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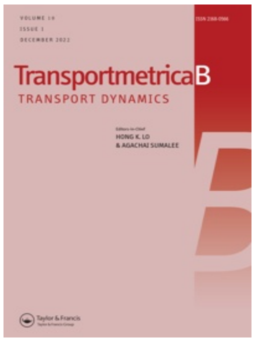

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Day-to-day dynamics in two-sided ridesourcing markets

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ABSTRACT

To understand why ridesourcing markets may be prone to evolve towards potentially socially undesirable equilibrium states, we conceptualize the network effects present in ridesourcing provision. In addition, we propose an agent-based model that allows simulating the effect of market conditions and platform strategies on system performance, accounting for such network effects. This day-to-day model captures sequential decentralized processes characterizing both sides of the two-sided ridesourcing market, i.e. information diffusion, platform registration, platform participation, and learning based on experience. We apply the model on a case representing Amsterdam, the Netherlands. Our simulation results suggest that a profit-maximizing ridesourcing platform may trade-off market transaction volume for higher earnings on successful transactions, a strategy that is harmful to the interests of travellers and drivers, and possibly of (very) limited benefit to the platform. Moreover, we find that ridesourcing operations may be viable even when potential supply and demand in an area are limited.

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Ridesourcing; network effects; critical mass; pricing; evolution

1. Introduction

In many cities around the world, ride-hailing constitutes an alternative to using a private car or line-based public transport. The uptake of services like Uber and DiDi can be attributed to combining the benefits associated with private transport – i.e. door-to-door mobility – as well as with public transport – i.e. being exempted from the burden associated with private vehicle ownership. While ride-hailing may be used in isolation from other modes, it may also be used as an access or egress mode for more affordable and efficient public transport services (Stiglic et al. 2018; Young, Allen, and Farber 2020).

The effect of the introduction of ride-hailing services is not limited to the transportation sector per se. Most ride-hailing companies are exemplars of the gig economy, which means that they are essentially operators of a two-sided marketplace between travellers and self-employed drivers. This practice is referred to as *ridesourcing*. Ridesourcing drivers enjoy freedom in selecting their working hours and days (Ashkrof et al. 2020; Chen, Rossi et al. 2019; Hall and Krueger 2018) while losing access to social securities provided by traditional labour contracts. Their financial reward is typically based on satisfied demand rather than the time spent working.

Outsourcing supply to freelancers may allow service providers to respond more adequately to changing circumstances, e.g. to declining demand as a result of a pandemic. Whereas traditional transportation service providers are restricted by long-term labour contracts, ridesourcing market operators benefit from a day-to-day balancing mechanism for supply and demand that is inherent in two-sided markets. This mechanism consists of two feedback loops (Parker, Van Alstyne, and Paul

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Choudary 2016). First, market participants compete with each other for the service offered by participants on the other side of the market. Hence, market participation is less attractive when there are many participants on this side of the market. At the same time, competition on one side is advantageous for participants on the other side, as it gives them more options to choose from.

While feedback loops between supply and demand may be an advantageous property of two-sided markets, there is no guarantee that the achieved market equilibrium approaches the social optimum. For instance, considering that two-sided markets generate value by exploiting cross-group network effects, they may require a minimum level of supply and demand to be viable (Evans and Schmalensee 2016). As a result, an insufficient user base on either side may result in a downward spiral that leads to the termination of the service. Particular market conditions may inhibit the attraction of travellers and drivers to the market. A platform may for example struggle to attract drivers when job seekers have plenty of alternative labour opportunities in the market, or when social security is highly valued by workers.

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 and Tirole 2003), it is interesting to find out under which conditions ridesourcing services will yield the utmost societal value, taking into account the perspectives of travellers, drivers and the intermediate platform, i.e. the mobility service provider. This requires accounting for network effects – including potential asymmetries – in the two-sided ridesourcing market.

Several scientific works study ridesourcing systems with endogenous supply and demand. These studies have revolved around the optimization of a platform's matching procedure (Ausseil, Pazour, and Ulmer 2022; Chen, Zheng et al. 2020; Wang, Wang et al. 2023; Wang, Wu et al. 2023; Xie, Liu, and Chen 2023) and pricing strategy (Bai et al. 2019; Banerjee, Johari, and Riquelme 2015; Bimpikis, Candogan, and Saban 2019; Chen, Yao et al. 2021; Lei and Ukkusuri 2023; Meskar, Aslani, and Modarres 2023; Nourinejad and Ramezani 2020; Sun et al. 2019; Taylor 2018; Turan, Pedarsani, and Alizadeh 2020; Xu, Saberi, and Liu 2022; Zha, Yin, and Du 2018a; Zha, Yin, and Xu 2018b), (Ke, Yang, and Zheng 2020; Ke et al. 2021; Qian and Ukkusuri 2017; Yu et al. 2020; Zhu et al. 2020), competition between platforms (Sun and Liu 2023; Zha, Yin, and Yang 2016; Zhou et al. 2020), the evaluation of wider transportation effects, and the exploration and evaluation of potential regulations (Li, Szeto, and Zou 2022; Li et al. 2019; Vignon, Yin, and Ke 2023; Yu et al. 2020; Zha, Yin, and Du 2018a; Zha, Yin, and Xu 2018b). A common property of these works is that a static, i.e. an equilibrium-based, model is applied to describe the ridesourcing market. Such an approach neglects however several key day-to-day processes in ridesourcing provision.

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 generate and exploit network effects that are key to the success of these platforms. At the same time, the speed among which awareness spreads may depend on the number of users as well as on the experience of these users.

Second, a registration decision needs to be made before the platform can be used. While for travellers there are no financial costs associated with the registration decision, drivers may need to acquire a vehicle, insurance and/or a taxi licence. Although registration barriers may be lower than for conventional taxis (Hall and Krueger 2018), an increase in vehicle ownership associated with the emergence of ridesourcing (Gong, Greenwood, and Amy Song 2017) demonstrates that not all ridesourcing drivers may have owned a car before signing up with the platform. On the one hand, registration is a barrier which may prevent people from driving for the platform. On the other hand, registration may lead to more frequent participation given that drivers are financially more dependent on the service once they have contracts or debts that need to be paid off.

Third, the participation decisions of travellers and (potential) drivers are path dependent. For instance, interested job seekers rely on past earnings as an indicator for the financial reward for a day of platform work, in the absence of a guaranteed wage. With limited means of communication amongst drivers (Robinson 2017), individual experience is likely the most important source of information available to drivers when making a participation decision. Drivers may experience different earnings from the system average due to luck (randomness) in the matching process, which can be substantial in ridesourcing (Bokányi and Hannák 2020). Other sources of day-to-day fluctuations in driver earnings are systematic and random changes in the number of fellow job seekers deciding to work for the platform as well as in the number of travellers deciding to request a ride on the platform. Similarly, randomness in matching, and systematic and random changes in two-sided participation volumes may lead to biased expectations of waiting time among travellers. This phenomenon could be more predominant if travellers are highly sensitive to waiting time or to being denied service.

In consideration of previously mentioned dynamic processes, we establish two main benefits associated with developing a day-to-day model of the ridesourcing market. First, accounting for dynamic processes related to ridesourcing supply and demand (including their interaction) may yield different equilibria than suggested by models neglecting these processes. For instance, network effects in the matching of travellers and drivers could imply that a critical mass exists in ridesourcing provision, i.e. with too few drivers and users the service is not interesting enough for participants (on both sides of the market) to continue using the service. When platform awareness spreads slowly in the population of potential consumers and suppliers, the critical mass may not be reached as initial market participants experience inadequate service and will opt out from participating in the future before other potential participants are informed. In addition, initial variations in earnings (across drivers) and waiting time (across users) following from randomness in matching may affect participation in the long run, given that 'unlucky' drivers (travellers) – having experienced relatively poor earnings (level of service) compared to the system average over a certain period of time – are less likely to continue working for (requesting rides on) the platform than 'lucky' drivers (travellers), preventing them from learning that the overall earnings (level of service) are better than what they personally experienced. A day-to-day model for the ridesourcing market can be useful in exploring the system effect of attributes associated with these dynamic processes, including the diffusion of platform information, registration and participation.

Second, compared to a single-day model, a multi-day model can provide several additional insights about the ridesourcing market. This includes information about (i) system performance in different stages of evolution, which is also useful in explaining why certain equilibria are reached, (ii) day-to-day variations in system performance following from randomness in participation decisions, (iii) distributional effects following from matching luck and path dependency in participation, and (iv) the range of equilibria towards which a ridesourcing market may evolve in order to determine the importance of random events and path dependency in day-to-day processes in the ridesourcing market.

Third, a multi-day model allows to explore the effect of day-to-day pricing strategies, including penetration pricing, as well as investigating how ridesourcing markets respond to changing circumstances, such as shocks in travel demand.

So far, few studies have represented the day-to-day dynamics of the ridesourcing market, none of which have captured all previously mentioned dynamic processes. Djavadian and Chow (2017), for example, account for learning income and waiting time from experience, but neglect the steps preceding platform usage, i.e. information diffusion and registration. In addition, the scalability of their model is unclear given that it has only been applied to a small case study, consisting of a maximum of 10 drivers and 20 requests. Yu et al. (2020) and Cachon, Daniels, and Lobel (2017) propose a semi-dynamic model with a single registration phase and a subsequent platform utilization phase. Consequently, their models disregard the feedback loop existing from platform utility to new registrations. Their models also neglect disaggregate spatio-temporal relations between supply and demand. de Ruijter et al. (2022) consider information diffusion, registration and daily experience-based utilization decisions for drivers, but not for travellers, with demand for ride-hailing being considered exogenous. Finally, Mo et al. (2023) introduce a stochastic evolutionary dynamic game model to analyse ridesourcing market evolution, focusing on trust dynamics, complaint mechanisms, and rating systems. Their approach overlooks the interplay between market participation (supply and demand) and market performance (service quality and driver income).

We address the stated 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 daily platform utilization model and (iv) a learning model. The proposed model integrates a within-day operational model for ride-hailing (Kucharski and Cats 2022) to account for spatial path-dependent processes in vehicle-passenger assignment.

We apply the model to a case study representing a realistic urban network. The model allows us to investigate the range of equilibria to which the market may evolve as well as day-to-day dynamics and distributional effects in system performance before and after reaching the equilibrium. Considering the presence of network effects in ridesourcing provision, we also investigate how the ridesourcing market equilibrium is affected by the size of the potential market. This may determine whether matches of high-quality are produced, and ultimately, whether the market attains a critical mass. Furthermore, we construct an experiment to find how pricing policies, specifically ride fares and platform commission, influence the ridesourcing market equilibrium. Together, these two pricing instruments determine to what extent travellers and drivers are charged for the service offered by the platform, i.e. for utilizing its marketplace. Because the total transaction volume in a two-sided market is inherently dependent on the allocation of the service fee over consumers and suppliers (Rochet and Tirole 2006), we expect pricing to have significant implications for the market equilibrium. With the experiment, we specifically investigate the implications of a profit-maximizing pricing strategy for travellers and drivers, which provides indications for the need to regulate pricing in the ridesourcing market.

In order to understand emergent equilibria in ridesourcing provision, we need to comprehend which specific network effects govern the interaction between ridesourcing supply and demand, and how they relate to each other. We therefore propose in the following subsection a conceptual framework encompassing the main interactions between potential (double-sided) ridesourcing market participants. From this framework, we derive the key network effects in the market.

2. Conceptual framework

Demand for ridesourcing follows from travellers choosing ridesourcing over other modes of transportation for a given trip. Potential demand thus equals the number of trips in an area in which a ridesourcing provider is active in a given time period. Here, we assume that there is only one ridesourcing provider. Ceteris paribus, greater overall demand for travel will lead to more demand for the ridesourcing service (relation *1* in Figure 1). Suppliers in the market are individuals looking to earn money by driving for the platform. Hence, we can define potential supply in the market as the number of individuals open to a job opportunity. It needs to be considered that a vehicle, insurance and potentially a license is required before an individual can drive for the platform. Hence, job seekers decide whether they would like to gain access to the market by considering the costs associated with registration in addition to the financial reward for supplied labour. Ceteris paribus, more job seekers results in more individuals with access to the market (*2*), which yields more market participation (*3*). It should be noted that registration costs on the demand side are limited, and therefore not included in the analysis.

In reality, neither the probabilities that travellers opt for ridesourcing nor the probabilities that job seekers register and participate are static. There are several attributes influencing the outcome of these decisions, several of which may directly depend on the state of the market. For travellers, this pertains to waiting time, which is perceived negatively in their mode choice decision making process (*4*). Ridesourcing riders experience waiting when the platform is looking for a match (*5*) and when the assigned driver is driving to the request pick-up location (*6*). Considering that travellers with pending ridesourcing requests compete for the same limited pool of resources, i.e. drivers, the average time needed by

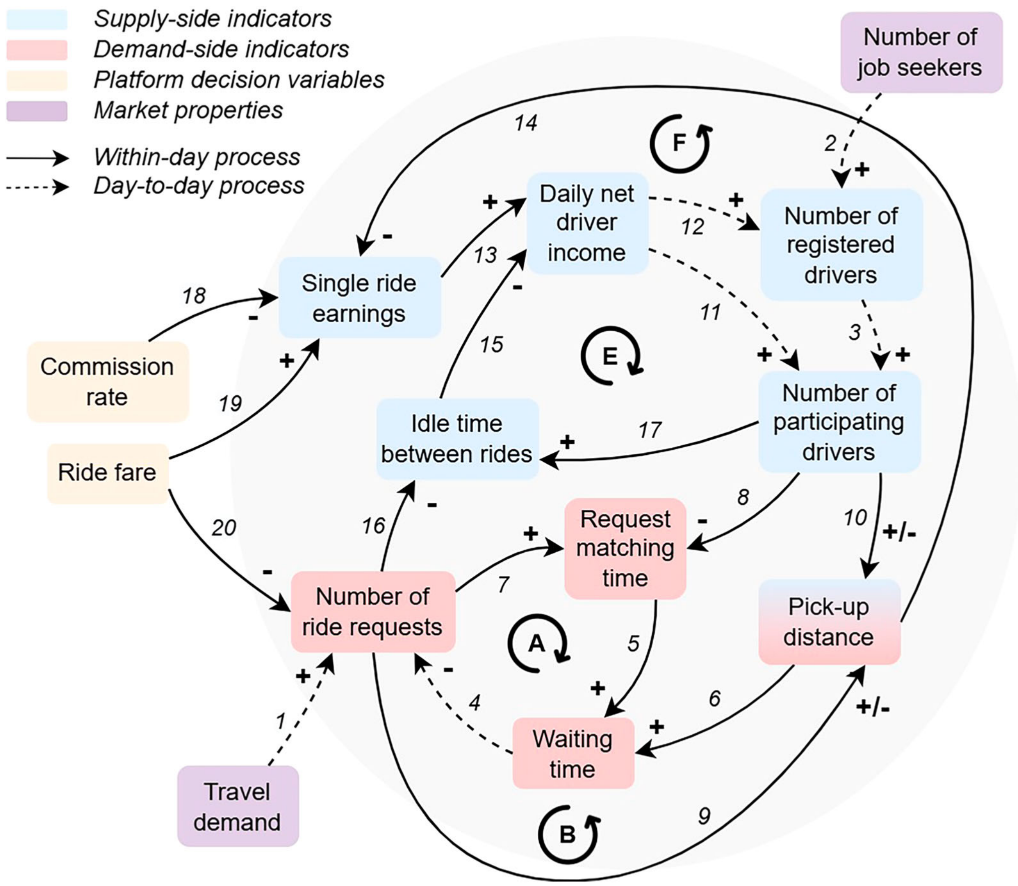

Figure 1. Conceptual representation of the ridesourcing market.

the platform to match a request to a driver increases with the number of ride requests, all other factors held constant (*7*). Conversely, when more drivers participate in the system, the average assignment time of a request will decrease (*8*).

The average request pick-up time (after assignment) is also dependent on the number of ridesourcing requests and the number of drivers in the market. Pick-ups at any given moment in time are short either when there are many idle drivers or when there are many unassigned requests. Imagine for instance a market with a (large) pool of idle drivers but no pending requests. Under these circumstances, a new travel request will increase the average pick-up time of following requests, as a driver is removed from the pool of drivers to serve this request, which leaves subsequent requests with fewer idle drivers. An additional driver on the other hand will decrease the pick-up time of the next request as the platform can assign more drivers to this request. Contrarily, when there are pending requests but no idle drivers, an additional driver will increase the average pick-up distance as the next driver that becomes available (after dropping off a passenger) can be assigned to fewer travellers. In such a market additional travellers on the other hand will yield a lower average pick-up time. Hence, the relation between the number of requests and the average pick-up distance (*9*), and the relation between the number of participating drivers and the average pick-up distance (*10*), can be negative or positive, depending on the ratio of supply to demand.

The financial reward for labour supplied to the ridesourcing market is a key attribute in job seekers' decisions to register with the platform, to participate in the market, and how many hours to work when they choose to participate. In this study we neglect the latter, i.e. we focus on labour supply at the extensive margin. There are two theories for how the amount of labour supplied to a market depends on earnings. The neoclassical theory of labour supply assumes a positive wage elasticity of labour supply. It represents the notion that labour becomes more attractive when earnings are high, which has been supported by several empirical studies on ridesourcing supply (Chen and Sheldon 2016; Sun, Wang, and Wan. 2019; Xu et al. 2020). A second theory considers labour decisions as reference-dependent, implying that suppliers have a target income, which results in a negative wage elasticity of labour supply. Although evidence has been found for a negative wage elasticity in taxi markets (Camerer et al. 1997; Chou 2002), this has been dismissed as an econometric artefact in a later work (Farber 2015). We follow the neoclassical theory of labour supply in conceptualizing the participation decision (*11*). Similarly, we expect a positive relationship between participation reward and registration probability (*12*). Like waiting time for travellers, the participation reward is directly affected by the volume of supply and demand in the market. Participation earnings depend not only on the number of rides that can be served on a given day, but also on the net earnings per ride (*13*). As ridesourcing drivers bear operational costs, deadheading reduces ride earnings (*14*), which means that drivers, like travellers, benefit when pick-up times are short. Idle time is another important variable explaining participation earnings. No income is generated when drivers are idle (*15*). Considering competition for passengers, an increase in the number of ride requests results in less idle time (*16*), and an increase in the number of participating drivers in more idle time (*17*).

Finally, we consider how a platform's pricing strategy affects the co-evolution of supply and demand in the ridesourcing market. A higher commission directly reduces driver's earnings per satisfied request (*18*). Ride fares on the other hand increase driver's earnings per request, all other factors being equal (*19*). As travel costs are perceived negatively in mode choice, higher fares reduce demand for ridesourcing (*20*). In this study, we assume a constant commission rate and fare structure, i.e. there is no surge pricing and there are no day-to-day adjustments of the pricing strategy based on the state of the market, i.e. the platform's pricing strategy is assumed constant. We believe that the key network effects in ridesourcing provision (described in Section 2) can be captured without consideration of such complex pricing dynamics. Hence, commission and ride fares are exogenous variables in the conceptual framework presented in Figure 1.

2.1. Network effects

From the conceptual framework we can identify several network effects in the ridesourcing market. First, we highlight the network effects associated with an increase in ridesourcing demand:

(A) *Increasing request assignment time* (arrows *7-5-4* in Figure 1). Negative, same-side network effect. There is competition amongst travellers with ridesourcing requests, increasing the average time needed by the platform to find a driver that can serve the request.
(B) *Change in pick-up time* (*9-6-4*). Positive or negative, same-side network effect. Depending on market conditions, better or worse matches are found when there are more requests, resulting in a lower or higher average time between being matched to a driver and being picked up.
(C) *Change in deadheading* (*9-14-13-11, 9-14-13-12-3*). Positive or negative, cross-side network effect. Change in pick-up time also affects drivers, decreasing or increasing operational costs associated with serving a request.
(D) *Decreasing driver idle time* (*16-15-11, 16-15-12-3*). Positive, cross-side network effect. More requests means that drivers spend less time waiting to be matched.

There are four corresponding network effects associated with the volume of participating drivers.

(E) *Increasing driver idle time* (*17-15-11, 17-15-12-3*). Negative, same-side network effect. There is competition amongst participating drivers for pick-ups, increasing the time drivers spend waiting for assignment.

(F) *Change in deadheading* (*10-14-13-11, 10-14-13-12-3*). Positive or negative, same-side network effect. Depending on market conditions, better or worse matches are found when there are more participating drivers, resulting in a decrease or increase in operational costs associated with deadheading to the pick-up location.

(G) *Change in pick-up time* (*10-6-4*). Positive or negative, cross-side network effect. Change in pick-up time directly affects travellers that opt for ridesourcing.

(H) *Decreasing request assignment time* (*8-5-4*). Positive, long-term, cross-side. More participating drivers makes it easier for the platform to find a driver that can serve a pending request.

2.2. Key market variables

Based on the previous analysis, three within-day variables govern all network effects in the ridesourcing market: (i) the average time drivers are idle before being assigned to a request, (ii) the average time before a request is matched to a driver, and (iii) the average time a driver needs to pick-up a traveller after assignment. The first two variables are essentially the **matching time** for drivers and travellers, respectively. When assignment happens immediately when there is at least one idle driver and one unassigned request independent of the proximity between requests and drivers, matching time is directly – yet not merely – related to the *ratio between supply and demand*. For instance, when there are many drivers relative to travellers with a ridesourcing request, drivers will spend a relatively large share of their shift in an idle state, while requests will be quickly answered. Conversely, when there are many requests relative to the number of drivers, it will take long before requests are answered, while drivers will be able to serve many requests in a given time frame.

The third mentioned variable that governs network effects in the ridesourcing market – the average request pick-up distance – relates to the **quality of matches** rather than matching speed. As we have previously explained, whether additional requests and participating drivers increase or decrease the average match quality depends on the ratio of idle drivers to pending requests. Next to the supply-demand ratio, match quality depends on the *scale of the (two-sided) market*. The matching algorithm yields more efficient matches when there is a lot of supply and demand.

We have established that the ratio between supply and demand affects both match time (request match time and driver idle time) and match quality (average pick-up distance). In Table 1 we summarize how match time and quality depend on the supply-demand ratio. Below, we provide an argument for why ridesourcing markets may evolve towards equilibria in which supply and demand are not well adjusted, i.e. one in which one side has many unassigned participants. Per definition unbalanced markets yield matches with a limited pick-up distance between traveller and driver, as a platform is guaranteed to have options in its assignment of drivers to requests. A low pick-up time benefits both travellers and drivers. In such an asymmetrical market, one side experiences a very high level of service, benefiting both from limited matching time and limited pick-up time. Participants on the other side are faced with a long average matching time, but this is at least partially compensated for by quick pick-ups. In a well-balanced market, in contrast, the average pick-up time is not necessarily low, although it may be depending on the number of drivers and unassigned requests and the adopted matching algorithm. In such a market, participants on both sides may be faced with matching time depending on whether at that particular moment in time there are more idle drivers or more unassigned requests. Such a market equilibrium could be sub optimal for travellers and drivers alike. We therefore propose that ridesourcing markets could evolve towards asymmetrical equilibria in which one side 'pays' with matching time for the high match quality that benefits both travellers and drivers. Which of the sides would be on the wrong end of this two-sided market phenomenon depends on how sensitive their market participation decisions are to match time and match quality.

Table 1. Matching quality and speed depending on the ratio between supply and demand.

Market state	Driver idle time	Request match time	Pick-up time
Many idle drivers	Long	Short	Short
Many pending requests	Short	Long	Short
Balanced supply and demand	Medium	Medium	Medium

3. Methodology

We develop a model representing the day-to-day and within-day behaviour of potential consumers and suppliers in the two-sided ridesourcing market. Potential consumers in the market are formalized as travellers with a daily (repetitive) trip request, for which they reconsider their mode of transportation everyday. Potential suppliers are represented as job seekers deciding whether they want to register with and 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. An operational representation of the model is presented in Figure 2 and explained below.

In the ensuing, we describe the main modelling elements and pinpoint similarities and differences in the processes on the two sides of the market. First, both sides include a macroscopic model to represent the *diffusion of exposure to information* about the platform, which is a prerequisite for individual agents to participate in the market. This process is captured in modules S1 and D1, for supply and demand respectively. Second, job seekers, unlike travellers, are confronted with an additional *(de)registration* decision, capturing the trade-off between anticipated earnings and long-term investment costs (module S2). Third, both registered drivers and informed travellers are faced with a daily *platform utilization* decision. Drivers decide whether they expect the participation reward to outweigh opportunity costs for a day of work (module S3), whereas travellers decide whether they expect ridesourcing to offer them most utility, compared to a private car, bike and public transport alternative. The expectations are updated by means of a *learning* process. In modules S4 and D3, respectively, we capture how drivers and travellers trade-off previous experiences. These modules also include how unregistered agents learn about income and waiting time. The model is integrated in an agent-based model (module O1) for *within-day ride-hailing operations* (Kucharski and Cats 2022). This module accounts for variations in experience across participating drivers as well as across passengers, which may follow from microscopic spatio-temporal relations between supply and demand. Throughout the multi-day simulation, the platform's matching rules and pricing policies are fixed. The assumption here is that the service operations remain unchanged during the analysis period. The simulation is terminated once income and waiting time hardly evolve anymore from one day to the other.

In the following subsections, we describe each model component in more detail. For a list of used notations, we refer the reader to Appendix 1.

3.1. Information diffusion

Slow diffusion of ridesourcing market awareness among travellers and job seekers can hinder the build-up towards a critical mass and ultimately result in the failure of the service. In general, there is limited empirical evidence for how potential users become aware about innovations, and particularly, how travellers and job seekers become aware about the ridesourcing market. The diffusion of platform awareness likely depends on highly complex, context-specific information processes, including peer-to-peer interactions, mass media communication and platforms' marketing strategies. In consideration of the lack of empirical underpinning for awareness diffusion in the ridesourcing market, particularly when it comes to the effect of global communication sources, we opt for a simple model based on peer-to-peer communication between informed and uninformed agents. The model satisfies two features that we consider likely to be important in the process: (i) platform diffusion is likely slow in early phases of adoption, when few travellers and job seekers are already aware about the

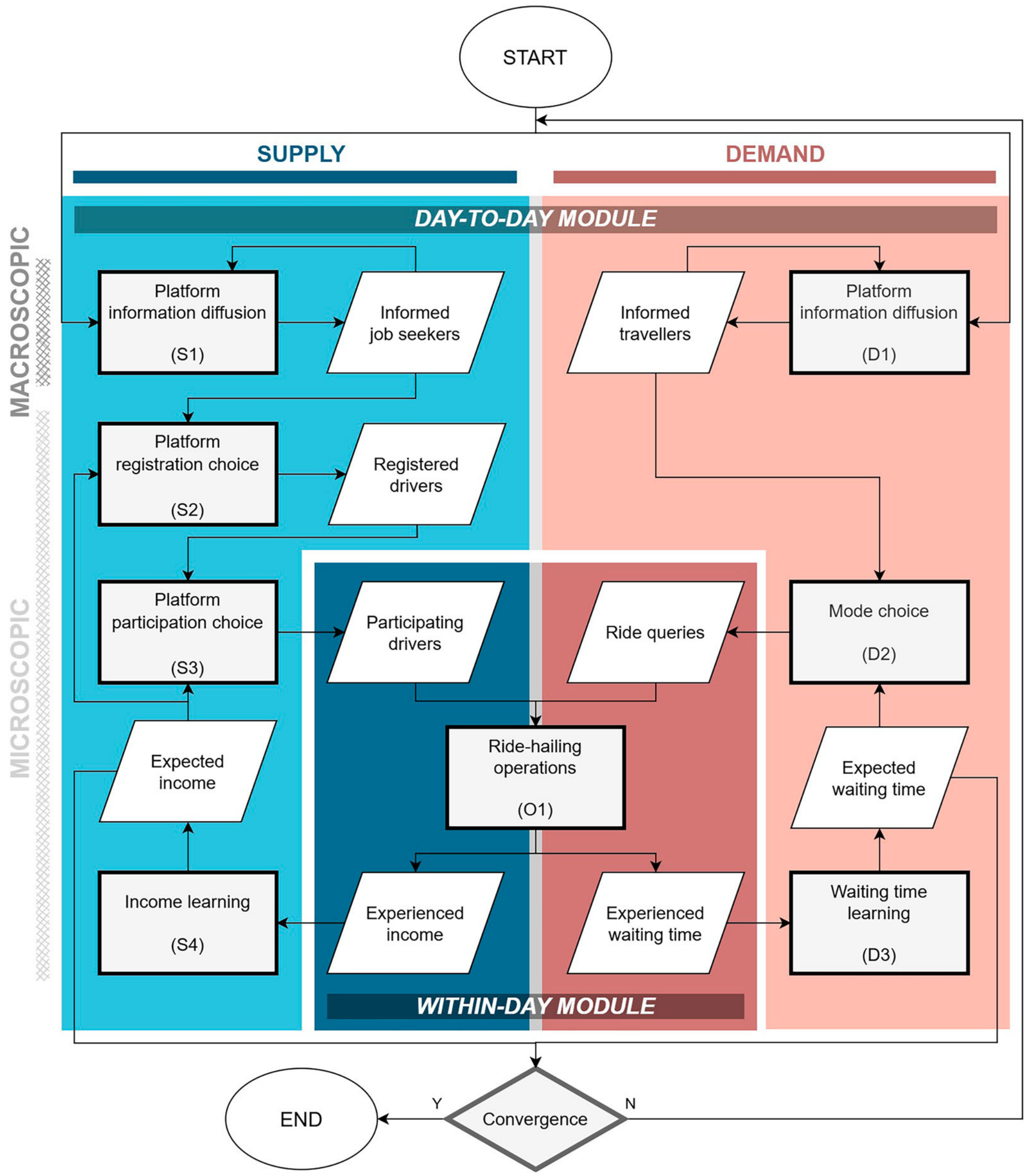

Figure 2. Operational framework for the ridesourcing market.

existence of the platform, before speeding up, and (ii) ultimately all agents are informed about the existence of the ridesourcing market, in line with the wide-spread familiarity with ridesourcing platforms nowadays, for instance in the Netherlands (Geržinič et al. 2023). Specifically, we model the diffusion of platform awareness with an epidemic compartment model with 'infected' (informed) and 'susceptible' (uninformed) agents. As information diffusion in social networks has been found to resemble virus spreading (Zhang et al. 2016), epidemic models are a common method for representing information diffusion processes. Past applications include word-of-mouth communication in marketing (Goldenberg, Libai, and Muller 2001), information diffusion through blogs (Gruhl et al. 2004; Su, Huang, and Zhao 2015) and the diffusion of rumours over social networks (Trpevski, Tang, and Kocarev 2010).

Considering the lack of empirical underpinning for the adopted platform awareness model, we analyse the sensitivity of our results to the awareness diffusion process in Subsection 5.4.

3.1.1. Supply-side (S1)

Assume a pool $S = \{s_1, \ldots, s_N\}$ of N job seekers, which at the start of a given day t are divided into three subpools: those that are uninformed about the platform S_t^{u}, those that are informed yet not registered with the platform S_t^{i}, and those that are registered with the platform S_t^{r}, so that:

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

Information about the existence of the platform is transmitted from informed job seekers to uninformed job seekers at a rate ψ_{sup}, i.e. ψ_{sup} represents 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 job seeker. The probability that a random uninformed job seeker $s \in S_t^{\mathrm{u}}$ is informed about the ridesourcing platform's existence on day t then equals:

$$p_{\mathrm{st}}^{\mathrm{inform}} = \frac{\psi_{\mathrm{sup}} \cdot |S_t^{\mathrm{i}} \cup S_t^{\mathrm{r}}|}{N} \tag{2}$$

3.1.2. Demand-side (D1)

Consider a pool of K travellers $C = \{c_1, \ldots, c_K\}$. At the start of day t, the pool is subdivided into a group of travellers previously informed about the ridesourcing service C_t^{i} and those that have not yet been informed C_t^{u}. In other words:

$$C = C_t^{\mathrm{i}} \cup C_t^{\mathrm{u}} \tag{3}$$

Information diffusion rate ψ_{dem} represents 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 traveller. We define the probability that an uninformed traveller $c \in C_t^{\mathrm{u}}$ receives information on day t as:

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

3.2. Registration

3.2.1. Supply-side (S2)

Before job seekers can participate as drivers in the ridesourcing market, they need to register themselves with a ridesourcing platform. There may be substantial costs associated with being registered, i.e. with the ability to work in the market as opposed to operational costs when driving. For instance, participation in the ridesourcing market requires access to a vehicle, which may be subject to several requirements imposed by the platform and/or regulators. For instance, in many contexts ridesourcing platforms are regulated as taxi services, which implies that registering with a ridesourcing platform may come with acquiring a taxi license, an on-board computer, an appropriate number plate and suitable insurance coverage. As self-employed agents, ridesourcing drivers may be confronted with other business expenses such as social security contracts (pension, disability insurance, etc.) and financial administration costs.

To account for previously described (possibly medium- to long-term) expenses associated with being registered (i.e. able to drive) with a ridesourcing platform, we assume that job seekers are confronted with a daily cost b when they are registered with the ridesourcing service. We assume that there are no investment costs in registering, i.e. ridesourcing drivers opt to lease required assets. Given the unlikelihood of daily reconsideration of one's registration status, job seekers have a probability γ of considering (de)registration at the end of day t.

The registration decision is modelled as a trade-off between registration costs and anticipated ridesourcing earnings. Because the registration horizon is unknown, we consider the registration decision as a trade-off between registration costs b and anticipated earnings for the coming day $\hat{i}_{\mathrm{st}}$, the latter being determined by previous experiences (further explained in Subsection 3.4.1). The underlying assumption is that agents expect no fundamental changes (while allowing for day-to-day variations) in system performance until the next time registration is (re)considered. In establishing anticipated earnings, we need to account for the possibility of part-time driving, i.e. that registered drivers do not necessarily receive a participation reward everyday. The probability $p_{st}^{\mathrm{participate}}$ that a registered driver $s \in S_t^{\mathrm{r}}$ participates on a given day t is defined in Subsection 3.3.1. The anticipated earnings for a day of work in the ridesourcing market equal $\hat{i}_{st}$ and its opportunity costs r_s. In labour theory, the opportunity cost associated with a job is referred to as the reservation wage for the job, representing the minimum earnings for which a job seekers is willing to do a certain job. It integrates alternative income opportunities as well as job-related preferences. We assume that the reservation wage required for driving in the ridesourcing market is independent of time and day. For each job seekers, it is drawn from a normal distribution once with mean μ_{rw}, and standard deviation such that the expected Gini-coefficient of the reservation wage distribution equals g_{rw}.

The utility $U_{st}^{\mathrm{registered}}$ of being registered on a day t follows from having the opportunity to work on that day, i.e. the opportunity to earn more than the labour opportunity costs. We formalize the registration decision with a binary random utility model with parameter β_{reg} and error term $\varepsilon_{\mathrm{reg}}$ to account for other variables in the registration decision. Hence:

$$U_{st}^{\mathrm{registered}} = \beta_{\mathrm{reg}} \cdot p_{st}^{\mathrm{participate}} \cdot (\hat{i}_{st} - r_s) + \varepsilon_{\mathrm{reg}} \tag{5}$$

The utility of not being registered on a day follows from saving money associated with being registered:

$$U_{st}^{\mathrm{unregistered}} = \beta_{\mathrm{reg}} \cdot b + \varepsilon_{\mathrm{reg}} \tag{6}$$

The probability that an informed, yet unregistered job seeker $s \in S_t^{\mathrm{i}}$ registers with the platform at the end of day t is then formulated as follows:

$$p_{s \in S_t^{\mathrm{i}}, t}^{\mathrm{regist}} = \frac{\gamma \cdot \exp\left(U_{s \in S_t^{\mathrm{i}}, t+1}^{\mathrm{registered}}\right)}{\exp\left(U_{s \in S_t^{\mathrm{i}}, t+1}^{\mathrm{registered}}\right) + \exp\left(U_{s \in S_t^{\mathrm{i}}, t+1}^{\mathrm{unregistered}}\right)} \tag{7}$$

Accounting for day-to-day variations in earnings, registered job seekers will remain registered for at least λ days, even when earnings in this period are less than expected. The probability that a job seeker $s \in S_t^{\mathrm{r}}$ that has been registered for n_{st} days on day t cancels its registration equals:

$$p_{s \in S_t^{\mathrm{r}}, t}^{\mathrm{deregist}} = \frac{\eta \cdot \gamma \cdot \exp\left(U_{s \in S_t^{\mathrm{r}}, t+1}^{\mathrm{unregistered}}\right)}{\exp\left(U_{s \in S_t^{\mathrm{r}}, t+1}^{\mathrm{registered}}\right) + \exp\left(U_{s \in S_t^{\mathrm{r}}, t+1}^{\mathrm{unregistered}}\right)} \tag{8}$$

with:

$$\eta = \begin{cases} 1 & n_{\mathrm{st}} \geq \lambda \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

3.2.2. Demand-side

For travellers, registration does not yield significant cost, safe for downloading an app and a few minor administrative tasks. We ignore these and assume all informed travellers have direct access to the platform.

3.3. Platform participation

3.3.1. Supply-side (S3)

Registered job seekers are faced with a daily platform participation decision. We follow the neoclassical theory of labour supply (Chen and Sheldon 2016; Sun, Wang, and Wan. 2019; Xu et al. 2020), i.e. registered job seekers supply labour to a ridesourcing platform when the anticipated income $\hat{i}_{\text{st}}$ exceeds the opportunity costs of working time r_s. 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 job seekers' reservation wage as a result of varying activity schedules. The error term is defined as ε_{ptp} and the choice model parameter as β_{ptp}. The utility of participating, the utility of choosing an alternative activity, and the resultant probability of participating in the ridesourcing market on day t for registered job seeker $s \in S_t^{\text{r}}$ are respectively formulated as:

$$U_{st}^{\text{participate}} = \beta_{\text{ptp}} \cdot \hat{i}_{st} + \varepsilon_{\text{ptp}} \tag{10}$$

$$U_{\text{st}}^{\text{alt}} = \beta_{\text{ptp}} \cdot r_s + \varepsilon_{\text{ptp}} \tag{11}$$

$$p_{\text{st}}^{\text{participate}} = \frac{\exp(U_{\text{st}}^{\text{participate}})}{\exp(U_{\text{st}}^{\text{participate}}) + \exp(U_{\text{st}}^{\text{alt}})} \tag{12}$$

3.3.2. Demand-side (D2)

Each informed traveller agent $c \in C_t^{\text{i}}$ makes a daily trip. Next to ridesourcing, their mode choice set M consists of a bike, private car and public transport alternative. Travellers consider time and cost attributes in choosing their travel mode, as well as alternative-specific preferences. The value of time varies by mode and traveller. In-vehicle time, waiting time, and vehicle access time are perceived differently, i.e. there are separate time parameters β_{cm}^{ivt}, β_{cm}^{wait}, and $\beta_{cm}^{\text{access}}$. The travel cost associated with the choice for mode m is defined as ρ_{cm} (constant from day to day), which has a weight of β_{cost} in the utility function. Alternative-specific preferences may also 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. Each transfer induces a penalty β_{transfer}, which applies to the public transport alternative alone. The attributes – and hence utilities – of all modes except ridesourcing are constant. For ridesourcing, the anticipated waiting time is an endogenous variable, all other variables are constant. A random utility model with error term $\varepsilon_{\text{mode}}$ is applied to account for other variables in mode choice (such as weather conditions). With v_{ctm} as the time in or on a vehicle, a_{ctm} as the access time to reach a pick-up location, $\hat{w}_{ctm}$ as the anticipated waiting time at a pick-up location, and q_{ctm} as the number of transfers, we can formulate the utility of different modes in M for traveller c on day t, and the probability that those modes are chosen, as:

$$\begin{aligned} U_{ctm}^{\text{mode}} = {} & \beta_{cm}^{\text{ivt}} \cdot v_{ctm} + \beta_{cm}^{\text{access}} \cdot a_{ctm} + \beta_{cm}^{\text{wait}} \cdot \hat{w}_{ctm} + \beta_{\text{transfer}} \cdot q_{ctm} \\ & + \beta_{\text{cost}} \cdot \rho_{cm} + ASC_{cm} + \varepsilon_{\text{mode}} \end{aligned} \tag{13}$$

$$p_{ctm}^{\text{mode}} = \frac{\exp(U_{ctm}^{\text{mode}})}{\sum_{m \in M} \exp(U_{ctm}^{\text{mode}})} \tag{14}$$

It should be noted that only the decision whether ridesourcing is chosen is a relevant output of the choice model in the broader context of our day-to-day ridesourcing model.

3.4. Learning

Travellers and job seekers are faced with imperfect information in decisions related to the ridesourcing market. In this subsection, we describe how travellers learn about waiting time and job seekers about income. We assume that those agents that can participate in the market, i.e. informed travellers C_t^{i} and registered job seekers S_t^{r}, will rely solely on own experience. Those agents that cannot participate, i.e. uninformed travellers C_t^{i} and unregistered job seekers $S_t^{\mathrm{u}} \cup S_t^{\mathrm{i}}$, lack personal experience and instead rely on information from other agents.

Considering memory decay (Ebbinghaus 2013), it is unlikely that agents weigh all experiences or received information equally when anticipating utility of platform utilization for the coming day. Lacking empirical evidence for the specification of the learning function in a ridesourcing setting, we rely on findings from learning in route choice behaviour (Bogers, Bierlaire, and Hoogendoorn 2007). Hence, we describe learning using a Markov process formulation, in which $\kappa \in (0,1)$ represents the weight that agents attribute to the most recent piece of information as opposed to previously gathered information.

3.4.1. Supply-side (S4)

We assume that at the end of day t unregistered, informed job seekers S_t^{i} receive a daily private signal about the earnings of participating drivers. There is no systematic error in the communication between unregistered and registered drivers, which means that signal x_{st} received by job seeker $s \in S_t^{\mathrm{i}}$ at the end of day t is drawn from a normal distribution with mean equal to the average experienced income of registered drivers on this day $\overline{i_t}$. We assume that the standard deviation of this distribution equals ω times the standard deviation σ_t^{i} of experienced income on day t. Registered job seekers instead learn from personal experience. No learning takes place when those registered job seekers did not participate on this day.

Consider a group of participating drivers $S_t^{\mathrm{p}} \subseteq S_t^{\mathrm{r}}$ on day t. The ridesourcing income of participating driver $s \in S_t^{\mathrm{p}}$ equals i_{st} on this day. Information y_{st} collected by job seeker s about the income on this day depends on whether they were registered and whether they participated:

$$y_{st} = \begin{cases} x_{st} & s \in S_t^{\mathrm{i}} \\ i_{st} & s \in S_t^{\mathrm{p}} \\ \hat{i}_{st} & \text{otherwise} \end{cases} \tag{15}$$

$$x_{st} \sim \mathcal{N}(\overline{i_t}, \omega \cdot \sigma_t^{\mathrm{i}}) \tag{16}$$

The earnings expected by driver s for day t is now formulated as:

$$\hat{i}_{st} = (1-\kappa) \cdot \hat{i}_{s,t-1} + \kappa \cdot y_{s,t-1} \tag{17}$$

When a job seeker is first informed about ridesourcing income, they fully rely on the first income signal, hence $\hat{i}_{st} = x_{st}$.

3.4.2. Demand-side (D4)

When travellers are first informed about the ridesourcing service, they receive a waiting time signal x_{ct}. There is no systematic error in the communication between agents. Signal x_{ct} is drawn from a log-normal distribution with mean equal to the average experienced waiting time of ridesourcing users on this day $\overline{w_t}$. The resulting standard deviation of the distribution equals ω times the standard deviation σ_t^{w} of the experienced waiting time on day t, i.e. $x_{ct} \sim \mathcal{N}(\overline{w_t}, \omega \cdot \sigma_t^{\mathrm{w}})$. The maximum waiting time that can be communicated to a traveller is one hour. Once informed, travellers rely on personal experience for learning waiting time.

Assume on day t a group of travellers $C_t^{\mathrm{p}} \subseteq C_t^{\mathrm{i}}$ opts for the ridesourcing service. Ridesourcing user $c \in C_t^{\mathrm{p}}$ experiences a waiting time for pick-up w_{ct}. For day t, travellers anticipate waiting time $\hat{w}_{ct}$. With κ as the weight attributed by travellers to the most recent piece of information as opposed to previous information received, the anticipated waiting time for day t is defined as:

$$\hat{w}_{ct} = (1-\kappa) \cdot \hat{w}_{c,t-1} + \kappa \cdot w_{c,t-1} \tag{18}$$

3.5. Within-day operations (O1)

A discrete-event within-day model for ride-hailing operations Kucharski and Cats (2022) allows us to establish the earnings of drivers (following from collected trip fares, platform commission and operating costs associated with serving passengers and deadheading, all captured in the within-day model) and the waiting time of travellers opting for ridesourcing, including variations across agents, based on the supply and demand on a given day. In the adopted within-day model, market participants accept all match offers by the platform. Drivers follow shortest paths to pick-up and drop-off locations, and when unassigned stay idle at their last drop-off location until assigned to a new request. We assume that passengers do not need time to embark and disembark the vehicle. In this subsection, we introduce the matching procedure and how earnings and waiting time are determined. We refer to the study of de Ruijter et al. (2022) for more details.

3.5.1. Matching

At any moment during day t, there is a (virtual and possibly empty) queue of idle drivers $Q_{\text{driver}} \subseteq S_t^{\text{p}}$ waiting to be assigned to a traveller, and a (virtual and possibly empty) queue of travellers with unsatisfied requests on the platform $Q_{\text{req}} \subseteq C_t^{\text{p}}$. We define τ_{sc} as the travel time from the location of an idle driver $s \in Q_{\text{driver}}$ to the pick-up location of an unassigned traveller $c \in Q_{\text{req}}$. The matching function to find the traveller-driver pair (c^*, s^*) with the least intermediate travel time, given that both queues are non-empty, is formulated as follows:

$$(c^*, s^*) = \arg\min_{c \in Q_{\text{req}}, s \in Q_{\text{driver}}} \tau_{sc} \tag{19}$$

3.5.2. Income

Drivers directly collect the fares paid by passengers they serve. Ride fares comprise of a base rate f_{base} and a per-kilometre rate f_{km}. The platform withholds a fixed portion π – the commission rate – on each transaction between a traveller and a driver. Let us denote the direct distance from a the request location of traveller $c \in C_t^{\text{p}}$ to their destination as d_c. The revenue of a driver for serving this traveller is then defined as:

$$R_c = (f_{\text{base}} + f_{\text{km}} \cdot d_c) \cdot (1 - \pi) \tag{20}$$

The total revenue R_{st} of driver $s \in S_t^{\text{p}}$ on a specific day t is the sum of the payouts R_c from requests served by this specific driver on this day. Defining ξ_{sct} as a binary assignment variable indicating whether driver s picks up passenger c on day t, their daily revenue is formulated as follows:

$$R_{st} = \sum_{c \in C_t^{\text{p}}} R_c \cdot \xi_{sct} \tag{21}$$

The net experienced income of a participating job seeker i_{st} can now be formulated as:

$$i_{st} = R_{st} - O_{st} \tag{22}$$

where, in consideration of deadheading distance D_{st} (distance for picking up assigned travellers) and per-kilometre operational costs δ, the total operational costs of driver s on day t are:

$$O_{st} = \left(\sum_{c \in C_t^{\text{p}}} d_c \cdot \xi_{sct} + D_{st} \right) \cdot \delta \tag{23}$$

3.5.3. Waiting time

The experienced waiting time w_{ct} of a traveller with a ridesourcing request $c \in C_t^{\text{p}}$ comprises of the time between requesting a ride and getting assigned, i.e. the matching time, and the time it takes for the driver assigned to the traveller to reach the pick-up location, i.e. the pick-up time. We lack empirical evidence for how travellers perceive denied service. In this paper, we simply assume a (constant) high cost P in case waiting time exceeds a patience threshold θ.

3.6. Implementation

Our day-to-day ridesourcing model is implemented in Python and integrated into MaaSSim, a simulation environment for two-sided mobility platforms. The public transport alternative available to each traveller is determined based on a query in OpenTripPlanner (OTP). Only the public transport itinerary with the earliest arrival time is considered by a traveller.

3.6.1. Convergence

The multi-day simulation can be terminated once the system reaches a steady state. We establish two criteria for convergence, corresponding to the two sides of the market. First, for five days in a row, the average expected earnings I_t of registered job seekers should not change more than a convergence parameter φ. This indicates (i) that ridesourcing earnings are fairly constant and (ii) that job seekers have learned about it. The first criterion is formalized as:

$$\frac{|I_{t-z} - I_{t-z-1}|}{I_{t-z-1}} \leq \varphi \quad \forall z \in \{0, \ldots, 4\} \tag{24}$$

with:

$$I_t = \frac{1}{|S^{\mathrm{r}}_t|} \cdot \sum_{s \in S^{\mathrm{r}}_t} \hat{i}_{st} \tag{25}$$

Second, the average expected waiting time W_t of informed travellers should not change more than the previously defined convergence parameter φ, again for five days in a row:

$$\frac{|W_{t-z} - W_{t-z-1}|}{W_{t-z-1}} \leq \varphi \quad \forall z \in \{0, \ldots, 4\} \tag{26}$$

with:

$$W_t = \frac{1}{|C^{\mathrm{i}}_t|} \cdot \sum_{C \in C^{\mathrm{i}}_t} \hat{w}_{ct} \tag{27}$$

3.6.2. Replications

The simulation model includes stochastic components in information diffusion, platform registration and participation. We determine the number of required replications $Z(n^{\mathrm{init}})$ based on a number of initial replications m, using a formula commonly used in stochastic traffic simulations (Ahmed 1999; Burghout 2004). We apply their formula to both sides of the market, i.e. both equilibrium waiting time and income need to be statistically significant.

Let us denote the average anticipated ridesourcing income by registered job seekers in equilibrium in a single iteration as I^*, and the the corresponding average anticipated waiting time of informed travellers as W^*. Then $\overline{I^*}(n^{\mathrm{init}})$ and $\overline{W^*}(n^{\mathrm{init}})$, and $s_{\mathrm{I}}(n^{\mathrm{init}})$ and $s_{\mathrm{W}}(n^{\mathrm{init}})$ are, respectively, the estimated mean and standard deviation of I^* and W^* from a sample of n^{init} runs. When we define the allowable percentage error of estimate $\overline{I^*}(n^{\mathrm{init}})$ and $\overline{W^*}(n^{\mathrm{init}})$ of the actual mean as $\varepsilon_{\mathrm{repl}}$, and the level of significance as α, the minimum number of replications is:

$$Z(n^{\mathrm{init}}) = \max\left(\left(\frac{s_{\mathrm{I}}(n^{\mathrm{init}}) \cdot t_{n^{\mathrm{init}}-1,\frac{1-\alpha}{2}}}{\overline{I^*}(m) \cdot \varepsilon_{\mathrm{repl}}}\right)^2, \left(\frac{s_{\mathrm{W}}(n^{\mathrm{init}}) \cdot t_{m-1,\frac{1-\alpha}{2}}}{\overline{W^*}(n^{\mathrm{init}}) \cdot \varepsilon_{\mathrm{repl}}}\right)^2\right) \tag{28}$$

3.6.3. Traveller subpopulation

Considering that mode-specific constants are heterogeneous in the pool of travellers, some travellers are more likely to choose ridesourcing for their trip than others. To reduce the computational complexity of the simulation, we filter travellers based on their probability to choose ridesourcing when there is no waiting time, i.e. when $\hat{w}_{\mathrm{ct}} = 0$. If in such an 'ideal' scenario traveller agents have a probability below parameter χ, they will be removed from the original pool of travellers.

4. Experimental design

4.1. Set-up

We apply our simulation framework to a case study devised based on the City of Amsterdam, in terms of the potential ridesourcing market, the underlying road network, ridesourcing operations and characteristics of alternative modes.

Our case study represents roughly a 10% sample of travel demand in Amsterdam over a period of eight hours, as well as an estimated 10% sample of all job seekers. A sample size of 10% is comparable to the samples taken in other works studying transportation problems with agent-based models (Bischoff and Maciejewski 2016; Kaddoura 2015). Tests with larger sample sizes confirm that a 10% sample is sufficiently indicative for system performance under the full population of travellers and job seekers. In absolute terms, the sampling yields K equal to 75,000 travellers and N to 2500 job seekers. Travellers with a below 5% probability to opt for ridesourcing even in the event of an immediate pick-up are assumed to never consider ridesourcing for their trip, i.e. χ is set to 0.05.

Travel demand is drawn once from a database of trips generated based on the activity-based model of Albatross for the Netherlands (Arentze and Timmermans 2000), in which only trips longer than 2 km are considered. The average value of in-vehicle time in the population of travellers is set to €10 per hour, based on the most recent estimation of the value of in-vehicle time for car commuters in the Netherlands (Kouwenhoven et al. 2014). The standard deviation of the value of in-vehicle time distribution is set so that the resulting Gini-index for inequality in value-of-time equals 0.35, similar to the observed inequality in gross income in the Netherlands (Arts et al. 2019). Travellers perceive walking time to a stop/pick-up location 2 times more negatively than in-vehicle time, i.e. $\beta^{\text{access}}_{\text{cm}} = 2\beta^{\text{ivt}}_{\text{cm}}$, and time waiting for a vehicle 2.5 times more negatively, i.e. $\beta^{\text{wait}}_{\text{cm}} = 2.5\beta^{\text{ivt}}_{\text{cm}}$, based on Wardman (2004). Biking time is perceived twice as negative as in-vehicle time to represent the strenuous and 'unproductive' nature of cycling (Börjesson and Eliasson 2012). The penalty for transfers in public transport is set to 5 min of in-vehicle time (Yap, Cats, and van Arem. 2020). Mode-specific constants are based on preferences observed in urban areas in the Netherlands (Geržinič et al. 2023). Travellers with a ridesourcing request are assumed to be willing to wait up to 10 min for a match ($\theta = 10$ min) and to perceive a rejected request as equivalent to 30 min of waiting time ($P = 30$ min).

Similar to travellers' perception of in-vehicle time, job seekers' reservation wage is drawn from a log-normal distribution with a standard deviation that results in a Gini-index g_{rw} of 0.35. The mean reservation wage μ_{rw} equals €25 per hour, based on the average gross hourly income in the Netherlands (voor de Statistiek 2022). Informed job seekers are expected to (re)consider registration every 10 days, i.e. γ is set to 0.1. Job seekers that participate start their working day at a random location in the network.

We assume a road network with a (static) universal link travel speed of 36 km/h for cars and 14.4 km/h for bikes. The public transport alternative for each traveller is based on service operations on November 1st, 2021, both in terms of its timetable and fares (i.e. €0.99 base fare and an additional €0.174 per km). Private cars are assigned with a parking time of 10 min, as well as parking costs of €15 in the city centre and €7.5 elsewhere. The total per-kilometre operating costs of cars are set to €0.5, based on an estimation of the operating costs of a medium-sized car in the Netherlands (Nibud 2022). We assume that ridesourcing drivers have lower operating costs, i.e. €0.25 per kilometre, representing more intensive usage of their cars compared to other car owners. Ridesourcing pricing is based on Uber's pricing strategy in Amsterdam, surge pricing is not considered in this study. It implies that commission π, base fare f_{base} and per-kilometre fare f_{km} are set to 25%, €1.5 and €1.5/km in the reference scenario. The daily costs b associated with being registered with the ridesourcing platform (for job seekers) are set to €20.

At the start of the simulation, registered job seekers expect earnings equal to their reservation wage, while (informed) travellers expect no waiting time upon initialization. 10% of all agents (job seekers and travellers) are initially informed. Of the originally informed job seekers, 20% is immediately

Table 2. Specification of other model parameters, with references to sensitivity analyses.

Indicator	Parameter	Value	Unit	Sensitivity test
Information transmission speed	$\psi_{\text{sup}}, \psi_{\text{dem}}$	0.1	–	Section 5.4.1
Learning weight	κ	0.2[a]	–	Appendix A.5
Income sensitivity in registration	β_{reg}	0.2	util/€	Appendix A.6
Income sensitivity in participation	β_{ptp}	0.1	util/€	Appendix A.6
Minimum registration time	λ	5	days	Appendix A.7
Rel. variation in wait time and inc. signals[a]	ω	0.5	–	Appendix A.9
Convergence condition	φ	0.01	–	–
Allowable percentage error of estimate of mean	$\varepsilon_{\text{repl}}$	0.1	–	–
Level of significance	α	0.05	–	–

[a]Selected after learning of travel time in route choice (Bogers, Bierlaire, and Hoogendoorn 2007).

registered with the ridesourcing platform. The model's sensitivity to these starting conditions is evaluated in Appendix 2.

The specification of the remaining model parameters is provided in Table 2.

4.2. Scenario design

To investigate how the size of the potential ridesourcing market affects system performance, we sample from the pool of travellers and job seekers specified in Section 4.1. We assume a fixed ratio of 50 travellers per job seeker, i.e. the (relative) sample size is similar for supply and demand. We test the following relative sample sizes: {0.05, 0.1, 0.2, 0.4, 0.6, 0.8, 1.0}, corresponding to potential demand ranging between 3750 and 75,000 travellers, and potential supply ranging between 125 and 2500 job seekers.

We also evaluate the platform's pricing strategy, comprising of a (time-independent) per-kilometre fare f_{km} and commission rate π. We test per-kilometre fares ranging between 0.5 and 2.5 €/km, in steps of €0.5/km, in combination with commission rates ranging from 5% to 55%, in steps of 5%.

4.3. Performance indicators

We formulate four surplus-related performance indicators, one for drivers, travellers and platform each, and one the sum of the previous three.

First, registered job seekers obtain a positive value from the ridesourcing platform when participation earnings in the long run outweigh experienced labour opportunity costs and registration costs. Hence, we formulate the total driver surplus on day t as the summed difference between experienced earnings i_{st} and reservation wage r_s for all participating drivers, minus the total costs associated with registration:

$$V_t^{\text{drivers}} = \sum_{s\in S_t^{\text{p}}} (i_{st} - r_s) - |S_t^{\text{r}}| \cdot b \tag{29}$$

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. In this study, we only consider the welfare gain of those opting for ridesourcing (i.e. $C_t^{\text{p}} \subseteq C_t^{\text{i}}$). The Logsums are formulated as:

$$LS_t^{\text{old}} = \sum_{c\in C_t^{\text{p}}} \ln \left[\sum_{m\in(M-\{\text{RS}\})} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{30}$$

$$LS_t^{\text{new}} = \sum_{c\in C_t^{\text{p}}} \ln \left[\sum_{m\in M} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{31}$$

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

$$V_t^{\text{travellers}} = \frac{LS_t^{\text{new}} - LS_t^{\text{old}}}{\beta_{\text{cost}}} \tag{32}$$

Assuming that the service provider has no operational costs, the value for the service provider equals the total commission collected off satisfied ridesourcing requests:

$$V_t^{\text{platform}} = \pi \cdot \sum_{c \in C_t^{\text{p}}} \left((f_{\text{base}} + f_{\text{km}} \cdot d_c) \cdot \sum_{s \in S_t^{\text{p}}} \xi_{sct} \right) \tag{33}$$

In this study, we do not analyse the contribution of ridesourcing to total vehicle mileage, i.e. we assume that the contribution is negligible. We define the value derived from the ridesourcing market by society on day *t* as the (unweighted) sum of the driver surplus, traveller surplus and platform profit:

$$V_t^{\text{society}} = V_t^{\text{drivers}} + V_t^{\text{travellers}} + V_t^{\text{platform}} \tag{34}$$

5. Results

Here, we present the results of our experiments. In Section 5.1, we specifically explore the evolution of the ridesourcing market, the effect of stochasticity in starting conditions and agent decisions, and their effect on within-day outcomes, and distributional effects in the reference scenario. In Sections 5.2 and 5.3, we demonstrate how the ridesourcing market equilibrium is affected by the size of the potential market and by platform pricing strategies, respectively. In Section 5.4, we evaluate the effect of two attributes related to dynamic processes in the market: the two-sided information diffusion rate and (supply-side) costs associated with registration.

5.1. Dynamics, randomness and heterogeneity

In Figure 3, we present the evolution of the main system performance indicators – the average of different instances of the experiment – in the reference scenario.

The majority of travellers and job seekers is initially unaware about ridesourcing platform existence. Those that are informed are optimistic about earnings and waiting time, i.e. informed travellers expect no waiting time and informed drivers expect earnings equal to their reservation wage. We then observe four phases in the evolution of the market:

(1) **Double-sided market correction after unrealistic expectations** *(days 0–5)*. With informed travellers and job seekers initially optimistic about the service, a relatively large share of them tries the platform. On the first day for instance, around 50% of registered job seekers and nearly 3% of informed travellers – which appears to be the upper bound for the ridesourcing market share – participate in the market (Figure 3A). Job seekers quickly learn that anticipated earnings cannot not be realized (Figure 3B), while travellers observe that there is waiting associated with choosing ridesourcing for their trip (Figure 3E). Therefore, registered job seekers become increasingly less likely to participate and informed travellers increasingly less likely to choose ridesourcing in this early phase. Since the decrease in participation probability is larger for job seekers than for travellers, the number of satisfied requests per driver increases in this phase. This results in increased daily earnings (Figure 3B) even though the earnings per satisfied request decreases (Figure 3C) due to higher deadheading costs. At the same time, travellers' matching time increases (Figure 3E). Figure 3B demonstrates that the average reservation wage of registered job seekers drops, i.e. job seekers with an above average reservation wage are relatively likely to deregister and relatively unlikely to register with the platform.

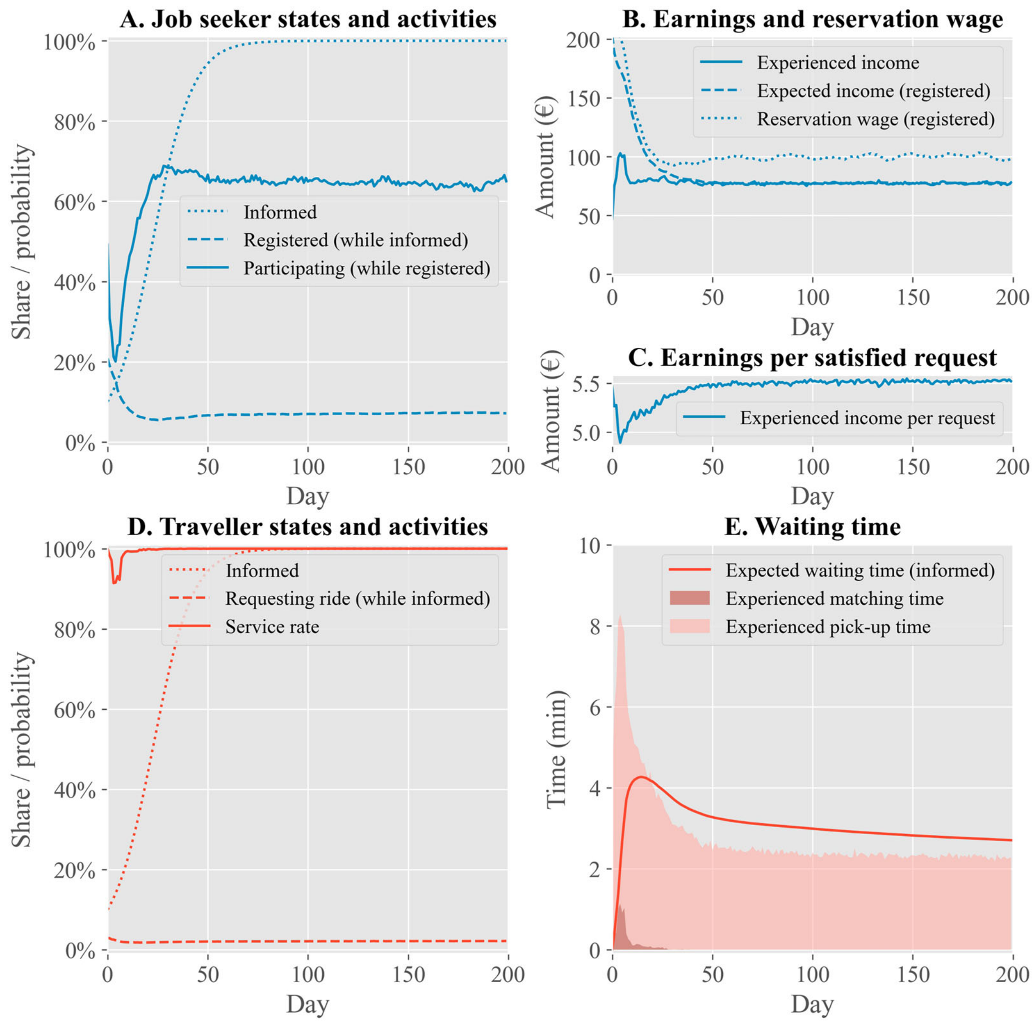

Figure 3. Evolution of the ridesourcing market in the reference scenario. (A) Job seeker states and activities. (B) Earnings and reservation wage. (C) Earnings per satisfied request. (D) Travellar states and activities. (E) Waiting time.

(2) **Bounce-back in supply** *(days 5–25)*. The average reservation wage of registered job seekers drops further (Figure 3B) as job seekers with a high reservation wage continue to deregister, while those that register have a below average reservation wage. As a result, the probability that a registered job seeker participates increases significantly, from just over 20% to more than 60%. An increase in supply results in a higher likelihood that requests can be assigned to a driver (Figure 3D and E). It also leads to a decrease in the average pick-up time (Figure 3E). In this market evolution phase, however, the average probability that ridesourcing is chosen for a trip still decreases, given that the average expected waiting time is still increasing.

(3) **Double-sided growth** *(days 25–50)*. In this phase, there is a net growth in the share of informed agents that are registered. The average reservation wage of registered drivers is relatively stable. Considering that the number of informed job seekers increases while earnings are fairly constant (a relatively minor increase in driver idle time is approximately compensated for by a decrease in deadheading costs per request, (Figure 3C), supply-side market participation increases as well. On the demand side of the market, more travellers have become aware about the service. Those informed are increasingly likely to use ridesourcing as the average pick-up

time drops. The latter is caused by more favourable matches with a growing number of users on both sides of the market.

(4) **Market equilibrium** *(days 50+)*. In this phase, the key system performance indicators only change marginally (satisfying the convergence criteria defined in Section 3.6.1). Nearly all agents are now aware about the existence of the service, and the probability that they use the platform is approximately constant.

We observe a discrepancy in the pace in which job seekers and travellers learn. Figure 3 shows that at the end of the second transition phase, there is no fundamental difference in what job seekers expect to earn and what they actually earn. On the demand side, however, the average time that a traveller expects to wait when choosing ridesourcing is higher than the average experienced waiting time of users (Figure 3E). A reason why demand-side learning may be slow in the ridesourcing market is that its market share is relatively low, i.e. in equilibrium around 2.2% of all travel demand. In other words, the average informed traveller has a low probability of receiving private information about the waiting time. This applies especially to travellers who have been relatively unlucky in their experiences with the platform (Figure 4C), i.e. those who on average experienced a high waiting time when opting for ridesourcing compared to travellers with similar trip requests. With a high expected waiting time, they become less likely to use the service in the future. In other words, the waiting time of travellers that have been relatively unlucky in the matching process will regress to the mean more slowly than the waiting time of travellers who have been relatively lucky. As shown by Figure 3E, travellers requesting a ride with the platform expect a waiting time that is close to the actual experienced waiting time. It may take a very long time for the other travellers to learn about the average experienced waiting time.

The observation that job seekers learn much more quickly than travellers in the reference scenario may not solely be explained by a discrepancy in the market participation probabilities between potential suppliers and consumers in the market. Another possible explanation follows from our modelling assumption that job seekers – due to market asymmetry in costs required for registration – exchange more information with peers than travellers do with fellow travellers.

When we further examine distributional effects in system performance (in equilibrium), we find that job seekers can expect relatively large day-to-day variations in income. The experienced earnings of participating drivers resembles a normal distribution with a relatively large standard deviation compared to the mean (Figure 4A). It implies that on an average day under steady-state conditions some drivers earn very little and some earn a lot. We find that random effects play a non-negligible role also in travellers' experiences. The majority of travellers have to wait less than two minutes to be picked-up, while some others are faced with a waiting time exceeding 10 min (Figure 4C). The waiting time distribution resembles an exponential distribution.

We observe that, at least in the reference scenario, spatial properties have a limited effect on experienced system performance. There is no significant relationship between drivers' starting location and their income (Figure 4B) and between travellers' request location and their waiting time (Figure 4D).

Finally, we investigate the effect of random variations in agents' preferences and stochastic processes in the simulation, i.e. in information diffusion, registration choice and participation choice. We observe minor differences in the performance indicators in the market equilibrium when comparing different instances of the simulation. We find the variability in market participation across instances – based on 20 instances – to be larger on the supply side of the market. Based on the 20-day moving average, the market converges to a supply-side participation volume between 110 and 122 job seekers (Figure 5A), depending on randomness in initial conditions and evolutionary processes. The (relative) variation in market participation across instances is more limited on the demand side (Figure 5C), with the the 20-day moving average ridesourcing demand in equilibrium ranging from 1580 to 1700 requests.

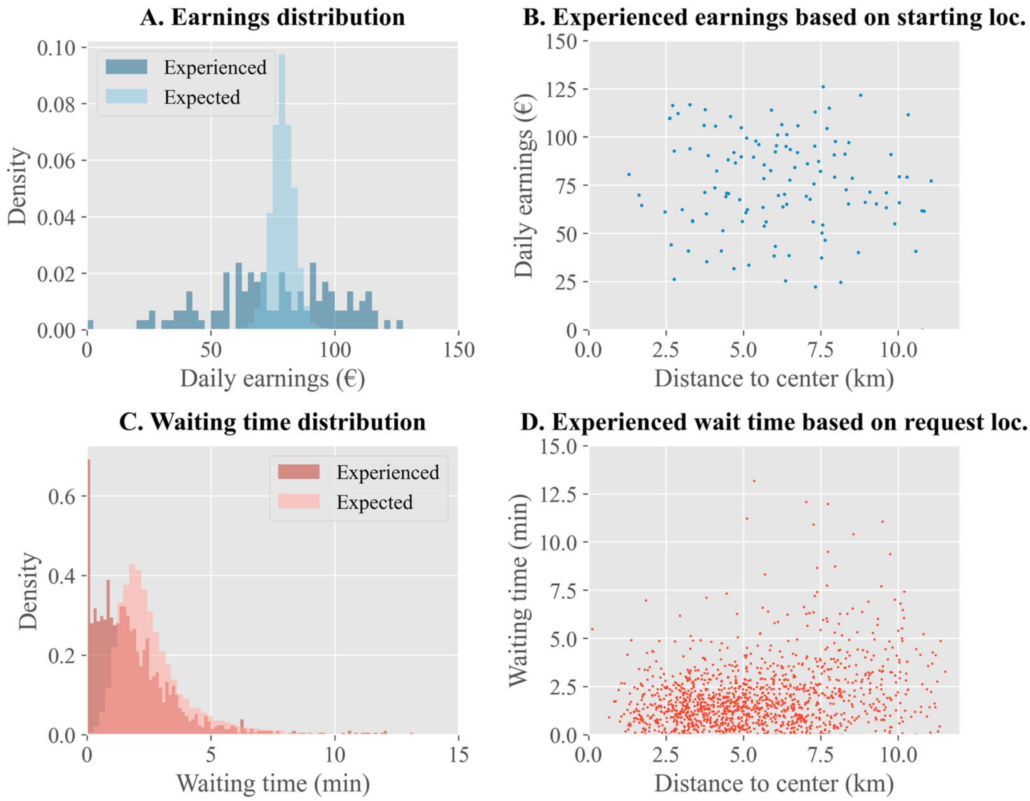

Figure 4. Distributional effects in earnings and waiting time in the ridesourcing market equilibrium (single instance of the reference scenario). (A) Earnings distribution. (B) Experienced earnings based on starting loc. (C) waiting time distribution. (D) Experienced wait time based on request loc.

The relative difference in the range of market participation volumes to which the market converges between both sides can at least partially be explained by the absolute volume of market participation on both sides, i.e. there are substantially more travellers than drivers, implying that the decisions and attributes of individual travellers have a more limited effect than the decisions and attributes of individual drivers. Another explanation could be that travellers are less sensitive to waiting time than job seekers are to income. The relative variation between instances in the 20-day moving average of average experienced driver earnings (Figure 5B) and experienced user waiting time (Figure 5D) is comparable.

Another characteristic of the ridesourcing market provided by the dynamic model are day-to-day variations in system performance, which can occur even in the market equilibrium. Figure 5 demonstrates that even when the market has converged, there are non-negligible variations in daily ridesourcing supply (Figure 5E) and demand (Figure 5G), which result in substantial day-to-day variations in the average experienced driver earnings (Figure 5F) and user waiting time (Figure 5H). For instance, in a particular instance of the experiment, the average daily earnings in the market equilibrium are found to be as low as €70 on some days, and as high as €85 on other days, whereas the average waiting time is found to vary between 2 and 3.5 min from day to day. We observe that random variations in registration and participation decisions are not the sole explanation for these day-to-day variations in system performance, i.e. initial random variations affect the likelihood that agents participate in the future. We take as example one of the instances of the experiment highlighted in Figure 5. A period of a few days around day 125 with slightly lower participation compared to the average – possibly intensified by random spikes in ridesourcing demand – leads to temporarily higher ridesourcing

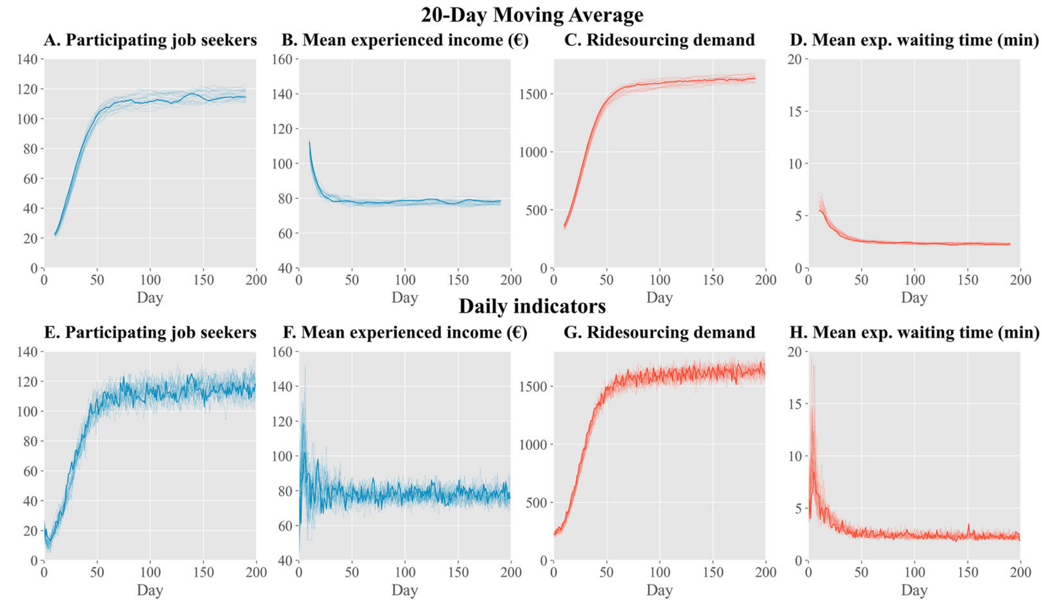

Figure 5. 20-Day Moving Average (MA_{20}) and daily values of ridesourcing market participation and system performance indicators for different instances (replications) of the reference scenario. System performance for one of the instances is highlighted. (A) Participating job seekers. (B) Mean experienced income (€). (C) Ridesourcing demand. (D) Mean exp. waiting time (min). (E) Participating job seekers. (F) Mean experienced income (€). (G) Ridesourcing demand. (H) Mean exp. waiting time (min).

earnings. This yields a spike in supply-side participation (up to 125 drivers on a day). Due to increased competition, the ridesourcing earnings drop substantially, which is followed by a drop in supply-side participation levels (down to just over 100 drivers per day). In the end, market participation and earnings converge back to the average in equilibrium. It demonstrates that in ridesourcing provision not just day-to-day variations but also more structural fluctuations (in this case for approximately 25 days) in system performance can occur, following from path dependency in market participation decisions.

5.2. Potential market size

Figure 6 shows how ridesourcing system performance is affected by the (double-sided) size of the potential market. We find for instance that when there are only 3750 travellers and 125 individuals open to a job opportunity, the market will evolve towards an equilibrium in which hardly any trip requests are satisfied (Figure 6D). Under these conditions, critical mass cannot be achieved as ridesourcing supply and demand are too thin resulting with large temporal variations in supply and demand. Consequently, drivers are occasionally idle (when there are no unassigned trip requests), while at other times there are unassigned requests without any driver available. Supply shortage is then likely to be sustained due to the long average pick-up time (long deadheading) following from the inefficiency of the matching algorithm when supply and demand are scarce (Figure 6E). As drivers on an average day serve few requests (Figure 6G), participating in the market is unattractive. This further reduces the probability that a request can be assigned to a driver.

Already with 7500 travellers and 250 job seekers in the market we observe sustained supply and demand for ridesourcing. This corresponds to just 1% of the estimated potential market size of ridesourcing in Amsterdam. In this scenario, only 3.5% of all job seekers are registered in equilibrium (Figure 6A), of which on an average day less than 30% participate (Figure 6B). Although limited supply results in a matching failure for 24% of trip requests (Figure 6D) and in relatively long waiting for the other requests (Figure 6E), each day still a small portion (0.5%) of travellers is willing to request a ride with the platform (Figure 6C).

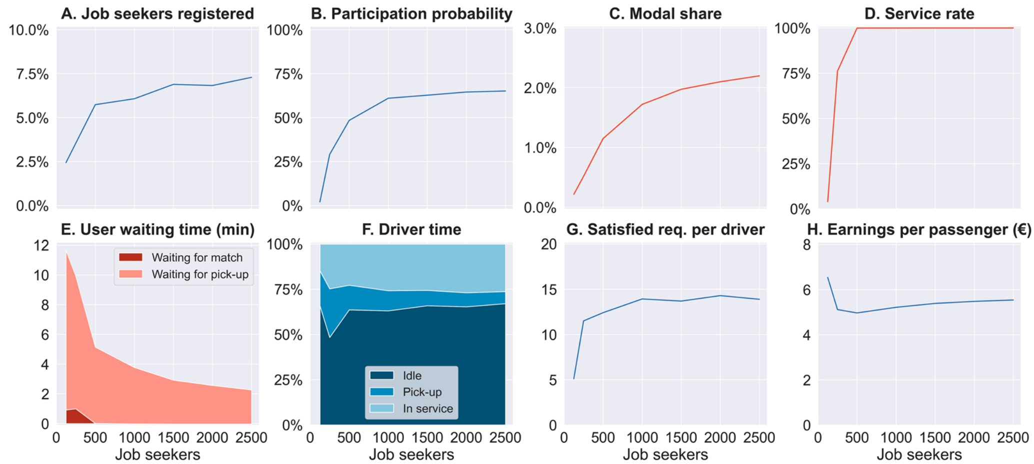

Figure 6. Equilibrium system performance indicators depending on the size of the potential market (in which there are 30 travellers for each job seeker). (A) Job seekers registered. (B) Participation probability. (C) Modal share. (D) Service rate. (E) User waiting time (min). (F) Driver time. (G) Satisfied req. per driver. (H) Earning per passenger (€).

We observe that system performance improves considerably with the size of the potential market. This resonates with the existence of positive network effects (specifically B, C, G and H in Section 2.1) in the ridesourcing market, i.e. users facilitating the matching algorithm by enabling better matches. We find for instance that the average pick-up time decreases from five minutes when there are 15,000 travellers and 500 job seekers to around two minutes when there are 75,000 travellers and 2500 job seekers (Figure 6F). As a result, the modal share of ridesourcing more than doubles (Figure 6C). Lower deadheading costs (associated with driving to the request pick-up location) yields higher per-request earnings for drivers (Figure 6H). We establish that network effects marginally diminish as the potential market grows larger. In other words, with each additional traveller and job seeker in the market, the marginal increase in ridesourcing market share decreases (Figure 6C). This is an inherent feature of the ridesourcing market, given that there is a theoretical minimum pick-up time of 0 min, corresponding to a situation with unlimited supply. Hence, as the potential market grows, the market share will converge to the market share that is attained when travellers expect no waiting time. We find that in a potential market with 75,000 travellers and 500 job seekers, the pick-up time is already limited to just over two minutes (Figure 6F). More dense potential supply and demand at this point will yield only minor benefits.

5.3. Double-sided pricing strategy

In this subsection, we analyse the effect of a platform's pricing settings, i.e. the per-kilometre fare and platform commission, on the market equilibrium. The main system performance indicators are shown in Figures 7 and 8.

In our experiment, a profit-maximizing service provider will opt for a per-kilometre fare of €1 and a commission of 30% (Figure 8C). With this strategy, approximately 3.9% of all travellers opt to request a ride using the ridesourcing platform (Figure 7C), of which 99.5% is successfully matched to a driver (Figure 7D). There are however two near-optimal pricing strategies, which result in more than 99% of the maximum profit. These alternative strategies comprise of charging a higher fare, i.e. €1.25 per kilometre, as well as a higher commission, i.e. either 35% or 40% (Figure 8C). As a result, the platform profit per request is respectively 45.8% and 66.7% higher than when a platform opts for the profit-maximizing strategy with a fare of €1.0 per kilometre and a 30% commission. It shows that pricing decisions for the service provider represent a trade-off between the number of transactions in the

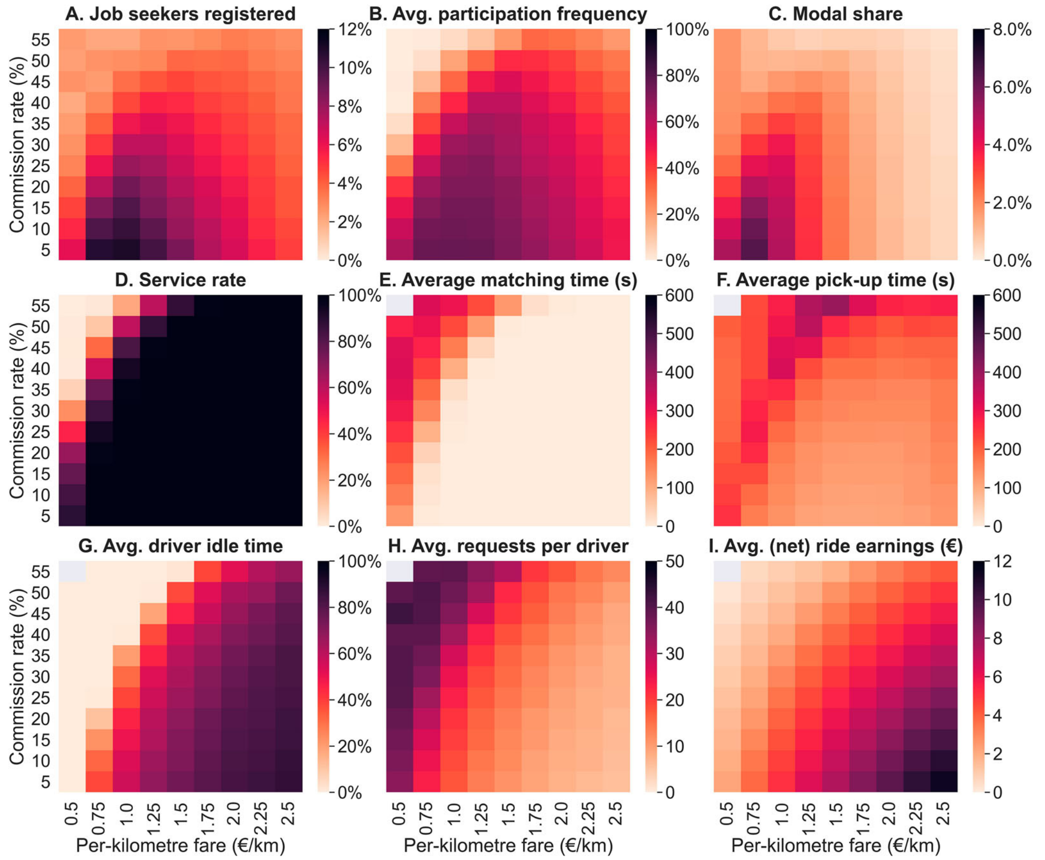

Figure 7. Equilibrium system performance indicators depending on the pricing strategy adopted by the platform. (A) Job seekers registered. (B) Avg. participation frequency. (C) Modal share. (D) Service rate. (E) Average matching time (s). (F) Average pick-up time (s). (G) Avg. driver idle time. (H) Avg. request per driver. (I) Avg. (net) ride earnings (€).

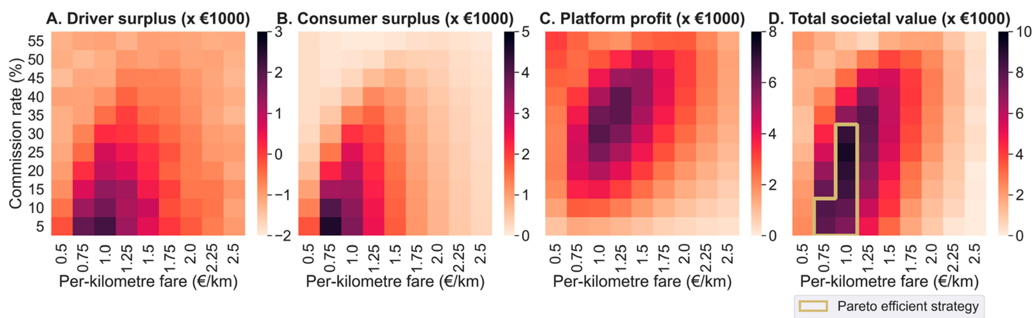

Figure 8. Societal value in equilibrium depending on the pricing strategy. (A) Driver surplus (×€1000). (B) Consumer surplus (×€1000). (C) Plateform profit (×€1000). (D) Total societal (×€1000).

market and the earnings per transaction. In the experiment, the profit-maximizing strategy prioritizes the former, the two near-optimal strategies the latter. Compared to the profit-maximizing strategy, the alternative near-optimal strategies for instance result in a significantly lower ridesourcing market share, i.e. a reduction of 27.4% when $\pi = 35\%$ and a reduction of 36.3% when $\pi = 40\%$ (Figure 7C). As a result, fewer job seekers participate in the market (Figure 7A and B). We can conclude that several (near-)optimal pricing strategies may result in a vastly different value derived by job seekers (Figure 8A) as well as by travellers (Figure 8B), depending on whether the transaction volume or earnings per transaction is prioritized. From a wide societal value, the latter may be undesired.

We also note that only two fares – €0.75 or €1.0 per kilometre – are Pareto efficient in the ridesourcing market. This demonstrates the significance of network effects in the ridesourcing market. Without network effects, travellers would prefer a minimal fare as they benefit directly from lower travel costs, while job seekers prefer a maximum fare as they would earn more. In our experiment, however, the per-kilometre fare in the optimal pricing strategies for travellers and job seekers, respectively, is relatively close, i.e. €0.75 for travellers (Figure 8B) and €1.0 for job seekers (Figure 8A). To understand why the interests of travellers and job seekers are relatively well aligned, we analyse ridesourcing system performance under very low and very high fares.

First, a very low per-kilometre fare, corresponding to €0.5 in the experiment, comes at the expense of the level of service offered to travellers. With this strategy, fares are so low that ride earnings barely cover for drivers' operating costs, which include costs associated with deadheading (Figure 7I). As a result, job seekers are relatively unlikely to register (Figure 7A) and participate (Figure 7B) in the market. With few other drivers, those that still participate will not face any idle time (Figure 7G) and may be able to serve over 40 passengers a day (Figure 7H). Yet, the net earnings per ride are so low, down to €1, that a lack of competition will not incentive more job seekers to participate in the market. With low supply, the platform has difficulties assigning drivers to ride requests. The probability that no driver is found before a traveller loses patience (Figure 7D) is high, and so is the average matching time for requests for which a driver is found before the request is cancelled (Figure 7E). With low level of service, travellers become significantly less likely to opt for ridesourcing (Figure 7C).

With travel cost as one of the main determinants of mode choice, high per-kilometre fares also significantly reduce the probability that ridesourcing is chosen by travellers (Figure 7C). While high fares lead to high earnings per ride (Figure 7I), a low ridesourcing market share of ridesourcing implies that drivers serve only few requests on any given day (Figure 7H) and earn less than in a scenario with a lower per-kilometre fare. Drivers spend over 80% of their time in an idle state (Figure 7G) when the per-kilometre fare equals €2.5, even though there are relatively few other job seekers participating in the market (Figure 7B). We can conclude that under high ridesourcing fares the loss of ridesourcing demand outweighs the increase in earnings per request and the reduction in the number of participating colleagues.

Travellers and job seekers also have similar interests when it comes to the commission rate applied by the platform. As it directly reduces the money that a driver receives for serving a passenger (Figure 7I), a high commission makes participating in the market less attractive (Figure 7B). With relatively few participating drivers relative to ridesourcing demand, drivers spend less time waiting to be assigned (Figure 7G), while travellers may start to experience longer matching times (Figure 7E). On both sides of the market there will be fewer participants, which implies that the matching algorithm yields matches with a lower quality, i.e. with a higher average pick-up time/more deadheading (Figure 7F). In other words, due to the presence of network effects in the ridesourcing market, the costs that a commission induces for drivers is partially redistributed to travellers. A profit-maximizing platform (Figure 8C) will raise the commission up to the point that the loss of satisfied ridesourcing demand – either because travellers do not opt for ridesourcing or because their request cannot be fulfilled – outweighs the higher profit per satisfied request.

5.4. Information diffusion & registration

5.4.1. Information diffusion rate

We explore the effect of the platform awareness diffusion rate to test the hypothesis that ridesourcing markets may fail to reach a critical mass when information diffusion is slow. The results presented in Figure 9 do not provide evidence for this hypothesis. For different (two-sided) diffusion speeds, the market converges to approximately the same equilibrium, with approximately 115 daily drivers and

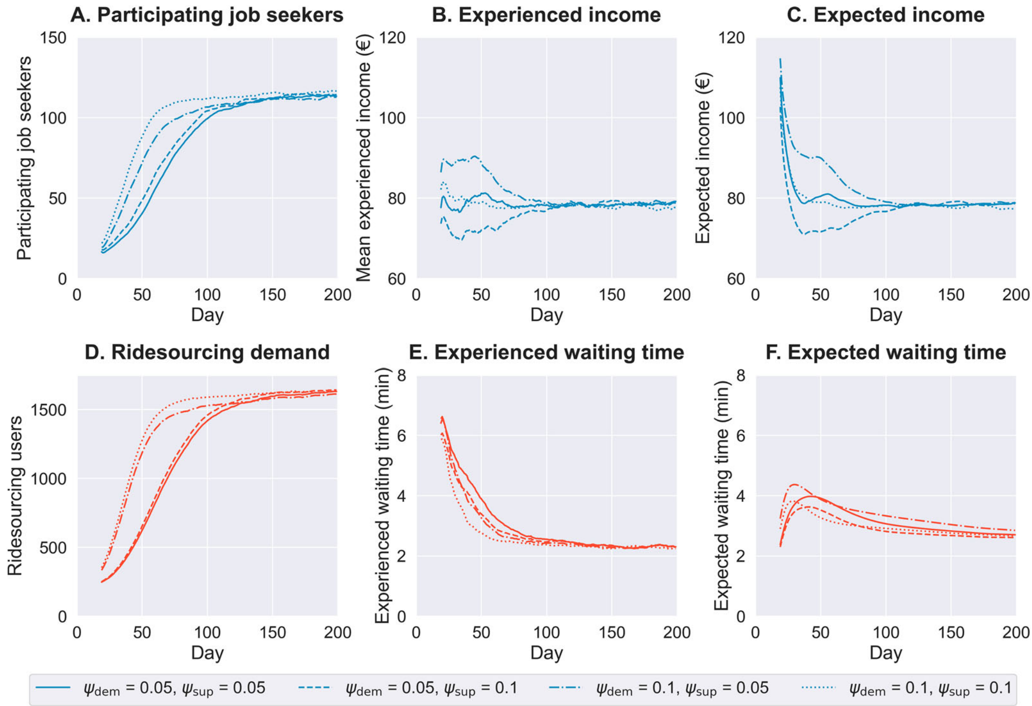

Figure 9. 20-Day moving average of key ridesourcing market performance indicators for different two-sided information diffusion speeds. (A) Participating job seekers. (B) Experienced income. (C) Expected income. (D) Ridesourcing demand. (E) Experienced waiting time. (F) Expected waiting time.

1600 daily travel requests. Logically, the equilibrium is achieved faster when (double-sided) information diffusion is fast. We find that the demand-side diffusion speed is substantially more decisive for the time to reach an equilibrium than the information diffusion rate among job seekers. The reason is that more demand – when more travellers are informed about the service – results in substantially higher driver earnings (Figure 9B), attracting more suppliers to the market (Figure 9A), even though fewer job seekers are informed about the platform. The more limited sensitivity of travellers to waiting time implies that fast diffusion of platform awareness among job seekers in early stages of adoption only yields a minor increase in the ridesourcing market share.

5.4.2. Registration barriers

Figure 10 demonstrates how costs associated with supply-side registration affect the adoption of ridesourcing platforms. We observe that when registration costs are limited to 5 euro per day, there is a substantial increase in the number of job seekers that register in the first 25 days of the simulation, whereas there is a net decrease in registration for the scenarios with daily registration costs of 20 or 35 euro (Figure 10A). As initially equal earnings are anticipated in the different scenarios, more registered job seekers also implies more supply-side participation when registration costs are limited (Figure 10B). Although this results in lower waiting time for travellers (Figure 10E and F), the associated increase in ridesourcing market share is limited (Figure 10D). Hence, the average number of drivers per ride request increases and the average earnings of drivers drop (Figure 10C). While those that are registered will participate less frequently compared to scenarios with higher registration costs due to their lower expectations of income, the difference in registration volume is large enough to compensate for the decrease in participation likelihood, i.e. those registered still participate in the market sporadically, which in reality may happen for instance when they are in need of money and/or when they have limited alternative activities on that day. In other words, we find

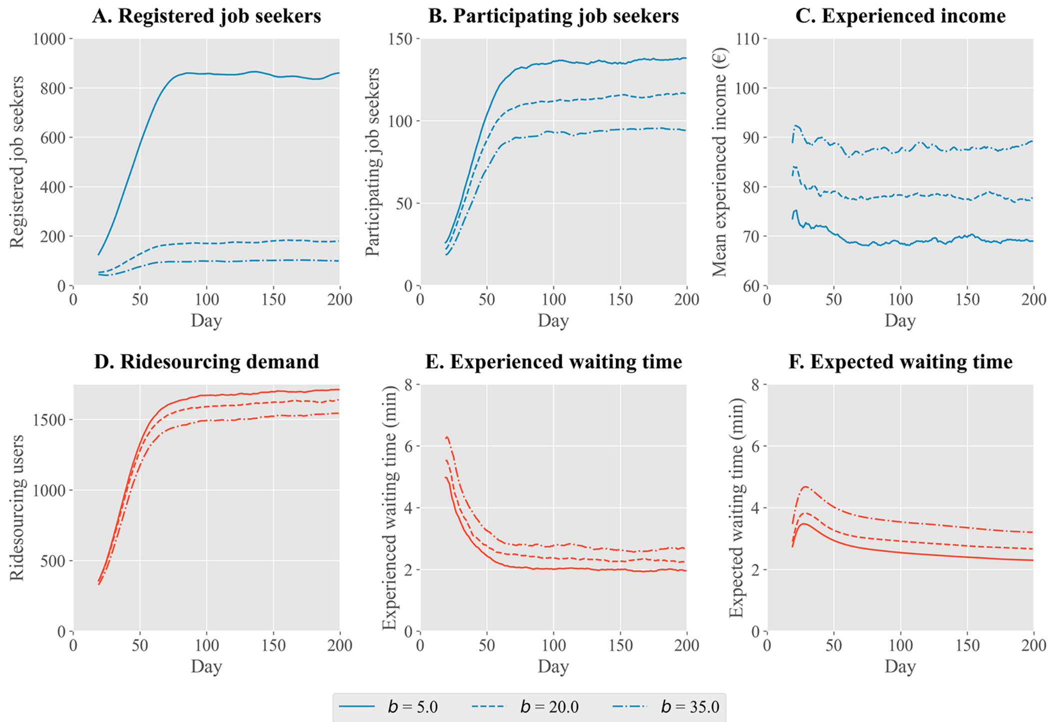

Figure 10. 10-Day moving average of key ridesourcing market performance indicators for different daily costs b associated with registration for job seekers. (A) Registered job seekers. (B) Participating job seekers. (C) Experienced income. (D) Ridesourcing demand. (E) Experienced waiting time. (F) Expected waiting time.

that in a scenario with limited registration costs more job seekers participate in the market equilibrium, resulting in a better level of service for travellers yet substantially lower participation earnings for drivers. The latter implies that drivers may not benefit from lower costs associated with platform registration.

6. Conclusions

6.1. Study significance

This study pioneers in mapping the network effects that shape the co-evolution of supply and demand in the two-sided ridesourcing market. The novel conceptual representation of the ridesourcing market allows us to better understand why the ridesourcing market may be prone to evolving towards particular – not necessarily socially optimal – market equilibria. Furthermore, we also mimic the co-evolution of demand and supply in ridesourcing with a simulation model that accounts for subsequent disaggregate processes on both sides of the market. These processes include word-of-mouth communication about the service (both sides), long-term registration decisions (supply), daily platform utilization decisions (both sides) and learning from individual experience (both sides). By integrating our model into a within-day model for ride-hailing operations, we allow for the emergence of non-uniform earnings and waiting times across market participants. We apply the model to a case study that mimics the City of Amsterdam, studying day-to-day processes in the adoption of ridesourcing, the relation between the size of the potential ridesourcing market and system performance, as well as the societal implications of platforms' double-sided pricing strategies.

6.2. Takeaways

We now formulate the key takeaways from our analysis of the two-sided ridesourcing market.

6.2.1. Conceptual framework

The ridesourcing market is characterized by the presence of numerous (same-side and cross-side) network effects. Network effects are governed by changes in the total waiting time for travellers and the non-revenue time of drivers. Both variables are determined by match time – how quickly are users assigned to users on the other side – and match quality – once assigned, how quickly can a driver reach a traveller. Whereas there is a conflict in the match time of travellers and drivers, i.e. both prefer many unassigned users on the other side of the market, travellers and drivers have similar interests when it comes to match quality. Match quality is optimal when there are many idle users on one side of the market. This could be a reason why ridesourcing markets may evolve towards an asymmetrical equilibrium state in which pick-ups are quick, but one side is confronted with a relatively long matching time. This may be a point of attention for authorities in areas in which ridesourcing platforms are active (or even dominant).

6.2.2. Dynamics and heterogeneity

The ridesourcing market may undergo several transitions before ending up in a steady state condition. In each transition phase, system performance changes rapidly. Even in the steady state, job seekers and travellers experience significant day-to-day variations in earnings and waiting time, respectively. This is not only due to randomness in the matching process, but also due to random components in individual registration and participation decisions. Initially small (two-sided) day-to-day variations in participation levels can result in larger day-to-day variations as market participation levels affect the earnings and waiting time experienced by drivers and travellers, respectively. We find that matching luck explains variations in experiences across market participants much more than spatial properties do. The long-term wage gaps that may follow from matching luck is an issue previously addressed by Bokányi and Hannák (2020).

Path dependency in mode choice yields a systematic discrepancy between market experiences and expectations on the demand side of the ridesourcing market. Due to differences in registration costs and the probability to participate between (potential) suppliers and consumers, learning is likely more successful on the supply side of the market.

The speed at which the market reaches the equilibrium is affected more by platform awareness diffusion on the demand side than on the supply side. This follows from increased driver earnings when demand-side platform awareness spreads quickly, as newly informed travellers try the service. Adequate supply is attracted to the market even when relatively few job seekers are informed about the platform. We observe that the information diffusion rate on both sides has limited affect on the eventual equilibrium.

6.2.3. Potential market size

A ridesourcing system may fail to attain a critical mass in markets with limited potential supply and demand. In our experiment, only around 1% of the estimated density of potential ridesourcing supply and demand in Amsterdam is needed to realize a critical user mass. We find that there may be sustained supply and demand even though the service is unreliable and pick-up times are long. The above findings suggest that ridesourcing may be viable – although possibly substantially less beneficial for travellers and drivers – even in (more) rural areas.

6.2.4. Double-sided pricing strategy

In setting commission and ride fares, a service provider weighs the (emergent) market transaction volume and the profit per transaction. A strategy in which the former is traded off for the latter is per definition harmful to passengers and drivers. Consequently, two strategies resulting in an approximately equal (and potentially near maximum) profit may yield a significantly different value when the interests of travellers and job seekers are also considered.

We find that the conflicting interests between market participants and platform are associated with platform commission more than with fares. Due to the presence of network effects, the interests of travellers, drivers and platform are relatively well-aligned when it comes to fares. A low (per-kilometre) fare repels drivers, which makes market participation unattractive for travellers, while a high (per-kilometre) fare repels travellers, making driving unattractive. While commission also reduces market participation, the crucial difference is that the reduction in market share may be compensated for by higher earnings on the remaining transactions. In our experiment, a profit-maximizing service provider opts for a 30% commission at the great expense of travellers and drivers.

Transport authorities may consider to regulate the commission rate to manage the distribution of benefits amongst stakeholders. As such regulations will lead to an increase the ridesourcing market share, its effect on platform profit may be limited.

6.2.5. Registration barriers

Based on our analysis, ridesourcing drivers do not necessarily profit from low costs associated with registration. In such a scenario, many more job seekers register with the platform, leading to strong competition among drivers, and consequently low driver earnings. Although lower earnings imply that registered agents are less likely to participate in the market, the total participation volume is still larger as substantially more job seekers are registered when there are hardly any registration costs.

6.3. Future research

Our conceptual analysis of the ridesourcing market hints at the emergence of asymmetrical market equilibria as the match quality – important to passengers and drivers alike – is jeopardized when supply and demand are well-balanced. World-wide driver protests over income suggest that drivers as opposed to travellers end up paying for a low pick-up time by means of a relatively long idle time between rides. We would like to know if an asymmetrical ridesourcing market favouring travellers is indeed an inherent property of the ridesourcing market. It will require investigating the effect of market conditions other than those considered in this study.

Such market conditions include the spatial distribution of demand, the characteristics of competing modes, how many job seekers are available in an area relative to the total demand for travel, and how socio-economic attributes (incl. vehicle ownership) are distributed in the population. We observe for instance that the economic attributes of job seekers participating in the ridesourcing market are non-representative for the full population of job seekers, i.e. they have a below average reservation wage. Socio-economic inequalities may hence explain why the ridesourcing market may be prone to evolving towards an equilibrium in which drivers incur significant waiting. At the same time, future research could differentiate between drivers with and without private vehicles, to establish how vehicle ownership affects market dynamics.

While this study assumes constant pricing strategies, both our conceptual framework and day-to-day simulation model of the ridesourcing market can be extended with pricing dynamics. This would allow inspecting how a ridesourcing service provider can steer its evolution with (day-to-day) penetration pricing – to overcome slow adoption and capture a critical mass – and with (within-day) surge pricing. The latter requires more insights into the work shift decisions of ridesourcing drivers – so as to balance supply and demand. Our models can also be extended to feature multiple platform agents competing for drivers and travel demand. In consideration of scaling effects observed in this study, it is relevant to explore whether platforms can co-exist and at what societal cost (or benefit). As ride-pooling may fundamentally change how supply and demand co-evolve, with users potentially benefiting from the presence of travellers with similar itineraries, future research may also explore the evolution of ridesourcing services offering pooled rides.

In the model specification process, we observed a significant knowledge gap regarding how travellers evaluate attributes related to ridesourcing and, particularly, how job seekers decide whether they wish to supply labour to a ridesourcing platform. Due to this lack of insights, we opted for relatively simplified submodels for behaviour in our agent-based simulation, while also testing for model's sensitivity to several key parameters. Generally, agent-based simulation models like the one presented in this study rely heavily on detailed behavioural insights, both as model input and for validation. Hence, we emphasize the need for empirical studies investigating ridesourcing labour supply – including registration, working days and work hours – as well as travellers' perception of ridesourcing. This is especially relevant in anticipation of needed research on the societal implications of platform competition in ridesourcing markets.

Notation

Notation	Definition
Sets	
$S = \{s_1, \ldots, s_N\}$	Set of job seekers (potential market suppliers)
$C = \{c_1, \ldots, c_K\}$	Set of travellers (potential market consumers)
$S_t^{\mathrm{u}} \subseteq S$	Job seekers uninformed about the platform on day t
$S_t^{\mathrm{i}} \subseteq S$	Job seekers informed about the platform, yet not registered with it on day t
$S_t^{\mathrm{r}} \subseteq S$	Job seekers registered with the platform on day t
$S_t^{\mathrm{p}} \subseteq S_t^{\mathrm{r}}$	Set of participating drivers on day t
$C_t^{\mathrm{u}} \subseteq C$	Travellers not (previously) informed about the platform on day t
$C_t^{\mathrm{i}} \subseteq C$	Travellers (previously) informed about the platform on day t
$C_t^{\mathrm{p}} \subseteq C_t^{\mathrm{i}}$	Set of travellers opting for ridesourcing on day t
$Q_{\mathrm{driver}} \subseteq S_t^{\mathrm{p}}$	A (virtual and possibly empty) queue of idle drivers at a given moment in time (within-day)
$Q_{\mathrm{req}} \subseteq C_t^{\mathrm{p}}$	A (virtual and possibly empty) queue of travellers with unsatisfied requests on the platform at a given moment in time (within-day)
Indices	
s	Job seeker
c	Traveller
m	Mode
t	Day
Parameters	
N	Number of job seekers in population
K	Number of travellers in population
ψ_{sup}	Platform awareness diffusion rate among job seekers
ψ_{dem}	Platform awareness diffusion rate among travellers
b	Daily cost to be registered as driver with the platform
γ	Probability of considering (de)registration on a given day (job seekers)
λ	Minimum registration period with the platform (in days)
μ_{rw}	Mean of the normal reservation wage distribution
g_{rw}	Gini-coefficient corresponding to the reservation wage distribution
β_{reg}	Income sensitivity in job seekers' registration decisions
β_{ptp}	Income sensitivity in job seekers' participation decisions
β_{cost}	Cost perception in mode choice
$\beta_{\mathrm{transfer}}$	Perception of transfers in trips
κ	Weight that agents attribute to the most recent piece of information as opposed to previously gathered information
ω	Multiplier of the standard deviation of the experienced income and waiting time distributions used to generate the distribution of corresponding signals

f_{base}	Base ridesourcing rate
f_{km}	Per-kilometre rate of ridesourcing
π	Platform commission rate
δ	Per-kilometre operational costs of ridesourcing drivers
θ	Traveller's maximum waiting time (patience threshold) for assignment
P	Constant cost experienced by traveller with trip request in case waiting time exceeds patience threshold θ
φ	Threshold value for relative change in convergence indicator (used to determine whether indicator has converged)
$\varepsilon_{\text{repl}}$	Allowable percentage error of the average income and waiting time estimates of the actual mean (in determining number of replications)
α	Level of significance in determining number of replications
χ	Threshold value for filtering travellers out of the simulation (based on the probability of choosing ridesourcing when the waiting time is zero)
Variables	
$U_{st}^{\text{registered}}$	Utility of being registered on day t for job seeker s
$U_{st}^{\text{unregistered}}$	The utility of not being registered on day t
$U_{st}^{\text{participate}}$	Utility of participating in the market on day t for registered job seeker $s \in S_t^{\text{r}}$
U_{st}^{alt}	Utility of choosing another activity on day t
U_{ctm}^{mode}	Utility of using mode m for traveller c's trip on day t for registered job seeker $s \in S_t^{\text{r}}$
p_{st}^{inform}	Probability that a random uninformed job seeker $s \in S_t^{\text{u}}$ is informed about the ridesourcing platform's existence on day t
p_{st}^{deregist}	Probability that registered job seeker $s \in S_t^{\text{r}}$ cancels its registration on day t
$p_{st}^{\text{participate}}$	Probability of participating in the market on day t for registered job seeker $s \in S_t^{\text{r}}$
p_{ct}^{inform}	Probability that an uninformed traveller $c \in C_t^{\text{u}}$ receives information on day t
p_{ctm}^{mode}	Probability that traveller c chooses mode m for their trip on day t
n_{st}	Consecutive days that job seeker s has been registered with platform on day t
η	Binary indicator for whether job seeker can deregister from platform depending on n_{st}
r_s	Reservation wage of ridesourcing work for job seeker s
ε_{reg}	Error term in job seeker's registration decision
ε_{ptp}	Error term in job seekers' participation decisions
$\varepsilon_{\text{mode}}$	Error term in mode choice
β_{cm}^{ivt}	In-vehicle time perception associated with mode m for traveller c
β_{cm}^{wait}	Waiting time perception associated with mode m for traveller c
$\beta_{cm}^{\text{access}}$	Access time perception associated with mode m for traveller c
ρ_{cm}	Travel cost of traveller c's trip with mode m
ASC_{cm}	Alternative-specific constant (ASC) of traveller c for mode m
$\hat{i}_{st}$	Anticipated earnings by job seeker s for day t
i_{st}	Experienced earnings by job seeker s on day t
y_{st}	Processed income by job seeker s for day t (used in learning)
v_{ctm}	Time in or on a vehicle using mode m for traveller c's trip on day t
a_{ctm}	Time to access a stop using mode m for traveller c's trip on day t
$\hat{w}_{ctm}$	Anticipated waiting time at a pick-up location using mode m for traveller c's trip on day t
q_{ctm}	Number of transfers using mode m for traveller c's trip on day t
x_{st}	Income signal received by job seeker s on day t
$\overline{i_t}$	Average experienced income of registered drivers on day t
σ_t^{i}	Standard deviation of the experienced income
$\overline{w_t}$	Average experienced waiting time of ridesourcing users on day t

σ_t^{w}	Standard deviation of the experienced waiting time distribution distribution
τ_{sc}	Travel time from the location of an idle (participating) job seeker $s \in Q_{\mathrm{driver}}$ to the pick-up location of an unassigned traveller $c \in Q_{\mathrm{req}}$ (within-day)
(c^*, s^*)	Traveller-driver pair with least intermediate travel time at a given moment in time (within-day)
d_c	Direct distance from a the request location of passenger $c \in C_t^{\mathrm{p}}$ to their destination (within-day)
R_{st}	Total revenue of participating job seeker $s \in S_t^{\mathrm{p}}$ on day t
R_c	Payout from satisfying the trip request of passenger $c \in C_t^{\mathrm{p}}$
ξ_{sct}	Binary assignment variable indicating whether (participating) job seeker s picks up passenger $c \in C_t^{\mathrm{p}}$ on day t
O_{st}	Total operational costs of participating job seeker $s \in S_t^{\mathrm{p}}$ on day t
D_{st}	Deadheading distance of participating job seeker $s \in S_t^{\mathrm{p}}$ on day t
w_{ct}	Experienced waiting time of passenger $c \in C_t^{\mathrm{p}}$ on day t
I_t	Average expected earnings of registered job seekers on day t
W_t	Average expected waiting time of informed travellers on day t
$Z(n^{\mathrm{init}})$	Number of required replications based on a number of initial replications n^{init}
I^*	Average anticipated ridesourcing income by registered job seekers in equilibrium (single replication)
W^*	Average anticipated waiting time of informed travellers (single replication)
$\overline{I^*}(n^{\mathrm{init}})$	Estimated mean of I^* from a sample of n^{init} runs
$\overline{W^*}(n^{\mathrm{init}})$	Estimated mean of W^* from a sample of n^{init} runs
$s_{\mathrm{I}}(n^{\mathrm{init}})$	Estimated standard deviation of I^* from a sample of n^{init} runs
$s_{\mathrm{W}}(n^{\mathrm{init}})$	Estimated standard deviation of W^* from a sample of n^{init} runs

Author contributions

The authors confirm contribution to the paper as follows. **Arjan de Ruijter:** Conceptualization, Methodology, Software, Investigation, Writing – Original Draft, Visualization, Project administration **Oded Cats:** Conceptualization, Methodology, Writing – Review & Editing, Funding acquisition, Supervision **Hans van Lint:** Writing – Review & Editing, Supervision

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Appendices

Appendix 1. Model validation

While our agent-based model and case study have been designed based on the characteristics of the ridesourcing operations in Amsterdam, we do not claim that they are exactly the same. For instance, considering the availability of trip demand data, we model a service area that is substantially smaller than the one in which services are operating in reality.

Table A1. Comparing simulation model outcome (equilibrium attained in the reference scenario) to estimated ridesourcing properties in Amsterdam.

Indicator	Simulation	Real-world
Rides per active driver hour	1.74	1.26[a]
Modal split (%)	2.2	3.4[b]
Average part-time factor	0.65	0.60[c]
Average driver revenue (€/h)	15.47	22.85[c]
Average trip distance (km)	5.4	9.0[c]

[a]Based on the total number of ordered taxi rides in Amsterdam (Amsterdam 2020), and the total number of Uber drivers in Amsterdam and their active hours (Fouarge and Steens 2021). [b]Based on the modal split of taxi in Amsterdam (Amsterdam 2019) and the share of taxi rides that were ordered online (Amsterdam 2020). [c]Reported based on Uber data (Fouarge and Steens 2021).

We intend to explore possible network effects in the ridesourcing market, using Amsterdam as an example, rather than to quantify such network effects specifically for Amsterdam.

Nevertheless, we can compare the simulation outcomes with real-world values as a sanity check for whether the experiments resemble real ridesourcing operations in Amsterdam. In Table A1, we present how our simulation results (reference scenario) compare to metrics of Uber in Amsterdam. It is important to note that (i) considering limited available data, the real-world values are based on rough estimations, requiring combining different data sources for some indicators, and (ii) that the presented real-world metrics of Uber only provide a snapshot of ridesourcing operations in Amsterdam, which have been observed to undergo significant variations (Fouarge and Steens 2021).

We find that all considered performance indicators are of the same order of magnitude in our simulation as observed in the real-world (Table A1). For instance, we find that the average time that a driver works relative to a 40-hour working week is similar in the simulated ridesourcing market (65%) as for Uber in Amsterdam (60%). Notwithstanding, there are a few apparent differences. The average Uber driver in Amsterdam earns more in reality than in our simulations. Several explanations are possible for this difference. First, the accuracy of the income data provided by Uber has been criticized (Amsterdam 2022; van Bergeijk 2017). Second, Uber's operations in Amsterdam may not have attained a steady state yet, a hypothesis supported by data demonstrating significant double-sided growth in the period from 2015 to 2019 (Fouarge and Steens 2021). Third, as mentioned previously, ridesourcing operations in our simulation are strictly limited by Amsterdam's municipality boundaries. In reality, Uber's service coverage extends far beyond Amsterdam, including international airport Schiphol, nearby cities Alkmaar, Almere and Haarlem, and larger and more distant cities such as Utrecht, Rotterdam and The Hague. Consequently, the average ride distance of Uber in Amsterdam (9.0 km) is indeed considerably longer than simulated for the reference scenario (5.4 km). As long-distance rides are more profitable than short-distance rides, spatial coverage is a plausible explanation for the difference between simulated and real-world ridesourcing earnings. Finally, our simulation model assumes that ride fares are strictly distance-based, while drivers in reality can earn more under surge pricing. The relatively short average ride distance in the simulated ridesourcing market may also explain why the number of rides per active driver hour is high relative to Uber's operations in Amsterdam.

Considering the difference in case study area and possible inaccuracy in the estimation of real-world performance indicators, we believe that it suffices for the simulation results to be of the same order of magnitude as the estimated indicators for the real world, which is the case based on Table A1.

Appendix 2. Sensitivity to starting conditions

In this section of the Appendix, we describe how sensitive our simulation outcomes are to starting conditions.

A.1 Informed agents

The share of job seekers and the share of travellers that are initially informed have no effect on the equilibrium, only on how fast the equilibrium is reached.

A.2 Registered job seekers

The share of informed job seekers that are registered at the start of the simulation has no effect on the equilibrium, only on system performance before the equilibrium is reached.

A.3 Income

Below, we describe the sensitivity of simulation outcomes to the ridesourcing earnings anticipated by (registered) job seekers at the start of the simulation. We observe that when registered job seekers expect half of their reservation wage

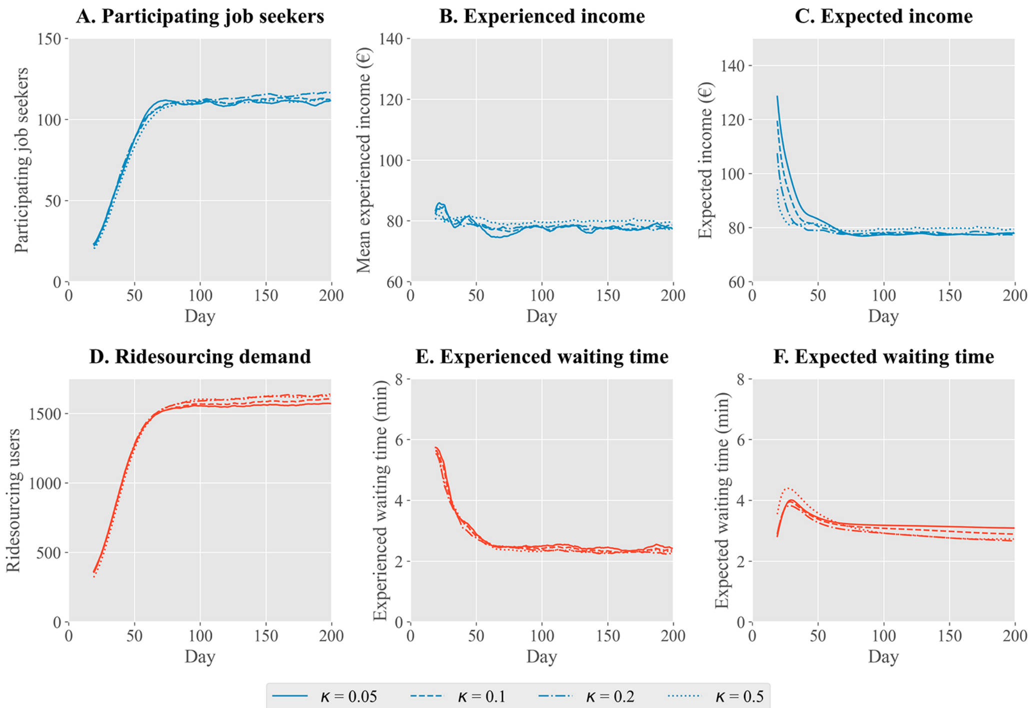

Figure A1. Ridesourcing system evolution depending on learning parameter κ.

at the start of the simulation, slightly fewer (i.e. approximately 1–2% fewer) job seekers and travellers end up participating in the market in equilibrium. The mechanism leading up to this difference is that initially very few job seekers participate, which leads to large variations in the experiences of travellers, i.e. some experience short waiting while others are denied service. These mixed experiences are communicated to travellers that are newly informed, i.e. those that receive negative signals may never try the service (and thereby never gain new information). As mentioned before, the effect on the market equilibrium is not significant.

A.4 Waiting time

The waiting time anticipated by informed travellers at the start of the simulation has no effect on the equilibrium, only on system performance before the equilibrium is reached.

Appendix 3. Sensitivity to model parameters

In Subsection 5.4, we test the effect of double-sided information diffusion rates and supply-side registration costs on system outcomes. Below, we present sensitivity analyses for several other model parameters associated with day-to-day processes in the ridesourcing market.

A.5 Learning

Below, we describe the effect of learning parameter κ, the weight that travellers and job seekers assign to the latest piece of information as opposed to previously gathered information (own or other agents' experiences). The results are presented in Figure A1.

We observe that while agents learn more quickly when the system transitions from one phase to another when they assign more value to recent information, the learning parameter overall has very limited influence on the emerging market equilibrium, i.e. (most) agents ultimately learn about changes in system performance indicators. One way in which the learning parameter affects the equilibrium is that when agents assign very little value to recent information ($\kappa = 0.05$), the effect described in Subsection 5.1 that some travellers with above average experienced waiting never learn about the system average waiting time becomes more predominant.

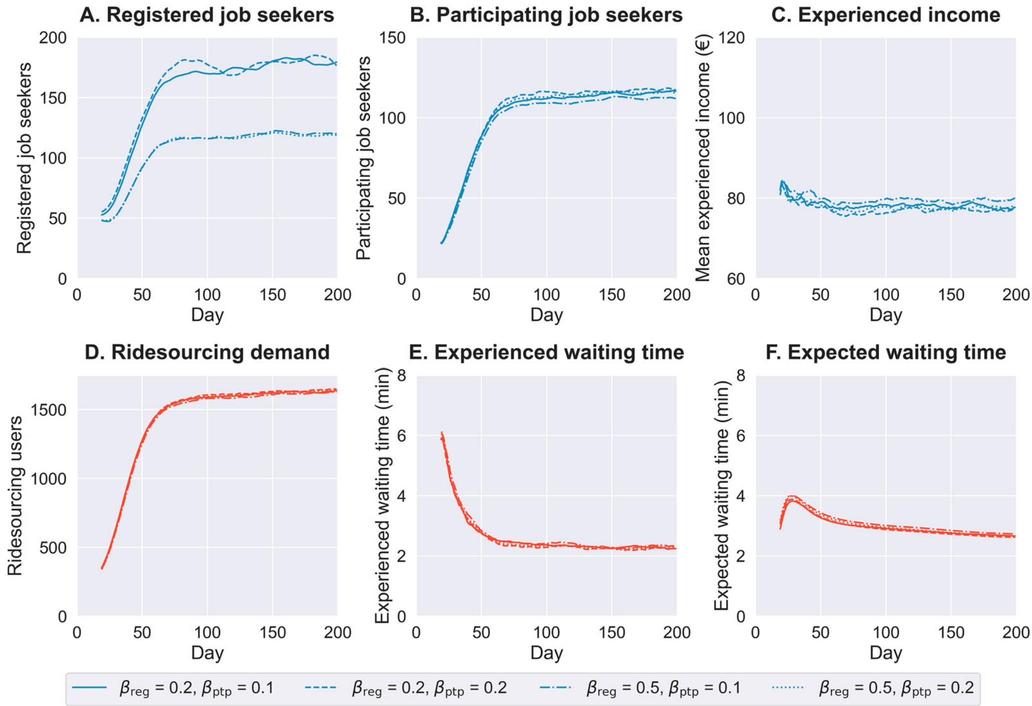

Figure A2. 20-Day moving average of key system performance indicators depending on job seekers' sensitivity to income in registration and particpation decisions.

A.6 Job seekers' sensitivity to income

In this subsection of the appendix, we evaluate the effect of the relative value assigned by job seekers to income in registration and participation decisions: β_{reg} and β_{ptp}, respectively (Figure A2).

We find that the specification of β_{reg} has a significant effect on the number of job seekers that end up registering with the platform. However, the effect on market participation is limited. In other words, when job seekers assign more value to income in the registration decision, fewer job seekers will register, but those that register are more likely to eventually participate in the market. Ultimately, supply and demand volumes are hardly affected by the adopted beta's in the registration and participation models.

A.7 Minimum registration duration

Below, we describe the sensitivity of our results to the number of days λ that job seekers are assumed not to be able to deregister after registering with the ridesourcing platform (Figure A3). We observe that this may have a significant impact on the number of job seekers that are registered with the platform in the equilibrium. When registered job seekers are bound to long-term commitments after registering, for instance for 50 days in the simulation, dissatisfied job seekers need to wait long before they can deregister. These dissatisfied job seekers are, however, unlikely to participate in the market, implying that the total participation volume is affected only minorly by the minimum registration duration. The effect on travellers is even more limited, i.e. the market attracts hardly any additional travellers when the registration commitment is long, following from slightly higher supply-side participation.

A.8 Registration decision frequency

Here, we investigate the sensitivity of the simulation outcomes to the probability γ that job seekers consider (de-)registration on a day (Figure A4). We observe that this parameter has a similar, albeit much smaller, effect as the minimum registration duration, i.e. when job seekers are less likely to make a (de-)registration decision, more job seekers will end up registered in equilibrium, as dissatisfied registered agents are less likely to deregister from the platform. However, these dissatisfied job seekers are unlikely to participate even when registered, so the effect on actual labour supply to the platform is limited to a few drivers per day. The effect on the demand-side market share of ridesourcing is even smaller.

Figure A3. 20-Day moving average of system performance indicators depending on the minimum duration of platform registration λ.

Figure A4. 20-Day moving average system performance indicators depending on registration decision probability γ.

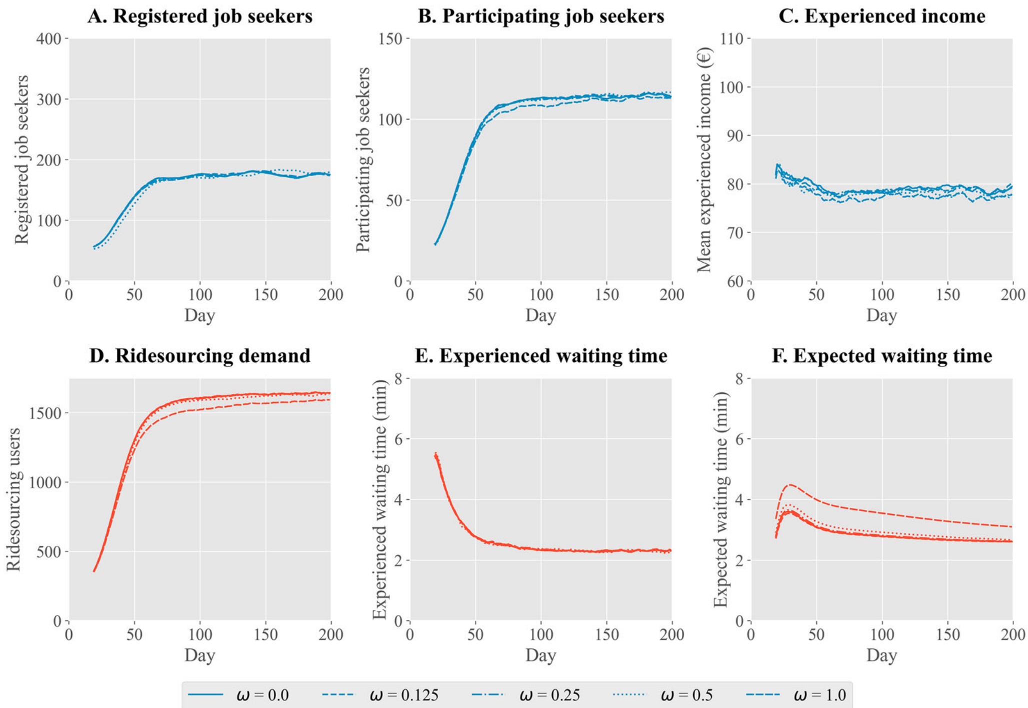

Figure A5. 20-Day moving average system performance indicators depending on the multiplier of the standard deviation of the experienced income and waiting time distributions used to generate the distribution of corresponding signals (ω).

A.9 Variation in income and waiting time signals

Figure A5 shows how ω, the multiplier of the standard deviation of the experienced income and waiting time distributions used to generate the distribution of corresponding signals, affect our simulation results for the reference scenario. We observe that there is no fundamental difference in system indicators depending on ω, except when this parameter is very high (i.e. 1, corresponding to a scenario in which agents each communicate with just 1 other agent). In such a scenario, the average traveller anticipates a longer waiting time (approximately 1 minute extra) when choosing ridesourcing, resulting in a slightly lower demand for ridesourcing. The higher expected waiting time when the standard deviation of income and waiting time distributions in information signals is relatively large is likely a model artifact. The assumed normal distribution for waiting time signals is restricted to non-negative values given that negative waiting times are impossible. This can produce a (positive) waiting time bias in communication between agents.