard of either site: 'Have you ever **visited** the following sites and services?' Of all respondents, 7% said that they had ever visited AMT or TR. Later in the survey, we asked those who had visited AMT or TR whether they had an account on them. Again, the two platforms were among a list of sites. Three percent of the sample had an account on either platform. Then, to assess who had ever participated on either site, we asked those who reported having an account whether they had ever done activities including: 'Completed a task on Mechanical Turk (mTurk)' and 'Performed a task on TaskRabbit' with 'no' and 'yes' as the possible answers. A small minority, 2%, of the sample responded in the affirmative for either AMT or TR. Because both sites have low levels of participation among respondents, we combine them to create the dependent variables (e.g., whether respondents had visited *either* Amazon Mechanical Turk or TaskRabbit).

Measures: independent variables

We include key predictors of labor market participation and online participation identified in prior research. NORC provided background variables about respondents including their age, gender, education, income, and race/ethnicity, based on earlier data collection for the AmeriSpeak panel. We report *age* (in years) as a continuous variable. We code *gender* as a dichotomous variable and *education* into three categories: 'high school or less,' 'some college,' and 'college degree or more.' The 'high school or less' category is the baseline in the regression models. NORC provides *household income* as an 18-category variable, which we recode to continuous by assigning each category to the midpoint of its range (in thousands of dollars). We also include a count for *household size*.

Race and ethnicity variables include indicators for *White*, *Hispanic*, *African American*, *Asian American*, *Native American*, and *Other*. A dichotomous *coupled* measure identifies participants who are either married or living with a partner as that shapes economic and employment needs (Cherlin, 2014). Another indicator identifies participants' *employment status* (full or part time versus not employed). To capture geographic biases in gig economy participation (Braesemann et al., 2020; Haight et al., 2014), we include a *rural* indicator for residence.

Our other background variables focus on Internet experiences and skills. *Autonomy of use* measures the number of locations where a respondent can access the Internet. The question had nine answer options, including home, workplace, and friend's home. We measure *frequency of use* with two questions: one asking for the number of hours spent on the Internet on an average weekday and the other asking for the number of hours on an average Saturday or Sunday. Both had six answer options ranging from 'None' to '6 hours or more.' We recoded these into counts that capture the weekly hours spent on the Web. We also asked respondents when they started using the Internet, which we report as a continuous number for *years of use*.

The measure of *Internet skills* uses a validated index that incorporates several Internet technologies and concepts (Hargittai & Hsieh, 2012; Wasserman & Richmond-Abbott, 2005). The question asks respondents to evaluate their understanding of thirteen Internet-related terms (such as tagging, PDF, spyware) on a five-point scale ranging from none (1) to full (5). We then calculate the arithmetic mean of these item responses, giving a continuous score between 1 and 5 (Cronbach's $\alpha = .94$).

For regression analysis, we center continuous measures around the sample mean. Because income is very right skewed, we take the square root of each recoded value before centering to approximate a normal distribution.

Analysis

As noted above, participation on gig economy platforms remains a rare experience in the U.S. population, with less than 10% of adults having done any kind of online gig work, including driving for a ridesharing app such as Lyft or Uber, as of 2016 (Smith, 2016). Our analysis focuses exclusively on two specific platforms and thus the focal outcomes become even less common, with only 30 of the 1,512 study participants ever having completed a gig through either AMT or TR.

The Online Supplement reports descriptive statistics about the sample (Table S1); bivariate analyses comparing survey participants who have ever completed a gig on AMT or TR to those who have never done so (Table S2); as well as a correlation matrix of all variables (Table S3).

The main analysis below focuses on the determinants of participation in online gig work. We model the four outcomes corresponding to the pipeline stages involved in completing gig work through either AMT or TR: *having heard of either site*, *having visited either site*, *having had an account on either site*, and *having completed a gig on either site*. Following the approach of Shaw and Hargittai (2018), we fit an identical multiple regression model for each of these 'stage' outcomes. By stratifying our dataset in this way, we estimate how specific predictors relate to the individual outcomes in the pipeline. We also observe how those relationships shift depending on the stage. Similar 'stage model' approaches have been used to analyze rare and/or skewed outcomes in online communication and behavior (Cheng et al., 2014; Gan et al., 2018). For each outcome, we fit a logistic regression. The dependent variable is the log-odds of having completed one of the four pipeline behaviors in either AMT or TR. The model predictors are the sum of the parameter estimates multiplied by the corresponding observed values for each of the independent variables.

Prior studies on gig work (Hargittai & Shaw, 2020; Hoang et al., 2020) and the pipeline of online participation (Shaw & Hargittai, 2018) suggest key predictors of the different stage outcomes. These include age, education, Internet skills and experiences, and (potentially) income. Hoang and colleagues find no evidence of a direct relationship between income and gig work participation; but report an inverse association between gig work and 'income-based needs.' We do not have a similar measure and cannot draw a direct comparison with their results in this respect.

We adopt a Bayesian regression framework with several advantages over available alternatives and prior studies. A brief overview of Bayesian regression modeling, further details of our approach, and comments on important differences from frequentist approaches appear in the Online Supplement. We note only some key points here. First, Bayesian regression is well-suited to modeling rare (sparse) outcomes with many predictors without imposing parametric assumptions (Greenland, 2007). Second, Bayesian models allow direct comparisons of parameter estimates and uncertainty intervals across models (Morey et al., 2016). Frequentist regression does not support this kind of inference coherently.

The regression results include a subset of the predictors and unweighted observations. The predictors are *age*, *education*, *coupled*, *rural*, *Internet use frequency*, and *Internet use skills*. We drop the others (*gender*, *income*, *employed*, *race*, *ethnicity*, *household size*, and *Internet experience*) following a variable selection procedure described in the Online Supplement, where we also report alternative specifications with all predictors (Table S4). The variable selection procedure does not alter the substance of the results. The Online Supplement elaborates on the decision to present unweighted results and reports alternative specifications that apply the weights provided by NORC (Table S5). Some results are sensitive to weighting, and we address this below and in the Online Supplement.

As is typical for Bayesian regression, we present summaries of the posterior parameter distributions, including the median for each predictor in each stage model. These medians correspond roughly to the coefficients recovered from frequentist regression models. Null hypothesis significance tests are not coherent within a Bayesian framework. Instead, we use the marginal standard deviation for each parameter's posterior distribution to construct a Bayesian 'credible interval' (Gabry & Goodrich, n.d.). We provide a 90% interval, which is preferred for computational and inferential reasons (Gelman & Carlin, 2014; Morey et al., 2016) and may be treated analogously to frequentist confidence intervals. To facilitate interpretation, we use the *tidybayes* (Kay, 2020) and *ggplot2* (Wickham, 2016) software packages in R to generate 'quantile dotplots' of the posterior parameter distributions and model-predicted probabilities across plausible ranges of key predictors (Kay et al., 2016). All parameter estimates and intervals are reported in terms of odds-ratios.

Results

Participation in the gig economy

Table 1 describes the dependent variables, which represent the four stages of participation in the gig platforms included in the study. The frequency of completing each outcome decreases over each stage. All outcomes, however, are infrequent: only 15% of the sample has heard of either platform and only 2% has completed a gig.

Table 1. Descriptive statistics for dependent variables.

	Percent	*N*
Heard of gig sites	15	1499
Visited gig sites	7	1499
Account on gig sites	3	1499
Completed task on gig sites	2	1499

Modeling participation in the gig economy

Table 2 and Figure 1 summarize the results (posterior parameter distributions) of the stage-stratified Bayesian logistic regression models. We walk through these results in the order of the stages before summarizing patterns across them.

For the first stage, younger age, not being coupled, having a bachelor's degree or more, and higher Internet skills predict increased odds of having heard of gig economy sites. Higher education and Internet skills stand out with median increases of about 90% and 80% in the odds of the outcome, respectively. In contrast, coupled individuals are about 75% as likely as uncoupled individuals to have heard of either site. Age differences predict minimal (just a few percent in the odds ratio) differences in the outcome, but at extremes of the observed distribution yield substantially different odds of stage completion.

Looking at the second stage, younger age, not being coupled, possessing at least some college education, and higher Internet skills predict increased odds of having visited gig economy sites. These results are similar to those in the first stage with some noteworthy differences. The credible intervals for some college and BA or more overlap and are wide (estimates of 20–400% increased odds). The credible interval and median odds increase associated with Internet skills also shift higher (without a comparable expansion of the range). The parameter distributions for age and coupled are nearly identical to the first model.

When it comes to ever having had an account on either gig site, the models estimate more noticeable shifts. The relationship with age remains nearly unchanged, with (slightly) younger age predicting (slightly) increased odds of the outcome. Higher Internet skills again predict increased odds of having had an account, but the low end of the credible interval approaches even odds. In contrast to the first two models, the credible interval for Internet use frequency lies above even odds while the range for rural residence drops below even odds. The median posterior parameter estimates for some college and BA or more levels of education predict substantially increased odds of completing this stage, but small portions of the credible intervals for both cross even odds.

Table 2. Regression model results.

	Has heard of either platform median [CI]	Has visited either platform median [CI]	Has an account on either platform median [CI]	Has performed a task on either platform median [CI]
(Intercept)	0.12 [0.09, 0.17]	0.03 [0.02, 0.05]	0.01 [0.01, 0.02]	0.00 [0.00, 0.01]
Age	0.99 [0.98, 0.99]	0.97 [0.96, 0.99]	0.97 [0.95, 0.99]	0.96 [0.94, 0.99]
Coupled	0.73 [0.57, 0.95]	0.66 [0.46, 0.94]	0.88 [0.54, 1.45]	0.76 [0.40, 1.42]
Rural	0.72 [0.47, 1.08]	0.64 [0.32, 1.19]	0.30 [0.06, 0.85]	0.53 [0.12, 1.61]
Education (base = HS or less)				
Some college	1.44 [1.00, 2.14]	2.27 [1.31, 4.19]	2.47 [1.12, 6.04]	3.77 [1.19, 15.91]
Bachelor's or higher	1.84 [1.28, 2.64]	2.19 [1.27, 4.09]	2.71 [1.26, 6.67]	4.38 [1.49, 17.88]
Internet experiences				
Internet use frequency	1.01 [0.99, 1.02]	1.01 [1.00, 1.03]	1.03 [1.01, 1.05]	1.02 [0.99, 1.05]
Internet skills	1.76 [1.50, 2.06]	2.10 [1.65, 2.71]	1.55 [1.14, 2.16]	1.85 [1.21, 2.93]

Note: Point estimates are median values of the posterior distribution for each parameter. Bayesian 90% 'credible intervals' (CIs) appear in brackets and are estimated using the 'median absolute deviation' (analogous to the standard deviation of the median) from the posterior draws.

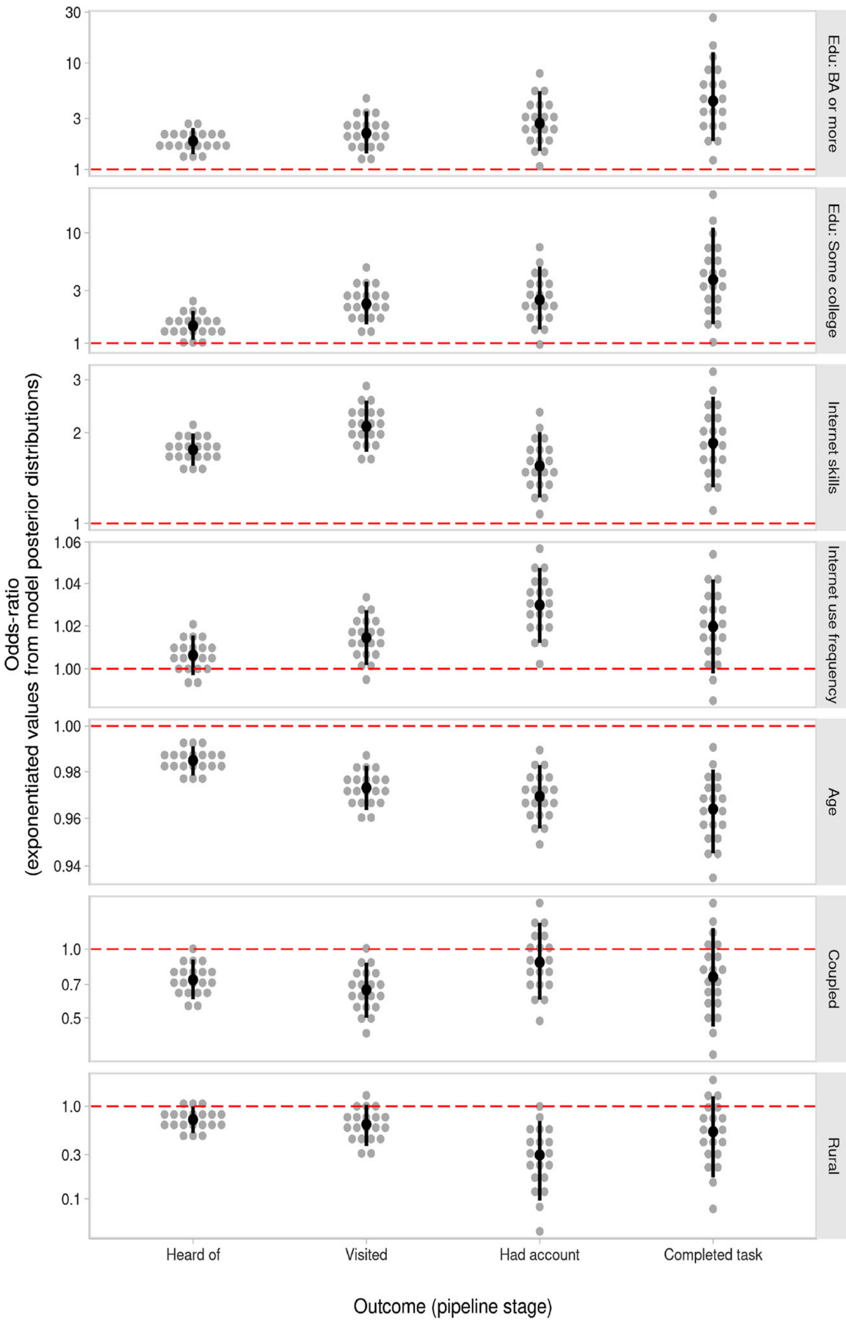

Figure 1. Quantile dotplot of posterior distributions of parameter estimates for all pipeline stage regression models. Points and line-ranges correspond to posterior median and 90% credible intervals. Red dashed lines indicate odds ratio equal to 1 (unchanged odds). Each dot corresponds to 5% of the posterior distribution (Kay et al., 2016).

Finally, when it comes to ever having completed a gig, we find increased odds associated with lower age, higher levels of education, and higher Internet skills. This model has a very rare outcome, and (unsurprisingly) the credible interval for some of the predictors expands. In particular, we observe very wide intervals for both of the education categories (above the baseline level high school or less). Both the median and credible interval for the parameter on Internet skills indicate increased odds of having completed a gig. Again, (slightly) younger age remains associated with (slightly) increased odds in the outcome.

Several patterns emerge across the four models. First, the models estimate increased odds of completing all four pipeline stages for three predictors: lower age, higher levels of education, and higher Internet skills (this replicates a similar pattern observed in the study of Wikipedia participation by Shaw and Hargittai [2018]). The credible intervals for Internet skills are stable across the models and consistently greater than even odds. The intervals for education expand substantially over the four outcomes (see Figure 1). By contrast, the intervals for age remain nearly constant and the range is very narrow. The intervals of other parameters associate with increased or decreased odds in subsets of the models. Specifically, coupled status predicts reduced odds of completing earlier stages (having heard of or having visited gig sites). Internet use frequency and rural residence predict having an account on either site (and most of the posterior parameter values for Internet use frequency also correspond to increased odds in having visited or completed a gig).

Using the models to generate predictions that incorporate combinations of predictors further illustrates these patterns. Figure 2 shows the distributions of predicted probabilities of completing each pipeline stage across the three levels of education and the interquartile range of the observed distribution of Internet skills (holding other predictors at the observed mean/mode).

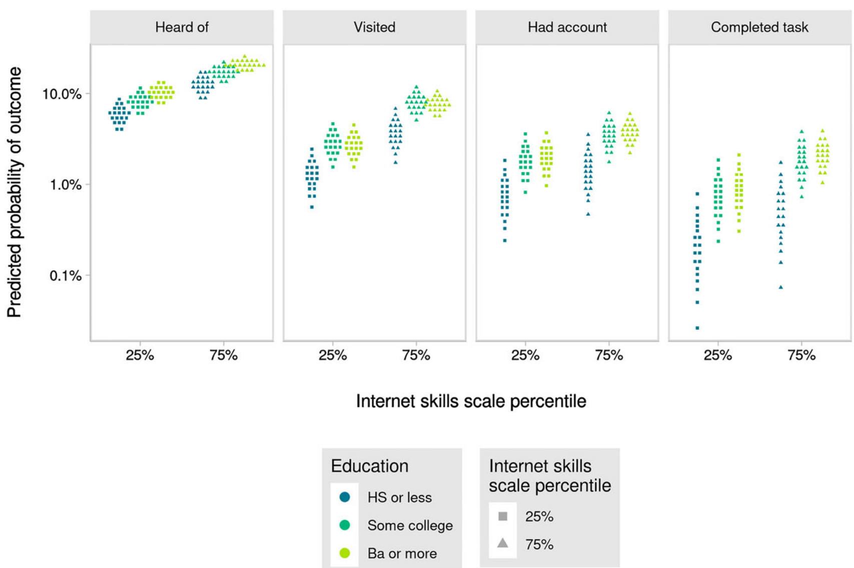

Figure 2. Quantile dotplot of model-estimated predicted probabilities for completing pipeline stages at observed values of education across the interquartile range of Internet use skills. Each dot corresponds to 5% of the model-predicted values (Kay et al., 2016).

For every outcome, lower levels of education and Internet skills correspond to lower probabilities. The differences are most pronounced at earlier pipeline stages.

Model-generated predictions can also illustrate how hypothetical variations in education, Internet skills, and age jointly relate to the outcomes (again holding other predictors at their observed mean/mode). The models estimate that among 65-year-olds with a low (25th percentile) level of Internet skills and no college education, about 8% will have heard of, 2% will have visited, 1% will have had an account, and none (0%) will have completed a task on gig economy sites. By contrast, among 30-year-olds with a high (75th percentile) level of Internet skills and a bachelor's degree or higher, about 26% will have heard of, 13% will have visited, 6% will have had an account on, and 5% will have completed a task on gig economy sites. These values correspond to at least fourfold increases in the estimated probability of completing each pipeline stage.

Discussion

The results suggest several patterns of stratification across multiple stages of participation in online gig platforms by adults in the U.S. Overall, higher levels of education and Internet skills as well as lower (younger) ages predict higher odds of completing any pipeline stage. Being coupled predicts decreased odds of completing earlier stages of participation (ever hearing of or visiting gig economy sites), whereas rural residence marginally predicts decreased odds of creating an account. Greater frequency of Internet use predicts slightly increased odds of completing later stages (ever having an account or completing a gig).

These findings extend prior work on gig economy labor market participation, introducing several novel findings with respect to participation pipelines and divides. The results reinforce that education and Internet skills predict variations in online participation across many domains of activity. For both variables (and age as well) our results closely resemble Shaw and Hargittai's (2018) study of Wikipedia. The findings of Hoang et al. (2020) support a similar conclusion with respect to education. We also find further evidence in support of skills divides in the domain of gig work (Hargittai & Shaw, 2020).

Our results also reinforce some earlier analysis of participation divides, as increased frequency of Internet use predicts increased odds of participation in the latter stages of the pipeline. While this does not align with the results from Wikipedia participation (Shaw & Hargittai, 2018), it is similar insofar as greater levels of online activity correspond with higher odds of taking intermediate steps towards gig economy participation.

Socioeconomic shifts in cohabitation and labor market participation may explain why being coupled or living in a rural area predict decreased odds of having heard of or visited gig economy sites. Cohabitation is negatively correlated to lower socioeconomic status (Binder & Bound, 2019; Cherlin, 2014), which also predicted reduced preliminary stages of engagement with Wikipedia (Shaw & Hargittai, 2018). The reduced probability of creating an account among rural residents extends mixed findings on the geographic patterns of gig economy use (Braesemann et al., 2020; Thebault-Spieker et al., 2017). However, we have no precise explanation for the relationships suggested here, where other socioeconomic factors we might expect to predict gig economy participation (such as gender, income, household size, employment status, or race and ethnicity) do not. Freelance gig work provides neither a living wage nor benefits, and prior studies of gig work had emphasized that differentiated participation might be more directly linked to economic factors (see, e.g., Gray & Suri, 2019; Hargittai & Shaw, 2020; Hoang et al., 2020; Schor, 2017). Employment status and income seem especially likely to relate to gig economy participation. We note that some of these (non-)results are sensitive to applying survey weights (see the Online Supplement and Table S5), but the overall picture remains similar. We encourage caution with these aspects of the results as null relationships may derive from features of the empirical phenomena, the sample, or the study design. We recommend further research into the labor economics, demography, and geography of gig work, particularly work that investigates how gig work relates to other employment.

Our analyses imply that those with higher levels of education and Internet skills have increased odds of participation in online gig work. In this sense, the gig economy does not expand work opportunities for those without alternatives or resources. Rather, gig work environments are accessible and attractive to more privileged social groups, even if the structure of gig economy labor relations incorporates gig workers into a precarious 'new global underclass' (Gray & Suri, 2019). This extends earlier studies that have also indicated that a variety of gig work opportunities employ relatively more well-off and well-resourced individuals in the U.S. and elsewhere (e.g., Gray & Suri, 2019; Hoang et al., 2020; Newlands & Lutz, 2020). In particular, the results show how Internet skills play a contributing role in shaping who knows about and pursues paid work in the gig economy.

Limitations

Several constraints of the research design merit consideration. The study reflects a single sample drawn within a single country at a single point in time. While the quality of the AmeriSpeak panel and the NORC data collection inspire confidence in both the sample and the measurements, the generalizability of the findings may be limited. Also, due to the low prevalence of gig economy work in the sample, we refrain from comparisons across AMT and TR. Bayesian models with weakly-informative priors handle sparse data well, but alternative strategies exist (see, e.g., Greenland, 2007) that could yield alternative inference. Future work may overcome this through larger samples that include larger numbers (or proportions) of gig workers. Such samples could also support more fine-grained investigations of multiplicative relationships in the data, which could yield insights into, for example, how gig work connects to other kinds of employment, gender, or income-based needs. Future work along these lines can also pursue more fine-grained investigations of how worker experiences and trajectories may vary across different kinds of gig work and gig economy sites.

Turning to measurement considerations, the survey asks about having visited or having an account on either gig platform. We cannot rule out that some study participants may have completed either of these actions as a gig work employer ('requester'). We did not anticipate this issue and cannot directly estimate whether it introduced errors into our measurements. That said, workers vastly outnumber employers on AMT and we anticipate a similar pattern on TR (Hitlin, 2016). As a result, the number of misclassified data points that could have resulted from this ambiguity in our instrument should be small.

Also, the pipeline metaphor and measures probe a very limited set of outcomes within a narrow scope. The social dynamics and structures that shape how people come to adopt specific online behaviors are complex. The survey questions differentiate participation along some dimensions, but not others. Extending the pipeline concept to measure additional participation steps for specific platforms or online activities (e.g., completed a gig, received payment for a gig, etc.) or combining the type of survey data we collect with more in-depth qualitative observations might allow insights into the obstacles to participation. Our analysis cannot speak to these more fine-grained stages of participation, nor can we assess more nuanced explanations of why participants in our study have not completed any particular stage in the pipeline as we operationalize it.

Conclusion

The stratification of participation in gig economy work illustrates how digital inequality compounds broader socioeconomic and labor process inequalities. By disaggregating participation on two online gig platforms and incorporating measures of Internet skills and experiences, this study provides new insights into the factors that determine who works in the gig economy. Higher levels of education and Internet skills along with younger age predict increased odds of participation in gig work. Other factors, including Internet use frequency, residing in a rural area, and being coupled also shape specific stages of engagement with the gig economy. In general, these results are consistent with long-standing patterns of stratification in online and labor market participation.

Future work should expand the analysis of participation pipelines to incorporate additional websites and services as well as longitudinal data. This can uncover whether and how skills, education, and age (all found to shape participation in gig work and Wikipedia [Shaw & Hargittai, 2018]) may explain participation in other domains of online activity. Additional studies might also probe the reasons for and experiences of non-participants more deeply. Such investigations would deepen understanding of the stratification of online behavior.

Based on this study, we expect that online participation inequality in the gig work labor market exacerbates existing social inequalities. Further research will be necessary to evaluate the implications of the gig economy more fully, as well as variations across platforms, time, regulatory regime, and political geography. Gig work may extend opportunities for flexible and part-time employment at a time when more people in many places are seeking such arrangements. However, to the degree that gig work reproduces and worsens existing inequalities, it stands to exacerbate the concentration of labor market participation among already skilled and privileged workers (Chetty et al., 2017; Deming, 2017; Gray & Suri, 2019; Kalleberg, 2018). Attempts to regulate the gig economy will also need to address the multiple mechanisms by which such inequalities persist, including differentiated Internet uses and skills.

Since we gathered the data for this study, online labor and gig work have taken on new importance. The global COVID-19 pandemic and expanded unemployment in the U.S. and other regions have transformed the world of work. Our results provide a snapshot of an earlier moment. Stratification in the gig economy merits continued scrutiny given increasing unemployment, job instability, and shifts of labor relations into online domains. If anything, we expect the inequalities described here have only grown.

Online supplement and replication materials

An Online Supplement together with all data, analysis code, instruments, and documentation associated with this study will be deposited in the Harvard Dataverse (https://doi.org/10.7910/DVN/BYOWID) under a Creative Commons Attribution (CC-BY) 4.0 license.

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