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Research paper

Assessing the economic sustainability of gig work: A case of hyper-local food delivery workers in Kolkata, India

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ABSTRACT

Gigs were once heralded as work ushering in flexibility, freeing workers from the constraints of time, space, and nagging human managers. However it has been marked by long work hours and an unstable income. This has led to a situation where gig workers are increasingly demanding labor rights. Gig work has been qualitatively explored, highlighting the elements of control exercised by the platform companies. However, there is a dearth of quantitative assessment of the economic sustainability of gig work. In this context, this study explores gig work using the case of hyper-local food delivery in India. The first part uses an agent-based and discrete event simulation (parameterized using primary data) to map the net earnings of workers under varying wage rates. The results show that, at the present wage rate, the food delivery worker has an average net earning of INR 265/day (USD 12.10), considering both the fixed and variable cost of operation. This earning is far below that of an average self-employed worker and casual laborer in urban India. Finally, this study proposes a fixed hourly wage rate of INR 37.84 (USD 1.72) to eliminate the variability in worker earnings without inflating the cost of food delivery.

1. Introduction

Work outside the bounds of standard employment has been loosely described as gigs (De Stefano, 2015). Gig work can be categorized into '*Crowdwork*' and '*Work-on-demand*' (Aloisi, 2015; de Stefano, 2015). '*Crowdwork*' systems are platforms that assign jobs that can be completed and delivered online. The platform's role is typically limited to matching workers with the end purchasers of their services. Prominent examples include Amazon Mechanical Turk, UpWork, etc. '*Work-on-demand*' systems involve more traditional, physical, or 'real world' tasks. These jobs are organized through online platforms but need local human inputs and interactions, like ride-hailing, food delivery, cleaning services, etc. Examples include Uber, Lyft, and DoorDash in the USA and Zomato and Swiggy in India. The platform may also retain control over important aspects of the work, including setting prices and standards and selecting and managing the workforce, as in the case of food delivery.

Hyper-local food delivery involves delivering cooked food from neighborhood eateries to consumers by engaging these gig workers. The legal term used by hyper-local meal delivery platforms for delivery workers in India is *partners.* According to the Indian food delivery platforms, *partners are independent contractors, engaged on a principal-to-principal basis, with the platform merely acting as an intermediary* (Swiggy, 2020; Zomato, 2021). Thus, Indian hyper-local food delivery platforms do not accept any standard employment relationship with the delivery worker and the job of hyper-local food delivery can definitely be termed as a gig.

Scholars have argued that gig work heralds a future of precarious work, where workers are denied labor rights and the protection of a social security net (de Stefano, 2015). The supposed flexibility offered by these platforms often results in workers working even longer shifts at wages far below the prescribed minimum wage (Goods et al., 2019). This situation has led to a demand for the extension of labor rights, like minimum wage, to gig workers. However, the extension of the present standard minimum daily wage to gig workers will have serious cost implications for the platform companies relying on these workers. Thus, policymakers need to find a middle ground where gig work becomes more remunerative without significantly affecting the present cost of service delivery.

The study and analysis of gig work assumes significance considering the *Sustainable Development Goal* 8 that seeks to promote "*Decent work and economic growth*". Though the present literature is replete with the

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qualitative analysis of gig work, the quantification of the economic sustainability of gig work is lacking (Fielbaum & Tirachini, 2021; Henao & Marshall, 2019). Therefore, there exists the need for a framework that can accurately map the erratic earnings of gig workers. This study takes up the case of hyper-local food delivery in India and proposes a simulation framework for mapping the net earnings of food delivery workers. The simulation is parameterized using data collected from delivery workers using an intercept survey. The net earnings of these gig workers are then compared to the other classes of urban workers. Finally, an alternative compensation structure is proposed, that eliminates the variability in worker earnings without significantly altering the present cost of food delivery.

Although primary data were collected concerning the earnings of food delivery workers, a simulation was deemed necessary to obtain a clearer picture of their earnings. The reasons are as follows. The compensation structure for food delivery is similar across platforms and comprises a variable pay and incentive system. The most significant component of the variable pay is the travel pay. The travel pay is the product of distance travelled per delivery and the travel pay rate. Though the compensation structure is similar across food delivery platforms, the travel pay rate varies. The variation is not only across platforms but also exists within the same platform. Within a platform, the travel pay rates vary not only from one city to another but also within the same city. Different workers are offered different travel pay rates, based on the time of their joining. Thus, older workers command a higher travel pay rate compared to new entrants. Platforms are also constantly revising travel pay rates, most often downwards. Even a minor downward revision of these rates can result in a major fall in earnings due to the prevailing wage and incentive structure. Gig work, by nature, is also characterized by erratic earnings (Henao & Marshall, 2019) and this was observed during the primary survey, too. In this context, a simulation framework can be used to constantly monitor the earnings of workers engaged by different platforms with different travel pay rates.

Another drawback associated with a primary survey was its inability to discern between gross and net earnings. In the current scenario, the distance travelled per order comprises the distance travelled from the worker's current location to the eatery (first mile) and from the eatery to the customer location (last mile). But the distance travelled per order does not include the dead mile i.e., the distance travelled to relocate back to an eatery, and workers are not compensated for it. Accordingly, the application used by delivery workers records their first and last mile but leaves out the dead mile travelled. As a result, the total cost of fuel, and consequently the net earnings can never be accurately assessed from gross earnings data obtained using a primary survey.

The simulation framework proposed in this research can be applied to gauge the distribution of erratic earnings of other gig workers, helping policymakers to evaluate their true state. Secondly, this simulation offers the added advantage of beta testing strategies targeted at augmenting earnings of these gig workers.

The article is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology adopted and the data used. Section 4 elucidates the results of this study. Section 5 discusses the need to regulate the sector and the problems associated with such regulation for low and middle-income countries.

2. Literature review

Gig work can be identified by its five broad organizational features (Stanford, 2017).

- Performance of work on a contingent or on-demand basis.
- Compensation on a piece-rate basis.
- Supply of capital equipment by the workers themselves.
- A triangular relation between the worker, end-user, and the intermediary and
- Digital intermediation for commissioning and supervising work and for determining the compensation amount

The three major organizational features of gig work – on-demand labor, piece-rate compensation, and the requirement that workers provide their capital equipment – were features of early merchant capitalism, too (Stanford, 2017). For example, the 'putting out' system was common in Europe and 18th century colonial India. In this case, a merchant distributed production tasks along with the requisite raw materials, and producers performed the work in their own homes, using simple capital equipment they owned. The merchant took control of the finished goods on a piece-rate basis and sold them for a hefty profit in far-flung markets. Merchants hired the producer on-demand and deferred payments till the goods were sold. Scholars argue that gig work is only a digitally enabled version of this system of production (Alkhatib et al., 2017; Stanford, 2017).

Researchers have used ethnographic surveys to analyze gig work globally. Some of them pertain to platform-based ride-hailing services (Chen, 2018; Rosenblat & Stark, 2016; Wu et al., 2019), while others have taken up the case of food delivery services (Aguilera et al., 2022; Goods et al., 2019; Griesbach et al., 2019; Sun, 2019; Veen et al., 2020; Wood et al., 2019). Standard employment practices are characterized by bureaucratic control over workers. But with the rise of the platform-based gig economy, pure market-based mechanisms proved inadequate for control over workers. In this context, these studies have tried to uncover the tools employed by the platforms to manage the workers.

These qualitative studies also point to the *low income-high working hour* conundrum faced by food delivery workers globally. But surprisingly, the quantification of this problem is almost non-existent. A study by Fielbaum et al. (2023) highlights the fact that COVID-19 has resulted in Chilean food delivery workers earning less money per hour, being more exhausted, and expressing the largest decrease in their job satisfaction when compared to traditional transport workers. However, quantification of earnings is absent. Allen et al. (2021) use primary data to discern the traffic and environmental impact of meal delivery but ignore the earnings of gig workers. Aguilera et al. (2022) use questionnaire survey to analyze the profiles, motivations and mobility patterns of food delivery workers in Paris but again disregard worker earnings. Agarwal et al. (2023) identify only the increase in congestion as a result of ride-hailing services in Indian cities. However, the study by Henao and Marshall (2019) assesses the earnings per hour of Uber drivers based on a single-person data, one of the authors himself. But no such study exists for Indian food delivery workers. Indian delivery workers use their own vehicle to conduct deliveries and have to bear the cost of fuel. As such, any simple enumeration will reveal only their gross earnings. As already discussed, delivery worker applications only store first and last mile distances, ignoring the dead mile. However, to truly quantify their net earnings, a mechanism is needed that can quantify the total distance travelled per delivery, inclusive of the dead mile. In addition, the wage rates offered to the workers are also declining (Nanisetti, 2021; Tandon, 2021), and there is a need to constantly monitor the earnings of workers engaged by different platforms with different wage rates. Moreover, platforms supplement higher order earnings with higher rates of incentives, which form a significant portion of worker earnings. Incentives are not offered as a percentage of order earnings but only when the order earnings reach a predetermined slab. This compensation structure forces workers to work long and arduous hours as failing to reach the nearest order earnings slab will deny him a higher incentive. Moreover, order volumes fluctuate across the day, meaning workers earn differently even after spending equal amounts of time. The situation of these food delivery workers stand in sharp contrast to those of the traditional Mumbai lunchbox delivery workers, popularly called the *dabbawallahs* (Baindur & Macário, 2013). The Mumbai *dabbawallahs* deliver lunch from homes and eateries to workers in their offices but are organised as cooperatives, with fixed monthly incomes and other forms of social security (Baindur & Macário, 2013). This situation of the hyper-local food delivery workers has led to a demand for better wages (Nanisetti, 2021), and a quantitative assessment of the actual worker earnings per hour will aid policymakers.

3. Research method and data

3.1. Data collection

To develop an understanding of the nature of on-demand meal delivery, group interviews of food delivery workers engaged by the two major Indian platforms were conducted. This was followed by intercept surveys and in-depth interviews of 49 food delivery workers in March 2020, just before a nationwide lockdown was announced. The survey was conducted in the Salt Lake-New Town hyper-local zone in Kolkata, India (Fig. 1). The hyper-local zone has an area of 19.47 square kilometers, with 102 eateries serving on-demand delivery through a major online aggregator platform. The hyper-local zone is predominantly residential with an exclusive industrial township, housing information technology companies, electronics manufacturers, banks, hotels, and healthcare facilities. The structured part of the questionnaire enumerated two types of data from the delivery workers. The first part sought the variation of daily earnings with working hours over a week. The second part collected the details of each order delivered in a single day. The order details comprised of the originating eatery, first mile, and last-mile distance travelled, the waiting time at the eatery, the earning, and the time at which the order was received, picked up, and delivered. This data was used for parameterizing the simulation model. A total of 270 orders were enumerated from the 49 delivery workers. More details regarding the primary survey can be gleaned from the authors' previous publication (Sinha & Pandit, 2021). Though the underlying compensation structure remains static, travel pay rates undergo revisions over shorter durations of time. Keeping this in mind, the knowledge about the platforms and their travel pay rates were constantly updated via the use of online forums and is reflected in the research.

3.2. Methodology

The research uses an agent-based discrete event simulation to model the net earnings of the workers under various travel pay rates. Agent based simulation is one of the most popular technique in simulating urban freight (Jlassi et al., 2018; Sakai et al., 2020). Agent based simulation has been used for estimating the amount of emission as a result of hyper-local food delivery (Sinha & Pandit, 2021) and amount of emission as a result of grocery home delivery (Heldt et al., 2021).

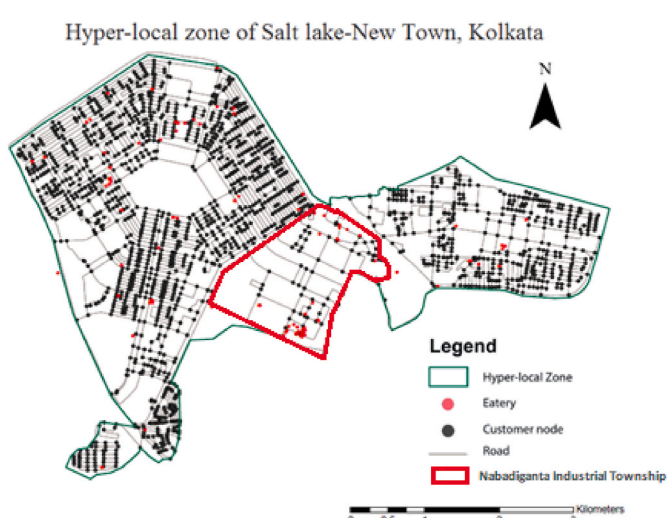

Fig. 1. Study area.

Two types of scenarios are evaluated in this article. In the first scenario, delivery worker earnings are evaluated under past and present wage rates. The average net earnings of delivery workers are then compared to that of self-employed workers and casual laborers in urban India. In the second proposed scenario, the delivery workers are offered fixed hourly wages and the number of workers per shift is capped. The proposed scenario is then compared to the first scenario in terms of the average cost incurred by the platform per delivery.

The simulation model used in this research is a modified version of the one used by the Sinha & Pandit, 2021. The simulation entails two steps, which are described below.

Step 1: A heuristic estimation of required fleet size

In the first step, the fleet size required for the hyper-local zone at a particular order volume is determined. This fleet size will serve as an input for Step 2, where actual worker earnings will be determined. To determine the required fleet size a heuristic has been resorted to. This heuristic, in the form of the *Agent synthesis and order assignment module,* is shown in Fig. 3 and is part of the overall simulation framework as shown in Fig. 2.

The gig worker is modelled as the agent in the simulation. The simulation starts by synthesizing an order list. An *agent synthesis and assignment module* (detailed in Fig. 3) then assigns an agent to each order. As the simulation starts with zero agents, an agent is created when the first order comes up for assignment. Similarly, whenever the system runs out of active agents, new agents are synthesized. An agent is deemed active if its designated work hours are not over and it is currently not involved in a delivery. For assignment, the agent located closest to the originating eatery is assigned the order. If there are multiple agents equidistant from the eatery, the one with the lowest earnings per unit of time spent is assigned the order. Post-assignment, the agent travels the *first mile* to the eatery from its current location, followed by the *last mile* to the customer location. On completion of delivery, it again relocates to an eatery, covering the *dead mile* in the process. The relocation choice of the agent is based on the attractiveness of an eatery, arrived at using a gravity model formulation. The simulation is parameterized using the data obtained from the primary survey.

Using the simulation framework and the heuristic described above, the fleet size required at different order volumes is assessed. By summing the number of workers spawned between the starts of consecutive shifts, the shift-wise fleet size requirement is obtained. The shift start times used in the simulation (as obtained from the primary survey) are 8:00 h (Shift 1), 12:00 h (Shift 2), and 19:00 h (Shift 3).

Increasing the workers beyond the stated shift-wise requirement may sometimes be desirable for the platform in order to lower the delivery times (and improve service levels). However, as shown in the study by Sinha & Pandit, 2021, this improvement in service delivery time stagnates at a point and no further improvement can be affected by the addition of new delivery agents.

Step 2: Determining the gross and net earnings of agents

The shift-wise fleet size requirement from Step 1is fed into a modified version of the simulation, where the *Agent synthesis & order assignment module* has been tweaked. The tweaked *Agent synthesis & order assignment module (Module II)* is shown in Fig. 4. Module II synthesizes all required agents at the start of their corresponding shift, unlike the original Module I, where agents were synthesized as and when required. Thus, the *All Agent List* in Module I (in Step 1) is empty at the beginning of the simulation, whereas the *All Agent List* in Module II (in Step 2) contains all the agents. As the modified simulation spawn agents at the start of their corresponding shift, it gives a more realistic picture of the actual working hours spent by the worker. Using this modified simulation, the gross earnings of each worker is assessed, along with the total

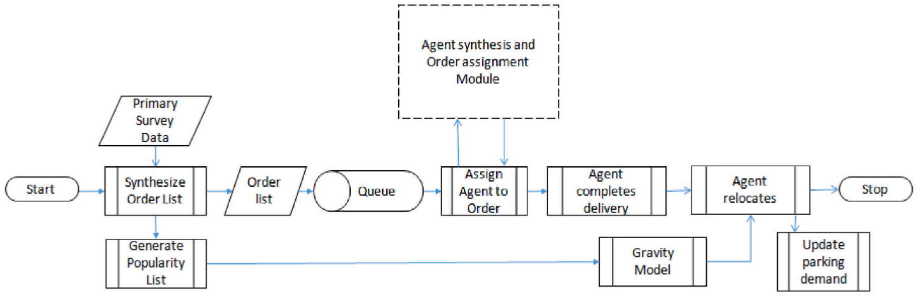

Fig. 2. Simulation framework (Sinha & Pandit, 2021).

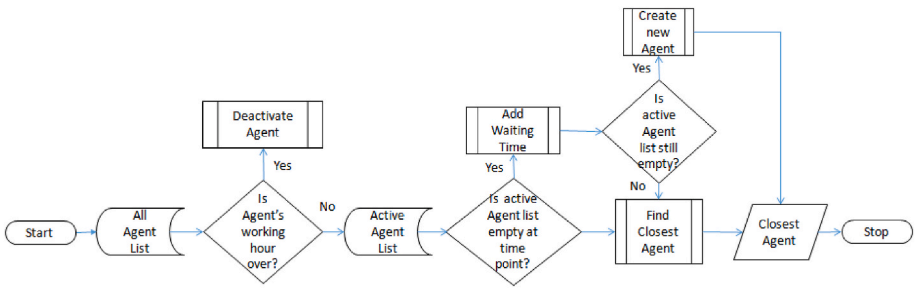

Fig. 3. Agent synthesis & order assignment module (Module I) (Sinha & Pandit, 2021).

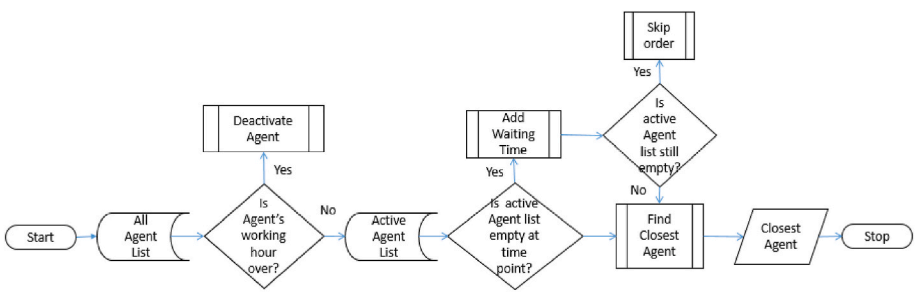

Fig. 4. Tweaked *Agent synthesis & order assignment module* (Module II).

first, last and dead miles travelled. The earnings of a worker vary from one day to the other, depending on the number of orders assigned and their value. Thus, to obtain a more comprehensive picture, the earnings of each worker agent were simulated for 30 simulation days and averaged.

The average net daily earning per hour of a worker is given by Equation (1).

$$\text{Avg. net daily earning per hour of a worker} = \frac{\textit{Avg. net daily earning of worker}}{\textit{Dailyworkinghour}}$$

Equation 1

The Average Net daily earning of a worker is given by Equation (2).

$$\textit{Average net daily earning of a worker} = \frac{\sum_{0}^{t} \textit{Net daily earning of a worker}}{t}$$

Equation 2

where t = 30 days.

The Net daily earning of a worker is given by Equation (3).

$$\text{Net daily earning of a worker} = \text{Gross daily earning} - \text{Daily cost of operation}$$

Equation 3

Two measures of net earnings are calculated. In the first, only the cost of fuel incurred is deducted (Equation (4)). The cost of vehicle ownership is considered a sunk cost, in this case, presuming that vehicles were not purchased for the sole purpose of delivery (Henao & Marshall, 2019). Assuming a mileage of 48.5 km/l (Goel et al., 2016) and the cost of petrol as INR 105 per litre (as of 5th December 2021), the average cost of fuel/km is estimated.

$$\text{Daily Cost of operation } (\textit{Case } 1) = \sum_{0}^{n} (\textit{Firstmile} + \textit{Lastmile} + \textit{Deadmile}) * \text{Avg. Cost of fuel} \Big/ \text{km}$$

Equation 4

where n is the number of orders delivered in a day.

In the second case, a more comprehensive total cost of ownership (TCO) is subtracted from the gross earnings to obtain net earnings (**Equation (5)**). The total cost of ownership takes into account the operational cost (fuel and maintenance) as well as the fixed cost of the vehicle and is obtained from Kumar and Chakrabarty (2020).

$$\text{Daily Cost of operation } (Case\ 2) = \sum_{0}^{n}(Firstmile + Lastmile + Deadmile) * TCO \Big/ km \quad \text{Equation 5}$$

where n is the number of orders delivered in a day and TCO is the total cost of operation.

The Gross daily earning per worker is given by Equation (6).

$$\text{Gross daily earning of a worker} = Daily\ order\ earnings + Incentives \quad \text{Equation 6}$$

The incentive slabs used in the simulation are shown in Fig. 5. The incentive structure is graduated, promoting higher order earnings and in turn longer working hours. The delivery worker is entitled to two types of incentives-*daily* and *weekly*. If his daily earnings reach INR 325 he is awarded an incentive of INR 75; if his earnings reach INR 475, he is given an incentive of INR 125; and if his daily earnings reach INR 800 he is given an incentive of INR 250. Similarly, if his weekly earnings reach INR 600, he receives a weekly incentive of INR 200; and if his weekly earnings are INR 2700, he receives an incentive of INR 600.

Equation (7) and Equation (8) give the Daily order earnings and Earnings per order, respectively.

$$\text{Daily order earnings} = \sum^{n} Earnings\ per\ order \quad \text{Equation 7}$$

where n is the number of orders delivered by the worker in a day.

$$\text{Earnings per order} = Travel\ pay + Wait\ time\ pay + \text{Customer Pay} \quad \text{Equation 8}$$

The Earnings per order is a combination of Travel pay, Wait time pay, and Customer pay. The Travel pay and Wait time pay are given by Equation (9) and Equation (10), respectively. Customer pay is a fixed pay given for completing the order.

$$\text{Travel pay} = (First\ mile + Last\ mile) * Travel\ pay\ rate \quad \text{Equation 9}$$

$$\text{Wait time pay} = Waiting\ time\ post\ assignment\ in\ front\ of\ eatery\ (min) * Wait\ time\ pay\ rate \quad \text{Equation 10}$$

3.3. Proposed scenario: offering fixed hourly wages

A possible solution to this problem of low and varying earnings can be the offer of fixed wages. But the demand for delivery workers varies during the day and offering fixed daily wages for workers can be financially burdensome for the platforms. However, the payment of fixed hourly wages, along with the cost of fuel, can reduce the variability in earnings without financially burdening the platform. Besides offering fixed hourly wages, the number of workers per shift also needs to be capped to prevent cost escalation for the delivery platform.

In order for the platform to accept a fixed hourly wage rate, the average cost of delivery should be least impacted. Thus, to identify an acceptable hourly wage rate, the average cost of delivery is calculated under three fixed wage rates. To arrive at the average cost of delivery, the total cost of fuel was added to the total cost of wages and divided by the cumulative volume of orders delivered (Equation (11)). The cost of fuel was the product of cumulative distance travelled by the workers (first, last, and dead mile) and the fuel cost per kilometer (Equation (13)). The total cost of wage was the product of the wage rate and the cumulative hours spent at work by the workers (Equation (12)).

$$\text{Average cost of delivery} = (Total\ cost\ of\ wages + Total\ cost\ of\ fuel)/n \quad \text{Equation 11}$$

where n is the total number of orders delivered in a day.

$$\text{Total cost of wages} = \sum^{N}(Total\ hours\ worked * Hourly\ wage\ rate) \quad \text{Equation 12}$$

where N is the total number of workers in a day.

$$\text{Total cost of fuel} = \sum^{\mathrm{N}}(\text{Total distance travelled} * \text{fuel cost per unit distance}) \quad \text{Equation 13}$$

where N is the total number of workers in a day.

The worker earnings calculated for the present scenario and the proposed scenario is presented in Section 4.

3.4. Limitations of the model

Due to the competitive nature of their businesses, platforms were not willing to share the exact volume of orders or the number of delivery workers in the hyperlocal zone under study. Therefore, a range of order volumes were assumed (Sinha & Pandit, 2021). A heuristic has been used to determine the number of workers required to fulfill this range of order volumes. The heuristic used may have resulted in the estimation of a fleet size that is sub-optimal or near-optimal in nature. This fleet size, obtained using the heuristic, is also likely to differ from the fleet size operating in the real world scenario. Moreover, offering fixed hourly wages in the future may alter the fleet requirements of the platform. The lure of a fixed wage rate is likely to attract surplus delivery workers during off-peak hours and platforms may have to introduce an hourly cap on their numbers. This cap will be determined by the platform's objective of either achieving a higher service level or a higher capacity utilization level. To achieve a higher capacity utilization level, the platform will have to lower the cap on the number of workers and as a result forego orders. Whereas, to achieve a better service level, the cap on the fleet size needs to be increased. In the present study these scenarios were not modelled. Additionally, the following assumptions were made in the study.

a) There is a single online aggregator in the hyper-local zone and all orders are serviced by it.
b) Agents deliver only one order at a time.
c) For the simulation, the nodes of the road network have been considered as customer locations. Delivery workers may need to expend additional travel and time costs for delivery in the real world.
d) The shortest distance between any two points via the road network is obtained using the Network Analyst tool of ArcGIS.
e) Traffic restrictions like one-way streets have not been modelled.
f) The working hours of a delivery agent are based solely on the distribution obtained from the sample survey and are not influenced by other parameters like earnings.
g) The delivery agent is assigned the next order only on completion of the dead mile.
h) An agent is not free to reject an order.
i) Delivery worker decision making is assumed to be based on the gravity model heuristic, which may not be the case in the real world.
j) An average velocity based on the sample survey is used for all the delivery agents.

4. Results

4.1. Present scenario

This section calculates the present net earnings of gig workers and draws a comparison with other classes of urban workers in India. During the survey, workers reported travel pay rates of INR 6 and INR 8 per kilometer. Post the Covid-19 induced lockdown and disruption, this rate

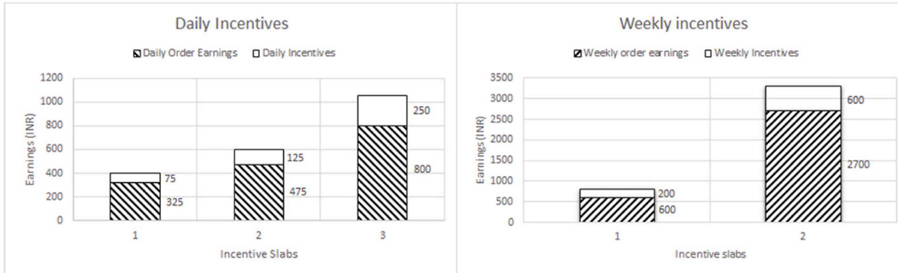

Fig. 5. Order earnings & Incentive slabs.

dropped to INR 5 per kilometer. Wait time pay was found to be INR 1/minute and Customer pay (a flat payment for completing the order) was INR 5. Earnings were simulated with travel pay rates of INR 4, INR 5, INR 6, and INR 8 per kilometer to discern future and past scenarios. Worker earnings also vary with the total order volume, but the severe nature of competition has made platforms reluctant to share data on the daily quantum of orders served by them in a zone. As a countermeasure, a range of order volumes, varying from 500 to 2000, were simulated (Sinha & Pandit, 2021).

The shift-wise optimal fleet size requirement obtained using the simulation in Step 1 (with Module I) is shown in Table 1. The simulation was iterated thirty times, resulting in fractional fleet sizes, which were subsequently rounded off to their nearest whole number ceiling. Table 1 shows that for an order volume of 500 in the hyper-local zone, 16.43 workers were required in Shift 1, 17.33 workers were required in Shift 2, and 4.66 workers were required in Shift 3. This data was fed into the modified simulation in Step 2 to map workers' earnings.

The earnings of a worker vary from one day to the other, depending on the number of orders assigned and their value. Thus, to obtain a more comprehensive picture, the earnings of each worker agent were also simulated for 30 simulation days and averaged. The median values of gross earnings per hour are shown in Table 2. The gross earnings are a combination of order earnings, daily incentives, and weekly incentives. The median values of net earnings per hour (*Case 1*) are shown in Table 3. The net earnings in *Case 1* are calculated by deducting only the cost of fuel from the gross earnings. Table 4 shows the median net earnings per hour (*Case 2*) of delivery workers. In *Case 2* the net earnings have been obtained by deducting the total cost of ownership (fixed and variable cost) from the gross earnings.

Fig. 6 shows the box and whisker plot for the variation in net earnings per hour (*Case 2*) with travel pay rates at different order volumes. At each order volume, four cases are shown in blue, red, yellow, and green. Blue or Case 1 corresponds to net worker earnings at a wage rate of INR 4/km. Red or Case 2 corresponds to net worker earnings at a wage rate of INR 5/km. Yellow or Case 3 corresponds to net worker earnings at a wage rate of INR 6/km. Green or Case 4 corresponds to net worker earnings at a wage rate of INR 8/km. The variation in Worker earnings with the four wage rates are shown at four order volumes of 500, 1000, 1500, and 2000. Thus, the variation of net worker earnings corresponding to 16 scenarios are shown in the figure. It is observed that net earnings improve with the increase in total order volume.

A comparison of the mean net earnings/day and working hours/day of delivery workers (at an order volume of 2000) with other male urban workers in India is shown in Table 5 and Fig. 7 (Ministry of Statistics and

Table 1
Shift-wise fleet size requirements.

Order Volume	Shift 1	Shift 2	Shift 3
500	16.43	17.33	4.66
1000	31.33	33.50	5.90
1500	44.53	43.46	15.33
2000	60.60	58.93	14.83

Table 2
Median Gross Hourly earnings (INR) at varying order volume & travel pay rates.

Travel Pay	Median Gross Hourly Earnings (INR)			
	At 500 orders	At 1000 orders	At 1500 orders	2000 orders
INR 4/km	40.45	45.66	48.23	48.08
INR 5/km	49.91	51.73	57.35	56.94
INR 6/km	58.71	62.55	67.53	65.61
INR 8/km	73.11	73.56	83.72	85.49

Table 3
Median Net Hourly earnings (INR) at varying order volume & travel pay (Case 1).

	Median Net Hourly earnings (INR)			
Travel Pay	At 500 orders	At 1000 orders	At 1500 orders	At 2000 orders
INR 4/km	25.69	29.29	30.45	31.27
INR 5/km	26.09	32.10	35.66	36.44
INR 6/km	43.27	46.90	50.66	48.56
INR 8/km	58.45	58.57	67.06	68.18

Table 4
Median Net Hourly earnings (INR) at varying order volume & travel pay (Case 2).

	Median Net Hourly earnings (INR)			
Travel Pay	At 500 orders	At 1000 orders	At 1500 orders	At 2000 orders
INR 4/km	13.40	19.09	17.28	19.09
INR 5/km	18.67	23.26	25.70	26.21
INR 6/km	32.72	36.52	38.77	37.85
INR 8/km	48.60	48.78	56.02	57.00

Programme Implementation G. of I, 2021). There exists a substantial gender gap in the earnings of workers in India and the average net earnings of delivery workers are compared to that of other male workers in urban India. This is because the food delivery workers were exclusively males (as observed during the primary survey). Fig. 7 reveals that, on average, the Indian food delivery worker spends a much higher amount of working hours per day compared to self-employed workers and casual laborer. But still, his average net earnings per day, considering the total cost of operation, is in no case close to that of a self-employed worker. At the past travel pay rate of INR 8/km, his average daily earnings surpass that of the casual laborer. But at the present travel pay rate of INR 5/km, his average earnings fall below that of the casual laborer.

4.2. Proposed scenario: offering fixed hourly wage

In order for the platform to accept a fixed hourly wage rate, the average cost of delivery should be least impacted. Thus, to identify an acceptable hourly wage rate, the average cost of delivery is calculated in the present scenario and under three fixed wage rates. Table 6 quantifies

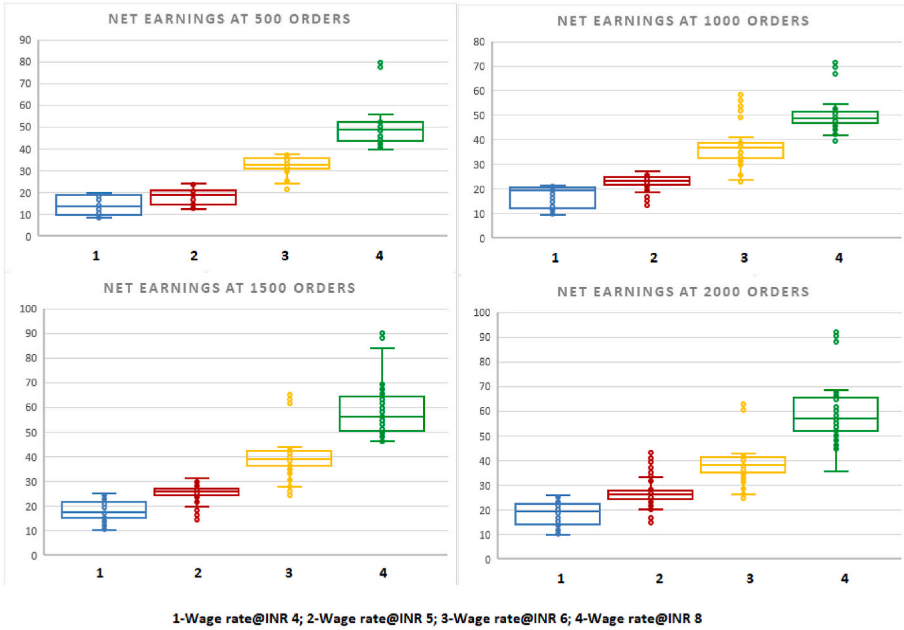

Fig. 6. Net earnings/hour with varying *Travel pay rates* considering Total Cost of Ownership (TCO) at Order volume of 500, 1000, 1500 & 2000.

Table 5
Average daily working hours & net earnings of different categories of urban male workers compared to net earnings (Case 2) of food delivery workers (at an order volume of 2000).

Travel Pay	Working hours/day	Avg. Daily earnings (INR)	Effective hourly earnings (INR)
Casual laborer	7.55	391	51.79
Self-employed worker	9.41	683.84	72.67
Food delivery worker, wage rate @INR4/km	10.09	192.63	19.09
Food delivery worker, wage rate @INR5/km	10.09	264.45	26.21
Food delivery worker, wage rate @INR6/km	10.09	381.85	37.84
Food delivery worker, wage rate @INR8/km	10.09	575.15	57.00

[1] Calculated based on data for Jan–Mar 2020, Periodic Labour Force Survey Report 2019-20.

Fig. 7. Average daily working hours & earnings of different categories of urban male workers compared to net earnings (Case 2) of food delivery workers (at an order volume of 2000).

the average delivery cost that has to be borne by the platform under four different wage regimes. The first is the present case of wages and incentives. The next three cases document the cost if a fixed standard hourly wage is provided in addition to the cost of fuel. The three standard hourly wage rates considered are that of the casual laborer, self-employed worker, and the average hourly earnings of the food delivery worker (at the wage rate of INR 6/km).

The results show that adopting a standard hourly wage rate increases the average cost of delivery. The adoption of the average wage rate of the casual laborer increases the average cost of delivery by 30.76% (at 2000 order volume). While adopting the average wage rate of the self-employed worker increases the average cost of delivery by 71.79% (at 2000 order volume). However, adopting the average earning of the food delivery worker (at travel pay rate of INR 6/km) as the standard hourly wage rate, increases the cost by a mere 2.56%. Thus, adopting a standard hourly wage rate of INR 37.84 should be acceptable to the platform and consumer (USD 1.72, using 2020 PPP exchange rate of 21.9).[1]

5. Discussion and conclusion

The exploration of actual net earnings of delivery workers shows that, despite the high degree of variability in earnings, the average net earnings of food delivery workers were, once, close to urban self-employed workers and greater than that of the casual laborer. But with the recent downward revision of travel pay rates, his average net earnings drop below the level of an urban casual laborer. Besides the low earnings, the variability in the earnings also pose a major problem for the food delivery workers. Thus, the flexibility and earning opportunities advertised by the food delivery platforms were not accurate.

A possible solution to the problem of variability in earnings is the adoption of fixed hourly wage rates along with compensation for fuel by the platform. This will eliminate the variability in earnings and provide workers with a stable earning. However, with the provision of fixed hourly wages, platforms are likely to take away the right of the worker to reject orders. Presently, workers are also free to relocate anywhere post-delivery. Their relocation choice is guided by their desire to be assigned the next order as soon as possible. In this endeavor they are assisted by a

[1] https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm.

Table 6
Average delivery cost for the platform under different scenarios (in INR).

	Avg. delivery cost (INR)			
	At 500 orders	At 1000 orders	At 1500 orders	At 2000 orders
i. Present scenario	37	38	39	39
Proposed scenarios:				
ii. Standard hourly wage @ 72.67 (Self-employed worker)	81	73	68	67
iii. Standard hourly wage @ 51.79 (Casual laborer)	62	55	52	51
iv. Standard hourly wage @ 37.84 (Food delivery worker @INR6/km)	48	43	41	40

heatmap in their delivery application, provided by the platform. However, with the institution of an hourly wage, platforms will also desire control over the movement of these delivery workers. But presently the worker has the flexibility to reject only a maximum of one or two orders per day. Moreover, the choice of relocation means that workers have to bear the time and fuel cost of the dead mile. Thus, the loss of these rights will hardly matter to the food delivery worker.

The institution of a fixed hourly wage will also require the platform to issue caps on the number of workers it can accommodate during any shift. This removal of surplus workers will reduce externalities like idle parking but may increase the entry barrier for workers looking for part-time employment.

Providing for a higher fixed hourly wage will negatively affect the delivery cost and platforms are unlikely to adopt them soon. A possible compromise would be the adoption of an hourly wage that is almost cost neutral. The results show that adopting a standard hourly wage of INR 37.84 (USD 1.72) is almost cost neutral for the platforms. However, though interventions on behalf of the platform can reduce variability, improvement in earnings would require intervention from a higher public authority.

In view of the growing prevalence of the gig economy, public policymakers at the national level should deliberate the need for a new minimum wage policy. This minimum wage should be applicable to all forms of work-on-demand jobs, like ride-hailing and delivery. However, keeping in mind the special needs of the gig economy, this minimum wage can be on an hourly basis, instead of the standard practice of daily minimum wage. This minimum hourly wage should not only consider the cost of living but also consider the maturity of the gig economy in India. A higher minimum wage, at present, may stifle the growth of this sector and halt the formalization of jobs in the Indian economy.

This study makes two distinct and novel contributions. First, it proposes a simulation framework to accurately map the erratic earnings of gig delivery workers under varying travel pay rates. Second, the study proposes and evaluates an alternative compensation structure that eliminates the variability and uncertainty in gig earnings, without significantly affecting the present cost of food delivery. This framework of mapping the variable earnings and arriving at a cost neutral wage rate can be applied to gig work in other industries and geographies, in pursuit of the goals of decent and fair work.

CRediT authorship contribution statement

Dipyaman Sinha: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, revisions. **Debapratim Pandit:** Conceptualization, Resources, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors have no competing interest to declare.

Data availability

Data will be made available on request.

References

Agarwal, S., Mani, D., & Telang, R. (2023). *The impact of ride-hailing services on congestion: Evidence from Indian cities*. Manufacturing & Service Operations Management. https://doi.org/10.1287/msom.2022.1158

Aguilera, A., Dablanc, L., Krier, C., & Louvet, N. (2022). Platform-based food delivery in Paris before and during the pandemic: Profile, motivations and mobility patterns of couriers. *European Transport Research Review, 14*(1), 1–9. https://doi.org/10.1186/S12544-022-00569-8/TABLES/6

Alkhatib, A., Bernstein, M. S., & Levi, M. (2017). Examining crowd work and gig work through the historical lens of piecework. In *Conference on human factors in computing systems - proceedings, 2017-may* (pp. 4599–4616). https://doi.org/10.1145/3025453.3025974

Allen, J., Piecyk, M., Cherrett, T., Juhari, M. N., McLeod, F., Piotrowska, M., Bates, O., Bektas, T., Cheliotis, K., Friday, A., & Wise, S. (2021). Understanding the transport and CO2 impacts of on-demand meal deliveries: A london case study. *Cities, 108*. https://doi.org/10.1016/j.cities.2020.102973

Aloisi, A. (2015). Commoditized workers the rising of on-demand work, A case study research on a set of online platforms and apps. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2637485

Baindur, D., & Macário, R. M. (2013). Mumbai lunch box delivery system: A transferable benchmark in urban logistics? *Research in Transportation Economics, 38*(1), 110–121.

Chen, J. Y. (2018). Thrown under the bus and outrunning it! The logic of Didi and taxi drivers' labour and activism in the on-demand economy. *New Media & Society, 20*(8), 2691–2711. https://doi.org/10.1177/1461444817729149

Fielbaum, A., Ruiz, F., Boccardo, G., Rubio, D., Tirachini, A., & Rosales-Salas, J. (2023). The job of public transport, ride-hailing and delivery drivers: Conditions during the COVID-19 pandemic and implications for a post-pandemic future. *Travel Behaviour and Society, 31*, 63–77. https://doi.org/10.1016/J.TBS.2022.11.004

Fielbaum, A., & Tirachini, A. (2021). The sharing economy and the job market: The case of ride-hailing drivers in Chile. *Transportation, 48*(5), 2235–2261. https://doi.org/10.1007/S11116-020-10127-7/FIGURES/7

Goel, R., Mohan, D., Guttikunda, S. K., & Tiwari, G. (2016). Assessment of motor vehicle use characteristics in three Indian cities. *Transportation Research Part D: Transport and Environment, 44*, 254–265. https://doi.org/10.1016/j.trd.2015.05.006

Goods, C., Veen, A., & Barratt, T. (2019). Is your gig any good?" Analysing job quality in the Australian platform-based food-delivery sector. *Journal of Industrial Relations*. https://doi.org/10.1177/0022185618817069

Griesbach, K., Reich, A., Elliott-Negri, L., & Milkman, R. (2019). Algorithmic control in platform food delivery work. *Socius: Sociological Research for a Dynamic World, 5*, Article 237802311987004. https://doi.org/10.1177/2378023119870041

Heldt, B., Matteis, T., von Schmidt, A., & Heinrichs, M. (2021). Cool but dirty food?– Estimating the impact of grocery home delivery on transport and CO2 emissions including cooling. *Research in Transportation Economics, 87*, Article 100763.

Henao, A., & Marshall, W. E. (2019). An analysis of the individual economics of ride-hailing drivers. *Transportation Research Part A: Policy and Practice, 130*, 440–451. https://doi.org/10.1016/j.tra.2019.09.056

Jlassi, S., Tamayo, S., & Gaudron, A. (2018). Simulation applied to urban logistics: A state of the art. *City Logist, 3*, 65–87. https://doi.org/10.1002/9781119425472.ch4

Kumar, P., & Chakrabarty, S. (2020). Total cost of ownership analysis of the impact of vehicle usage on the economic viability of electric vehicles in India. *Transportation Research Record, 2674*(11), 563–572. https://doi.org/10.1177/0361198120947089

Ministry of Statistics and Programme Implementation, G. of I. (2021). *Periodic labour force survey (PLFS) annual Report*. https://mospi.gov.in/documents/213904/301563//Annual_Report_PLFS_2019_20m1627036454797.pdf/18afb74a-3980-ab83-0431-1e84321f75af.

Nanisetti, S. (2021). *Poor wages, punishing hours, and lack of labour rights make food delivery a thankless gig*. The Hindu. https://www.thehindu.com/society/poor-wages-punishing-hours-and-lack-of-labour-rights-make-food-delivery-a-thankless-gig/article36012013.ece.

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of uber's drivers. *International Journal of Communication*. https://doi.org/10.2139/ssrn.2686227

Sakai, T., Romano Alho, A., Bhavathrathan, B. K., Chiara, G. D., Gopalakrishnan, R., Jing, P., Hyodo, T., Cheah, L., & Ben-Akiva, M. (2020). SimMobility Freight: An agent based urban freight simulator for evaluating logistics solutions. *Transportation Research Part E Logist. Transp. Rev., 141*, Article 102017. https://doi.org/10.1016/j.tre.2020.102017

Sinha, D., & Pandit, D. (2021). A simulation-based study to determine the negative externalities of hyper-local food delivery. *Transportation Research Part D: Transport and Environment, 100*, Article 103071.

Stanford, J. (2017). The resurgence of gig work: Historical and theoretical perspectives. *Economic and Labour Relations Review, 28*(3), 382–401. https://doi.org/10.1177/1035304617724303

de Stefano, V. (2015). The rise of the "just-in-time workforce": On-demand work, crowd work and labour protection in the "gig-economy.". *SSRN Electronic Journal, 71*. https://doi.org/10.2139/ssrn.2682602

Sun, P. (2019). Your order, their labor: An exploration of algorithms and laboring on food delivery platforms in China. *Chinese Journal of Communication, 12*(3), 308–323. https://doi.org/10.1080/17544750.2019.1583676

Swiggy. (2020). *Terms and conditions*. https://www.swiggy.com/terms-and-conditions.

Tandon, S. (2021). *Zomato looks to counter gig worker criticism*. Hindusthan Times. https://www.hindustantimes.com/business/zomato-looks-to-counter-gig-worker-criticism-101630097721099.html.

Veen, A., Barratt, T., & Goods, C. (2020). Platform-Capital's 'app-etite' for control: A labour process analysis of food-delivery work in Australia. *Work, Employment & Society, 34*(3), 388–406. https://doi.org/10.1177/0950017019836911

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment & Society, 33*(1), 56–75. https://doi.org/10.1177/0950017018785616

Wu, Q., Zhang, H., Li, Z., & Liu, K. (2019). Labor control in the gig economy: Evidence from Uber in China. *Journal of Industrial Relations, 61*(4), 574–596. https://doi.org/10.1177/0022185619854472

Zomato. (2021). *Terms of service*. https://www.zomato.com/policies/terms-of-service/.