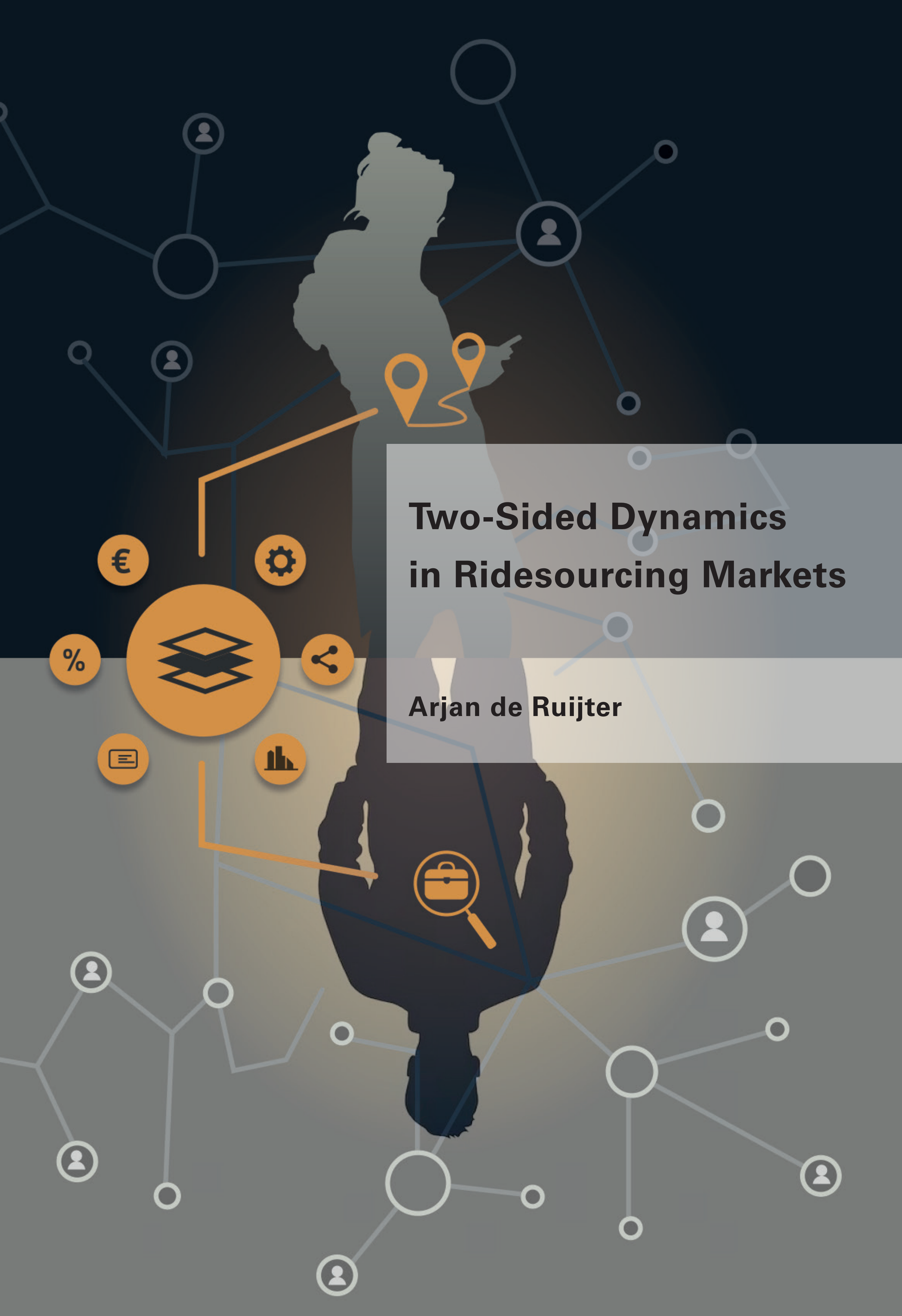

Two-Sided Dynamics in Ridesourcing Markets

Arjan de Ruijter

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Arjan de Ruijter
Delft University of Technology

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Two-Sided Dynamics in Ridesourcing Markets

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by

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To those who saved my life,
and those who have always been there for me.

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Sincerely,

Arjan de Ruijter
Delft, December 2024

Contents

Chapter 1

Introduction

1.1 Motivation

Ridesourcing enterprises such as Uber, Lyft, DiDi, Grab, and Bolt have revolutionised the taxi industry by introducing two-sided platforms. Awaiting the deployment of fully autonomous vehicles, these platforms utilise advanced real-time algorithms to seamlessly connect travellers with private car owners. Operating on a commission-based model, they charge a fee for each transaction between passengers and drivers — a strategy that minimises risk in fluctuating circumstances. By treating drivers as independent contractors rather than direct employees, these platforms enable flexible work hours tailored to personal commitments (Chen et al., 2019). At the same time, increased revenues during peak demand can motivate drivers to adjust their schedules and driving behaviour in response to demand, especially when surge pricing is introduced. This inherent supply-demand balancing mechanism facilitates prompt servicing with minimal waiting times for travellers and minimal idle time for drivers.

The emergence of ridesourcing however does not inherently guarantee an increase in social welfare. Ridesourcing driver protests, strikes and lawsuits around the world for instance highlight that the gig economy business model might not universally benefit all drivers. One of the possible factors contributing to ridesourcing driver dissatisfaction is the lack of access to social securities provided by traditional employment, by which drivers bear risks previously carried by service providers. These risks encompass income loss during individual hardships (e.g., illness) as well as market-wide downturns (e.g., sudden demand drops, as seen during the COVID-19 pandemic). In fact, it has been found that ridesourcing platform may result in systematically low earnings, even below the local minimum wage (Mishel, 2018; Manzo IV & Bruno, 2021). This can possibly be attributed to the flexibility these services offer, allowing individuals to work during periods of low labor opportunity cost, even when limited earnings are anticipated. Financial commitments - following for instance from access to a vehicle - may also compel drivers to work despite low earnings. Both factors can contribute to a ‘prisoner’s dilemma’ in ridesourcing supply, where drivers’ work decisions lead to an oversupplied market, at the expense of the income of all drivers. In addition, excessive driver idle time in such oversupplied markets could induce what is known as a 'wild goose chase' (Castillo et al., 2017), where idle drivers cover substantial distances in anticipation of trip requests, not only incurring additional operational costs but also contributing to increased traffic congestion. Tirachini & Gomez-Lobo (2020) found that ridesourcing platforms may also contribute to road congestion by drawing users away from public transport and active modes, and through induced travel demand. A study initiated by Uber and Lyft based on their own data confirmed the potential contribution of ridesourcing providers on congestion levels in six cities in the US (Balding et al., 2019). Finally, the emergence of ridesourcing platforms has been found to be potentially harmful for taxi operators and their drivers (Yu et al., 2020; Ling et al., 2023).

While empirical evidence showcases both positive and negative impacts of ridesourcing systems in specific cities (Tirachini et al., 2020; Yang et al., 2021; Schaller, 2021; Cats et al., 2022; Oh et al., 2022; Erhardt et al., 2022), uncertainty persists regarding the circumstances dictating whether these systems prove more or less advantageous for various stakeholders. The societal implications of ridesourcing may extend beyond the effects on ridesourcing users, drivers, and service providers to encompass individuals using, working for, or providing alternative transportation services, as well as road users and local residents. The limited available data provided by ridesourcing providers, typically delivered only when mandated by local authorities, falls short in facilitating a comprehensive cross-context analysis of ridesourcing impacts as well as in identifying the mechanisms contributing to positive and negative ridesourcing impacts. At the same time, insights derived from generalised two-sided markets (Rochet & Tirole, 2003, 2006; Armstrong, 2006; Armstrong & Wright, 2007; Rysman, 2009; Weyl, 2010; Belleflamme & Peitz, 2019), for instance regarding social welfare effects associated with such (monopolistic or oligopolistic) markets, likely do not readily apply to ridesourcing markets due to the intricate and highly spatio-temporal nature of ridesourcing service delivery.

Enhanced understanding of how context and service configurations impact the performance of ridesourcing systems would allow establishing under which conditions and how ridesourcing operations can be stimulated or constrained in order to improve the social welfare generated in these markets. This requires a thorough analysis encompassing key ridesourcing system indicators influenced by factors such as traveller preferences, labour market dynamics, service configurations, and transportation system characteristics.

1.2 Theoretical background

The majority of studies investigating ridesourcing system performance contingent upon context and market attributes focus on examining the impact of platform strategies on the ridesourcing market equilibrium. This includes exploring the effect of static dual-sided pricing mechanisms (Taylor, 2018; Bai et al., 2019; Sun et al., 2019b; Nourinejad & Ramezani, 2020; Hu & Zhou, 2020; Ke et al., 2020a; Xue et al., 2021), analysing both fares and commissions. Other works specifically investigate spatial and dynamic pricing strategies (Banerjee et al., 2015; Cachon et al., 2017; Castillo et al., 2017; Zha et al., 2018a; Guda & Subramanian, 2019; Chen & Hu, 2020; Besbes et al., 2021; Ma et al., 2022). Another key research topic is the optimisation and exploration of platforms' matching rules, both for (private) ride-hailing (Feng et al., 2021; Xu et al., 2018; Özkan & Ward, 2020; Baccara et al., 2020; Bokányi & Hannák, 2020) and ride-pooling (Santi et al., 2014; Alonso-Mora et al., 2017a; Qian et al., 2017; Vazifeh et al., 2018; Simonetto et al., 2019; Yan et al., 2020; Ke et al., 2020b). Other platform strategies that have garnered interest in the scientific community are the optimisation of reward schemes (Yang et al., 2020), penalising request cancellations (Wang et al., 2019), service design of pick-up and drop-off locations (Stiglic et al., 2015; Fielbaum et al., 2021), routing and repositioning instructions (Wallar et al., 2018; Braverman et al., 2019; Yu et al., 2019, 2023; Engelhardt et al., 2023), and hiring dedicated drivers to ensure a minimum level of supply (Lee & Savelsbergh, 2015; Dong et al., 2021).

Another body of literature delves into platform regulation and subsidies designed to enhance the social welfare generated within these markets. Explored regulations encompass a range of measures such as limiting platforms' commissions (Zha et al., 2016, 2018a,b; Vignon et al., 2023), imposing fare restrictions (Yang et al., 2022; Li et al., 2022), implementing per-trip or zone-based congestion taxes (Li et al., 2019), setting limits on fleet sizes (Li et al., 2019; Yu et al., 2020; Zhang & Nie, 2022; Li et al., 2022), capping cruising activities (Zhang & Nie, 2022), and establishing a minimum wage for drivers (Li et al., 2019; Benjaafar et al., 2022). Subsidisation strategies aimed at enhancing overall social welfare include subsidising pooled rides (Fang et al., 2017), rides to or from public transport stops (Liu et al., 2023), and socially desirable routes (Ke & Qian, 2023).

While previous studies primarily investigate the strategies of monopolistic ridesourcing providers, several works focus on platform competition in markets with multiple service providers (Zha et al., 2016; Séjourné et al., 2018; Bryan & Gans, 2019; Zhou et al., 2020; Cohen & Zhang, 2022; Zhang & Zhang, 2022). Other studies explore 'coopetition' strategies aimed at addressing the decline in matching efficiency resulting from market fragmentation when multiple platforms compete for demand and supply (Pandey et al., 2019; Vignon et al., 2023; Guo et al., 2023b; Bao et al., 2023).

As two-sided platforms, ridesourcing system performance also depends on travel demand and properties of the local labour market. Prior research on travel demand has looked into the effect of trip density (Kondor et al., 2022), the spatio-temporal distribution of trips (Bimpikis et al., 2019; Bokányi & Hannák, 2020; Soza-Parra et al., 2022; Meskar et al., 2023; Lotze et al., 2023), travellers' sensitivity to delays (Taylor, 2018) and their propensity to sharing a ride with other passengers (Beojone & Geroliminis, 2021; Zhu & Mo, 2022). Supply-side attributes of which the effect has previously been examined include the size of the labour market (Benjaafar et al., 2022), workers' opportunity costs (Cachon et al., 2017; Taylor, 2018) and their sensitivity to income (Dong et al., 2021).

Finally, operating within a broader transportation system, the characteristics of the road network and alternative modes also impact ridesourcing system performance.

The existing literature on this topic is limited to examining the effect of the average vehicle velocity (Bilali et al., 2022; Lotze et al., 2023) and the provision of dedicated parking locations (Xu et al., 2017; Beojone & Geroliminis, 2021).

The above-mentioned works have in common that they rely on aggregate functions for describing ridesourcing supply and demand. In reality, supply and demand are the result of many complex and interdependent decisions by individual (potential) users and suppliers, across various temporal dimensions. Travellers for instance encounter a spectrum of decisions ranging from contemplating the acquisition of a private vehicle depending on the service quality of ridesourcing (a strategic decision) to the choice of registering with a ridesourcing platform (a tactical decision) and accepting specific ride offers (an operational decision). Prospective ridesourcing drivers encounter strategic decisions like investing in a vehicle based on projected earnings and costs, tactical decisions such as deciding about their working days, and operational decisions including their working hours, movement patterns when assigned or idle, and whether to accept or decline specific ride requests.

There are many interdependencies in these decisions. For instance, travellers' and workers' platform utilisation decisions hinge on a prior decision to sign up, often linked with associated costs. Furthermore, agents encounter imperfect information in many of their decision-making processes. Take, for instance, drivers who lack a guaranteed wage; instead, their earnings can fluctuate considerably depending on luck in the matching processes (Bokányi & Hannák, 2020) and on work decisions of other drivers. This underscores that drivers and travellers at least partially rely on (personal and shared) information from past experiences. Consequently, learning and communication processes may wield considerable influence over the supply and demand dynamics in the ridesourcing ecosystem.

The concept of path dependency within processes influencing supply and demand dynamics could imply that minor alterations in initial conditions may lead to vastly diverse market outcomes. For instance, the provision of ridesourcing services — relying on harnessing network effects within the user-driver matching process — might be susceptible to a critical mass (Navidi et al., 2020). Guo & Huang (2022) note that, owing to these network effects, the initial market shares of ridesourcing providers in a duopolistic market significantly influence their equilibrium market shares. When all other factors are held constant, both travellers and drivers tend to opt for the larger platform, as it tends to facilitate superior overall matches, thereby minimising travellers' waiting times and drivers' idleness.

Previous studies have overlooked the intricate nature of disaggregated components within ridesourcing supply and demand, particularly the nuanced spatio-temporal interactions involved in travellers' and workers' decisions and in matching drivers and users. Consequently, these studies fail to consider the influence of path dependencies in ridesourcing supply and demand, neglecting how past conditions or decisions shape the current dynamics of ridesourcing supply and demand. This oversight has led to the following knowledge gaps, hindering a comprehensive understanding of the societal implications of ridesourcing systems:

1. Understanding how ridesourcing system performance may evolve over time. This concerns transitional phases during its evolution as well as day-to-day variations in the steady state arising from stochastic processes in agents' day-to-day and within-day decisions.

2. Comprehending the potential diverse equilibria achievable in ridesourcing provision, stemming from path dependency triggered by initial variations. This encompasses systematic disparities — for instance, differences in market shares in duopolistic markets due to varied entry times — as well as random differences resulting from stochasticity in travellers' and workers' decisions and experiences.

3. Understanding how individual travellers' and drivers' decision-making processes influence ridesourcing market performance. This encompasses various factors including peer-to-peer communication processes, learning behaviour, opportunity costs, registration costs, etc. Furthermore, there is a need to explore the diverse nature of these attributes across the population to better understand the effect of heterogeneity within ridesourcing dynamics.

4. Grasping (possibly long-term) distributional effects within ridesourcing. It includes comprehending which agents ultimately are most likely to utilise ridesourcing platforms, depending on individuals' characteristics such as drivers' opportunity costs, travellers' travel preferences and spatio-temporal trip characteristics.

5. Understanding the robustness of ridesourcing systems to market disruptions, such as regulatory changes, the rise of alternative services, evolving economic situations, or a pandemic.

1.3 Research questions

This dissertation provides an answer to knowledge gaps 1-4, investigating the effect of variables associated with the decision-making processes of the three key stakeholders in ridesourcing markets: platform providers, consumers and suppliers. We do not explicitly vary the properties of the transportation system (Fig. 1.1).
Specifically, the following research question is answered in this dissertation:

How do market features (such as the number of service providers, platform pricing and service type), along with travel demand and labour market characteristics, influence the evolution of ridesourcing systems?

The following sub questions are addressed to answer the main research question:

1. What is the impact of fleet decentralisation in ridesourcing for drivers, travellers and service providers? (*Chapter 2*)

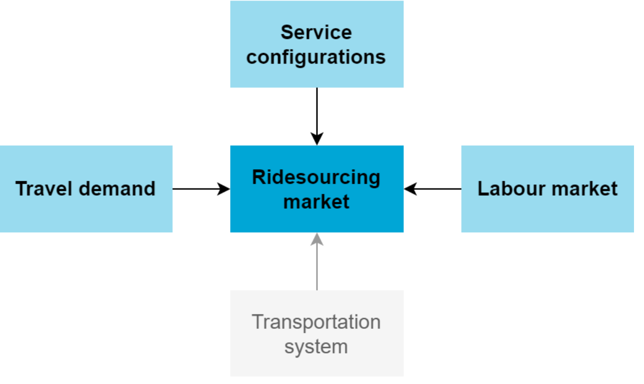


Figure 1.1: Conceptual representation of key factors influencing in ridesourcing provision. In this dissertation, we focus on the effect of service configurations, travel demand and labour market characteristics.

2. What are the main network effects in two-sided ridesourcing markets, and what is their aggregated effect on system performance? (*Chapter 3*)

3. How do ridesourcing performance indicators depend on the degree of socio-economic inequality in society? (*Chapter 4*)

4. How does social welfare from the ridesourcing market differ between duopolistic and monopolistic settings, and under what conditions is each market outcome more likely to emerge? (*Chapter 5*)

1.4 Research approach

We adopt an agent-based modelling approach for representing the decisions of travellers (potential consumers) and job seekers (potential suppliers) associated with the ridesourcing market. Besides modeling within-day ridesourcing operations — such as user-driver matching, user pairing in ride-pooling, and driver repositioning — we also model various day-to-day processes that affect ridesourcing supply and demand. These include platform information diffusion, registration decisions, and daily work choices.

Fig. 1.2 illustrates captured (day-to-day and within-day) interactions between supply and demand in the ridesourcing market. These interactions allow us to model two-sided network effects in ridesourcing provision. The figure identifies which interactions are relevant to each sub-research question and specifies the attributes associated with the labour market, provided services, and travel demand that are investigated in this dissertation. Additionally, it highlights key performance indicators for different market stakeholders as derived from our model.

To answer the first research question, we model the labour supply decisions of drivers, including how they are exposed to platform information and how learn from

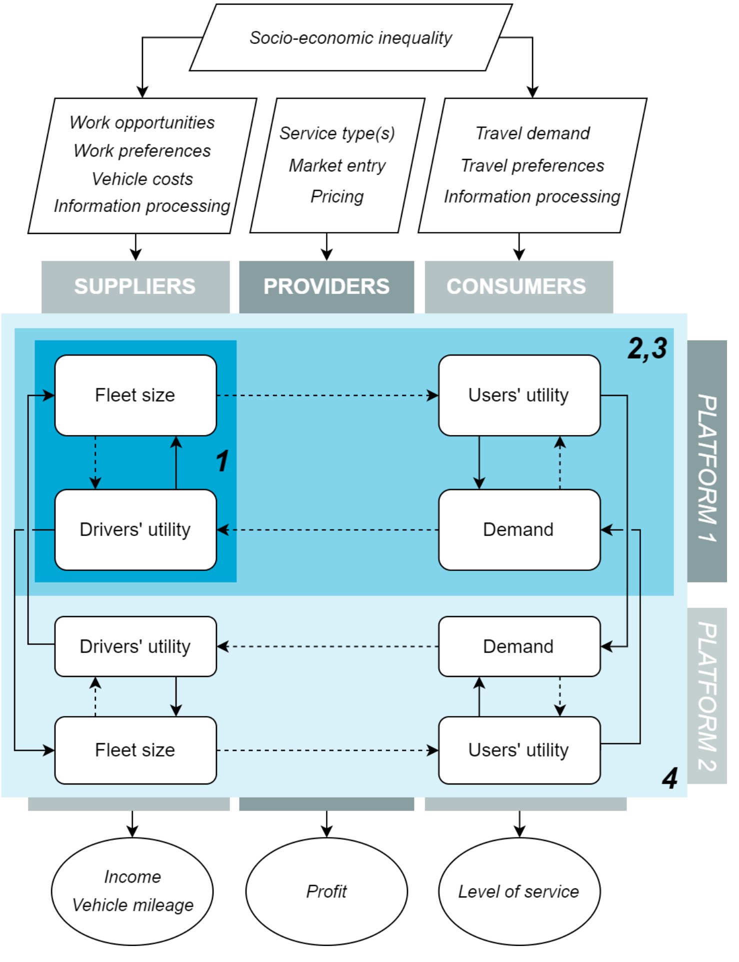


Figure 1.2: Conceptual representation of the methodology adopted in this dissertation, including references to the sub research questions. Solid lines indicate day-to-day interactions, dashed lines represent within-day interactions.

experience. By representing within-day operations, we capture supply-side competition, i.e. the negative feedback loop between ridesourcing supply and driver income. As a reference, we evaluate ridesourcing operations based on fixed fleet sizes, allowing a comparison of the fleet size following from decentralised work decisions with the socially optimal fleet size. Furthermore, we vary job seekers' labour opportunity costs, their work preferences, learning and communication processes, costs incurred to get access to a vehicle, and platform pricing.

To answer the second and third research question, we add the day-to-day decisions of travellers, inducing positive feedback loops (cross-side network effects) between supply and demand. We vary the effect of travel demand characteristics, platform pricing instruments, information processes affecting travellers' and job seekers' decisions, and vehicle costs. To answer the third research question, we vary the degree of heterogeneity in travellers' value of time and job seekers' opportunity costs, mimicking the effect of socio-economic inequality in society.

To address the fourth research question, we model the decisions of job seekers and travellers in a market with two service providers, capturing network effects across platforms. Our approach accounts for individuals that will exclusively use a single platform and individuals that will opt to use multiple platforms simultaneously. We then evaluate the effect of offered service types (private or pooled rides), supply-side market registration costs and travellers' and job seekers' multi-homing preferences.

The following assumptions apply throughout our approach:

- Platforms opt for static pricing, both within-day and day-to-day.
- Ridesourcing operations do not affect travel times in the network, i.e. travel speeds are exogenous variables in our models.
- The emergence of ridesourcing provision does not result in induced demand for travel (but can reduce demand for other modes).
- Operators of alternative modes do not change their operations in response to the state of the ridesourcing market.

1.5 Research context

This study is part of the CriticalMaaS project, funded by the European Research Council and the Amsterdam Institute for Advanced Metropolitan Solutions. The project's focus is to analyse supply and demand dynamics within two-sided mobility markets. It involves exploring the behavioral patterns of both travellers and drivers within these markets and investigating the systemic impacts of their decisions through simulations. To facilitate this, the open-source simulation framework MaaSSim (Kucharski & Cats, 2022) was developed. The day-to-day ridesourcing model presented in this dissertation is integrated into this framework.

The case study used throughout this dissertation aims to replicate ridesourcing operations in the municipality of Amsterdam, the Netherlands. We do so by mimicking the demand for travel, labour market characteristics, the road network, ridesourcing pricing, and attributes of alternative transportation modes. Specifically, we utilise a dataset generated by the activity-based model Albatross (Arentze & Timmermans, 2004) as a point of departure for the representation of travel demand in Amsterdam. Ridesourcing fares mirror Uber's strategy in Amsterdam, excluding surge pricing. In addition to ridesourcing, travellers have access to bicycles, private cars and public transport. Considering the widespread ownership of bicycles in the Netherlands, cycling does not involve any cost. Public transportation choices are based on the route that provides the fastest arrival at the destination, determined using OpenTripPlanner.

Public transport fares correspond to the standard rates established by the Amsterdam transport authority.

1.6 Thesis contributions

1.6.1 Scientific contributions

This dissertation pioneers the examination of ridesourcing market evolution through the development of a day-to-day model for ridesourcing supply and demand, including their interaction. Our innovative approach allows for a comprehensive exploration of the market's dynamics before and after reaching an equilibrium state. By delving into the (stochastic) decision-making processes of potential drivers and travellers, our research offers a holistic understanding of the varied market equilibria that could arise. Moreover, the agent-based nature of our models unveils insights into (possibly long-term) heterogeneous outcomes in ridesourcing provision, accounting for path dependency in supply and demand processes.

Below, we present the key contributions by chapter:

Chapter 2: Evaluating decentralised ridesourcing supply dynamics.

We model the feedback loop between job seekers' ridesourcing market decisions and their earnings. This allows us to compare decentralised ridesourcing supply levels to fleet sizes when platforms opt to employ drivers. We also investigate the socially optimal fleet size, considering the perspectives of travellers, drivers and the service provider. We explore uncharted contextual variables' effects on ridesourcing dynamics, such as registration costs, information diffusion, reservation wage heterogeneity, and more.

Chapter 3: Mapping and modelling two-sided network effects in ridesourcing provision.

First, we outline and explain the key network effects in ridesourcing provision. Then, we model them by incorporating travellers' mode choices — accounting for trip-specific alternatives — in the decentralised model for ridesourcing supply, thereby endogenously modelling ridesourcing demand and supply. This allows for examining how the size of the potential market — i.e. the number of travellers and job seekers — and two-sided pricing strategies impact ridesourcing system performance.

Chapter 4: Investigating the influence of socio-economic inequality on ridesourcing performance.

We investigate the impact of socio-economic inequality on ridesourcing demand and supply by examining the effect of heterogeneity in travellers' value of time and job seekers' labour opportunity costs. We explore platforms' tuning of pricing based on the degree of socio-economic inequality in society, including the consequences for travellers and drivers.

Chapter 5: Analysing duopolistic ridesourcing market outcomes depending on service types and multi-homing behaviour.

We analyse traveller and job seeker choices in an initially duopolistic ridesourcing market, examining conditions favouring either market domination or co-existence. Besides ride-hailing, our study encompasses ride-pooling, allowing the exploration of the impact of platforms' service type on platform co-existence. We comprehensively assess ridesourcing effects on vehicle kilometers, considering drivers' deadheading decisions as well as modal shifts following ridesourcing provision. This study also pioneers the investigation of market outcomes in scenarios where some travellers and job seekers engage in multi-homing while others do not.

1.6.2 Societal contributions

This dissertation delves into the evolution of ridesourcing markets depending on diverse aspects such as ridesourcing configurations, pricing strategies, travel demand, and labour market properties. Specifically, it examines drivers' earnings, traveller experience, the total vehicle distance associated with ridesourcing, and service providers' profitability under these conditions, shedding light on underlying mechanisms. These insights may inform effective regulations and subsidies to enhance societal outcomes of ridesourcing in urban settings worldwide.

For example, in Chapter 2 we compare fleet sizes and driver earnings between two-sided ridesourcing platforms and one-sided mobility services. Such an analysis unveils the prisoners' dilemma in the decision to work for a ridesourcing platform, advocating for regulatory interventions to ensure fair driver earnings. Furthermore, our assessment of two-sided pricing strategies (Chapters 2-5) highlights the trade-offs that exist between user experience, driver earnings and platform revenue, informing possible pricing regulations to safeguard multiple stakeholders' interests.

Chapters 3 and 4 explore the influence of contextual factors like travel demand, the size of the job market and socio-economic inequality on ridesourcing performance, including two-sided welfare effects. This analysis elucidates likely target markets for ridesourcing. Chapter 5 delves into the societal ramifications based on service offerings, considering modal shifts and deadheading kilometers associated with ridesourcing. Understanding performance indicators under varying competition levels and service types can aid policymakers in shaping market configurations conducive to societal welfare.

Beyond offering insights into potential target markets for ridesourcing providers, shaped by labour market and travel demand specifics, service providers can leverage knowledge gained regarding the transitional phases inherent in ridesourcing markets. This includes understanding their durations, contingent upon various factors. Additionally, understanding how (initial) variations in market shares impact market outcomes can serve as valuable guidance for new market entrants.

1.7 Thesis outline

The main body of this thesis is structured into three parts, as illustrated in Fig. 1.3. Part I delves into network effects within ridesourcing provision. Within this part, Chapter 2 focuses on exploring supply-side network effects, while Chapter 3 illuminates two-sided network effects in ridesourcing provision. Part II, encompassing Chapter 4, examines ridesourcing dynamics in various socio-economic contexts. Part III, consisting of Chapter 5, investigates diverse market structures, i.e. monopolistic and duopolistic markets with private and shared rides. The dissertation is concluded in Chapter 6, which offers comprehensive responses to the research questions posed, provides recommendations for policy makers to improve the social outcomes of ridesourcing markets and suggests potential avenues for future research.

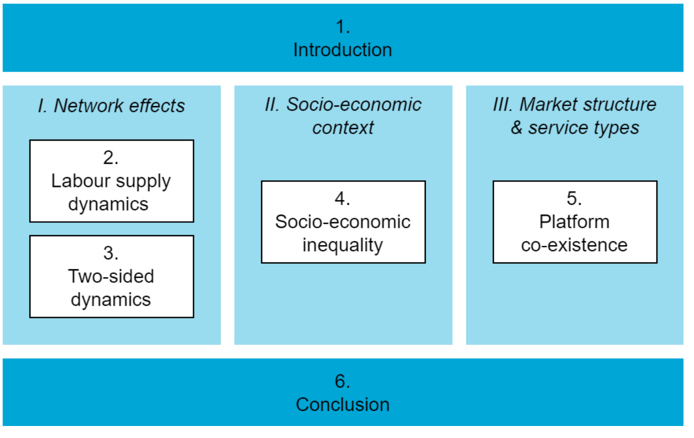


Figure 1.3: Outline of this dissertation.

Chapter 2

Evolution of Labour Supply in Ridesourcing

In this chapter, we investigate the effect of decentralisation in supply - inherent to the gig economy - on the evolution of on-demand transit services. To this end, we propose a dynamic model comprising of the subsequent supply-side processes: (i) initial exposure to information about the platform, (ii) a long-term registration decision, and (iii) daily participation decisions, subject to day-to-day learning based on within-day matching outcomes.

A series of experiments is constructed to study the effect of supply market properties and pricing strategies, providing indications for the need, effectiveness and costs of potential market regulations. We also compare the fleet size following from individual workers' decisions to the fleet size in one-sided service provision, based on profit-maximisation or maximisation of social welfare considering the perspectives of travellers, drivers and service providers. We specifically investigate dynamics in ridesourcing supply, resulting from growing ridesourcing awareness and path dependency in workers' registration and participation decisions.

This chapter is based on the following article:

de Ruijter, A., Cats, O., Kucharski, R., & van Lint, H. (2022). Evolution of labour supply in ridesourcing. *Transportmetrica B: Transport Dynamics, 10*(1), 599-626.

2.1 Introduction

In many service industries the role of businesses is shifting from service provision to facilitating the exchange of services, typically through the creation of virtual two-sided marketplaces. When suppliers in a two-sided market are individual contractors rather than businesses, the market is considered to be part of the gig economy. In contrast to traditional fixed labour contracts offering long-term security to all parties involved, labour in the gig economy is organised through more flexible arrangements. Not only does this allow service providers to respond more adequately to changes in demand than operators with more traditional forms of labour, it also means that they may be exempted from paying employee benefits (Prassl & Risak, 2015). Unfortunately, recent protests demonstrate that the value gig workers derive from the flexibility to set their own working schedules (Hall & Krueger, 2018; Chen et al., 2019) may not outweigh the loss of financial security associated with flexible labour agreements. While the social desirability of these new forms of labour agreements is disputed, the gig economy has gained ground across many industries.

Transportation is a predominant example with platform businesses in food delivery (Just Eat Takeaway, Uber Eats, DoorDash), package delivery (Amazon Flex) and passenger services (Uber, Lyft, DiDi). Service providers in the third category are commonly referred to as ridesourcing providers or Transport Network Companies (TNCs). Typically, ridesourcing businesses reward drivers based on satisfied demand rather than based on time spent working for the platform. Hence, in contrast to traditional transit operators with employed drivers, they do not bear the cost of excess labour available through their platform. This is beneficial especially in times of rapidly declining travel demand, such as during the COVID-19 pandemic.

The question remains whether a decentralisation of supply is truly a win-win for service provider, suppliers and consumers in the ride-hailing market. Early evidence suggests that in addition to losing access to social provisions related to employment, ridesourcing drivers may receive inadequate financial compensation for supplied labour. In Chicago for example, strong competition between suppliers has led to average driver earnings below the local minimum wage (Henao & Marshall, 2019). Besides suppressing driver earnings, oversupply contributes to road congestion by inducing repositioning by idle drivers waiting to be matched (Beojone & Geroliminis, 2021). Travellers on the other hand may benefit from an oversupplied market through low waiting times and few denied requests.

Sustained supply of labour to a platform with low payouts suggests that the tragedy of the commons may apply to the ridesourcing market. It occurs when excessive participation leads to a depletion of the total value derived from participation on the platform. A potential reason why drivers may continue to participate under these conditions is that they have limited alternative opportunities in the labour market. Oversupply in the ridesourcing market may also be explained by large temporal variations in labour opportunity costs underlying the value of flexible work (Chen et al., 2019; Ashkrof et al., 2020). When a potential driver is not involved in alternative activities - such as alternative employment or education - on a particular day, (s)he may be tempted to work for the platform even when expected earnings are low. In other words, varying opportunity costs caused by activity schedules may disturb the balancing loop of competition in labour supply.

In contrast, ridesourcing platforms may struggle to attract enough suppliers to the market when the labour market is strong, especially when employment yields high social security benefits. This hampers travellers' chances to find a (quick and cheap) ride. When ride requests have to be rejected or when travellers stop making requests altogether, the service provider is confronted with lost revenue. This may ultimately result in the termination of the service. Farrell & Greig (2017) have observed that the growth of on-demand service platforms in many cities is indeed limited by the availability of workers rather than customers.

In order to comprehend the societal implications of ridesourcing, we thus need to understand how the decentralisation of supply affects the fleet size of a ride-hailing service. Considering the bottom-up nature of ridesourcing supply, its analysis requires investigating system-level effects of factors influencing individual driver's labour decisions. This includes not only strategical decisions by the platform, but also labour market properties and driver characteristics. In this study, we therefore focus on structural supply deficits / surpluses that may exist in the ridesourcing market. Hence, we study labour supply only at the extensive margin as opposed to highly temporal imbalances in supply and demand which may follow from hourly variations in opportunity costs and/or travel demand, i.e. we will capture how many drivers work on a day, but not how long they work on that day.

2.1.1 Ridesourcing system dynamics

The emergence of ridesourcing has not gone unnoticed in the scientific community. In a review of ridesourcing literature, Wang & Yang (2019) have identified four major research problems related to the impact of emerging ridesourcing services. These topics include the effect of ridesourcing on other modes of transportation (Qian & Ukkusuri, 2017; Zhu et al., 2020; Ke et al., 2020b; Yu et al., 2020; Ke et al., 2021), its broader societal and environmental impacts (Rayle et al., 2016; Clewlow & Mishra, 2017; Yu et al., 2017; Jin et al., 2018), competition between service providers (Zha et al., 2016; Zhou et al., 2020), and the effectiveness of regulations in the ridesourcing market (Zha et al., 2018a,b; Li et al., 2019; Yu et al., 2020). A key factor when identifying the societal impacts of ridesourcing is the pricing strategy adopted by the service provider. Hence, many studies revolve around the optimisation of ridesourcing pricing strategies, including the specification of ride fares and driver wages (Banerjee et al., 2015; Taylor, 2018; Zha et al., 2018a,b; Bai et al., 2019; Sun et al., 2019b; Bimpikis et al., 2019; Nourinejad & Ramezani, 2020; Dong et al., 2021).

A common feature of previously mentioned works is that the ridesourcing market is represented using a static steady-state model. While allowing insightful analyses into ridesourcing equilibria, there are two downsides to this approach. First, static models are incapable of explaining system evolution towards proposed equilibria. Second, these models fail to capture key dynamic processes that are inherent to ridesourcing provision. Arguably, the equilibria sketched in previous studies may not be realised in practice. In the following, we distinguish several complex day-to-day processes underlying the emergence of decentralised ridesourcing supply.

First, labour supply decisions are affected by a driver's participation history. Because there is no guaranteed participation reward and drivers lack proper means of communicating with other drivers (Robinson, 2017), drivers' own experiences form an important source of information in the participation decision. Given that ridesourcing earnings are highly sensitive to system variables such as travel demand and other drivers' labour decisions (Bokányi & Hannák, 2020), there may be large day-to-day variations in the average participation reward. Moreover, due to path-dependent spatial relations between successive matchings of drivers and travel requests, ridesourcing earnings may be distributed unevenly among participating drivers. To illustrate, a driver who is assigned to deliver a passenger in a low demand area may struggle to find a subsequent ride. 'Unlucky' individuals with below average earnings may decide to leave the platform before learning that the system average earnings were higher than their personal earnings. Hence, the unpredictability of ridesourcing earnings can affect the amount of labour available for platform operations.

Second, participation may require making financial investments or entering into contracts. Even though entry barriers for ridesourcing are typically lower than those for conventional taxis (Hall & Krueger, 2018), empirical findings still show an increase in vehicle ownership in the population associated with the launch of a ridesourcing service (Gong et al., 2017). This demonstrates that ridesourcing drivers do not necessarily drive for the platform with a vehicle they already owned. In addition, a taxi license or appropriate driver insurance may need to be obtained to enter the ridesourcing market (Baron, 2018). Hence, participation decisions are preceded by a registration decision in which required investments are traded off against anticipated future revenues from participation. The discrepancy in costs between registration (with entry costs) and participation (when entry costs are sunk) implies that studies neglecting registration choice may either overestimate or underestimate the ridesourcing fleet size. This depends on whether the drop in the number of registered drivers outweighs more frequent participation by registered drivers to compensate for the capital costs associated with platform registration (Hall & Krueger, 2018).

Based on a theory of innovation diffusion (Rogers, 2010), there are two more steps preceding drivers' platform participation choice: (1) becoming aware of its existence and (2) being persuaded to gather more information about its utility. Variations in attitudes, preferences and social network may explain why individual agents may undergo these stages at different moments in time. The rate at which potential drivers may start considering registration is relevant because a very rapid increase in supply may lead to sharply decreasing participation earnings. A slow diffusion on the other hand may lead to a prolonged situation with long waiting times and therefore dissatisfied travellers.

To gain a better understanding of equilibria in ridesourcing systems, we need dynamic models that can account for the previously mentioned processes in drivers' labour supply decisions. To the best of our knowledge, applications of day-to-day learning models for ridesourcing systems have been limited to only a few studies.

One of these has represented ridesourcing evolution with learning behaviour by drivers. Djavadian & Chow (2017) proposed a stochastic day-to-day approach with an integrated within-day operating policy, in which travellers choose ridesourcing if it maximises their expected consumer surplus, anticipating travel time based on experience. Drivers supply labour when their learned perceived income exceeds a deterministic income threshold, implying that variables other than expected income that play a role in drivers' labour supply decisions are neglected. The model proposed by Djavadian & Chow (2017) also does not account for the stages preceding participation, such as the registration process. The method is applied only to a minimal case study representing access to and egress from a single railway station, with supply levels limited to 20 drivers or lower.

Cachon et al. (2017) and Yu et al. (2020) propose a semi-dynamic model consisting of a registration phase and a participation phase. Both phases are strictly separated in time, which means that the model cannot capture interactions between participation decisions of existing drivers and the registration decisions of potential drivers. Dong et al. (2021) apply a similar methodology when studying ridesourcing service providers opting for a dual-sourcing strategy. Drivers in their study first decide whether they take up an employment offer by the provider, giving up work schedule flexibility in return for reduced income uncertainty. In the second phase, those that rejected the offer decide on platform participation. Drivers are only offered employment once, i.e. there is no feedback loop between participation and employment. The aforementioned studies apply macroscopic models to represent the within-day matching process, neglecting complex disaggregate spatio-temporal within-day relations between supply, demand and service provider that influence drivers' labour supply decisions.

2.1.2 Study contributions

We represent the long-term evolution of ridesourcing supply by explicitly considering complex interactions between within-day ride-hailing operations, registration barriers and day-to-day variations in opportunity costs. We do so by proposing a day-to-day learning model with a decentralised labour supply, explicitly distinguishing between two dimensions: registration and participation. For platform registration, we develop a probabilistic agent-based model that accounts for registration costs, opportunity costs and anticipated income levels. We propose a macroscopic model based on an epidemiological process to represent diffusion of information between registered and non-registered drivers, concerning the awareness of and satisfaction with the ridesourcing platform. For the daily participation decision, we establish a probabilistic agent-based choice model that acknowledges that drivers' daily participation decision is not merely based on the expected income on a given day derived from accumulated day-to-day experience, but which also depends on unobserved factors such as variations in opportunity costs.

We integrate our day-to-day model into MaaSSim, an agent-based discrete event simulator of mobility-on-demand operations (Kucharski & Cats, 2022). The agent-based nature of this model allows us to capture heterogeneity in ridesourcing earnings following from disaggregate and spatially-dependent interactions between demand, supply and platform dynamics in ridesourcing operations, which may affect the emergent ridesourcing fleet.

The model is applied to a case study representing a realistic urban network, with up to 1000 vehicles, to allow for the examination of emergence properties in a decentralised supply market in ridesourcing provision. More specifically, we construct an experiment to find the extent to which labour supply in the market is dependent on the availability and cost of labour in the market. This allows us to answer whether ridesourcing provision risks attaining undesired levels of supply, i.e. over- or undersupplied. In addition, our experiment includes an investigation of the commission rate charged by the platform, in order to explore the implications of profit maximisation in a decentralised market, for both drivers and travellers. Other variables that we study are platform registration barriers and variability in drivers' daily opportunity costs, in order to understand how they characterise supply in ridesourcing provision. Finally, we employ an exhaustive search for establishing the optimal ridesourcing fleet size for travellers, drivers and service provider, which we compare to the equilibrium participation volume in decentralised ridesourcing provision.

2.2 Methodology

We develop an agent-based day-to-day model with driver agents potentially willing to work for the platform. These agents are at any given moment in time in one of three states: uninformed, interested or registered. Uninformed driver agents are potential drivers currently unaware of the existence of the service. Interested drivers are those that have been informed about the existence of the platform and now monitor the average participation reward. They make an occasional registration decision. Once drivers are registered, they make a daily participation choice, based on the expected income that is learned from previous driving experiences. This is simulated by integrating our day-to-day model, comprising of information diffusion, registration and participation, with a within-day ride-hailing model (Figure 2.1). This model simulates within-day interactions between driver agents, traveller agents and the platform agent.

In this section, we describe the five sub models constituting our approach. We also provide more information about the implementation of the model.

2.2.1 Information diffusion

Rogers (1995) argues that the diffusion of information about an innovation is a social process. Individuals seek information from peers to guide the adoption decision, especially from those that have previously adopted the innovation. Information spreading via word-of-mouth is considered to be, to some extent, similar to virus transmission in a network. Hence, many information diffusion models are based on compartment models from epidemics (Zhang et al., 2016). In these models, the population is divided into different classes depending on their current stage of the disease, typically distinguishing susceptible, infectious and recovered agents, although many other com-

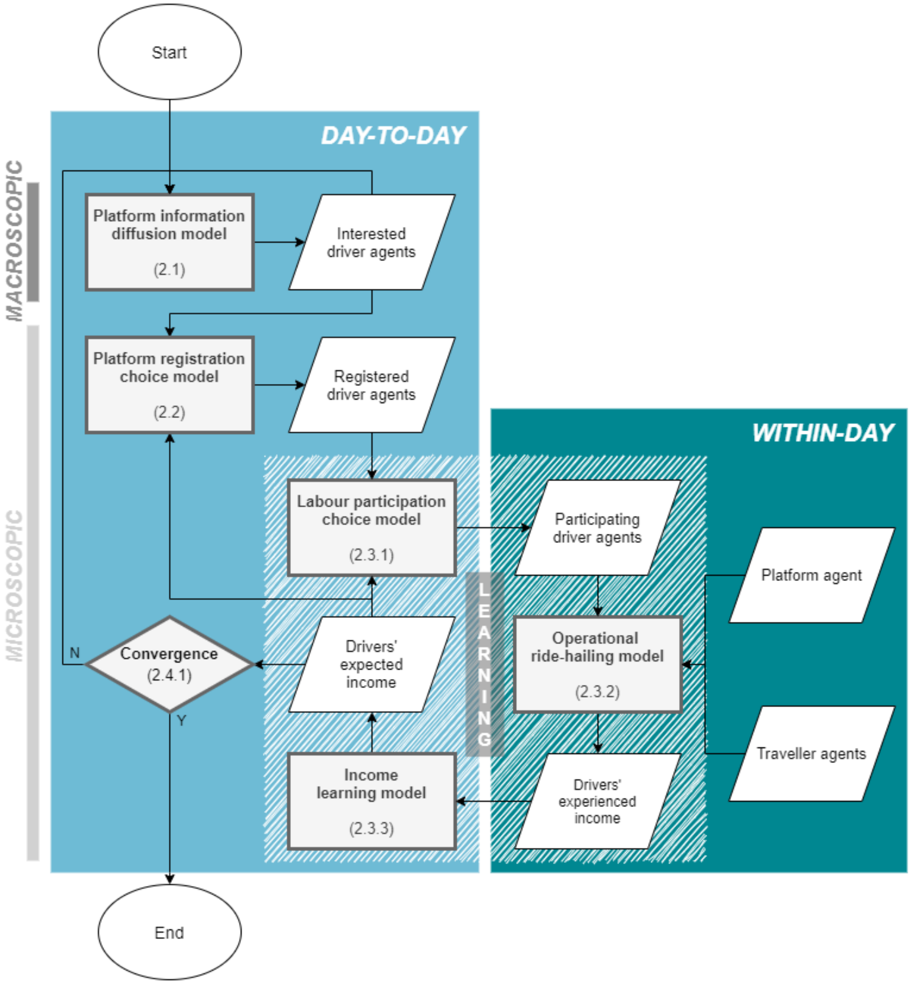


Figure 2.1: Conceptual framework of the proposed dynamic ridesourcing model, including references to subsections in which a particular submodel is explained

partments are possible (Pastor-Satorras et al., 2015). One of the main benefits of representing information diffusion with epidemic compartment models is that they do not require the specification of the underlying (social) network, which is typically hard to observe in word-of-mouth communication.

We assume that an SI model with susceptible (i.e. uninformed) and infectious (i.e. informed) agents suffices. Consider a pool of N potentially interested drivers, of which $I(t-1)$ are informed (i.e. interested or registered) at the start of day $t-1$. If we assume that all uninformed drivers are equally likely to be informed on a given day, then we can formulate the probability for an uninformed driver to be informed at the start of the next day as:

$$p^{\text{inform}}(t) = \frac{\beta_{\text{inf}} \cdot I(t-1)}{N} \tag{2.1}$$

in which β_{inf} represents the average information transmission rate, or more specifically, the probability that information is transmitted in a contact between an informed an uninformed agent multiplied by the average daily number of contacts of agents.

2.2.2 Platform registration

Before informed driver agents can participate, they need to trade off registration costs and participation benefits. In contrast to the approach of Cachon et al. (2017) - one of the few works to represent the registration process in ridesourcing supply - we assume that informed drivers base their registration decision on the average expected income of already registered drivers, rather than on a probability distribution of incomes presented to drivers in advance. Since registration represents a relatively long-term labour decision, we model the decision to be occasional rather than daily. More specifically, we assume that on any given day drivers have a probability γ of making a registration decision.

Drivers register with the platform when the expected earnings from participating exceed the total costs related to participation and registration. Participation cost includes the opportunity cost of the time spent working as well as a potential disutility associated with the driving activity. From hereon, participation cost will be referred to as the reservation wage, a term used in labour economics to define the minimum income level for which drivers are willing to accept specific work (Franz, 1980). Registration costs, on the other hand, correspond to capital expenses which are independent of participation, such as investment in a vehicle and insurance. We formalize drivers' registration choice with a binary random utility model, in which the registration utility of an informed driver agent d is determined by the net income that drivers expect to collect with participation on the platform, which is defined as the average expected income of already registered drivers $\overline{I_t^{\text{exp}}}$ minus a constant penalty C_d to represent capital registration costs. The alternative utility - to remain unregistered - is determined by the reservation wage to represent the time cost of participation on the platform. We apply a logit model with parameter β_{reg}, and an error term ε_{reg} to account for unknown dynamics in registration choice. The particular utilities and the resulting probability of registration for a driver d on day t are, respectively, formulated as:

$$U_{dt}^{\text{regist}} = \beta_{\text{reg}} \cdot (\overline{I_t^{\text{exp}}} - C_d) + \varepsilon_{\text{reg}} \tag{2.2}$$

$$U_{dt}^{\text{unregist}} = \beta_{\text{reg}} \cdot W_d + \varepsilon_{\text{reg}} \tag{2.3}$$

$$p^{\text{regist}}(d,t) = \frac{\gamma \cdot \exp(U_{dt}^{\text{regist}})}{\exp(U_{dt}^{\text{regist}}) + \exp(U_{dt}^{\text{unregist}})} \tag{2.4}$$

2.2.3 Labour participation

In the following, we introduce the specification of registered drivers' participation choice, including how drivers anticipate future income based on personal experience.

Participation choice

Similar to other studies representing ridesourcing supply (Banerjee et al., 2015; Djavadian & Chow, 2017; Taylor, 2018; Bai et al., 2019), we model participation based on drivers' expected income and reservation wage. We assume a positive relation between income and labour supply, thus following the neoclassical theory of labour supply (Chen & Sheldon, 2016; Angrist et al., 2017; Xu et al., 2020). Notwithstanding, there are likely to be other factors in play driving participation choice, such as planned activities for the particular day, which are typically difficult to observe. Therefore, in the determination of the utility to participation or to remain idle, next to the reservation wage W_d and expected income I_{dt}^{exp}, we include an error term ε_{ptp}. We apply a logit model with parameter β_{ptp} and error term ε_{ptp} to represent the degree of randomness in the participation choice model, which indicates the significance of non-observed factors influencing the participation choice. The utility and corresponding probability of participating for a driver d on day t are specified as follows:

$$U_{dt}^{\text{participate}} = \beta_{\text{ptp}} \cdot I_{dt}^{\text{exp}} + \varepsilon_{\text{ptp}} \tag{2.5}$$

$$U_{dt}^{\text{idle}} = \beta_{\text{ptp}} \cdot W_d + \varepsilon_{\text{ptp}} \tag{2.6}$$

$$p^{\text{participate}}(d,t) = \frac{\exp(U_{dt}^{\text{participate}})}{\exp(U_{dt}^{\text{participate}}) + \exp(U_{dt}^{\text{idle}})} \tag{2.7}$$

Ride-hailing operations

The financial reward for participation is modeled with the within-day simulation model of the MaaSSim simulator (Kucharski & Cats, 2022). It allows to capture complex spatiotemporal within-day interactions in ridesourcing between three types of agents: travellers, (participating) drivers and the platform. The following assumptions are made about the operational strategies of these agents in the operational model.

Driver agents' labour supply decisions are limited to the extensive margin, i.e. they will work during all hours considered by the within-day model. Drivers will accept all ride requests assigned to them in this time frame. Unassigned drivers do not reposition, instead they remain idle at their drop-off location until assigned to a new request. Driver agents are faced with per-kilometre operating costs δ.

Each day, a *traveller* agent makes an identical trip for which it requests a ride on the platform. If the time to receive an offer exceeds a threshold θ, the traveller will revoke its ride request. If an offer is received within the tolerance threshold, it will be accepted. Ride offers cannot be cancelled at a later stage.

The *platform* agent offers private rides on a road network with static travel times. It assigns requests to drivers whenever two constraints are met: (1) there are unassigned requests on the platform, and (2) there are idle drivers. It allocates the request-driver pair with the least amount of travel time from the driver's location to the request location. For each transaction, the ridesourcing platform charges a commission rate π. Ride fares on the platform are comprised of a base fare f_{base} and per-kilometre fare f_{km}.

We now specify Q_{req} as the (virtual) queue of unassigned requests on the platform and Q_{driver} as the (virtual) queue of idle drivers. tt_{iu} corresponds to the travel time from the location of an idle driver $i \in Q_{\text{driver}}$ to the pick-up location of an unassigned request $u \in Q_{\text{req}}$. The matching function to find the request-driver pair (u^*, i^*) with the least intermediate travel time is then formulated as follows:

$$(u^*, i^*) = \underset{u \in Q_{\text{req}}, i \in Q_{\text{driver}}}{\arg\min} \; tt_{iu} \tag{2.8}$$

The earnings of ridesourcing drivers follow directly from ride fares paid by travellers. If the daily pool of travel requests is denoted as R, and the direct distance from request location to destination is denoted as s_r, the payout PO_r to a driver for serving a single request $r \in R$ is defined as:

$$PO_r = (f_{\text{base}} + f_{\text{km}} \cdot s_r) \cdot (1 - \pi) \tag{2.9}$$

The total payout PO_{dt} to a driver on a specific day is the sum of the payouts PO_r from requests served by this specific driver on a particular day t. Defining a_{rdt} as a binary assignment variable indicating whether driver d picks up request r on day t, we can formulate driver's daily payout as:

$$PO_{dt} = \sum_{r \in R} PO_r \cdot a_{rdt} \tag{2.10}$$

The net experienced income of a participating driver I_{dt}^{act} can now be formulated as:

$$I_{dt}^{\text{act}} = PO_{dt} - OC_{dt} \tag{2.11}$$

where, in consideration of deadheading distance DH_{dt}, OC_{dt} represents a driver's operational costs on day t:

$$OC_{dt} = (\sum_{r \in R} s_r \cdot a_{rdt} + DH_{dt}) \cdot \delta \tag{2.12}$$

Learning

As stated before, participation choice depends on the earnings that are expected on a particular day. Given that the typical ridesourcing driver has limited connections to other drivers (Robinson, 2017), anticipated earnings are predominantly based on individual experiences. Considering memory decay (Ebbinghaus, 2013) and dynamics in ridesourcing system variables, we cannot assume that drivers weigh all experiences equally. In the absence of empirical evidence for the specification of the learning function in ridesourcing labour supply, we rely on findings from learning in another travel-related context. Bogers et al. (2007) demonstrate that conditional on sufficient experience, learning in route choice can be described using a Markov formulation. In this study, we propose a two-phase learning model for driver's perceived income to differentiate learning behaviour by experienced and inexperienced drivers. When the number of days of participation experience E_{dt} exceeds a threshold ω, learning is described with a Markov formulation similar to Bogers et al. (2007). However, when E_{dt} is below ω, drivers compute the unweighted average past income as a proxy for their expected income, to prevent oversensitive and abrupt reactions to the first few experiences. With the actual experienced income on the previous day specified as $I^{\text{act}}_{d,t-1}$, we define the expected income I^{exp}_{dt} of driver d for day t as:

$$I^{\text{exp}}_{dt} = (1-\kappa)\cdot I^{\text{exp}}_{d,t-1} + \kappa \cdot I^{\text{act}}_{d,t-1} \tag{2.13}$$

in which κ represents the weight attributed to the last experience as opposed to all previous experiences, which is formulated as:

$$\kappa = \begin{cases} 0 & w_{d,t-1} = 0 \\ 1/(E_{dt}+1) & 0 < E_{dt} \cdot w_{d,t-1} < \omega \\ 1/\omega & \text{otherwise} \end{cases} \tag{2.14}$$

in which w_{di} is a binary variable to indicate whether a driver participated on a past day $i \in \{1,\ldots,t-1\}$ and E_{dt} defines the number of days during which the driver has so far gained a participation experience:

$$E_{dt} = \sum_{i \in \{1,\ldots,t-1\}} w_{di} \tag{2.15}$$

2.2.4 Implementation

In this subsection, we describe the definitions for convergence and the number of replications in the experiment.

Simulation framework

We implement our day-to-day driver model in MaaSSim, an open-source agent-based discrete event simulator of mobility-on-demand operations, programmed in Python (Kucharski & Cats, 2022). Both supply and demand are represented microscopically. For supply this pertains to the explicit representation of single vehicles and their movements in time and space, while for demand this pertains to exact trip request time and destinations defined at the graph node level. Travel times in the network are precomputed and stored in a skim matrix.

Convergence

A key property of ridesourcing systems is that the size of the fleet may fluctuate on a day-to-day basis. Due to a random component in participation choice, these variations even occur when the system is otherwise in a steady state. To determine whether a ridesourcing system has achieved a steady state, we therefore need to examine other indicators. We argue that a combined analysis of two indicators suffices to establish the convergence of the system. First, there should be few new entrants in the market, i.e. the number of agents with the ability to participate is relatively stable. Second, the degree of learning among registered drivers needs to be minimal, i.e. their expected reward of participation is relatively stable. Together, those criteria imply that the expected fleet size shows limited variations from day to day. The number of drivers that actually decide to participate may still fluctuate due to stochasticity in the participation decision.

We formalise the convergence criteria by checking whether relative day-to-day changes in the number of registered drivers G_t and the expected income of registered drivers $I_{d,t}^{\text{exp}}$ exceed a convergence parameter φ. The supply evolution process has sufficiently converged when φ, which is set to approach 0, has not been exceeded on k consecutive days:

$$\frac{G_{t-j} - G_{t-j-1}}{N_{t-j-1}} \leq \varphi \quad ,\forall j \in \{0,1,\ldots,k-2,k-1\} \tag{2.16}$$

$$\frac{|I_{d,t-j}^{\text{exp}} - I_{d,t-j-1}^{\text{exp}}|}{I_{d,t-j-1}^{\text{exp}}} \leq \varphi \quad \forall d \in G_t, \forall j \in \{0,1,\ldots,k-2,k-1\} \tag{2.17}$$

Replications

Due to stochastic components in information diffusion, platform registration and participation, we need to replicate the experiment for statistical significance. We determine the number of required iterations $R(m)$ based on a number of initial replications m, with a formula commonly used in stochastic traffic simulations Burghout (2004):

$$R(m) = \left(\frac{S(m) \cdot t_{m-1,\frac{1-\alpha}{2}}}{\overline{X}(m) \cdot \varepsilon_{\text{repl}}} \right)^2 \tag{2.18}$$

where $\overline{X}(m)$ and $S(m)$ are, respectively, the estimated mean and standard deviation of the mean expected income in the population in equilibrium from a sample of m runs, $\varepsilon_{\text{repl}}$ is the allowable percentage error of estimate $\overline{X}(m)$ of the actual mean, and α is the level of significance.

2.3 Experimental design

A series of experiments are constructed for investigating the significance of supply market conditions, platform pricing and service entry barriers in ridesourcing provision. In this section, we introduce the experimental design.

2.3.1 Set-up

We apply the proposed approach to the city of Amsterdam, currently hosting ridesourcing service UberX. It is estimated that in 2019, a total of 8 million taxi or ridesourcing rides took place in Amsterdam, served by 5,000 - 7,000 drivers (Gemeente Amsterdam, 2019). On an average day, this amounts to approximately 20,000 hailed rides. Considering that it is not likely that all people in Amsterdam potentially interested in driving for a ridesourcing platform actually served at least a single ridesourcing ride in 2019, we assume that the total ridesourcing supply pool in Amsterdam consists of 10,000 drivers.

Demand is sampled once from a database of rides longer than 2.5 kilometres, generated by the activity-based model Albatross for the Netherlands (Arentze & Timmermans, 2004). It is assumed that travellers are willing to wait five minutes to be matched after requesting their ride, i.e. patience threshold θ is set to 5. Participating drivers do not make within-day work shift decisions. A single day in the simulation consists of eight hours, corresponding to a typical working day. We simplify the performance of the underlying road network with a universal (constant) traffic speed of 36 km/h on all network links. Ride fares in the experiment are equal to the standard tariffs charged to travellers by Uber in Amsterdam (Uber Technologies Inc., 2020a), i.e. a base fare of €1.40 and an additional €1.21 per kilometre. Unlike Uber's pricing model, there is no minimum ride tariff. In the reference scenario that is used throughout the experiment, the commission rate π is set to Uber's 25% (Uber Technologies Inc., 2020b). As it has been demonstrated that the reservation wage of Uber drivers might be higher or lower than the minimum wage in a given labour market (Chen et al., 2019), we set the reservation wage W_d in the experiment to €80, which is close to the minimum daily wage in the Netherlands (Government of the Netherlands, 2020).

We set the information transmission rate β_{inf} to 0.2 so that after around 50 iterations all potential drivers are likely to be informed. Choice model parameters β_{reg} and β_{ptp} are set to 0.2 and 0.1 respectively, representing that unobserved factors are likely to play a larger role in short-term participation, when drivers have more information about the specification of these variables, compared to registration. With γ set to 0.2, we expect 20% of informed drivers to make a registration decision on a given day. The learning threshold ω is set to 5 days, implying that after five experiences the weight of each new experience in the determination of the expected income has dropped to 0.2, and remains equal afterwards. Convergence parameters φ and k are set to 0.01 and 10, respectively.

With each driver assigned a probability of $10/N$ to be registered at the start of the simulation, we expect an initial registration volume of 10 drivers. Their initial expected income I_0^{exp} is set to the sum of reservation wage W_d (€80 in the reference scenarios) and the daily share of registration costs C_d (€20 in the reference scenarios). All other driver agents start in the uninformed state.

We empirically establish that the computational load of a single day in the simulation scales directly with the number of requests and vehicles in the system, implying that if we represent the real-world population with a 10% sample for supply and demand, similar to other studies applying agent-based models in the transportation field

(Kaddoura, 2015; Bischoff & Maciejewski, 2016), we can reduce the total computational load of our experiment by 90%. Given that we perform a scenario analysis in which each scenario requires multiple replications of our day-to-day simulation approach, we can benefit greatly from the efficiency gain offered by sampling. However, we need evidence that sampling has a limited effect on our simulation results, especially given that ridesourcing may benefit from economies of scale (Zha et al., 2016). Therefore, we compare the resulting system performance indicators for a 10% sample of demand and supply to the indicators when we do not apply sampling. Based on three replications for each scenario, we observe that a less efficient matching algorithm in the scenario with sampled supply and demand may lead to a slightly higher average waiting time for travellers, indicating that simulation based on a 10% sample might lead to slightly overestimated travel times. Remarkably, other performance indicators of the service do not seem to be affected by sampling. The expected income in equilibrium, for example, differs by less than 1%. Only in the early driver adoption stage, with limited supply, we note a discrepancy in the average income of drivers, which is quickly overcome once supply increases. Our analysis demonstrates that registration and participation volumes scale directly from a 10% sample to supply and demand levels representing the full population, which indicates that in this case a 10% sample of supply ($N = 1000$) and demand ($M = 2000$) is sufficiently large to represent ridesourcing dynamics for the whole city.

When deciding how many replications of the experiment are needed, we allow a relative error $\varepsilon_{\text{repl}}$ of 0.01, based on statistical significance α of 0.01.

2.3.2 Scenario design

Supply market

In this part of the experiment, we investigate the extent to which the volume of the pool of potential drivers N is a decisive factor for ridesourcing supply in equilibrium. Compared to the reference scenario (*DP1000* in Table 2.1), which assumes a relatively large pool of potential drivers compared to current supply in the network, in alternative scenarios (*DP200 - DP800*) we test values for N that are smaller, i.e. between 200 and 800 drivers with intervals of 200.

Another supply market condition that is expected to affect emergent ridesourcing supply is the reservation wage, which may be high or low depending for example on the ease of access to alternative sources of income (Baron, 2018; Chen et al., 2019). First, we examine six alternative scenarios in which the reservation wage is considered to be homogeneous across the population of drivers. With these scenarios, labeled *RW50 - RW110* in Table 2.1, we cover the range of reservation wages from €50 to €110. Then, we consider three additional scenarios with heterogeneity in reservation wage W_d, to represent that the opportunity cost of ridesourcing participation may vary across the population due to uneven opportunities in the labour market. We represent the heterogeneity in W_d with a normal distribution in which the mean is equal to the homogeneous reservation wage value from the reference scenario (€80). In scenarios *HR0 - HR30*, we test the effect of reservation wage heterogeneity on ridesourcing

Table 2.1: Scenario design

Label	N (-)	W_d (€)	β_{ptp} (util/€)	π (-)	C_d (€)
DP200	200	80	0.2	0.25	20
DP400	400	80	0.2	0.25	20
DP600	600	80	0.2	0.25	20
DP800	800	80	0.2	0.25	20
DP1000*	1,000	80	0.2	0.25	20
RW50	1,000	50	0.2	0.25	20
RW60	1,000	60	0.2	0.25	20
RW70	1,000	70	0.2	0.25	20
RW80*	1,000	80	0.2	0.25	20
RW90	1,000	90	0.2	0.25	20
RW100	1,000	100	0.2	0.25	20
RW110	1,000	110	0.2	0.25	20
HR0*	1,000	$\mathcal{N}(80,0)$	0.2	0.25	20
HR10	1,000	$\mathcal{N}(80,10)$	0.2	0.25	20
HR20	1,000	$\mathcal{N}(80,20)$	0.2	0.25	20
HR30	1,000	$\mathcal{N}(80,30)$	0.2	0.25	20
IV005	1,000	80	0.05	0.25	20
IV010	1,000	80	0.1	0.25	20
IV020*	1,000	80	0.2	0.25	20
IV050	1,000	80	0.5	0.25	20
IV100	1,000	80	1.0	0.25	20
CF5	1,000	80	0.2	0.05	20
CF15	1,000	80	0.2	0.15	20
CF25*	1,000	80	0.2	0.25	20
CF35	1,000	80	0.2	0.35	20
CF45	1,000	80	0.2	0.45	20
CF55	1,000	80	0.2	0.55	20
RC0	1,000	80	0.2	0.25	0
RC10	1,000	80	0.2	0.25	10
RC20*	1,000	80	0.2	0.25	20
RC30	1,000	80	0.2	0.25	30
RC40	1,000	80	0.2	0.25	40

* Reference scenario

supply with four values for the standard deviation of the reservation wage distribution: €0 (i.e. homogeneous reservation wage), €10, €20 and €30.

Since participation in our approach is modelled with a probabilistic participation choice model, we can also investigate how opportunistic behaviour in labour supply affects ridesourcing supply levels. We do this by varying the participation logit model parameter β_{ptp}, representing the relative weight that drivers assign to income as opposed to other, in our model unobserved, variables. Lacking empirical evidence for the value of β_{ptp}, in scenarios *IV005 - IV100* we test a relatively large range of values: from 0.05 to 1.0.

Platform pricing

The main instrument that ridesourcing platforms hold to steer supply is their pricing strategy, including the ride fare structure and the commission rate, i.e. the proportion of each transaction retained by the platform. We investigate the implications of price settings in the ridesourcing market for drivers and travellers, accounting for the dynamics related to supply, by analysing a series of scenarios covering a relatively large range of commission rates π: from a limited 5% to more than half of the ride fare, 55%, with intervals of 10%. The scenarios are included in Table 2.1 as scenarios *CF5 - CF55*.

Entry barriers

Ridesourcing uptake - and potentially excessive competition - on the supply side may partially be accredited to low entry barriers (Rayle et al., 2016). On the other hand, a lack of capital participation costs may also lead to less frequent participation (Hall & Krueger, 2018). Hence, we investigate the effect of financial entry barriers, such as a taxi license, on emergent ridesourcing supply. We examine five scenarios for which we vary the registration cost parameter C_d, which represents costs that are sunk in participation but not in registration. We consider two extreme scenarios, one in which capital costs are absent, and one in which capital costs add up to half the reservation wage (€40). In the three intermediate scenarios, the relative penalty for registration amounts either €10, €20 or €30. In Table 2.1, the scenarios are labeled *RC0 - RC40*.

2.3.3 User equilibrium optimality

Unlike transportation services in which drivers are employed by the service provider, supply in ridesourcing is a decentralised process centered around the labour decisions of individual drivers. So far, we have considered how to test the effect of labour market characteristics, platform policies and entry barriers on ridesourcing supply, but not yet how the emerging user equilibria compare to supply if controlled by a central service provider or organisations representing the interests of travellers and drivers. Specifically, we investigate the optimality of decentralised ridesourcing supply from three different perspectives:

- *Service provider (platform)*: Aims to maximise the profit from collecting a fee from each transaction between travellers and drivers
- *Traveller union*: Representing the interests of travellers, it aims to minimise travel times and rejected requests. We formalize this objective with a value of time of €8/h, which was found to be the average value for travellers in the Netherlands (Rijkswaterstaat, 2020), and assigning a penalty of €8 for each rejected request.
- *Driver union*: Representing the interests of the driver community, it aims to maximise total driver surplus in the system. The surplus for an individual driver

is defined as the difference between its actual earnings I_{dt}^{act} and reservation wage W_d (Chen et al., 2019).

We search for the optimal fleet size for the three different parties by performing a brute-force search, testing their respective objective functions for a single day assuming various participation volumes. We test values around the user equilibrium in the base scenario: from 20 to 300 participating drivers in steps of 20, i.e. $m = [20, 40, \ldots, 280, 300]$.

2.4 Results

We analyse the results of our experiments focusing on the evolution process of ridesourcing and specifically the role of the supply market and pricing policy. Table 2.2 contains the comprehensive list of KPIs on day 200 of our iterative simulation, when all replication runs have converged to an equilibrium.

2.4.1 Phases in ridesourcing provision

In this subsection, we examine the evolution of ridesourcing supply and the implications for suppliers specifically for one of the reference scenarios, *RW80* (Figure 2.2a,b). In accordance with the specification of the information diffusion process, all 1,000 driver agents are eventually informed about the existence of the service. In equilibrium, considering multiple simulation iterations, after 200 days on average less than half of those agents (420) are registered, of which on a typical day approximately a third participate (145 drivers). We identify five phases in the evolution process:

1. *Day 0 - 10*: Due to a lack of information, few driver agents have registered, meaning participation is low as well. Participating drivers profit from a lack of competition and can make a high profit.

2. *Day 10 - 20*: Information transmission speeds up. Informed drivers are likely to register as they observe a high average income. Participation increases rapidly, leading to a collapse in the experienced income. Drivers start to learn that their anticipated income may not be feasible.

3. *Day 20 - 50*: Information diffusion continues. Drivers further downscale their income expectation based on new participation experiences. As a result of the drop in expected income, the average driver participates less frequently. The number of registered drivers still increases, albeit at a slower pace than before. As a consequence, the total participation volume increases marginally, leading to a further decrease in the experienced income level.

4. *Day 50 - 100*: All drivers are now informed. Registration continues at a decreasing pace, yet participation increases only marginally since individual drivers participate less frequently, as a result of the continuing decrease in the average expected income.

Table 2.2: KPIs in equilibrium for all scenarios

Label	**Informed drivers**	**Registered drivers**	**Participating drivers**	**Expected income, mean (€)**	**Expected income, std. among drivers (€)**	**Experienced income, mean (€)**	**Experienced income, std. among drivers (€)**	**Satisfied requests (%)**	**Average waiting time (s)**	**Daily platform profit (€)**	**Convergence criterion satisfied (day)**
DP200	200	198	125	85.96	10.49	89.36	19.93	100.0	162.8	5217	47.0
DP400	400	301	136	77.56	10.62	82.25	20.75	100.0	153.6	5217	58.8
DP600	600	350	140	75.04	10.57	80.38	21.15	100.0	151.1	5217	68.2
DP800	800	377	142	73.79	10.77	79.48	20.85	100.0	150.5	5217	61.3
DP1000	1000	425	145	71.83	10.29	77.58	21.47	100.0	148.8	5217	64.8
RW50	1000	572	228	45.11	11.38	51.19	21.27	100.0	127.0	5351	58.1
RW60	1000	504	192	54.17	11.33	60.63	22.49	100.0	137.7	5351	68.5
RW70	1000	454	167	63.34	11.21	69.41	22.02	100.0	145.5	5351	62.0
RW80	1000	422	147	72.42	11.03	78.36	21.51	100.0	153.5	5351	64.2
RW90	1000	396	133	81.53	10.81	86.49	21.92	100.0	164.2	5351	74.2
RW100	1000	368	118	90.98	10.21	96.56	20.89	100.0	185.3	5351	75.8
RW110	1000	339	106	100.33	9.76	105.14	17.58	99.7	227.9	5334	71.0
HR0	1000	398	143	71.56	13.62	78.98	23.22	100.0	152.8	5230	70.0
HR10	1000	382	149	67.46	14.23	75.76	24.07	100.0	149.2	5230	55.4
HR20	1000	393	168	60.95	14.01	67.51	24.12	100.0	138.0	5230	52.4
HR30	1000	410	188	55.43	14.49	60.56	22.90	100.0	130.5	5230	53.6
IV005	1000	401	158	70.36	10.67	72.51	22.33	100.0	150.0	5312	56.5
IV010	1000	415	148	72.86	10.32	77.48	20.77	100.0	155.8	5312	60.3
IV020	1000	432	137	74.15	10.30	83.11	20.94	100.0	161.3	5312	65.5
IV050	1000	482	125	75.86	10.63	90.79	21.00	100.0	173.8	5312	68.5
IV100	1000	538	120	77.67	10.51	93.86	20.70	100.0	176.9	5312	91.7
CF5	1000	472	181	73.23	16.91	85.61	30.94	100.0	129.2	1042	56.4
CF15	1000	441	163	72.95	13.11	82.15	25.47	100.0	137.5	3125	62.4
CF25	1000	400	144	72.85	10.24	77.94	20.29	100.0	148.0	5195	72.6
CF35	1000	356	120	72.25	7.61	75.25	14.24	100.0	166.1	7265	73.4
CF45	1000	240	70	70.70	3.88	72.04	8.26	86.7	363.3	7962	77.0
CF55	1000	52	11	67.03	2.08	67.29	4.14	16.9	194.1	1751	18.4
RC0	1000	885	168	62.52	10.73	69.30	22.75	100.0	143.4	5394	68.3
RC10	1000	632	157	66.57	10.95	74.35	21.72	100.0	148.6	5388	63.0
RC20	1000	429	149	72.12	11.19	78.13	20.49	100.0	152.9	5384	68.7
RC30	1000	287	138	78.87	11.08	84.04	20.53	100.0	158.0	5384	60.0
RC40	1000	205	128	85.84	11.24	89.75	19.09	100.0	164.1	5383	55.7

5. *Day 100 - 200*: Equilibrium is reached. Registrations and the decrease in experienced and expected income are now limited. Participation remains constant over time.

There are two aspects in Figure 2.2b worth highlighting. First, the average expected income of drivers converges to a value below the average experienced income. Figure 2.2c provides an explanation for the discrepancy in expected and experienced income: drivers with a low expected income are relatively unlikely to participate compared to drivers with a higher expected income, and consequently less likely to 'update' their expected income based on a new (likely more positive) driving experience. Convergence is reached when the average experienced income is equal to the average

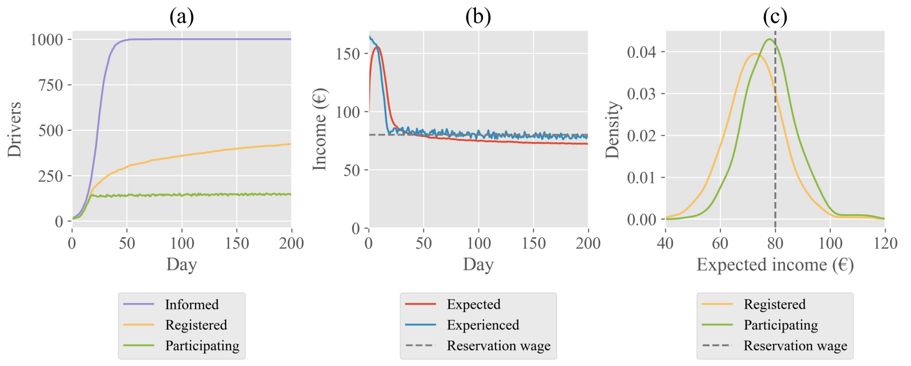


Figure 2.2: (a) The evolution of the number of registered, informed and participating drivers, (b) the evolution of the average expected and experienced income, and (c) the distribution of expected income for participating drivers versus registered drivers in equilibrium

expected income of participating drivers, which is higher than the average expected income of all - also non-participating - drivers. Second, the presented evolution process demonstrates that, when we assume that variables other than expected income play a role in participation choice, the average daily income of participating drivers on the platform may converge to a value below the reservation wage (Figure 2.2b). This can be attributed to unobserved variables in participation, like scheduled activities for a given day, which cause a significant group of drivers to work even when their experienced income is below the reservation wage (Figure 2.2c). In fact, more than half of the drivers that participate on a given day in the equilibrium expect to earn less than their reservation wage. This finding emphasizes that the main value of a ridesourcing service may be found in the flexibility it offers, as suggested also by Chen et al. (2019), rather than in providing a satisfactory level of income over a longer period of time.

2.4.2 Supply market conditions

In this subsection, we present the effect of the size of the driver pool, the reservation wage and unobserved variables in participation on dynamic ridesourcing provision. The information diffusion process is not affected in scenarios, except for those with an alternative size of the driver pool (see Equation 2.1).

Driver pool

When the pool of drivers is limited to 200 (scenario *DP200* in Table 2.1), we find that an equilibrium state is reached around day 50 (Table 2.2). In this state, nearly all potential drivers have registered (Figure 2.3e) and the participation frequency is fairly stable at a high level (Figure 2.3f). When the pool of potential drivers is larger, there are still unregistered drivers left around this time in the simulation, of whom a part decides to sign up in a later phase. This explains why the transition process takes longer in our experiment when the pool of potential drivers is large.

For 200 potential drivers, we find an equilibrium average expected income for registered drivers that exceeds their reservation wage by nearly 10%. In all other scenarios, representing supply markets of 400 potential drivers or more, the average drivers fails to match the reservation wage, falling short by 5 - 10% (Figure 2.3a). It is striking that there seems to be little difference in service performance when a supply market consists of 1000 drivers as opposed to 400 drivers. In both cases, after approximately 25 iterations supply is sufficient to saturate the market and serve all requests in the system (Figure 2.3b), without a significant difference in the average waiting time for travellers (Figure 2.3c). Figure 2.3d shows that the similarity in travellers' level of service follows directly from the daily participation volume, which is approximately equal in both scenarios. Apparently, 600 additional potential drivers in the supply market only yield around 125 more registrations around the 200th day (Figure 2.3e), while those that are registered also participate less frequently when the potential supply market is large (Figure 2.3f), on average 34% versus 46% of the days.

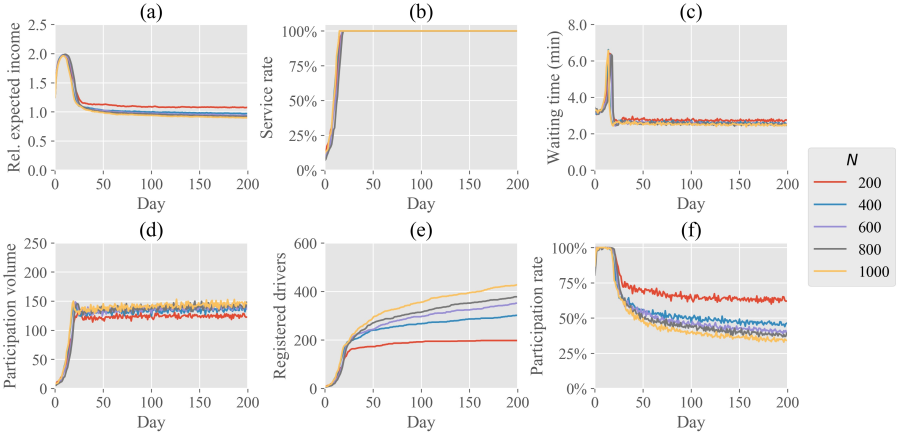


Figure 2.3: The effect of the size of the driver pool on the evolution of (a) the expected income of registered drivers as ratio of their reservation wage, (b) the share of requests that are satisfied, (c) the average waiting time for pick-up for travellers, (d) daily participation volumes, (e) the total number of registered drivers, and (f) the share of registered drivers that participate

The finding that ridesourcing supply converges to an invariant participation volume for different sizes of the labour supply market, as long as the total supply volume is relatively high compared to demand, demonstrates the existence of a balancing effect in ridesourcing supply. In such a market, the frequency of participation compensates for the size of the pool of registered drivers, which means that negative consequences related to oversupply have an inherent upper bound. Notwithstanding, in this upper bound, expected income may be below the reservation wage. Only when the size of the supply market is limited to a value close to the invariant participation volume when the supply market is sufficiently large, we find expected income to exceed the reservation wage. This resonates with the introduction of supply caps, implemented for example in New York City, in raising ridesourcing drivers' average income. The results also show that travellers may not suffer much from a supply cap, at least as long as the cap is set to a sensible level.

Homogeneous reservation wage

Based on our experiments, the reservation wage of potential drivers has a minor effect on the duration of the transition process. The equilibrium condition is reached marginally more quickly when the reservation wage of drivers is low (Table 2.2). This may be caused by more registrations in an early phase of the evolution (Figure 2.4e) due to lower labour opportunity costs. While there are still new registrations in a later phase, the relative increase in the size of the pool of registered drivers is low compared to scenarios with higher reservation wages.

Remarkably, we find that in equilibrium the ratio between expected income and reservation wage is constant for various reservation wages (Figure 2.4a), slightly under 1. It means that as the reservation wage in a market increases, the expected income in equilibrium increases proportionally. The effect of reservation wage on the level of service for travellers seems to be limited. Even in scenario *RW110*, in which labour costs are least favourable for supply, i.e. the reservation wage equals 110 euros, supply is sufficient to serve all requests (Figure 2.4b), albeit travellers are confronted with longer travel times than in scenarios with a lower cost of labour (Figure 2.4c). The additional waiting time is, however, limited to a maximum of two minutes and thereby fairly limited. The differences in waiting time stem from participation volumes that vary between 100 and 230 for different specifications of the reservation wage (Figure 2.4d). Lower participation when labour supply is costly results both from fewer registrations (Figure 2.4e) and less frequent participation among those registered (Figure 2.4f).

The results imply that a weak labour market, associated with low reservation wages, leads to reduced income levels for suppliers in the ridesourcing market, because new suppliers are attracted to the market as a result of a lack of alternative employment, creating competition for pick-ups. Ridesourcing providers on the other hand can potentially profit from the inflow of supply in times of economic recession by means of reduced waiting time for travellers, which may attract new demand, or alternatively, by giving them the opportunity to increase the commission rate without sacrificing the level of service for travellers.

Heterogeneous reservation wage

It can be expected that the minimum income that drivers want to collect with ridesourcing participation is not equal for all drivers, for example because some drivers have better access to alternative employment than others. To capture reservation wage heterogeneity, one of the set of scenarios included in our experiment is directed at

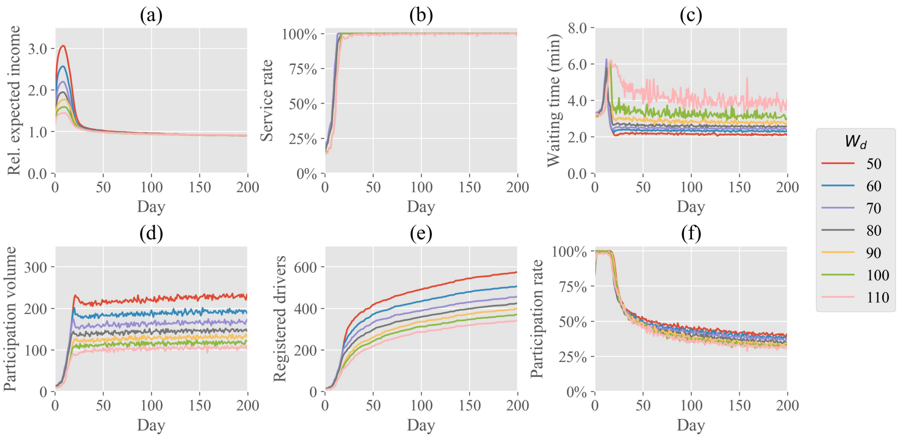


Figure 2.4: The effect of (homogeneous) reservation wage on the evolution of (a) the expected income of registered drivers as ratio of their reservation wage, (b) the share of requests that are satisfied, (c) the average waiting time for pick-up for travellers, (d) daily participation volumes, (e) the total number of registered drivers, and (f) the share of registered drivers that participate

investigating ridesourcing supply for different reservation wage distributions, with the same mean μ as the reference scenario but different standard deviations σ.

Figure 2.5a shows that when there is a lot of variation in drivers' reservation wage (scenario *HR30*), the expected income of registered drivers in equilibrium is relatively low. Yet, a high value for σ does not seem to lead to a slower registration process (Figure 2.5b). In fact, participation appears to be higher with strong heterogeneity in the reservation wage (Figure 2.5c). Figure 2.5d demonstrates that in such a scenario, a relatively high share of registered drivers has a low reservation wage, meaning that they are relatively like to supply labour on a given day, even when they expect a low income. It explains also why registration (Figure 2.5b) peaks early in a scenario with high σ: drivers with a reservation wage below the mean benefit significantly from registration and are thus relatively likely to register. Due to the quick influx of drivers and the fact that drivers that are still unregistered have a relatively high reservation wage, registrations then slow down quickly. High participation volumes in scenarios with strong heterogeneity result in a low average income for drivers in the system (Figure 2.5e) and slightly lower waiting times for travellers (Figure 2.5f).

The results imply that with a high degree of inequality in the labour market, ridesourcing markets may be flooded with drivers with limited labour opportunities elsewhere. Due to their weak position in the labour market, they are willing to work for ridesourcing platforms even when wages are low, providing competition for other participating drivers. Our experiment demonstrates that high participation may only yield limited benefits in terms of the average waiting time for travellers, while the income for drivers may be significantly lower than in scenarios with lower participation. We

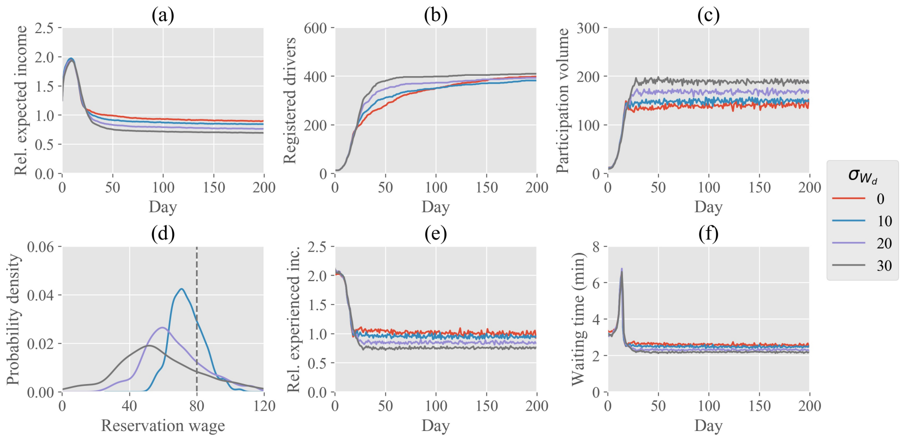


Figure 2.5: The effect of heterogeneity in reservation wage on (a) the evolution of the average expected income of registered drivers as ratio of their reservation wage, (b) the evolution of the total number of registered drivers, (c) the evolution of daily participation volumes, (d) the probability density function of reservation wage for registered drivers, (e) the evolution of average experienced income of participating drivers as ratio of their reservation wage and (f) the evolution of the average waiting time for pick-up for travellers

conclude that especially in labour markets characterised by large inequalities supply caps may be necessary to guarantee a socially desired minimum income for ridesourcing drivers.

Unobserved variables in participation

Choice parameter β_{ptp} represents the value drivers attach to income as opposed to other variables in participation decisions. A low β_{ptp} indicates that drivers supply labour to the platform more opportunistically, potentially working one day but not the next even when the income they anticipate is the same. Our results show that while β_{ptp} has a limited effect on the average expected income of drivers registered with a platform (Figure 2.6a), there is a clear difference in the average actual income generated by participating drivers (Figure 2.6b). The reason for this discrepancy is that in the scenario with the highest value for β_{ptp} (scenario *IV100*), despite a slightly higher average expected income, on average approximately 40 fewer drivers actually decide to participate compared to the scenario with lowest β_{ptp} (Figure 2.6c). Figure 2.6d provides an explanation for this phenomenon. With expected income as the dominant variable for participation when β_{ptp} is high, a driver that expects to make an income just below their reservation wage is relatively unlikely to participate, and consequently, also to update its income expectation based on new, potentially more positive, experiences. In this scenario, drivers confronted with a negative driving experience are therefore less likely to participate thereafter compared to scenarios with a lower value of β_{ptp}, resulting in a large group of 'dissatisfied' drivers with an income just below the reservation wage, but ultimately also in a (relatively small) group of drivers profiting from the lack of competition when it comes to serving rides. Participating drivers in this scenario earn on average approximately 15% more than their reservation wage, compared to 10% less in the scenario with a β_{ptp} of 0.05. The average waiting time for travellers is, however, also highest in this scenario (Figure 2.6f).

Due to slightly higher expected earnings when income is the dominant factor in the participation decision, more unregistered drivers decide to sign up in later phases of the transition process (Figure 2.6e) compared to scenarios in which β_{ptp} is low. Hence, the equilibrium market state is achieved more quickly when drivers attribute more value to variables other than income.

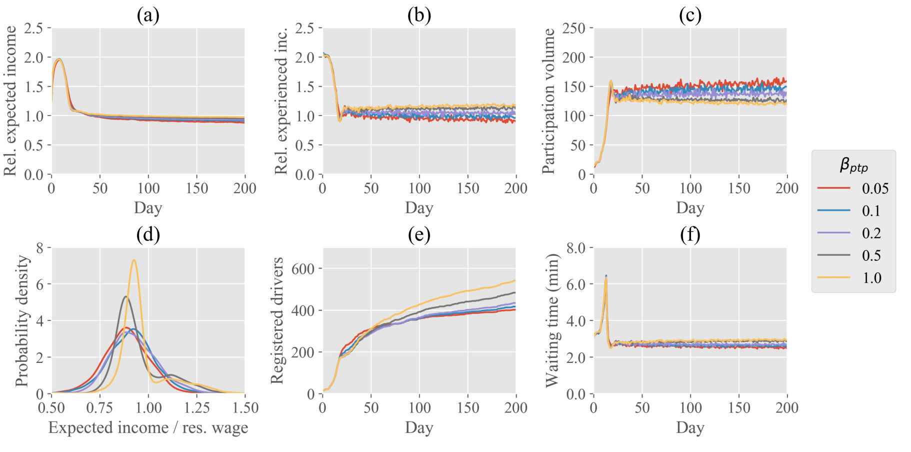


Figure 2.6: The effect of the valuation of income in participation choice on (a) the evolution of the average expected income of registered drivers as ratio of their reservation wage, (b) the evolution of average experienced income of participating drivers as ratio of their reservation wage, (c) the evolution of daily participation volumes, (d) the probability density function of expected income (as ratio of their reservation wage) for registered drivers, (e) the evolution of the total number of registered drivers and (f) the evolution of the average waiting time for pick-up for travellers

To summarize, if we assume that income is not the sole explanatory variable for participation, in line with what is suggested by early research on labour supply of ridesourcing drivers Chen et al. (2019), the average income for participating drivers in a ridesourcing system is likely to turn out relatively low, since every day a portion of drivers is willing to participate for a wage below their reservation wage, increasing competition for supply in the system. This implies that, in such a scenario, the ridesourcing service may be valuable for drivers wishing to supply labour flexibly, utilising the service for example only on days without planned activities or other work, but less so for drivers using the platform as a replacement for a full-time job.

2.4.3 Platform policies

We observe that a lower commission allows for higher earnings in early transition phases (Figure 2.7a), which convinces more potential drivers to register in this time frame (Figure 2.7e). After increased supply-side competition has brought earnings down, the number of new registrations slows down in all scenarios. In scenarios in which initially many drivers register, the relative increase in the size of the pool of registered drivers is lower than in scenarios in which fewer drivers registered. This means that these markets end up in an equilibrium state more quickly. This trend applies however only up to a certain point. When commissions are increased further, corresponding to a commission rate of 55% in the experiment, hardly any drivers will register at all. In that case, the market equilibrium is achieved very quickly.

Interestingly, we find that the expected income of drivers in equilibrium is hardly affected by the commission fee that is charged by the platform (Figure 2.7a). A commission rate of 55% (scenario *CF55*) yields an expected driver income which is not more than 10% lower than when the commission rate is set to only 5%. Ridesourcing users, on the other hand, can strongly be affected by the platform commission rate. The additional inconvenience is fairly limited when the commission rate is set to 35% as opposed to 5%, inducing an average additional waiting time of less than one minute. However, with a commission rate of 45% or 55%, a part of the requests needs to be rejected and the waiting time of the remaining travellers is significantly longer (Figure 2.7b, 2.7c). In fact, when the commission rate is 55%, only 20% of requests can be satisfied in equilibrium. Figures 2.7d and 2.7e demonstrate that supply adjusts itself to the commission rate that is in effect, which provides an explanation for why income levels are largely unaffected, while the level of service for an average ride strongly deteriorates. In this particular experiment, a commission rate of 45% appeared to be the optimal strategy for the ridesourcing provider, generating approximately 8,000 euros per day in equilibrium (Figure 2.7f).

These findings demonstrate that, profit-wise, the collection of a higher share per request may outweigh revenue loss from not being able to serve all incoming requests. This implies that profit maximisation in ridesourcing provision may come at the expense of travellers, who are exposed to longer waiting times and a higher probability of being rejected altogether. Interestingly, ridesourcing drivers are hardly affected by strategical platform behaviour relating to the commission rate, since driver registration is slower when commission rates are high. At the same time, we observe that within a certain range, platform profit can be vastly improved without significantly affecting riders in the system. Our experiment shows that a non-optimal pricing strategy in terms of profit (in the experiment a commission rate of 35% as opposed to 45%), may result in near-optimal platform profit and driver income, with a much improved level of service for travellers. Thus, it might be worthwhile for authorities to consider regulating the commission rate while considering its consequences for service affordability.

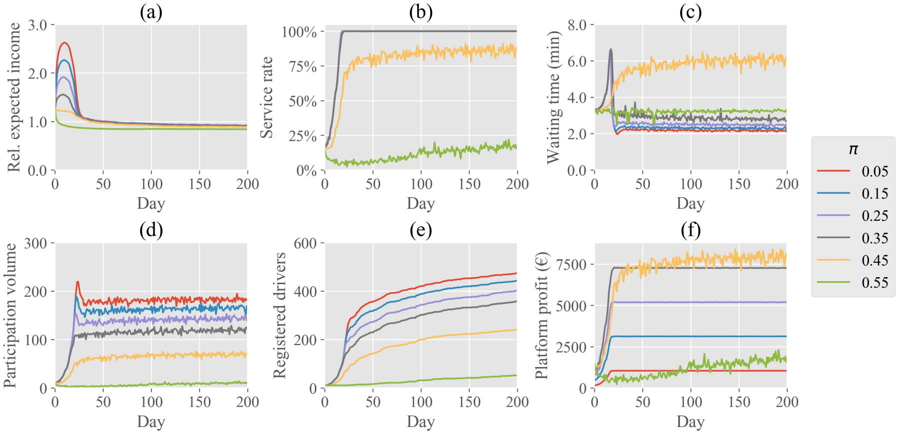


Figure 2.7: The effect of platform commission rate on the evolution of (a) expected income of registered drivers as ratio of their reservation wage, (b) the share of requests that are satisfied, (c) the average waiting time for pick-up for travellers, (d) daily participation volumes, (e) the total number of registered drivers, and (f) daily platform profit

2.4.4 Entry barriers

The need for vehicle, insurance and medallion acquisition may prevent interested drivers from registering with a ridesourcing platform. In some markets, these factors are more prevalent than in others. We mimic markets with different registration regimes by varying registration cost parameter C_d. We find that when registration costs are high, indeed, significantly fewer drivers will register with a ridesourcing platform (Figure 2.8a). The markets corresponding to these scenarios more quickly reach a state in which the number of new registrations is negligible in terms of its effect on the daily number of participating drivers.

We observe that the marginal decrease in registration volume when C_d grows is especially large when registration costs are limited. In a scenario without registration costs (scenario *RC0*), nearly 900 drivers register with the platform, compared to approximately 430 when registration costs add up to €20 per day, and just over 200 when the daily registration penalty amounts to €40. The consequence is that registration costs lead to reduced participation (Figure 2.8b) and ultimately to a higher average experienced (Figure 2.8c) and expected (Figure 2.8d) income. Registration costs can thus be a crucial factor for whether drivers, on average, end up earning above or below the reservation wage. However, considering that registration costs need to be subtracted from the income of drivers, a scenario with C_d equal to 40 still turns out to be least favourable for drivers, as demonstrated by Figure 2.8e. In this scenario drivers that participate earn back on average 75% of their total costs (including the cost of participation and registration), compared to 88% when registration does not bear any costs and the total costs are made up of the reservation wage (and operational costs). This, however, considers only the income of participating drivers. It should not be forgotten that also registered drivers that do not participate on a given day end up with a negative daily profit due to their capital registration costs. In case they cannot easily discard their registration costs, for example by selling their car, it might still be their best option to keep participating, even when this results in a negative net income. Due to reduced supply, travellers may also be worse off when a ridesourcing service comes with high registration barriers for drivers (Figure 2.8d), the extent to which likely dependent on context-specific variables. In our particular experiment, travel times are hardly affected by registration costs.

The results imply that ridesourcing providers, drivers and travellers may also suffer from high entry barriers for potential suppliers. Consequently, policies that aim at reducing the costs related to registration may be beneficial, for example offering affordable vehicle insurance deals to drivers.

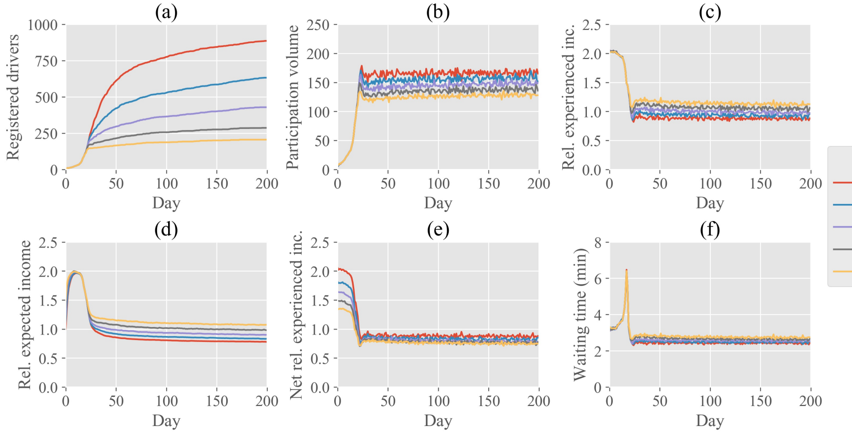


Figure 2.8: The effect of registration costs on the evolution of (a) the average expected income of registered drivers as ratio of their reservation wage, (b) the total number of registered drivers, (c) daily participation volumes, (d) average experienced income of participating drivers as ratio of their reservation wage, (e) average experienced income of participating drivers as ratio of the sum of their reservation wage and daily share of registration costs and (f) the average waiting time for pick-up for travellers

2.4.5 System optimum supply and user equilibrium solutions

In this section, we elaborate on the social optimality of a decentralised ridesourcing supply and discuss the implications for how regulation should be designed to safeguard the interests of different stakeholders in the process. The user-equilibrium solution obtained from our model is compared with the system optimum supply-level that is obtained from a brute force search for the optimal fleet size. Figure 2.9a shows the profit of a ridesourcing platform for different participation levels. Next to the typical ridesourcing scenario in which self-employed drivers get paid based on the rides they serve, we consider an alternative scenario in which drivers, instead, earn a guaranteed hourly wage, while also getting their operational costs reimbursed. Comparing platform profit in both scenarios, we observe a major difference in the financial consequences of oversupply for the service provider. In the typical ridesourcing scenario with fare-based payouts, oversupply does not induce additional costs, because ridesourcing providers pay drivers based on served demand, not participation. In the event of abrupt market contraction (e.g. pandemic crisis), for example, compared to service providers with employed drivers, ridesourcing providers benefit from reduced driver payouts that will partially offset the lower earnings from fares. Hence, a consequence of transaction-based driver payments is that, in contrast to more traditional transit providers paying drivers based on the number of hours worked, ridesourcing providers lack an incentive to curb their supply. In fact, as Figure 2.9b shows, they can benefit from oversupply as it leads to lower travel times for travellers, and thus, potentially, increased demand. These benefits are, however, relatively limited after supply reaches a specific point, which appears to be the minimum supply for which (nearly) all requests can be served. More supply will result in more efficient matches between drivers and travellers, yet yielding a minor effect on the travel times for riders in the system.

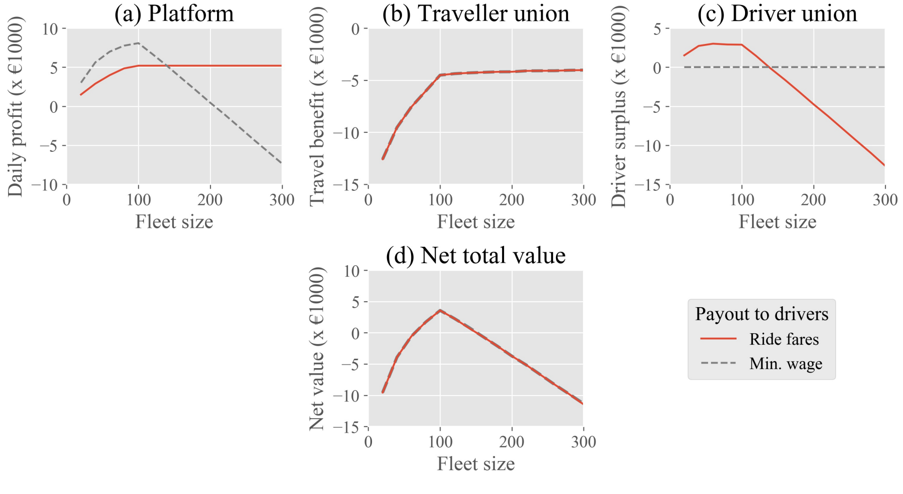


Figure 2.9: Optimality of supply in a system with fare-based driver payouts (assuming a platform commission rate of 25%) and a system with wage-based driver payouts, for (a) the service provider, aiming at maximum profit, (b) the traveller union, minimising costs from waiting and rejected requests, (c) the driver union, maximising driver earnings over the reservation wage, and (d) an authority that evaluates the three previous objectives equally, maximising the summed net value

Figure 2.9a also shows that fare-based driver payments are not necessarily optimal for the service provider. In the presented scenario, the service provider would actually be better off paying an hourly wage to a relatively limited number of drivers, thereby earning the full share of ride fares, than allowing self-employed drivers to collect these fares in return for a fee. It should be noted that this particular example does not consider that employed drivers may be entitled to social benefits and that drivers may not be willing to work for the minimum wage.

When taking the driver perspective, we find that the optimal fleet size in the fare-based scenario is relatively low (Figure 2.9c), peaking between 40 and 100 participating drivers. If supply is even lower, a lot of potential income is lost due to rejected requests, however, if it is higher, excessive competition leads to incomes below the reservation wage, and consequently, dissatisfied drivers. For supply volumes over 120 the total driver surplus is in fact negative. Yet, remarkably, in the reference scenarios of our experiment with decentralised supply, we find average daily participation volumes of approximately 150 drivers in equilibrium. This demonstrates that in the ridesourcing market the notion of 'the tragedy of the commons' may apply, in which the self-interested labour decisions of individual drivers lead to a suboptimal result for the whole group: excessive competition for rides and ultimately low payouts.

If we consider a society in which the societal value of a single monetary unit is independent of the party that it is assigned to, i.e. an extra profit of one euro for the platform or a single driver has the same value as a travel cost saving of one euro for one traveller, we find that the optimal ridesourcing fleet size for our particular experiment is 100 drivers, as illustrated by the total net value sketched in Figure 2.9d. Lower supply levels are undesired from the platform's and travellers' perspective, while higher supply leads to a significantly deteriorated driver income with only a very limited benefit for travellers. The social optimum in this case is thus considerably lower than the user equilibrium, which depicts the potential value of supply caps in ridesourcing markets. Although ridesourcing providers are typically reluctant to accept the implementation of supply caps, our analysis illustrates that their negative effect on rider level of service and ultimately platform profit may be very limited, especially in a saturated market. In this particular case, a reduction of supply from 300 to 100 drivers only induces a single minute of extra waiting time per request.

We note that the socially optimal fleet size for ridesourcing services is equal to that of a transit service with employed drivers, because the objective function for the net total value ultimately contains the same elements: revenue from fares, operational costs and labour participation costs. The only difference is the distribution of those over different stakeholders. If a society indeed considers a single monetary unit equally valuable to all stakeholders, it can thus be stated that only the fleet size of an on-demand transit service matters from a societal perspective, not whether drivers are paid for participating or based on the travel requests they satisfied.

2.4.6 Model sensitivity

Learning

Learning parameter ω indicates how drivers value recent experiences compared to preceding experiences over time. A low value of ω corresponds to a situation in which drivers assign a relatively high value to their recent experience (see Equation 2.14), for example because they believe old experiences are not representative for the present state of the system or because they cannot perfectly memorize their income from previous days. In contrast, if ω goes to infinity, drivers' expected income equals their average experienced income. In this study, we assumed ω to be equal to 5, indicating that the weight of new experiences decreases to 0.2 within 5 days, and stays constant thereafter. To establish to what extent the results presented in this section are specific to the learning parameter, we have repeated the experiment for the reference scenarios, while varying the value of the learning parameter ω between 3 and 100.

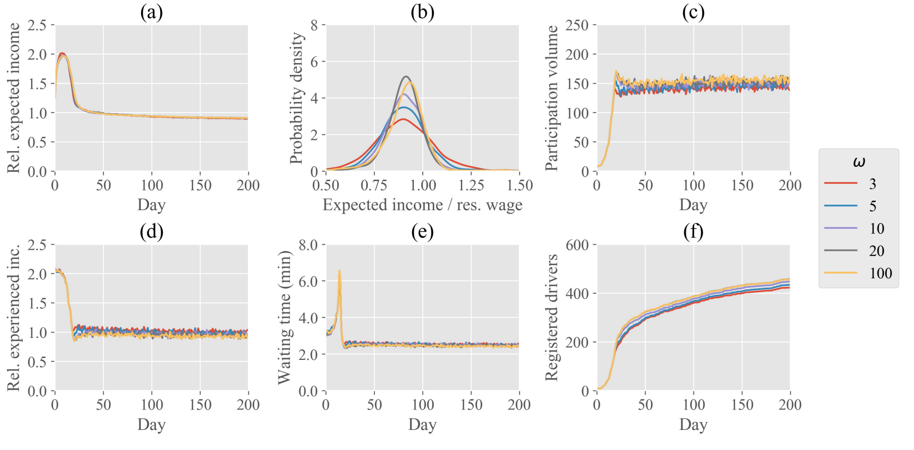


Figure 2.10: The effect of the rate of learning on (a) the evolution of the average expected income of registered drivers as ratio of their reservation wage, (b) the probability density function of expected income (as ratio of their reservation wage) for registered drivers, (c) the evolution of daily participation volumes, (d) the evolution of average experienced income of participating drivers as ratio of their reservation wage, (e) the evolution of the average waiting time for pick-up for travellers and (f) the evolution of the total number of registered drivers

We find that ω has a limited effect on ridesourcing provision. One of the notable differences is that, although the mean expected income in equilibrium is unaffected by ω (Figure 2.10a), the distribution of expected income over registered drivers differs (Figure 2.10b). This can be explained by the fact that when ω is small, drivers are more likely to 'overreact' to a single negative experience, resulting in a pool of 'unsatisfied' drivers with expected income levels significantly below the reservation wage. These drivers will not be tempted to participate again, limiting participation on the platform (Figure 2.10c) and driving up the experienced income (Figure 2.10d) and ultimately the expected income of the other registered drivers (Figure 2.10b). It also results in a minor difference in the average waiting time for travellers (Figure 2.10e). Moreover, we establish that registration volumes slightly diverge in an early stage of adoption (Figure 2.10f). The reason is that when ω is small, drivers more quickly observe that earnings are dropping (Figure 2.10d), which they communicate to drivers that have not yet registered. Nevertheless, the effect of ω was found to be limited and we do not expect a major impact on the main findings regarding dynamics in ridesourcing supply.

Information diffusion

This study considers that drivers need to become aware about the existence of a ridesourcing service before they can supply labour to it. To this end, we introduce an information diffusion process with a transmission rate β_{inf} of 0.2. Lacking empirical evidence of the specification of the information diffusion process, we need to test whether our findings also apply under different diffusion settings. We test four alternative values for β_{inf}, ranging between 0.05 and 1.0. We find that, given a value for β_{inf} that allows (nearly) all drivers to be informed at the end of the simulation (Figure 2.11a), the specification of the diffusion process has hardly any effect on labour supply in equilibrium. The different scenarios for β_{inf} converge to the same participation volume (Figure 2.11b), with a similar average expected income (Figure 2.11c), average waiting time for travellers (Figure 2.11d) and service rate (Figure 2.11e), which demonstrates the generalisability of the results, concerning the value of β_{inf}. Although the indicators are similar in equilibrium, we note clear differences in the adoption process. When β_{inf} is high, many drivers become aware about the service at the same time. In an early phase of adoption (phase 1 as introduced in Subsection 2.4.1), when there are few drivers supplying labour to the platform and income levels are high, this leads to a big registration peak (Figure 2.11f) and excessive participation, with relatively low driver incomes and limited waiting times for travellers. In scenarios with a lower information transmission rate we do not observe such a peak in participation, but rather a steady increase towards the equilibrium value. As a consequence, in scenarios in which communication about innovations takes place slowly, it takes longer before the level of service reaches a satisfactory level, with the large majority of rides accepted and a relatively low average waiting time for travellers.

2.5 Conclusions

2.5.1 Study significance

This study is pioneering in analysing the dynamics of (decentralised) ridesourcing supply while accounting for labour supply decisions considering both long-term platform registration and short-term participation. Our platform registration submodel considers that registration requires information about earnings, and that it comes with

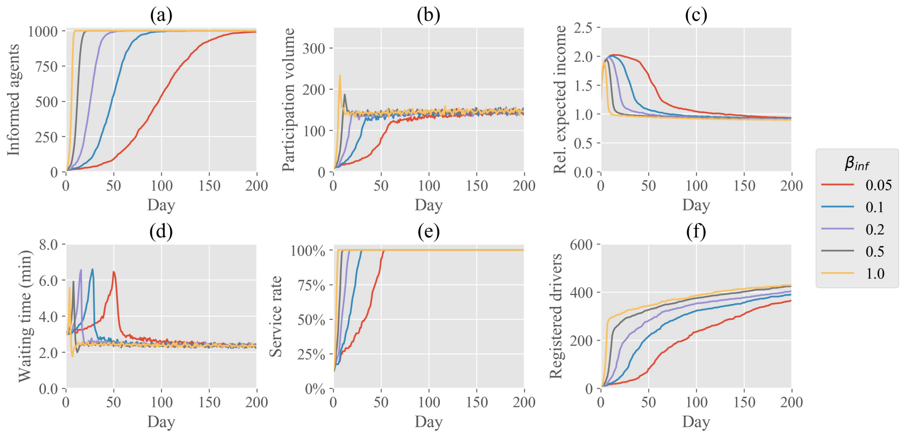


Figure 2.11: The effect of the information transmission rate on the evolution of (a) the number of informed agents, (b) daily participation volumes, (c) the average expected income of registered drivers as ratio of their reservation wage, (d) the average waiting time for pick-up for travellers, (e) platform profit and (f) the total number of registered drivers

one-off registration costs like insurance and vehicle acquisition, which are sunk in subsequent participation decisions. With a probabilistic participation choice submodel, we account for unobserved variables in the decision to work on a given day, like planned activities for this particular day. The model is applied to the case of Amsterdam in order to investigate the effect of supply market properties, platform pricing and supply-side entry barriers on the evolution of ridesourcing supply. In addition, we comment on the optimality of decentralised ridesourcing supply from the perspectives of drivers, travellers and service provider, based on an exhaustive search.

The results demonstrate that labour supply in ridesourcing may be non-linear and undergo several transitions, hereby inducing significant variations in average income, profit and level of service. It highlights the need for models capturing dynamic interactions in ridesourcing provision, such as the one presented in this work.

2.5.2 Key findings

Fleet size. We find that in a decentralised system, as long as drivers earn a competitive income and not yet all potential drivers are registered, new suppliers are attracted to the market at a relatively high pace. For the base scenario of our experiment, this phenomenon results in an equilibrium participation volume of 150 drivers. With this level of supply, there is relatively strong competition for pick-ups, resulting in payouts below drivers' reservation wages. Instead, for the community of (potential) ridesourcing drivers in our experiment, a fleet size of 40 - 100 drivers is considered to be optimal. Such a solution implies that the fewer drivers participating will earn a significantly higher income. The above findings demonstrate that the tragedy of the commons may apply in ridesourcing provision, in which the self-centered labour decisions of individuals ultimately harm the common interests of the group.

Unlike traditional transit providers with employed drivers, ridesourcing providers lack a direct financial incentive to curb supply. Our results demonstrate however that there may be an alternative balancing loop in ridesourcing supply, i.e. profit-maximising service providers may be best off claiming a relatively high rate on fares collected through their platforms, even when this means that fewer drivers will participate and, consequently, that a portion of the travel requests has to be rejected. In our experiment, in equilibrium approximately 60 drivers participate when a platform opts for a profit-maximising commission rate of 45%, compared to 180 drivers when the commission rate is 25%. This results in a decline in the probability that a request can be matched from 100% to 85%, and in an increase in the average waiting time from 2 to 6 minutes. Remarkably, average drivers earnings in the experiment are hardly affected by the commission rate of the platform. The rationale here is that the influx of new drivers on the platform is limited when the commission rate is high. This implies that registration barriers may mitigate the tragedy of the commons in ridesourcing supply.

Labour market effect. The expected income is especially low when the average reservation wage is low. In this case, drivers are relatively quick to register, leading to a fierce competition and ultimately a decreasing income for those already registered. Free-lance workers in the market will thus suffer from a shrinking economy in which other labour opportunities are scarce. The same applies to a labour market with large inequalities, in which ridesourcing services are flooded with drivers that have limited opportunities in the market, and are willing to work even when earnings are low.

2.5.3 Policy implications

Supply regulation. Similarly to the results of the semi-dynamic model by Yu et al. (2020), our findings provide support for the potential effectiveness of a supply cap, which has for example been implemented in New York City. It may push earnings over the reservation wage without significantly impeding travellers' waiting times. At the same time, our results show that the value to which the cap is set is crucial. For instance, in our experiment, supply caps above 400 drivers or more would yield no effect on driver income. On the other hand, we find that when supply caps are too restrictive, they may be detrimental to the level of service offered by the platform. This is in line with the results of the queuing theoretic equilibrium model formulated by Li et al. (2019), demonstrating that a supply cap can lead to reduced driver earnings when too many consumers leave the market. In any case, given that capital registration costs jeopardise the income of drivers, transit authorities should avoid supply caps that assign an additional cost to operation under the supply cap.

Pricing strategy. A profit-maximising platform will increase its commission rate up to the point that so many drivers opt out that lost commission from rejected requests outweighs the higher revenue on remaining requests. Our experiments demonstrate that at this point already a significant portion of ride requests may need to be rejected. In addition, we find that such a profit-maximising strategy may result in relatively long waiting times for travellers. These results suggest that the pricing strategy of a ridesourcing platform may need to be regulated. Our results in fact demonstrate that this may be highly beneficial from a societal standpoint, given that a near-optimal profit can be achieved with a significantly lower commission rate, yielding a much improved level of service for travellers. This confirms earlier findings based on an analytical economic model by Zha et al. (2016) regarding the effectiveness of regulation of the commission in increasing the social welfare generated by ridesourcing platforms.

2.5.4 Future research

In this study, we focus on supply evolution in order to understand its dynamics and describe emerging phenomena, which can be further embedded in models of co-evolution of supply and demand. An interesting direction for future research is the extent to which outcomes of a monopolistic market are also applicable to markets in which service providers compete for supply and demand. For example, future research may consider how supply evolution is affected by aggressive penetration pricing strategies aimed at pushing other service providers out of the market. It may also be interesting to analyse how external shocks to the market lead to swings in the transition process. Our model can be extended to study supply evolution of ridesourcing services offering pooled rides, which will affect the income of participating drivers. In essence, our approach with a day-to-day shell and a core capturing within-day dynamics allows to analyse ridesourcing supply evolution under various operational within-day strategies.

As a concluding remark, we stress the need for more empirical evidence on labour supply by ridesourcing drivers, as model input - based on cross-sectional data - and for validation of the results - based on longitudinal data. Enhancing the empirical underpinning on labour supply behaviour by (potential) ridesourcing drivers will support the specification of a simulation framework like the one presented here and thereby allow to significantly improve our knowledge on ridesourcing implications for drivers, travellers, platforms and society at large.

Chapter 3

Day-to-day Dynamics in Two-Sided Ridesourcing Markets

In this chapter, we present a conceptual representation of the interaction between supply and demand in the ridesourcing market to understand why these markets may be prone to evolve towards particular - potentially socially undesirable - equilibrium states. This analysis considers the speed and quality of matches for travellers and drivers.

In addition, we add travellers' platform registration and participation decisions to the previously introduced day-to-day model for ridesourcing supply. Modelling two-sided network effects in ridesourcing provision allows us to investigate the effect of two-sided market conditions and platform strategies on system performance. In this chapter we for instance vary the size of the potential ridesourcing market — i.e. the number of travellers and job seekers in an area — to establish how the success of ridesourcing provision is dependent on the scale of the market. Additionally, we examine different per-kilometre fares, commission rates, platform awareness diffusion speeds, and registration costs.

This chapter is based on the following article:

de Ruijter, A., Cats, O., & van Lint, H. (in press). Day-to-Day Dynamics in Two-Sided Ridesourcing Markets. *Transportmetrica B: Transport Dynamics*.

3.1 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 et al., 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 (Hall & Krueger, 2018; Chen et al., 2019; Ashkrof et al., 2020) 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 et al., 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 & 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 & 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 optimisation of a platform's matching procedure (Chen et al., 2020; Ausseil et al., 2022; Wang et al., 2023a,c; Xie et al., 2023) and pricing strategy (Banerjee et al., 2015; Taylor, 2018; Zha et al., 2018b,a; Bai et al., 2019; Sun et al., 2019b; Bimpikis et al., 2019; Nourinejad & Ramezani, 2020; Turan et al., 2020; Chen et al., 2021; Xu et al., 2022; Lei & Ukkusuri, 2023; Meskar et al., 2023), competition between platforms (Zha et al., 2016; Zhou et al., 2020; Sun & Liu, 2023), the evaluation of wider transportation effects (Qian & Ukkusuri, 2017; Zhu et al., 2020; Ke et al., 2020b; Yu et al., 2020; Ke et al., 2021), and the exploration and evaluation of potential regulations (Zha et al., 2018b,a; Li et al., 2019; Yu et al., 2020; Li et al., 2022; Vignon et al., 2023). 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 & Krueger, 2018), an increase in vehicle ownership associated with the emergence of ridesourcing (Gong et al., 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 & 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 & 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 et al. (2017) propose a semi-dynamic model with a single registration phase and a subsequent platform utilisation 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. (2022a) consider information diffusion, registration and daily experience-based utilisation 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 utilisation model and (iv) a learning model. The proposed model integrates a within-day operational model for ride-hailing (Kucharski & 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 utilising 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 & Tirole, 2006), we expect pricing to have significant implications for the market equilibrium. With the experiment, we specifically investigate the implications of a profit-maximising 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.

3.2 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 3.1). 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.

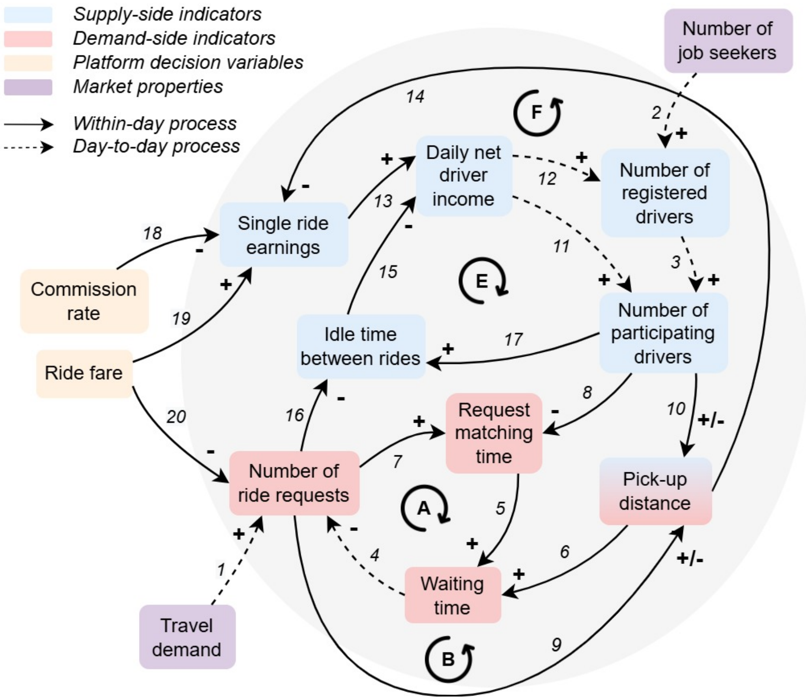


Figure 3.1: Conceptual representation of the ridesourcing market

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 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 & Sheldon, 2016; Sun et al., 2019a; 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 conceptualising 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 3.2) 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 3.1.

3.2.1 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 3.1). 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.

3.2.2 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 3.1 we summarise 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 3.1: 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

3.3 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 formalised 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 3.2 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 utilisation* 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

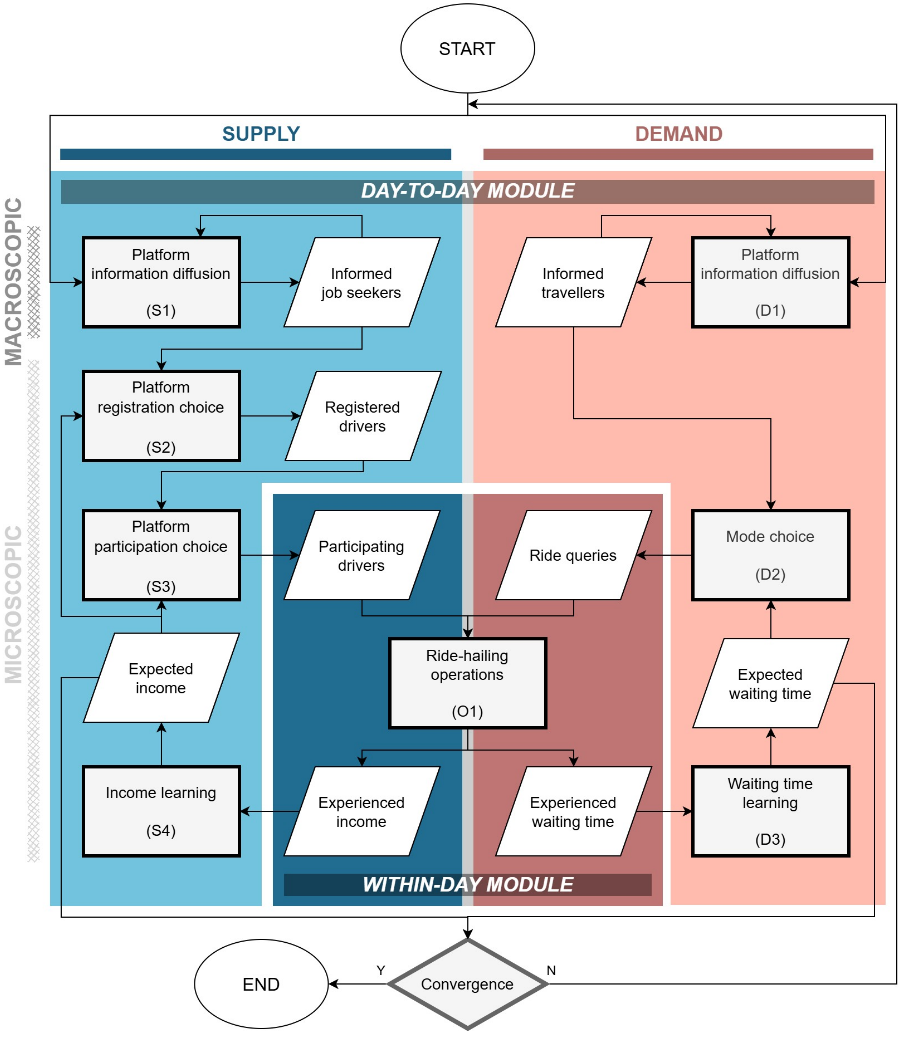


Figure 3.2: Operational framework for the ridesourcing market

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 & 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.

3.3.1 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 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 et al., 2001), information diffusion through blogs (Gruhl et al., 2004; Su et al., 2015) and the diffusion of rumours over social networks (Trpevski et al., 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 3.5.4.

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:

$$S = S_t^{\mathrm{u}} \cup S_t^{\mathrm{i}} \cup S_t^{\mathrm{r}} \tag{3.1}$$

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 $s \in S_t^{\text{u}}$ is informed about the ridesourcing platform's existence on day t then equals:

$$p_{st}^{\text{inform}} = \frac{\psi_{\text{sup}} \cdot |S_t^{\text{i}} \cup S_t^{\text{r}}|}{N} \tag{3.2}$$

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:

$$C = C_t^{\text{i}} \cup C_t^{\text{u}} \tag{3.3}$$

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 $c \in C_t^{\text{u}}$ receives information on day t as:

$$p_{ct}^{\text{inform}} = \frac{\psi_{\text{dem}} \cdot |C_t^{\text{i}}|}{K} \tag{3.4}$$

3.3.2 Registration

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 with a ridesourcing platform, we assume that job seekers are confronted with a daily cost b when they are registered with the ridesourcing service. Given the unlikelihood of daily reconsideration of one's registration status, we assume that 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 $\hat{i}_{st}$, the latter being determined by previous experiences (further explained in Subsection 3.3.4). 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 $p_{st}^{\text{participate}}$ that a registered driver $s \in S_t^{\text{r}}$ participates on a given day t is defined in Subsection 3.3.3. The anticipated earnings for a day of work equal $\hat{i}_{st}$ and the opportunity costs of a day of work r_s. The latter is referred to as the reservation wage in labour theory. We assume that the reservation wage is job seeker dependent but independent of time and day, i.e. reservation wage r_s 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 $U_{st}^{\text{registered}}$ 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 formalise the registration decision with a binary random utility model with parameter β_{reg} and error term ε_{reg} to account for other variables in the registration decision. Hence:

$$U_{st}^{\text{registered}} = \beta_{\text{reg}} \cdot p_{st}^{\text{participate}} \cdot (\hat{i}_{st} - r_s) + \varepsilon_{\text{reg}} \tag{3.5}$$

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

$$U_{st}^{\text{unregistered}} = \beta_{\text{reg}} \cdot b + \varepsilon_{\text{reg}} \tag{3.6}$$

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

$$p_{s \in S_t^{\text{i}},t}^{\text{regist}} = \frac{\gamma \cdot \exp(U_{s \in S_t^{\text{i}},t+1}^{\text{registered}})}{\exp(U_{s \in S_t^{\text{i}},t+1}^{\text{registered}}) + \exp(U_{s \in S_t^{\text{i}},t+1}^{\text{unregistered}})} \tag{3.7}$$

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 $s \in S_t^{\text{r}}$ that has been registered for n_{st} days on day t cancels its registration equals:

$$p_{s \in S_t^{\text{r}},t}^{\text{deregist}} = \frac{\eta \cdot \gamma \cdot \exp(U_{s \in S_t^{\text{r}},t+1}^{\text{unregistered}})}{\exp(U_{s \in S_t^{\text{r}},t+1}^{\text{registered}}) + \exp(U_{s \in S_t^{\text{r}},t+1}^{\text{unregistered}})} \tag{3.8}$$

with:

$$\eta = \begin{cases} 1 & n_{st} \geq \lambda \\ 0 & \text{otherwise} \end{cases} \tag{3.9}$$

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.

3.3.3 Platform participation

Supply-side (S3)

Registered job seekers are faced with a daily platform participation decision. We follow the neoclassical theory of labour supply (Chen & Sheldon, 2016; Sun et al., 2019a; Xu et al., 2020), i.e. registered job seekers supply labour to a ridesourcing platform when the anticipated income $\hat{i}_{st}$ 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:

$$U_{st}^{\text{participate}} = \beta_{\text{ptp}} \cdot \hat{i}_{st} + \varepsilon_{\text{ptp}} \tag{3.10}$$

$$U_{st}^{\text{alt}} = \beta_{\text{ptp}} \cdot r_s + \varepsilon_{\text{ptp}} \tag{3.11}$$

$$p_{st}^{\text{participate}} = \frac{\exp(U_{st}^{\text{participate}})}{\exp(U_{st}^{\text{participate}}) + \exp(U_{st}^{\text{alt}})} \tag{3.12}$$

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:

$$U_{ctm}^{\text{mode}} = \beta_{cm}^{\text{ivt}} \cdot v_{ctm} + \beta_{cm}^{\text{access}} \cdot a_{ctm} + \beta_{cm}^{\text{wait}} \cdot \hat{w}_{ctm} + \beta_{\text{transfer}} \cdot q_{ctm} + \beta_{\text{cost}} \cdot \rho_{cm} + ASC_{cm} + \varepsilon_{\text{mode}} \quad (3.13)$$

$$p_{ctm}^{\text{mode}} = \frac{\exp(U_{ctm}^{\text{mode}})}{\sum_{m \in M} \exp(U_{ctm}^{\text{mode}})} \quad (3.14)$$

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.

3.3.4 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 $S_t^{\text{u}} \cup S_t^{\text{i}}$, 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 utilisation 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 et al., 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.

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 $s \in S_t^{\text{i}}$ 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:

$$y_{st} = \begin{cases} x_{st} & s \in S_t^{\mathrm{i}} \\ i_{st} & s \in S_t^{\mathrm{p}} \\ \hat{i}_{st} & \text{otherwise} \end{cases} \tag{3.15}$$

$$x_{st} \sim \mathcal{N}(\overline{i_t}, \omega \cdot \sigma_t^{\mathrm{i}}) \tag{3.16}$$

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

$$\hat{i}_{st} = (1-\kappa) \cdot \hat{i}_{s,t-1} + \kappa \cdot y_{s,t-1} \tag{3.17}$$

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

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:

$$\hat{w}_{ct} = (1-\kappa) \cdot \hat{w}_{c,t-1} + \kappa \cdot w_{c,t-1} \tag{3.18}$$

3.3.5 Within-day operations

A discrete-event within-day model for ride-hailing operations Kucharski & 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. (2022a) for more details.

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:

$$(c^*, s^*) = \underset{c \in Q_{\text{req}}, s \in Q_{\text{driver}}}{\arg\min} \quad \tau_{sc} \tag{3.19}$$

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:

$$R_c = (f_{\text{base}} + f_{\text{km}} \cdot d_c) \cdot (1 - \pi) \tag{3.20}$$

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:

$$R_{st} = \sum_{c \in C_t^{\text{p}}} R_c \cdot \xi_{sct} \tag{3.21}$$

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

$$i_{st} = R_{st} - O_{st} \tag{3.22}$$

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:

$$O_{st} = \Big(\sum_{c \in C_t^{\mathrm{p}}} d_c \cdot \xi_{sct} + D_{st}\Big) \cdot \delta \tag{3.23}$$

Waiting time

The experienced waiting time w_{ct} of a traveller with a ridesourcing request $c \in C_t^{\mathrm{p}}$ 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.

3.3.6 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.

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 formalised as:

$$\frac{|I_{t-z} - I_{t-z-1}|}{I_{t-z-1}} \leq \varphi \qquad \forall z \in \{0, \dots, 4\} \tag{3.24}$$

with:

$$I_t = \frac{1}{|S_t^{\mathrm{r}}|} \cdot \sum_{s \in S_t^{\mathrm{r}}} \hat{i}_{st} \tag{3.25}$$

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:

$$\frac{|W_{t-z} - W_{t-z-1}|}{W_{t-z-1}} \leq \varphi \qquad \forall z \in \{0, \ldots, 4\} \tag{3.26}$$

with:

$$W_t = \frac{1}{|C_t^{\mathrm{i}}|} \cdot \sum_{C \in C_t^{\mathrm{i}}} \hat{w}_{ct} \tag{3.27}$$

Replications

The simulation model includes stochastic components in information diffusion, platform registration and participation. We determine the number of required replications $Z(n^{\text{init}})$ based on a number of initial replications n^{init}, 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 $\overline{I^*}(n^{\text{init}})$ and $\overline{W^*}(n^{\text{init}})$, and $s_{\mathrm{i}}(n^{\text{init}})$ and $s_{\mathrm{w}}(n^{\text{init}})$ are, respectively, the estimated mean and standard deviation of I^* and W^* from a sample of m runs. When we define the allowable percentage error of estimate $\overline{I^*}(n^{\text{init}})$ and $\overline{W^*}(n^{\text{init}})$ of the actual mean as $\varepsilon_{\text{repl}}$, and the level of significance as α, the minimum number of replications is:

$$Z(n^{\text{init}}) = \max\left(\left(\frac{s_{\mathrm{i}}(n^{\text{init}}) \cdot t_{n^{\text{init}}-1,\frac{1-\alpha}{2}}}{\overline{I^*}(n^{\text{init}}) \cdot \varepsilon_{\text{repl}}}\right)^2, \left(\frac{s_{\mathrm{w}}(n^{\text{init}}) \cdot t_{n^{\text{init}}-1,\frac{1-\alpha}{2}}}{\overline{W^*}(n^{\text{init}}) \cdot \varepsilon_{\text{repl}}}\right)^2\right) \tag{3.28}$$

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 $\hat{w}_{ct} = 0$. If in such an 'ideal' scenario traveller agents have a probability below parameter χ, they will be removed from the original pool of travellers.

3.4 Experimental design

3.4.1 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 (Kaddoura, 2015; Bischoff & Maciejewski, 2016). 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 2,500 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 & Timmermans, 2004), in which only trips longer than 2 kilometres 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. $\beta_{cm}^{\text{access}} = 2\beta_{cm}^{\text{ivt}}$, and time waiting for a vehicle 2.5 times more negatively, i.e. $\beta_{cm}^{\text{wait}} = 2.5\beta_{cm}^{\text{ivt}}$, 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 & Eliasson, 2012). The penalty for transfers in public transport is set to 5 minutes of in-vehicle time (Yap et al., 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 minutes for a match ($\theta = 10$ min) and to perceive a rejected request as equivalent to 30 minutes 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 (Centraal Bureau 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 36km/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

Table 3.2: Specification of other model parameters, with references to sensitivity tests.

Indicator	**Parameter**	**Value**	**Unit**	**Sensitivity test**
Information transmission speed	ψ_{sup}, ψ_{dem}	0.1	-	Subsection 3.5.4
Learning weight	κ	0.2[a]	-	Appendix A.3.1
Income sensitivity in registration	β_{reg}	0.2	util/€	Appendix A.3.2
Income sensitivity in participation	β_{ptp}	0.1	util/€	Appendix A.3.2
Minimum registration time	λ	5	days	Appendix A.3.3
Rel. variation in wait time and inc. signals	ω	0.5	-	Appendix A.3.5
Convergence condition	φ	0.01	-	-
Allowable percent. 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 et al., 2007).

fares (i.e. €0.99 base fare and an additional €0.174 per km). Private cars are assigned with a parking time of 10 minutes, 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 initialisation. 10% of all agents (job seekers and travellers) are initially informed. Of the originally informed job seekers, 20% is immediately registered with the ridesourcing platform. The model's sensitivity to these starting conditions is evaluated in Appendix A.2.

The specification of the remaining model parameters is provided in Table 3.2.

3.4.2 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 Subsection 3.4.1. 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 3,750 and 75,000 travellers, and potential supply ranging between 125 and 2,500 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%.

3.4.3 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:

$$V_t^{\text{drivers}} = \sum_{s \in S_t^{\text{p}}} (i_{st} - r_s) - |S_t^r| \cdot b \tag{3.29}$$

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:

$$LS_t^{\text{old}} = \sum_{c \in C_t^{\text{p}}} \ln \left[\sum_{m \in (M - \{\text{RS}\})} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{3.30}$$

$$LS_t^{\text{new}} = \sum_{c \in C_t^{\text{p}}} \ln \left[\sum_{m \in M} (\exp(U_{ctm}^{\text{mode}}) - \varepsilon_{\text{mode}}) \right] \tag{3.31}$$

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

$$V_t^{\text{travellers}} = \frac{LS_t^{\text{new}} - LS_t^{\text{old}}}{\beta_{\text{cost}}} \tag{3.32}$$

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

$$V_t^{\text{platform}} = \pi \cdot \sum_{c \in C_t^{\text{p}}} \left((f_{\text{base}} + f_{\text{km}} \cdot d_c) \cdot \sum_{s \in S_t^{\text{p}}} \xi_{sct} \right) \tag{3.33}$$

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:

$$V_t^{\text{society}} = V_t^{\text{drivers}} + V_t^{\text{travellers}} + V_t^{\text{platform}} \tag{3.34}$$

3.5 Results

Here, we present the results of our experiments. In Subsection 3.5.1, 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 Subsections 3.5.2 and 3.5.3, we demonstrate how the ridesourcing market equilibrium is affected by the size of the potential market and by platform pricing strategies, respectively. In Subsection 3.5.4, 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.

3.5.1 Dynamics, randomness and heterogeneity

In Figure 3.3, 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 3.3A). Job seekers quickly learn that anticipated earnings cannot not be realised (3.3B), while travellers observe that there is waiting associated with choosing ridesourcing for their trip (3.3E). 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 (3.3B) even though the earnings per satisfied request decreases (3.3C) due to higher deadheading costs. At the same time, travellers' matching time increases (3.3E). Figure 3.3B 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.

2. **Bounce-back in supply** *(days 5-25).* The average reservation wage of registered job seekers drops further (3.3B) 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

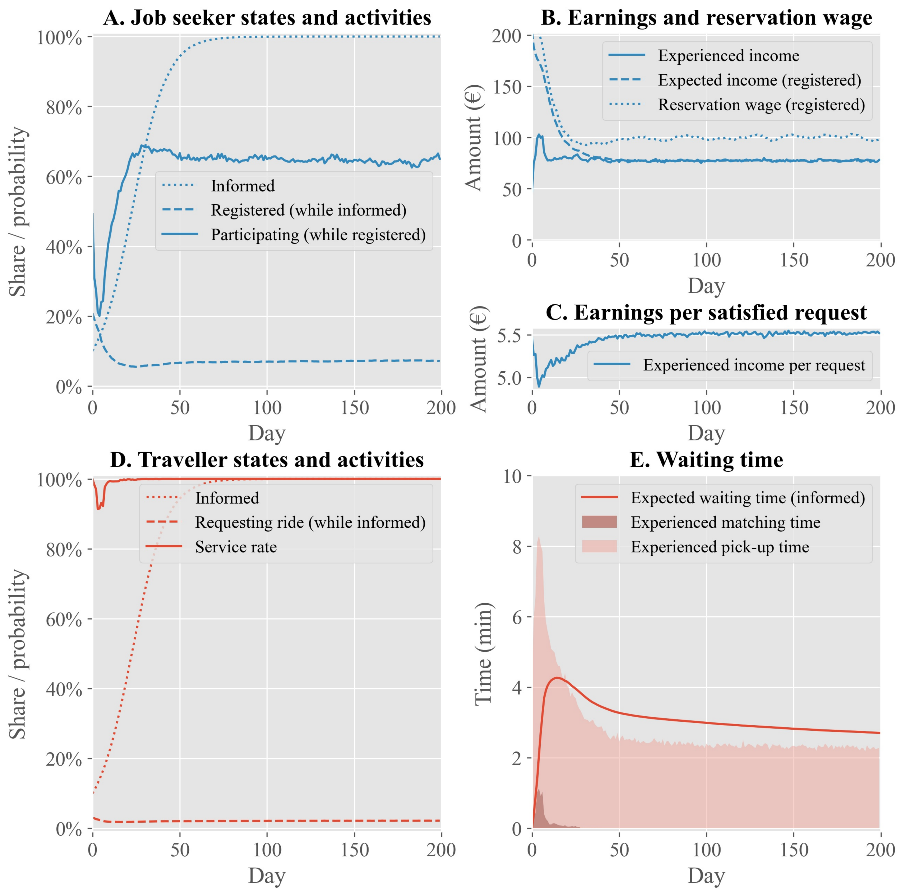


Figure 3.3: Evolution of the ridesourcing market in the reference scenario

(3.3D and 3.3E). It also leads to a decrease in the average pick-up time (3.3E). 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, Fig. 3.3C), 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 Subsection 3.3.6). 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 3.3 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 (3.3E). 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 3.4C), 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 3.3E, 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 3.4A). 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 minutes (3.4C). 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 (3.4B) and between travellers' request location and their waiting time (3.4D).

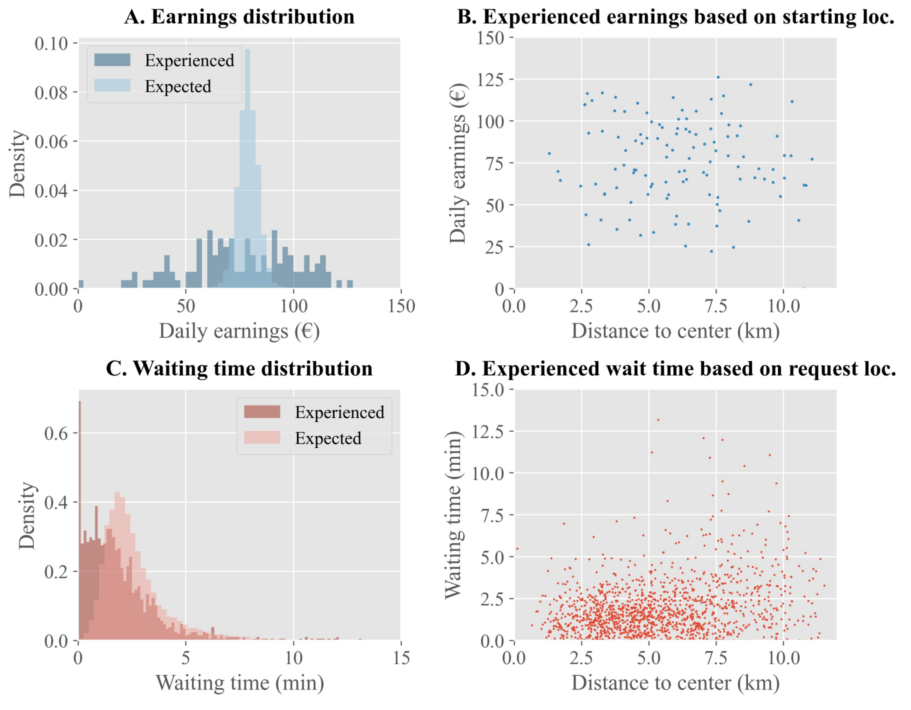


Figure 3.4: Distributional effects in earnings and waiting time in the ridesourcing market equilibrium (single instance of the reference scenario)

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 (Fig. 3.5A), depending on randomness in initial conditions and evolutionary processes. The (relative) variation in market participation across instances is more limited on the demand side (3.5C), with the the 20-day moving average ridesourcing demand in equilibrium ranging from 1,580 to 1,700 requests.

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 (3.5B) and experienced user waiting time (3.5D) is comparable.

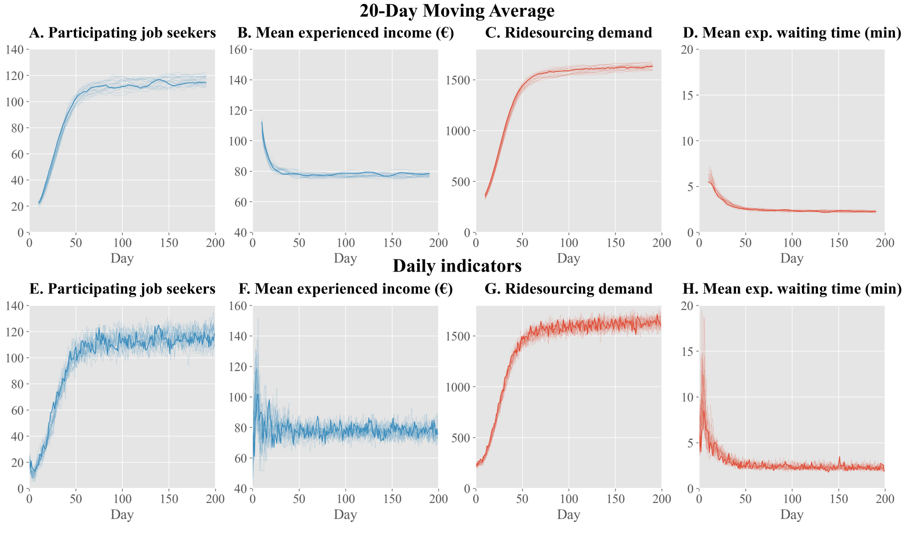


Figure 3.5: 20-Day Moving Average (MA_{20}) and daily values of ridesourcing market participation and system performance indicators for different instances (replications) of the reference scenario. System performance for one of the instances is highlighted.

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. Fig. 3.5 demonstrates that even when the market has converged, there are non-negligible variations in daily ridesourcing supply (3.5E) and demand (3.5G), which result in substantial day-to-day variations in the average experienced driver earnings (3.5F) and user waiting time (3.5H). 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 minutes 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 Fig. 3.5. 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 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.

3.5.2 Potential market size

Figure 3.6 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 3,750 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 3.6D). 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 (3.6E). As drivers on an average day serve few requests (3.6G), participating in the market is unattractive. This further reduces the probability that a request can be assigned to a driver.

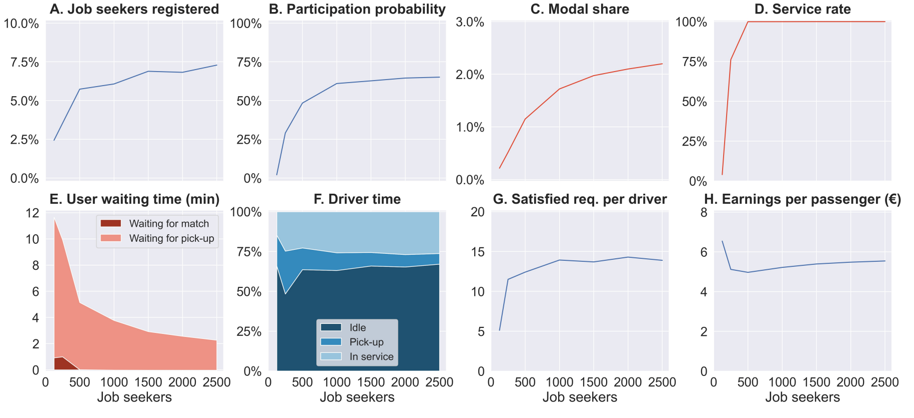


Figure 3.6: Equilibrium system performance indicators depending on the size of the potential market (in which there are 30 travellers for each job seeker)

Already with 7,500 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 (3.6A), of which on an average day less than 30% participate (3.6B). Although limited supply results in a matching failure for 24% of trip requests (3.6D) and in relatively long waiting for the other requests (3.6E), each day still a small portion (0.5%) of travellers is willing to request a ride with the platform (3.6C).

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 Subsection 3.2.1) 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 2,500 job seekers (3.6F). As a result, the modal share of ridesourcing more than doubles (3.6C). Lower deadheading costs (associated with driving to the request pick-up location) yields higher per-request earnings for drivers (3.6H). 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 (3.6C). This is an inherent feature of the ridesourcing market, given that there is a theoretical minimum pick-up time of 0 minutes, 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 (3.6F). More dense potential supply and demand at this point will yield only minor benefits.

3.5.3 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 3.7 and 3.8.

In our experiment, a profit-maximising service provider will opt for a per-kilometre fare of €1 and a commission of 30% (Figure 3.8C). With this strategy, approximately 3.9% of all travellers opt to request a ride using the ridesourcing platform (3.7C), of which 99.5% is successfully matched to a driver (3.7D). 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% (3.8C). As a result, the platform profit per request is respectively 45.8% and 66.7% higher than when a platform opts for the profit-maximising 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 market and the earnings per transaction. In the experiment, the profit-maximising strategy prioritises the former, the two near-optimal strategies the latter. Compared to the profit-maximising strategy, the alternative near-optimal strategies for instance result in a significantly lower ridesourcing market share, i.e. a reduction of 27.4% when π is 35% and a reduction of 36.3% when π is 40% (3.7C). As a result, fewer job seekers participate in the market (3.7A, 3.7B). We can conclude that several (near-)optimal pricing strategies may result in a vastly different value derived by job seekers (Figure 3.8A) as well as by travellers (Figure 3.8B), depending on whether the transaction volume or earnings per transaction is prioritised. From a wide societal value, the latter may be undesired.

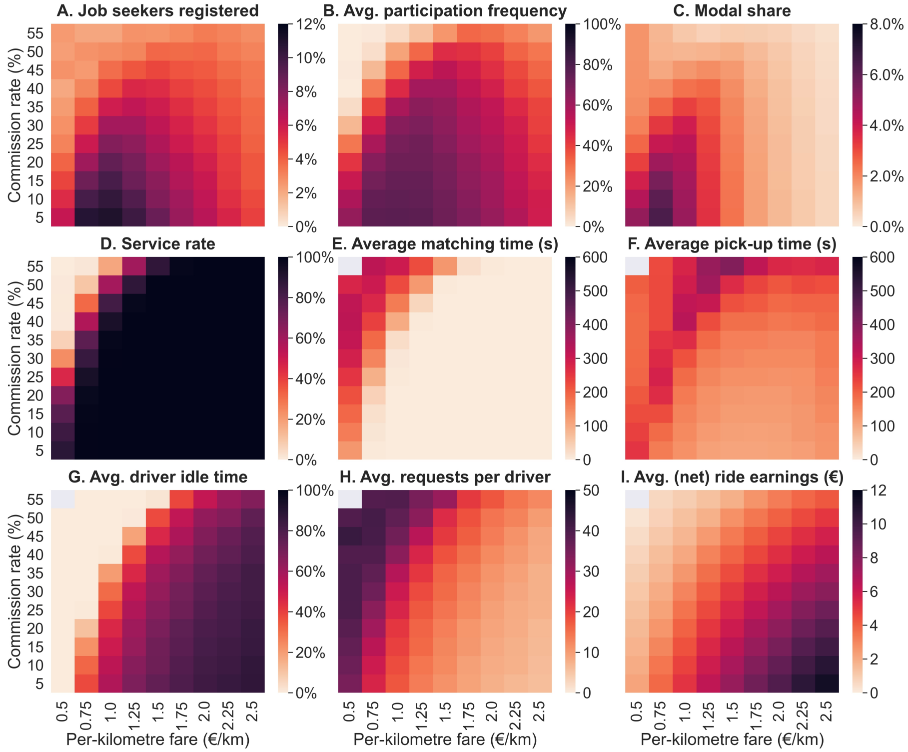


Figure 3.7: Equilibrium system performance indicators depending on the pricing strategy adopted by the platform

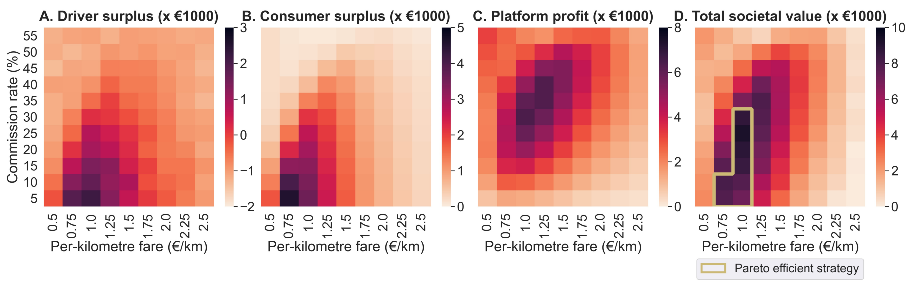


Figure 3.8: Societal value in equilibrium depending on the pricing strategy

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 (3.8B) and €1.0 for job seekers (3.8A). 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 (3.7I). As a result, job seekers are relatively unlikely to register (3.7A) and participate (3.7B) in the market. With few other drivers, those that still participate will not face any idle time (3.7G) and may be able to serve over 40 passengers a day (3.7H). 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 (3.7D) is high, and so is the average matching time for requests for which a driver is found before the request is cancelled (3.7E). With low level of service, travellers become significantly less likely to opt for ridesourcing (3.7C).

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 (3.7C). While high fares lead to high earnings per ride (3.7I), a low ridesourcing market share of ridesourcing implies that drivers serve only few requests on any given day (3.7H) and earn less than in a scenario with a lower per-kilometre fare. Drivers spend over 80% of their time in an idle state (3.7G) when the per-kilometre fare equals €2.5, even though there are relatively few other job seekers participating in the market (3.7B). 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 (3.7I), a high commission makes participating in the market less attractive (3.7B). With relatively few participating drivers relative to ridesourcing demand, drivers spend less time waiting to be assigned (3.7G), while travellers may start to experience longer matching times (3.7E). 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 (3.7F). 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-maximising platform (3.8C) 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.

3.5.4 Information diffusion & registration

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 Fig. 3.9 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 1,600 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 (3.9B), attracting more suppliers to the market (3.9A), 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.

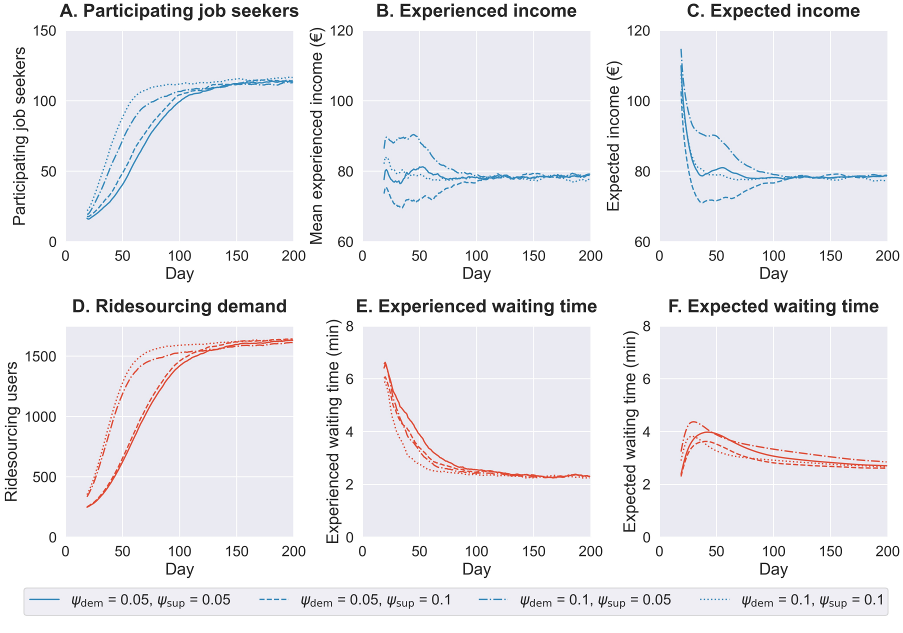


Figure 3.9: 20-day moving average of key ridesourcing market performance indicators for different two-sided information diffusion speeds.

Registration barriers

Fig. 3.10 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 (3.10A). 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 (3.10B). Although this results in lower waiting time for travellers (3.10E,F), the associated increase in ridesourcing market share is limited (3.10D). Hence, the average number of drivers per ride request increases and the average earnings of drivers drop (3.10C). 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 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.

3.6 Conclusions

3.6.1 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 utilisation 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.

Figure 3.10: 10-day moving average of key ridesourcing market performance indicators for different daily costs b associated with registration for job seekers.

3.6.2 Takeaways

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

Conceptual framework

The ridesourcing market is characterised 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).

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 & 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.

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 realise 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.

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-maximising 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.

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.

3.6.3 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 jeopardised 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.

Chapter 4

Ridesourcing Platforms Thrive on Socio-Economic Inequality

Limited available market share data seems to suggest that ridesourcing platforms benefit from, even thrive on, socio-economic inequality. We suspect that this is associated with high levels of socio-economic inequality allowing for cheap labour as well as increasing the share of travellers with a considerably above-average willingness to pay for travel time savings and comfort. In this chapter, we adopt the agent-based, two-sided day-to-day model for ridesourcing markets presented in the previous chapter to test the relation between inequality and system performance, considering also two-sided network effects in ridesourcing provision. We do so by varying the heterogeneity in travellers' values of time and job seekers' reservation wages. Our experiments cover scenarios for the entire spectrum ranging from perfect equality to extreme inequality. For several of such scenarios, we explore how platforms will adjust their two-sided pricing strategies. In our analyses of ridesourcing performance, we specifically examine the earnings of drivers, the quality of the service for travellers and the service provider's profit.

This chapter is based on the following article:

de Ruijter, A., Cats, O., & van Lint, H. (2024). Ridesourcing platforms thrive on socio-economic inequality. *Scientific Reports, 14*(1), 7371.

4.1 Introduction

In the gig economy, independent contractors provide services to consumers via intermediary platforms. Industries in which the gig business model has become especially prevalent include passenger transportation, delivery of food and goods, provision of household tasks, and care work (Vallas & Schor, 2020). The main benefit associated with working in the gig economy is autonomy (Manyika et al., 2016; Forde et al., 2017; Hall & Krueger, 2018; Chen et al., 2019; Berger et al., 2019; Schor, 2021). In principle, gig workers can freely decide which platforms to work for, when to work for these platforms, which jobs to take, and how to fulfil these jobs. In reality, autonomy may be limited by rules and mechanisms imposed by platforms, as well as by demand fluctuations (Rosenblat & Stark, 2016; Calo & Rosenblat, 2017; Rosenblat, 2018; Ravenelle, 2019; Schor, 2021). In fact, courts in the United Kingdom and the Netherlands have ruled that workers of ride-hailing provider Uber are self-employed only on paper (The Supreme Court, 2021; Rechtbank Amsterdam, 2021), assessing the relationship between drivers and platform to meet all conditions of traditional employment. In Amsterdam, there was a similar ruling for food delivery platform Deliveroo (Gerechtshof Amsterdam, 2021), which led to its departure from the Netherlands (Vlaanderen, 2022).

While average hourly earnings on gig platforms are not necessarily lower than the wage paid by employers that are active in similar industries (Sundararajan, 2017), gig workers lack access to social security provisions, including a guaranteed minimum wage, retirement plans and paid (sick) leave. Consequently, workers in the gig economy are exposed to much more uncertainty when it comes to income than employees. Essentially, gig workers now bear the risks that were previously carried by business and state. These risks include shrinking demand, as in the recent COVID-19 pandemic (Benner et al., 2020), health issues, damage to assets and (financial) impropriety by customers (Rosenblat, 2018; Ravenelle, 2019), but also chance in platform matching (Sühr et al., 2019; Bokányi & Hannák, 2020). With a substantial share of gig workers relying on highly volatile income from platform work to cover costs of living (Smith, 2016; Benner et al., 2020), the emergence of the gig economy may result in larger income inequality in society. More so, dependency on platform earnings limits gig workers' freedom, which can contribute to below average earnings in the gig economy (Schor et al., 2020).

While the provision of some services exchanged in the gig economy demands extensive training (e.g. writing, consulting, designing), many other gig economy services require limited skills. This includes driving, housekeeping and specific online tasks such as filling out surveys. As a result, many gig markets predominantly attract workers with a below average income (Smith, 2016; Berger et al., 2019), in particular migrant workers (Hall & Krueger, 2018; Hua & Ray, 2018; Berger et al., 2019; Holtum et al., 2022). Due to a scarcity of alternative income opportunities, these individuals might find themselves compelled to work for such platforms despite earning limited wages. While minimum wages ensure a foundational income for workers in conventional markets, self-employed individuals engaged in the gig economy do not have this income safeguard. This situation suggests that platforms within the gig economy are particularly likely to - more than service providers with employed staff - gain advantages from socio-economic disparities by leveraging inexpensive labour.

The ridesourcing (or ride-hailing) sector, represented by platforms such as Uber, Lyft, and DiDi, stands out as a gig industry that may significantly benefit from socio-economic disparities. Ridesourcing platforms not only profit from accessing abundant inexpensive labour but also cater primarily to individuals with above-average socio-economic positions. That is to say, users are assured a direct and private ride resembling a taxi service, at a typically substantially higher fare compared to traditional public transportation (Cats et al., 2022). Moreover, as the average distance between a matched traveller and driver (at the time of assignment) decreases with the (double-sided) size of the ridesourcing market (de Ruijter et al., 2022b), socio-economic inequalities may allow ridesourcing platforms to exploit network effects in matching that yield benefits for travellers (less waiting), drivers (less idle time) and platform (more profit through induced demand). Because taxi market supply is typically regulated, it is expected that taxi operators profit less from such network effects than ridesourcing platforms do.

Fig. 4.1 seems to suggest that there may be a correlation between socio-economic inequality in a country and the usage of ridesourcing. This is based on data for just eight countries however, for which one-time Uber usage is used as a proxy for the prevalence of ridesourcing. Unfortunately, reliable city-level indicators for ridesourcing across numerous cities are not available. We therefore need alternative means to testify the relation between socio-economic inequalities and ridesourcing system performance. We argue that an agent-based simulation is very well suited for this purpose, as it allows to examine the effect of heterogeneity in socio-economic characteristics, and in isolation of other market properties that may affect ridesourcing performance. Such conditions may include the quality of alternative modes of transportation, ridesourcing pricing and imposed regulations.

Previous agent-based modelling exercises have provided insights into ridesourcing as a first / last mile solution for public transport (Djavadian & Chow, 2017; Alemi & Rodier, 2018), driver earnings (Djavadian & Chow, 2017; de Ruijter et al., 2022a,b), platform pricing policies (Djavadian & Chow, 2017; Chen et al., 2021; de Ruijter et al., 2022a,b), the effect of labour market characteristics (Djavadian & Chow, 2017; de Ruijter et al., 2022a,b), ride-pooling system performance (Nourinejad & Roorda, 2016; Beojone & Geroliminis, 2021; Wilkes et al., 2021), and the design of charging infrastructure for an electric fleet (Bauer et al., 2019; Alam et al., 2022). An agent-based representation of the ridesourcing market was also used for studying income inequalities resulting from ridesourcing operations (Bokányi & Hannák, 2020). In this study, in contrast, we investigate the dependency of ridesourcing platforms on socio-economic inequalities, including pricing decisions of profit-maximising platforms, which has hitherto remained unexplored. Due to network effects in ridesourcing, selecting a profit-maximising strategy entails a complex trade-off between market volume and the profit per transaction (de Ruijter et al., 2022b), of which the outcome is not obvious. At the same time, it is not evident how socio-economic inequality af-

Figure 4.1: The share of adults in selected countries (based on data availability) that used Uber at least once in a 1-year period following April 1st 2021 (Fleck, 2022) plotted against the country's Gini coefficient for income inequality (The World Bank, 2022). It suggests that a positive relationship exists between socio-economic inequality and ridesourcing market share.

fects the distribution of social welfare between travellers and workers, which depends on the ratio between supply and demand (de Ruijter et al., 2022b).

We fill this knowledge gap by adopting an agent-based simulation model of double-sided ridesourcing markets, MaaSSim (Kucharski & Cats, 2022), integrated into a day-to-day framework representing network effects in the ridesourcing market (de Ruijter et al., 2022b). The model simulates daily labour supply decisions in consideration of the anticipated income and the reservation wage of ridesourcing, i.e. the minimum wage required to be willing to work for the platform. The latter depends on a job seeker's access to alternative employment opportunities. Mode choice is represented with a logit model incorporating several attributes, including the anticipated waiting time when opting for ridesourcing. Platform earnings and waiting time are learned primarily from personal experience, determined with an operational ride-hailing model in which travellers and drivers are matched based on their proximity (Kucharski & Cats, 2022). The adopted simulation model also accounts for diffusion of platform awareness which may hinder market participation in early phases. In addition, it captures suppliers' (medium- to long-term) trade-off between registration costs (which are negligible for travellers) and anticipated participation benefits.

As participation is modeled endogenously on both sides of the market (as daily labour supply and mode choice), the day-to-day ridesourcing model generates disaggregate output on which travellers and job seekers participate in the market, depending on their socio-economic properties. This is in turn used to identify how socio-economic inequality affects ridesourcing system performance indicators, considering (exclusively) the direct effect of heterogeneity in travellers' and job seekers' time perceptions. This includes analysing how a profit-maximising platform adjusts its pricing strategy depending on the distribution of income in society, evaluating also the implications for riders and drivers.

4.2 Application and Results

We apply the double-sided ridesourcing market simulation model to a case study resembling the city of Amsterdam, the Netherlands. In addition to ridesourcing, travellers can choose between private car, bike and public transport. The first three modes operate on a road network with the same spatial configuration as the road network of Amsterdam, yet with universal (mode-specific) link travel speeds. Public transport service quality is based on GTFS data for Amsterdam.

Each traveller and each job seeker in the simulation represents 10 individuals in reality, in correspondence with other transportation studies in which agent-based models are applied (Kaddoura, 2015; Bischoff & Maciejewski, 2016; de Ruijter et al., 2022b). This procedure results in 75,000 traveller agents and 2,500 job seeker agents that can potentially participate in the ridesourcing market in Amsterdam. Trip attributes are taken from data generated based on the activity-based model of Albatross (Arentze & Timmermans, 2004). Behavioural preferences related to travel and employment choices are specified based on findings reported in past studies (Wardman, 2004; Börjesson & Eliasson, 2012; Kouwenhoven et al., 2014; Yap et al., 2020; Geržinič et al., 2023; Centraal Bureau voor de Statistiek, 2022).

Model outputs include the profit generated by the platform, the share of requests that are satisfied, the average time travellers spent waiting before being picked-up, and the income of drivers. In addition, we formulate subsequent surplus-based welfare indicators for travellers and drivers.

We investigate the effect of socio-economic inequalities by adjusting the parameter σ of the log-normal distributions used to describe heterogeneity in travellers' value of time (VoT) and job seekers' ridesourcing reservation wage. Our experiments cover scenarios for the entire spectrum ranging from perfect equality to extreme inequality, i.e. standard deviations resulting in Gini coefficients g between 0 and 0.95 (in steps of 0.05). In the following, we focus primarily on scenarios corresponding to urban Gini coefficients observed in the real world. This concerns Gini coefficients (in terms of disposable income) between 0.23 (Astana) and 0.67 (Curitiba, Pretoria and Johannesburg) (Knudsen et al., 2020). Most European and US cities fall in the middle of this range (e.g. Oslo 0.27, Amsterdam 0.37 and (Greater) New York 0.42). We devote a separate subsection to discuss ridesourcing system performance under extreme (i.e. unobserved) (in)equality.

4.2.1 Macroscopic effects

Our experiments show that within the range of observed urban Gini coefficients, the greater the socio-economic inequality is, the higher the participation on both sides of the ridesourcing market is. Fig. 4.2A suggests a strong near-linear positive relationship between socio-economic inequality and demand for ridesourcing. To illustrate, ceteris paribus, a ridesourcing market attracts approximately three times as much travel demand in an area with a Gini coefficient of 0.65 compared to one in an area with a Gini of 0.25 (4.4% vs 1.5% market share). The relative increase in market participation is even larger on the supply side of the market. Here, we observe an

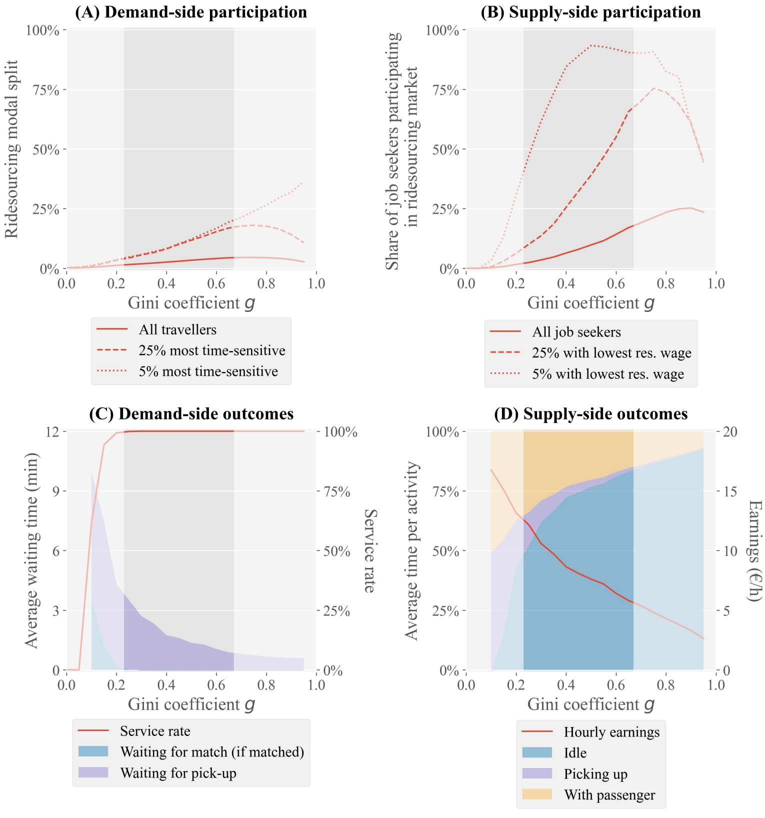


Figure 4.2: Key ridesourcing system indicators as a function of the degree of socio-economic inequality in society. (A) Modal split of ridesourcing, for the entire population as well as for the 25% and 5% most time-sensitive travellers (i.e. those with the highest willingness to pay for travel time reductions). (B) Share of job seekers participating in the ridesourcing market, for the entire population as well as for the 25% and 5% of job seekers with the lowest reservation wage. (C) Level of service indicators: service rate (share of requests that is satisfied) and customer waiting time before pick-up. (D) Driver activities and income. The highlighted area in each graph corresponds to observed values of the Gini coefficient in cities around the world.

exponential increase in market participation with growing socio-economic inequality (Fig. 4.2B). When g is 0.65, on average 17.0% of all job seekers work in the ridesourcing market, compared to just 2.4% when $g = 0.25$.

The difference in income inequality elasticities between supply and demand sides of the market implies that ridesourcing markets operating in more unequal societies tend to end up in a more oversupplied market state. When comparing an environment

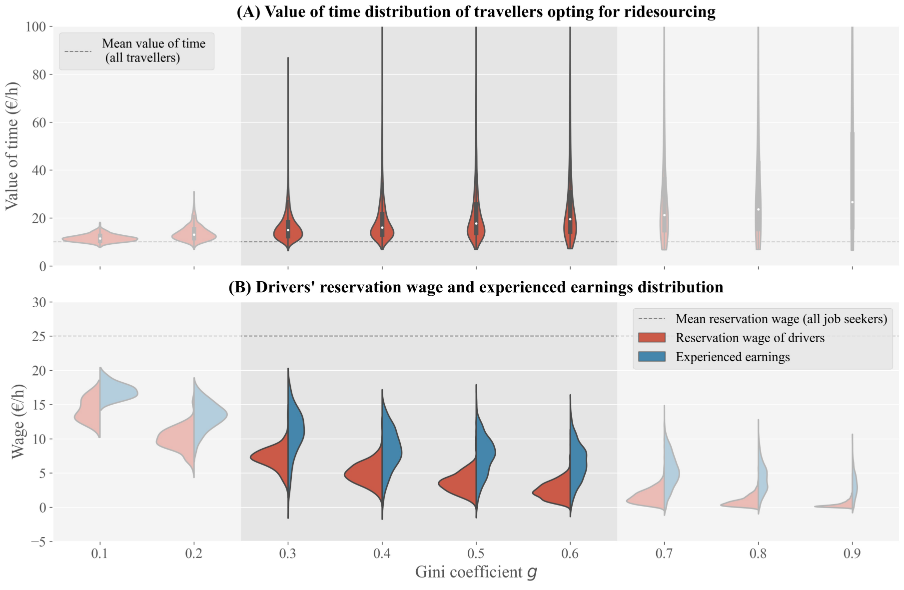


Figure 4.3: Distribution of (A) value of time of travellers opting for ridesourcing, and (B) reservation wage and earnings of job seekers participating in the ridesourcing market, for different values of Gini coefficient g. Mean value of time and reservation wage are provided for the entire population as reference. The highlighted area in each graph corresponds to observed values of the Gini coefficient in cities around the world.

where $g = 0.25$ to one where $g = 0.65$, approximating the most equal and the most unequal urban region worldwide, respectively, the ratio of supply to demand more than doubles. While in both scenarios customers are guaranteed instant assignment to a driver (Fig. 4.2C), the average distance between matched travellers and drivers decreases with socio-economic inequality, particularly in the lower range of social inequality. This results in shorter waiting times for travellers (down to less than a minute when $g = 0.65$, Fig. 4.2C) and less deadheading for drivers (Fig. 4.2D). Yet, due to strong competition for rides, drivers spend substantially more of their time in an idle state (i.e. waiting to be matched): 83% vs 52% (Fig. 4.2D). Consequently, driver earnings are, ceteris paribus, considerably lower in contexts where socio-economic inequality is high (Fig. 4.2D). In our experiment, the average driver earns €5.81 per hour when $g = 0.65$ compared to €12.17 when $g = 0.25$.

4.2.2 Societal implications

Our results demonstrate that the extent to which ridesourcing is more popular among travellers with an above average value of time depends on the socio-economic inequality level (Fig. 4.3A). For instance, when g equals 0.25, of the 5% travellers with

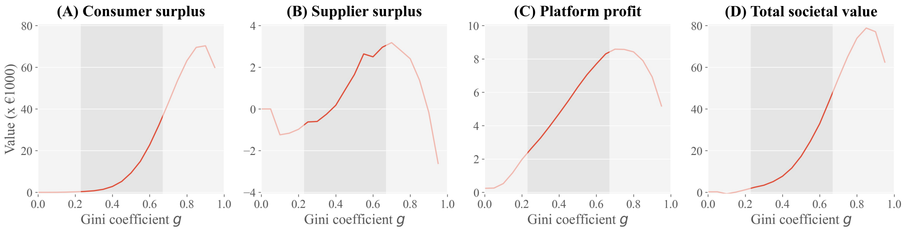


Figure 4.4: Social welfare generated by ridesourcing markets depending on the degree of socio-economic inequality. We present four indicators (de Ruijter et al., 2022b). (A) Consumer surplus, defined as the increase in logsums when ridesourcing is added to the choice set. (B) Supplier surplus, defined as the summed difference between job seekers' earnings and costs associated with the ridesourcing market, including labour opportunity costs and registration costs. (C) Profit from commissions. (D) The total social welfare, defined as the sum of the previous three. The highlighted area in each graph corresponds to observed values of the Gini coefficient in cities around the world.

the highest value of time, 4.7% chooses ridesourcing as their mode of travel for their trip (Fig. 4.2A), around three times the population average. When g is 0.65, almost 1 in 5 individuals in the respective group opts for ridesourcing, nearly five times the population average. The ridesourcing market then attracts travellers with an average value of time of more than 20 euro per hour, including some extremely time-sensitive travellers, compared to an average value of time of approximately 13 euro per hour when $g = 0.25$.

We observe even greater differences in supply-side participation depending on job seekers' reservation wage. When $g = 0.25$, of the 5% individuals with the lowest reservation wage, 46.9% participate in the ridesourcing market on an average day (Fig. 4.2B), compared to just 2.9% for the entire population of job seekers. This results in an average driver reservation wage of just over a third of the average job seekers' reservation wage. The participation rate of the 5% job seekers with the lowest reservation wage peaks at $g = 0.5$ (93.3%), after which it marginally decreases due to diminishing earnings. Yet, if we take the 25% job seekers with the lowest reservation wage instead, we find increasing participation rates beyond $g = 0.5$ (Fig. 4.2B). When g exceeds 0.6, the average ridesourcing driver's reservation wage lies below €2 per hour (Fig. 4.3B), less than 10% of the population average. Fig. 4.3B demonstrates that the average hourly ridesourcing earnings exceed the average reservation wage of drivers by €2-€4 independent of the geographical area's Gini coefficient. Since both indicators vary between drivers, particularly earnings, not all drivers earn more than their reservation wage.

We observe that the consumer surplus increases exponentially with the Gini coefficient (Fig. 4.4A). This increase stems from (i) ridesourcing becoming more attractive due to increased supply, and (ii) the presence of highly time-sensitive travellers that

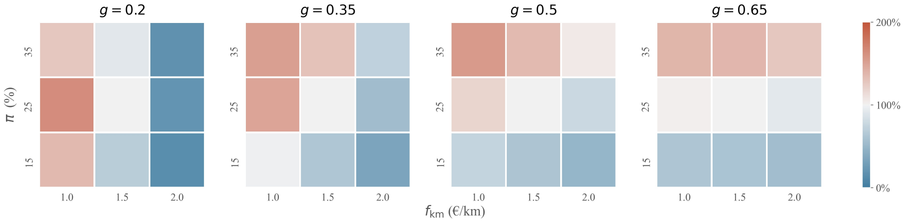


Figure 4.5: Platform profit depending on platform's pricing strategy and the degree of socio-economic inequality in society. Profit is given relative to the profit under reference strategy with $f_{\text{km}} = 1.5$ €/km *and* $\pi = 25\%$.

benefit considerably from a direct service. Fig. 4.4B shows that in scenarios with limited inequality, the aggregated supplier surplus, which also accounts for costs associated with registration (the ability to participate), may be negative. Due to the relatively low participation probability in this case, registration costs are not offset by participation earnings. Platform profit increases linearly with the Gini coefficient (Fig. 4.4C). Considering fixed pricing, this follows directly from a linear increase in ridesourcing demand (Fig. 4.2A). In socio-economically unequal urban areas, the societal value generated by ridesourcing platforms, defined as the sum of the consumer surplus, supplier surplus and platform profit, consists predominantly of the consumer surplus (Fig. 4.4D).

4.2.3 Pricing

In all previous scenarios, the platform per-kilometre fare f_{km} and the commission rate π were set to €1.5 and 25%, respectively, based on Uber's pricing in Amsterdam (Uber Technologies Inc., 2020a). We hypothesize, however, that a higher degree of socio-economic inequality allows for higher fares - as the demand-side target group of ridesourcing becomes more cost-insensitive - and a higher commission rate - as the supply-side target group of ridesourcing becomes more insensitive to income. We therefore proceed with analysing platform profit and other social welfare indicators for eight alternative pricing strategies, with $f_{\text{km}} = \{€1, €1.5, €2\}$ and $\pi = \{15\%, 25\%, 35\%\}$. Furthermore, we do so for four different levels of socio-economic inequality, i.e. $g = \{0.2, 0.35, 0.5, 0.65\}$. The results are presented in Figs. 4.5 and 4.6.

We find that when $g = 0.2$, a low per-kilometre fare is crucial to maximising platform profit (Fig. 4.5). A platform then generates 63.4% more profit when opting for a per-kilometre fare of €1 instead of €1.5, assuming an optimal 25% commission rate. This strategy yields a nearly 50% increase in demand-side participation and a 15% increase in supply-side participation. The moderate commission rate of 25% is then found optimal for the platform whereas a high commission rate, in combination with low fares, deters too many job seekers. In contrast, a low commission rate generates

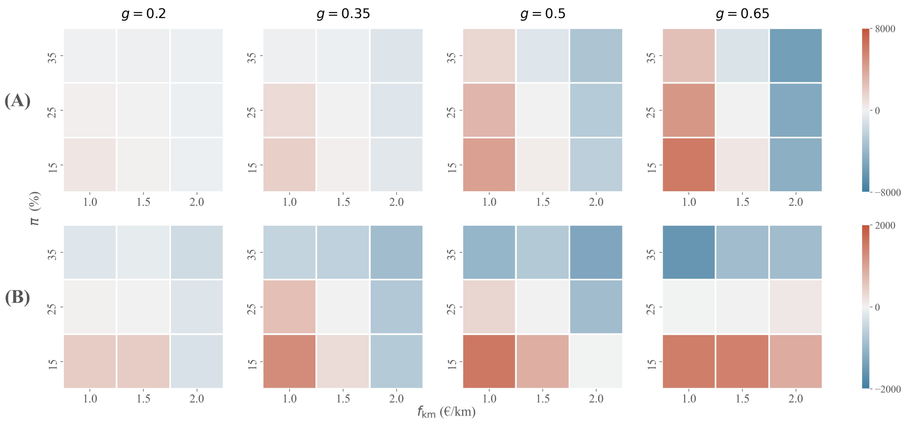


Figure 4.6: (A) consumer surplus and (B) supplier surplus depending on platform's pricing strategy, for different levels of socio-economic inequality. Values are relative to reference pricing strategy with $f_{\mathrm{km}} = 1.5$ €/km and $\pi = 25\%$.

insufficient induced demand (through reduced waiting following from latent supply) to compensate for a lower profit per satisfied request.

When $g = 0.65$, we find that the per-kilometre fare f_{km} has a limited effect on platform profit. The reason is that induced demand from lower fares (while accounting for changes in supply) is counteracted by a lower profit per market transaction. Conversely, the commission rate π is a crucial platform pricing instrument for profit maximisation in socio-economically unequal societies. A commission rate of 35% compared to 25% (with $f_{\mathrm{km}} =$ €1.5) for instance yields 36.9% more platform profit. Having a very low reservation wage, few drivers are deterred when a platform opts for such a commission (14.8% of drivers), so that the increase in platform commission only results in a marginal reduction of ridesourcing demand (2.3%). In terms of platform profit, the lower market share is substantially compensated for by a higher profit margin on remaining demand.

Platform pricing decisions may not only strengthen the previously proposed (positive) relationship between socio-economic inequality and platform profit (in Fig. 4.4C), but also the (negative) relationship between socio-economic inequality and driver earnings (in Fig. 4.2B). Fig. 4.6B shows that a higher commission rate results in a substantially lower supplier surplus, suggesting that profit-maximising behaviour in socio-economically unequal societies is likely to come at the expense of drivers. Such a strategy also harms travellers, albeit to a much lesser extent as the relation between commission and consumer surplus is much less pronounced (Fig. 4.6A). In areas with limited inequality, on the other hand, profit-maximising strategies are less costly for participants in the two-sided market. Due to the presence of few job seekers with a low reservation wage, the platform is more restricted in setting its commission. In fact, in a relatively equal society a profit-maximising pricing strategy entails charging low fares, which is likely to benefit both travellers (directly) and drivers (less idle time through induced demand).

4.2.4 Extreme (in)equality

In the preceding, we provided evidence for a positive relationship between socio-economic inequality and ridesourcing market share within the range of observed inequality. In this subsection, we analyse ridesourcing performance under degrees of socio-economic inequality which extent beyond the range of those currently observed amongst urban societies worldwide.

First, we observe that in hypothetical societies with g above the observed maximum of 0.67, (a further) increase in Gini coefficient does not induce a further increase in (demand-side) ridesourcing market share (Fig. 4.2A). In fact, from $g = 0.8$ onward, there is a strong negative relationship between inequality and ridesourcing modal split, and thereby platform profit. The reason is that, in such societies, few travellers have an extremely high value of time, while everyone else is very insensitive to travel time and therefore unlikely to opt for the relatively expensive ridesourcing service. With few customers and many drivers willing to work for little, driver earnings are very low in highly unequal societies, down to less than €3 per hour on average when $g = 0.95$ (Fig. 4.2D). Travellers, on the other hand, experience a supreme service with just a one minute average pick-up time (Fig. 4.2C).

At the other end of the spectrum, i.e. for g below the minimum observed real-world value of 0.23, we observe that the ridesourcing market ends up in an undersupplied state. Even though drivers face little to no matching time given limited competition for requests, their earnings are limited by considerable deadheading for picking up customers (Fig. 4.2D). With very little heterogeneity in reservation wages, few job seekers are willing to drive for the resulting wage. At the same time, the ridesourcing platform fails to attract substantial demand, which is required to minimise drivers' deadheading, because (i) there are few time-sensitive travellers that otherwise benefit most from the existence of ridesourcing, and (ii) the presence of few drivers implies a poor level of service. In other words, ridesourcing dependency on network effects - i.e. few market participants resulting in low matching efficiency - can exacerbate general unwillingness to participate in the market when the pools of travellers and drivers are relatively homogeneous in terms of their socio-economic properties. This indicates that operating a ridesourcing platform in a society with limited socio-economic inequalities may not be viable. In fact, in our experiment when g is below 0.1, not a single job seeker is willing to drive for the platform (Fig. 4.2B).

4.3 Discussion

Our findings show that the profit generated by ridesourcing platforms increases substantially with socio-economic inequality. We identify four (intertwined) mechanisms which contribute to this relation. First, there are more time-sensitive travellers in unequal societies. These travellers are relatively likely to opt for the direct, private service offered by ridesourcing platforms. Second, there are more job seekers willing to participate for limited market earnings. In fact, we observe that ridesourcing supply is even more elastic than demand in relation to inequality, so that ridesourcing markets are more likely to end up substantially oversupplied in unequal societies. This results in an improved level of service due to shorter waiting times. The difference between supply and demand elasticity (in relation to inequality) arguably stems from two underlying reasons: (i) asymmetry in the distributions of reservation wage and value of time, i.e. both distributions are right-skewed, implying that the majority of individuals have a below average value of time / reservation wage, and (ii) that income is likely more important in working decisions than travel time is in mode choice; whereas at the same time it is undeterred by decreasing driver earnings and increased level of service as inequality grows. Third, increased market participation (on both sides) yields better quality matches, i.e. the average pick-up distance decreases with the scale of the market. This results in an even better level of service, and ultimately, a larger market share. Fourth, the abundant presence of job seekers with a low ridesourcing reservation wage allows the platform to raise its commission rate, which yields a higher profit per served traveller.

Whereas socio-economic inequality is beneficial for companies operating ridesourcing markets as well as for travellers requesting rides on these platforms, the earnings of drivers participating in these markets decrease considerably with socio-economic inequality. This is the outcome of increased competition for ridesourcing requests as a result of the abundance of job seekers with a low ridesourcing reservation wage in socio-economically unequal societies. Furthermore, this may be aggravated by profit-maximising pricing decisions, i.e. platforms opting for a higher commission under large inequality. Based on our experiments, it is highly unlikely that ridesourcing markets evolve towards an undersupplied market equilibrium, a market state potentially benefiting drivers. In our experiments, it only occurs for Gini coefficient g of 0.15 or smaller, whereas the minimum value observed in reality is 0.23.

Our results indicate that societies with a high degree of socio-economic inequality are likely target markets for ridesourcing service providers. We observe low driver earnings particularly in these markets, down to less than one fifth of the average job seeker's reservation wage of €25 per hour. Authorities may therefore consider policies aimed at improving the earnings of ridesourcing drivers in socio-economically unequal urban areas. This may include regulation of the commission, which we find to benefit travellers as well. Alternatively, driver earnings may be boosted with supply caps, as implemented for instance in New York City, aiming to reduce supply-side competition.

The presented results follow from applying an agent-based model representing the interactions between the key actors in the ridesourcing market to a case study resembling the city of Amsterdam. While this approach allows to explore the effect of the entire range of inequality levels - from perfect equality to extreme inequality - as well as platform's pricing strategy in isolation from other factors, results should not be interpreted without caveats. For instance, our method assumes that travellers' value of time and job seekers' reservation wage follow a log-normal distribution (resulting in a similar Gini coefficient), based on an estimation of the distribution of (gross) income in the Netherlands. While there is evidence that the reservation wage of a job is related to income in previous work (Feldstein & Poterba, 1984), it is also influenced by other factors, including the (personal) perceived attractiveness of the job. Yet, given its association with income, it seems likely that the reservation wage distribution is in reality right-skewed, a key condition for the supply elasticity related to socio-economic inequality to exceed the corresponding demand elasticity. Furthermore, future research can account for spatial correlations in travellers' and job seekers' time perceptions associated with socio-economic inequality, i.e. spatial clustering of high and low income households, the effect of which on ridesourcing systems is uncertain. At the same time, heterogeneity in travellers' and job seekers' time valuations may not be the sole mechanism through which socio-economic inequality can affect ridesourcing systems. For instance, socio-economic inequalities may contribute to safety concerns (Wilkinson & Pickett, 2010; Hummelsheim et al., 2011; Vieno et al., 2013). In the literature, there is no consensus whether ridesourcing is perceived positively or negatively with regard to safety (Glöss et al., 2016; Acheampong, 2021; Liu et al., 2022), and therefore it is undetermined how such a consideration would affect the market share of ridesourcing.

All in all, we consider it probable that ridesourcing platforms thrive on socio-economic inequality. While the transportation and demand features vary from one location to another, the mechanism of cheap labour and time-sensitive ridesourcing users allowing for network effects and higher platform commission in unequal urban areas is likely universal. We recommend future research investigating exactly how context attributes such as labour market conditions, demand and transportation system features affect the relationship between socio-economic inequality and ridesourcing performance. We anticipate that repositioning - not captured in this work - may further contribute to a negative relationship between socio-economic inequality and ridesourcing drivers' income. The reason is that travellers' waiting times are already minimal (and the service rate maximal) without drivers repositioning, implying that repositioning - while potentially benefiting individual drivers in the short run - is likely to yield minimal induced demand at the system level, instead resulting only in additional operational costs for drivers.

It would be valuable to delve deeper into the intricate, bidirectional relationship between ridesourcing platforms and socio-economic inequality, in addition to examining the effect of other factors than inequality, such as the average income in the population. While a previous study has touched upon how ridesourcing platforms may contribute to socio-economic inequality (Bokányi & Hannák, 2020), their analysis omitted the daily decisions made by both ridesourcing users and job seekers. This omission presents an opportunity to investigate how these decisions influence the dynamics of inequality. Understanding the potential existence and magnitude of a reinforcing feedback loop in this context could shed light on the complexities of the ridesourcing market's influence on socio-economic disparity, and vice versa.

Finally, examining the impact of socio-economic inequalities on various mobility services beyond ridesourcing could also offer intriguing insights. At the same time, we expect that gig platforms outside of passenger mobility may benefit in a similar way from socio-economic inequality as ridesourcing providers do. This applies particularly to markets for low-skill services that are most interesting for cost-insensitive individuals, such as platforms for household jobs, meal delivery or grocery delivery.

4.4 Methods

4.4.1 Travel demand data

Travel demand is taken from a data set generated with an activity-based model for the Netherlands (Arentze & Timmermans, 2004), selecting trips with origin and destination in the studied area, with a trip distance of at least 2 kilometres, and a request time between 09:00 and 18:00. Travellers' value of time is drawn from a log-normal distribution with a mean of €10 per hour, and a standard deviation corresponding to Gini coefficient g. Each day, travellers make the same trip, for which they reconsider their travel mode on a daily basis. To reduce the computational complexity of the simulation, all travellers with a below 5% probability of choosing ridesourcing when no waiting time is anticipated are assumed to never opt for ridesourcing.

4.4.2 Modelling framework

Our model captures daily participation decisions in the ridesourcing market (Fig. 4.7). We thereby represent how agents learn from individual participation experience, or through the experience gained by others. Experiences are represented with a within-day operational model for ride-hailing (Kucharski & Cats, 2022), based on double-sided participation volumes. Our day-to-day model accounts for barriers to participation, i.e. platform registration. This requires platform awareness and trading off potential investments associated with the ability to participate in the market against anticipated participation earnings. In the ensuing we describe the processes captured in our model in more detail.

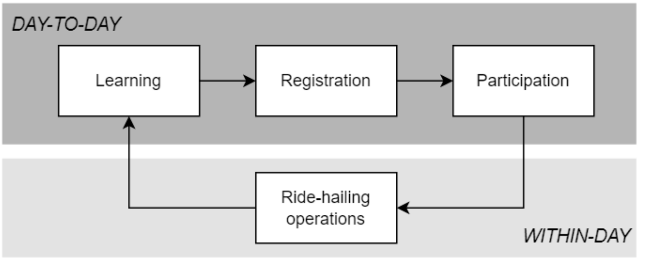


Figure 4.7: Day-to-day processes captured in the simulation model, for a single side of the ridesourcing market.

Participation

Assume job seeker s has a reservation wage r_s, drawn once from a log-normal distribution with a mean of €25 per hour and a standard deviation that yields Gini coefficient

g. It represents the minimum wage for which they are - on a typical day - willing to drive for the ridesourcing platform. With this assumption, our model follows the neo-classical theory of labour supply (Chen & Sheldon, 2016; Sun et al., 2019a; Xu et al., 2020). Our participation model considers that variables other than the anticipated income $\hat{i}_{st}$ (for day t) and the reservation wage r_s may play a role in participation decisions, by means of applying a random utility model with sensitivity parameter β_{ptp} and error term ε_{ptp}. The utility and the resulting probability that job seeker s participates in the market on day t are as follows:

$$U_{st}^{\text{participate}} = \beta_{\text{ptp}} \cdot (\hat{i}_{st} - r_s) + \varepsilon_{\text{ptp}} \tag{4.1}$$

$$p_{st}^{\text{participate}} = \frac{1}{1 + \exp(-U_{st}^{\text{participate}})} \tag{4.2}$$

At the same time, each day traveller c chooses a transport mode from a choice set M. In addition to ridesourcing, this set contains three alternative modes: private car, bike and public transport. Walking is not considered given its limited modal share for trips longer than 2 kilometres (Schaap et al., 2015). Travellers consider five attributes in their mode choice: in-vehicle time v_{cm}, the sum of access and egress time a_{cm}, waiting time $\hat{w}_{ctm}$, the number of required transfers q_{cm}, and travel cost ρ_{cm}. The choice model parameters associated with these attributes are denoted β_m^{ivt}, β_m^{access}, β_m^{wait}, β_{transfer}, and β_{cost}, respectively. Only the stop waiting time $\hat{w}_{ctm}$ of ridesourcing is dynamic, i.e. depending on supply and demand levels on that particular day. Mode-specific preferences are captured by means of an alternative-specific constant ASC_{cm}. A random utility model with an error term $\varepsilon_{\text{mode}}$ is applied to account for unobserved variables in the mode choice. The utility associated with mode m and the probability of choosing that mode are as follows:

$$U_{ctm}^{\text{mode}} = \beta_m^{\text{ivt}} \cdot v_{cm} + \beta_m^{\text{access}} \cdot a_{cm} + \beta_m^{\text{wait}} \cdot \hat{w}_{ctm} + \beta_{\text{transfer}} \cdot q_{cm} + \beta_{\text{cost}} \cdot \rho_{cm} + ASC_{cm} + \varepsilon_{\text{mode}} \tag{4.3}$$

$$p_{ctm}^{\text{mode}} = \frac{\exp(U_{ctm}^{\text{mode}})}{\sum_{m \in M} \exp(U_{ctm}^{\text{mode}})} \tag{4.4}$$

Ride-hailing operations

We adopt an agent-based model, *MaaSSim*, for simulating the within-day dynamics of ride-hailing systems (Kucharski & Cats, 2022), in order to obtain passengers' waiting time and drivers' income depending on supply and demand levels. Each day, eight hours are simulated. Participating drivers work all eight hours, i.e. there is no work shift choice. We assume that drivers lease their vehicles, bearing per-kilometre operational costs of 0.25 €/km (Nibud, 2022), which covers for fuel, insurance, and minor maintenance costs. Matching takes place whenever there is a non-empty virtual queue of unassigned requests and a non-empty virtual queue of idle drivers. The platform agent assigns idle drivers to pending requests based on their proximity, i.e. the closest pair is selected. All match offers are accepted by travellers and drivers. A ride request is revoked if unanswered after 10 minutes, which is perceived as 30 minutes of waiting to account for inconvenience associated with not finding a driver. Drivers remain idle at their last drop-off location until assigned to a new request. When driving, they move at a (constant) speed of 36 km/h (Kfzteile24, 2019). The platform applies a distance-independent base fare f_{base}, an additional per-kilometre fare f_{base}, and a commission rate π.

Learning

We apply a Markov model to represent learning from experience, i.e. each agent assigns a weight of 20% to their last experience as opposed to all previous information. Agents that are not registered do not gain first-hand experience and instead rely on information from other (registered) agents. Each day, each passenger (driver) receives a private signal of the waiting time (earnings) in the system, which we draw from a random distribution with mean equal to the average experienced waiting time (earnings), and standard deviation equal to 0.5 times the standard deviation of the distribution of experienced waiting time (income).

Registration

We assume that agents can only participate in the market if they have been informed about the existence of the service. We model this with two (separate) epidemic compartment models, one for job seekers and one for travellers. The probability to be informed on day t depends on the share of fellow job seekers or travellers, respectively, that have been previously informed, and information transmission rate ψ.

In addition, we assume that driving for the platform - unlike requesting a ride on the platform - requires medium- to long-term investments, representing entering into vehicle leasing and insurance contracts for instance. Every day, (informed) job seekers have a 10% probability of evaluating their registration status. We assume that the daily costs associated with being registered (vehicle leasing costs) are 20 euros (ANWB, 2024), which cannot be cancelled in the first 5 days after registration. In (de)registration decisions, they consider participation probability $p_{st}^{\text{participate}}$, i.e. the fact that participation earnings $\hat{\imath}_{st}$ may need to outweigh reservation wage r_s by more than the daily registration costs, to cover for participation-independent registration costs on days that they do not participate in the market. (De)registration choice is - similar to participation choice - modeled with a random utility model, with sensitivity parameter β_{reg} and error term ε_{reg}.

4.4.3 Implementation

The simulation is terminated once both the average expected waiting time and the average expected income change by less than 1% for five days in a row. The model is implemented in Python. We replicate the experiment for statistical significance, with the number of replications based on the average anticipated driver earnings and the average anticipated user waiting time.

4.5 Data availability

Network data for Amsterdam is retrieved from OpenStreetMap, public transport itineraries from OpenTripPlanner. Travel demand is harvested from the Albatross data set (Arentze & Timmermans, 2004). The code to generate ridesourcing system performance indicators in market equilibrium for given socio-economic inequality and pricing settings is available here: https://github.com/Arjan-de-R/MaaSSim.

Chapter 5

Two-Sided Dynamics in Duopolistic Ridesourcing Markets with Private and Pooled Rides

In the analyses presented in previous chapters, the provision of ridesourcing was limited to a single service provider. In this chapter, we extend the model for two-sided dynamics in ridesourcing markets to allow for markets with two service providers, each offering either private or pooled rides. This allows us to (i) analyse how fragmentation costs — potential efficiency losses in matching in a market with fragmented demand and supply — vary with market features and user attributes, and (ii) under which of these conditions markets with multiple service providers are sustainable.

Our experiments consist of two parts. First, we evaluate how the evolution of the market is affected by whether private or shared rides are offered by each ridesourcing provider, assuming drivers and users enter in exclusive arrangements with platforms. Second, for a market with two platforms offering private rides, we analyse whether multi-homing can be effective in countering market fragmentation costs, which includes evaluating how rewarding such a strategy is for travellers and drivers.

This chapter is based on the following article:

de Ruijter, A., Engelhardt, R., Dandl, F., Geržinič, N., van Lint, H., Bogenberger, K. & Cats, O. (2024). Two-Sided Dynamics in Duopolistic Markets with Ride-hailing and Ride-pooling. *12th Symposium of the European Association for Research in Transportation (hEART)*, Aalto, June 2024.

5.1 Introduction

Ridesourcing platforms have revolutionised the taxi industry by leveraging the ubiquity of smartphones and mobile data to connect travellers directly with private drivers. Advanced real-time algorithms for matching trip requests and drivers adopted by these platforms allow for efficient pick-ups. At the same time, the outsourcing of vehicle and labour supply to freelance drivers can enhance the alignment between supply and demand levels. The platform business model allows ridesourcing providers to seamlessly expand from one city to others, which may explain why in numerous cities worldwide, ridesourcing service is offered by various platforms concurrently. For example, Uber and Lyft provide ridesourcing services in New York City, while Uber and Bolt offer similar services in Amsterdam.

As the efficiency of the matching of drivers and riders in ridesourcing services is intricately linked to the scale of the market (de Ruijter et al., 2022b), the overall system efficiency is likely to be smaller in ridesourcing markets with multiple service providers compared to monopolistic markets (Séjournè et al., 2018). This affects travellers through longer waiting, drivers through less productive working, platforms through lower market shares and the general public through higher vehicle mileage. In New York City, it was estimated that fragmentation of a market with only private rides (from hereon referred to as a ride-hailing market) leads to a 4-6% increase in the minimum fleet size required to serve all trips in case of two providers and 6-10% if there are three providers (Vazifeh et al., 2018). (Frechette et al., 2019; Kondor et al., 2022; Zhou et al., 2022a,b) establish that market fragmentation costs strongly depend on context variables, including the number of service providers, the initial fleet size, trip density, the market share of ride-hailing and traffic speeds. While in Manhattan, for example, the increase in the minimum fleet size associated with market fragmentation (assuming fixed taxi demand) is estimated at just 2.5%, it is estimated at 8.5% for Singapore, 37% for San Francisco, 55% for Vienna, and even 67% for Curitiba (Kondor et al., 2022). Variations in fragmentation costs between cities are mainly driven by differences in the average urban traffic speed and the density of demand, both of which have been observed to have a negative correlation with fragmentation costs.

An important shortcoming of the aforementioned studies on market fragmentation costs is that they assumed fixed demand and supply per service provider, while in reality ride-hailing markets may be prone to developing towards a winner-takes-all equilibrium (Bai & Tang, 2022). Kondor et al. (2022) highlight that smaller players (platforms) face a comparatively higher cost associated with market fragmentation. This could trigger a feedback loop where the declining service quality of the smaller platform diminishes its attractiveness to potential consumers and suppliers, further exacerbating the reduction in service quality. Ultimately, this cycle might lead to a scenario where the larger platform emerges as the sole provider in the market. As a consequence, monopolists could exploit their market dominance by raising fares and commission to the detriment of travellers and drivers.

Multi-homing behaviour by travellers and drivers can possibly prevent or mitigate potential undesirable consequences associated with ride-hailing market fragmentation

(Loginova et al., 2022), i.e. the emergence of monopolistic markets or a suboptimal service when multiple platforms co-exist. Multi-homing enables both suppliers and consumers to use multiple platforms concurrently. Drivers can receive requests from various platforms, while travelers can check vehicle locations on different platforms or request rides from multiple platforms simultaneously, thereby increasing the likelihood that an idle driver is in the proximity of a pending trip request. However, substantial (financial and non-financial) costs may be associated with the practice of multi-homing (Guo et al., 2023a), explaining the mere 25% multi-affiliation among drivers in Chicago (Zhang & Nie, 2021) and the 17% of ride-hailing consumers in New York City using multiple platforms (Chitla et al., 2023).

It is plausible that market fragmentation costs are even larger — and consequently winner-takes-all markets even more likely — in the provision of ride-pooling, compared to ride-hailing. The reason is that ride-pooling system efficiency is highly scale-dependent (Tachet et al., 2017) given that pooling relies on compatibility in trip requests in addition to driver-request pairings. Similarly to ride-hailing, trip density and market shares are crucial for generating sufficient demand to obtain acceptable waiting times, i.e. the likelihood of finding a driver in proximity. However, in the case of ride-pooling there is the additional need to obtain acceptable detour times, i.e. the likelihood of finding in addition to a driver also several travel requests within spatial and temporal proximity. Passenger utility can either increase (better matches, occurring particularly when demand for ride-pooling is already high) or decrease (longer detours, particularly when demand is moderate) with demand for ride-pooling (Fielbaum et al., 2023). Ride-pooling fragmentation costs further depend on pooling thresholds set by the platform and the spatial distribution of trip requests (Zhang et al., 2022).

At the same time, markets with service differentiation between platforms, for instance when one service provider offers hailing and the other one pooling, may be less prone to winner-takes-all equilibria (Vignon et al., 2021). These service types target (at least partially) different market segments: pooling serves cost-sensitive users, while hailing accommodates the preferences of time-sensitive individuals.

Previous research examining ridesourcing market equilibria following from competition among ridesourcing providers, including traveller and driver responses, has focused on three key areas. First, a substantial body of literature has delved into the intricate dynamics of pricing arising from the strategic decisions of competing service providers in the market (Zha et al., 2016; Nikzad, 2017; Ahmadinejad et al., 2019; Wu et al., 2020; Benjaafar et al., 2020; Ni et al., 2021; Zhang & Nie, 2021; Sun & Ertz, 2021; Bai & Tang, 2022; Zhang et al., 2023; Sen & Ghosh, 2023; Huang et al., 2023; Cai et al., 2023; Sun & Liu, 2023). Notably, research by Zha et al. (2016) and Nikzad (2017) demonstrate that competition in the ride-hailing market may not necessarily lead to lower service prices as platforms compete for suppliers in addition to consumers. Second, multiple studies evaluate the impact of multi-homing in ridesourcing markets based on analytical models (Bryan & Gans, 2019; Bernstein et al., 2020; Zhang & Nie, 2021; Loginova et al., 2022; Bai & Tang, 2022; Li et al., 2023). Resulting from a trade-off between enhanced matching efficiency and increased platform pricing power (as platform competition is more limited) under multi-homing, whether multi-homing increases or decreases social welfare remains subject of debate without a unanimous consensus. Lastly, a separate strand of research examines 'coopetition' strategies, where competitors collaborate to mitigate matching inefficiencies in competitive ridesourcing markets (Pandey et al., 2019; Vignon et al., 2021; Cohen & Zhang, 2022; Engelhardt et al., 2022b; Guo et al., 2023b; Wang et al., 2023b; Bao et al., 2023). These studies investigate a range of strategies, including bilateral and centralised trading, as well as launching joint services with profit-sharing arrangements.

In determining ridesourcing market equilibria, previous studies substantially simplify interaction effects between supply and demand in the evolution of ridesourcing services, visualised in Fig. 5.1. First, previous works utilise aggregate matching functions for determining how double-sided market participation utilities depend on double-sided participation levels (relations marked *(A)* in Fig. 5.1), by which they neglect the spatio-temporal nature of within-day ride-hailing and ride-pooling operations. This includes matching based on current trip requests and vehicle locations, driver repositioning and ride offer acceptance decisions. Second, macroscopic functions are applied for the reverse relationship, i.e. to establish platform participation levels depending on system performance (relations marked *(B)* in Fig. 5.1). Hereby, previous studies into ridesourcing fragmentation effects neglect market participation barriers, uncertainty in participation decisions, and spatio-temporal properties affecting mode choice. This also applies to generic studies investigating competition among two-sided platforms (Rochet & Tirole, 2003; Armstrong, 2006; Armstrong & Wright, 2007; Jeitschko & Tremblay, 2019; Belleflamme et al., 2019).

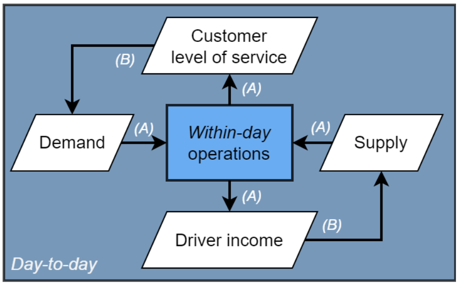


Figure 5.1: Conceptual representation of the interaction between supply and demand in the ridesourcing market.

We address the stated research gap with an agent-based model capturing both within-day ride-hailing and ride-pooling operations as well as day-to-day processes affecting market participation levels. In particular, our study has the following specific (interrelated) contributions:

I. **Day-to-day Dynamics in the Two-Sided Market**: In our day-to-day model, we represent diffusion of platform awareness, tactical registration decisions and daily market participation decisions in consideration of imperfect information, i.e. following from learning from own and others' experience. The need for accounting for such (disaggregate) dynamic processes has been reiterated by Guo

& Huang (2022). The day-to-day model enables exploring under which conditions initial differences in market shares between platforms — resulting from platform entry timing or random advantages — translate to winner-takes-all (or asymmetric) market outcomes. In addition, accounting for day-to-day processes in ridesourcing provision allows for establishing day-to-day variations that may occur in system performance in the market equilibrium, a feature that has not been commented on in previous research.

II. **Detailed Ridesourcing Dynamics with Competition**: We model the within-day interactions between individual service providers, users and drivers, accounting for their spatio-temporal attributes and possibly resulting in distributional effects. Specifically, the model represents platform matching, ride offer acceptance decisions and repositioning decisions, all affecting experiences with the platform and, consequently, market participation levels. In addition, accounting for drivers' repositioning allows us to give a more complete picture of the effect of ridesourcing on the vehicle kilometres travelled.

III. **Ride-Hailing and Ride-Pooling**: In addition to modelling within-day operations exclusively for platforms offering private rides, we extend our analysis to incorporate ride-pooling services. This allows us to examine the likelihood of winner-takes-all markets in ride-pooling compared to ride-hailing, considering network effects in traveller pairing. We also explore market competition effects when one platform offers ride-hailing and the other offers ride-pooling, potentially targeting distinct user groups based on trip-related attributes, mode preferences, and socio-economic characteristics, the importance of which has been underlined by the results of Zhang & Nie (2021).

IV. **Single- and Multi-Homing**: We account for multi-homing practices in our day-to-day and within-day models, i.e. (participating) drivers and travellers can be tied to a single platform or open to offers on multiple platforms. Contrary to previous works investigating multi-homing, our approach allows for investigating mixed multi-homing scenarios, i.e. scenarios in which some agents multi-home while others single-home, in line with what is observed in reality (Jiang et al., 2018; Zhang & Nie, 2021; Chitla et al., 2023). We can explore the effect of different multi-homing scenarios on aggregated system performance as well as the experiences of single-homers and multi-homers separately.

V. **Endogenous Demand**: Unlike previous approaches, our model accounts explicitly for alternative modes, thereby capturing how ridesourcing propensity depends on travellers' departure time and their trip origin and destination. This allows us to investigate modal split shifts associated with the introduction of ridesourcing services depending on several factors, including multi-homing and which service types are offered by each provider. Hereby, the model provides a more complete picture of the potential effect that ridesourcing provision has on the number of vehicle kilometres travelled.

The remainder of the paper is organised in the following way. In Section 5.2, we describe the developed simulation model, including day-to-day and within-day processes associated with multi-homing and single-homing agents in the ridesourcing market. We describe our case study, designed to mimic the city of Amsterdam, and the scenario design of our experiments in Section 5.3. Section 5.4 contains a description of the results of our analyses, which are summarised in Section 5.5 along with their implications for policy makers and future research.

5.2 Methodology

Assume a ridesourcing market with platforms $P = \{p_1, \ldots, p_n\}$, each offering ride-hailing ('solo' rides) or ride-pooling in area A. Platforms in P generate revenue by charging a commission on each transaction between travellers and drivers in the market. We assume constant pricing and commissions, both within-day (operational) and day-to-day (tactical). Demand for each platform follows from the mode choice decisions of traveller agents $T = \{t_1, \ldots, t_b\}$ which make a daily trip within the boundaries of A. The fleet size of ridesourcing platforms depends on the daily work decisions of job seeker agents $J = \{j_1, \ldots, j_l\}$, who compare the utility derived from driving in the ridesourcing market to the utility of alternative opportunities.

We study the implications of ridesourcing market fragmentation using a simulation model designed to capture multiple day-to-day processes associated with ridesourcing supply and demand, as well as the within-day operations of such markets, as visualised in the conceptual framework in Fig. 5.2. Specifically, on each day in our day-to-day simulation model of the ridesourcing market the following five subsequent processes take place:

I. *Diffusion of market awareness* — a precondition for platform registration — is captured through a peer-to-peer communication process for the aggregated ridesourcing market, i.e. agents learn about the existence of all platforms in P when (first) exposed to information about the ridesourcing market. The awareness diffusion speed depends on the number of unaware individuals as well as the number of market participants. The platform awareness diffusion process is described in more detail in Subsections 5.2.1 (single-homing agents) and 5.2.2 (multi-homing agents).

II. Agents that are aware of the existence of the market make an occasional *platform registration decision*, in which they trade off expected benefits from participating in a platform with long-term costs associated with platform registration. Here, we also model how they learn about system performance by communicating with agents about recent experiences in the market. The registration decision of travellers and job seekers is described in more detail in Subsections 5.2.1 and 5.2.2.

III. Registered agents then make a daily *platform participation decision*, in which they compare the expected utility derived from platform participation to the utility of alternatives, i.e. alternative modes for travellers and alternative activities for job seekers. The expected utility derived from using the platform for travellers depends on the expected waiting time, in-vehicle time and ride fare. For job seekers, it depends on the expected financial return. We refer the reader to Subsections 5.2.1 and 5.2.2 for more information about the participation decisions.

IV. In representing the *within-day ridesourcing operations* following from previously mentioned participation decisions, we capture platforms' matching of customers to drivers and in case of ride-pooling also to other customers, customers' ride offer acceptance decisions, as well as drivers' repositioning behaviour. The within-day model is described in more detail in Subsections 5.2.1 and 5.2.2.

V. Customers and drivers update their expected participation utility for the next day based on their individual experience participating in the ridesourcing market. *Day-to-day learning* is modelled using a Markov process formulation, which we further elaborate on in Subsections 5.2.1 and 5.2.2.

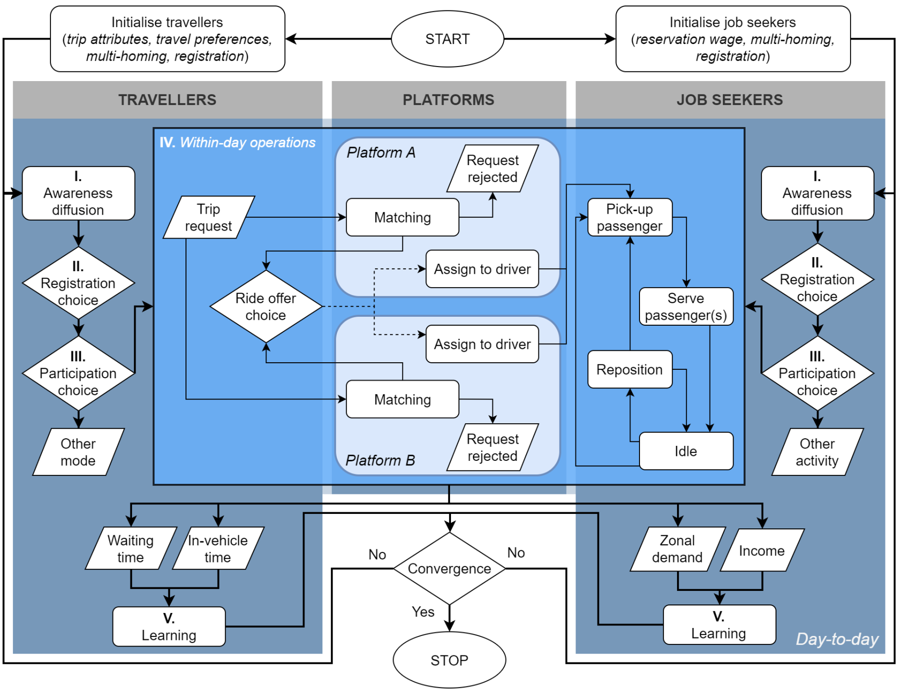


Figure 5.2: Conceptual representation of the day-to-day simulation model.

Both traveller agents and job seeker agents in the model are either (inherently) unwilling or willing to multi-home. Specifically, travellers T are subdivided into two subsets: single-homing travellers T', who will only enter in exclusive arrangements with platforms, and multi-homing travellers T'' who will always register with all platforms in P if they decide to incur market registration costs. Similarly, single-homing job seekers J' will exclusively register with a single platform, whereas multi-homing job seekers J'' will register with all platforms in P. The probability that travellers and job seekers are open to multi-homing are denoted ρ^{trav} and ρ^{js}, respectively.

In Subsection 5.2.1, we describe previously mentioned day-to-day processes in the ridesourcing market in more detail for single-homing agents. In Subsection 5.2.2, we elucidate the distinctions in these processes for agents engaged in multi-homing. In Subsection 5.2.3 we explain how market convergence is established based on double-sided platform participation levels, how we determine the number of replications for statistical significance, and how the computational complexity of the simulation model is kept low.

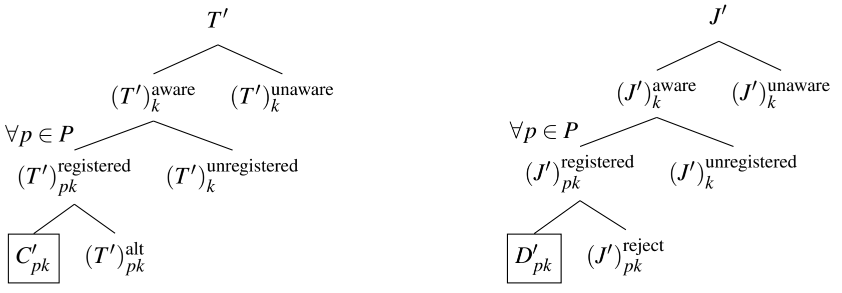
5.2.1 Single-homing

For the description of the different model components in the remainder of this section, we use set notations for relevant (single-homing) traveller and job seekers subpopulations. These notations are visualised in Fig. 5.3. First, the populations of single-homing travellers T' and job seekers J' are subdivided into those aware of the ridesourcing market on any given day k — $(T')_k^{\text{aware}}$ and $(J')_k^{\text{aware}}$, respectively — and those not aware — $(T')_k^{\text{unaware}}$ and $(J')_k^{\text{unaware}}$, respectively. Aware agents are further subdivided into individuals registered with platform p (for each $p \in P$) and individuals that are not registered with any platform on day k. Registered agents can be further classified depending on the result of their participation decision on this day. Following from the participation decisions in the day-to-day model, Travellers opting to (exclusively) use a ridesourcing platform p on day k are from hereon referred to as customers C'_{pk}, job seekers working (exclusively) for this platform as D'_{pk}. $(T')_{pk}^{\text{alt}}$ denotes travellers registered with p that choose another mode, $(J')_{pk}^{\text{reject}}$ registered job seekers with p that opt for another activity.

Awareness diffusion (I)

Insufficient awareness during the initial stages of innovation adoption can impede innovation's uptake. For ridesourcing specifically, slow propagation of awareness could result in a service's failure if it prevents the formation of a critical user mass. There is generally limited empirical evidence regarding how potential users become aware of innovations, particularly within the context of the ridesourcing market. It is likely influenced by a complex interplay of factors, including peer-to-peer interactions, mass media communication, and platform marketing strategies. Due to the dearth of empirical underpinning for the awareness diffusion process in the ridesourcing market, especially concerning the impact of marketing strategies and global communication sources, we have chosen to employ a model based on peer-to-peer interactions.

Specifically, we propose a diffusion model in which the (aggregated) awareness diffusion rate on each side of the market depends on market participation levels. During interactions between a ridesourcing market participant — i.e. a customer or a driver, and independent of whether they single-home or multi-home — and someone unaware of ridesourcing — $t \in (T')_k^{\text{unaware}}$, $j \in (J')_k^{\text{unaware}}$ — there exists a probability



(a) *(b)*

Figure 5.3: Tree diagrams visualising set notations associated with (a) single-homing travellers and (b) single-homing job seekers. Each branch is related to one of the day-to-day processes in ridesourcing evolution, either awareness diffusion (first branch level in the tree), registration decisions (second level) or participation decisions (third level).

ψ of transmitting awareness about ridesourcing. We assume that every day travellers $T = \{t_1, \ldots, t_b\}$ and job seekers $J = \{j_1, \ldots, t_l\}$ communicate randomly with respectively $y^{\text{awareness,trav}}$ and $y^{\text{awareness,js}}$ individuals on their side of the market. With C''_k as the set of multi-homing customers and D''_k as the set of multi-homing drivers on day k, the probabilities that unaware travellers and unaware job seekers become aware of ridesourcing market P on this day, respectively, are:

$$\phi_{tk}^{\text{inform,traveller}} = \frac{\psi \cdot y^{\text{awareness,trav}} \cdot \left(|C''_k| + \sum_{p \in P} |C'_{pk}|\right)}{b}, \quad \forall t \in (T')_k^{\text{unaware}} \tag{5.1}$$

$$\phi_{tk}^{\text{inform,js}} = \frac{\psi \cdot y^{\text{awareness,js}} \cdot \left(|D''_k| + \sum_{p \in P} |D'_{pk}|\right)}{l}, \quad \forall j \in (J')_k^{\text{unaware}} \tag{5.2}$$

The preceding specification of the awareness diffusion model contains the following implicit assumptions:

1. Individuals are either entirely unaware or aware of the entire ridesourcing market, i.e. of all or none of the platforms in P.

2. Travellers do not receive information about the ridesourcing market's existence from job seekers, and vice versa.

3. Ultimately, all travellers and job seekers learn about the ridesourcing market, unless the market reaches an equilibrium in which no travellers or no job seekers participate in the ridesourcing market. This is in line with the widespread familiarity with ridesourcing platforms seen today, as exemplified in the Netherlands (Geržinič et al., 2023).

Platform registration (II)

Since the process of (de-)registering with a platform can be time-consuming and comes with substantial medium- to long-term (financial) commitments, registration decisions have a more tactical nature compared to travellers' and job seekers' daily market participation decisions. Therefore, it is assumed that on a given day travellers and job seekers that are aware of the ridesourcing market reevaluate their registration status — being registered or unregistered — with a probability γ. In addition, we assume that they cannot deregister in the first ν days after registering with a platform.

Our model assumes two subsequent decision-making processes in the registration decisions of (single-homing) job seekers. The first one entails the choice between platforms, the second one the choice between being registered with the preferred platform and not being registered at all. Travellers in our model do not make the second decision, following the limited burden associated with demand-side registration, i.e. a few administrative procedures. In other words, we assume that they will always register with one of the platforms in P.

Prior to the registration decision, travellers seek information about waiting time and pooling detours when using ridesourcing platform p, while job seekers seek information about the earnings when driving for this platform. Specifically, we assume that travellers and job seekers are informed about the experiences of y^{regist} agents participating (on their side of the market) in platform p on day $k-1$. We apply a Markov process formulation to represent a higher valuation of recent information in comparison to past information, considering possibly on-going evolution of ridesourcing platforms' participation levels. Particularly, travellers and job seekers assign a weight κ^{comm} to the average received information signals $\tilde{x}_{tpk}$ and $\tilde{x}_{jpk}$, respectively, relative to their (personal) previous expectation for relevant indicator $\hat{x}_{tp,k-1}$ and $\hat{x}_{jp,k-1}$. Hence:

$$\hat{x}_{tpk} = (1-\kappa_{tpk}^{\text{comm}}) \cdot \hat{x}_{tp,k-1} + \kappa_{tpk}^{\text{comm}} \cdot \tilde{x}_{tpk} \tag{5.3}$$

$$\hat{x}_{jpk} = (1-\kappa_{jpk}^{\text{comm}}) \cdot \hat{x}_{jp,k-1} + \kappa_{jpk}^{\text{comm}} \cdot \tilde{x}_{jpk} \tag{5.4}$$

The assigned weight can vary between registered agents and unregistered agents, considering that the former group can accumulate personal experiences:

$$\kappa_{tpk}^{\text{comm}} = \begin{cases} \kappa^{\text{comm,registered}} & t \in (T')_{pk}^{\text{registered}} \\ \kappa^{\text{comm,unregistered}} & \text{otherwise} \end{cases} \tag{5.5}$$

$$\kappa_{jpk}^{\text{comm}} = \begin{cases} \kappa^{\text{comm,registered}} & j \in (J')_{pk}^{\text{registered}} \\ \kappa^{\text{comm,unregistered}} & \text{otherwise} \end{cases} \tag{5.6}$$

Specifically, the indicators travellers learn about are platforms' waiting time w_{tpk}, and relative detour factor z_{tpk} when opting for pooling. Job seekers learn about income i_{jpk} when spending a day driving for the platform.

Travellers When making a registration decision, (single-homing) travellers choose to register with one or none of the platforms in P. The utility derived from registering with platform p depends on the expected utility when travelling with this platform U_{tpk}^{travel}, the composition of which is described in Subsection 5.2.1. We assume that unobserved variables are less prominent in (more tactical) registration decisions compared to daily participation decisions, which we account for by multiplying the travel (participation) utility associated with platform p with parameter θ^{trav}, taking the value of 1 or more, when determining the utility of being registered with this platform:

$$U_{tpk}^{\text{registered}} = \theta^{\text{trav}} \cdot U_{tpk}^{\text{travel}} \tag{5.7}$$

We apply a Logit model so that the probability of being registering with platform p at the end of day k is formulated as follows:

$$\phi_{tpk}^{\text{registered}} = \frac{\exp(U_{tpk}^{\text{registered}})}{\sum_{p \in P} \exp(U_{tpk}^{\text{registered}})} \tag{5.8}$$

Job seekers Single-homing job seekers first decide on their preferred platform, assuming they need to register with one, followed by an actual registration decision for this platform. In the first decision, they compare, for all platforms in P, the expected daily surplus s_{jpk} associated with being registered with platform p over not being registered at all. The definition of the (economic) surplus in our model is taken from Small & Rosen (1981). Specifically, the surplus depends on the expected utility $U_{jpk}^{\text{participate}}$ derived from driving for the platform and the expected utility U_j^{alt} derived from alternative opportunities in the time otherwise spent working. The surplus value accounts for observed and unobserved variables in the participation decision by integration of income sensitivity parameter β^{inc}:

$$s_{jpk} = \frac{\ln\left(\exp(U_{jpk}^{\text{participate}}) + \exp(U_j^{\text{alt}})\right)}{\beta^{\text{inc}}} \tag{5.9}$$

We refer the reader to Subsection 5.2.1 for the definitions of $U_{jpk}^{\text{participate}}$ and U_j^{alt}.

We apply a Logit model with sensitivity parameter $\beta^{\text{reg,platform}}$ and error term $\varepsilon^{\text{register}}$, so that the utility and probability of registering with platform p (if market registration were to be required) are, respectively, defined as:

$$U_{jpk}^{\text{registered}} = \beta^{\text{reg,platform}} \cdot s_{jpk} + \varepsilon^{\text{register}} \tag{5.10}$$

$$\phi_{jpk}^{\text{registered}} = \frac{\exp(U_{jpk}^{\text{registered}})}{\sum_{p \in P} \exp(U_{jpk}^{\text{registered}})} \tag{5.11}$$

Based on probabilities $\Phi = \left\{\phi_{jk1}^{\text{registered}}, \cdots, \phi_{jkn}^{\text{registered}}\right\}$, single-homing job seekers select platform p^* as their preferred platform when registering.

We posit that job seekers incur a daily expense denoted as Υ when they are registered in the ridesourcing market. With $\beta^{\text{reg,market}}$ as the monetary sensitivity parameter in the market registration decision, the utility of registering in the ridesourcing market (considering the previous choice for platform p^*) is now denoted as:

$$U_{jk}^{\text{registered}} = \beta^{\text{reg,market}} \cdot (s_{jp^*k} - \Upsilon) + \varepsilon^{\text{register}} \tag{5.12}$$

As for the platform registration model, we assume a logit model specification for the market registration decision (Eq. 5.10). With the utility of the alternative choice — not registering to the market — fixed to 0, the probability of being registered in the ridesourcing market on day k for a job seekers making a registration decision on that day is formulated as:

$$\phi_{jk}^{\text{registered}} = \frac{\exp(U_{jk}^{\text{registered}})}{\exp(U_{jk}^{\text{registered}}) + 1} \tag{5.13}$$

Job seekers' sensitivity to monetary gains may be different in platform choice compared to market registration choice. We therefore introduce two separate multipliers $\theta^{\text{js,platform}}$ and $\theta^{\text{js,market}}$ for converting job seekers' income sensitivity β^{inc} (in participation choice) to the monetary sensitivity parameter in registration choice:

$$\beta^{\text{reg,platform}} = \theta^{\text{js,platform}} \cdot \beta^{\text{inc}} \tag{5.14}$$

$$\beta^{\text{reg,market}} = \theta^{\text{js,market}} \cdot \beta^{\text{inc}} \tag{5.15}$$

Market participation (III)

Travellers Every day, travellers $(T')_{pk}^{\text{regist}}$ registered with ridesourcing platform p decide to request a ride offer using this platform or to opt for another mode of transportation for their daily trip. In making their choices, travellers assess travel time, cost, and mode-specific preferences. Notably, in our model travellers' value of time may vary across modes, and different time attributes, namely in-vehicle time, waiting time at a stop, and stop access time, may be perceived distinctively. Value of time and mode-specific attributes may also vary among individuals.

Hence, we specify time parameters β_{tm}^{ivt}, β_{tm}^{wait}, and $\beta_{tm}^{\text{access}}$ to describe a traveller's perception of in-vehicle time, waiting time and stop access time, respectively. Financial costs associated with the selection of mode m on day k are expressed as f_{tmk} and allocated a weight of β^{cost} in the utility function. Preferences associated with modes are accounted for by specifying ASC_{tm} as the constant of traveller t related to mode m. If public transport is offered, transfers induce an above and beyond utility penalty denoted as β^{transfer}.

Mode attributes and consequently utilities are considered constant from day-to-day for all modes other than ridesourcing. In contrast, in the case of ridesourcing, the (expected) waiting time (when opting for solo or pooling) and in-vehicle time (when opting for pooling) are endogenous variables, while all other variables remain constant.

To address attributes other than time, cost and mode-specific constants in mode choice, a random utility model is employed with error term $\varepsilon^{\text{mode}}$. We define $\hat{v}_{tmk}$

as the (anticipated) time spent on-board a vehicle, a_{tmk} as the access time required to reach a pick-up location / stop, $\hat{w}_{tmk}$ as the (anticipated) waiting time at a pick-up location / stop, and o_{tmk} as the number of transfers with mode m on day k. The set of modes is denoted M_k and includes platform p if a traveller is registered with this platform on day k. The utility associated with each mode in M_k for traveller t and the subsequent probability of choosing that particular mode are, respectively, determined as follows:

$$U_{tmk}^{\text{travel}} = \beta_{tm}^{\text{ivt}} \cdot \hat{v}_{tmk} + \beta_{tm}^{\text{access}} \cdot a_{tmk} + \beta_{tm}^{\text{wait}} \cdot \hat{w}_{tmk} + \beta^{\text{transfer}} \cdot o_{tmk} + \beta^{\text{cost}} \cdot f_{tmk} + ASC_{tm} + \varepsilon^{\text{mode}} \quad (5.16)$$

$$\phi_{tmk}^{\text{travel}} = \frac{\exp(U_{tmk}^{\text{travel}})}{\sum_{m \in M_k} \exp(U_{tmk}^{\text{travel}})} \quad (5.17)$$

Job seekers Every day, registered job seekers decide whether they want to spend their day driving for the platform. We assume that they decide to work when the expected income, denoted as $\hat{i}_{jk}$, surpasses the opportunity costs associated with their working time, represented as r_j. This assumption is in line with the principles of the neoclassical theory of labour supply, as detailed in previous research (Chen & Sheldon, 2016; Sun et al., 2019a; Xu et al., 2020).

Similar to the previously described registration decision, we utilise a random utility model to account for various factors influencing the participation decision apart from income. These factors include day-to-day fluctuations in job seekers' reservation wage due to varying activity schedules. We introduce an income sensitivity parameter β^{inc} and an error term $\varepsilon^{\text{participate}}$ to encompass income-related and random elements and imperfect knowledge in the decision-making process.

The utility associated with driving, the utility associated with alternative opportunities, and the resulting likelihood that registered job seeker $j \in (J')_{pk}^{\text{registered}}$ works for platform p on a given day k are, respectively, defined as:

$$U_{jpk}^{\text{participate}} = \beta^{\text{inc}} \cdot \hat{i}_{jpk} + \varepsilon^{\text{participate}} \quad (5.18)$$

$$U_j^{\text{alt}} = \beta^{\text{inc}} \cdot r_j + \varepsilon^{\text{participate}} \quad (5.19)$$

$$\phi_{jpk}^{\text{participate}} = \frac{\exp(U_{jpk}^{\text{participate}})}{\exp(U_{jpk}^{\text{participate}}) + \exp(U_j^{\text{alt}})} \quad (5.20)$$

Within-day simulation (IV)

The within-day model captures the short-term decision-making of drivers, customers and platforms on day k in a time-based simulation. The goal is to model travel and driving experiences in the market to establish (actual) experienced attributes for ridesourcing customers (i.e. fare, travel time, waiting time) and drivers (i.e. revenue, cost), which likely differ from their expectations in (pre-day) participation decisions. The within-day model's outcomes for the most recent day, combined with historical data, inform travellers' and job seekers' decisions about future market registration and participation.

As an outcome of the day-to-day model, input to the within-day simulation are job seekers $D'_{pk} \subset J'$ that decided to work as drivers for platforms $p \in P$. Single-homing drivers have exclusive arrangements with platforms, i.e. $\bigcap_{p \in P} D'_{pk} = \emptyset$. Likewise, travellers that seek to use ridesourcing service p on a given day are described by the set of customers $C'_{pk} \subset T'$. Each customer $c \in C'_{pk}$ is described by an origin location o_c^{req}, destination location d_c^{req} and a request time t_c^{req}. Again, single-homing customers are tied to a single platform, i.e. $\bigcap_{p \in P} C'_{pk} = \emptyset$. During the simulation, the goal of each platform is to assign schedules (a sequence of stops) to drivers working for the platform that serve incoming customer requests.

A simulation time step (typically set in seconds or minutes) consists of three main steps: 1) Driver states (e.g. position, on-board customers) are updated according to the currently assigned plan. 2) Incoming customer requests are treated sequentially. Requests are replied by corresponding platforms with an offer consisting of estimated waiting time, travel time and fare, which is used by the customer to decide for (or against) a platform. 3) The platform centrally re-optimises currently assigned driver schedules.

A platform is here assumed to either offer only solo or only pooled rides. In this study, the trip assignment objective for both platforms is to minimise the *total driving time* (for the platform). For a ride-hailing service, this will minimise the time deadheading to pick-up locations and for a ride-pooling service, two customers will share a trip unless the total vehicle time to perform both rides with a single vehicle is longer than two vehicles providing the service. For this study, time constraints are introduced to provide an attractive, yet operationally efficient service for customers. A maximum waiting time of σ^{wait} and a maximum relative detour/delay time of σ^{detour} (compared to the direct route travel time) are imposed. The detour/delay time also includes boarding of other passengers, where each boarding process is modelled to last υ seconds.

Offers are created by the platform by inserting the pick-up and drop-off of a customer request into the current schedules of its drivers, and selecting the one with the best change in the above-mentioned criterion. If no feasible option is found, a request is rejected by the platform. From this schedule, expected waiting time and travel time for the customer is extracted. Platforms offering solo rides are operated based on a base fare f^{base} and a solo km fare f^{km}. Pooling is offered to travellers at a discount λ (on the whole fare). If they receive an offer, single homing customers will accept this offer, i.e. they do not wait for future offers or (re)consider alternative transport options. After a customer booked the service with one of the platforms, this platform will inform the assigned driver about the new plans. For simplicity, it is assumed that drivers accept all new assignments.

As the insertion procedure usually results in sub-optimal assignments of trip schedules to drivers, a global re-optimization is triggered and performed by each platform. The algorithm is based on Alonso-Mora et al. (2017b). As this algorithm is not the focus of this study, the reader is referred to Engelhardt et al. (2020) for details of its implementation.

Once drivers become idle (i.e. do not have a trip assigned by a platform), they might consider driving to network regions where they expect demand to increase the probability for a new assignment and therefore to increase revenue. It is assumed that these repositioning trips are not suggested by the platform, but rather — similar to platforms like Uber or Lyft — chosen by drivers themselves. Specifically, we assume that idle drivers at the end of each hour consider repositioning to neighbouring zones based on the anticipated (daily) demand (explained in Subsection 5.2.1) in each of these zones and their current zone. The probability of repositioning to each zone equals the relative share of expected trips in the zone.

After the simulation, drivers evaluate their profit by subtracting driving costs from their revenue, which includes the sum of all fares of customers they served, while considering platform commission rate π.

Learning (V)

To capture learning from own experience travelling or working with a platform, we apply a similar Markov process formulation as for learning from other people's experience, i.e. the process which is described in Section 5.2.1. To be precise, a weight κ^{private} is assigned to personally experienced system performance indicators on day k relative to previously gathered information up to this day, including information from communicating with others when deciding about platform registration. Hence, if customer $t \in C'_{pk}$ (driver $j \in D'_{pk}$) experiences indicator x_{tk} (x_{jk}) on day k, their expectation for the value of this indicator $\hat{x}_{t,k+1,p}$ ($\hat{x}_{t,k+1,p}$) associated with platform p for the next day is defined as:

$$\hat{x}_{t,k+1,p} = (1-\kappa^{\text{private}}) \cdot \hat{x}_{tpk} + \kappa^{\text{private}} \cdot x_{tpk} \tag{5.21}$$

$$\left(\hat{x}_{j,k+1,p} = (1-\kappa^{\text{private}}) \cdot \hat{x}_{jpk} + \kappa^{\text{private}} \cdot x_{jpk}\right) \tag{5.22}$$

The indicators that customers learn about are waiting time (if a request is denied by the platform, waiting time is perceived to be Γ minutes) and in-vehicle pooling detour times, whereas drivers learn about income.

In addition, job seekers also learn about the ridesourcing demand per zone, albeit not from own experience. Our model assumes that at the end of each day all (registered) job seekers are informed about the total ridesourcing demand per zone on that day (e.g. by a transport authority), information that (merely) guides their within-day repositioning decisions (described in Section 5.2.1). We assume a similar learning process as for the other indicators, i.e. they assign a weight κ^{demand} to the information provisioned on the last day as opposed to all previously provisioned information.

5.2.2 Multi-homing

In this Subsection, we describe how the relevant day-to-day and within-day processes in the ridesourcing market are adapted for multi-homers, i.e. travellers and job seekers that are open to being matched on all platforms in P when they decide to participate in the ridesourcing market on any given day.

Awareness diffusion (I)

The market awareness diffusion process is independent of agents' willingness to multi-home.

Platform registration (II)

Considering limited demand-side registration costs, multi-homing travellers will choose to be registered with all platforms in P when making a registration decision. Accordingly, multi-homing travellers are not interested in platform-specific indicators and will inquire only about (recent) experiences of multi-homers participating in the ridesourcing market, information that is used to guide future mode choice decisions. We assume that single-homing agents only communicate with registered agents that single-home, specifically about the utility associated with individual platform usage ($U_{tpk}^{\text{participate}}$, $\forall p \in P$). Contrary to single-homing travellers, multi-homing travellers also learn about the expected fare when multi-homing, which in a market with a ride-hailing and a ride-pooling provider depends on whether they get assigned to a private or shared ride. Their platform-independent registration decision implies that they experience uncertainty in ride fares, given that solo and pooling providers offer different fares.

The same general principle applies for supplying labour to the ridesourcing market. Multi-homing job seekers do not make a platform decision, and hence are only interested in learning the aggregated market utility $U_{jk}^{\text{participate}}$. Single-homing job seekers instead learn about individual platform utilities $U_{jk}^{\text{participate}}$ ($\forall p \in P$). However, contrary to multi-homing travellers, multi-homing job seekers do make a market registration decision, given (possibly substantial) costs Υ associated with the ability to drive for ridesourcing platforms. These costs are equal for single-homers and multi-homers, i.e. they are only incurred for the first platform.

Market participation (III)

Similar to the registration decision, multi-homing agents either participate with all platforms or with none of them. To be precise, if multi-homing travellers opt for ridesourcing over other modes of transportation they request offers on all platforms in P. Essentially, the entire ridesourcing market P is included in the available set of modes M_k, the utility of which depends on platform-independent performance indicators, learnt from other multi-homing agents as well as own experience. Similarly, multi-homing job seekers that choose to work are available to serve requests on all platforms in P. Hence, as opposed to single-homing agents, the participation decisions of multi-homing agents are based on aggregated ridesourcing market utilities $U_{jk}^{\text{participate}}$ rather than platform-specific utilities $U_{jpk}^{\text{participate}}$, $\forall p \in P$.

Within-day (IV)

When multi-homing is enabled, small adaptations for drivers and customers in the within-day model are made. In this case, multi-homing drivers D''_k are available for work on all platforms in P. Similarly, multi-homing customers C''_k request trips from all platforms in P.

For multi-homing drivers, it is assumed that they are available for service for all platforms $p \in P$ only when they are idle and looking for new assignments. Once they receive a new assignment from platform $\tilde{p}$, they log off from all other platforms and are no longer available for driving tasks there until completing assignments from $\tilde{p}$. During this time, they can get subsequent assignments from $\tilde{p}$. Only when they become idle again, they log in again to the other platforms. It is additionally assumed that drivers always accept an assigned driving task immediately by any platform. In the model, driver j^* is therefore complemented by a set $\tilde{P}_{j^*}$ describing the set of currently logged in platforms, which is updated accordingly when a driver receives a new assignment or becomes idle. Before creating an assignment, a platform always checks the logged in drivers.

Multi-homing customers request trips from all platforms in P. The platforms then check feasible solutions, and compute the best solution according to their matching objective — minimising total driving time — and produce an offer based on this solution. If multiple platforms offer the service, the offer (and therefore platform) with the highest utility as given in Eq. (5.16) (with actual ride offer characteristics and without the error term) is chosen.

Learning (V)

In our model, the way multi-homers learn from experience is similar to how single-homers learn from experience. There is again one key distinction: single-homers acquire insights into the service quality of individual platforms, while multi-homers gain knowledge about the collective ridesourcing market.

5.2.3 Implementation

Convergence

We determine market convergence based on double-sided participation levels. For this purpose, we evaluate the evolution of the number of (single-homing) agents choosing each individual platform as well as the number of multi-homers participating in the market, for both sides of the market. Formally, we define the following two sets of participation indicators, the first set associated with market demand and the second set associated with market supply:

$$G^{\text{dem}} = \left(\bigcup_{p \in P} \left\{|(C')_{pk}|\right\}\right) \cup \left\{|(C'')_k|\right\} \tag{5.23}$$

$$G^{\text{sup}} = \left(\bigcup_{p \in P} \left\{|(D')_{pk}|\right\}\right) \cup \left\{|(D'')_k|\right\} \tag{5.24}$$

In determining convergence, we should neglect random — i.e. non-systematic — day-to-day variations in market participation levels following from random components in peer-to-peer communication and decision-making processes. Formally, we define that the simulation has converged on day k when the absolute day-to-day change in the μ^{MA2}-day Moving Average (MA) of the μ^{MA1}-day Moving Average (MA) — nested to further smoothen out random, short-term fluctuations — has been below ω^{demand} for all demand-side participation indicators $g \in G^{\text{dem}}$ and below ω^{supply} for all supply-side participation indicators $g \in G^{\text{sup}}$, each for η days in a row:

$$\left| MA_{\mu^{\text{MA2}}}\left(MA_{\mu^{\text{MA1}}}(g)\right)_{k-h} - MA_{\mu^{\text{MA2}}}\left(MA_{\mu^{\text{MA1}}}(g)\right)_{k-h-1} \right| \leq \omega^{\text{demand}} \quad \forall h \in \{0,\dots,\eta\}, \forall g \in G^{\text{dem}} \tag{5.25}$$

$$\left| MA_{\mu^{\text{MA2}}}\left(MA_{\mu^{\text{MA1}}}(g)\right)_{k-h} - MA_{\mu^{\text{MA2}}}\left(MA_{\mu^{\text{MA1}}}(g)\right)_{k-h-1} \right| \leq \omega^{\text{supply}} \quad \forall h \in \{0,\dots,\eta\}, \forall g \in G^{\text{sup}} \tag{5.26}$$

Replications

In light of previously described stochastic processes pertaining to ridesourcing supply and demand, we need to run multiple replications to test and prove the statistical significance of our simulation results. In doing so, we utilise the same indicators that are used to determine convergence. We opt for a method previously applied in simulating monopolist ridesourcing markets (de Ruijter et al., 2022a,b).

This method is based on the sample mean $\overline{g}(q)$ and standard deviation $s_g(q)$ of convergence indicators $g \in G^{\text{dem}} \cup G^{\text{sup}}$ based on q initial simulation runs. The number of simulation runs that are needed, depending on confidence level $1-\alpha$ and allowable error $\varepsilon^{\text{repl}}$ of each indicator estimate $\overline{g}$ is determined by:

$$Z(q) = \max_{g \in G^{\text{dem}} \cup G^{\text{sup}}} \left(\frac{s_g(q) \cdot t_{m-1,\frac{1-\alpha}{2}}}{\varepsilon^{\text{repl}}} \right)^2 \tag{5.27}$$

in which the allowable error depends on the absolute value of indicator g:

$$\varepsilon^{\text{repl}} = \begin{cases} \varepsilon^{\text{repl,rel}} \cdot \overline{g}(q) & \overline{g}(q) \geq \zeta \\ \varepsilon^{\text{repl,rel}} \cdot \zeta & \text{otherwise} \end{cases} \tag{5.28}$$

Computational complexity

Each day in our simulation model requires modelling numerous decision-making processes involving a substantial population of agents as well as accounting for computationally complex within-day matching between customers and drivers, particularly when ride-pooling is offered. We limit the computational complexity of the simulation model by applying a filter to the traveller population based on their propensity of selecting ridesourcing based on their individual mode choice preferences. Specifically, if traveller agents exhibit a probability lower than the threshold defined by parameter χ even in the ideal conditions — i.e. in a situation where they expect neither waiting time nor in-vehicle delays, while receiving (pooling) discount λ on their fare — then they are subsequently excluded from the initial pool of travellers, i.e. they are assumed to choose another mode on any given day.

Simulation framework

The day-to-day processes associated with ridesourcing supply and demand are implemented in MaaSSim (Kucharski & Cats, 2022), and the within-day operational model in FleetPy (Engelhardt et al., 2022a), both of which are open-source agent-based simulators of mobility-on-demand services programmed in Python. The overarching simulation framework (FleetMaaS) is available here: https://github.com/Arjan-de-R/FleetMaaS.

5.3 Experimental design

5.3.1 Set-up

In this section, we outline the set-up of our experiments, which has been designed to mimic the city of Amsterdam, the Netherlands. This pertains to relevant aspects such as the potential ridesourcing market, the underlying road network, ridesourcing operations, and characteristics of alternative modes.

For the travel demand in Amsterdam, we employ a data set generated with the activity-based model Albatross (Arentze & Timmermans, 2004), selecting only trips of 2 kilometres and longer. In terms of the number of trip requests, we sample one-tenth of the total estimated demand in Amsterdam during an eight-hour window to limit the computation time of the day-to-day simulation. Similarly, we aim to represent one-tenth of all job seekers residing in Amsterdam. This relative sample size, 10%, aligns with prior research in the domain of agent-based modeling for transportation problems (Kaddoura, 2015; Bischoff & Maciejewski, 2016; de Ruijter et al., 2022a,b). In absolute terms, this sampling yields a total of $b = 100,000$ travellers and $l = 2,500$ job seekers. In the reference scenario, all of these agents single-home, i.e. $\rho^{\text{trav}} = 0\%$ and $\rho^{\text{js}} = 0\%$. In our analysis, travellers with a likelihood of below 5% to select ridesourcing, even under ideal conditions, are assumed to completely disregard ridesourcing, i.e. we set χ to 0.05. This amounts to approximately 70% of travellers in the reference scenario, aligning with the cumulative share of travellers found in a latent class model to be unlikely to adopt ridesourcing for urban trips in the Netherlands (Geržinič et al., 2023).

Ridesourcing vehicles utilise a road network with spatially heterogeneous yet static travel speeds. Concretely, we assume that drivers operate with a speed of 85% the speed limit. This value has been set so that the average travel speed based on the shortest paths (in terms of travel time) for all origin-destination pairs in Amsterdam approximates the average observed traffic speed in Amsterdam on a working day in reality (TomTom, 2023). We set 30 seconds as the time needed for pick-ups and drop-offs in ride-hailing ($\upsilon = 30$). In ride-pooling, each additional stop results in a 10-second delay. Each ride-pooling vehicle has capacity for 4 passengers.

Drivers incur per-kilometre operational costs δ^{km} of €0.25. Pricing of solo ridesourcing rides is set following Uber's approach in Amsterdam, omitting surge pricing. This entails charging a base fee f^{base} of 1.5€ and a per-kilometre fee f^{km} of €1.5. We assume that pooling platforms offer travellers a guaranteed one-third discount on solo trip fares, i.e. λ is 33.33%, even when no sharing eventually occurs. Platforms withhold 25% of the fares transferred from travellers to drivers, i.e. $\pi = 25\%$. The daily costs associated with being registered in the ridesourcing market for job seekers is set to €15. Market information about past demand that is communicated to job seekers to guide their repositioning decisions is provided per *Gebied* (area, majority of which are in the range of 2-10 km^2) as established by the municipality of Amsterdam (Gemeente Amsterdam, 2023). Platforms adopt a maximum allowed pooling delay σ^{detour} of 40% the direct in-vehicle time when matching customers to other customers. The time interval between consecutive (re-)assignments is one minute. Travellers with a ridesourcing request are willing to wait at most 10 minutes until pick-up, i.e. $\sigma^{\text{wait}} = 10$ minutes.

Beyond ridesourcing, the set of potential travel modes encompasses cycling, private vehicle usage and public transportation. The (in-vehicle) travel time with private car is the same as with a ride-hailing (private ride) provider. Access and egress take 5 minutes each. In addition to per-kilometre operational costs of 0.5 €/km, which are twice as high as those of ridesourcing drivers due to less frequent usage of their cars, private car users are charged a fixed fee of 15€ for parking in the city centre — i.e. in areas Centrum-West and Centrum-Oost as specified by the municipality (Gemeente Amsterdam, 2023) — and €7.50 elsewhere. Cyclists are assumed to use a private bike, i.e. this travel option is always free of charge. They travel using the same network as cars, yet, at a fixed speed of 15 km/h. Travellers' travel time and the number of required transfers when travelling with public transport is based on the itinerary leading to the quickest arrival at the destination, queried using OpenTripPlanner for September 19th 2023, based on travellers' origin, destination and trip request time. Public transport fares are determined based on the (full rate) fares as established by the transport authority of Amsterdam, i.e. a base charge of €1 and an additional €0.20 for every kilometer travelled.

Travellers' in-vehicle time perceptions, cost perceptions and mode-specific constants are based on a mixed logit model estimated using a data set of stated preference choices (Geržinič et al., 2023) for urban travel behaviour in the Netherlands. In the estimated choice model, in-vehicle time is distributed lognormally and mode-specific constants are distributed normally in the population of travellers. The ride-pooling constant equals the solo (ride-hailing) constant minus a (uniformly distributed) sharing penalty. We refer to Table 5.1 for the estimated values of the distributions of in-vehicle time, mode-specific constants and willingness to share.

We assume that all travellers perceive waiting time at a stop or pick-up location 2.5 times more negatively and walking time (for access and egress) 2 times more negatively than in-vehicle time (Wardman, 2004). A minute spent on a bike is perceived 2 times more negatively than a minute spent in a motorised vehicle, accounting for

Table 5.1: Mode choice parameter distributions

Parameter	**Distribution**
In-vehicle time	Lognormal(-2.760, 1^2)
Ride-hailing constant	$\mathscr{N}$(-5.18, 1.92^2)
Pooling penalty	$\mathscr{U}$[0, 0.554]
Bike constant	$\mathscr{N}$(0, 5.75^2)
Private car constant	$\mathscr{N}$(-1.96, 3.19^2)
Public transport constant	$\mathscr{N}$(-4.14, 1.15^2)

required physical exertion and limited productivity otherwise (Börjesson & Eliasson, 2012). Each transfer in public transport is perceived as 5 minutes of in-vehicle time (Yap et al., 2020) by all travellers. Compared to daily mode choice decisions, we assume that unobserved variables are less dominant in registration decisions by assigning a value of 3 to registration utility multiplier θ^{trav}.

Job seekers' reservation wage is distributed lognormally, with a mean of 25€/h — equal to the average hourly wage in the Netherlands (Centraal Bureau voor de Statistiek, 2022) — and chosen standard deviation so that the resulting Gini coefficient of reservation wage in the lognormal distribution equals 0.35 — close to the Gini coefficient of gross income in the Netherlands (Arts et al., 2019). Income sensitivity parameter in participation β^{inc} is set to 0.05. We set $\theta^{\text{js,market}}$ to 20 and $\theta^{\text{js,platform}}$ to 100 to represent that job seekers are more income sensitive in tactical registration decisions — particularly in the choice between platforms — than in daily participation decisions. The probability γ that job seekers (re)evaluate their ridesourcing registration status on a given day is set to 15%. They cannot deregister from a platform in the first 5 days after registering, i.e. $\nu = 5$. Daily costs Υ for being registered in the ridesourcing market add up to 20€, based on (short-term) vehicle leasing costs in the Netherlands (ANWB, 2024).

In learning, travellers and job seekers assign a weight of 0.2 to their last private experiences (i.e. $\kappa^{\text{private}} = 0.2$), a weight of 0.2 to the most recent information provided by the platform about zonal demand (i.e. $\kappa^{\text{demand}} = 0.2$), a weight of 0.2 to recent information from others, based on communication with $y^{\text{regist}} = 50$ agents, when personally registered in the market (i.e. $\kappa^{\text{comm,registered}} = 0.2$) and of 0.333 when unregistered (i.e. $\kappa^{\text{comm,unregistered}} = 0.333$). We configure Γ to be 30 minutes, i.e. we assume that travellers perceive denied service as 30 minutes of waiting time.

For the assigned parameter values in awareness diffusion, and determining convergence (established empirically) and the required number of replications in our experiments, we refer to Table 5.2.

At the beginning of the simulation, registered job seekers expect to earn the average reservation wage, while informed travellers expect no waiting time and no detour when opting for pooling. Initially, 20% of all agents (job seekers and travellers) are informed. Each initially informed (single-homing) traveller is registered with one of the platforms, while each initially informed job seeker has a 50% probability to be

Table 5.2: Awareness diffusion (left) and convergence/replication (right) parameters.

Parameter	**Value**	**Unit**
ψ	50	%
$y^{\text{awareness,trav}}$	8	travellers
$y^{\text{awareness,js}}$	2	job seekers

Parameter	**Value**	**Unit**
μ_{MA1}	25	days
μ_{MA2}	100	days
ω^{demand}	2	customers/day
ω^{supply}	0.05	drivers/day
η	25	days
α	5	%
$\varepsilon^{\text{repl,rel}}$	5	%
ζ	200	agents

registered with one of the platforms. The initial choice between platforms is random. Each day, drivers start at a randomly selected location in the network.

5.3.2 Scenarios

In our first set of experiments, we evaluate and compare three duopolistic (two platforms at the start of the simulation) market structures depending on whether each platform offers ride-hailing or ride-pooling. We compare the results to two monopolistic benchmark scenarios.

- **Solo-solo:** two platforms each offering a solo (ride-hailing) service
- **Solo-pool:** one platform offering a solo service, the other a ride-pooling service
- **Pool-pool:** two platforms each offering a ride-pooling service
- **Solo:** monopolistic platform offering solo (ride-hailing) service (benchmark)
- **Pool:** monopolistic platform offering ride-pooling service (benchmark)

The following set of experiments is focused on a market with two service providers each offering ride-hailing (*solo-solo*). We test the effect of multi-homing behaviour by simultaneously varying the share of travellers and the share of job seekers that are willing to multi-home. For each of the two, we test three values: 0% (only single-homing), 50% (half single-homing, half multi-homing) and 100% (only multi-homing).

The total set of experiments is summarised in Table 5.3.

5.4 Results

5.4.1 Market structure & service types

Fig. 5.4 shows that the market may develop towards a winner-takes-all market equilibrium when two platforms offer a solo service (*solo-solo* scenario). Fig. 5.5 provides an

Table 5.3: Design of the two experiments. The values in bold are reference variable values used in the other experiments.

#	Variable(s)	Tested values
1	Market structure (1)	**solo-solo**, solo-pool, pool-pool, solo, pool
2	Demand-side multi-homing (1)	**0%**, 50%, 100%
	Supply-side multi-homing (2)	**0%**, 50%, 100%

explanation for this development, highlighting the evolution of key performance indicators for five different replications. In early phases of market evolution, both demand (Fig. 5.5A) and supply (Fig. 5.5C) are subject to (purely) random day-to-day variations resulting in (random) differences in the average customer waiting time (Fig. 5.5B) and driver income (Fig. 5.5D) between platforms. This kick-starts a reinforcing feedback loop that leads travellers and drivers to gradually switch to the initially more lucky (and consequently larger) platform, which previously offered lower waiting times and higher earnings. Fig. 5.5 illustrates that the time required to reach a winner-takes-all outcome varies substantially between replications, influenced by the randomness in participation decisions during the initial days. Fig. 5.4 demonstrates that the resulting (winner-takes-all) equilibrium in the *solo-solo* market is similar to the equilibrium if only one platform had initially entered the market (*solo*).

In a market in which one platform offers a solo service and the other a pooling service (*solo-pool*), both platforms can co-exist. We observe that the solo platform attracts more demand and particularly more supply than the ride-pooling platform. With more active drivers per trip request, travellers opting for the solo provider experience a lower waiting time than users of the ride-pooling platform. For instance, nearly all solo users are picked up within five minutes of requesting a ride, whereas a substantial number of ride-pooling users experience a waiting time of over five minutes (Fig. 5.6A). In addition, the majority of ride-pooling users faces an additional delay due to detouring to pick-up other passengers, with a maximum of 9 minutes (Fig. 5.6B). Yet, approximately 4,000 travellers prefer ride-pooling over ride-hailing due to the lower pooling fares. Notably, drivers experience (roughly) the same earnings on both platforms, the distribution of which is shown in Fig. 5.6C for a random day in the equilibrium state. Selecting the platform that offers solo rides results in a higher revenue per served traveller; however, also leads to elevated operational costs per served traveller. Additionally, drivers face more idle time when working for the solo platform, a consequence of heightened supply-side competition within this platform.

The market with two ride-pooling providers (*pool-pool*) evolves towards an equilibrium with two approximately equally large platforms. A likely contributing factor for why a winner-takes-all scenario does not occur in such a market in our experiments (as opposed to a *solo-solo* market) is that pooling discounts are offered ex-ante, i.e. discounts are independent of actual sharing. Hereby, travellers will opt for the platform with the fewest other users to limit the chance of actually sharing their trip with other travellers, providing them with a (more) direct trip for the same fare. This

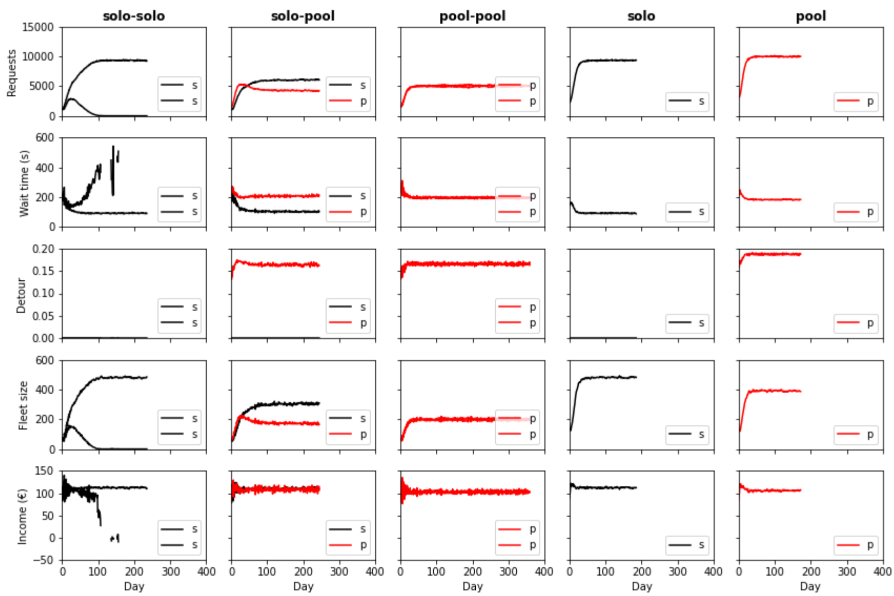


Figure 5.4: Evolution of five key ridesourcing market indicators (demand for ridesourcing, the average time from requesting a trip to being picked up by a driver, the average ride-pooling detour time relative to travellers' average shortest-path travel time, ridesourcing fleet size, and the average income of a ridesourcing driver per day) based on a single replication of the experiment for each of the market types. A market with one initial service provider converges to equilibrium within 200 days, whereas markets with two initial providers take more time to converge. Specifically, when both providers offer ride-pooling, convergence takes the longest —– nearly 400 days. While this figure shows the evolution of performance indicators for only one replication of each scenario, we observe similar patterns in other replications, even though the speed of convergence varies. Figure 5.5 illustrates the evolution of the ridesourcing market across different replications of the solo-solo market scenario.

negative network effect in ride-pooling has been described as the *extra-detour* effect by Fielbaum et al. (2023). In this case, this effect prevails over two positive network effects in ride-pooling: (i) the so-called *better-matching* network effect (more compatible trips result in less detouring) which generally occurs under already dense demand (ride-pooling in our experiments has a limited market share), and (ii) a network effect resembling the *Mohring* effect in public transport (drivers choosing the platform with most demand to maximise their productivity).

When considering the (demand-side) market share of ridesourcing markets depending on which services are offered (Fig. 5.7), we find that the largest market share (over 10%) is attained when one platform offers a ride-hailing service and the other a

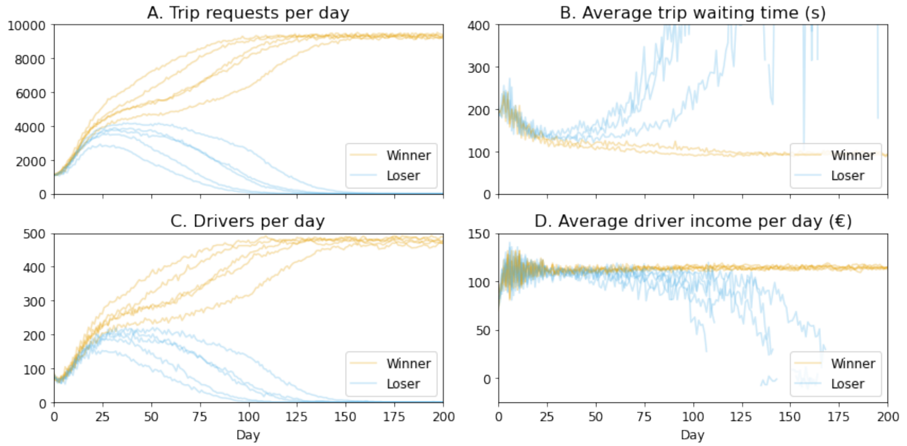


Figure 5.5: Evolution of five key ridesourcing market indicators (first 200 days) in the solo-solo market (demand for ridesourcing, the average time from requesting a trip to being picked up by a driver, the average ride-pooling detour time relative to travellers' average shortest-path travel time, ridesourcing fleet size, and the average income of a ridesourcing driver per day) for multiple replications of the experiment. We observe a similar, though more gradual, development when travellers / job seekers communicate with fewer others about travel time / income, i.e. for values of γ^{regist} *lower than 50.*

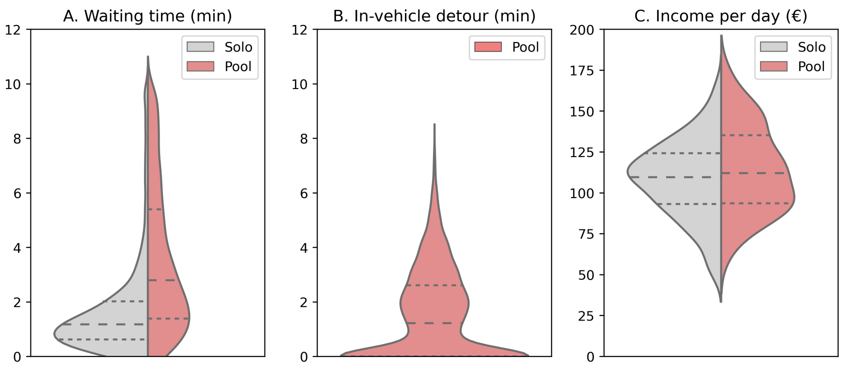


Figure 5.6: Distribution of A. Experienced waiting (pick-up) time, B. Experienced in-vehicle time, and C. Experienced driver income for each platform in the solo-pool market, for a random day in the equilibrium (based on a single replication of the experiment).

ride-pooling service. The ride-hailing platform in this market caters for time-sensitive users and the ride-pooling platform for less time-sensitive users, typically with relatively long trips (Fig. 5.8). If only ride-pooling is offered, either by a single provider or two providers, the market share is still close to 10%, as time-sensitive users may prefer ride-pooling over other modes when no private rides are offered in the market. We find that in all scenarios in which ride-pooling is provided by at least one platform a relatively large share (compared to other scenarios) of ridesourcing users would have otherwise opted for public transport (2.3-2.4% of all travellers). The market share of ridesourcing is most limited when only the solo service is provided, as some cost-sensitive users prefer using public transport considering its lower fares. Yet, still over 9% of travellers will choose ridesourcing in such a scenario.

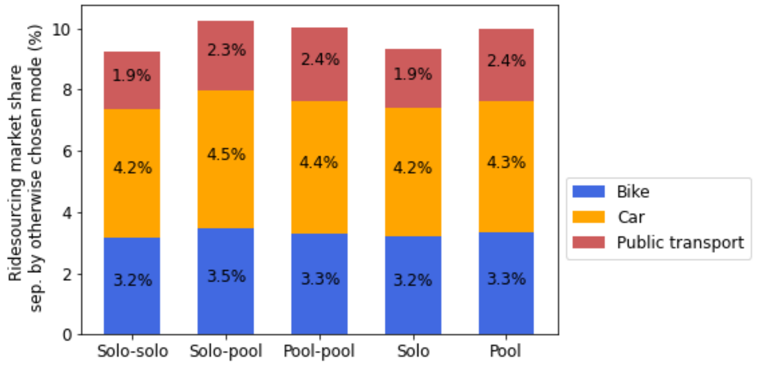


Figure 5.7: Market share of ridesourcing in the market equilibrium depending on the number of (initial) service providers and their service types, including what modes would have been chosen if ridesourcing had not been offered.

Ride-pooling is anticipated to provide a more efficient service in terms of the vehicle mileage needed to serve a single user compared to ride-hailing. Fig. 5.9 shows for different market types the number of ridesourcing vehicle kilometres divided by the sum of the shortest path distances between users' origins and destinations in the market equilibrium. A value of less than 1 essentially implies that the ridesourcing system is more efficient than a system in which everybody uses a private car to travel between their origins and destinations. We observe, however, that in all scenarios, independent of the number of (initial) service providers and service types that are offered, the number of vehicle kilometres per effective passenger kilometre (defined as the sum of vehicle kilometres divided by the sum of shortest path distances of all trips served in the ridesourcing market) is at least 1. It implies that ridesourcing in our experiments is never more efficient (in terms of the total vehicle distance) than private car usage. The ridesourcing market is least inefficient when ride-pooling is offered by a single service provider (*pool*). In such a scenario, multiple passengers share a vehicle for a substantial portion of all vehicle kilometres. Yet, high-occupancy sharing is rare given the fairly limited market share of the ride-pooling provider. At the same time, a substantial number of empty vehicle kilometres are generated due to repositioning and driving to users' pick-up locations. When the ride-pooling market is subdivided

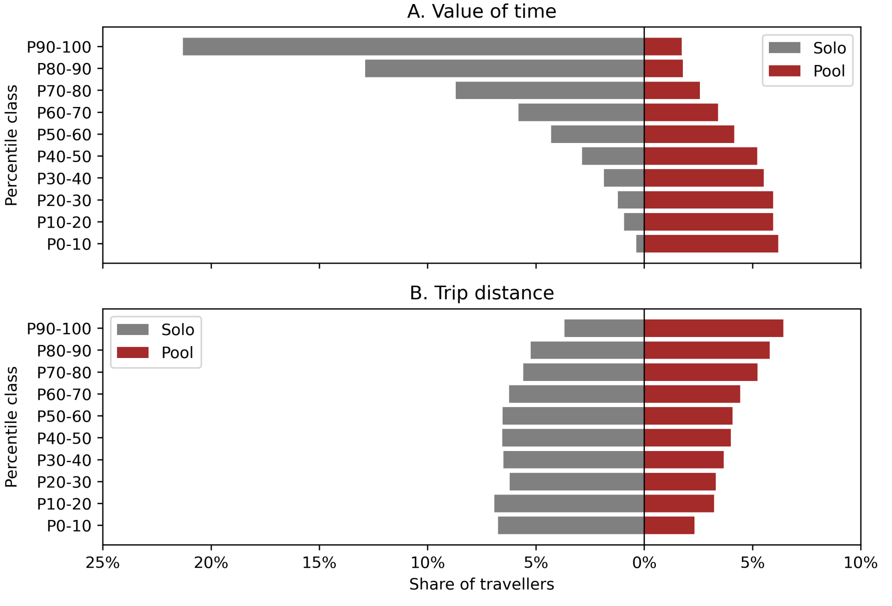


Figure 5.8: Relative market share of ride-hailing (solo) and ride-pooling (pool) depending on A. travellers' value of time, and B. the distance of their trip.

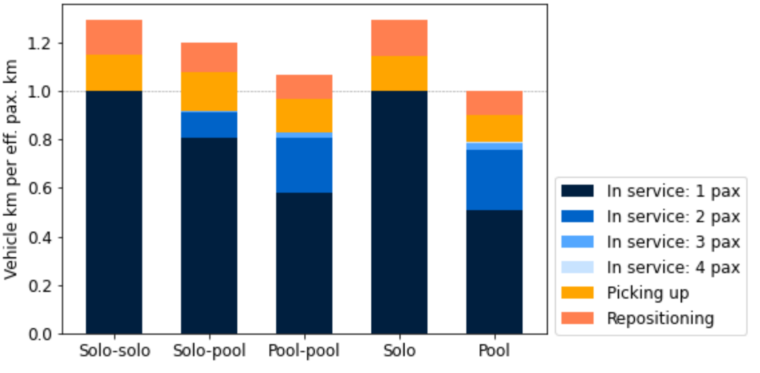


Figure 5.9: Total mileage of ridesourcing vehicles divided by the sum of the shortest path distances between ridesourcing users' origins and destinations.

over two platforms (*pool-pool*), less efficient matches are produced, and hence, the total vehicle mileage (to serve similar demand) is 6.4% higher than in a market with one ride-pooling provider.

When one platform offers a ride-hailing service and the other a ride-pooling service (*solo-pool*), substantially less sharing takes place. Users opting for the ride-pooling platform for instance never share their vehicle with more than one co-rider at a time. At the same time, more repositioning takes place as more drivers are attracted to the ridesourcing market (relative to ridesourcing demand), inducing higher driver idle time. In such a market, approximately 1.20 vehicle kilometres are generated for each effective kilometre on the shortest path between users' origins and destinations. A ridesourcing market without ride-pooling (*solo* or *solo-solo*) is least beneficial from a vehicle mileage standpoint as each effective passenger kilometre induces 1.29 vehicle kilometres. Not only do drivers never serve multiple passengers simultaneously, they also spend significant time repositioning in anticipation of new requests. The reason is that relatively many drivers are attracted by the higher fares of the solo service compared to the pooling service, resulting in substantial driver idle time, which induces repositioning.

5.4.2 Multi-homing

Insofar, we assumed that all agents (travellers and job seekers) enter in exclusive arrangements with platforms. Our model allows to test alternative scenarios in which some or all travellers and/or job seekers are open to multi-homing (i.e. will register either with all or none of the platforms). We do so for a market with two ride-hailing platforms (*solo-solo*). First, we examine a scenario in which half of travellers and half of job seekers multi-home.

In Fig. 5.10 we present key performance indicators differentiating single-homing and multi-homing agents. Fig. 5.10A shows that nearly 5,000 multi-homing travellers (10% of the total) request a ride in the ridesourcing market (i.e. using both platforms). Of the single-homing travellers, a small majority requests a ride on the platform that offers the lowest waiting time (Fig. 5.10B), whereas a smaller share of travellers requests with the competitor (following past personal luck with the platform or positive information signals from others). On average, travellers open to multi-homing are marginally more likely to request in the ridesourcing market than travellers unwilling to engage in multi-homing. We observe a similar pattern on the supply-side (Fig. 5.10C), i.e. one platform attracts a higher number of single-homing job seekers than its competitor. This stems from the difference in earnings observed between the two platforms (Fig. 5.10D). As for travellers, job seekers that are willing to multi-home are more likely to participate in the market than those that are not willing to do so. This difference is more pronounced among job seekers than among travellers.

Fig. 5.10 also provides insights into the added value of multi-homing for both travellers and job seekers (explaining previous described differences in market participation between single-homing and multi-homing agents). For travellers, it increases their chances of being matched to nearby drivers, reducing their average experienced pick-up time to approximately 78 seconds, compared to 94 using only the leading platform and 111 requesting only on the competitor platform (Fig. 5.10B). For drivers, it increases their chances of being assigned to nearby trip requests, reducing their idle time. It results in an average income of €120.97 per day, compared to €106.90 for drivers working only for the leader platform and €102.34 for drivers working only for the competitor.

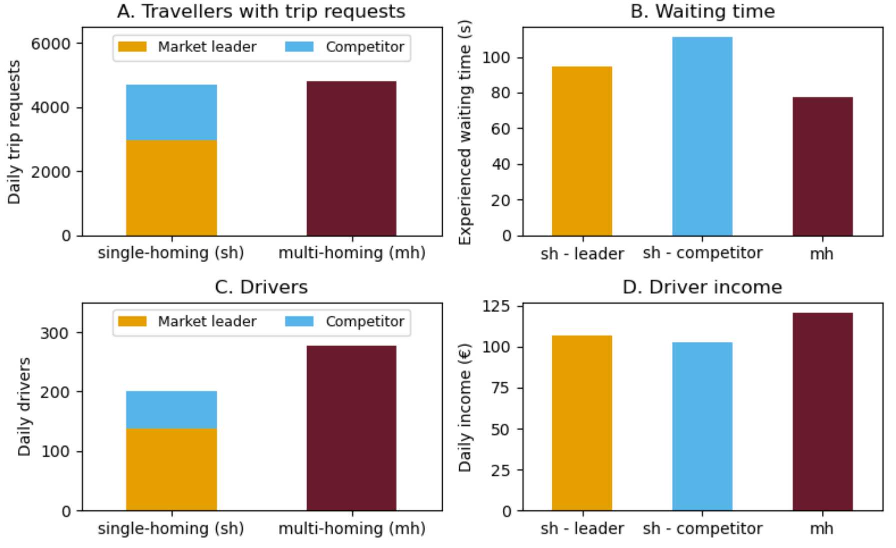


Figure 5.10: Market participation volumes and experiences, differentiating between agents opting exclusively for the leading platform, agents opting exclusively for the competitor (smaller platform), and agents opting for both platforms (multi-homing) in a scenario in which 50% of job seekers and 50% of travellers are open to multi-homing. Indicators presented are (A) The number of travellers requesting in the market, (B) The average waiting time (pick-up time), (C) The number of job seekers driving in the ridesourcing market, and (D) The average drivers' income.

Our results highlight that in the scenario in which half of travellers and half of job seekers prefer to multi-home each platform manages to attract both multi-homing travellers / job seekers and single-homing travellers / job seekers, even though one platform offers a lower waiting time and higher earnings than the other. We observe a similar market equilibrium when half of travellers multi-home but none of the job seekers do (Fig. 5.11A,D). When half of job seekers multi-home but none of the travellers do, all single-homing job seekers will opt for the same platform, as this platform offers substantially higher earnings. On the smaller platform, they compete for too limited demand with multi-homers available on both platforms. It illustrates that a general lack of willingness to multi-home may result in a more skewed market equilibrium in terms of platforms' market shares.

We observe that when all travellers multi-home, all job seekers multi-home, or both, the market evolves towards an equilibrium with two equally large platforms. In such a scenario, either demand or supply (or both) is guaranteed to be equal due to one side of the market's multi-homing behaviour, hence, platform choice becomes irrelevant for single-homing agents on the other side of the market. Hence, single-homers are equally likely to opt for either platform.

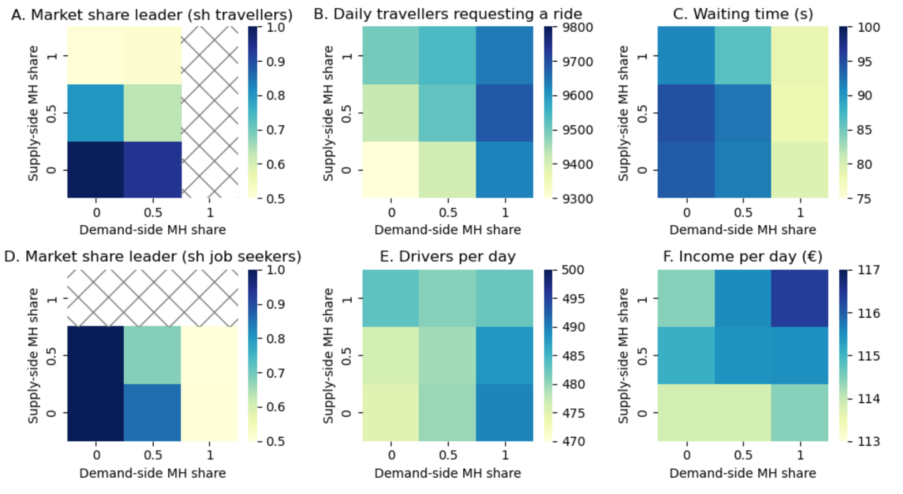


Figure 5.11: Key ridesourcing performance indicators for different two-sided multi-homing shares: (A) Relative demand-side market share (trip requests) of the leading ridesourcing platform, (B) The number of unique ridesourcing trip requests, (C) The average time before a traveller with a request is picked up, (D) Relative supply-side market share (drivers) of the leading ridesourcing platform, (E) The number of unique drivers, and (F) The average driver's income per day.

Our results show that as multi-homing counteracts market fragmentation costs in markets with more than one service provider, an increase in the willingness to multi-home in the population results in higher total demand for ridesourcing (Fig. 5.11B), associated with a decrease in the average request pick-up time (Fig. 5.11C). Similarly, multi-homing can result in higher supply (Fig. 5.11E) following an increase in driver earnings (Fig. 5.11F). Notably, market supply and demand are (slightly) higher in the scenario in which all agents multi-home and both platforms are equally large than in the market equilibrium in which only one platform remains as the sole provider (the scenario in which no agent is willing to multi-home), even though the ridesourcing market is not confronted with market fragmentation costs in either case. This can be explained by the fact that in the multi-homing scenario, travellers always choose between two offers, opting for the one that offers them the highest utility (minimal pick-up time when no ride-pooling is offered). The ride offer can differ between platforms as drivers that are assigned to serve a request on a platform are assumed to temporarily log off from the other platform. It implies that they can be scheduled to serve a consecutive request on the first platform but not on the second. Apparently, in our experiments a system in which travellers choose between offers results in a better system performance than a system in which platforms decide about the offer, which in this case is based on a minimisation of the total driving time in the system (excluding driver repositioning).

5.5 Conclusion

5.5.1 Study significance

In this work, we develop an agent-based model that allows studying the evolution of two-sided ridesourcing platforms operating in duopolistic markets. The model represents day-to-day market participation decisions by potential consumers (travellers' mode choice decisions) and suppliers (job seekers' work decisions) in the ridesourcing market, accounting for information diffusion processes, learning from experience and platform registration decisions. A key component of the model is the detailed within-day representation of ridesourcing operations, capturing platforms' matching decisions, drivers' repositioning decisions, and travellers' trip offer acceptance decisions, including their interactions. It supports both ride-hailing and ride-pooling.

The developed model allows exploring under which conditions duopolistic ridesourcing markets evolve into a winner-takes-all state and when both platforms maintain their presence in the market. In addition, the model offers insights into the implications of market fragmentation when platforms co-exist, including (possibly unevenly distributed) effects on driver earnings, travel times, platform revenues, and vehicle mileage. Integrating mode choice, the model can also be used to shed light on modal shifts following the introduction of ridesourcing. In this study, we demonstrate the model's capabilities by evaluating the effect of platforms' service type (private or pooled rides) and two-sided multi-homing behaviour.

5.5.2 Key findings

Our experiments demonstrate that network effects in the provision of ride-hailing (solo rides only) facilitate winner-takes-all markets. Random initial differences in platforms' two-sided participation levels translate into structural differences as participation with the larger platform yields shorter waiting times and higher earnings. We observe that a winner-takes-all scenario does not occur when at least one of the service providers opts for pooled rides. When both platforms offer ride-pooling, ex-ante pricing discounts incentivise travellers to opt for the platform with more limited demand to minimise detours from pooling, even though drivers prefer the platform with most trip requests. Apparently, negative network effects in ride-pooling (extra detours, increased competition for matches) may outweigh positive network effects (induced supply, better matches). Based on our findings, two platforms can also co-exist when one offers ride-hailing and the other ride-pooling. Both services cater to different travellers, not only based on their sensitivity to time — as shown by our analysis and previously by a latent class analysis of urban travel behaviour in the Netherlands (Geržinič et al., 2023) — but also on the distance of their trip. In our experiments, the solo provider attracts more users and particularly more drivers than the ride-pooling provider. Drivers face the same earnings on both platforms, with shorter idle time on the ride-pooling platform and higher revenue per served request on the ride-hailing platform.

We find that markets in which ride-pooling is offered by at least one platform are more efficient (in terms of vehicle distance) than markets without ride-pooling. This effect is not only attributed to passengers sharing a vehicle but also to more limited (empty-vehicle) repositioning. As ride-pooling platforms attract fewer drivers than ride-hailing platforms, they experience reduced idle time, which diminishes their incentive to reposition themselves. Our results also provide insights into the market fragmentation costs associated with duopolistic ride-pooling markets. Due to less efficient matches, each effective passenger kilometre requires 6.4% more vehicle kilometers in such a market compared to a monopolistic ride-pooling market. The effect of market fragmentation on travel time, driver earnings and platform revenue are limited.

Furthermore, our study sheds light on potential modal shift patterns following the introduction of ridesourcing, indicating that markets in which ride-pooling is offered attract relatively many (generally cost-sensitive) public transport users relative to markets without ride-pooling. This may at least partially negate the benefits of ride-pooling when it comes to serving passengers with minimal vehicle mileage. At the same time, our results demonstrate that there is a large overlap in the target group of ride-hailing and ride-pooling platforms, i.e. the total market share of ridesourcing is only marginally larger when both ride-hailing and ride-pooling are offered compared to markets in which one of the two is offered.

Our experiments highlight that multi-homing can prevent the emergence of a winner-takes-all platform in markets with two initial ride-hailing providers. When either all travellers, job seekers, or both, multi-home, both platforms reach approximately equal sizes in the market equilibrium. An equilibrium state with one larger and one smaller platform can also emerge. This occurs when some travellers and/or some job seekers (but not all) multi-home. In that case, there may be a discrepancy in earnings and waiting time between two platforms, with the majority or all single-homing travellers and job seekers choosing the larger (better) platform (and multi-homers participating on both platforms). Our results also provide insights into the benefit derived from multi-homing. In a market in which half of travellers and half of job seekers multi-home, multi-homing drivers earn approximately €14 per day more than drivers working solely for the larger platform and approximately €18 more than drivers working solely for the smaller platform. Travellers are also better off multi-homing. Their average waiting time is 16 seconds shorter than the waiting time of travellers requesting only with the larger platform, and approximately half a minute shorter than travellers requesting only with the smaller platform.

5.5.3 Policy implications

Our model enables a more comprehensive perspective on the potential impact of ridesourcing services on the number of vehicle kilometers on urban roads. Based on a case study modelled after Amsterdam, using a 10% sample of travel demand, we for instance find that in addition to serving passengers more efficiently, ride-pooling platforms likely induce less repositioning with those platforms attracting fewer drivers than ride-hailing platforms. Our findings however also highlight that negative network effects associated with detours in ride-pooling (prevalent particularly when ride-pooling demand is limited) can contribute to markets with multiple co-existing ride-pooling providers, substantially reducing the overall efficiency of ride-pooling matches. It does not only result in lower distance savings but it also reduces the market's value for users, suppliers and service providers. Hence, transport authorities can consider policies limiting market entry for service providers or encouraging multi-homing among travellers and job seekers in order to minimise market fragmentation effects. Ride-pooling matching efficiency is also compromised when a ride-pooling provider operates alongside a ride-hailing provider, with the latter drawing significant demand from the former. Finally, our results provide evidence that ride-pooling (as well as ride-hailing) induces significant modal shifts away from active modes (bicycles) and efficient modes (public transport), which negates at least a part of (already limited) distance savings attained with shared rides, and possibly more.

In summary, the potential of ride-pooling to reduce traffic levels is limited when (i) relatively few travellers opt for ride-pooling, and (ii) those who do predominantly switch from more distance-efficient modes. In Amsterdam, both conditions likely apply, with the city featuring high-quality bicycle infrastructure and public transport, along with relatively short trips. In our experiments, representing 10% of trips in Amsterdam, ride-pooling actually results in additional vehicle kilometers compared to private cars. However, distance savings from ride-pooling have been observed to be highly dependent on scale (Engelhardt et al., 2019), suggesting that a reduction in vehicle kilometres could be feasible under real-world trip densities.

5.5.4 Future research

While this study has explored several aspects of ridesourcing market evolution, many areas remain under-investigated and warrant further research. For instance, the evolution of ridesourcing markets can be studied in alternative contexts. This includes examining markets with more than two initial service providers and those where platforms simultaneously offer private and shared rides. Other factors of which the effect can be tested using our model include the properties of alternative modes, travel demand characteristics (including trip density and travellers' preferences), and labour market conditions. Such studies would help to determine the conditions under which ridesourcing platforms are likely to coexist, a single platform is likely to dominate, or all platforms may cease to exist (possibly due to the tragedy of the commons in ridesourcing provision). While the current study assumed static market conditions, our model can also be used to investigate how ridesourcing markets respond to changing contexts, such as a sudden drop in demand like the one witnessed during the COVID-19 pandemic.

In addition, future research can focus on evaluating (possibly dynamic) platform pricing strategies — i.e. platforms strategically setting fares of ride-hailing and ride-pooling (with pooling discounts determined ex-ante or ex-post) as well as platform commission — to gain better insights into the implications of platform competition, rather than platform co-existence as studied in this work. This includes studying the effect of (possibly two-sided) loyalty programs. At the same time, future research may explore in more detail cooperation strategies to minimise market fragmentation costs among platforms, such as the introduction of a broker platform (Engelhardt et al., 2022b).

Finally, there is a significant gap in understanding several day-to-day processes in the ridesourcing market, presenting a crucial area for future research, particularly regarding information diffusion. Given the limited empirical evidence, we used simplified models as a starting point for model development, with the intention of incorporating more complex factors as more data becomes available. Market awareness could for instance be influenced by market utility or participation levels. Additionally, there could be platform-specific awareness not accounted for here. Furthermore, the model could be extended to include endogenous multi-homing, where travellers and job seekers decide to multi-home based on a comparison of the benefits and costs associated with multi-homing. Addressing these research gaps will provide deeper insights into the dynamics of ridesourcing markets, which can support effective policies for improving driver income, reducing user travel time, increasing platform revenue, and decreasing overall traffic levels.

Chapter 6

Conclusions

In this chapter, we present our main findings and conclusions per research question, followed by overall conclusions and implications for practice. Finally, we provide recommendations for future research.

6.1 Main findings

Below, we answer each of the proposed research questions.

What is the impact of fleet decentralisation in ridesourcing for drivers, travellers and service providers? *(Chapter 2)*

In Chapter 2, we modeled the daily evolution of ridesourcing platform supply by examining how individuals make decisions regarding registration and work opportunities within the platform. This includes understanding how platform awareness spreads among potential drivers and how they learn from their previous experiences with the platform. Our analysis explores the differences between a decentralised, emergent fleet and a centralised, selected fleet, presenting implications for various stakeholders in the ridesourcing market.

Our findings indicate that the supply decisions of ridesourcing workers mimic the prisoners' dilemma. In the reference scenario of our experiments, approximately 150 drivers are active daily in the ridesourcing market, whereas coordination among drivers would result in a smaller workforce, between 40 and 100 drivers. The prisoners' dilemma arises due to variations in the opportunity costs for workers, resulting in significant market participation even when workers anticipate limited average financial returns. Each driving worker imposes costs on other drivers, contributing to higher idle times, which are not factored into individual decisions based on comparing earnings with time-dependent opportunity costs. Consequently, we find that ridesourcing earnings decline with the population's reservation wage.

Furthermore, we note that the ridesourcing fleet might surpass the fleet size of centralised mobility-on-demand services. In our experiments, an operator would opt for a fleet of 100 drivers based on the minimum wage, 50 fewer drivers than the fleet in decentralised ridesourcing. A smaller fleet than 150 vehicles leads to more unmet demand, while the expenses of a larger fleet than 150 are not compensated by additional revenue from serving more trip requests.

Our results illustrate that a higher platform commission may be more harmful to travellers than to drivers, reducing participation levels among drivers and subsequently decreasing driver idle time. Notably, a profit-driven service provider might choose a higher commission even if it results in a substantial share of unmet trip requests due to reduced labour supply.

Lastly, we highlight that ridesourcing labor supply might experience non-linear shifts and transitions, causing significant variations in average income, profit, and service levels. The trajectory of ridesourcing supply depends on multiple factors, including the diffusion of platform awareness, traveller learning behavior, and platform registration costs.

It is crucial to examine the extent to which our findings in Chapter 2 are reliant on the assumption of exogenous ridesourcing demand, which is further explored in Chapter 3.

What are the main network effects following from ridesourcing demand and supply, and what is their effect on ridesourcing system performance? *(Chapter 3)*

In Chapter 3, we outline two-sided network effects present in ridesourcing provision. We find that network effects are governed by changes in travellers' waiting time and drivers' non-revenue time. While both travellers and drivers benefit from high-quality matches (how fast drivers reach travellers after being matched), they have conflicting interests when it comes to matching time, i.e. long matching time for drivers typically implies a limited matching time for travellers, and vice versa. We reason that high-quality matches are more likely when one side has many idle users, which may lead ridesourcing markets toward an uneven equilibrium, with swift pick-ups but longer matching times on one side.

We also simulate supply and demand dynamics in the ridesourcing market by integrating a mode choice model, considering trip-specific alternatives to ridesourcing, into the day-to-day model for ridesourcing supply presented in Chapter 2. Our simulation results confirm that the ridesourcing market may undergo multiple transitional phases before reaching a steady state, marked by rapid changes in performance indicators. Even after the market equilibrium is attained, job seekers and travellers encounter significant day-to-day variations in earnings and wait times due to initial randomness in the matching process and in individual registration decisions, amplified by path-dependent market participation decisions. For instance, drivers experiencing unfavorable luck might grow dissatisfied, causing them to abstain from participation and hindering learning that their experiences were due to bad luck in matching.

Based on our simulation results, we can also conclude that ridesourcing provision may be feasible even when the potential market is small. In such markets, however, the service tends to be more unreliable and generally of lower quality than in markets with more travel demand and individuals looking for a job opportunity.

A service provider weighs the number of trips against the profit per trip when setting commission rates and ride fares. Prioritising per-trip earnings over transaction volume harms both passengers and drivers, with possibly only marginal gains for the service provider. We observe that network effects align interests for passengers, drivers and the platform when it comes to ride fares. Therefore, conflicting interests between service providers and market participants mostly stem from platform commission rather than from (per-kilometre) ride fares.

Finally, we observe that ridesourcing drivers do not necessarily benefit from low costs associated with the ability to work in the market, such as vehicle leasing costs. A surge in job seekers registering with the platform intensifies driver competition, resulting in reduced earnings, which at least partially compensates for the reduction in fixed costs.

How do ridesourcing performance indicators depend on the degree of socio-economic inequality in society? *(Chapter 4)*

We hypothesize that ridesourcing platforms benefit from, even thrive on, socio-economic inequality, as high levels of socio-economic inequality allow for cheap labour as well as increasing the share of travellers with a considerably above-average willingness to pay for travel time savings and comfort. We test this hypothesis in Chapter 4 by concurrently modifying the standard deviation of travellers' value of time distribution and job seekers' reservation wage distribution to correspond to different Gini-coefficient values.

Based on scenarios within the range of real-world Gini-coefficient values, our findings show two mechanisms contributing to a substantial positive relationship between socio-economic inequality and demand for ridesourcing. First, as mentioned previously, there are more travellers with a high willingness to pay a premium for using ridesourcing over other, more time-consuming modes of transportation in socio-economically unequal societies. Second, a significantly larger number of job seekers opt to work in these markets, even when anticipating meager earnings, given that more job seekers lack adequate alternative work opportunities. In fact, we observe that the supply elasticity (in relation to inequality) is larger than the demand elasticity. This arguably stems from two underlying reasons: (i) asymmetry in the distributions of reservation wage and value of time, i.e. both distributions are right-skewed, implying that the majority of individuals have a below average value of time / reservation wage, and (ii) that income is likely more important in work decisions than travel time is in mode choice; whereas at the same time it is undeterred by decreasing driver earnings and increased level of service as inequality grows. The increase in supply (absolutely as well as relative to demand) results in faster matching and pick-ups for travellers, and thereby in induced demand for ridesourcing.

Our results demonstrate that the benefits associated with providing a ridesourcing service in a socio-economically unequal society is not limited to servicing more demand. Inequality also allows platform operators to charge a higher commission, by which they capitalise on the abundance of job seekers with a low ridesourcing reservation wage. This, in addition to intensified competition between drivers, implies that the earnings of ridesourcing drivers decrease considerably with socio-economic inequality, down to less than one fifth of the average job seeker's reservation wage in societies with extreme levels of socio-economic inequality.

How is the social welfare derived from the ridesourcing market different in duopolistic and monopolistic markets, and under which circumstances is each market structure more likely to emerge? *(Chapter 5)*

We show that network effects in ride-hailing provision (private rides) can lead to winner-takes-all markets, where larger platforms offer shorter wait times and higher earnings. However, this effect diminishes when at least one platform provides ride-pooling. When both platforms offer ride-pooling, pricing incentives lead travellers to choose platforms with less demand to avoid detours, despite drivers preferring platforms with more requests. If one platform offers ride-hailing and the other one ride-pooling, both cater for different user needs. Drivers earn the same on both platforms, experiencing less idle time on the ride-pooing platform and higher per-trip earnings on the ride-hailing platform.

We find that markets in which ride-pooling is offered by at least one platform are more efficient (in terms of vehicle distance) than markets without ride-pooling. This effect is not only attributed to passengers sharing a vehicle but also to more limited (empty-vehicle) repositioning following higher driver productivity. At the same time, our findings illustrate that modal shifts away from public transport partially negate the benefits of ride-pooling when it comes to serving passengers with minimal vehicle mileage. When ride-hailing is offered next to ride-pooling, most users will opt for the former service.

We observe that market fragmentation in ride-pooling yields a 6.4% increase in vehicle kilometers. It also reduces the overall quality of service, driver earnings and platform revenue, although effects are limited.

Our experiments highlight that multi-homing can prevent the emergence of a winner-takes-all platform in markets with two initial ride-hailing providers. We observe that an increase in the share of travellers and job seekers open to multi-homing is associated with a more evenly split market equilibrium. When half of travellers and half of job seekers multi-home, multi-homing drivers earn approximately €10 per day more than drivers working solely for the larger platform and approximately €20 more than drivers working solely for the smaller platform. Travellers are also better off multi-homing. Their average waiting time is approximately 10 seconds shorter than the waiting time of travellers requesting only with the larger platform, and more than a minute shorter than travellers requesting only with the smaller platform.

This brings us to answering the main research question that was posed in Chapter 1 of this dissertation.

How do market features (such as the number of service providers, platform pricing and service type), along with travel demand and labour market characteristics, influence the evolution of ridesourcing systems?

In this dissertation, we investigate the effect of several conditions associated with travel demand and the labour market, as well as different platform strategies and market configurations. Below, we summarise our findings.

We analyse various market features, primarily focusing on platforms' two-sided pricing approaches. In Chapter 2, we explore how a platform might set its commission to optimise profits, assuming that changes in supply do not influence travellers' choices. We find that a platform may choose a high commission, even at the cost of attracting too few drivers to meet all ridesourcing demand. This holds true even when incorporating traveller mode choice influenced by supply levels into the model. We note that a high platform commission adversely affects both drivers (reduced earnings) and travellers (reduced quality of service). Conversely, the interests of the platform, drivers, and travelers tend to align regarding ride fares. Both low fares (resulting in insufficient supply) and high fares (resulting in inadequate demand) harm all stakeholders. In Chapter 4, we explore how a platform might adapt its pricing strategy based on socio-economic inequality levels. We illustrate that in egalitarian societies, high commissions may not be viable as they deter suppliers, drastically reducing the number of completed rides. In such scenarios, low fares maximise platform profits, given that few users are willing to pay a premium to save travel time. However, in unequal societies, operators might leverage the low opportunity costs of job seekers by implementing high commissions, further reducing driver earnings. In Chapter 5, we explore the effect of platforms' service offerings, specifically private or shared rides. Our results show that platforms are more likely to co-exist when at least one of them offers ride-pooling. At the same time, we observe that ride-pooling is most efficient when offered by a single provider and in the absence of a ride-hailing provider.

We also delve into the impact of various travel demand and labour market characteristics. In Chapter 3, we highlight the significance of the size of the potential market in which a provider operates, in terms of the total number of trips and the number of job seekers. Our findings reveal that although larger markets produce better matches, ridesourcing provision may remain viable even in smaller markets. Chapter 4 examines the influence of socio-economic inequality on ridesourcing provision. It showcases that, in addition to allowing for a higher commission rate, ridesourcing service providers benefit from attracting more travellers in unequal societies, by catering to time-sensitive users and through improved quality of service following from an increase in ridesourcing supply. Additionally, in Chapter 2, we examine the isolated effect of drivers' reservation wages, unveiling that lower reservation wages intensify competition among drivers, resulting in reduced earnings. This chapter underscores the divergence between the individual decisions of ridesourcing drivers and the collective interests of drivers, as drivers fail to internalise their impact — increased idle time — on fellow drivers. Chapter 5 showcases how (two-sided) willingness to engage in multi-homing can prevent winner-takes-all ride-hailing markets without inducing market fragmentation costs.

We observe that ridesourcing markets may undergo several transition phases. We observe how information diffusion processes, associated with awareness and market performance, affect ridesourcing evolution. Generally, we find that these processes affect the speed at which a steady state is achieved but not the ultimate equilibrium state, in terms of the number of drivers and trip requests. Our results also provide insights into how random processes in travellers' and job seekers' market participation decisions affect ridesourcing performance indicators, even in the steady state. Finally, we observe that costs associated with platform registration incentivises full-time work in the market. A significant portion of the additional costs incurred by registered drivers may be offset by increased productivity, resulting from reduced competition.

6.2 Implications for practice

First, the identification of the prisoner's dilemma in job seekers supply decisions (Chapter 2) provides support for the potential effectiveness of supply caps, implemented for instance in New York City. Our findings show that a cap in supply may push earnings over the reservation wage without significantly impeding travellers' waiting times. At the same time, our results show that the value to which the cap is set is crucial. Supply caps that are set too loose yield no effect on driver income, whereas limits that are too strict are detrimental to the quality of the service offered by ridesourcing platforms.

Our analyses of platform pricing strategies (Chapters 2-4) also yield implications for the need of regulating the pricing decisions of ridesourcing providers. Our experiments provide evidence that profit-driven platforms may increase their commission rates to levels that induce substantial costs on both drivers (resulting in considerably lower earnings) and customers (yielding a significantly slower and less reliable service). Specifically, we observe that the marginal decline in supplier and consumer surpluses associated with a higher platform commission may be substantially larger than the corresponding marginal increase in platform profit. Hereby, our results suggest that regulating the commission rate of ridesourcing providers can effectively improve the social welfare derived from ridesourcing markets, which is in line with findings of Zha et al. (2016). This insight is most valuable in areas with strong inequality in socio-economic opportunities, where profit-driven operators opt for the highest commission rates. Given that our results suggest that operating a ridesourcing platform is generally more profitable under socio-economically unequal conditions, it is particularly likely that ridesourcing providers will start offering services in such contexts. Our results furthermore suggest that there is no need for fare regulation in ridesourcing markets, as the interests of travellers, drivers and service providers associated with fares are largely aligned due to presence of cross-side network effects in ridesourcing provision.

We find that ride-pooling, compared to ride-hailing, tends to reduce repositioning and attracts fewer drivers, leading to more efficient passenger service (Chapter 5). However, when ride-pooling demand is low, ride-pooling provision is prone to negative network effects due to inefficient detours. Hence, a transport authority can consider limiting market entry for new service providers. Alternatively, it can encourage multi-homing among travellers and job seekers to mitigate market fragmentation costs. Additionally, our analyses provide evidence that ridesourcing — particularly ride-pooling — may draw users from active modes and public transport. In areas in which active modes and public transport have a high market share, such as in Amsterdam, ridesourcing provision is therefore likely to increase traffic following described modal shift patterns.

6.3 Limitations & future research

We identify four avenues for future research based on the research gap introduced in Chapter 1 and the answers provided by this dissertation.

Examining the effect of other context variables on ridesourcing provision.
In this work, we examine the effects of various travel demand and labour market factors. Although we cover several key aspects, many remain unexplored. To provide a more comprehensive picture of the societal implications of ridesourcing, it could be valuable for instance to analyse how alternative transport services such as public transport and micromobility influence ridesourcing provision (and vice versa).

Moreover, examining system performance under varying spatio-temporal demand distributions would offer valuable insights, particularly when ride-pooling is offered. While our research emphasizes how socio-economic inequality affects ridesourcing through variations in travellers' value of time and drivers' reservation wage distributions, it is important to recognise other ways in which socio-economic factors might impact ridesourcing, including for example their influence on travellers' valuation of safety and on the number of job seekers in the population. Future studies could further investigate alternative socio-economic indicators, such as mean income levels, rather than focusing solely on the distribution of income.

Additionally, our research did not delve into the dependency of ridesourcing provision on road network conditions, including road topologies and travel speeds. Understanding how ridesourcing markets operate in uncongested networks or in scenarios where ridesourcing vehicles have access to dedicated lanes could offer crucial insights into the benefits and costs of ridesourcing services.

Investigating market dynamics under changing circumstances.
In this dissertation, we capture interactions between ridesourcing supply and demand under static market conditions. In real-world scenarios, market conditions are subject to change, as exemplified by the recent COVID-19 pandemic. Exploring the adaptive responses of two-sided ridesourcing markets to changing conditions would therefore be insightful. Our day-to-day ridesourcing model facilitates such an analysis. Future research might encompass investigating the market's reactions to the following changes:

- **Regulatory changes:** Alterations in government regulations, such as new operational constraints and licensing requirements can directly affect ridesourcing companies, drivers, and users.
- **Market competition:** Increased competition from alternative transportation services can disrupt the market.
- **Economic Factors:** Economic downturns, changes in fuel prices, or fluctuations in consumer disposable income can influence user demand, driver participation, and overall market stability.

- **Technological advancements:** Rapid technological changes, including the introduction of autonomous vehicles or innovations in transport technology, may transform the ridesourcing landscape, affecting market dynamics and employment for drivers.
- **Natural disasters or pandemics:** Unforeseen events like natural disasters or global health crises (e.g., pandemics like COVID-19) can profoundly impact ridesourcing markets by causing fluctuations in demand, altering travel patterns, and influencing user behavior due to safety concerns.
- **Labour market conditions:** Changes in labour markets, including shifts in employment opportunities or alterations in wage expectations, can influence the supply of drivers and their willingness to participate in the ridesourcing market.
- **Consumer preferences:** Evolving user preferences, such as growing environmental consciousness or changes in convenience expectations, can lead to shifts in demand patterns, favouring certain types of transportation services over others.

Exploring the effectiveness and implications of more complex (possibly dynamic) platform strategies.
This study illuminates the key pricing mechanisms employed by ridesourcing service providers: traveller fares and driver commissions. Future research can delve into the broader societal implications arising from more intricate pricing strategies. This involves for instance studying how ride-pooling discounts can attract users away from less efficient ride-hailing platforms.

Our day-to-day model for ridesourcing can also be extended to analyse dynamic pricing decisions like penetration pricing, pricing wars, and loyalty programs. Such extensions facilitate the examination of platform competition (rather than just platform co-existence), considering realistic responses from travellers and drivers. Our model can also integrate within-day dynamic pricing, such as surge pricing, by modelling drivers' work shift decisions in response to changing operational circumstances. This approach enables an exploration of the societal impacts of surge pricing, including its long-term effects on driver wages.

Investigating cooperative strategies between competitors to avert pricing wars and address market fragmentation effects, while considering day-to-day dynamics in ridesourcing supply and demand, is another interesting avenue for future research.

Unravelling the strategic, tactical and operational decisions of (potential) ridesourcing users and drivers.
Our agent-based approach to studying ridesourcing markets relies heavily on empirical insights into the strategic, tactical, and operational choices made by potential users and suppliers within this domain. Many questions about these decisions remain unanswered, encompassing aspects such as (two-sided) selection processes between platforms, the considerations driving job seekers' decisions regarding driving-related investments, the comparative valuation of income versus other factors by drivers, the

mechanisms through which drivers and travellers interact to discuss market experiences, and a myriad of other related factors that shape decision-making in this ecosystem.

Strengthening the empirical foundation surrounding the mode choice decisions of travellers, and particularly, the work decisions of potential ridesourcing drivers, will improve the validity of the simulation framework presented in this study. This will notably advance our understanding of ridesourcing implications for drivers, travellers, platforms, and society on a broader scale.

Appendix A

In this appendix, we provide supplementary information that supports the analyses and findings presented in Chapter 3.

A.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. 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 A.1, 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 & 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 A.1). 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 criticised (van Bergeijk, 2017; Gemeente Amsterdam, 2022). 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 & Steens, 2021). Third, as mentioned previously, ridesourcing oper-

Table A.1: Comparing simulation model outcomes (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 (Gemeente Amsterdam, 2020), and the total number of Uber drivers in Amsterdam and their active hours (Fouarge & Steens, 2021).
[b] Based on the modal split of taxi in Amsterdam (Amsterdam, 2019) and the share of taxi rides that were ordered online (Gemeente Amsterdam, 2020).
[c] Reported based on Uber data (Fouarge & Steens, 2021).

ations 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 A.1.

A.2 Sensitivity to starting conditions

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

A.2.1 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.2.2 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.2.3 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 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.2.4 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.

A.3 Sensitivity to model parameters

In Subsection 3.5.4, 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.3.1 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 Fig. A.1.

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 3.5.1 that some travellers with above average experienced waiting never learn about the system average waiting time becomes more predominant.

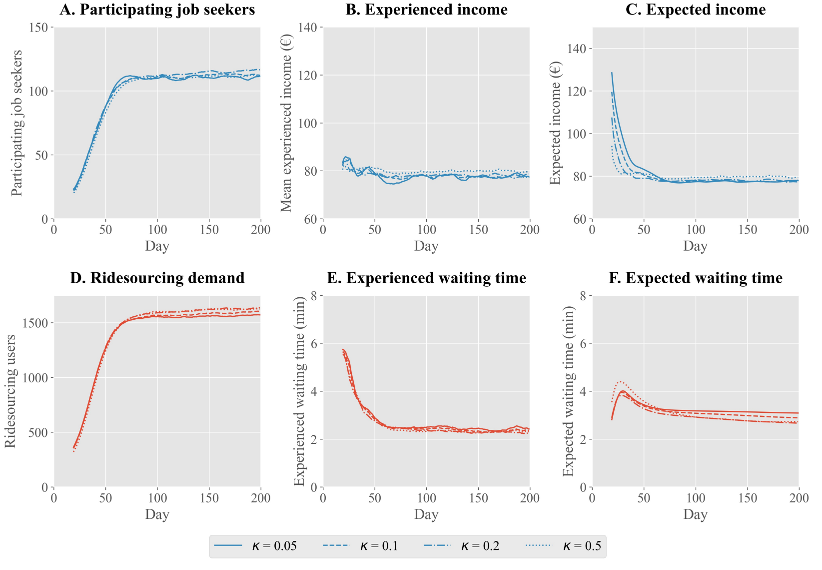


Figure A.1: Ridesourcing system evolution depending on learning parameter κ.

A.3.2 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 (Fig. A.2).

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.3.3 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

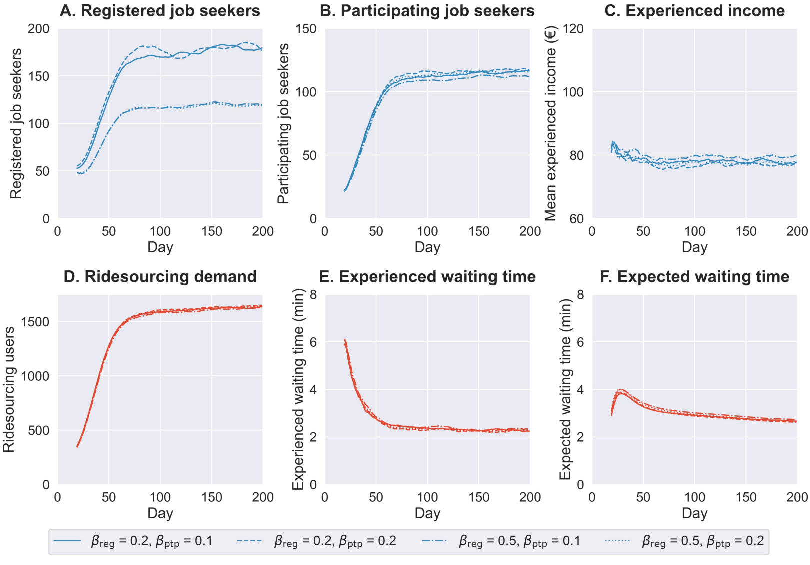


Figure A.2: 20-day moving average of key system performance indicators depending on job seekers' sensitivity to income in registration and particpation decisions.

platform (Fig. A.3). 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.3.4 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 (Fig. A.4). 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 A.3: 20-day moving average of system performance indicators depending on the minimum duration of platform registration λ.

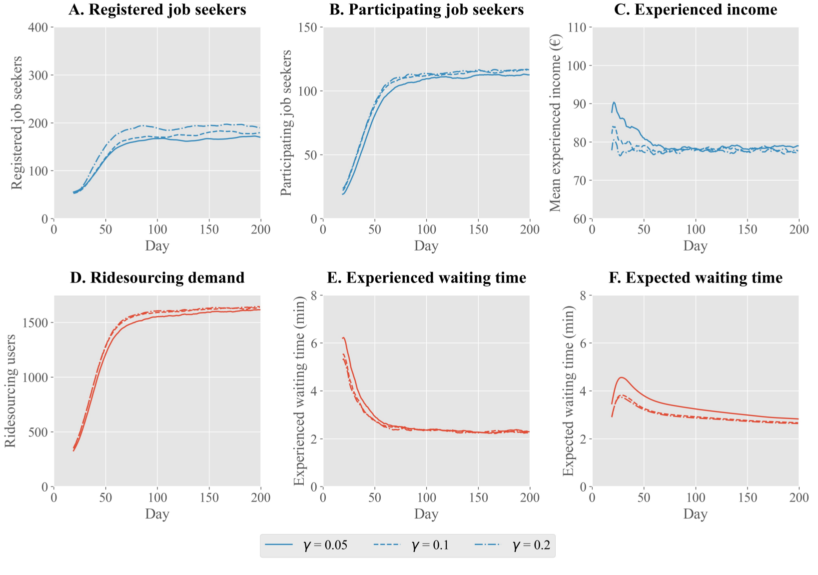


Figure A.4: 20-day moving average system performance indicators depending on registration decision probability γ.

A.3.5 Variation in income and waiting time signals

Fig. A.5 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.

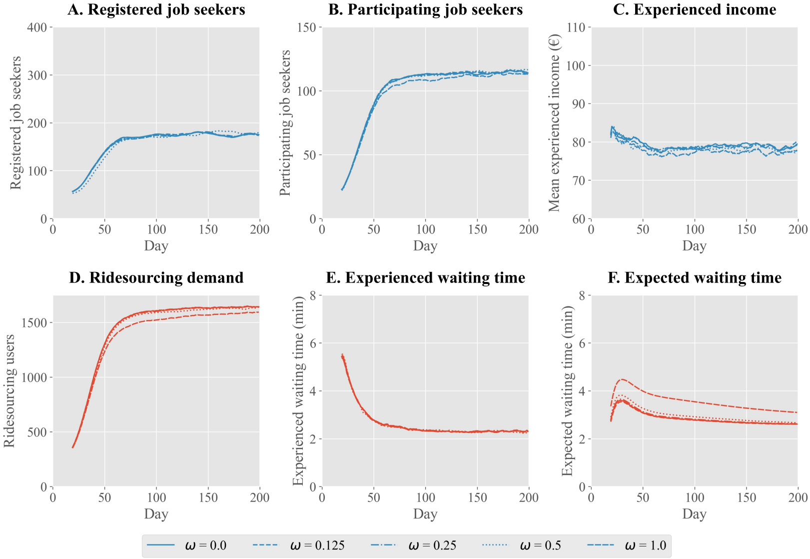


Figure A.5: 20-day moving average system performance indicators depending on the multiplier of the standard deviation of the experienced income and waiting time distributions used to generate the distribution of corresponding signals (ω)

Appendix B

In this appendix, we provide supplementary information that supports the analyses and findings presented in Chapter 4.

B.1 Gini coefficient of the lognormal distribution

The following formula is used to convert between lognormal parameter σ and Gini coefficient g:

$$\sigma = 2\,\mathrm{erf}^{-1}(g) \tag{B.1}$$

B.2 Replications

As our simulation model contains several processes with stochastic components (i.e. participation choice, registration choice and the diffusion of platform awareness), we replicate the experiment for statistical significance. To determine the number of required replications for each scenario, we apply a method originally used in traffic simulations (Ahmed, 1999; Burghout, 2004). We denote I^* as the average anticipated ridesourcing income by (registered) job seekers in equilibrium in a single iteration, and W^* as the corresponding average anticipated waiting time of (informed) travellers. We define $\overline{I^*}(m)$ and $\overline{W^*}(m)$, and $s_{\mathrm{i}}(m)$ and $s_{\mathrm{w}}(m)$, respectively, as the estimated mean and standard deviation of I^* and W^*, based on a sample of m runs. We denote the allowable percentage error of estimate $\overline{I^*}(m)$ and $\overline{W^*}(m)$ compared to the actual mean as $\varepsilon_{\mathrm{repl}}$, and the level of significance as α. Then, the minimum number of replications based on a sample of m runs is:

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

B.3 Experimental set-up

B.3.1 Alternative modes

Private cars use the same road network as ridesourcing vehicles and operate at the same speed. Private car users require 10 minutes to access and park their vehicle, and face per-kilometre costs of 0.5 €/km (Nibud, 2022), as well as (fixed) parking costs at their destination. These parking costs are 15 euro in the city centre (i.e. the area enclosed by IJ river and Singelgracht), and 7.5 euro elsewhere. Bikes operate on the same network, albeit with a 2.5 times lower speed (Fietstelweek, 2016). The choice for a bike comes without costs or access / parking time. For public transport, travellers consider the itinerary with the earliest possible arrival time based on their trip request time, queried using OpenTripPlanner based on a representative weekday (November 1st, 2021). Public transport fares are based on the fare scheme operated by Amsterdam's public transport provider GVB on this same date.

B.3.2 Mode choice parameters

One minute of walking and waiting time are perceived 2 and 2.5 times more negatively than one minute of in-vehicle time (Wardman, 2004), i.e. $\beta_m^{\text{access}} = 2 \cdot \beta_m^{\text{ivt}}$ and $\beta_m^{\text{wait}} = 2.5 \cdot \beta_m^{\text{ivt}}$. Each transfer in public transport is perceived as 5 minutes of in-vehicle time (Yap et al., 2020). Bike time is perceived twice as negative as in-vehicle time (Börjesson & Eliasson, 2012; van Ginkel, 2014). Cost parameter β_{cost} and alternative specific constants (ASCs) are taken from a study investigating urban travel in the Netherlands (Geržinič et al., 2023).

B.3.3 Other model parameters

Table B.1 presents the specification of the remaining model parameters.

Table B.1: Specification of model parameters.

Parameter	Value	Unit	Description
ψ	0.1	-	Information transmission speed
β_{reg}	0.2	util/€	Income sensitivity in registration
β_{ptp}	0.1	util/€	Income sensitivity in participation
$\varepsilon_{\text{repl}}$	0.1	-	Allowable percentage error of estimate of mean
α	0.05	-	Level of significance

B.3.4 Initialisation

Job seekers and travellers have a 10% probability to be aware about the platform at the start of the simulation. Informed job seekers have an initial 20% probability to be registered. Lacking experience, they expect earnings equal to their reservation wage. Informed travellers expect no waiting time.

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Summary

Ridesourcing providers like Uber, Lyft, and others have transformed the taxi industry by employing two-sided platforms, connecting travellers with private car owners through real-time algorithms. These platforms offer flexible work hours to drivers in exchange for renouncing access to social and financial securities. Early evidence suggests that ridesourcing markets may end up being oversupplied, which can result in low driver earnings and possibly increase traffic levels. Ridesourcing may also contribute to congestion by drawing users from public transport or inducing new trips. The limited available data provided by ridesourcing platforms does not allow for investigating how the performance indicators of ridesourcing for various stakeholders depends on characteristics of travel demand, the labour market, the provided service, and the wider transportation system, hindering effective regulations or subsidies for improving the social welfare associated with these markets.

Previous modelling approaches for such an analysis rely on aggregate functions for describing ridesourcing supply and demand. In reality, supply and demand are the result of many complex and interdependent decisions by individual (potential) users and suppliers, across various temporal dimensions. By overlooking the intricate and path-dependent nature of disaggregated components within ridesourcing supply and demand, the existing literature fails in providing insights into how ridesourcing systems evolve over time. This encompasses how the market may evolve to different equilibria — for instance monopolistic versus duopolistic markets — depending on starting conditions and random components in stakeholders' decisions, matching and peer-to-peer communication processes.

To address the stated research gap, we opt for an agent-based modelling approach representing the decisions of travellers (potential consumers in the ridesourcing market) and job seekers (potential suppliers). In addition to modelling within-day ridesourcing operations, including user-driver matching, traveller pairings (in ride-pooling) and drivers' repositioning decisions, we model numerous day-to-day processes affecting ridesourcing supply and demand, including the diffusion of platform information, registration decisions and daily work decisions. We apply this model to a case study aimed at replicating ridesourcing operations in the municipality of Amsterdam, the Netherlands. We do so by mimicking Amsterdam's travel demand, labour market characteristics, road network, ridesourcing pricing, and attributes of alternative transportation modes.

First, we investigate the effect of decentralisation of supply inherent in ridesourcing provision, assuming exogenous demand (Chapter 2). To this end, we propose a dynamic model comprising of the subsequent supply-side processes: (i) initial exposure to information about the platform, (ii) a long-term registration decision, and (iii) daily participation decisions, subject to day-to-day learning based on within-day matching outcomes. A series of experiments is constructed to study the effect of supply market properties and pricing strategies, providing indications for the need, effectiveness and costs of potential market regulations. Our experiments reveal a similarity between ridesourcing workers' decisions and the prisoners' dilemma. In the reference scenario, approximately 150 independent drivers engage daily in the market, in contrast to around 40 to 100 drivers had potential drivers coordinated their market participation decisions. Fluctuations in labour opportunity costs drive platform work, resulting in increased idle times and reduced earnings. Our study shows that, perhaps counter-intuitively, higher platform commissions impact travellers more negatively than drivers, reducing competition between drivers. A platform may accept an increase in denied trips in order to generate a higher profit on satisfied requests. Our results also demonstrate that ridesourcing labour supply may evolve non-linearly due to factors like platform awareness and traveller behavior, influencing income, profits, and service levels, showcasing the complex relationship between market dynamics and influencing factors.

Second, we present a conceptual representation of the interaction between supply and demand in the ridesourcing market to understand why these markets may be prone to evolve towards particular — potentially socially undesirable — equilibrium states (Chapter 3). We explain why an equilibrium state with matching time asymmetry — i.e. a market that is either considerably over- or undersupplied — may yield high-quality matches, mitigating matching time disutility on the competitive side of the market. We then add travellers' platform registration and participation decisions to the previously introduced day-to-day model for ridesourcing supply to model previously mapped two-sided network effects in ridesourcing provision. It allows us to investigate the effect of two-sided market conditions and platform strategies on system performance. For instance, we vary the size of the potential ridesourcing market — i.e. the number of travellers and job seekers in an area — to establish how the success of ridesourcing provision is dependent on the scale of the (potential) market. We demonstrate that ridesourcing operations may be viable even when potential supply and demand in an area are limited. Our simulation results also suggest that a profit-maximising 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.

Third, we test the hypothesis that ridesourcing platforms benefit from, even thrive on, socio-economic inequality, enabling cheap labour as well as increasing the share of travellers with a considerably above-average willingness to pay for travel time savings and comfort (Chapter 4). We do so by varying the heterogeneity in travellers' values of time and job seekers' reservation wages in the previously described agent-based model for two-sided ridesourcing markets. Our experiments cover scenarios for the entire spectrum ranging from perfect equality to extreme inequality. For several of such scenarios, we explore how platforms will adjust their two-sided pricing strategies. In our analyses of ridesourcing performance, we specifically examine the earnings of drivers, the quality of the service for travellers and the service provider's profit. Our analysis shows a strong, positive relationship between socio-economic inequality and ridesourcing market share. This is the outcome of the combination of cheap labour and time-sensitive ridesourcing users, reinforced by network effects inherent to ridesourcing markets. We find that driver earnings are minimal in urban areas with large socio-economic inequality. In such contexts, drivers are more likely to face a high platform commission, and yet, fierce competition for passengers.

Fourth, we extend our model for two-sided dynamics in monopolistic ridesourcing markets to allow for markets with two service providers, each offering either private or pooled rides. This allows us to (i) analyse how fragmentation costs — resulting from potential efficiency losses in matching in a market with fragmented demand and supply — vary with market features and user attributes, and (ii) under which of these conditions markets with multiple service providers are sustainable. Our experiments reveal a winner-takes-all outcome only when both platforms offer private rides, and conditional on neither riders nor drivers engaging in multi-homing. Service providers are more likely to co-exist when ride-pooling is offered by one of them — following differences in target demographics — or by both — following longer detours as demand increases. In our experiments, fragmented ride-pooling markets (based on two providers) produce 6.4% additional vehicle kilometres in comparison to monopolistic ride-pooling markets. There are also notable market fragmentation costs for platform users, drivers and service providers. In addition, our results indicate that ridesourcing, especially ride-pooling, can draw considerable demand away from distance-efficient modes like bicycles and public transport. It highlights that possible benefits and costs associated with ridesourcing depend on local preferences and transportation system characteristics. Finally, the developed model allows us to shed light onto the impact of daily costs associated with platform registration as well as the potential (individual) benefits of engaging in multi-homing for users and drivers.

To summarise, in this dissertation we explore the impacts of various factors linked to travel demand, labour market conditions and service configurations on ridesourcing market evolution. This encompasses the assessment of two-sided pricing strategies, platform co-existence, service type, market scale effects and socio-economic indicators. Specifically, we analyse the dynamic nature of ridesourcing indicators, delving into the influence of learning and communication processes, alongside the impact of different traveller and job seeker decision-making attributes. Our findings showcase that the ridesourcing market can potentially gravitate towards significantly varied equilibria, influenced by initial conditions and previously mentioned processes linked to travellers' and job seekers' ridesourcing market decisions. By shedding light on the mechanisms contributing to undesirable market outcomes, this dissertation aims to offer policymakers valuable insights into regulating the ridesourcing market to enhance overall social welfare.

Samenvatting

Ridesourcing-aanbieders zoals Uber en Lyft hebben de taxibranche getransformeerd door tweezijdige platforms te lanceren die reizigers via realtime algoritmes verbinden met particuliere autobezitters. Deze platforms bieden chauffeurs flexibele werktijden in ruil voor het afzien van toegang tot sociale en financiële zekerheden. Er zijn aanwijzingen dat ridesourcing-markten te veel chauffeurs kunnen aantrekken, wat kan leiden tot lage inkomsten voor chauffeurs en tot extra verkeersbewegingen. Ridesourcing kan verder bijdragen aan congestie door gebruikers van het openbaar vervoer te trekken of door nieuwe reizen uit te lokken. De beperkte beschikbare data over ridesourcing-platforms maakt het lastig om te onderzoeken hoe de verschillende prestatie-indicatoren van ridesourcing afhangen van de kenmerken van de reisvraag, de arbeidsmarkt, de aangeboden dienst en het bredere transportsysteem, waardoor effectieve regelgeving of subsidies voor het verbeteren van de sociale welvaart in deze markten worden belemmerd.

Eerdere modelbenaderingen voor een dergelijke analyse vertrouwen op geaggregeerde functies voor vraag en aanbod in de markt. In werkelijkheid zijn vraag en aanbod het resultaat van vele complexe en onderling afhankelijke beslissingen van individuele (potentiële) gebruikers en chauffeurs, over verschillende tijdsdimensies. Door voorbij te gaan aan de ingewikkelde en padafhankelijke aard van deze processen, slaagt de bestaande literatuur er niet in om inzicht te verschaffen in hoe ridesourcing systemen zich in de loop van de tijd ontwikkelen. Dit omvat hoe de markt kan evolueren naar verschillende evenwichten — bijvoorbeeld monopolistische of duopolistische markten — afhankelijk van startcondities en willekeurige componenten in de beslissingen van belanghebbenden, matching van reizigers en chauffeurs, en peer-to-peer communicatieprocessen.

Om deze onderzoeksleemte op te vullen, kiezen we voor een agentgebaseerde modelbenadering die de beslissingen van reizigers (potentiële gebruikers van ridesourcing-diensten) en werkzoekenden (potentiële chauffeurs) nabootst. Naast het modelleren van alledaagse ridesourcingactiviteiten, waaronder het matchen van gebruikers en chauffeurs, het onderling koppelen van passagiers (bij ride-pooling), en het herpositioneren van chauffeurs, modelleren we talrijke dagelijkse processen die van invloed zijn op vraag en aanbod in de ridesourcing-markt, waaronder de verspreiding van informatie, registratiebeslissingen en werkbeslissingen. We passen dit model toe op een casestudy gericht op het nabootsen van ridesourcing-activiteiten in de gemeente Amsterdam, Nederland. We doen dit door kenmerken met betrekking tot de reisvraag, de arbeidsmarkt, het wegennetwerk, prijsstrategieën in de markt, en alternatieve vervoerswijzen in Amsterdam te repliceren.

Eerst onderzoeken we het effect van de decentralisatie van het aanbod dat inherent is aan het aanbieden van ridesourcing, uitgaande van een exogene vraag (hoofdstuk 2). Daartoe ontwikkelen we een dynamisch model dat bestaat uit de volgende processen aan de aanbodzijde: (i) initiële blootstelling aan informatie over het platform, (ii) een registratiebeslissing op lange termijn, en (iii) dagelijkse deelnamebeslissingen, onderhevig aan leerprocessen volgend uit de toewijzing van gebruikers aan chauffeurs. Een reeks experimenten is geconstrueerd om het effect van eigenschappen van de aanbodmarkt en prijsstrategieën te bestuderen, wat aanwijzingen oplevert voor de noodzaak, effectiviteit en kosten van mogelijke marktregulering. Onze experimenten laten een gelijkenis zien tussen de beslissingen van ridesourcing-chauffeurs en het gevangenendilemma. In het referentiescenario nemen ongeveer 150 onafhankelijke chauffeurs dagelijks deel aan de markt, in tegenstelling tot ongeveer 40 tot 100 chauffeurs als werkzoekenden hun beslissingen om deel te nemen aan de markt zouden coördineren. Dagelijkse schommelingen in het reserveringsloon van werkzoekenden leidt tot meer chauffeurs op het platform, wat resulteert in meer inactiviteit en minder inkomsten. Onze studie toont aan dat, misschien contra-intuïtief, hogere platformcommissies een negatiever effect hebben op reizigers dan op chauffeurs, doordat ze de concurrentie tussen chauffeurs verminderen. Een platform kan een toename van geweigerde reizen accepteren om een hogere winst te genereren op vervulde aanvragen. Onze resultaten tonen ook aan dat het aanbod van ridesourcing-arbeid niet-lineair kan evolueren door factoren zoals platformbekendheid en reizigersgedrag, wat een invloed heeft op inkomsten, winsten en serviceniveaus, wat de complexe relatie tussen marktdynamiek en beïnvloedende factoren aantoont.

Ten tweede presenteren we een conceptuele voorstelling van de interactie tussen vraag en aanbod in de ridesourcing-markt om te begrijpen waarom deze markten geneigd kunnen zijn te evolueren naar bepaalde — potentieel sociaal ongewenste — evenwichtstoestanden (hoofdstuk 3). We leggen uit waarom een evenwichtstoestand met asymmetrie in de matching tijd — d.w.z. een markt die ofwel aanzienlijk over- of onderaanbod heeft — matches van hoge kwaliteit kan opleveren, wat een hogere wachttijd voor een match aan de competitieve kant van de markt kan mitigeren. Vervolgens voegen we de registratie- en deelnamebeslissingen van reizigers toe aan het eerder geïntroduceerde dag-tot-dag model voor het aanbod van ridesourcing om eerder in kaart gebrachte tweezijdige netwerkeffecten in het aanbod van ridesourcing te modelleren. Hierdoor kunnen we het effect van tweezijdige marktomstandigheden en platformstrategieën op de systeemprestaties onderzoeken. We variëren bijvoorbeeld de omvang van de potentiële ridesourcingmarkt — d.w.z. het aantal reizigers en werkzoekenden in een gebied — om vast te stellen hoe het succes van ridesourcing-voorziening afhangt van schaaleffecten. We tonen aan dat ridesourcing-activiteiten levensvatbaar kunnen zijn, zelfs als het potentiële aanbod en de vraag in een gebied beperkt zijn. Onze simulatieresultaten suggereren daarnaast dat een winstmaximaliserend ridesourcing platform een lager transactievolume kan accepteren in ruil voor hogere winsten op succesvolle transacties, een strategie die schadelijk is voor de belangen van reizigers en chauffeurs, en mogelijk van (zeer) beperkt nut voor het platform.

Ten derde testen we de hypothese dat ridesourcing platforms profiteren van, en zelfs gedijen bij, sociaaleconomische ongelijkheid, door goedkope arbeid mogelijk te maken en het aandeel van reizigers met een aanzienlijk bovengemiddelde bereidheid om te betalen voor reistijdbesparingen en comfort te verhogen (Hoofdstuk 4). We doen dit door de heterogeniteit in de tijdswaarderingen van reizigers en de reserveringslonen van werkzoekenden te variëren in het eerder beschreven agentgebaseerde model voor tweezijdige ridesourcingmarkten. Onze experimenten omvatten scenario's voor het hele spectrum van perfecte gelijkheid tot extreme ongelijkheid. Voor verschillende van deze scenario's onderzoeken we hoe platforms hun tweezijdige prijsstrategieën zullen aanpassen. In onze analyses van de prestaties van ridesourcing markten kijken we specifiek naar de inkomsten van chauffeurs, de kwaliteit van de dienstverlening voor reizigers en de winst van de dienstverlener. Onze analyse laat een sterke, positieve relatie zien tussen sociaaleconomische ongelijkheid en het marktaandeel van ridesourcing. Dit is het resultaat van de combinatie van goedkope arbeid en tijdgevoelige gebruikers van ridesourcing, versterkt door netwerkeffecten die inherent zijn aan ridesourcingmarkten. We vinden dat de inkomsten van chauffeurs minimaal zijn in stedelijke gebieden met grote sociaaleconomische ongelijkheid. In dergelijke contexten is de kans tevens groter dat chauffeurs te maken krijgen met een hoge commissie van het platform, en desalniettemin met hevige concurrentie om passagiers.

Ten vierde breiden we ons model voor tweezijdige dynamiek in monopolistische ridesourcing markten uit naar markten met twee dienstverleners, die elk ofwel private ofwel gepoolde ritten aanbieden. Dit stelt ons in staat om (i) te analyseren hoe fragmentatiekosten — als gevolg van potentiële efficiëntieverliezen bij matching in een markt met gefragmenteerde vraag en aanbod — variëren met marktkenmerken en gebruikersattributen, en (ii) onder welke van deze voorwaarden markten met meerdere dienstverleners levensvatbaar zijn. Onze experimenten laten alleen een winner-takes-all uitkomst zien wanneer beide platforms privéritten aanbieden, en op voorwaarde dat gebruikers noch chauffeurs aan multi-homing doen. Dienstverleners hebben meer kans om naast elkaar te bestaan wanneer ride-pooling wordt aangeboden door één van hen — als gevolg van demografische verschillen in doelgroep — of door beide — als gevolg van langere omwegen naarmate de vraag toeneemt. In onze experimenten produceren gefragmenteerde ride-pooling markten (gebaseerd op twee aanbieders) 6,4% extra voertuigkilometers in vergelijking met monopolistische ride-pooling markten. Deze marktfragmentatie gaat gepaard met kosten voor platformgebruikers, chauffeurs en dienstverleners. Daarnaast geven onze resultaten aan dat ridesourcing, met name ride-pooling, een aanzienlijke vraag kan onttrekken aan afstandsefficiënte vervoerswijzen zoals de fiets en het openbaar vervoer. Het benadrukt dat mogelijke voordelen en kosten in verband met ridesourcing afhangen van lokale voorkeuren en kenmerken van het transportsysteem. Tot slot laat het ontwikkelde model ons toe om licht te werpen op de impact van de dagelijkse kosten die gepaard gaan met platformregistratie en op de potentiële (individuele) voordelen van multi-homing voor gebruikers en chauffeurs.

Samenvattend onderzoeken we in dit proefschrift de effecten van verschillende factoren die verband houden met de reisvraag, arbeidsmarktomstandigheden en dienstconfiguraties op de ontwikkeling van ridesourcing-markten. Dit omvat de verkenning van tweezijdige prijsstrategieën, platform coëxistentie, diensttype, schaaleffecten in de markt en sociaaleconomische indicatoren. Specifiek analyseren we de dynamische aard van ridesourcing-indicatoren, waarbij we ons verdiepen in de invloed van leer- en communicatieprocessen, naast de impact van verschillende beslissingskenmerken van reizigers en werkzoekenden. Onze bevindingen laten zien dat de ridesourcing-markt potentieel kan evolueren naar aanzienlijk gevarieerde evenwichten, beïnvloed door initiële omstandigheden en eerder genoemde processen die verband houden met de beslissingen van reizigers en werkzoekenden in de markt. Door licht te werpen op de mechanismen die bijdragen aan ongewenste marktuitkomsten, beoogt dit proefschrift beleidsmakers waardevolle inzichten te bieden in het reguleren van de ridesourcing-markt met als doel om de totale sociale welvaart volgend uit de markt te vergroten.

About the author

Arjan de Ruijter was born in Wageningen, Netherlands, in 1994. From a young age, he was interested in both mobility and simulation. As a kid he spent time playing with toy cars and trains, and later he enjoyed simulating football competitions. During ski holidays, he was more fascinated by the logistics of the ski lifts than by skiing down the slopes. His passion for transportation led him to pursue a Bachelor's degree in Civil Engineering at University of Twente, during which he also completed a minor in Geographical Information Systems (GIS) at Lund University, Sweden. In July 2015, he graduated with a thesis on improving traffic flow on a Dutch highway.

After a full-time board year organising the 44th Batavierenrace, he moved to Delft to pursue a Master's in Transport, Infrastructure & Logistics (TIL) at Delft University of Technology, focusing on mobility service design. His master's thesis explored the efficiency and service levels of ride-pooling services, considering context factors and pricing strategies. He graduated cum laude in May 2019. A paper based on his thesis was published in an issue of Transportation Planning and Technology.

Inspired by his thesis work, he continued his academic journey in the Smart Public Transport Lab (SPTL) at Delft University, joining the CriticalMaaS project as a PhD researcher. His research focused on the two-sided dynamics of ridesourcing markets. During his PhD, he supervised several master's theses, he represented the interests of PhD candidates in the department of Transport & Planning, and he managed the website of the Smart Public Transport lab.

In January 2024, he began working as a researcher on the Dit4TRAM project, exploring the impact of Tradable Mobility Credit (TMC) systems to mitigate the negative externalities of mobility. In September 2024, he joined the Sustainable Urban Multimodal (SUM) lab, working on the Seamless Shared Urban Mobility (SUM) project, where he continues his research on shared mobility services.

Research output

Journal papers

1. **de Ruijter, A.**, Cats, O., Kucharski, R., & van Lint, H. (2022). Evolution of labour supply in ridesourcing. *Transportmetrica B: Transport Dynamics, 10*(1), 599-626.

2. **de Ruijter, A.**, Cats, O., & van Lint, H. (in press). Day-to-Day Supply-Demand Dynamics in Ridesourcing Markets. *Transportmetrica B: Transport Dynamics*.

3. **de Ruijter, A.**, Cats, O., & van Lint, H. (2024). Ridesourcing platforms thrive on socio-economic inequality. *Scientific Reports, 14*(1), 7371.

4. **de Ruijter, A.**, Engelhardt, R., Dandl, F., Geržinič, N., van Lint, H., Bogenberger, K. & Cats, O. (in review). Two-Sided Dynamics in Duopolistic Ridesourcing Markets with Private and Shared Rides.

Conference contributions

1. **de Ruijter, A.**, Cats, O., Kucharski, R., & van Lint, H. (2021). Evolution of labour supply in ridesourcing. *100th Transportation Research Board (TRB) Annual Meeting*, Virtual conference, January 2021.

2. **de Ruijter, A.**, Cats, O., Kucharski, R., & van Lint, H. (2021). Day-to-day Supply Side Evolution of Ride-Sourcing. *9th Symposium of the European Association for Research in Transportation (hEART)*, Virtual conference, February 2021.

3. **de Ruijter, A.**, Cats, O., & van Lint, H. (2022). Emerging Dynamics of Two-Sided Ridesourcing Platforms. *101st Transportation Research Board (TRB) Annual Meeting*, presented online, January 2022.

4. **de Ruijter, A.**, Cats, O. & van Lint, H. (2022). Emerging Dynamics in Ridesourcing Platforms. *10th Symposium of the European Association for Research in Transportation (hEART)*, Leuven, June 2022.

5. **de Ruijter, A.**, Cats, O. & van Lint, H. (2022). Service Dynamics of Two-Sided Ridesourcing Platforms: A Bottom-Up Approach. *15th International Conference on Advanced Systems in Public Transport (CASPT)*, Tel Aviv, October 2022.

6. **de Ruijter, A.**, Cats, O., & van Lint, H. (2023). Ridesourcing Platforms' Reliance on Socio-Economic Inequalities. *8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, Nice, June 2023.

7. **de Ruijter, A.**, Engelhardt, R., Dandl, F., Geržinič, N., van Lint, H., Bogenberger, K. & Cats, O. (2024). Two-Sided Dynamics in Duopolistic Markets with Ride-hailing and Ride-pooling. *12th Symposium of the European Association for Research in Transportation (hEART)*, Aalto, June 2024.

Press releases

1. **de Ruijter, A.**, Cats, O. (2024). Platforms als Uber gedijen op sociaaleconomische ongelijkheid. TU Delft.

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Summary

This PhD dissertation examines the societal implications of newly emerged, two-sided ridesourcing platforms that connect travellers with self-employed drivers. It uses an agent-based approach to model the dynamic interaction between ridesourcing supply and demand, exploring how market outcomes are influenced by travel demand, labour market conditions, and platform strategies. The findings inform policymakers on how to enhance the welfare effects of these markets for travellers, drivers, and the broader public.

About the Author

Arjan de Ruijter conducted his PhD research (CriticalMaaS project) at Delft University of Technology. He holds a Master's degree in Transport, Infrastructure & Logistics from Delft University of Technology and a bachelor's degree in Civil Engineering from University of Twente.

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