What do walking and e-hailing bring to scale economies?
A general microeconomic model for on-demand mobility

Kenan Zhang[1,*], Andres Fielbaum[2,3], and Javier Alonso-Mora[2]

[1]Automatic Control Laboratory, ETH Zürich, Switzerland
[2]Department of Cognitive Robotics, Delft University of Technology, The Netherlands
[3]School of Civil Engineering, University of Sydney, Australia
[*]Corresponding author and presenter: kenzhang@ethz.ch

Short summary

This paper investigates the impact of walking and e-hailing on the scale economies of on-demand mobility services. A microeconomic model is developed to explicitly characterize the physical interactions between passengers and vehicles in the matching, pickup, and walking processes under different market conditions and matching mechanisms. We show that passenger competition plays a critical role in scale economies. When unmatched passengers do not compete for idle vehicles, both street-hailing and e-hailing exhibit increasing returns to scale, although such property in e-hailing is less significant. In contrast, when there exists passenger competition, e-hailing service shows decreasing returns to scale. Street-hailing, however, is free of this detrimental effect thanks to its limited matching radius. While walking does not change the scale economies, it does benefit the system by reducing the total vehicle supply required to serve the same level of demand and improving the overall vehicle utilization rate.

Keywords: passenger-vehicle matching, on-demand mobility service, scale economies, walking.

1 Introduction

The emergence of ride-hailing companies, such as Uber and Didi, has revolutionized the industry of on-demand mobility services, which has long been dominated by taxis. With advanced mobile communication technologies, passengers and vehicles can now be connected online. Such an e-hailing matching mechanism is believed to be far more efficient than the traditional street-hailing that relies on visual contact on streets (Cramer & Krueger, 2016).

However, evidence from Shenzhen (China) suggests that, in a highly dense market, street-hailing can perform comparably well or even better than e-hailing (Nie, 2017). The unlimited connectivity in e-hailing has also shown negative impacts during demand peaks (Castillo et al., 2017). These observations motivate Zhang et al. (2019) to model the physical matching process in ride-hailing and analyze its scale effect. It concludes that street-hailing has better scale economies than e-hailing because i) its matching efficiency does not suffer from passenger competition as e-hailing, and ii) the nature of linear search is more prone to scale effect compared to spatial search in e-hailing. However, the analysis in Zhang et al. (2019) does not distinguish the matching and pickup processes and does not consider the network topology. Another missing factor is walking. In street-hailing, passengers often walk towards major streets to find taxis. On the other hand, e-hailing mostly serves door-to-door trips. Accordingly, sometimes drivers have to make long detours and enter local streets to pick up and drop off passengers. In fact, leaving the door-to-door scheme has shown great potential to increase the efficiency of shared on-demand systems by several previous studies (e.g. Fielbaum et al. (2021); Gurumurthy & Kockelman (2022)). These findings suggest walking might also play a role in the scale economies of ride-hailing.

This study thus sets out to analyze the scale economies in street-hailing and e-hailing at the system level and investigate the impact of walking. To this end, we model the ride-hailing market on a grid network with detailed specifications of each component in passenger and vehicle time. The scale economies are then evaluated according to how the system cost under optimal fleet size varies with the demand rate.

2 Methodology

Settings

Consider a grid network with two types of streets shown in Fig. 1. The major streets form the skeleton of the network. Between every two major streets, there are K local streets with equal spacing s. Accordingly, three types of intersections are identified: (i) Type-1: between major streets; (ii) Type-2: between local streets; and (iii) Type-3: between local and major streets.

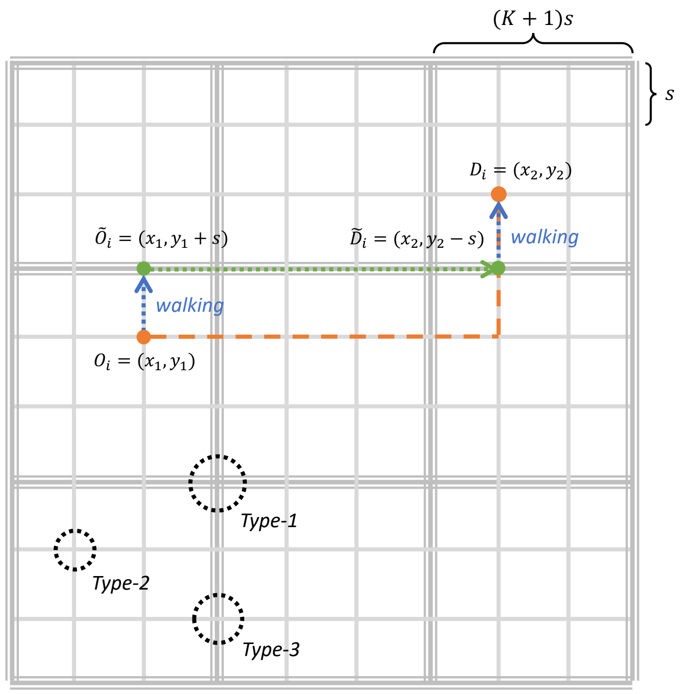


Figure 1: Illustration of a grid network.

Assume the travel speed on major streets is v and it takes $\delta = s/v$ to traverse a block. Two factors $\alpha_l, \alpha_a > 1$ are introduced to denote the vehicle speed on local streets and walking speed, respectively. In other words, it takes $\alpha_l\delta$ for a vehicle to pass a block on local streets and $\alpha_a\delta$ for a passenger to walk through a block.

Assume passenger demand and vehicle supply are both uniformly distributed in space and the market has reached a steady state. Then, the market conditions can be described by the idle vehicle density V, the unmatched passenger density W, and the demand rate q (i.e., the passenger arrival rate per unit area). As per the steady state condition, q also equals the matching and pickup rates.

Scenarios

In this study, we consider four scenarios: (i) street-hailing without walking (DS), (ii) street-hailing with walking (WS), (iii) e-hailing without walking (DE), and (iv) e-hailing with walking (DS). In all scenarios, trips are generated at Type-2 intersections (i.e., passengers travel between local blocks). When walking is considered, passengers are picked up and dropped off on major streets and thus pickups and dropoffs happen at Type-3 intersections. For simplicity, we assume passengers would randomly walk to one of the closest major streets, not necessarily the closest to their destinations.

On the supply side, we assume vehicles randomly cruise in the network. In DS, vehicles cruise on local streets to maximize the probability to find a passenger, while in other cases, they cruise on major streets.

Matching model

Here we present a general matching model and use $k \in \{DS, WS, DE, WE\}$ to denote the scenario. For both street-hailing and e-hailing, we first define the matching interval δ_k that denotes how frequently matching is performed. We then define R_k and A_k as the matching radius and area, respectively, both in units of road links (arc). Specifically, street-hailing passengers can only see vehicles moving in four directions, and thus $A_k = 4R_k,\ k \in \{DS, WS\}$. For e-hail, the matching area can be derived as $A_k = 2(R_k^2 + R_k),\ k \in \{DE, WE\}$.

To capture the possible competition among waiting passengers, we further introduce the notion of *dominant area* Yang et al. (2020), denoted by $\tilde{A}$, to represent the area within which any idle vehicle is for sure matched to the passenger. In this study, we specify the dominant area as follows:

$$\tilde{A}_k = \frac{A_k}{\gamma_k}, \quad \gamma_k = \max(A_k W, 1), \tag{1}$$

which implies the matching area is evenly distributed to unmatched passengers within A_k.

With the assumptions introduced above, we can easily show the number of "matchable" vehicles at each matching instance follows a spatial Poisson process. Then, the expected matching time is derived as

$$w_m^k = \left(\frac{\gamma_k}{A_k \theta_k V} + \frac{1}{2}\right)\delta_k. \tag{2}$$

where the first term in the parentheses gives the expected number of matching intervals and the second accounts for the average elapsed time before the first matching instance. The density correction factor θ_k is introduced to reflect the accumulation of vehicles on a certain type of street. It only affects street-hailing whereas in e-hailing $\theta_k \equiv 1$.

The pickup time in street-hailing is simple thanks to the linear matching mechanism. In contrast, that in e-hailing is rather complicated because matching is performed in space and the potential passenger competition affects the effective matching radius R. With some algebra, we derived the expected pickup distance (in units of arcs) as follows:

$$D_p = \sum_{i=1}^{R-1} \left(1 - \frac{i^2 + i}{R^2 + R}\right)^{V(R^2+R)}. \tag{3}$$

To make the model tractable, we introduce the following approximation and replace R with $R_k/\sqrt{\gamma_k}$ to capture the impact of passenger competition:

$$d_p^k = \frac{c_1}{V} - \frac{c_2\sqrt{\gamma_k}}{V R_k}. \tag{4}$$

As shown in Fig. (2), where the approximation parameters are set to be $c_1 = c_2 = 1/6$, the approximation error diminishes rapidly with the idle vehicle density.

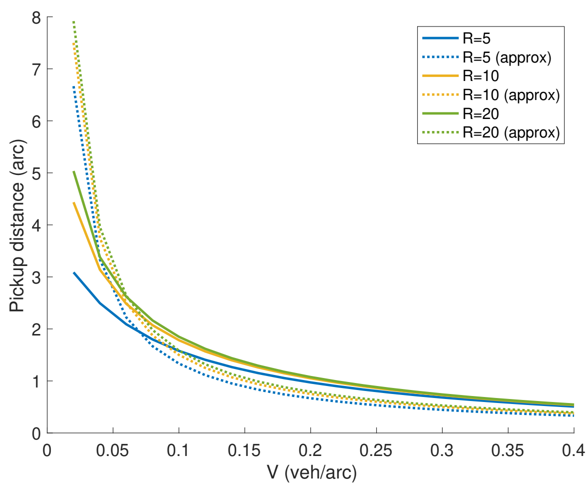


Figure 2: Comparison of exact and approximated pickup distance.

Finally, the expected pickup time is derived as follows

$$w_p^k = \alpha_p^k \left(d_p^k + d_a^k + \frac{1}{2}\right)\delta, \tag{5}$$

where

$$\alpha_p^k = \begin{cases} \alpha_l, & k = DS \\ 1, & k \in \{WS, DE, WE\} \end{cases}, \tag{6}$$

$$d_p^k = \begin{cases} R_k - 1, & k \in \{DS, WS\} \\ \frac{c_1}{V} - \frac{c_2\sqrt{\gamma_k}}{VR_k}, & k \in \{DE, WE\} \end{cases}, \tag{7}$$

$$d_a^k = \begin{cases} 0, & k \in \{DS, WS, WE\} \\ (\alpha_l - 1)D_a, & k = DE \end{cases}, \tag{8}$$

where D_a is the average walking distance derived as $D_a = \frac{(K+1)(K+2)}{6K}$.
Finally, the total passenger waiting time is written as

$$w_k = w_a^k + w_m^k + w_p^k, \tag{9}$$

where the walking time is $w_a = \alpha_a D_a \delta$ in scenarios WS and WE, otherwise zero.
Another adjustment to make in the scenarios of walking is the in-vehicle time. Let $\bar{\tau}$ be the average door-to-door trip duration. Then, the in-vehicle time is given by

$$\tau_k = \begin{cases} \bar{\tau}, & k \in \{DS, DE\} \\ \bar{\tau} - 2\alpha_l D_a \delta, & k \in \{WS, WE\} \end{cases}. \tag{10}$$

Analysis of scale economies

Consider demand rate q as the only system input. Then, the scale economies can be expressed by how the system cost varies with q under the optimal fleet size N^*, which is solved from the following optimization problem:

$$\min_N \quad c(N, q), \tag{11a}$$

$$s.t. \quad N = V + q(w_p + \tau), \tag{11b}$$

$$W = qw_m, \tag{11c}$$

$$w_p = f_{w_p}(V, W), \tag{11d}$$

$$w_m = f_{w_m}(V, W), \tag{11e}$$

The objective of (11) is the sum of vehicle operating cost and passenger travel cost:

$$c(N, q) = c_0 N + q(\beta_m w_m + \beta_p w_p + \beta_a w_a + \beta_\tau \tau), \tag{12}$$

where c_0 is the operation cost of each vehicle and $\beta_j,\ j \in \{m, p, a, \tau\}$ is the value of time specified for different legs of a trip.
To get N^*, we need to solve the following two implicit functions

$$W = qf_{w_m}(V, W) \quad \Rightarrow \quad W = f_W(V, q), \tag{13}$$

$$N = V + q(f_{w_p}(V, f_W(V, q)) + \tau) \quad \Rightarrow \quad V = f_V(N, q). \tag{14}$$

Accordingly, N^* can be derived from the first-order condition, which reads

$$0 = \frac{\partial c}{\partial N} = c_0 + q\left[\beta_m\left(\partial_V f_{w_m} + \partial_W f_{w_m} \partial_V f_W\right) + \beta_p\left(\partial_V f_{w_p} + \partial_W f_{w_p} \partial_V f_W\right)\right] \partial_N f_V. \tag{15}$$

Let $c^*(q)$ denote the system cost with the optimal fleet, then a market exhibits increasing (constant/decreasing) returns to scale if its marginal cost decreases (does not change/increases) with input.

3 Results and discussion

Scale economies in different scenarios

Note that the walking distance d_a is exogenously determined by the network property (K) rather than the demand-supply relationship. Neither does it affect other endogenous variables in the market (see Eqs. (11b)-(11e)). Hence, walking does not fundamentally change the property of returns to scale. On the other hand, the passenger competition does make a difference, particularly for e-hailing. Hence, in what follows, we investigate the scale economies for street-hailing without passenger competition, e-hailing without passenger competition, and e-hailing with passenger competition. The case of street-hailing with passenger competition is neglected because it rarely happens in practice, which will be further discussed in the next section.

Street-hailing without passenger competition
In this case, the matching time is independent of W while the pickup time is independent of V. Hence, we can easily derived the optimal fleet size is solved as

$$N^* = \sqrt{\frac{\beta_m \delta_k q}{c_0 A_k \theta_k}} + \left[\alpha_p^k \left(R_k - \frac{1}{2}\right)\delta + \tau_k\right] q, \tag{16}$$

which yields the system cost

$$c^* = 2c_0 \sqrt{\left(\frac{\beta_m \delta_k}{c_0 A_k \theta_k}\right) q} + \left[\frac{\beta_m \delta_k}{2} + (c_0 + \beta_p)\alpha_p^k \left(R_k - \frac{1}{2}\right)\delta + \beta_a w_a^k + (c_0 + \beta_\tau)\tau_k\right] q \tag{17}$$

E-hailing without passenger competition
In this case, the matching time is still independent of W whereas the pickup time becomes a function of V. Thus, we first solve the implicit function Eq. (14). With some algebra, we derive the following equations:

$$V = \frac{N - \hat{\tau}_k q}{2} + \sqrt{\left(\frac{N - \hat{\tau}_k q}{2}\right)^2 - \left(c_1 - \frac{c_2}{R_k}\right)\delta q}, \tag{18}$$

$$\partial_N f_V = \frac{V^2}{V^2 - \left(c_1 - \frac{c_2}{R_k}\right) q\delta}, \tag{19}$$

where $\hat{\tau}_k = \left(d_a^k - \frac{1}{2}\right)\delta + \tau_k$ can be interpreted as the exogenous trip duration.
Plugging Eqs. (18) and (19) into Eq. (15) yields

$$V^* = \sqrt{\left[\frac{\beta_m \delta_k}{c_0 A_k} + \left(1 + \frac{\beta_p}{c_0}\right)\left(c_1 - \frac{c_2}{R_k}\right)\delta\right] q}. \tag{20}$$

Accordingly, the optimal system cost is given by

$$\begin{aligned} c^* &= 2c_0 V^* + \left[\frac{\beta_m \delta_k}{2} + (c_0 + \beta_p)\left(d_a^k + \frac{1}{2}\right)\delta + \beta_a w_a^k + (c_0 + \beta_\tau)\tau_k\right] q \\ &= 2c_0 \sqrt{\left[\frac{\beta_m \delta_k}{c_0 A_k} + \left(1 + \frac{\beta_p}{c_0}\right)\left(c_1 - \frac{c_2}{R_k}\right)\delta\right] q} \\ &\quad + \left[\frac{\beta_m \delta_k}{2} + (c_0 + \beta_p)\left(d_a^k + \frac{1}{2}\right)\delta + \beta_a w_a^k + (c_0 + \beta_\tau)\tau_k\right] q \end{aligned} \tag{21}$$

E-hailing with passenger competition
In this case, we need to solve both implicit functions:

$$W = \frac{\delta_k q V}{2(V - \delta_k q)} \tag{22}$$

$$V = \frac{N - \hat{\tau}_k q}{2} + \sqrt{\left(\frac{N - \hat{\tau}_k q}{2}\right)^2 - \left(c_1 - \frac{c_2\sqrt{A_k W}}{R_k}\right) q}. \tag{23}$$

Note that Eq. (23) still involves W and thus $\partial_N f_V$ cannot be directly solved as in the previous cases. Instead, we consider the right-hand-side of Eq. (23) as a function $h_V(N, W)$ and conduct implicit differentiation. Accordingly,

$$\begin{aligned} \partial_N f_V &= \frac{\partial_N h_V}{1 - (\partial_W h_V)(\partial_V f_W)} \\ &= \frac{V^2}{V^2 - \left[c_1 - \frac{c_2}{R_k}\left(1 + \frac{W}{V}\right)\sqrt{A_k W}\right] q\delta} \end{aligned} \tag{24}$$

Plugging into Eq. (15) yields

$$V^* = \sqrt{\left\{ \frac{\beta_m \delta_k W^*}{c_0} \left(1 + \frac{2W^*}{V^*}\right) + \left(1 + \frac{\beta_p}{c_0}\right) \left[c_1 - \frac{c_2}{R_k}\left(1 + \frac{W^*}{V^*}\right)\sqrt{A_k W^*}\right] \delta \right\} q}, \tag{25}$$

where W^* is the unmatched passenger density under V^* as per Eq. (22). Thus, solving Eq. (25) gives us V^* as a function of q. However, the exact form of such an equation is challenging to derive. Instead, we numerically solve V^* with various q and explore their relationship. The default parameters used in these numerical experiments are reported in Tab. 1.
Fig. 3 illustrates both sides of Eq. (25) as a function of V under different demand rates q. V^* is then given by the intersection of two curves, which increases with q as expected. We then numerically solve V^* at each q by bisection search and plot the results in Fig. 4, along with those in e-hailing without competition. It can be observed that V^* with passenger competition first increases sublinearly below the case without passenger competition (Eq. (20)). This is expected as fewer vehicles are required when holding some passengers waiting. As q continues to increase, however, the relationship becomes linear and V^* with competition exceeds the other case. As will be shown later, this seemingly counter-intuitive result is due to the violation of assumption $A_k W < 1$ in the case of no competition.

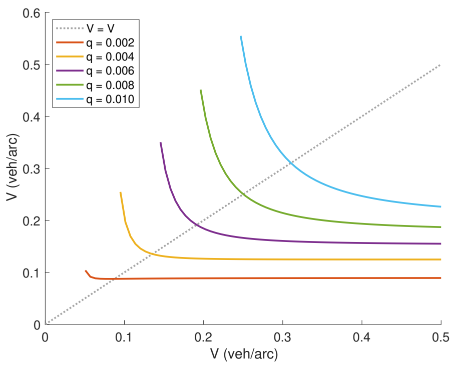


Figure 3: V^* as a fixed point.

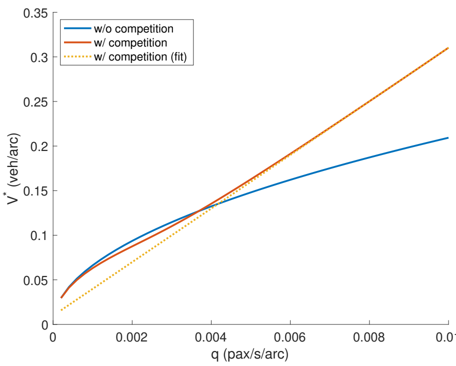


Figure 4: V^* in e-hailing.

A simple linear approximation is also plotted in Fig. (4) and fits well when q is relatively large (> 0.004 pax/s/arc) with an intercept close to zero (0.0098). Also, in theory, V^* should reduce to zero when $q = 0$ (when there is no demand, the optimal fleet size is also zero). Therefore, we propose to approximate V^* by a simple linear function

$$V^*(q) = \eta q, \tag{26}$$

and thus the unmatched passenger density is also a linear function of q, which reads

$$W^*(q) = \frac{\eta \delta_k}{2(\eta - \delta_k)} q. \tag{27}$$

Finally, the optimal system cost is derived as

$$\begin{aligned} c^* = c_0 &\left\{ \left[\eta + \frac{\beta_m \delta_k}{c_0} \frac{\delta_k}{2(\eta - \delta_k)}\right] q + \frac{\delta}{\eta}\left(1 + \frac{\beta_p}{c_0}\right)\left[c_1 - \frac{c_2}{R_k}\sqrt{\frac{\eta \delta_k A_k q}{2(\eta - \delta_k)}}\right] \right\} \\ &+ \left[\frac{\beta_m \delta_k}{2} + (c_0 + \beta_p)\left(d_a^k + \frac{1}{2}\right)\delta + \beta_a w_a^k + (c_0 + \beta_\tau)\tau_k\right] q \end{aligned} \tag{28}$$

Comparing Eqs. (17), (21) and (28), one can easily observe the optimal system cost consists of two parts: (i) cost related to matching that can be represented as the extra supply cost to sustain a certain demand rate, and (ii) cost independent of matching that is proportional to the demand rate.
The impact of walking reflects in the second part. On the one hand, it helps reduce pickup and in-vehicle times and thus saves these costs on both sides of the market. On the other hand, passengers endure an extra walking cost. As will be shown in the numerical results, when the walking distance is reasonable and the vehicle unit cost is high, the former effect is dominant. Besides, the benefit is more significant in street-hailing because walking also helps increase vehicle cruising efficiency.

The more intriguing findings regard the impact of passenger competition. The marginal costs in the three scenarios discussed above are given by

$$\text{Street-hailing w/o competition: } mc^*_{(s,w/o)} = \frac{B_{(s,w/o)}}{\sqrt{q}} + C_{(s,w/o)}, \tag{29}$$

$$\text{E-hailing w/o competition: } mc^*_{(e,w/o)} = \frac{B_{(e,w/o)}}{\sqrt{q}} + C_{(e,w/o)}, \tag{30}$$

$$\text{E-hailing w competition: } mc^*_{(e,w/)} = -\frac{B_{(e,w/)}}{\sqrt{q}} + C_{(e,w/)}, \tag{31}$$

where $B_k, C_k, k \in \{(s,w/o),(e,w/o),(e,w/)\}$ are constants determined by the exogenous variables. It thus concludes that both street-hailing and e-hailing exhibit increasing returns to scale when there is no passenger competition, whereas e-hailing leads to decreasing returns to scale when there exists passenger competition. Further, we can compare $B_{(s,w/o)}$ and $B_{(e,w/o)}$ to which service has a more considerable scale economies:

$$B_{(s,w/o)} = c_0\sqrt{\frac{\beta_m \delta_k}{c_0 A_k}}, \tag{32}$$

$$B_{(e,w/o)} = c_0\sqrt{\frac{\beta_m \delta_k}{c_0 A_k} + \left(1+\frac{\beta_p}{c_0}\right)\left(c_1 - \frac{c_2}{R_k}\right)\delta}. \tag{33}$$

As per Eqs. (32) and (33), the two scalars are only different in the term $\left(1+\frac{\beta_p}{c_0}\right)\left(c_1 - \frac{c_2}{R_k}\right)\delta$. Our numerical results suggest the parameters $c_1 = c_2 = 1/6$ and the matching radius in e-hailing is often large (e.g., $R_k = 14$ with a threshold pickup time of 4 min). Therefore, it is safe to conclude $B_{(s,w/o)} < B_{(e,w/o)}$ and thus the street-hailing enjoys higher economies of scale. This result also aligns with empirical evidence (e.g., Zhang et al., 2019; Frechette et al., 2019).

Numerical experiments

In this section, we compare the system performances in different scenarios under the optimal fleet size. The values of exogenous variables and approximation parameters are reported in Tab. 1.

Existence of passenger competition

Recall that e-hailing presents the opposite scale economies with and without passenger competition. Hence, we first examine whether passenger competition often exists in an e-hailing market. Fig. 5 plots the number of unmatched passengers within a matching area (i.e., $A_k W$) solved for DS and DE under the assumption of no passenger competition. Clearly, for most tested demand levels, the condition $A_k W < 1$ holds for DS. In contrast, the assumption is easily violated for DE due to its much larger matching area. In other words, the increased matching radius of e-hailing not only reduces the matching friction between passengers and vehicles but also induces considerable competition among passengers. This phenomenon has also been recognized in some previous work (e.g., Zhang et al., 2019), but unfortunately not yet been widely adopted in recent studies on e-hailing services. Due to this observation, in what follows, we only present results of the model for e-hailing with passenger competition.

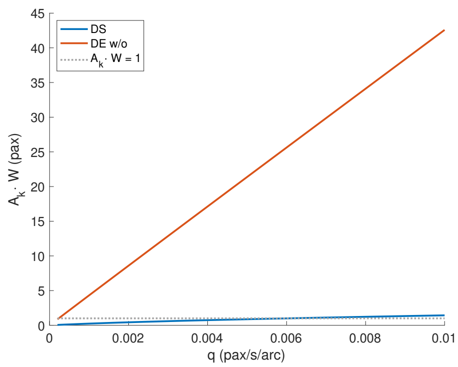
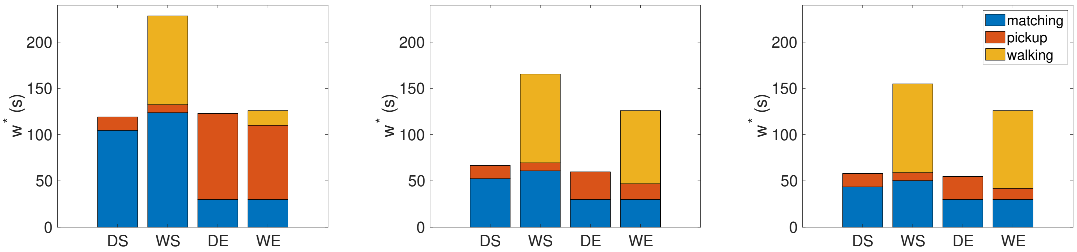


Figure 5: Violation of assumption on passenger competition.

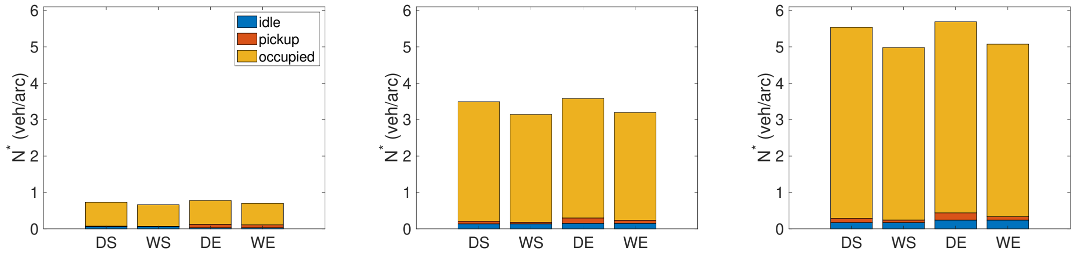
System performance

Figs. 6 and 7 plot the composition of passenger waiting time and vehicle operation time at different demand levels. For e-hailing, the pickup time is deducted from the original walking time. This is because, in practice, passengers usually start walking after they are matched. Accordingly, the total waiting time is the matching time plus the maximum between the walking time and the pickup time. Because of the small matching radius in street-hailing, passengers spend most of their waiting time in matching while vehicles spend most of their vacant time (idle or pickup) in cruising. On the other hand, the pickup time takes a majority of passenger waiting time and vehicle vacant time in e-hailing, whereas its fraction reduces rapidly with the demand rate.



(a) $q = 0.001$ (b) $q = 0.005$ (c) $q = 0.008$

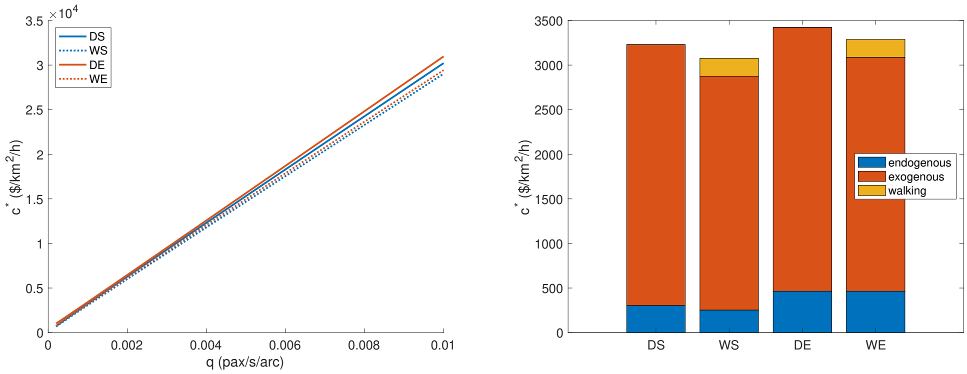
Figure 6: Passenger waiting time at different demand rates (pax/s/arc).



(a) $q = 0.001$ (b) $q = 0.005$ (c) $q = 0.008$

Figure 7: Vehicle time at different demand rates (pax/s/arc).

In the tested scenarios, walking does not really help passengers reduce their total waiting time because its benefit in improving the matching and pickup times is rather minor. Specifically, it does not help street-hailing passengers reduce their matching time as expected. A closer investigation reveals that this is mainly due to the decreased idle vehicle density. Although walking induces a higher concentration of vehicles on major streets, which yields a larger θ_k in Eq. (2), the optimal idle vehicle density becomes further lower, and thus the matching time increases.

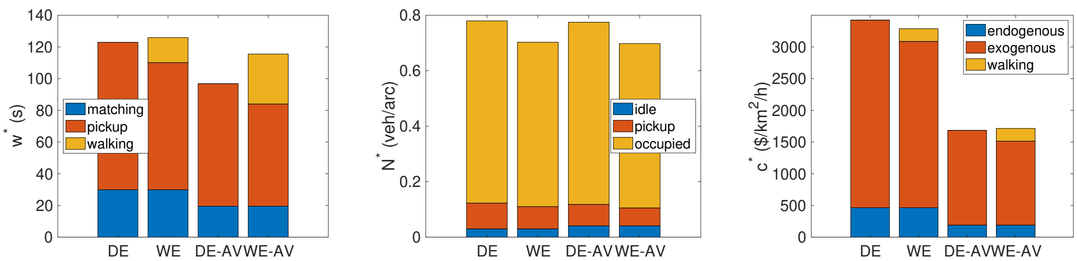


(a) Total cost (b) Cost by part ($q = 0.0001$)

Figure 8: System cost under optimal fleet size.

Nevertheless, as shown in Fig. (7), walking does help reduce the required vehicle supply to sustain the same level of demand, both for street-hailing and e-hailing. Besides, it can be found that most of the vehicle time is occupied. This finding deviates from the empirical observations that the vehicle utilization rate is often lower than 60% (Schaller, 2017). We note that this discrepancy is largely due to the fleet sizing objective. In 11, we aim to minimize the system cost, whereas, in practice, the fleet size is often determined to maximize the operator's profit or a consequence of drivers' competition. In these cases, the fleet size is normally smaller than that at system optimum (Douglas, 1972).
The large contribution of occupied vehicle time also leads to a quite linear system cost illustrated in Fig. 8a. In brief, the four studied scenarios share very similar costs when the demand is relatively low. As the demand rate increases, street-hailing presents a better efficiency. Walking benefits both service types, while, as expected, it brings a larger cost saving to street-hailing, which is better illustrated in Fig. 8b. Nevertheless, all these differences are rather small compared to the total system cost.

Adaption of autonomous vehicles (AVs)
In face of the increasing labor cost, many e-hailing platforms are proposing to replace human-driven vehicles with autonomous vehicles (AVs), which are believed to have a lower operation cost meanwhile fully controllable. In what follows, we compare the system performance of DE and WE by only changing the vehicle unit cost c_0 to reflect the adaption of AVs. Here, the demand rate is set to be $q = 0.001$ pax/s/arc.



(a) Passenger waiting time (b) Vehicle time (c) Cost by part

Figure 9: System performance with AVs.

As shown in Fig. 9a, the adaption of AVs reduces both the matching time and the pickup time because more idle vehicle time is devoted to cruising. Consequently, passengers enjoy a shorter waiting time in DE with an AV fleet. However, the benefit of walking diminishes, both for passengers (Fig. 9a) and for the system as a whole (Fig. 9c). On the supply side, the impact of AVs is rather minor. The lower cost of AVs does not induce a much larger supply size and the benefit of walking in terms of reducing the fleet size remains similar. Moreover, although the unit cost of AVs is one-fourth of human-driven vehicles, the system cost only cuts in half.

4 Conclusions

In this study, we model the street-hailing and e-hailing services on a grid network and analyze their scale economies with system optimum fleet size. We show the existence of passenger competition plays a critical role in the returns to scale. Without passenger competition, both street-hailing and e-hailing exhibit increasing returns to scale, while the scale effect in street-hailing is more significant. However, when subject to passenger competition, e-hailing shows decreasing returns to scale. Through numerical experiments, we show this is very likely to happen due to the large matching radius of e-hailing.
Although walking does not fundamentally change the scale economies, it produces two opposite impacts on the system cost. On the one hand, it reduces the pickup and in-vehicle times and specifically increases the matching efficiency in street-hailing. On the other hand, it imposes an extra cost on passengers. Our numerical results show that the cost-saving effect is in general more profound. However, when AVs are adapted with a much lower unit cost, the benefit of walking diminishes.
As a future direction, we will continue validating our findings with simulations on general road networks and demand profiles. It is also interesting to further analyze the scale economies with

different objectives in the fleet sizing problem (e.g., profit-maximization as in a monopoly market).

Table 1: Notations and default values

Variable	Description	Unit	Value
K	number of local streets between every two major streets		3
s	length of each street segment	m	120
v	vehicle travel speed on major street	km/h	25
α_l	speed scaling factor for local street		1.67
α_a	speed scaling factor for walking		5
R_s	matching radius in street-hailing		1
R_e	matching radius in e-hailing		14
A_s	matching area in street-hailing		4
A_e	matching area in e-hailing		420
δ_s	matching interval in street-hailing	s	20
δ_e	matching interval in e-hailing	s	20
δ	time to drive through one segment of major street	s	17.28
$\bar{\tau}$	average door-to-door trip duration	s	656.5
c_0	operation cost per human-driven (autonomous) vehicle	$/h	20 (5)
β_m	value of time for matching	$/h	15.00
β_p	value of time for pickup	$/h	12.51
β_a	value of time for walking	$/h	14.51
β_τ	value of time for in-vehicle time	$/h	10.00
$\theta_{DS}(\theta_{WS})$	vehicle density correction factor in street-hailing		1.345 (1.94)
c_1	first approximation parameter for pickup distance		1/6
c_2	second approximation parameter for pickup distance		1/6
η	approximation parameter for the optimal idle human-driven (autonomous) vehicle density		30.05 (41.00)

References

Castillo, J. C., Knoepfle, D., & Weyl, G. (2017). Surge pricing solves the wild goose chase. In *Proceedings of the 2017 acm conference on economics and computation* (pp. 241–242).

Cramer, J., & Krueger, A. B. (2016). Disruptive change in the taxi business: The case of Uber. *American Economic Review*, *106*(5), 177–182.

Douglas, G. W. (1972). Price regulation and optimal service standards: The taxicab industry. *Journal of Transport Economics and Policy*, 116–127.

Fielbaum, A., Bai, X., & Alonso-Mora, J. (2021). On-demand ridesharing with optimized pick-up and drop-off walking locations. *Transportation Research Part C: Emerging Technologies*, *126*, 103061.

Frechette, G. R., Lizzeri, A., & Salz, T. (2019). Frictions in a competitive, regulated market: Evidence from taxis. *American Economic Review*, *109*(8), 2954–92.

Gurumurthy, K. M., & Kockelman, K. M. (2022). Dynamic ride-sharing impacts of greater trip demand and aggregation at stops in shared autonomous vehicle systems. *Transportation Research Part A: Policy and Practice*, *160*, 114–125.

Nie, Y. M. (2017). How can the taxi industry survive the tide of ridesourcing? Evidence from Shenzhen, China. *Transportation Research Part C: Emerging Technologies*, *79*, 242–256.

Schaller, B. (2017). Empty seats, full streets: Fixing manhattan's traffic problem. *Schaller Consulting*, *1*(3), 1–27.

Yang, H., Qin, X., Ke, J., & Ye, J. (2020). Optimizing matching time interval and matching radius in on-demand ride-sourcing markets. *Transportation Research Part B: Methodological*, *131*, 84–105.

Zhang, K., Chen, H., Yao, S., Xu, L., Ge, J., Liu, X., & Nie, M. (2019). An efficiency paradox of uberization. *Available at SSRN 3462912*.