Simulations to Study Workers, Regulations, and Platforms in the Gig Economy

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ABSTRACT

Digital labour platforms act as asymmetrical market-makers in the gig economy. This is because platforms deliberately withhold information from workers, consumers and regulators to maximize firm profits and accelerate growth. Information withheld from workers and policy-makers limits their ability for collective-action and effective regulation. Lacking information such as job location, effective wage, and difficulty, workers are forced to estimate how these factors may affect job quality. Workers account for such limited information and uncertainty with mental models that have varying levels of fidelity, accuracy, and reliability.

This paper shows the potential of agent-based models (ABM) of workers and platforms in the gig economy to enhance our understanding of the effect of information asymmetries on platform actors. In doing so, we aim to identify opportunities for effective collective-action and regulation. We show where qualitative and quantitative field data can facilitate tuning model parameters. Additionally, we show how individual- and system-level effects of variations in workforce characteristics (e.g., percent of full-time vs. part-time workers), job types and locations, and pay and information structures can be studied in simulation. Finally, we present an early minimum-viable model and discuss future research opportunities.

KEYWORDS

ABM, Gig economy, Information asymmetry

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1 INTRODUCTION

The emergence of the digital platform economy over the past decade has transformed economic activity across many economic sectors, including transportation, care, and household deliveries. [6][9][13][7][5]. This transformation has been amplified by the COVID-19 pandemic, which substantially increased the use of digital labour platforms for services like grocery and package delivery. As platforms have expanded their operations, several challenges have emerged that impact workers, customers, and their communities [10][11][12]. Consequently, much public discussion and, increasingly, policy efforts have proposed to regulate the platform economy.

The lack of data and understanding concerning feedback dynamics between workers and gig economy platforms, however, means that the platform economy is at present rife with unintended consequences. This is particularly true for platform workers. While many workers are attracted to digital labor platforms because they provide workers with the promise of greater autonomy over work schedules and freedom from supervision, several years of social scientific research have proven that many workers also experience unfavorable labor conditions against which they have little bargaining power. For example, ride sharing platforms often withhold a passenger's drop-off location from the driver until after the driver has agreed to perform the task. If, upon learning the customer's destination, the driver wishes to cancel the job the driver must carefully weigh the costs and benefits of doing so. The platform, for example, may impose penalties such as limiting future job opportunities or even "deactivating" the driver. Other worker disadvantages in platform work include the lack of health insurance, minimum wage, problematic or even dangerous encounters with customers, and the use of algorithmic models to distribute work tasks (such as surge pricing) which produce externalities to communities (such as congestion).

To date, technical literature on the subject has focused on optimization from the perspective of platform developers/owners, seeking to make the deployment of labor within the system efficient. Here, efficiency means optimal deployment of labor at lowest cost to meet the consumption demands of the market the platform serves [3][2][4]. This approach neglects the problems outlined above for the other stakeholders in the market, namely those who supply the labor (the platform workers), those who are members of the communities in which these transactions take place, and representative governments, at levels from local to national. Indeed, governments are often tasked with regulating the market economy so as to account for civic goals like fairness and equity, in addition to notions of economic efficiency.

To fully understand the platform economy, we propose to conceptualize platforms as multi-agent systems (MAS) that encompass all of these players. In 2019, our research group, a cross-disciplinary team trained in social science, engineering, and law, embarked on a study of the algorithmic workplace from a perspective we call "comprehensive platform optimization" (CPO), with the aim of developing novel MAS solutions to social challenges flowing from the interaction of algorithmic labor-platforms and society. We conducted a two-year ethnographic study of the attitudinal and behavioral characteristics of platform workers.

In this position paper, we present an application of that qualitative research towards a technical solution to the problems outlined above. Specifically, we utilize an agent-based model (ABM) to deploy and test mechanisms to obtain more ethical and fair outcomes in platform labor and to resolve social challenges flowing from the interaction of algorithmic labor-platforms and society. We have two aims for this work to be presented here. First, in order to simulate the package delivery gig economy, we model the space and dynamics of agents' interaction. We create a 2D Cartesian coordinate plane to represent space and compute distances between the agents (jobs and workers). Workers are matched with jobs by the platform algorithm, whose goal is to reduce the cost of wages and speed of meeting market demand. Second, our ABM solution brings a new method into solving the problem that platforms are not "optimized" for the variety of actors involved with platforms and affected by them (i.e., the workers and the society on which factors are externalized). Here we aim to apply the concept of CPO towards the real-world deployment of MAS solutions in societies. Specifically, we hope to test policy reforms such as minimum wages, cap on profit margins, mandatory disclosures, etc. at the level of algorithms by using ABM to deploy and test dynamics to obtain more certain, ethical, and fair outcomes.

2 METHODOLOGY AND FUTURE WORK

Workers, customers, and the platform are each represented as agents that influence the environment of the gig economy. Agents in the ABM act sequentially, based on their agent type according to Figure 1. The model is initialized with a workforce (step-1), the platform then aims to efficiently match workers to jobs (step-2) and minimally communicates these matches to the workers (step-3). In step-4, the workers decide to accept or reject a job based on information from the platform, their own availability and internal behavioral states (e.g., frustration with the market). The workers inform the platform of their decision (step-5) and either work, wait, or log-off in step-6 while new jobs are added in step-2 before the simulation returns to step-3. These steps are enumerated in detail below.

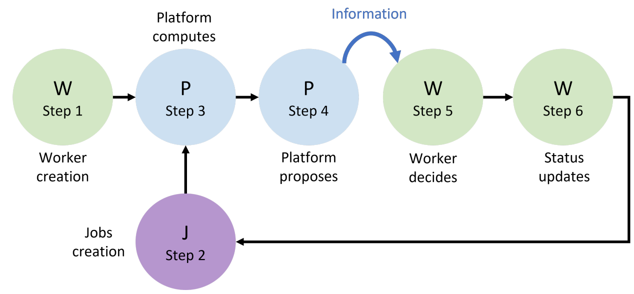

Figure 1: Flow chart of ABM simulation. Actions by workers (W) are green, by the platform (P) are blue, and by the jobs (J) are violet.

(1) **Creation of workforce population**: To create a worker, two main aspects need to be considered:

(a) **Arrival process**: For a worker to be considered for a job, a worker needs to login and hence their *starting* and *ending* times of the worker on the platform need to be defined. Based on the hours worked, two types of workers are created (i.e., *full-time*, or *part-time*). Moreover, arrival subtypes are created based on start times of the workers. The arrival subtypes can be *morning larks*, *afternooners*, and *night owls*. The authors have access to a closed-source business-to-consumer delivery company's dataset which is used to develop these arrival process types and parameters.

(b) **Motivation**: Only two main types of worker motivation are considered at this stage of research i.e., *wage maximizers*, *income targeting*. Other types of workers can be in the scope of future work. The 225 qualitative gig-worker interviews conducted as a part of the NSF funded project underway, *FW-HTF-RM: Collaborative Research: Regulating and Managing the Algorithmic Workplace: A Multi-Method Study for Comprehensive Optimization of Platforms* were used to extract the proportion of workers in full-time/part-time category and in subtypes wage maximizers/income targeting category. The motivation subtypes help in strategically initializing workers. The movement of workers from one subtype to another can be considered in the future.

(2) **Jobs creation**: Jobs are created with parameters of *price, starting location, ending location, and due time*. The starting location of a job can be part of a cluster to represent a grocery store, the ending location however is randomized to represent customer's home. The price of the job is the sum

of the distance between starting and ending location of the job, a deadheading fee charged by the platform, and platform's profit margin. The due time of the job is randomized during the day but has to be at least 2 hours after the job creation time. Parameters for the job creation model can be fit to open datasets such as the Instacart Market Basket dataset [1].

(3) **Platform computes**: Platform's algorithm *efficiently* matches workers with jobs based on the criteria:

(a) The worker is available
(b) The worker is within a radius of a job
(c) The worker is nearest to the start location
(d) The worker can complete the job before their shift end time.

A lot of research has been conducted to increase the efficiency of matching algorithms, and as one member of our team has developed commercially successful algorithms for gig economy before [8], we can use their experience to tailor the algorithms.

(4) **Platform proposes**: The matched workers are notified by the algorithm regarding the job match and are proposed a job with the corresponding job details of *wage*, *due time*, and *start location*.

(5) **Worker decides**: Consider a full-time worker that is available to work 8 hours daily. They would accept any jobs during the period they are available to maximize their daily wages. However, we consider part-time workers to be more discriminating in the jobs they accept. They may be wage maximizing, but with a minimum acceptable effective *reservation wage*, or they may be income targeting, accepting all jobs until their *daily income target* is met and rejecting all jobs thereafter.

(6) **Status updates**: Workers that accept job offers are marked as unavailable and only become available again after they have completed the job and if they are scheduled to come back online (determined by their arrival subtype). Workers that reject job offers are checked for their schedule to logoff. Worker *frustration* is a key metric that we propose that builds up and may cause workers to eventually log off while still available. Our interviews showed that workers waiting for a job is one of the most frustrating aspects of gig economy work. Upon reaching a *frustration threshold*, a worker can decide to log off the platform. Other aspects like safety, gamification, ratings, etc. can also contribute to frustration and will be modeled in the future work. Primarily, interview data would be used to model the mental models or the frustration thresholds of the workers.

A basic model was developed to establish the feasibility of the ABM model. The 2D representation of workers and jobs can be seen from Figure 2, where agents have been placed randomly on various coordinates. Agents that accept jobs move from one coordinate to another based on the distance, traffic delay (random number), and worker speed. For a more representative model of workforce and task geographic distribution, a map of a city can also be used to define start and end coordinates and Manhattan distance would be used to compute distances.

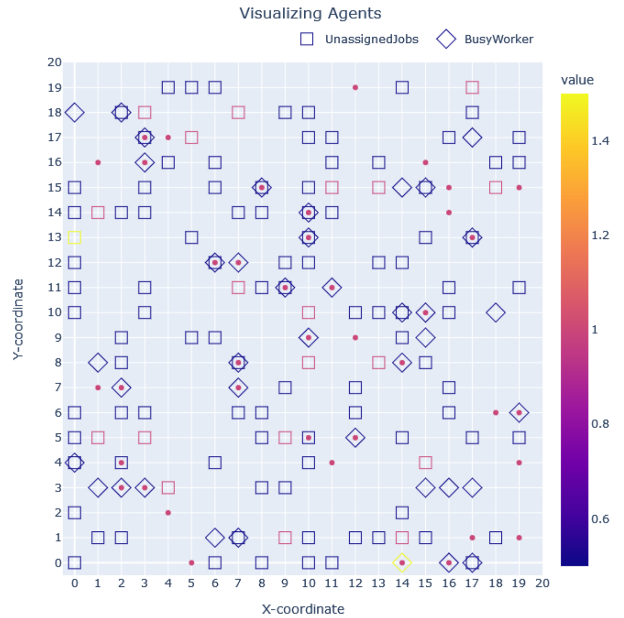

Figure 2: 2D canvas of a grid where agent interact; dots are Assigned Jobs, boxes are Unassigned Jobs, Circles are available workers, and Diamonds are busy workers; Color scale defines the value of agent in one coordinate

3 CONCLUSION

This paper discusses a proposed agent-based modeling methodology capable of studying important aspects of a gig economy. Parameters for workers like their schedule, reservation wage, locations, types, motivations etc. are crucial and eventually determine a worker's propensity towards financial or safety issues. Jobs can be modeled for their location, price and due time and the platform can be modeled for their algorithms to match workers with jobs, profit margins, dead heading fees, etc. Model parameters can be fit to quantitative data (some of which is available open-source) or to qualitative data extracted from interviews of gig workers.

This qualitatively and quantitatively grounded simulation environment will enable the study of critical system-level effects of regulations and algorithms. Experiments could include strategies such as sharing data among workers to estimate internal states of the platform and decentralized optimization strategies that a 3rd party could implement to assist workers. A tool like ABM can be used by regulators to study the impact of various regulations like supply of jobs or workers at an hour of the day, workers to study information sharing and develop best practices for platform usage, and platforms to increase worker retention rates and satisfaction.

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