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Ride-sharing with inflexible drivers in the Paris metropolitan area

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Abstract
In ride-sharing, commuters with similar itineraries share a vehicle for their trip. Despite its clear benefits in terms of reduced congestion, ride-sharing is not yet widely accepted. We propose a specific ride-sharing variant, where drivers are completely inflexible. This variant can form a competitive alternative against private transportation, due to the limited efforts that need to be made by drivers. However, due to this inflexibility, matching of drivers and riders can be substantially more complicated, compared to the situation where drivers can deviate. In this work, we propose a four-step procedure to identify the effect of such a ride-sharing scheme. We use a dynamic mesoscopic traffic simulator which computes departure-time choices and route choices for each commuter. The optimal matching of potential drivers and riders is obtained outside the simulation framework through an exact formulation of the problem. We evaluate the potential of this ride-sharing scheme on a real network of the Paris metropolitan area for the morning commute. We show that even with inflexible drivers and when only a small share of the population is willing to participate in the ride-sharing scheme, ride-sharing can alleviate congestion. Further improvements can be obtained by increasing the capacity of the vehicles or by providing small monetary incentives, but without jeopardizing the inflexibility of the drivers. Thereby, we show that ride-sharing can lead to fuel savings, CO_2 emission reductions and travel time savings on a network level, even with a low participation rate.

Keywords Ride-sharing · Carpooling · Matching · Dynamic congestion

JEL Classification R41 · R48

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Introduction

Ride-sharing, also known as carpooling, is a non-profit shared ride service where a car owner shares his/her vehicle with another person heading in the same direction to share expenses. It aims to solve one key problem of urban congestion: low vehicle occupancy, especially for commuting trips. In the Paris region, there are 1.05 persons per vehicle on average for commuting trips (Enquête Globale Transport 2010). This rate has been decreasing since 1976 (Cornut 2017). In urban areas, congestion also has severe implications with regards to air pollution. Ride-sharing offers the opportunity to raise average vehicle occupancy and to address public health and climate change issues. For travellers, it is also an opportunity to save on fuel cost.

In this work, we propose a ride-sharing scheme quite similar to conventional hitch-hiking. Drivers do not deviate from their predetermined itinerary, meaning they determine their optimal departure time and exact route without considering a potential rider. The rider then adapts to the itinerary of the matched driver. This implies that the rider may need to walk to reach the driver and to reach his/her final destination after being dropped off by the driver. However, similar to hitch-hiking, the trip is assumed to be completely free of charge for the rider.

Our key hypothesis is that the segment of the rider's trip spent in a personal vehicle, will be offered by a driver who has already planned to travel that segment on his/her own trip. This is the key feature of our system: drivers are inflexible. This hypothesis is explained by the observation that one of the setbacks in the development of the ride-sharing process is that drivers are reluctant to change their routes and schedules. One cannot avoid the a priori inconvenience to have another person in the car; later on, one can think of some certification systems to reduce the uncertainty to have somebody else (unknown) in their own car. Of course, such certification (of the car, the insurance status or the driving license) should preserve anonymity and should not be incompatible with privacy rules.

The emergence of ride-sharing services such as UberPool, Lyft Line, and Blablacar Daily (not to be confused with the ride hailing services provided by Uber and Lyft) has been a major competitor to the practice of ride-sharing (Shaheen and Cohen 2019). Ride-sharing consists of people with similar travel needs travelling together, whereas ride hailing consists of car owners offering paid lifts to gain money. The social benefits of ride-sharing are manifold: less traffic congestion (Xu et al. 2015; Cici et al. 2014), less CO_2 and NO_X emissions leading to better air quality (Bruck et al. 2017), and better transit accessibility in suburban areas (Teubner and Flath 2015; Li et al. 2016; Kong et al. 2020). Moreover, ride-sharing brings about travel cost sharing for riders and drivers (Malichová et al. 2020). However, the popularity of ride-sharing remains low for commuting trips.

Many forms of ride-sharing have been studied over the years to increase the mode's convenience and maximise the societal gains it provides in terms of traffic congestion as well as of emissions reduction. Nonetheless, each of them presents certain drawbacks. For instance, multi-hop ride-sharing explores the possibility for a rider to use multiple cars to complete his/her trip at the cost of a transfer penalty and waiting time. As for detours created by door-to-door ride-sharing services, they increase the driver's travel distance and time, all the more in the case of multiple passengers. Some ride-sharing companies have stopped door-to-door service and now ask riders to walk in order to reduce the extent of the detours (Schaller 2021; Lo and Morseman 2018).

This research proposes a four-step procedure to evaluate the effect of a ride-sharing scheme where the driver makes no detour at all and no concession on his/her schedule. The procedure can assess the impact of the ride-sharing scheme on congestion and CO_2 emissions reduction. The first step consists in running the mesoscopic dynamic traffic simulator Metropolis to identify the departure time and route chosen by the drivers. In the second step, the ride-sharing costs are computed. The ride-sharing scheme is such that the ride is free of charge for the riders and the inconvenience of the driver is completely compensated by state subsidies (later on, a monthly/annual public transport pass could be required). In the third step, the optimal matching is obtained by solving an Integer Linear Programming (ILP) problem. The matching is such that each rider is matched with a driver who travel next to his/her origin and destination and whose trip timing is compatible with the schedule-delay preferences of the rider. Finally, the fourth step consists in running another simulation of the traffic simulator to compute the new congestion level.

Whereas existing works have evaluated ride-sharing methods only on small scale networks, we evaluate the potential of our ride-sharing scheme for the Paris metropolitan area, under dynamic congestion. We consider different scenarios, with a different share of travellers willing to participate in the ride-sharing scheme. Scenarios with more than one rider in the car and scenarios where incentives are being proposed to riders are also considered.

In October 2022, the French government announced a subsidy of 100€ for new ride-sharing users, illustrating the willingness of governments to subsidize ride-sharing.[1] Our results show that a government-funded ride-sharing scheme can be beneficial for society. More precisely, we find that, even when only a small share of the population is willing to participate in the scheme, ride-sharing can significantly reduce congestion and CO_2 emissions. Additionally, as shown by Lian and Van Ryzin (2021), the optimal policy in two-sided markets like ride-sharing is to provide initially significant spending in order to reach, as early as possible, a critical mass of users. Therefore, a temporary government intervention, even if it is costly, can have a long-run impact on the modal share of ride-sharing and thus on congestion and CO_2 emissions.

The remainder of this paper is structured as follows. Section 2 reviews the ride-sharing literature and the ways it is modelled. Section 3 describes the proposed ride-sharing scheme, the dynamic traffic simulator, and the proposed driver-rider matching methodology. Section 4 presents the case study results for Île-de-France (Paris area) under three maximum walking time scenarios, and for various penetration rates. Section 5 concludes with the key results and explores further research steps needed to explore the feasibility of a real operational-system.

Literature review

Sharing mobility is part of the global trend towards a sharing economy (Standing et al. 2019). Shaheen and Cohen (2019) provide an overview of the different shared-ride services. Ride-sharing, also known as carpooling, and ride-hailing, also known as ride-sourcing, are two of the main shared-ride services. Whereas the former is associated with many societal benefits, the latter is an on-demand transportation service similar to taxi service with privately owned vehicles. Ride-hailing is often associated with an increased traffic congestion (Schaller 2021). Ride-sharing is inherently a non-profit mode that brings together people with similar trip itineraries to share their trip. The body of literature on

[1] https://www.service-public.fr/particuliers/actualites/A16012.

this topic has significantly increased in the last decade as it has become more convenient to plan, book, and pay for a ride (Shaheen and Cohen 2019). Indeed, Transportation Network Companies (TNCs) such as Uber and Lyft offer online ride-sharing services (UberPool and Lyft Line) in addition to their standard ride-hailing services.

The matching problem between the rider and the driver has been extensively studied. Matching problems can be either static (Liu et al. 2020; Herbawi and Weber 2012; Yan and Chen 2011; Ma et al. 2019a; Lu et al. 2020) or dynamic (Agatz et al. 2011; Kleiner et al. 2011; Di Febbraro et al. 2013). In static matching problems, all drivers and riders are known in advance and are matched at the same time. Dynamic matching problems consider that drivers and riders arrive gradually. In this case, partial matchings can be performed with a subset of the drivers and riders. This work uses static ride-sharing under dynamic congestion.

The main benefit of ride-sharing is that it eases traffic congestion (Xu et al. 2015; Cici et al. 2014). It hence offers a great potential for CO_2 emission reductions (Bruck et al. 2017; Chan and Shaheen 2012). Furthermore, it offers more accessibility to public transit as a first/last mile solution (Teubner and Flath 2015; Li et al. 2016; Kong et al. 2020). Ride-sharing may, however, increase the driver's trip time through detours to pick up and drop off riders (Diao et al. 2021). Schaller (2021) analyses extensive longitudinal data from TNCs in American cities. He observes that ride-sharing services mainly draw people from transit as it is mostly popular in neighbourhoods with low incomes and low car ownership rates. This phenomenon has become even more evident since UberPool and Lyft Line stopped door-to-door services, with the aim to reduce detours. This finding is in line with many other studies concluding that an increase in the modal share of ride-sharing does not cause a significant reduction in the modal share of car (Kong et al. 2020; Li et al. 2016; Coulombel et al. 2019; Xu et al. 2015; Shaheen et al. 2016).

Despite the many benefits of ride-sharing, it is still not widely used as a mode to commute (Liu et al. 2020). Amongst the challenges to have a successful ride-sharing system is the large population of drivers necessary to provide high-quality matches in terms of geographic and temporal proximity (Bahat and Bekhor 2016). Substantial research has been conducted to understand the individual motivations behind ride-sharing in order to increase its popularity. Cost savings followed by environmental concerns are the main motivations reported both by the drivers and the riders (Neoh et al. 2017; Pinto et al. 2019; Delhomme and Gheorghiu 2016; Gheorghiu and Delhomme 2018). Malichová et al. (2020) observed through a pan-European survey that travellers prefer to adopt ride-sharing for work compared to other purposes.

Ride-sharing has been modelled alongside transit both as a complement providing a solution to the first/last mile problem (Kumar and Khani 2020; Reck and Axhausen 2020; Masoud et al. 2017; Ma et al. 2019b) and as a competitor (Qian and Zhang 2011; Galland et al. 2014; Friedrich et al. 2018). Qian and Zhang (2011) use a theoretical bottleneck model where the modal choice between car, transit, and ride-sharing depends on the generalised travel time. They account for transit perceived-inconvenience depending on transit passenger-flow. Schedule delay is considered for the three modes. de Palma et al. (2022) build on this framework to add dynamic congestion. Coulombel et al. (2019) use a transportation-integrated land use model to consider the impact of ride-sharing on car and transit ridership for the Paris region. Finally, Galland et al. (2014) propose an agent-based model for ride-sharing to analyse individual mobility behaviour. They test their model on a population of 1000 agents only due to its computational complexity. To predict the route taken by the drivers in a large-scale scenario, this work uses the dynamic traffic-assignment simulator Metropolis (de Palma et al. 1997), which can account for the timings of the trips when matching riders with drivers. This traffic simulator computes, for each individual, the route, departure-time and mode choice, using a nested Logit model. The schedule-delay costs are based on idiosyncratic $\alpha - \beta - \gamma$ preferences (Vickrey 1969) and congestion is modelled with link-specific bottlenecks.

This work builds on the many ride-sharing models present in the literature. The methodology allows to assess the potential of ride-sharing in a large urban area under dynamic congestion, whereas previous models were either applied on simple bottleneck models (de Palma et al. 2022; Qian and Zhang 2011; Yu et al. 2019) or were too sophisticated to provide results for a large urban network (Galland et al. 2014). Alisoltani et al. (2021) also consider a medium sized urban network with traffic dynamics, but the main difference with our work is that their drivers are not commuters but employees of the company offering the ride-sharing service. Furthermore, we consider mode choice (including public transport) and departure time choices of commuters that consider scheduling delay preferences.

Methodology

Ride-sharing scheme

This paper explores a ride-sharing scheme where ride-sharing drivers make no detour and keep the exact same schedule as when driving alone. Ride-sharing drivers simply pick up a passenger at a defined road intersection on their itinerary and drop off their passenger at another intersection on their itinerary. As for the riders, they need to walk from their origin to a pick-up point and from a drop-off point to their destination. They face schedule-delay costs if their arrival time does not match their desired arrival time. However, the trip is free of fare for them.

Figure 1 provides an example of a ride-sharing trip under this scheme. The driver's itinerary is composed of the two blue parts (where he/she is alone) and the red part (where he/she has a passenger). The rider's trip consists of a walking leg from his/her origin to the pick-up point (in green), a car leg with the driver (in red) and another walking leg from the drop-off point to his/her destination (in green).

We emphasize that in this framework, in order to match drivers and passengers and evaluate the corresponding costs, drivers announce their complete itinerary (i.e., exact route and departure time), whereas riders only communicate their origin, destination and desired arrival time. The exact route of the riders follows directly from the route of the matched driver.

Implementing such a ride-sharing scheme on a large scale would require some sort of state intervention, e.g., through subsidies, in order to convince enough drivers and riders to subscribe to the scheme. As drivers do not deviate from their route nor from their desired departure time, drivers only need to be compensated for the inconvenience of having someone in their car (Li et al. 2020).

Riders may also experience an inconvenience cost, arising from the discomfort of sharing a ride with a stranger. On top of this, they also have to walk and may incur additional schedule-delay costs. However, the scheme allows them to save money on gas, car wear and tear, parking, and car insurances. Moreover, they do not spent time driving around for a parking slot any more. To convince more individuals, additional subsidies may be offered to reduce the generalised costs of ride-sharing.

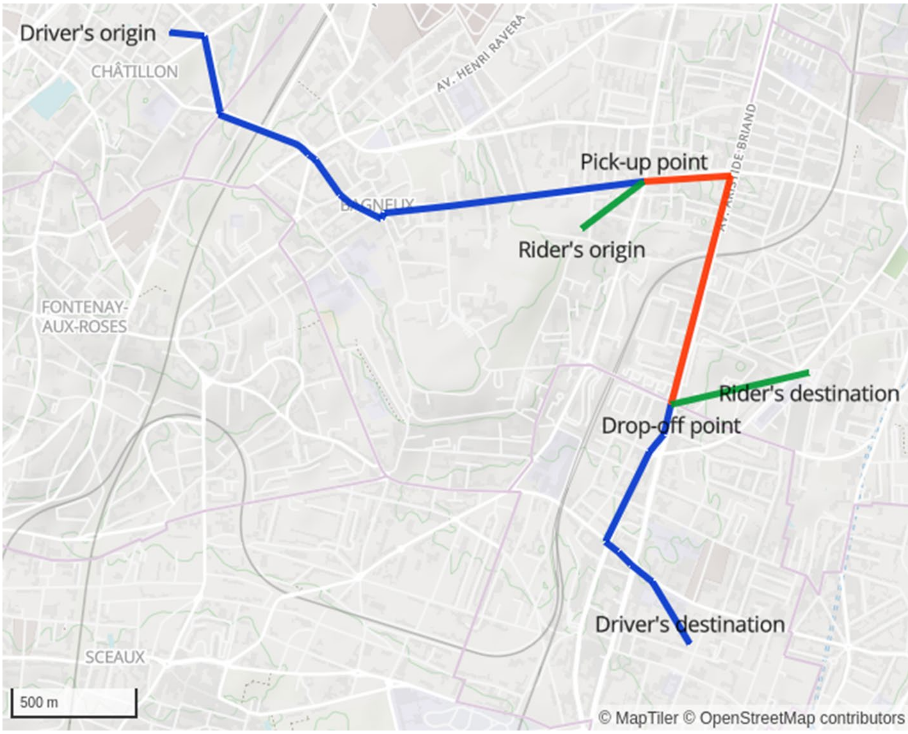


Fig. 1 Ride-sharing trip example where the blue lines represent the driver's trip alone, the red line represents the car trip shared between the driver and the rider and the green lines represent the walking trips of the rider

An increase in the modal share of ride-sharing can greatly reduce the congestion in a city. By increasing the occupancy of vehicles, the number of vehicles on the road decreases. In turn, the externalities associated with congestion (including air pollution, noise pollution and safety) also decrease. Public authorities may therefore be interested in subsidising ride-sharing to reduce congestion and its environmental cost.

Four-step procedure

We propose a four-step procedure to match drivers and riders in our ride-sharing framework and evaluate the impact of ride-sharing on congestion. A part of this procedure may be repeated to achieve convergence.

1. *Initialize* The traffic simulator METROPOLIS is used to simulate a reference scenario without ride-sharing. This means all commuters can choose between driving solo or using public transport. The simulator is run up to a stationary regime such that the mode choice, routes and departures times of every individual is identified. A detailed explanation of the traffic simulator and our definition of stationary regime is given in Sect. 3.3.
2. *Cost computation* The ride-sharing costs of any pair of commuters that is willing to participate in the ride-sharing scheme is computed. Section 3.4 describes how the costs are evaluated for every pair. The reference simulation is used to obtain the exact route

and departure time of a participating driver, as well as the origin, destination and desired arrival time of a participating rider.

3. *Optimal matching* Based on the computed costs, the optimal matching of drivers to riders is obtained by solving an Integer Linear Programming (ILP) problem. This is described in Sect. 3.5.
4. *Ride-sharing simulation* All riders that were matched to a driver in the previous step are excluded from the set of commuters and the traffic simulator is run to a new stationary regime with the remaining commuters.

Steps 2-4 can be repeated until convergence is observed. Then, the final simulation can be used to evaluate the effect of ride-sharing on congestion, mode share and total mileage. We emphasize that over the entire network, ride-sharing reduces congestion by reducing the total number of cars. However, due to mode changes to and from public transport, there may be a local increase in congestion in some parts of the network. Due to the change in congestion, additional commuters may choose to ride-share or individuals who chose to ride-share may regret this for the new congestion level. For this reason, an iterative framework using steps 2-4 can be used to evaluate this kind of behaviour, but this is omitted in this work due to its computational complexity.

Traffic simulator

To assess how congestion evolves as the number of cars decreases and car occupancy increases, we use Metropolis, a mesoscopic dynamic traffic simulator developed by de Palma et al. (1997). Since then, it has mostly been used to estimate various transport policies, including different road pricing schemes (Saifuzzaman et al. 2016; de Palma et al. 2005). The inputs of the simulator include a description of the road and public-transit networks, origin-destination matrices and travellers' preferences. The outputs are the choices of the travellers and the dynamic state of the road network (time-dependent congestion levels and travel times). In Metropolis, congestion is represented using link-level bottlenecks.

The choices made by each traveller can be summarised as:

1. Mode choice (between car and transit): The generalised cost for transit is compared with the generalised cost for car. The public transit cost is function of the value of time of transit, the transit travel time, and the transit fare. In the current version, generalised public transport costs are exogenous. The generalised cost for car is a function of the value of time of car, the endogenous travel-time, and the schedule-delay cost. The mode choice is given by a nested Logit model.
2. Departure-time choice: The probability of choosing a departure time t is given by a continuous Logit model, according to the generalised cost for each possible departure time.
3. Route choice: Each day, at each intersection, travellers observe the congestion on upstream roads and choose a road in order to minimize their generalised cost (closed loop equilibrium).

Note that commuters only choose between car and transit, while ride-sharing is not explicitly modelled as a mode in the simulator. By assumption, drivers are always fully compensated for ride-sharing inconvenience and riders only accept matches that decrease their generalised travel cost, which justifies their mode choice for ride-sharing.

Metropolis uses a day-to-day iterative procedure. At each iteration, the travellers choose their mode, departure-time and route, given the expected dynamic congestion levels. At the end of each iteration (day), the expected congestion levels are updated using the observed congestion levels, according to a day-to-day adjustment process: the expected congestion for the next iteration is a weighted average of the current expected congestion and the observed congestion. The simulation stops when the two levels are close, i.e., when a stationary regime is reached.

Ride-sharing cost

The cost of ride-sharing, for a rider, is the sum of walking cost, in-vehicle cost and schedule-delay cost. We consider the cost for a rider i when matched to a driver j.

The walking cost is the cost of walking from the origin to the pick-up point and from the drop-off point to the destination. Let v^{walk} be the walking speed. The duration of the walking trip from the rider's origin to the pick-up point is assumed to be $d_{ij}^{\text{pick}}/v^{\text{walk}}$, where d_{ij}^{pick} is the Euclidean distance between the rider's origin and the pick-up point, when matching rider i with driver j. The duration of the walking trip from the drop-off point to the rider's destination is assumed to be $d_{ij}^{\text{drop}}/v^{\text{walk}}$, where d_{ij}^{drop} is the Euclidean distance between the drop-off point and the rider's destination.

The time at which driver j picks up (resp. drops off) rider i is denoted t_{ij}^{pick} (resp. t_{ij}^{drop}). It is equal to the time at which driver j is predicted to reach the pick-up point (resp. drop-off point). Then, the duration of the car trip for the rider is $tt_{ij}^{\text{iv}} = t_{ij}^{\text{drop}} - t_{ij}^{\text{pick}}$ and the arrival time at destination is $t_{ij}^{a} = t_{ij}^{\text{drop}} + d_{ij}^{\text{drop}}/v^{\text{walk}}$.

Each rider i has a specific desired arrival time t_i^* and a tolerance for lateness or earliness Δ_i. Riders who reach their destination within the $t_i^* \pm \Delta_i$ window experience no schedule-delay penalty. Every minute outside this on-time window generates a schedule delay cost. The schedule delay cost of rider i, when matched with driver j, is

$$SD_{ij} = \beta_i \left[(t_i^* - \Delta_i) - t_{ij}^{a} \right]^+ + \gamma_i \left[t_{ij}^{a} - (t_i^* + \Delta_i) \right]^+,$$

where $t_{ij}^{a} = t_{ij}^{\text{drop}} + d_{ij}^{\text{drop}}/v^{\text{walk}}$ is the arrival time of the rider at destination, β_i is the penalty associated to early arrival, γ_i is the penalty associated to late arrival, and $[x]^+ = \max(0, x)$.

To sum up, the generalised cost of ride-sharing experienced by rider i, when matched with driver j, is

$$c_{ij}^{\text{R}} = \underbrace{\alpha_i^{\text{RS}} \cdot tt_{ij}^{\text{iv}}}_{\text{In-vehicle cost}} + \underbrace{\alpha_i^{\text{walk}} \cdot \left[\frac{d_{ij}^{\text{pick}} + d_{ij}^{\text{drop}}}{v^{\text{walk}}} \right]}_{\text{Walking cost}} + \underbrace{SD_{ij}}_{\text{Schedule-delay cost}},$$

where α_i^{RS} is the value of time of rider i during the ride and α_i^{walk} is the value of time of rider i when walking. The pick-up and drop-off points are chosen so as to minimize the generalised cost c_{ij}^{R}.

Matching

The matching of drivers and riders is determined through an Integer Linear Programming (ILP) formulation. We define N the set of individuals that are willing to participate in the ride-sharing program. According to the proposed ride-sharing scheme, drivers will not deviate from their route nor will they change their arrival time to account for riders. Therefore, drivers will not have costs involved with ride-sharing and the costs for driver $j \in N$ are equal to c_j^{NR}, independent of whether there are any riders on the car. We also emphasize that an individual can use public transport rather than drive. In this case, c_j^{NR} encompasses the costs of public transportation. Riders on the other hand, have a cost associated to ride-sharing, as defined in Sect. 3.4. We define c_{ij}^{R} the cost of rider $i \in N$ when taking a ride from driver $j \in N$. The total number of riders that driver $j \in N$ can take is equal to a_j. Here the driver is not accounted for, so for a car with 5 seats a_j would be equal to 4.

We define binary decision variable x_{ij} which is equal to 1 if rider $i \in N$ is matched to driver $j \in N$, and 0 otherwise. Furthermore, we define binary decision variable y_i which is equal to 1 if rider $i \in N$ is not matched to any driver. The objective is to minimize the total costs of all individuals that are willing to participate in the ride-sharing scheme. This is equivalent to maximizing the total cost reduction associated to ride-sharing.

$$\min \sum_{i,j \in N} c_{ij}^{\mathrm{R}} x_{ij} + \sum_{i \in N} c_i^{\mathrm{NR}} y_i \tag{1}$$

$$\text{s.t.}$$

$$y_i + \sum_{j \in N} x_{ij} = 1 \quad \forall i \in N \tag{2}$$

$$\sum_{i \in N} x_{ij} \le a_j y_j \quad \forall j \in N \tag{3}$$

$$x_{ij} \in \mathbb{B} \quad \forall i, j \in N \tag{4}$$

$$y_j \in \mathbb{B} \quad \forall j \in N \tag{5}$$

The objective in Eq. (1) is to minimize the joint cost of ride-sharing and travelling by car for all individuals. Constraints (2) imposes that all individuals are either matched to a driver or driving themselves. Constraints (3) enforces that a rider can only be matched to an individual that is driving and it enforces the capacity of the vehicle. Constraints (4) and (5) define the binary range of the decision variables. We note that when individual $j \in N$ uses public transit, $y_j = 1$. However, it is impossible to assign a rider to this individual as $c_{ij}^{\mathrm{R}} = \infty$ for all $i \in N$ if j is a public transport user.

Note that the total number of riders is not known a priori as individuals in the set N can be either rider, driver (with or without passenger) or public-transit user. Instead, the number of riders depends on the quality of the matches. Also observe that an individual i can be matched with a driver j only if the ride-sharing cost is smaller than the non ride-sharing cost, i.e., $c_{ij}^{\mathrm{R}} < c_i^{\mathrm{NR}}$. In this respect, the matching program proposes only Pareto-improving matches.

Case study: ride-sharing in Île-de-France

The Paris area, as many other large cities, experiences frequent heavy pollution episodes partly due to car emissions (Kumar et al. 2021; Degraeuwe et al. 2017). The regional government of Île-de-France created subsidy programs in 2017 to promote ride-sharing and

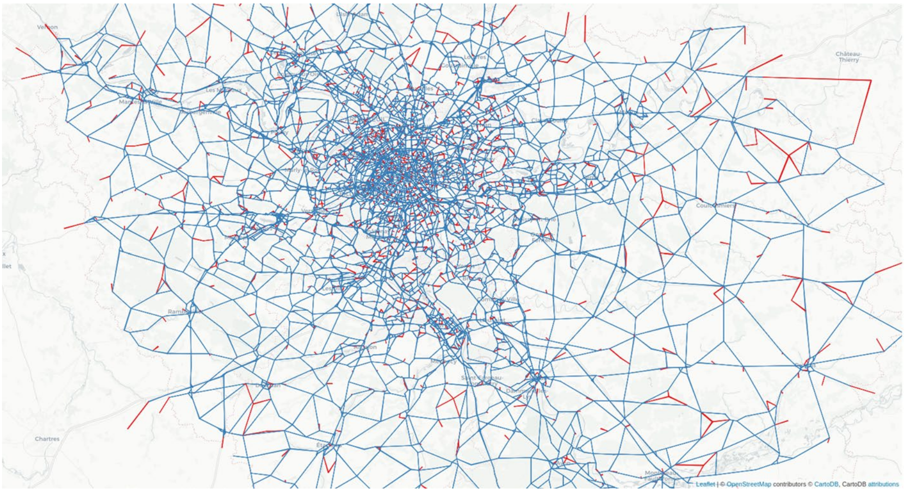


Fig. 2 Île-de-France road network. Note. Red lines are uncongested virtual roads connecting the centroids of the zones to the road network (in blue)

address this issue. The programs include, *inter alia*, direct subsidies for ride-sharing drivers, the funding of ride-sharing companies so that they offer lower fares to riders, and two monthly free rides to frequent transit users. Drivers receive from the government 1.50€ per passenger plus 0.10 €/km up until a maximum of 3€ per trip. Moreover, the regional government has made ride-sharing completely free for riders during peak pollution episodes and during transit strikes.[2,3]

The ride-sharing scheme proposed in this research is tested on the Île-de-France region. Île-de-France accounts for nearly a fifth of France's population with its 12 175 000 inhabitants in 2017. The region, mainly consisting of Paris and its suburbs, has a density of 1013 inhabitants per square kilometre. Region-wide, there are 43 million trips daily amongst which 42% are made by foot or bicycle, 22% by public transit, and 36% by car. There are however wide disparities between the city of Paris, the inner and the outer suburbs (Île-de-France Mobilités 2019).

Network modelling

We use the calibration of Metropolis for Île-de-France from Saifuzzaman et al. (2012), which is based on demand data from the 2001 Paris origin-destination survey. The road network consists of 43 857 links, 18 584 intersections, and 1360 zones. Each link is unidirectional and represents a bottleneck with a link-specific capacity. The origin and destination of travellers is set to the centroid of their origin/destination zone. The centroids are connected to the road network with uncongested links. Figure 2 is a visual representation

2 https://www.iledefrance.fr/la-prime-au-covoiturage-prolongee-et-etendue.

3 https://www.iledefrance.fr/covoiturage-jusqua-150-euros-par-mois-pour-les-conducteurs.

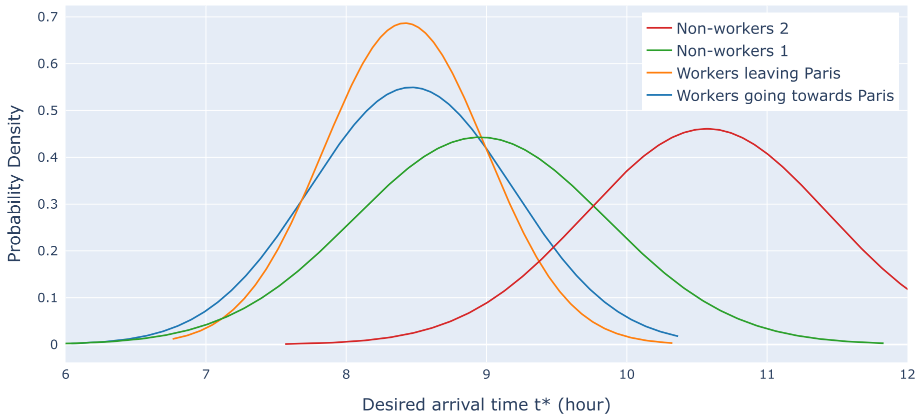


Fig. 3 Desired arrival time distribution of the four traveller groups

of the network. Compared to the original calibration by Saifuzzaman et al. (2012), we enable mode choice, which requires recalibrating the road capacities.

There is no public transit network per se, but rather exogenous travel times for each origin and destination pair of Île-de-France. The public-transit generalised costs are taken from the DRIEAT (*Direction régionale et interdépartementale de l'environnement, de l'aménagement et des transports d'Île-de-France*).

The pick-up and drop-off points can be any of the intersections of the road network. The computed walking distance is the Euclidean distance between the centroid of the zones and the intersections.

Travel demand

We simulate the morning commute, which is the most congested period of the day in Île-de-France. The simulation starts at 6AM and ends at 13PM. Travel demand is represented as an origin-destination matrix for different traveller groups. All demand data are taken from the calibration of Metropolis for Île-de-France (Saifuzzaman et al. 2012). Demand data is representative of a typical morning commute. A more thorough analysis would be needed to consider the impact of the day-to-day variations of demand on the ride-sharing matching.

Travel demand for the morning commute is divided in four traveller groups: workers going towards Paris, workers leaving Paris, and two groups of non-workers. Both the demand and the road capacity are scaled down to 50% to reduce computation time. All travellers are car owners and can choose between taking their car or taking the public transit. There is a total of 934,042 travellers.

In each group, the travellers have the same schedule-delay parameters and values of time but the desired arrival times are normally distributed. Figure 3 represents the desired arrival time distribution for the four groups of travellers. Workers coming from Paris are the ones with the narrowest distribution and the earliest desired arrival time. The workers originating from the suburbs and going towards Paris want to reach their destination, in average, a few minutes later. The desired arrival time of the non-workers

Table 1 Preference parameters for the two groups of workers, in €/h

Traveller group	β	γ	α_{car}	α_{RS}	α_{PT}	α_{Walk}
Workers going towards Paris	6.09	7.53	12.96	12.96	13.24	14.26
Workers coming from Paris	8.36	17.43	12.96	12.96	13.24	14.26
Non-workers 1	5.24	10.64	12.96	12.96	13.24	14.26
Non-workers 2	5.24	10.64	12.96	12.96	13.24	14.26

is represented by two normal curves with a standard-deviation of 90 minutes. Non-workers have a later desired arrival time than commuters.

All the preference parameters used in this research are presented in Table 1. The values of time for car and transit as well as the early and late penalties come from the work of Saifuzzaman et al. (2012). The value of time for riders is assumed to be equal to the value of time of car (i.e., $\alpha_{car} = \alpha_{RS}$), which means that for riders the savings incurred by ride-sharing are completely offset by its inconvenience. Workers starting their journey in Paris are more inflexible in their desired arrival time as shown by their penalty for late arrival being more than twice the one of workers starting their journey in the suburbs. The value of time of walking is assumed to be $\alpha_{walk} = 1.1 \cdot \alpha_{RS}$ (Hensher and Rose 2007; Wardman 2001). For all travellers, the walking speed is set to $v_{walk} = 4\,\text{km/h}$ and the length of the on-time window is set to $\Delta = 5\,\text{min}$..

We assume that the ride-sharing cost c_{ij}^{R} is computed based on the realised travel time of the driver, i.e. his/her departure time on the previous day (or any announced departure time). One justification is that the driver has to announce beforehand his/her departure time in order to make the matching procedure feasible. On the other hand, the cost as a driver, c_i^{NR}, is based on anticipated travel times, i.e., it is the expected minimum cost over the departure-time period. This discrepancy can introduce a bias towards ride-sharing if the anticipated travel times are over-estimated.

Estimating the actual willingness of travellers to participate in the ride-sharing scheme is outside the scope of this paper. Instead, we study five scenarios with a different *participation rate*: 10%, 20%, 30%, 40% and 50%. The travellers willing to participate are selected randomly among both car drivers and public-transit users. For simplicity, we assume that the set of drivers who participate in the ride-sharing scheme coincides with the set of drivers who accept to have a passenger in their car.

Results

Table 2 presents the results from the Metropolis simulation for the reference scenario (with no ride-sharing), and the five ride-sharing scenarios. The individual surplus is the sum, over any individual, of the (opposite of the) individual's generalised travel cost (for car, public-transit or ride-sharing). The surplus variation represents its absolute variation, compared to the reference simulation. The *Car VKT* indicator represents the total distance (in thousands of kilometres) travelled by cars during the morning commute. Congestion is computed as

Table 2 Comparison of results for the reference scenario and five scenarios with a different participation rate

Scenario	Reference	10%	20%	30%	40%	50%
Shares						
Transit modal share	25.5%	25.3%	24.8%	24.3%	23.9%	23.5%
Car modal share	74.5%	73.9%	73.2%	72.4%	71.5%	70.5%
Ride-sharing modal share	0.0%	0.9%	2.0%	3.3%	4.6%	6.0%
Surplus						
Individual surplus variation (€)	–	+20 326	+63 594	+104 897	+148 529	+248 744
Road network						
Car VKT (10^3 km)	10 799	10 740	10 686	10 595	10 499	10 377
Congestion	22.1%	21.7%	21.4%	20.6%	19.8%	19.2%
CO_{2eq} emissions reduction (tons)	–	11.387	21.809	39.372	57.900	81.446
Drivers						
Mean travel time	15’ 32”	15’ 31”	15’ 32”	15’ 27”	15’ 22”	15’ 19”
Mean travel cost (€)	6.03	6.02	6.02	6.00	5.97	5.95
Share of time spent with a passenger (for ride-sharing drivers only)	–	51.5%	56.1%	58.0%	59.8%	60.5%
Riders						
Mean Euclidean OD distance (meters)	–	5491	5972	6205	6425	6539
Mean walking distance (meters)	–	383	347	325	310	303
Mean walking distance (if positive, meters)	–	470	451	438	432	430
Mean car travel time	–	7’ 21”	8’ 00”	8’ 20”	8’ 38”	8’ 47”
Mean travel time	–	13’ 06”	13’ 12”	13’ 13”	13’ 17”	13’ 20”
Mean travel cost (€)	–	3.26	3.24	3.22	3.22	3.22
Riders at their best match	–	76.7%	69.3%	65.0%	62.2%	59.1%

The surplus, car VKT and CO_{2eq} emissions values are for a single representative morning commute

$$\frac{1}{|L|} \cdot \sum_{l \in L} \frac{tt_l^{avg} - tt_l^0}{tt_l^0},$$

where L is the set of all links in the network, $|L|$ is its cardinality, tt_l^{avg} is the average travel-time on link l for the simulation period and tt_l^0 is the free-flow travel-time of link l. The reduction in CO_{2eq} (carbon dioxide equivalent) emissions is computed assuming average CO_{2eq} emissions per car of 0.193kg/km (Agence de la transition écologique 2021).

In the ride-sharing scenarios, the individual surplus increases compared to the reference scenario for two reasons: (i) all the riders have now a lower generalised travel cost; (ii) there are less cars on the network and thus congestion and the average generalised cost of the drivers is smaller. In addition to the decrease in congestion, the reduction of the number of cars on the network also implies a significant decrease of CO_{2eq} emissions, less noise, and improved air quality.

The public-transit modal share decreases from 25.5% in the reference scenario to 23.5% in the 50% scenario. This is due to two different shifts: (i) public-transit users shifting to riders; (ii) public-transit users shifting to car drivers (more details in Sect. 4.4). As this

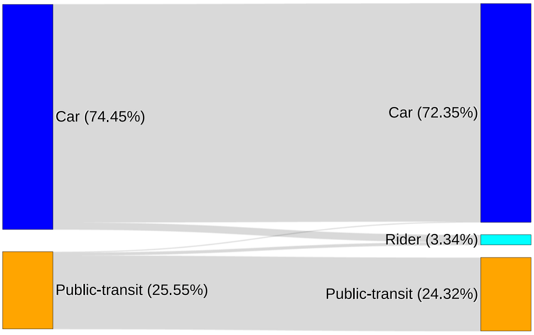


Fig. 4 Mode shifts between the reference scenario (on the left) and the 30% participation rate scenario (on the right)

work focuses on the impact of ride-sharing on congestion and CO_{2eq} emissions,[4] neither of these shifts is desirable. First, the shift of some public-transit users to riders imply that some potential good matches are no longer available to other potential riders. Therefore, the number of car users becoming riders is smaller than what it would be if the matching algorithm ignored all public-transit users. Second, the shift of some public-transit users to car drivers imply that the decrease in congestion and CO_{2eq} emissions is not as large as what it would be if public-transit users were forced to stick to public transit.

We can observe that the mean Euclidean distance between the origin and the destination of the riders increases with the participation rate (from 5.5 km in the 10% scenario to 6.5 km in the 50% scenario). An explanation for this increase would be that, as the participation rate increases, it gets easier to find good matches between drivers and riders with a large O-D distance. Even though the mean O-D distance increases with the participation rate, the mean generalised travel cost for the riders decreases (from 3.26€ to 3.22€), implying an increase of the match quality for the riders.

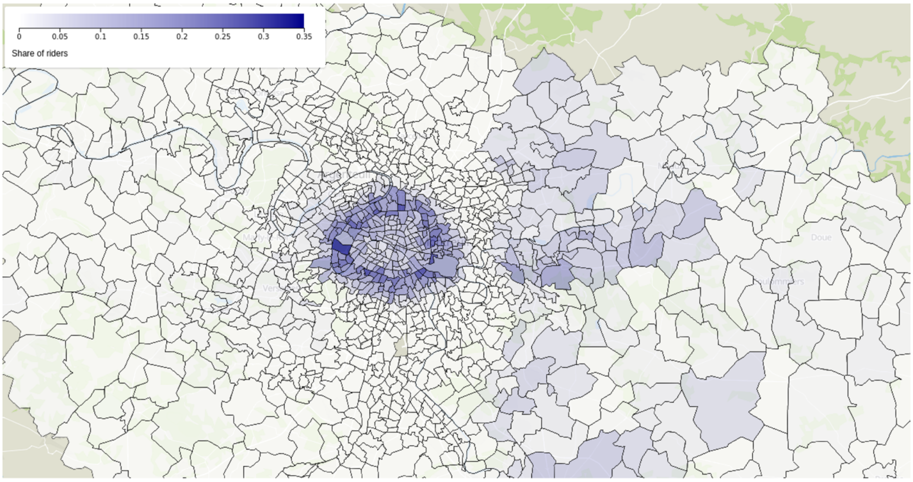
Detailed Results for the 30% scenario

In this section, we look at detailed results on the matches for the scenario with a participation rate of 30%. Figure 4 represents the mode shifts compared to the reference scenario without ride-sharing. It can be observed that the 3.34% of riders were either former car drivers or former public-transit users. Some public-transit users are shifting to the car because road congestion is smaller.

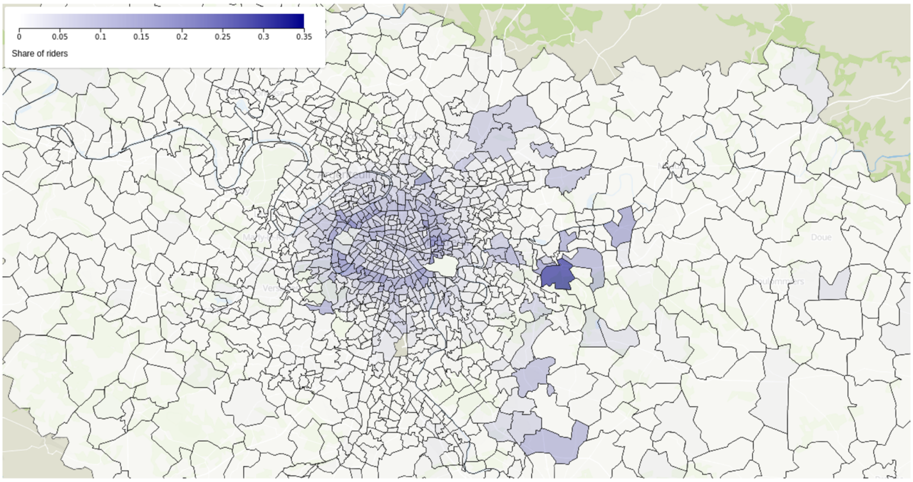
Figure 5 represents the spatial partition of the origins and destinations of the matched riders. It shows that riders' origins are mainly located in the closest to Paris, where population density is the highest. The intuition is that it is easier to find a matching driver within reasonable walking distance in areas where population density is higher.

The total walking distance displayed on Fig. 6 represents the sum of the Euclidean distances from the rider's origin to the pick-up intersection and from the drop-off intersection to the rider's destination. The walking distance is zero for about 28% of matches, meaning that the rider and the driver have the same origin-destination pair. Almost all

[4] In particular, we omit the impact of a decrease of public-transit use on in-vehicle congestion or service quality/frequency.



(a) Riders' origins



(b) Riders' destinations

Fig. 5 Origins and destinations of matched riders in Île-de-France

riders have a walking distance smaller than 1 km, which corresponds to a walking time of less than 15 min.

Figure 7 presents the schedule delay of riders. For around 66% of riders, the schedule delay is zero, i.e., they arrive at destination within their on-time window of 10 min. More riders are arriving early than late (arriving early is less costly than arriving late because $\beta < \gamma$).

Figure 8 presents the distribution of the generalised cost savings for riders, i.e., the difference between their generalised travel cost as a rider and their generalised travel cost in the reference scenario. It is the sum of the schedule delay cost, the walking cost, and the in-vehicle travel cost. An analysis of the ride-sharing cost reveals that the main

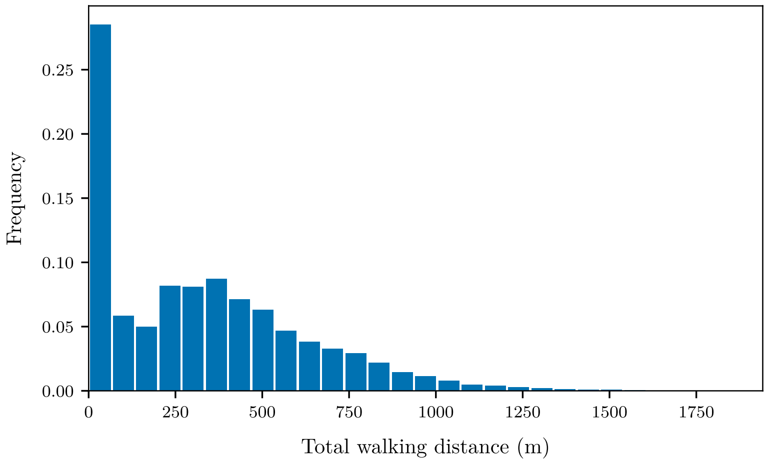


Fig. 6 Distribution of walking distance for the matched riders

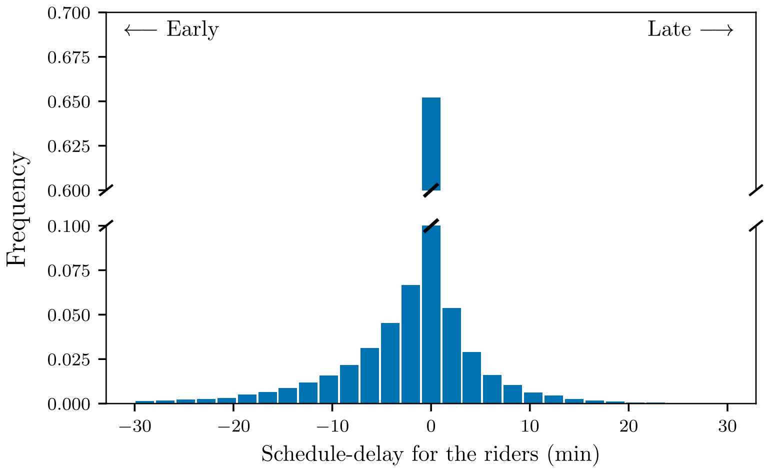


Fig. 7 Distribution of schedule delay for the riders

component is the in-vehicle travel cost: the mean cost of 5.09€ can be divided in 16% of schedule delay cost, 10% of walking cost, and 74% of in-vehicle travel cost.

Recall that the drivers are perfectly compensated for the inconvenience cost of having someone in their car and that the riders do not receive any subsidy. The cost of implementing such a ride-sharing scheme is thus equal to the sum of the inconvenience cost of all the drivers. As the literature on ride-sharing is still lacking good estimates of the inconvenience cost of having someone in their car, we cannot estimate precisely the cost of the policy that we propose. Instead, we analyse the results with different values for the inconvenience cost, ranging from 2 €/h to 16 €/h.[5] The results are reported in Table 3. Even

[5] Although inconvenience in public transit and with ride-sharing are not directly comparable, the value of crowding in public transit can be used as an approximation for the inconvenience cost of ride-sharing. Björklund and Swärdh (2017) estimates that, when sited, the value of time is multiplied by 1.48 when shift-

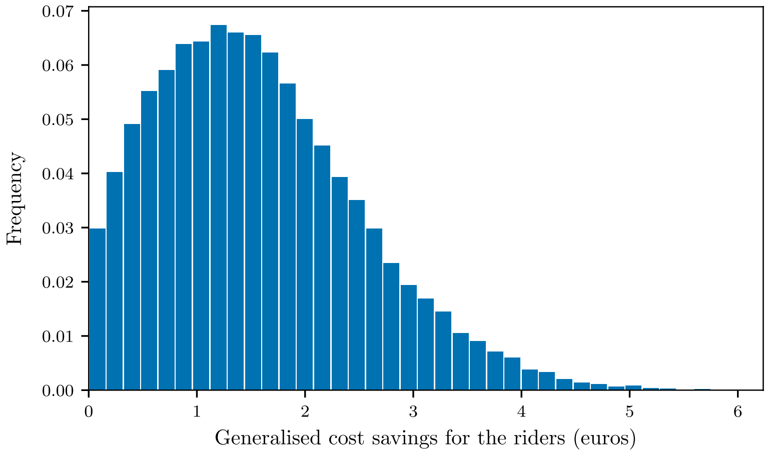


Fig. 8 Distribution of the decrease of the riders' generalised cost, compared to the reference scenario

Table 3 Average subsidy and cost of the policy as a function of the inconvenience cost for the drivers

Inconvenience cost (€/hour)	2	4	8	16
Average subsidy for drivers (€)	0.28	0.56	1.11	2.22
Total policy cost (€) [**I**]	8667.54	17 335.09	34 670.18	69 340.35
Individual surplus increase (€) [**II**]	104 896.96	104 896.96	104 896.96	104 896.96
Total surplus variation (€) [**II – I**]	96 229.42	87 561.87	70 226.79	35 556.61

with a large inconvenience cost of 16 €/h, the increase in individual surplus is larger than the cost of the policy. This suggests that the policy has a positive social impact, even before accounting for CO_{2eq} emissions reduction and the long-run impact of ride-sharing modal share.

Allowing multiple riders in the same car

The results presented so far assume that all the drivers accept at most one rider in their car. In practice, most cars can hold up to 4 passengers (excluding the driver). Allowing more than one rider in each car might increase the inconvenience cost for the driver but it should also increase the number of matches and match quality.

Table 4 presents the results of the simulations for the 30% participation rate scenario, assuming than each driver can accept 1, 2 or 3 riders in their car. The share of riders increases from 3.3% with at most 1 passenger to 4.0% with at most 2 passengers, implying a reduction in the number of vehicles on the road and thus a reduction in congestion and

Footnote 5 (continued)
ing from a situation with no crowding to a situation with overcrowding. In our model, the value of time is 12.96 €/h. A multiplier of 1.48 implies an inconvenience cost of 6.22 €/h.

Table 4 Comparison of results when drivers can have at most 1, 2 or 3 passengers in their car, for 30% of people willing to participate in the ride-sharing scheme

Passengers per driver	1	2	3
Shares			
Transit modal share	24.3%	24.1%	24.0%
Car modal share	72.4%	71.9%	71.8%
Ride-sharing modal share	3.3%	4.0%	4.2%
Surplus			
Individual surplus variation (€)	+104 897	+126 508	+137 374
Road network			
Car VKT (10^3 km)	10 595	10 534	10 538
Congestion	20.6%	20.1%	19.6%
CO_{2eq} emissions reduction (tons)	39.372	51.145	50.373
Drivers			
Mean travel time	15' 27"	15' 22"	15' 20"
Mean travel cost (€)	6.00	5.98	5.96
Ride-sharing drivers			
Share of ride-sharing drivers	3.3%	2.7%	2.4%
Average number of passengers	1.0	1.5	1.7
Share of time spent with a passenger	58.0%	59.4%	59.7%
Riders			
Mean Euclidean OD distance (meters)	6205	6174	6164
Mean walking distance (meters)	325	325	327
Mean walking distance (conditional on it being positive, meters)	438	438	440
Mean car travel time	8' 20"	8' 23"	8' 23"
Mean travel time	13' 13"	13' 15"	13' 17"
Mean travel cost (€)	3.22	3.26	3.27
Riders at their best match	65.0%	72.7%	76.0%

The share of time spent with a passenger is the average share of time spent with each passenger, for ride-sharing drivers

CO_{2eq} emissions. With at most 3 passengers per car, the ride-sharing share increases again to 4.2% but the decrease of the number of cars is less significant.

Although the share of riders is increasing with the maximum number of passengers per car, the share of ride-sharing drivers (i.e., drivers with a least one passenger) is decreasing at the same time, because each driver is carrying more passengers. Also, match quality is increasing because more riders are matched with the best potential driver for them.

Proposing incentives to the riders

The analysis conducted so far shows that a larger ride-sharing share implies less congestion and CO_{2eq} emissions. Therefore, the governments might be interested in subsidising ride-sharing in order to further increase the ride-sharing share. In this section, we assess the efficiency of proposing subsidies to travellers to induce them to switch to ride-sharing.

Table 5 Comparison of results with different incentive amount, for 30% of people willing to participate in the ride-sharing scheme (at most 1 passenger per car)

Incentive amount per rider	0€	0.5€	1€	1.5€
Shares				
Transit modal share	24.3%	24.2%	24.1%	23.9%
Car modal share	72.4%	72.1%	71.8%	71.7%
Ride-sharing modal share	3.3%	3.7%	4.1%	4.4%
Surplus				
Individual surplus variation (€)	+104 897	+127 972	+142 444	+158 876
Expenses (€)	0	17 421	38 132	61 003
Total surplus variation (€)	+104 897	+110 551	+104 312	+97 873
Road network				
Car VKT (10^6 km)	10 595	10 567	10 543	10 539
Congestion	20.6%	20.3%	20.2%	19.9%
CO_{2eq} emissions reduction (tons)	39.372	44.776	49.408	50.180
Drivers				
Mean travel time	15’ 27”	15’ 25”	15’ 26”	15’ 23”
Mean travel cost (€)	6.00	5.99	5.99	5.98
Share of time spent with a passenger (for ride-sharing drivers only)	58.0%	55.1%	52.9%	51.1%
Riders				
Mean Euclidean OD distance (meters)	6205	6077	6010	5970
Mean walking distance (meters)	325	366	406	449
Mean walking distance (conditional on it being positive, meters)	438	473	508	547
Mean car travel time	8’ 20”	8’ 10”	8’ 03”	7’ 58”
Mean travel time	13’ 13”	13’ 39”	14’ 9”	14’ 41”
Mean travel cost (excluding the subsidy, €)	3.22	3.34	3.48	3.63
Riders at their best match	65.0%	60.7%	56.2%	52.9%

More formally, we assume that the government gives a fixed amount of money to each traveller, each time they travel by ride-sharing (as a rider) instead of taking their car or the public transit services. Table 5 shows the results of the simulations for a subsidy amount of 0.5€, 1.0€ and 1.5€. The incentive is effective at increasing the share of riders, from 3.3% with no incentive to 4.4% with an incentive of 1.5€.

Compared to the scenario with no incentive, the individual surplus varies for three reasons (the first two have a positive impact, the third one has a negative impact):

1. Riders are receiving a subsidy which decreases their generalised travel cost.
2. There are less cars on the road, which decreases the generalised travel cost of all drivers.
3. Match quality decreases because the number of matched riders increasing while the number of potential drivers stays constant.

Table 5 shows that the two first effects largely dominates the third one as the individual surplus is increasing by around 54000€ from the scenario without incentive to the scenario with an incentive of 1.5€. However, the variation of the total surplus (which account for the amount of subsidies spent by the government) is more ambiguous. From the total surplus, it is unclear whether subsidies for ride-sharing have the desired positive effect. The main reason for this is that subsidies are awarded to ride-sharing participants coming from both private and public transportation. Whereas those coming from private transportation have a positive external effect in reducing congestion, those coming from public transportation may deteriorate the match quality and may therefore negatively influence the total surplus.

Conclusion

Ride-sharing is a tool with a great potential to reduce pollution and congestion in urban areas. It nevertheless remains unpopular amongst commuters, despite a growing number of ride-sharing apps. In this paper, we propose a ride-sharing scheme that any traveller can subscribe to and that propose them to be picked up by a driver for free or to pick up passengers (as a driver) in exchange for a subsidy. In this scheme, drivers are completely inflexible, i.e., they can keep the same route and schedule with and without passengers.

This study proposes a state-subsidised ride-sharing scheme to increase the modal share of ride-sharing. The potentials of this scheme are tested on the Île-de-France region to evaluate the individual and social benefits. Drivers and riders are matched through a linear-programming algorithm, based on their itineraries and preferences. The ride-sharing scheme induces a significant reduction of congestion and CO_{2eq} emissions, due to a smaller number of vehicles on the roads. The results might be further improved by considering these externalities directly in the objective function of the matching algorithm.

The ride-sharing scheme we propose considers, since no detour nor extra schedule delays are involved, that the vast majority of drivers would be ready to pick up someone in their car in exchange for a small monetary incentive. This state subsidy then only compensates for the inconvenience cost of sharing a car. Riders need to walk, but benefit from a free ride. Their individual savings are gasoline saving, time and monetary saving related to parking, and wear and tear (beside the reduced congestion).

In this paper, we consider the morning commute, which has to be seen as an intermediary step for two reasons. First, the evening commute is a not a mirror case of the morning commute in dynamic models [as shown for example by de Palma and Lindsey (2002)]. Second, if a user decides not to take his/her car the morning, he/she has to do ride-sharing or take public transport in the evening. Moreover, if the schedule preferences of two matched users are similar in the morning, this does not necessarily mean they will be similar in the evening for the same driver/rider couple. So, in general, the same match could not be arranged in the morning and in the evening. As a consequence, the riders are not guaranteed to find another convenient match for their return trip in the evening. Matching for round-trip commuting is a constraint that could be imposed on future research. A mathematical formulation of this problem was proposed by de Palma and Nesterov (2006), in the case of stable-dynamic models.

Also, the analysis conducted only explored the benefits of ride-sharing due to reduced road traffic. The generalised travel cost for public transit was assumed to be independent of the number of public-transit users. In reality, a reduction of the number of public-transit users can have an impact on in-vehicle congestion and the operating costs of the public-transit services.

To keep the analysis simple, this research only considered that riders take one car to complete their trip. Allowing for riders to take multiple vehicles to make their trip can increase the potential of ride-sharing. This type of ride-sharing, referred to as multi-hop ride-sharing, has been recently investigated (Herbawi and Weber 2012; Teubner and Flath 2015). Even though multi-hop ride-sharing generates transfer penalties between cars, it could be interesting for some segments of a network, in particular for OD pairs with low demand. The combinatorial issues (the multiple matching problem) remain widely unexplored in the matching literature in economics (labour market and marriage market, for rather obvious reasons).

Finally, it remains to be seen if riders and drivers are prepared to be involved in a more complex organization, with potential safety concerns. Empirical research is needed in order to evaluate the acceptance of such a system. A mobile application could be developed to mitigate the complexity and provide certifications guaranteeing the safety of the system. Such analysis is out of the scope of the present article.

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Declaration

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