Navigating the future labor landscape: Transitions between gigs and traditional forms of work

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Extended Abstract

Online gig platforms facilitate access to employment opportunities for workers around the world. However, there is still much we don't understand about the transition between traditional 'offline' occupations and platform or 'online' forms of work. Additionally, the two bodies of literature that study them have remained on mostly separate trajectories.

Studies at the intersection of the online and offline world have already been conducted in other areas, suggesting that digital and socioeconomic inequalities have compounded each other thus far. For example, online communication reflects segregation in offline interactions (Morales, Dong, Bar-Yam, et al., 2019), news polarization follows similar online and offline patterns (Fletcher, Cornia & Nielsen, 2020), and digital inequalities have been shown to affect the prospects of offline work (Karaoglu, Hargittai & Nguyen, 2022). Initial evidence suggests that platform work is also augmenting this inequality by allowing highly educated individuals with full-time jobs to engage in manual labor and, potentially, crowding out lower-skilled workers (Schor, 2017). Hence, there is an urgent need for more studies that inquire about the link between offline and online career patterns.

Using two different datasets containing anonymized resumes from US workers, we seek to understand what are the main occupations that precede and follow gig work, and if preceding occupations before gig work can predict workers' reincorporation into offline occupations. Our two datasets contain information on individual career trajectories (occupations, locations, and dates) and educational institutions. One database contains approximately 400K users, and the second is over 10M (only 2M have career trajectories longer than four jobs). The second dataset also contains the name of the companies that offered the positions. These datasets are compatible with the O*NET skill and task data and US Census data because they have occupation titles and codes that match the Bureau of Labor Statistics' Standardized Occupational Classification (SOC Codes).

To identify gig workers, we have to perform string-matching in occupation labels as well as the companies where the job was located. For example, to identify if workers from ride hailing apps, their occupation name has to include the words 'driver', 'contractor', or 'freelancer' and any of their variants, and their company name has to contain the words 'Uber' or 'Lyft'. A worker is considered a gig worker if, at any point during their careers, they engaged in gig work, regardless of whether they continue to engage in it or not. Using our string-matching methods we have identified over five thousand gig workers in our dataset working across ten different platforms. Workers from ride-hailing apps make up almost half of all the gig workers we identified.

Our descriptive explorations show that there is more diversity in the occupations that lead to gig work, than the occupations that follow it. For instance, in our sample of workers, there are 233 different occupations that precede gig work. For the same set of workers, there are only 182 occupations that follow it, and there is a greater concentration of workers who

go to one of those occupations (20%). Similarly, we find that most of the occupations that follow ride-hailing work are more related to the same type of work even if the job is performed as part of traditional employment. Our results suggest that gig work constrains future opportunities for workers in ways that are still not well understood.

Our next steps include using a Logistic model to predict which occupations co-occur with gig work. We will use variables for educational attainment, occupations prior to gig work, experience in the labor market, and year and/or city-fixed effects to control for their influence on the relationship between occupations and platform work. Additionally, we would like to analyze gig workers' career trajectories to understand which types of gigs lead to broader or narrower sets of occupations after engaging in gig work. Ideally, we would like to complement our quantitative analysis with surveys to capture other metrics that are not readily quantifiable with our data like work-life balance and schedule flexibility which might be gained by workers engaged in gig work. Finally, this model will be used in conjunction with other models to power a tool called CareerCrafter to help US workers make more informed career transitions.
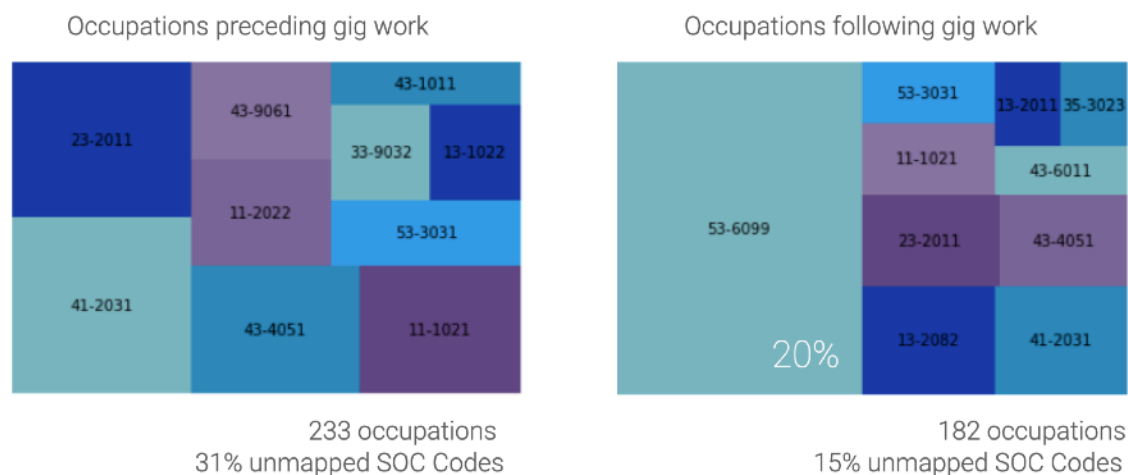

Figure 1. Shows tree maps for occupations preceding and following gig work for the same set of over two thousand gig workers of ride-hailing apps across the US.

References

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