Day-to-day Supply Side Evolution of Ride-Sourcing

Arjan de Ruijter *(Corresponding author)*
Delft University of Technology
Faculty of Civil Engineering and Geosciences
A.J.F.deRuijter@tudelft.nl

Oded Cats
Delft University of Technology
Faculty of Civil Engineering and Geosciences
O.Cats@tudelft.nl

Rafał Kucharski
Delft University of Technology
Faculty of Civil Engineering and Geosciences
R.M.Kucharski@tudelft.nl

Hans van Lint
Delft University of Technology
Faculty of Civil Engineering and Geosciences
J.W.C.vanLint@tudelft.nl

February 15, 2020

Abstract

In contrast to more traditional transit services in which the service provider employs drivers and thus has full control over supply, ride-sourcing supply is the result of a decentralized participation decisions by self-employed drivers, that each day decide to work for a ride-sourcing platform or not. Research on the dynamics of supply in ride-sourcing is scarce. One of the few works in this field has modeled the choice to work on a day based on expected income with a binary threshold, in which drivers are dependent on the experiences of others to decide to start working again after opting out. This study introduces an agent-based probabilistic participation choice model to account for the stochasticity to which drivers are exposed in daily ride-sourcing operations. The logic behind this is that when drivers expect earnings to be under a minimally desired reference income, they are aware of the fact that there is also a positive probability of having an income above the reference, and vice versa. With a day-to-day learning model, in which drivers weigh their latest and all previous experiences, we aim to find whether decentralized fleet evolution in ride-sourcing leads to an optimal fleet on a system level, considering the perspective of service providers, transit authorities and the community of drivers. The approach is applied to the road network of Amsterdam, with a maximum available fleet of 200 drivers and artificial demand. We find that decentralization in ride-sourcing supply can lead to oversupply, with high system costs and a low income for drivers. In addition, we conclude that the starting expectation of drivers does not have an affect on emergent supply.

Keywords: Ride-sourcing, decentralization, participation choice, fleet planning, day-to-day learning

1 Introduction

One of the main motivations for drivers to work for ride-sourcing platforms is the flexibility offered by these platforms in terms of their supply of labour (Hall & Krueger, 2018; Ashkrof et al., 2020). Because these drivers are self-employed, they can make daily decisions on whether to work (in labour theory also called 'participation choice') and if so, decide on their working hours (Wang & Yang, 2019). Both types of labour decisions have an impact on the service supply that is, at a specific moment in time, offered by a ride-sourcing platform. Ride-sourcing platforms have instruments to steer supply, such as surge pricing and setting the commission fee charged. Notwithstanding, their control under the gig-economy model is limited compared to a system where the daily vehicle schedule is centrally planned.

Previous research that investigated the effect of daily participation choices on service supply (Banerjee et al., 2015; Djavadian & Chow, 2017; Taylor, 2018; Bai et al., 2019) has assumed that drivers participate in a platform only when their expected earnings for a given day exceed their reservation wage. The latter is defined in the labor choice literature as the minimum daily income for which people are willing to work (Franz, 1980), thus representing the opportunity cost of working. With drivers' participation decisions modelled using a fixed threshold, past studies do not allow for incorporating earning uncertainty in drivers' daily participation choice. Uncertainty can follow from day-to-day stochasticity in ride-hailing operations that result from variations in supply and demand. Cachon et al. (2017) and Gurvich et al. (2019) constitute the first attempts to capture the effect of uncertainty in ride-hailing operations on participation choice. In these studies drivers at the start of each day draw an estimation of the expected supply and demand conditions for that given day from a probability distribution, which is then used to determine their daily expected income. These studies assumed that drivers opt out from the platform when their expected income is lower than a pre-defined threshold.

Day-to-day variability in driver's earnings may lead drivers to choose with a certain probability to work on a given day even if the expected value of the earning distribution falls short of the earning target. To this end, we propose in this study a probabilistic participation choice model to represent supply elasticity under uncertainty. We integrate this day-to-day learning choice model in an agent-based simulation model which represents ride-hailing operations including within-day traffic and demand variability. We investigate the effect of decentralized supply of ride-hailing services by comparing the fleet of active drivers obtained in equilibrium with the optimal, centrally set, fleet size for service providers, transit authorities and ride-sourcing driver unions that represent drivers collectively.

Furthermore, we examine the effect of the starting income expectation on the ride-sourcing supply equilibrium, which has not been done before. Our day-to-day driver participation approach is applied to a relatively large case study in Amsterdam with up to 200 drivers, compared to 20 in previous day-to-day works.

2 Methodology

Agent-based models are typically used to investigate emerging system effects from (potentially complex) strategies of individual agents (Abou-Zeid et al., 2013). Its bottom-up approach is suitable for modelling supply side ride-sourcing adoption, since ride-sourcing systems are decentralized in the sense that self-employed drivers can make individual and independent working choices, which will jointly determine to the fleet size on the system level.

Our agent-based approach consists of a few elements, as shown in Figure 1. First, we model the participation choice of ride-sourcing drivers on a given day based on the income that they expect to earn on this day (explained in more detail in Subsection 2.1). The outcome of the probabilistic participation choice model determines the ride-sourcing supply on this day, which we use as input in a within-day ride-hailing operations model (2.2). This model not only determines the level of service for travellers but also yields individual driving experiences for drivers (2.3). Those in turn will update their expected income based on their experienced income, if they decided to work. The day-to-day learning model (2.4) specifies how drivers weigh their last driving experience compared to the experience accumulated over all previous days.

This section also includes a description of the simulation stopping criterion (2.5), the main key performance indicators (2.6) and the model implementation (2.7).

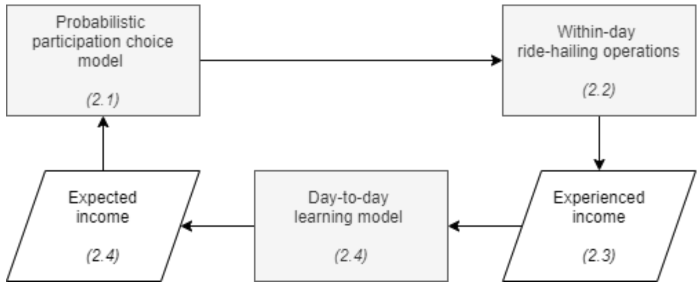

Figure 1: Overview of the methodology with a reference to the subsections that explain the respective parts of the approach in more detail

2.1 Participation choice

Similarly to Banerjee et al. (2015), Taylor (2018) and Bai et al. (2019), we assume that drivers' decision on whether to join the platform on a given day or not depends on their reservation wage. Notwithstanding, drivers experienced income might be higher than their expected income, resulting from stochasticity in within-day ride-hailing operations and the participation choices of other drivers. Consequently, in our model, a driver's participation choice has a probabilistic element. Based on driver's expected income $I_{d,t}^{exp}$ we determine the probability of driving on a given day using the Logit model, in which the utility of driving is tested against the utility of not driving, which is represented by driver's reservation wage I_d^{res}, i.e. opportunity cost. The parameter β_I determines the degree of randomness in the participation choice model, and thus represents the extent to which drivers are willing to try their luck when their expected income is below their reservation wage.

The utility of working (w) and not working (n), respectively, for a driver d on day t, is specified as follows:

$$U_{d,t}^{w} = \beta_I \cdot I_{d,t}^{exp} + \varepsilon \tag{1}$$

$$U_{d,t}^{n} = \beta_I \cdot I_{d}^{res} + \varepsilon \tag{2}$$

The corresponding probability of working ($w_{d,t} = 1$) and not working ($w_{d,t} = 0$) on day t is:

$$P(w_{d,t} = 1) = \frac{\exp(U_{d,t}^{w})}{\exp(U_{d,t}^{w}) + \exp(U_{d,t}^{n})} \tag{3}$$

$$P(w_{d,t} = 0) = 1 - P(w_{d,t} = 1) \tag{4}$$

2.2 Within-day operations

A simple ride-hailing matching algorithm is adopted in which pending requests are assigned to available drivers based on the minimum time required for a driver to reach a request. Formally, assignment takes place whenever there exists both a queue of pending drivers Q_{driver} and a queue of pending requests Q_{req}:

$$\underset{r \in Q_{req}, d \in Q_{driver}}{\arg\min} \; tt_{d,r} \tag{5}$$

In this study, drivers do not re-position, i.e. they remain idle at their last drop-off location until assigned to a new request.

2.3 Experienced income

Self-employed drivers who offer their labour to ride-sourcing platforms do not receive an hourly wage, but rather make earnings based on the requests that they serve. Commonly, they receive the ride fare minus a commission fee π for each satisfied request. Assuming that the fare is comprised of a base fare f_{base} and a per-kilometer fare f_{km}, the payout to driver P_r for serving a single request is:

$$P_r = (f_{base} + f_{km} \cdot s_r) \cdot (1 - \pi) \tag{6}$$

The total payout to driver d on a specific day t is then the sum of the payouts from all requests that are served by this specific driver on this day. Defining $a_{r,d,t}$ as a binary variable indicating whether driver d picks up request r on day t, we can formulate driver's daily payout as follows:

$$P_{d,t} = \sum_{r \in R} P_r \cdot a_{r,d,t} \tag{7}$$

Since freelance drivers have to cover for their own capital and operational costs, we have to subtract these costs from their payout to obtain drivers' daily income. In this study, we limit ourselves to variable costs, i.e. fuel, depreciation and maintenance costs, which we define with parameter o_{km}. The total operational costs $O_{d,t}$ of a driver on a specific day are formulated as follows:

$$O_{d,t} = (\sum_{r \in R} s_r \cdot a_{r,d,t} + DH_{d,t}) \cdot o_{km} \tag{8}$$

in which $DH_{d,t}$ indicates a driver's deadheading distance. The (actual) income of a driver d on a day t is:

$$I^{act}_{d,t} = P_{d,t} - O_{d,t} \tag{9}$$

2.4 Day-to-day learning

As stated earlier, the participation choice for a driver is dependent on the expected income for a given day. We assume that drivers assess what they expect to earn at the start of a day ($I^{exp}_{d,t}$) by integrating their latest experienced income from the previous day $I^{act}_{d,t-1}$ into their accumulated experienced $I^{exp}_{d,t-1}$, except if they were not active on the previous day. The parameter κ represents how much value a driver attaches to the last experienced income as opposed to the expected income at the start of the previous day, which encompasses the driver's experiences from all past days. This corresponds to a reinforced learning Markov decision making process. The expected income of a driver for a specific day is thus defined as follows:

$$I^{exp}_{d,t} = \begin{cases} (1 - (E_{d,t})^{-\kappa}) \cdot I^{exp}_{d,t-1} + (E_{d,t})^{-\kappa} \cdot I^{act}_{d,t-1} & w_{d,t-1} = 1 \\ I^{exp}_{d,t-1} & w_{d,t-1} = 0 \end{cases} \tag{10}$$

in which $E_{d,t}$ is defined as the number of days during which the driver gained a driving experience:

$$E_{d,t} = \sum_{i \in \{1,\ldots,t-1\}} w_{d,i} \tag{11}$$

If κ is equal to 1, a driver weighs all his previous experiences equally. If lower, more value is given to his latest experience. Note that in contrast to the work of Djavadian and Chow (2017), the value drivers attach to their latest experience as opposed to all previous ones is not constant but rather dependent on the number of experiences, which is arguably more likely to mimic learning behaviour in reality.

2.5 Stopping criterion

The fleet size of a ride-sourcing platform on a given day is the outcome of a random process. The simulation is terminated when the degree of learning expected income for all drivers has become fairly limited, which means that the expected fleet size also has converged. More specifically, the simulation is terminated when the following condition is first met:

$$\frac{|I^{exp}_{d,t+1} - I^{exp}_{d,t}|}{I^{exp}_{d,t}} \leq \varphi \quad \forall d \in D \tag{12}$$

and the convergence parameter φ is set to approach 0.

2.6 KPIs

In this study we investigate the daily number of active suppliers over a period of time. We also consider indicators at the agent level. As an indicator for travellers' service quality, we calculate the ride-hailing service rate, which is the percentage of requests satisfied, and the total travel time, which includes the pick-up time and the time that a traveller is waiting to be assigned. Driver profit is also determined, as explained in Subsection 2.3. In addition, we analyze driver surplus, which is defined as the difference between drivers' actual earnings and their reservation wage I_d^{res} (Chen et al., 2019).

2.7 Implementation

We implement the day-to-day driver model in MaaSSim, an agent-based discrete event simulator of mobility-on-demand operations, programmed in Python. It aims to reproduce the transport system dynamics used by two kind of agents: (i) travellers, requesting to travel from their origin to destination at a given time, and (ii) drivers supplying their travel needs by offering them rides. The intermediate agent, the platform, allows demand to be matched with supply and set prices. Both supply and demand are represented microscopically. For supply this pertains to the explicit representation of single vehicles and their movements in time and space, while for demand this pertains to exact trip request time and destinations defined at the graph node level.

3 Experimental design

3.1 Set-up

The total simulation time per day in the experiment is eight hours. Since labour choices in this study are limited to participation choices, we assume that all drivers work the full working day if they choose to opt-in. We run the day-to-day model until convergence is reached, with the convergence parameter φ set to 0.02.

We apply our approach to the road network of Amsterdam, a city currently hosting two ride-hailing companies. We assume that the travel speeds on the road are constant and the same for all roads in the network: 36 km/h. Demand is artificially generated and directed in the direction of the center of the network. Request time of travellers are drawn from a uniform distribution. For the ease of computation, total demand on a day is limited to 1,000 requests.

At the start of each day, drivers that have decided to work are randomly assigned a starting position in the network. The number of driver agents in the model is set to 200, which is relatively high compared to the total demand of 1,000 requests so that we can guarantee that the equilibrium fleet size will not be limited by the upper bound maximum number of available drivers. The reservation wage used in this experiment is €80, which is slightly higher than the minimum daily wage in the Netherlands (Government of the Netherlands, 2020). The operational costs in the experiment are set to 0.25 €/km, equal to the variable cost of the type of car typically used by ride-hailing suppliers (Nibud, 2020; Uber Technologies Inc., 2020c).

Ride fares in the numerical experiment are equal to the standard tariffs charged to travellers by Uber in Amsterdam (Uber Technologies Inc., 2020a), i.e. a base fare of €1.40 per ride and an additional €1.21 per kilometer. Unlike Uber's pricing model, there is no minimum ride tariff. The commission fee that is used in the experiment is set to Uber's 25% (Uber Technologies Inc., 2020b).

3.2 Scenarios & analyses

We investigate the effect of the starting expectation on the equilibrium fleet size. A hypothesis could be that when the starting expectation of drivers is relatively high, too many drivers will start using the platform at the same time, which will lead to a very negative first driving experience with few served requests per driver and a low income. If drivers put much weight on their last experience, drivers may not be tempted to work for the platform again.

In this experiment, we define the starting expectation as a ratio ρ of the reservation wage:

$$I_{d,0}^{exp} = \rho \cdot I_d^{res} \tag{13}$$

Type	Parameter	Value	Unit
Simulation time	τ_{day}	8	h
	φ	0.02	-
Network	v	36	km/h
Demand	n	125	requests/h
	$\tau_{patience}$	5	min
Supply	m_{total}	200	drivers
	I_d^{res}	80	€/day
	o_{km}	0.25	€/km
	β_I	0.1	-
	κ	1.0	-
Platform	f_{base}	1.40	€
	f_{km}	1.21	€/km
	π	0.25	-

Table 1: Parameter values in experiment

In each scenario we test a different value of ρ. A relatively large range of values is covered so that we can find out whether the same equilibrium is reached even when starting expectation differs greatly from the reservation wage. More specifically, in the experiment the following values are tested: $\rho = [0.2, 0.6, 1.0, 1.4, 1.8]$.

Moreover, in our experiments we compare the fleet size emerging from decentralized day-to-day participation decisions to a situation in which the fleet size is set by a central party pursuing its objective. We find the optimal ride-sourcing supply in a decentralized ride-sourcing system, assuming $\rho = 1$ for three different parties: a ride-hailing platform, a transport authority and a ride-sourcing union.

First, we consider a ride-hailing service provider. Its objective is to maximize profit from ride fares, while accounting for hourly wages paid to drivers. Note that we assume a more traditional taxi provider that pays drivers per hour here, rather than a ride-sourcing platform that collects a commission fee per ride, because ride-sourcing platforms don't have (direct) costs from hiring new drivers and will therefore always aim to maximize the number of drivers.

Secondly, we consider a transit authority with the objective to minimize the total societal costs. This includes not only the sum of travel time costs for travellers, but also drivers' labour costs, for the case that the on-demand services are tendered and will then reflect a cost. The labour costs per day are assumed to be equal to driver's reservation wage: €80. The total travel time costs are determined by multiplying total travel time in the system - including penalizing unsatisfied requests with a large travel time of 1 hour - by the average value of time of travellers in the Netherlands: €8/h (Rijkswaterstaat, 2020). Vehicle kilometers are not included in the objective since no vehicle re-positioning takes place.

Finally, we analyze the optimality of the equilibrium fleet in a ride-sourcing system for a hypothetical party that represents the interests of the ride-sourcing driver community, which we will from hereon call the 'driver union'. Basically, its objective is to guarantee a maximum drivers' satisfaction at the system level, which is not necessarily attained when individual drivers make decentralized participation decisions maximizing their own individual utility. More formally, the objective of the driver union is to maximize the total driver surplus, which is specified in Subsection 2.6.

We search for the optimal fleet size for the three different parties by performing a brute-force search, testing their respective objective functions in steps of 10 drivers between 10 and 200 drivers: $m = [10, 20, \ldots, 190, 200]$.

4 Results

4.1 Starting expectation

In Figure 2a, the evolution of the daily expected income is presented. It is clear that for most starting expectations, the expected income quickly converges to approximately the same value: €60. The same applies for the actual experienced income, shown in Figure 2b, however less quickly and with more volatility. The latter is caused by small variations in the daily fleet size, as shown by Figure 2c). Variations in fleet size are observed despite the constant mean expected income at the start of the day due to the stochasticity in ride-sourcing operations. Yet, we can state that the daily fleet of drivers in the day-to-day simulation (averaging over a few consecutive days) converges to one specific value, in this case to approximately 80 drivers, independent of the initial starting expectation. The only exception to this statement is the scenario in which the starting expectation is very low compared to the reservation wage (factor 0.2), in which the equilibrium fleet size is not reached before the end of the simulation. The reason for this is that the daily number of drivers that are willing to test the service is too low.

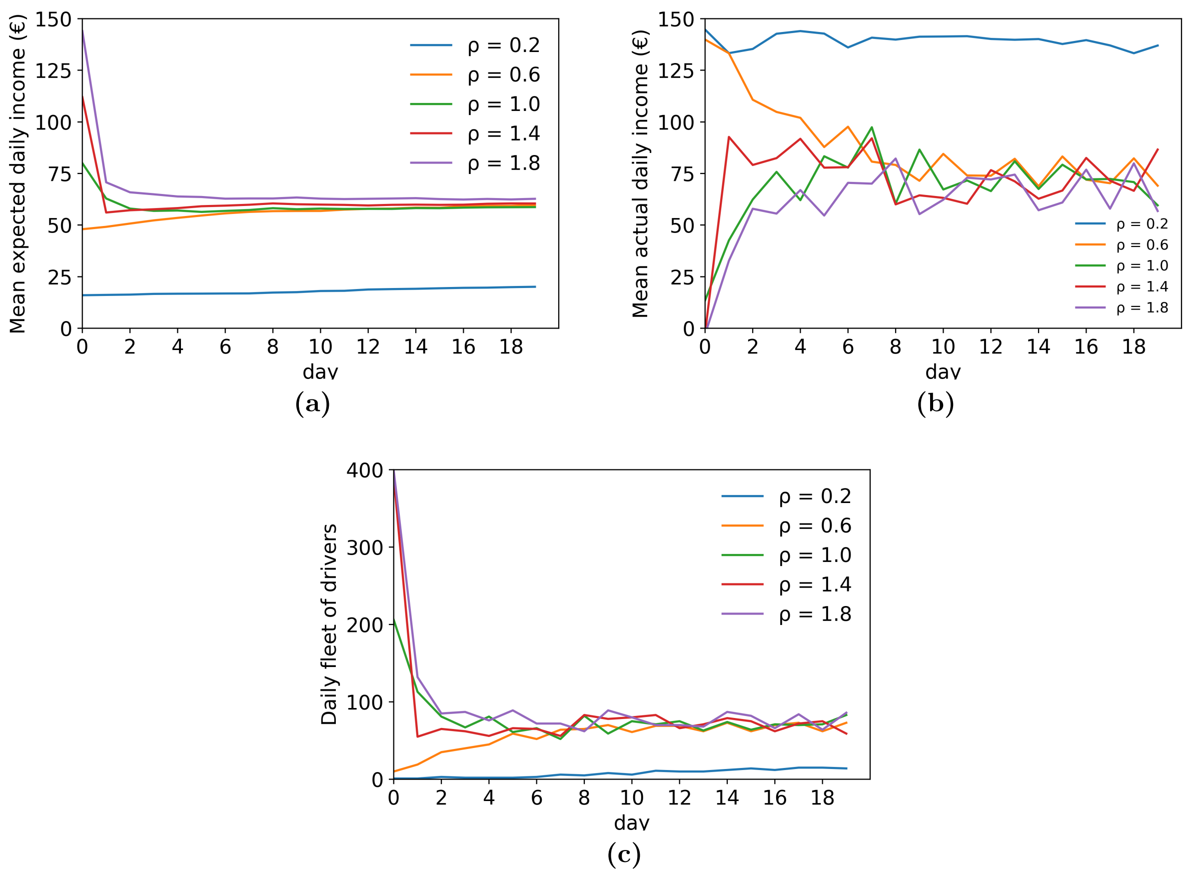

Figure 2: Evolution of (a) mean expected income at the start of a day, (b) mean actual experienced income on a day, and (c) the active fleet of drivers on a day

4.2 Optimality of a decentralized fleet

In this subsection we find the optimal fleet size for ride-hailing service providers, transit authorities and driver unions, and compare the resulting fleet size to the equilibrium fleet size in a decentralized ride-sourcing system. Interestingly, the fleet size that maximizes profit for the service provider, minimizes societal costs and maximizes driver surplus, shown respectively by Figure 3a, b and c, are all equal: 50 drivers. This can possibly be explained by the rejection rate that is shown in Figure 3d. Once the fleet size reaches 50, all requests can be served. When further increased, driver wages and societal labour costs keep increasing, while the marginal decrease in travel time is nullified and thus no additional revenue is generated, consequently leading to a lower profit for the provider and higher societal costs. When more drivers join the system, the total driver surplus goes down because drivers have to share an equal total revenue. Yet, in a decentralized system where self-employed drivers make participation choices, significantly more than 50 drivers join the system. The 'extra' 30 drivers only provide a very limited benefit in that they slightly reduce total travel costs as closer pick-ups are possible when more drivers are available. However, from a provider, societal and even from a driver perspective, these additional drivers are not desired given higher costs and the lack of additional revenue.

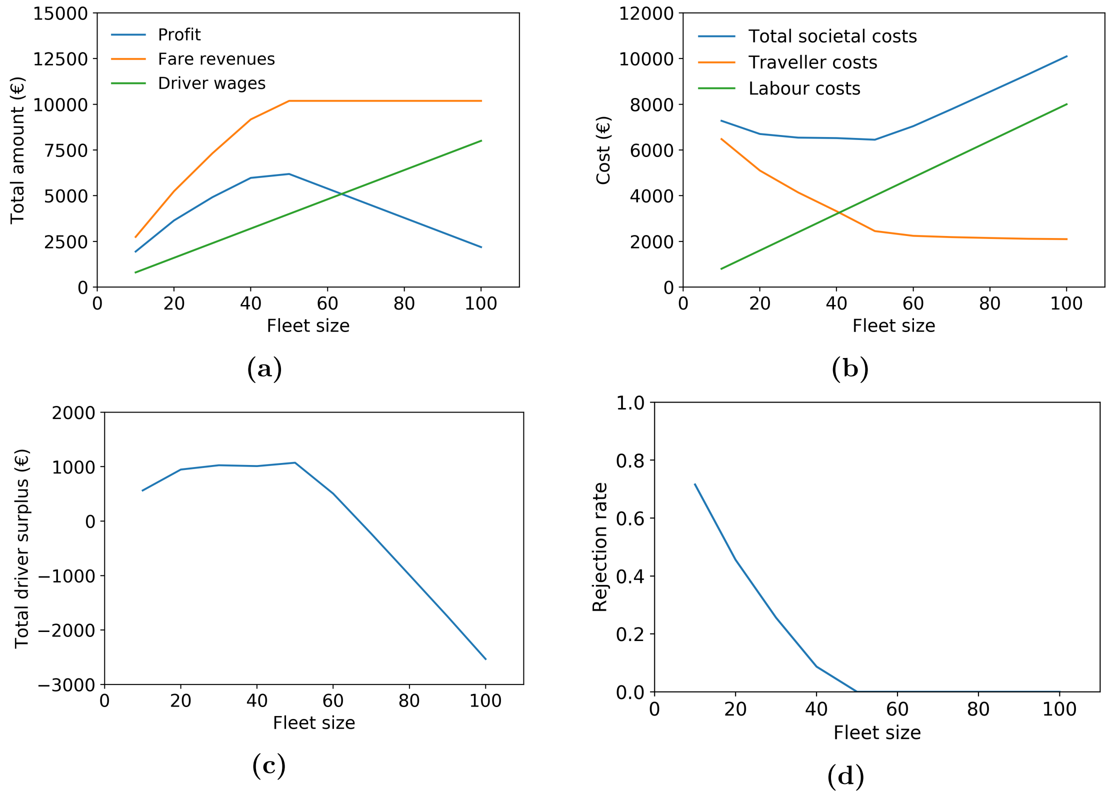

Figure 3: The effect of fleet size on (a) profit for the service provider, (b) societal costs, (c) the total driver surplus, and (d) the proportion of unsatisfied requests.

5 Conclusions & outlook

Our results show that drivers' starting income expectation has a limited effect on the equilibrium fleet when self-employed drivers make individual participation choices in which they learn from previous experiences. The mean expected income quickly converges to the average experienced income. Only in a scenario in which the starting expectation is very low compared to drivers' reservation wage, the equilibrium fleet size (of 80 drivers) was not reached, since drivers are highly unlikely to test the service, which means learning cannot, or only very slowly, take place.

Another conclusion from our work is that the equilibrium fleet size following from day-to-day decentralized participation decisions can differ from the optimal fleet size for service providers, transit authorities and the ride-sourcing drivers' community as a whole. We find that in a decentralized system, when participation choice is probabilistic, each day 'excess' drivers are active that only yield a very limited marginal value to the system as a whole, in terms of slightly lower waiting times for requests, while leading to significantly larger system costs and a lower mean average driver income, which, on most days, is in fact lower than drivers' reservation wage. These results suggest that regulation might be needed to improve system optimality for all actors involved, especially if externalities are also accounted for.

On-going work includes (i) the introduction of heterogeneous driver agents, (ii) the introduction of prospect theory elements in day-to-day participation decisions, where drivers consider not only mean but also day-to-day variations in income, (iii) the formulation of a platform registration model, allowing the number of available drivers to grow over time, and (iv) an analysis of supply elasticity when demand changes at certain instances in time, which can be modelled only with a day-to-day approach like the one adopted in this study.

For future research, we will expand the approach with a day-to-day mode choice model for travellers, in which the probability of choosing ride-sourcing depends on the number of suppliers. This will allow modelling the co-evolution of two-sided ride-sourcing platforms, and ultimately the emergence of critical mass in ride-sourcing provision.

Acknowledgements

This research was supported by the CriticalMaaS project (grant number 804469), which is financed by the European Research Council and the Amsterdam Institute of Advanced Metropolitan Solutions.

References

Abou-Zeid, M., Schmöcker, J.-D., Belgiawan, P. F., & Fujii, S. (2013). Mass effects and mobility decisions. *Transportation Letters*, *5*(3), 115–130.

Ashkrof, P., Correia, G., Cats, O., & van Arem, B. (2020). *Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis.* (Working paper)

Bai, J., So, K. C., Tang, C. S., Chen, X., & Wang, H. (2019). Coordinating supply and demand on an on-demand service platform with impatient customers. *Manufacturing & Service Operations Management*, *21*(3), 556–570.

Banerjee, S., Johari, R., & Riquelme, C. (2015). Pricing in ride-sharing platforms: A queueing-theoretic approach. In *Proceedings of the sixteenth acm conference on economics and computation* (pp. 639–639).

Cachon, G. P., Daniels, K. M., & Lobel, R. (2017). The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management*, *19*(3), 368–384.

Chen, M. K., Rossi, P. E., Chevalier, J. A., & Oehlsen, E. (2019). The value of flexible work: Evidence from uber drivers. *Journal of Political Economy*, *127*(6), 2735–2794.

Djavadian, S., & Chow, J. Y. (2017). An agent-based day-to-day adjustment process for modeling 'mobility as a service'with a two-sided flexible transport market. *Transportation research part B: methodological*, *104*, 36–57.

Franz, W. (1980). *The reservation wage of unemployed persons in the federal republic of germany: theory and empirical tests* (Tech. Rep.). National Bureau of Economic Research.

Government of the Netherlands. (2020). *Amount of the minimum wage.* Retrieved 2020-02-04, from `https://www.government.nl/topics/minimum-wage/amount-of-the-minimum-wage`

Gurvich, I., Lariviere, M., & Moreno, A. (2019). Operations in the on-demand economy: Staffing services with self-scheduling capacity. In *Sharing economy* (pp. 249–278). Springer.

Hall, J. V., & Krueger, A. B. (2018). An analysis of the labor market for uber's driver-partners in the united states. *ILR Review*, *71*(3), 705–732.

Nibud. (2020). *Wat kost een auto?* Retrieved 2020-02-07, from `https://www.nibud.nl/consumenten/wat-kost-een-auto/`

Rijkswaterstaat. (2020). *Kengetallen bereikbaarheid.* Retrieved 2020-02-19, from `https://www.rwseconomie.nl/kengetallen/kengetallen-bereikbaarheid-map`

Taylor, T. A. (2018). On-demand service platforms. *Manufacturing & Service Operations Management*, *20*(4), 704–720.

Uber Technologies Inc. (2020a). *Hoeveel kost een rit via uber?* Retrieved 2020-01-23, from `https://www.uber.com/nl/nl/price-estimate/`

Uber Technologies Inc. (2020b). *Tracking your earnings.* Retrieved 2020-01-23, from `https://www.uber.com/gh/en/drive/basics/tracking-your-earnings/`

Uber Technologies Inc. (2020c). *Vehicle requirements in the netherlands.* Retrieved 2020-02-07, from `https://www.uber.com/nl/en/drive/requirements/vehicle-requirements/`

Wang, H., & Yang, H. (2019). Ridesourcing systems: A framework and review. *Transportation Research Part B: Methodological*, *129*, 122–155.