# Emerging Dynamics in Ridesourcing Platforms

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## SHORT SUMMARY

Ridesourcing businesses operate virtual marketplaces to which free-lancers supply labour and vehicle capacity. A lack of central control over supply may increase the likelihood that socially undesirable levels of supply are attained. Currently, it is largely unknown how co-evolutionary relationships between decentralised supply and demand affect the ridesourcing market equilibrium. To this end, we propose a day-to-day model that accounts for multiple decentralised processes occurring on both sides of the market: (i) initial exposure to information about the platform, (ii) a long-term registration decision, and (iii) daily platform utilisation decisions, subject to day-to-day learning based on within-day matching outcomes. We construct a series of experiments to investigate the effect of different pricing variables and the availability of travellers and workers on ridesourcing system performance. Our results provide indications that regulating the commission fee may be highly beneficial to travellers and drivers, while inducing only a marginal cost for the platform.

**Keywords**: Emerging dynamics, Gig economy, Pricing, Ridesourcing, Two-sided market

## 1. INTRODUCTION

In addition to constituting a new travel alternative, ridesourcing services generate flexible job opportunities (Hall & Krueger, 2018; Chen et al., 2019; Ashkrof et al., 2020). The financial reward for supplied labour is typically based on satisfied demand, rather than the number of hours worked. Service providers such as Uber and DiDi profit from the platform business model in two ways: (i) they are not required to pay for social securities associated with long-term labour contracts, and (ii) they are not tied to labour contracts under changing circumstances, e.g. declining demand as a result of a pandemic.

There are however also downsides associated with the decentralisation of the vehicle fleet. While ridesourcing service providers have pricing instruments to attract drivers to the market, there is no guarantee that desired supply levels are achieved. Especially in a market in which job opportunities are abundant, it may be difficult to convince potential drivers to work for the platform, even when anticipated earnings are high. Network effects in two-sided markets imply that a failure to attract suppliers may lead to a negative feedback loop resulting in the collapse of the system. Contrarily, the market may also end up being oversupplied. This may happen for example when job seekers have few alternative labour opportunities and will drive for the platform even when the expected payout is limited. While an oversupplied market resulting in short pick-up times is beneficial for travellers and the platform, it is an example of the tragedy of the commons for drivers. It implies that utility-maximising labour decisions of individual drivers result in a suboptimal total value derived from labour supplied in the market (de Ruijter et al., 2021). This can be defined as the aggregated difference in what drivers earn and what they minimally require to work.

Clearly, there is uncertainty surrounding the market share that will be captured by ridesourcing services, in relation to the earnings of drivers participating in these markets, and the level of service offered to travellers. Considering that the social optimum in a two-sided market can be different than in a one-sided market (Rochet & Tirole, 2003), we are interested in finding out under which conditions ridesourcing services will yield the utmost societal value, taking into account the perspectives of the platform, travellers and drivers. This requires accounting for the (positive) cross-group network effects and (negative) intra-group competition effects that characterise the two-sided market (Parker et al., 2016).

A common property of scientific works studying ridesourcing systems is that a static, i.e. an equilibrium-based, model is applied to describe the two-sided market. There are however several key dynamic processes in ridesourcing provision that cannot be captured using a static model. First, according to the theory of innovation diffusion (Rogers, 1995), both sides of the market need to be exposed to information about a platform before they can decide to make use of it. When exposure to information is slow on at least one of the sides of the market, it may be difficult to exploit network effects that are key to the scaling of these platforms. Second, a registration decision needs to be made before the platform can be used. This is relevant when registration induces substantial fixed costs, which is the case for drivers in the ridesourcing market. Besides access to a vehicle, they may need to acquire insurance and/or a taxi licence to participate in the market. Third, potential drivers' participation decisions and travellers' mode choice decisions are influenced by previous experiences. Hence, day-to-day variations in earnings and level of service may affect the equilibrium state towards which the market evolves. There are a few studies representing the ridesourcing market using a dynamic model (Djavadian & Chow, 2017; Cachon et al., 2017; Yu et al., 2020; de Ruijter et al., 2021), however, all of those have represented only a single or a few of the previously mentioned dynamic processes.

We address this research gap by investigating the long-term co-evolution of supply and demand in the two-sided ridesourcing market by means of representing sequential individual decisions of drivers and travellers. Specifically, we propose an agent-based day-to-day model for ridesourcing demand and supply, consisting of (i) an information diffusion model, (ii) a platform (de)registration model, (iii) a platform utilisation model and (iv) a learning model. The proposed model integrates a within-day operational model for ride-hailing (Kucharski & Cats, 2020) to account for spatial path-dependent processes in the allocation of drivers to travellers. We then apply the model to a case study representing a realistic urban network. We construct an experiment to find how pricing policies, including ride fares and platform commission, influence the ridesourcing market equilibrium. This allows investigating the societal implications of a profit-maximising pricing strategy, and hence, the need to regulate pricing in the ridesourcing market. Moreover, considering the presence of network effects in ridesourcing provision, we investigate how the ridesourcing market equilibrium is affected by the number of potential suppliers and consumers.

## 2. METHODOLOGY

We develop a model representing the day-to-day behaviour of individual consumers and suppliers in the two-sided ridesourcing market. Consumers in the markets are formalised as travellers with a daily trip request, choosing a travel mode on a daily basis. Suppliers are interpreted as job seekers deciding whether they want to work for the ridesourcing platform based on anticipated earnings. A single platform agent matches ridesourcing requests to available drivers, charging a commission on each transaction. A conceptual framework of the model is presented in Figure 1.

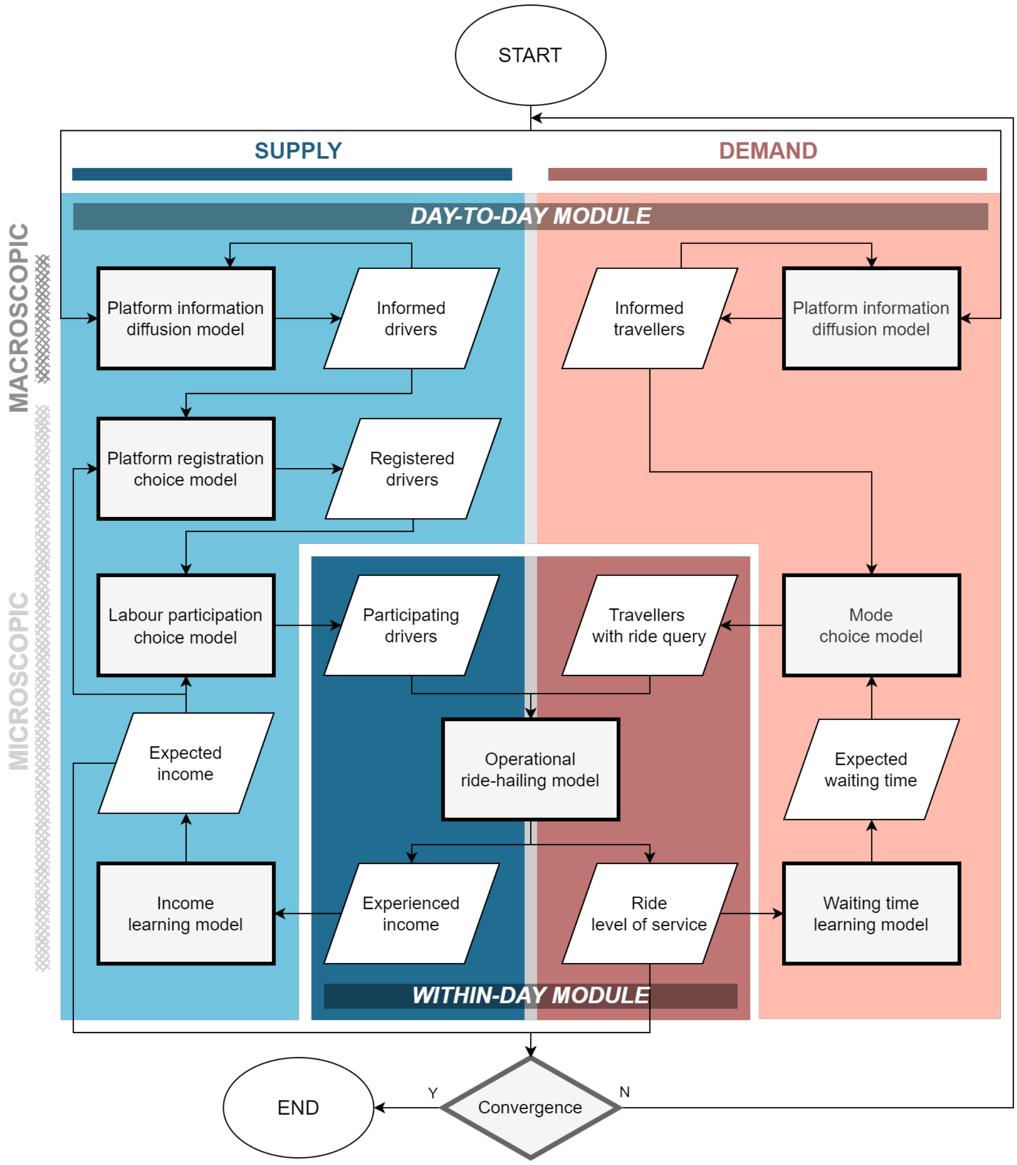


**Figure 1: Conceptual representation of the proposed simulation approach**

### *Information diffusion*

Assume a pool $S = \{s_1, \dots, s_N\}$ of $N$ driver agents, which on a given day $t$ is divided into a group of registered drivers $S_t^{\mathrm{r}}$, a group of informed yet unregistered agents $S_t^{\mathrm{i}}$, and a group of uninformed agents $S_t^{\mathrm{u}}$, so that:

$$S = S_t^{\mathrm{r}} \cup S_t^{\mathrm{i}} \cup S_t^{\mathrm{u}} \tag{1}$$

We also assume a pool of $K$ traveller agents $C = \{c_1, \dots, c_K\}$. Each day, the pool can be subdivided into a group of travellers previously informed about the ridesourcing service $C_t^{\mathrm{u}}$ and those that have not yet been informed $C_t^{\mathrm{u}}$:

$$C = C_t^{\mathrm{i}} \cup C_t^{\mathrm{u}} \tag{2}$$

Information about the existence of the platform is transmitted from informed drivers to uninformed drivers at a rate $\psi_{\text{drivers}}$, and from informed travellers to uninformed travellers at a rate $\psi_{\text{travellers}}$. These variables represent the multiplication of the average daily number of contacts of agents by the probability that information is transmitted in a contact between an informed an uninformed agent. The probability $p_{st}^{\text{inform}}$ that a random uninformed driver agent $s \in S_t^{\text{u}}$ is informed about the service on day $t$ and the probability $p_{ct}^{\text{inform}}$ that a random uninformed traveller agent $c \in C_t^{\text{u}}$ is informed about the service on that day are then defined as:

$$p_{st}^{\text{inform}} = \frac{\psi_{\text{drivers}} \cdot |S_t^{\text{i}} \cup S_t^{\text{r}}|}{N} \tag{3}$$

$$p_{ct}^{\text{inform}} = \frac{\psi_{\text{travellers}} \cdot |C_t^{\text{i}}|}{K} \tag{4}$$

### *Registration*

For travellers, registration does not induce a significant cost. This decision is therefore neglected in the model. Job seekers make an occasional (de)registration decision based on the anticipated earnings, labour opportunity costs and registration costs. We assume that the opportunity costs of a day of work - in labour theory referred to as the reservation wage - are constant over time and equal to $W_s$. Registration costs are included as a penalty $B$ that needs to be deducted from the anticipated daily earnings $AI_{st}$. We formalise the registration decision with a binary random utility model with parameter $\beta_{\text{reg}}$ and error term $\varepsilon_{\text{reg}}$ to account for other variables in the registration decision. Job seekers have a probability $\gamma$ of making a (de)registration decision on a given day $t$. Hence, the utilities and consequent probabilities of registering and deregistering / remaining unregistered on day $t$ are formulated as follows:

$$U_{st}^{\text{regist}} = \beta_{\text{reg}} \cdot (AI_{st} - B) + \varepsilon_{\text{reg}} \tag{5}$$

$$U_{st}^{\text{deregist}} = \beta_{\text{reg}} \cdot W_s + \varepsilon_{\text{reg}} \tag{6}$$

$$p_{st}^{\text{regist}} = \frac{\gamma \cdot \exp(U_{st}^{\text{regist}})}{\exp(U_{st}^{\text{regist}}) + \exp(U_{st}^{\text{unregist}})} \tag{7}$$

$$p_{st}^{\text{deregist}} = 1 - p_{st}^{\text{regist}} \tag{8}$$

### *Platform utilisation*

**Drivers** Registered drivers are faced with a working decision. We assume that driver agents follow the neoclassical theory of labour supply (Chen & Sheldon, 2016; Angrist et al., 2017; Xu et al., 2020), i.e. they are more likely to supply labour when earnings are high. We define the anticipated earnings on day $t$ by driver agent $s \in S_t^r$ as $AI_{st}$. Similar to the registration decision, we apply a random utility model to account for additional variables in the participation decision, such as day-to-day variations in drivers' reservation wage as a result of varying activity schedules. The error term is defined as $\varepsilon_{\text{ptp}}$ and the choice model parameter as $\beta_{\text{ptp}}$. The utility of participating, the utility of the alternative, and the resultant probability of participation on day $t$ for driver $s \in S_t^r$ are now formulated respectively as:

$$U_{st}^{\text{participate}} = \beta_{\text{ptp}} \cdot AI_{st} + \varepsilon_{\text{ptp}} \tag{9}$$

$$U_{st}^{\text{idle}} = \beta_{\text{ptp}} \cdot W_s + \varepsilon_{\text{ptp}} \tag{10}$$

$$p_{st}^{\text{participate}} = \frac{\exp(U_{st}^{\text{participate}})}{\exp(U_{st}^{\text{participate}}) + \exp(U_{st}^{\text{idle}})} \tag{11}$$

**Travellers** Each informed traveller agent $c \in C_t^{\text{i}}$ makes a daily trip. Next to ridesourcing, the agent can choose from a bike, private car and public transport alternative, i.e. the mode choice set available to informed drivers is $M = \{\text{rs}, \text{bike}, \text{car}, \text{pt}\}$. Travellers consider time and cost attributes in choosing their travel mode, as well as alternative-specific preferences. A random utility model with error term $\varepsilon_{\text{mode}}$ is applied to account for other variables in mode choice. Drivers may value in-vehicle time $IVT_{cm}$ differently than (anticipated) waiting time $AWT_{ctm}$ and vehicle access time $AT_{ctm}$, i.e. there are two separate time parameters $\beta_m^{\text{IVT}}$ and $\beta_m^{\text{WT}}$. $TC_{ctm}$ is the travel cost associated with the choice for mode $m$ on day $t$, which has a weight of $\beta_{TC}$ in the utility function. Alternative-specific preferences may vary across travellers in the population, hence we specify $ASC_{cm}$ as traveller $c$'s alternative-specific constant for mode $m$. We assume that mode attributes are valued equally by different travellers. We can now formulate the utility of different modes in $M$ for traveller $c$ on day $t$, and the probability that those modes are chosen, as:

$$U_{ctm}^{\text{mode}} = \beta_m^{\text{IVT}} \cdot IVT_{ctm} + \beta_m^{\text{WT}} \cdot AWT_{ctm} + \beta_m^{\text{AT}} \cdot AT_{ctm} + \beta_{\text{TC}} \cdot TC_{ctm} + ASC_{cm} + \varepsilon_{\text{mode}} \tag{12}$$

$$p_{ctm}^{\text{mode}} = \frac{\exp(U_{ctm}^{\text{mode}})}{\sum_{m \in M} \exp(U_{ctm}^{\text{mode}})} \tag{13}$$

### *Learning*

We describe learning using a Markov process formulation. Consider a driver's last earnings as $EI_{s,t-1}$ and a traveller's last experienced waiting time as $EWT_{c,t-1}$. $\kappa_{\text{driver}}$ and $\kappa_{\text{traveller}}$ respectively represent the weight that drivers and travellers attribute to the last experience as opposed to all previous experiences. $w_{s,t-1}$ and $w_{c,t-1}$ are binary variable indicating whether driver $s$ and traveller $c$ have participated in the ridesourcing market on the previous day $t-1$. No learning takes place when drivers / travellers did not participate on the previous day. The expected earnings of driver $s$ for day $t$ and the anticipated waiting time of traveller $c$ are now formulated as:

$$AI_{st} = (1 - \kappa_{\text{driver}} \cdot w_{s,t-1}) \cdot AI_{s,t-1} + \kappa_{\text{driver}} \cdot w_{s,t-1} \cdot EI_{s,t-1} \tag{14}$$

$$AWT_{ct} = (1 - \kappa_{\text{traveller}} \cdot w_{c,t-1}) \cdot AWT_{c,t-1} + \kappa_{\text{traveller}} \cdot w_{c,t-1} \cdot EWT_{c,t-1} \tag{15}$$

### *Within-day operations*

A within-day model for ride-hailing operations is adopted from the MaaSSim simulator for two-sided mobility platforms (Kucharski & Cats, 2020). It is used to establish earnings of drivers and waiting time and the rejection probability for ridesourcing travellers, including variability across agents, based on the supply and demand on day $t$. The matching algorithm is a myopic one, i.e. drivers are assigned to travellers based on the pick-up distance, immediately when there is at least a single driver and a single request in the queue. We refer to the study of de Ruijter et al. (2021) for more details about the within-day model.

### *Implementation*

The multi-day simulation is terminated once the expected earnings of all drivers and expected waiting time of all travellers has not changed more than $\varphi$ on five consecutive days. To reduce the computational complexity of the simulation, we filter out travellers with a below 5% probability to choose ridesourcing when there is no waiting time, i.e. when $AWT_{ct} = 0$. Due to stochastic components in information diffusion, platform registration and participation, we replicate the experiment for statistical significance.

## 3. EXPERIMENTAL DESIGN

### *Set-up*

We apply our simulation framework to a case study devised to mimic the City of Amsterdam, in terms of the underlying road network, ridesourcing operations and characteristics of alternative modes. Our case study represents roughly a 10% sample of the travel demand in Amsterdam, as well as a 10% sample of an estimation for ridesourcing supply. In absolute terms, this results in $K$ equal to 75,000 and $N$ to 1500.

Driver agents cannot make working hour decisions. If they decide to participate on a given day, they will work the full eight hours in which the service is in operation. Drivers' hourly opportunity costs are drawn from a normal distribution, with mean €25 - based on the average income in the Netherlands - and a standard deviation that corresponds to a Gini-coefficient of 0.35.

Traveller's trips are generated based on a spatial distribution of origins and destinations, with a minimum trip distance of 2 kilometres. The request time of rides is drawn from a uniform distribution. Preferences related to modes are based on a study of travel behaviour in a Dutch urban context (Geržinič et al., 2021).

### *Scenario design*

When investigating the effect of the size of the pool of potential drivers $N$ and the size of the pool of travellers $K$, we assess 49 scenarios, in which the number of travellers ranges between 3,750 and 75,000, and the number of potential drivers between 125 to 2,500.

When evaluating the pricing strategy of the service provider, we test values between 0% and 55% for commission rate $\pi$, in steps of 10%, and values between €0.50 and €3.00 for per-kilometre fare $f_{\text{km}}$, in steps of €0.50.

### *Performance indicators*

We formulate three surplus performance indicators, one for drivers, travellers and platform each.

An individual driver assigns value to the platform when it earns more than its opportunity costs. Hence, the total driver surplus is defined as:

$$DS_t = \sum_{s \in S_t^r} (EI_{s,t} - W_s) \cdot w_{s,t} \tag{16}$$

Travellers experience a welfare gain as a result of having an additional travel alternative. The welfare gain can be measured by computing the difference in Logsums (De Jong et al., 2007) with and without a ridesourcing alternative. The Logsums are formulated as:

$$LS_t^{\text{old}} = \sum_{c \in C_t^i} \ln \left[ \sum_{m \in (M - \{\text{RS}\})} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{17}$$

$$LS_t^{\text{new}} = \sum_{c \in C_t^i} \ln \left[ \sum_{m \in M} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{18}$$

The total traveller surplus is converted to a monetary unit by dividing the difference in Logsums by the marginal utility of income:

$$TS_t = \frac{LS_t^{\text{new}} - LS_t^{\text{old}}}{\beta_{\text{TC}}} \tag{19}$$

Assuming the service provider has no operational costs, the value for the service provider equals the total commission collected.

## 4. RESULTS AND DISCUSSION

### *Market size*

Figure 2 demonstrates that a denser travel demand is beneficial for all stakeholders in the ridesourcing market. When travel demand is dense, participating drivers can serve more travellers and thereby earn more. It appears that competition between ridesourcing users is limited, i.e. an increase in ridesourcing requests actually results in an improved level of service. The platform financially benefits from increased ridesourcing demand.

On the supply side of the market however, it seems that competition prevails over network effects. As shown by Figure 2, a larger number of job seekers may reduce the total driver surplus, which implies that competition leads to significantly lower driver earnings. The interests of travellers and the platform are opposite to the interests of drivers, i.e. they benefit from an increase in the number of job seekers as participation in the market reduces the average pick-up time, which makes the service more attractive to travellers. Only when the size of the labour market is very small, corresponding to a total of 125 job seekers, an increase in the number of job seekers raises the total driver surplus. In that case, the decrease in the average number of requests served by a driver is marginal, and financially compensated for by reduced costs associated with driving to a traveller's pick-up location.

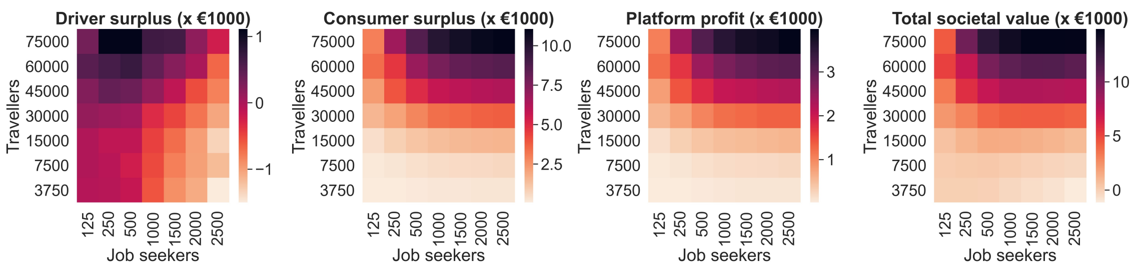


**Figure 2: Value derived from ridesourcing system for travellers, drivers and platform, for different sizes of the market.**

### *Pricing strategy*

Figure 3 shows the driver surplus, consumer surplus, platform profit, and the sum of the previous three for all pricing scenarios. We observe that only few pricing strategies are Pareto efficient, i.e. for most strategies there is an alternative strategy resulting in a higher utility for all stakeholders. In most of the Pareto efficient strategies, the service provider charges travellers €1.00 per kilometre. All strategies with a higher fare encourage too few travellers to use the service, even when the pick-up time is short, which in turn makes the platform less attractive for drivers. Contrarily, a service with a fare of only €0.50 per kilometre is generally not sufficiently attractive for drivers, which harms the number of rides satisfied on the platform. We can thus state that under the specific conditions of this experiment, the interests of drivers, travellers and platform are relatively aligned when it comes to the per-kilometre fare.

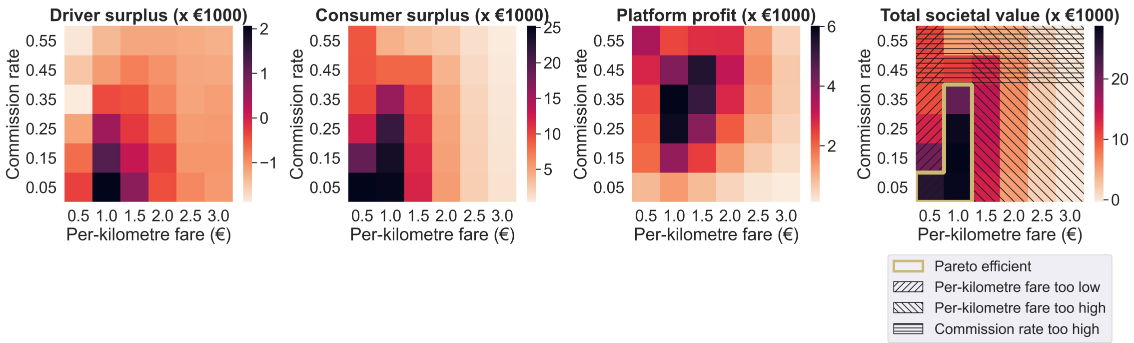


**Figure 3: Value derived from ridesourcing system for travellers, drivers and platform, under different pricing strategies.**

This is not necessarily the case for the commission rate. While travellers and drivers have a shared preference for a minimal commission rate, a profit-maximising platform will opt for a commission of 35% in on our experiment. A lower commission reduces the average pick-up time and therefore attracts more users. However, the increase in demand is not sufficient to cover for the decrease in earnings from rides served when the commission is higher. When the commission exceeds 35%, too few job seekers are willing to supply labour to the platform, resulting in not only vastly declining demand, but also the failure to find drivers for all rides requested on the platform.

The results also indicate that there may exist near profit-maximising pricing strategies - in the experiment (€1.00, 25%) and (€1.50, 45%) - resulting in a significantly higher or lower societal value than the profit-maximising strategy. This suggests that regulation may be effective in protecting the earnings of drivers and level of service experienced by travellers without an adverse impact on platform earnings.

## 5. CONCLUSIONS

In this study, we examine the two-sided ridesourcing market equilibrium considering different market sizes - in terms of the number of travellers and job seekers - and pricing strategies. We find that dense travel demand is a win-win condition for drivers, travellers and platform. We, however, also observe that certain conditions result in the tragedy of the commons for drivers. Especially when there is excessive unemployment in society, the ridesourcing market may be flooded with drivers. This results in strong competition for requests, and ultimately, low earnings. In fact, in several of the examined scenarios the equilibrium driver surplus is negative. Here lies a conflict of interest with travellers and the platform, who benefit from, respectively, shorter pick-up times and induced demand as a result of the presence of idle drivers. To protect the interests of drivers, ridesourcing supply may thus need to be capped.

Our results also indicate that regulation of the commission may be desired from a societal perspective. We find that a profit-maximising service provider may opt for a commission that is far from optimal for travellers and drivers. We also observe that a near-optimal profit may be achieved with a lower commission, resulting in a much improved driver and consumer surplus, and hence, that regulation of the commission may come with limited costs for the service provider. There seems to be less need to regulate ridesourcing fares, as both very low and high fares cause a big drop in the total transaction volume in the market. Such strategies will not be pursued by the service provider.

Many topics related to the ridesourcing market equilibrium remain unexplored. Whereas this study explores a monopolistic ridesourcing market, platform competition may induce new incentives when it comes to pricing, thereby affecting the market equilibrium. The same can be said about a ridesourcing provider offering pooled rides. It may however also be interesting to study the evolution of the system leading up to the market equilibrium, especially considering that market conditions may be dynamic.

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