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Regulatory policies to electrify ridesourcing systems

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ABSTRACT

This study examines regulatory policies for electrifying a ridesourcing system. To do so, we develop an aggregate modeling framework to analyze a ridesourcing market involving electric vehicles and examine the response of the ridesourcing platform to regulatory policies such as annual permit fees (AP), differential trip-based fees (TB) or differential commission caps (CC). Our modeling exercises and numerical analyses suggest that both AP and TB are effective at achieving a high electrification level, while CC may only electrify the system to a low level. However, CC is the most cost-efficient as it simultaneously benefits drivers and customers, and allows finer intervention to the market. TB is the least cost-efficient as the platform prefers to deliver fewer customers to avoid the trip-based fees and surcharge drivers and customers for higher per-trip profits. Under all policies, the platform's best response is always to adopt fast chargers and gradually expand the charging network to accommodate the increasing charging needs of its electric vehicle fleet.

1. Introduction

According to the International Energy Agency, road vehicles are responsible for 16% of the world's direct emission of carbon dioxide, the main greenhouse gas (GHG) (IEA, 2021). Replacing conventional vehicles (CVs) with electric vehicles (EVs) is an effective way to decarbonize the transportation sector. To promote EVs' adoption, governments worldwide have applied various incentives, ranging from purchase subsidies to charging discounts, to attract private customers to own EVs. However, most of these costly promotions failed to meet the expectation. For example, the Chinese government launched two rounds of EV demonstration projects in 2009 and 2012, but the market share of EV in China is still below 5% by 2019 (IEA, 2020; Wang et al., 2017). Given limited customer acceptance, we can envision a long way to go before the social fleet can be highly electrified (Muratori et al., 2019). In contrast, previous EV promotions on the commercial or government fleet have been quite successful. For example, Shenzhen, China has electrified 100% of its buses by 2017 and 99.06% of its taxis fleet by 2020 (CNR, 2020).

Ridesourcing vehicles are destined to be the next special fleet for electrification and hold great promise for reducing GHG emissions. The reasons are three-fold. First, the ridesourcing market grows rapidly. For example, Didi Chuxing, a ridesourcing platform in China, serves 30 million daily trips for its 550 million users in more than 400 cities nationwide (Didi, 2020). The global ridesourcing market share is predicted to double by 2030 (Clewlow and Mishra, 2017). Second, a ridesourcing vehicle generates three times as many as vehicle miles traveled (VMT) as a private vehicle (Bauer et al., 2018). These two factors imply a better return on investment for electrifying the ridesourcing market to reduce emissions. Lastly, governments have applied various forms

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of regulation, including authorization fees, operation fees, and commission caps, to ridesourcing markets (Li et al., 2019; Vignon et al., 2021). Thus, it is relatively easier to impose another type of regulation to promote the adoption of EVs in ridesourcing services.

The current electrification level of the ridesourcing sector is pretty low. For example, EVs only account for 0.15% of miles traveled by Uber drivers in the US and Canada between 2017 and 2019 (BBC, 2020). Many governments have set goals to electrify the ridesourcing sector. For example, China aims to fully electrify ridesourcing vehicles by 2035 (iCET, 2019). In California, Senate Bill 1014 was passed to establish annual GHG reduction targets and require the ridesourcing industry to implement an emission reduction plan (SB-1014, 2020). In response, some ridesourcing platforms are taking action. For example, with an aspiration to fully electrify its fleet by 2040, Uber plans to provide $1 per trip bonus and vehicle purchase discount for EVs (Uber, 2021). Didi Chuxing has been constructing its own nationwide fast-charging network to help its drivers adopt EVs and aims to operate 10 million EVs by 2028 (China-Daily, 2020).

The high EV purchase cost, lack of access to fast charging, and significant opportunity cost from charging downtime hinder the wide adoption of EVs for ridesourcing services (Fleming and Cohen D'Agostino, 2020; Dong et al., 2014; Chen et al., 2016, 2017). Instead of offering direct subsidies or banning conventional vehicles or CVs from registering, this paper seeks to design regulatory policies to steer ridesourcing systems towards electrification. In this quest, it is critical to understand how platforms react to a policy and how their reactions change the operations of the two-sided ridesourcing market and impact drivers' income and social welfare. For one thing, EV drivers may have to recharge during working time, and thus heavily rely on public fast-charging stations (George and Zafar, 2018; Jenn, 2020). The high opportunity costs from charging downtime may discourage drivers from choosing EVs. Apart from affecting drivers' choices, the charging downtime also impacts customers. When an excessive number of charging EVs are out of service, customers also suffer from the long wait and degraded service. To depict the operation of an electrified ridesourcing market, we first develop an aggregate modeling framework capturing the behavioral difference of EV drivers and the impact of charging downtime on drivers and customers. Utilizing the established framework, we then explore three potential regulatory policies, i.e., annual permit fees, differential trip-based fees, and differential commission caps, and discuss their effectiveness, cost-efficiency, and feasibility considering the platform's strategy.

The rest of this paper is organized as follows. Section 2 presents a summary of the relevant literature to highlight the contribution of this paper. Section 3 introduces our modeling framework, and Section 4 analyzes the market equilibrium through numerical examples. Section 5 discusses the potential policies to electrify the ridesourcing market, and Section 6 evaluates the effects of the policies and discusses the platform's strategy. Finally, conclusions, limitations, and future studies are presented in Section 7.

2. Literature review

2.1. Policy options to electrify ridesourcing sector

As per the literature, three types of policies are promising to accelerate ridesourcing electrification: pricing incentives, infrastructure support, and regulatory fee structures. First, the high costs of EV purchase and fast-charging are among the most significant barriers that discourage ridesourcing drivers from using EVs. Governments can provide pricing incentives, including subsidies on EV purchase and rental, to make EVs affordable for low-income drivers (Fleming and Cohen D'Agostino, 2020). Second, some ridesourcing EV drivers lack charging options at home and thus intensively rely on public charging. Jenn (2021) and Bauer et al. (2019) simulated the charging demand using empirical trip data and showed the necessity of providing public fast-charging services in the transition from CVs to EVs. Thus governments can offer financial support to charger installation and lower financial barriers. Mo et al. (2020) showed that given a limited budget, the government should subsidize charging stations before offering EV purchase support. Previous study on taxi market under regulatory policies also highlight the necessity of and financial support for vehicle purchase and public charging when promoting electric taxis (Yang et al., 2018). However, both pricing incentives and infrastructure support require considerable investment to achieve a high electrification level and may not be sustainable in the long run.

Instead of offering direct subsidies, the government can design regulatory fee structures to make EV economically attractive and promote its adoption for ridesourcing. Regulatory fee structures promise to be self-supporting and simultaneously manage ridesourcing externalities, but its implementation and potential effects remain largely unexplored in the literature. Slowik et al. (2019) sought to apply operation fees to accelerate electrification in ridesourcing services. They calculated the 5-year total operation cost and showed that charging additional $0.58 to $1.12 on one trip completed by CVs could make EVs more economically attractive than CVs for ridesourcing drivers. However, their study falls short of modeling platform's response to the taxes or fees directly imposed on drivers.

In addition to operation fees as proposed in Slowik et al. (2019), fees on authorization, like an annual permit for operations, can also force ridesourcing platforms to meet specific electrification targets. Capping the commission that the ridesourcing platform takes on each trip is another effective fee structure to regulate the ridesourcing market as argued by Zha et al. (2016, 2018a,b). Government can set a higher commission cap for EVs and make EVs more profitable to further incentivize the platform for electrification. This study analyzes the prospect of adapting three commonly-used regulatory fee structures, i.e., annual permit fees, differential trip-based fees, and differential commission caps, to steer the ridesourcing sector towards electrification.

Quantitative analysis of policy effects is essential to support the government's decision-making. Most previous studies offer only qualitative discussions, speculating how ridesourcing platforms may respond to proposed policies and how these spontaneous responses impact the effectiveness of the policies (Slowik et al., 2019; Fleming and Cohen D'Agostino, 2020). In contrast, this paper gauges the potential of each regulatory policy by explicitly modeling and predicting ridesourcing platforms' response strategy to the policy. Specifically, we develop an aggregate modeling framework to depict a ridesourcing market's operations and analytically examine three potential regulatory policies.

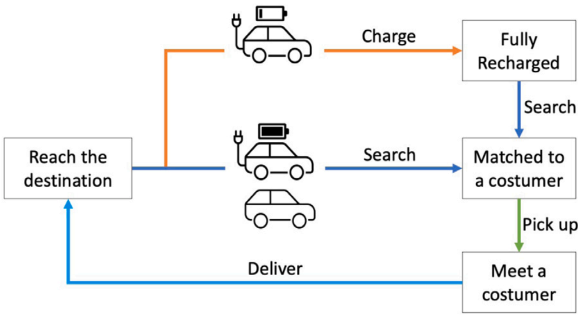


Fig. 1. An illustration of EV and CV operation in ridesourcing system.

2.2. Modeling electrified ridesourcing system

Compared with general EV users (Traut et al., 2012; Guo et al., 2018), ridesourcing EV drivers have different charging behaviors and require special consideration in modeling. First, ridesourcing EV drivers have to recharge during working time and faces much higher opportunity costs than private EV users. In the literature, electric taxis face similar charging opportunity costs (Qian et al., 2019), but taxi companies enjoy more autonomy than ridesourcing platforms on the EV adoption. Thus a few recent studies seek to capture drivers' opportunity cost from charging and integrate drivers' choice of vehicle in designing electrification policies. Among them, Ke et al. (2019) modeled EV drivers' behaviors with a time-expanded network and showed that deploying more chargers increases ridesourcing platform's profit and EV drivers' earnings. Mo et al. (2020) considered duopoly heterogeneous ridesourcing platforms and optimized government subsidies to promote the use of EVs. The results uncovered that the government budget should first focus on subsidizing charging stations and later extend to EV purchase subsidy.

Second, rental EV drivers may have no access to home charging, and full-time drivers need to charge their vehicles more than once a day. EV drivers thus intensively rely on public charging and may experience excessive queuing delays during peak hours given limited public chargers. In the literature, electric car-sharing systems also rely on public charging networks and car-sharing platforms can optimize station deployment and charging allocation to improve vehicle utilization rate (Zhang et al., 2019; Brandstätter et al., 2017; Huo et al., 2020). Similarly ridesourcing platforms can optimize station deployment, but it is drivers rather than the platform to decide when and where to charge to minimize their charging downtime Previous studies consider the charging downtime as an aggregate function of charger numbers and charging demand and capture the drivers' opportunity cost from charging downtime (Ke et al., 2019; Mo et al., 2020). However, previous studies fall short of capturing the impact of charging downtime on EV drivers, customers and the system. It is commonly assumed that EVs and CVs are equally capable of serving customers, despite that EVs in charging cannot serve customers. Customers in an electrified ridesourcing market may suffer additional delivery delays when excessive charging vehicles are out of service. This study proposes a deductive charging downtime function and captures the differences of EVs and CVs in serving customers.

3. Equilibrium model of electrified ridesourcing market

To facilitate the regulatory policy analysis, we consider the long-run equilibrium of an isotropic ridesourcing market with a single platform hiring drivers driving CVs (denoted by c) or EVs (e). In the long run, drivers decide whether to adopt EVs based on their preferences. We assume that during the matching process, the platform treats CVs and EVs equally. It is also assumed that trip fares for CVs and EVs are the same, just like the current practice. All customers are assumed to be solo riders and have no preference between EVs and CVs. However, CVs and EVs behave differently when they become idle. The former will always be available for matching while the latter, if their battery state of charge (SOC) is low, have to recharge themselves at the nearest chargers (see Fig. 1).

3.1. Matching and demand

We first consider the *matching* process where waiting customers are matched with idle ridesourcing vehicles. Similar as Castillo et al. (2017), we assume that arriving customers are instantly matched to the closest idle drivers as they arrive. After being matched to a driver, the customer experiences an expected pick-up time w^p and an expected delivery time w^r:

$$w^p = \frac{d^p}{v}$$
$$w^r = \frac{d^r}{v}$$

where v is the average operating speed and d^r is the average travel distance for ridesourcing trips, both of which are assumed to be given for simplicity. In contrast, average pick-up distance d^p is a decreasing function of the idle driver number N^I, i.e., $d^p = D^p(N^I)$ and $D^{p\prime} < 0$.

Denoting the trip fare for customers by F, their generalized trip cost μ is:

$$\mu = F + \gamma^p \cdot w^p + \gamma^r \cdot w^r$$

where γ^p and γ^r represent customers' value of out-of-vehicle waiting time and in-vehicle travel time, respectively. The hourly customer demand Q is assumed to be a decreasing function of the generalized trip cost:

$$Q = f(\mu)$$

with $f' < 0$, suggesting that an increase in trip cost leads to a decrease in customer demand.

3.2. Charging behavior

To complete a transaction/trip, CV drivers experience an expected pick-up time w^p, an expected delivery time w^r, and an expected idle time w^s between two transactions. In addition to w^p, w^r and w^s, EV drivers experience a ***per-trip*** charging downtime w^c (imagine that, on average, once an EV completes a trip, it will engage a 'virtual' charging event and spends w^c charging before searching for the next customer). Without loss of generality, EVs are assumed to have the same effective battery size E and the same energy consumption rate κ. It is assumed that chargers are uniformly distributed (Ahn and Yeo, 2015) and exclusive to EVs (Mo et al., 2020), and EV drivers choose to charge at the nearest charger.

Denote D and P as the number and charging power of chargers, and A as the size of the study area. The average distance between an EV and its nearest charger is estimated as $r = \frac{\delta}{2}\sqrt{\frac{A}{D}}$, where $\delta = \sqrt{\frac{\pi}{2}}$ is the detour ratio that adjusts Euclidean distance to Manhattan distance (Arnott, 1996). Therefore, an EV has to spend a time of $\frac{r}{v}$ traveling to the closest charger and incurs an energy cost of $\kappa \cdot r$ during the process.

We assume that an EV driver heads to chargers when her battery can only support the trip to the target charger, and fully recharges the battery at each charging event. Then the number of trips that a fully charged EV can support is $T^* = \frac{E - r\cdot\kappa}{\kappa\cdot(d^r + d^p + \sigma\cdot v\cdot w^s)}$, where $\sigma < 1$ represents the proportion of idle time that ridesourcing vehicles are cruising. On average, one EV serves $M_e^* = \frac{1}{w^p + w^r + w^s + w^c}$ trips in unit time, and the arrival rate of charging EVs at the charging station is accordingly calculated as:

$$\hat{K} = \frac{M_e^*}{T^*} \cdot \varphi \cdot N = \frac{\kappa \cdot (d^r + d^p + \sigma \cdot v \cdot w^s)}{(E - r \cdot \kappa) \cdot (w^p + w^r + w^s + w^c)} \cdot \varphi \cdot N$$

where the electrified fleet rate φ denotes the percentage of EVs in the ridesourcing fleet and N is the fleet size.

Without loss of generality, assuming the arrival of charging EVs follows a Poisson process, the charging process at a charger is thus an M/D/1 queuing system with arrival rate $\frac{\hat{K}}{D}$ and service rate $\frac{P}{E}$. As a result, the average queuing time experienced by one arriving EV is $\frac{\hat{K}\cdot E^2}{2P\cdot(D\cdot P - \hat{K}\cdot E)}$ and the recharging time is $\frac{E}{P}$. Note that the stationary condition holds only when the service rate is larger than the arrival rate, i.e., $P \cdot D > \hat{K} \cdot E$. The time for a charging event $\hat{w^c}$ includes three parts: traveling to the target charger, queuing, and recharging. Accordingly we have $\hat{w^c} = \frac{r}{v} + \frac{\hat{K}\cdot E^2}{2P\cdot(D\cdot P - \hat{K}\cdot E)} + \frac{E}{P}$. To facilitate presentation, we divide the charging downtime $\hat{w^c}$ equally among all trips served between two charging events and get the ***per-trip*** charging downtime w^c as:

$$w^c = \frac{\hat{w^c}}{T^*} = \frac{\hat{w^c} \cdot \kappa \cdot (d^r + d^p + \sigma \cdot v \cdot w^s)}{E - r \cdot \kappa}$$

The M/D/1 queuing model enables concise analytical solutions for queuing downtimes and maintain mathematical tractability for later policy analysis. Other methods, such M/M/x/s queuing system (Yang et al., 2017) and a cumulative prospect theory (Hu et al., 2019), can estimate charging downtime under more complicated charging behavior can be future research direction.

3.3. Drivers' EV adoption

Consider If the platform charges a commission rate τ^e on EVs and τ^c on CVs, a CV driver earns $(1-\tau^c)\cdot F$ for one trip she serves. Deducting her operations cost, the average hourly net earning can be defined as follows:

$$u^c = \frac{(1 - \tau^c) \cdot F - (d^r + d^p + \sigma \cdot v \cdot w^s) \cdot \lambda^c}{w^p + w^r + w^s}$$

where λ^c denotes the operation cost for unit distance. Aside from the opportunity cost of charging during their working hours, we assume that EV drivers own their vehicles and pay more to purchase an EV; the additional amortized per hour expense is η^e. We divide the average distance traveling to the target charging station r equally among all trips served between two charging events and an EV virtually travels additional $\frac{r}{T^*}$ per trip. The average hourly net earning of EV drivers is thus:

$$u^e = \frac{(1 - \tau^e) \cdot F - (\frac{r}{T^*} + d^r + d^p + \sigma \cdot v \cdot w^s) \cdot \lambda^e}{w^p + w^r + w^s + w^c} - \eta^e$$

where λ^e is EV's operation cost per unit distance. η^e is an increasing function of battery size, i.e., $\eta^e = H^e(E)$ with $H^{e\prime} > 0$.

At a long-run equilibrium, the percentage of drivers who choose to use EVs and CVs are assumed to follow a logit model. Let u^0 represent the drivers' reserve earning and N^0 represent the potential fleet size. Thus the number of EV drivers is $N^e = \frac{\exp(\theta u^e)}{\sum_{i\in\{e,c,0\}}\exp(\theta u^i)} \cdot N^0$, where 0 denotes drivers' reserve options and θ is a dispersion parameter. Then the ridesourcing fleet size is:

$$N = N^e + N^c = N^0 \cdot \left(1 - \frac{1}{1 + e^{\theta(u^c - u^0)} + e^{\theta(u^e - u^0)}}\right)$$

Thus the e-fleet rate φ is calculated as:

$$\varphi = \frac{N^e}{N^e + N^c} = \frac{1}{1 + e^{\theta(u^c - u^e)}}$$

3.4. Equilibrium

At a steady state, the following conservation holds as per Little's law:

$$N = (w^p + w^r + w^s) \cdot Q + \hat{w^c} \cdot \hat{K}$$

It implies that at any instant, the fleet consists of vehicles that are picking up, delivering passengers, idle, or engaging with a charging event. This fleet conservation condition can be written from another perspective. Denote the throughput undertaken by EVs as K, i.e., the number of passengers delivered to their destinations by EVs per unit of time. Mathematically, it can be defined as follows:

$$K = M_e^* \cdot \varphi \cdot N = \frac{\varphi \cdot N}{w^p + w^r + w^s + w^c}$$

It is trivial to validate that $w^c \cdot K = \hat{w^c} \cdot \hat{K}$. By definition, the system serves Q customers per unit of time, where K customers delivered to their destinations by EVs and $Q - K$ customers delivered by CVs. It takes $w^p + w^r + w^s + w^c$ for a EV to complete one trip and, according to Little's Law, the number of EVs can be denoted as $N^e = (w^p + w^r + w^s + w^c) \cdot K$. Similarly, it takes $w^p + w^r + w^s$ for a CV to complete one trip and the number of CVs is $(w^p + w^r + w^s) \cdot (Q - K)$. Thus the fleet conservation condition can be equivalently stated as:

$$N = N^c + N^e = (w^p + w^r + w^s) \cdot (Q - K) + (w^p + w^r + w^s + w^c) \cdot K$$

All of the formulations above yield our Equilibrium Model, a system of 10 equations and 10 unknowns. By specifying exogenous variables F, τ^e, τ^c, D, P, and E, we can solve the system to evaluate the performance of the ridesourcing market at the steady state.

[Equilibrium Model]

$$Q = f(F + \gamma^p \cdot w^p + \gamma^r \cdot w^r) \tag{1a}$$

$$N = (w^p + w^r + w^s) \cdot Q + \hat{w^c} \cdot \hat{K} \tag{1b}$$

$$w^p = \frac{D^p(w^s \cdot Q)}{v} \tag{1c}$$

$$\hat{K} = \frac{\kappa \cdot (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s)}{(E - \frac{\delta \cdot \kappa}{2}\sqrt{\frac{A}{D}}) \cdot (w^p + w^r + w^s + w^c)} \cdot \varphi \cdot N \tag{1d}$$

$$\hat{w^c} = \frac{\delta}{2v}\sqrt{\frac{A}{D}} + \frac{\hat{K} \cdot E^2}{2P \cdot (D \cdot P - \hat{K} \cdot E)} + \frac{E}{P} \tag{1e}$$

$$w^c = \frac{\hat{w^c} \cdot \kappa \cdot (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s)}{E - \frac{\delta\kappa}{2}\sqrt{\frac{A}{D}}} \tag{1f}$$

$$u^c = \frac{(1 - \tau^c) \cdot F - (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s) \cdot \lambda^c}{w^p + w^r + w^s} \tag{1g}$$

$$u^e = \frac{(1 - \tau^e) \cdot F - (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s) \cdot \frac{\lambda^e \cdot E}{E - \frac{\delta\kappa}{2}\sqrt{\frac{A}{D}}}}{w^p + w^r + w^s + w^c} - \eta^e \tag{1h}$$

$$N = N^0 \cdot \left(1 - \frac{1}{1 + e^{\theta(u^c - u^0)} + e^{\theta(u^e - u^0)}}\right) \tag{1i}$$

$$\varphi = \frac{1}{1 + e^{\theta(u^c - u^e)}} \tag{1j}$$

Besides the proportion of drivers who use EVs, i.e., electrified fleet rate φ, the governments are also concerned about the electrified VMT rate, which denotes the proportion of clean VMT completed by EV. For the rest of this paper, we refer to the electrified fleet rate φ and electrified VMT rate ϕ as *e-fleet rate* and *e-VMT rate*, respectively. It is easy to show that at the steady state, the throughput by CVs will be $Q - K = \frac{1}{w^p + w^r + w^s} \cdot (1 - \varphi) \cdot N$. The following equation connects these two rates:

$$\phi = \frac{K}{Q} = \frac{\varphi \cdot (w^p + w^r + w^s)}{w^p + w^r + w^s + (1 - \varphi) \cdot w^c}$$

Apparently, given a non-negative per-trip charging downtime (i.e., $w^c > 0$), the e-VMT rate ϕ is always smaller than the e-fleet rate φ. Excluding a number of $[\hat{K} \cdot \hat{w^c}]$ charging EVs, only a number of $[\varphi \cdot N - \hat{K} \cdot \hat{w^c}]$ EVs and a number of $[(1 - \varphi) \cdot N]$ CVs are actually in serve. Thus the e-VMT rate can also be calculated as the proportion of EVs in service to all vehicles in service. We further have:

$$\phi = 1 - \frac{1 - \varphi}{1 - \frac{\hat{K} \cdot \hat{w^c}}{N}}$$

Table 1
Parameter values for numerical examples.

Notation	Interpretation	Value
A	Area of study	931.58 km^2
N^0	Potential fleet size	25,000 veh
u^0	Reserve earning	25 RMB/h
d^r	Average trip length	7.5 km
w^r	Average trip time	0.3 h
v	Average operating speed	25 km/h
γ^p	Customer's value of waiting time	9 RMB/h
γ^r	Customer's value of in-vehicle travel time	2.5 RMB/h
Q^0	Potential customer demand	2,000,000/h
α^q	Demand function parameter	0.18
α^w	Matching function parameter	9.12
α^e	Parameter of vehicle upgrade	0.78
β^e	Parameter of vehicle upgrade	0.0248
σ	Proportion of cruising idle time	0.5
κ	Battery energy efficiency	0.17
λ^c	CV operation cost for unit distance	0.75 RMB/km
λ^e	EV operation cost for unit distance	0.65 RMB/km
θ	Dispersion parameter	0.3

It is easy to show that the e-VMT rate increases when more drivers choose EVs or the fleet size N expands, while larger charging arrival rate $\hat{K}$ and longer charging downtime $\hat{w^c}$ decreases the e-VMT rate. The gap between e-fleet rate and e-VMT rate, $\varphi - \phi = \frac{1-\varphi}{\frac{N}{\hat{K}\cdot\hat{w^c}}-1}$, shrinks with a higher e-fleet rate φ, a larger fleet N and fewer charging EVs $\hat{K}\cdot\hat{w^c}$.

4. Numerical analysis of market equilibrium

In this section, we conduct a case study to examine how various factors impact the equilibrium state of the electrified ridesourcing market. Such a sensitivity analysis provides insights on the formulation of effective policies to electrify the market. To do so, we adopt the following functional forms. Let Q^0 denote the potential customer demand, and the hourly customer demand is $Q = Q^0 \cdot \exp(-\alpha^q \cdot (F + \gamma^p \cdot w^p + \gamma^r \cdot w^r))$, where α^q is a positive parameter. The average pick-up distance follows $d^p = \frac{\alpha^w}{\sqrt{w^s \cdot Q}}$ (Arnott, 1996). The EV upgrade cost is calibrated as $\eta^e = \alpha^e \cdot \exp(\beta^e \cdot E)$, with parameter $\alpha^e > 0$ and $\beta^e > 0$. We assume the total cost of EV operation is less than CV operation cost in the long run, i.e. $\lambda^e < \lambda^c$ (Slowik et al., 2019).

As reported by Kim and Wallington (2013), battery energy efficiency κ decreases by 0.6% accordingly per 1% of vehicle weight reduction due to battery downsizing. However, given the relatively small battery size of ridesourcing vehicles, we ignore such a change in κ in this study. We consider a ten year life span for chargers and a five year life span for EVs to exclude the effect of vehicle replacement. The 5-year and 10-year discount rates for 2021 are 1.6% and 1.1% respectively (OMB, 2021). We annualize the charger construction cost and EV upgrade cost to an equivalent hourly cost. Other parameters' values are determined using the city of Chengdu, China as a reference. See the values of those parameters in Table 1.

By default, the average trip fare is $F = 20$ RMB/trip; commission rates for EVs and CVs are given as $\tau^e = \tau^c = 25\%$; there are 200 exclusive chargers with a charging power of 50 kW; and the battery size is set as $E = 40$ kWh. The rest of this section analyzes how exogenous variables τ^e, τ^c, D, P, and E, affect EV adoption and market performance at the steady state.

4.1. Effects of charging infrastructure

According to Fig. 2, deploying more chargers with higher charging power encourages the adoption of EVs and raises the e-VMT rate. On the one hand, EVs make fewer trips than CVs in the same amount of time due to charging downtime. On the other hand, the cheaper operations cost of EVs enables their drivers to make more money per trip. With a drop in the per-trip charging downtime, EVs can deliver more customers, and the negative effect of serving fewer trips is mitigated by higher per-trip income. As a result, when charging power or the number of chargers increases, EVs become more profitable and attract more drivers, yielding higher e-fleet and e-VMT rates.

As expected, given charger number D and power P, the e-VMT rate is always lower than the e-fleet rate in Fig. 2. However, the gap between them diminishes with higher charging power, thanks to the decrease in the per-trip charging downtime. The mechanisms for such a decrease, however, are different. As shown in Fig. 3, the charging downtime $\hat{w^c}$ is decomposed into three parts, i.e., traveling, queuing, and recharging. With more chargers deployed, EVs experience less queuing time at charging points and less travel time to target chargers (see Fig. 3(a)); while higher charging power yields less queuing time and shorter recharge time (see Fig. 3(b)). Fig. 4 shows charging downtime and per-trip charging downtime have similar trends, decreasing with higher charging power and more charger deployed.

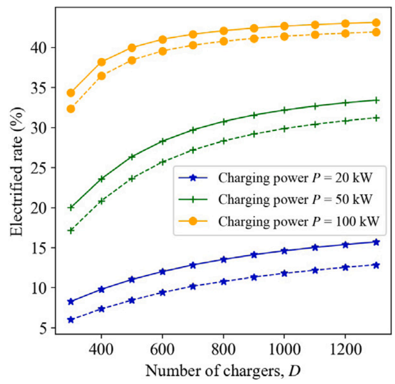


Fig. 2. Sensitivity analysis of the e-fleet rate and e-VMT rate to charging infrastructures. Solid lines represent e-fleet rates φ and dashed lines represent e-VMT rates ϕ.

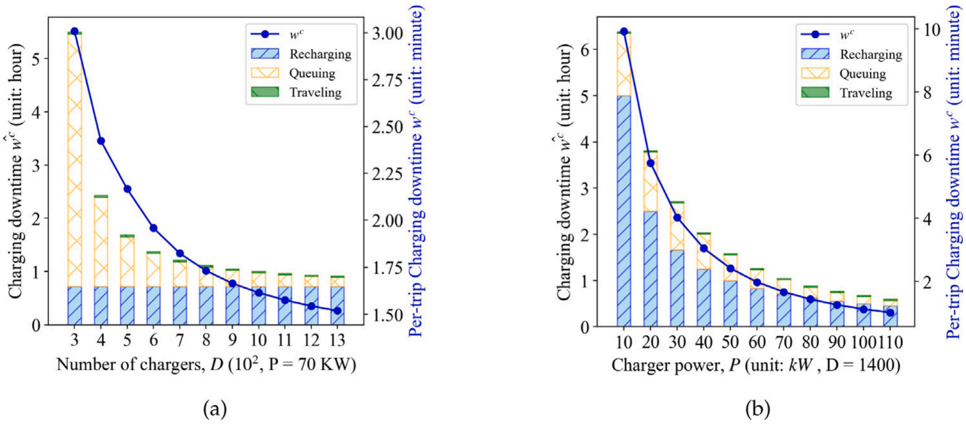


Fig. 3. Charging downtime $\hat{w}^c$ and per-trip charging downtime w^c under different (a) number of chargers and (b) charging power.

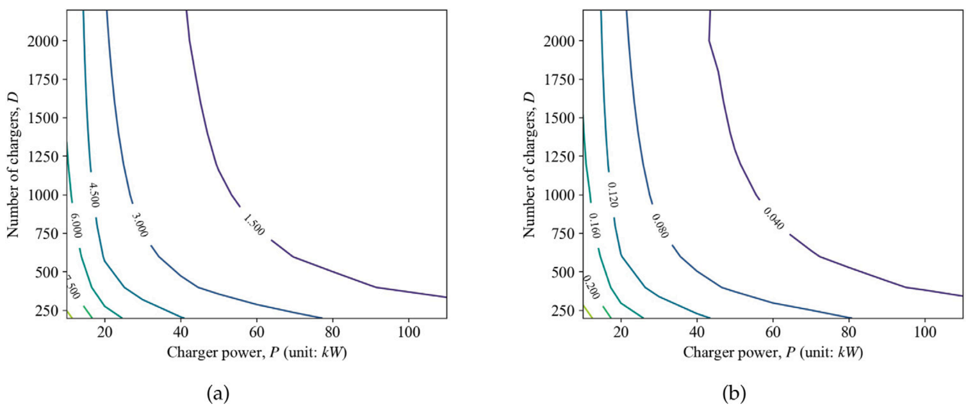
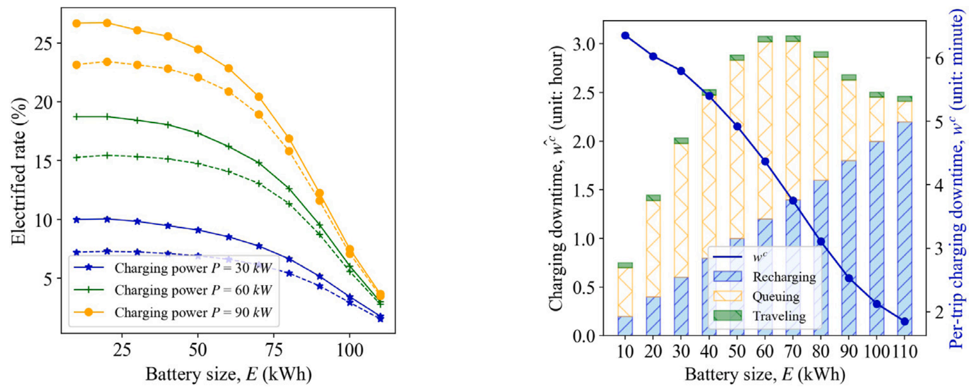


Fig. 4. Contour of (a) charging downtime and (b) per-trip charging downtime with respect to charging power and number of chargers.

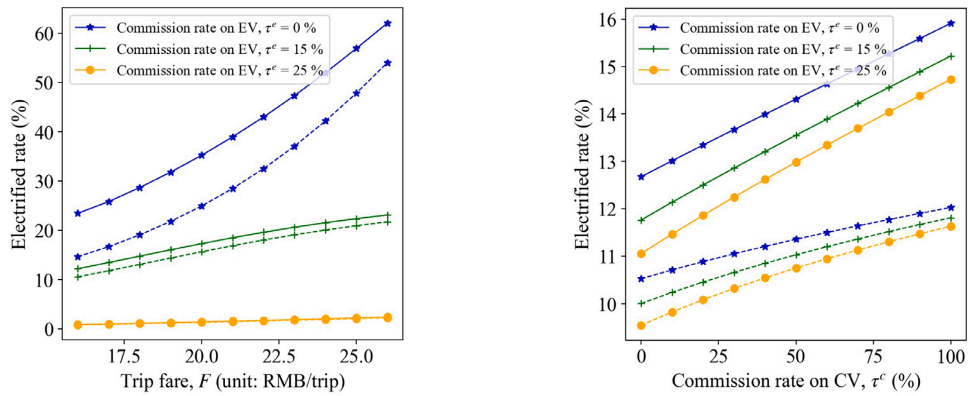
4.2. Effects of EV battery sizes

As shown in Fig. 5(a), a larger battery entails higher upgrade costs and discourages drivers from adopting EVs. Hence, a reasonably small battery is more desirable to increase drivers' hourly earnings. This mirrors previous findings that the use of less expensive EVs with shorter ranges is more profitable in the electrified ride-sharing market (Illgen and Höck, 2018). Fig. 5(b) depicts how the charging downtime and per-trip charging downtime may vary with the battery size. With larger battery size E, fewer drivers use EVs, and the number of trips served between charging increases, reducing the charging arrival rate $\hat{K}$. In the meantime,



(a) (b)

Fig. 5. (a) Sensitivity analysis of the e-fleet rate and e-VMT rate and (b) charging downtime $\hat{w}^c$ and per-trip charging downtime w^c under different battery sizes. Solid lines represent e-fleet rates φ and dashed lines represent e-VMT rates ϕ in (a).



(a) (b)

Fig. 6. Sensitivity analysis of the e-fleet rate and e-VMT rate to (a) trip fare and (b) commission rates. Solid lines represent e-fleet rates φ and dashed lines represent e-VMT rates ϕ.

larger batteries require longer recharge times, yielding a smaller charger service rate $\frac{P}{E}$. Thus the queuing time first increases due to decreased service rate when the battery size E increases from 10 kWh to 50 kWh, and then drops when the effect of decreased service rate is offset by decreased arrival rate (see Fig. 5(b)). Despite longer charging downtime $\hat{w}^c$, EV drivers experience shorter per-trip charging downtime w^c because a larger battery can support more trips between two sequential charging events.

4.3. Effects of trip fare and commission rates

Fewer customers use ridesourcing services when the platform raises the trip fare F. Though both CV and EV drivers serves fewer customers, the cheaper operation costs enable EV drivers to make more money per trip and the reduction in customers has a smaller effect on EVs. As shown in Fig. 6(a), increasing the trip fare F has a smaller negative impact on EV drivers' earnings and thus increases e-VMT rate. Fig. 6(b) shows that the e-VMT increases when the platform raises the commission rate on CVs and decreases the commission rate on EVs. This suggests that favorable commission rates do make EVs more profitable and attract more drivers to use EVs. As shown in Fig. 6(b), however, the e-VMT rate only increases to 16% when EVs are fully exempted from commissions ($\tau^e = 0\%$) and CVs are charged with the maximum possible commissions ($\tau^c = 100\%$). This suggests that varying commissions alone fails to electrify the ride-sourcing market to a high level. An explanation is shown in Fig. 7(a). According to Little's law, $[\hat{K} \cdot \hat{w}^c]$ represents the number of charging EVs in the system (denoted by a dimensionless gray line in Fig. 7(a)). This increasing curve suggests that if the platform imposes a higher commission rate on CVs without upgrading charging infrastructure, queuing delays surge when current charging infrastructures fail to handle the expanded charging demand. Consequently, more newly added vehicles are trapped at charging stations, leading to fewer EVs in service and an expanded gap between e-fleet and e-VMT rates (see Fig. 6(b)).

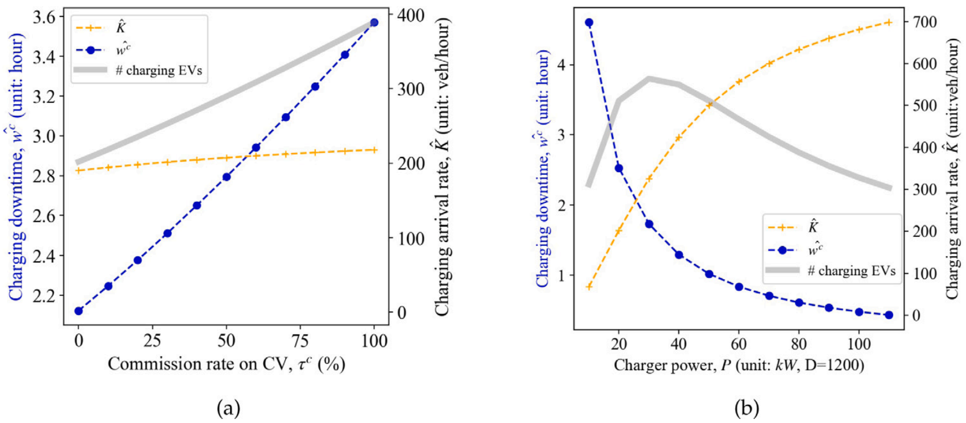


Fig. 7. Sensitivity analysis of the number of charging vehicles to (a) commission rate on CVs and (b) charging power. To facilitate the presentation, the number of charging EVs (gray lines) is denoted as dimensionless values.

The failure of favorable commissions on EV suggests that upgrading the charging infrastructure is necessary to level up the e-VMT rate and ensure the market efficiency. As shown in Fig. 7(b), increasing charging power P reduces the charging downtime $\hat{w^c}$ and attracts more EV drivers, yielding monotonously increasing charging arrival rate $\hat{K}$. As a result, the number of charging EVs $(\hat{w^c} \cdot \hat{K})$ first increases due to the increase in charging demand, then drops when the reduction in charging downtime offsets the increase in $\hat{K}$. In other words, customers will find it harder to hail ridesourcing vehicles until the charging power reaches a certain level. Similar results are observed when the number of chargers varies.

5. Policy discussion

5.1. Policy options

In this section, we seek to design regulatory policies to electrify the ridesourcing sector and evaluate policy effects by taking the platform's response into account. We consider the monopoly ridesourcing market equilibrium, where one ridesourcing platform manages to maximize its profit given the regulatory policy imposed by the government. We consider an utterly profit-driven situation for simplicity and ignore other implicit values of EVs, e.g., benefits on environments and corporate image. By definition, EV fleet contributes to $\phi \cdot Q$ trips, and CV fleet contributes to the rest $(1-\phi) \cdot Q$ trips. Then the platform's profit without regulation is calculated as:

$$z = \overbrace{\tau^e \cdot F \cdot \phi \cdot Q + \tau^c \cdot F \cdot (1-\phi) \cdot Q}^{\text{revenue}} - \overbrace{D \cdot \eta^d}^{\text{construction cost}}$$

where z is the platform profit. η^d is the amortized per hour construction cost for one charger, which is an increasing function of charging power $\eta^d = H^d(P)$ with $H^{d'} > 0$. The platform's operation costs are unaffected by a regulatory policy and thus ignored.

Three regulatory fee structures are examined in this study: annual permit fees (AP), differential trip-based fees (TB), and differential commission caps (CC). Previous studies suggest that both EV purchase and charger construction can be self-sustained in the long term (Slowik et al., 2019), therefore the government does not have to offer direct subsidies on EV purchase, EV operation or charger installment.

Policy 1: Annual permit fees

The government sets a target e-VMT rate $\hat{\phi}$ under AP. A platform is charged with an annual permit fee R if it fails to achieve the target and is exempted otherwise. Without loss of generality, we adopt an annual permit fee proportional to the difference between the target and actual e-VMT rate, i.e., $R = R_0 \cdot \max\{\hat{\phi} - \phi, 0\}$, where R_0 is the penalty for unit difference. Under this mandatory policy, the platform's profit turns into:

$$z = \tau^e \cdot F \cdot \phi \cdot Q + \tau^c \cdot F \cdot (1-\phi) \cdot Q - D \cdot \eta^d - R$$

Policy 2: Differential trip-based fees

As pointed out by Slowik et al. (2019), trip, mileage, or revenue-based fees are interchangeable in certain contexts, so we consider trip-based fees without loss of generality. The platform is charged with a fee of R^c for one trip completed by CVs and R^e for one trip completed by EVs. The government charges higher fees for trips completed by CVs (i.e., $R^c > R^e \geq 0$). The policy can be viewed as that CVs are charged with extra carbon emission tax or EVs are fully or partially exempted from operation fees. The latter is under consideration in Delhi, India (Delhi-Transport-Department, 2018). Considering that the government directly charges the platform, the platform profit is calculated as:

$$z = (\tau^e \cdot F - R^e) \cdot \phi \cdot Q + (\tau^c \cdot F - R^c) \cdot (1-\phi) \cdot Q - D \cdot \eta^d$$

Policy 3: Differential commission cap

When the government sets a higher commission cap on EVs, the platform can charge higher commissions from EVs and may thus eager to expand its EV fleet. Despite being charged with higher commissions, EVs still promise to be more profitable for drivers as previous studies show EVs enjoy lower operation cost than CVs (Slowik et al., 2019). Therefore, the government may set a higher commission cap on EVs than that on CVs (i.e., $\hat{\tau^e} > \hat{\tau^c}$) and require the commission charged by the platform to be no more than the commission cap, i.e., $\tau^e \le \hat{\tau^e}, \tau^c \le \hat{\tau^c}$.

5.2. Platform's response

The market equilibrium analysis in Section 4 suggests that expanding charging infrastructures, mitigating EV purchase costs, and offering favorable commission rates to EVs effectively attract drivers towards EVs. Given regulatory policies, the platform determines its response strategies from the following four aspects.

- *Charger construction*: the monopoly platform is assumed to be responsible for constructing dedicated chargers and determining the charger number D and charging power P. In reality, most existing public chargers are designed for private users and are poorly located in places like residuals and retails. Thus many ridesourcing platforms have been constructing their own fast-charging networks to cater to the charging need of their EV drivers (China-Daily, 2020).
- *EV adoption*: the platform sets up registration requirements regarding EVs' battery size E and offers EV upgrade subsidies to help drivers turn to EVs. More specifically, the platform decides the subsidy rate $s^e \in [0,1)$ and reimburses part of the vehicle upgrade costs ($\eta^e \cdot s^e$ per EV). In reality, the platform can choose to provide targeted vehicle adoption subsidies or rental subsidies to its drivers, both of which are under consideration by Uber (2021).
- *Commission support*: the platform can charge EV and CV drivers differently by distinguishing commission rate τ^e and τ^c.
- *Pricing*: the platform decides the trip fare F.

Under the monopoly market equilibrium, one ridesourcing platform determines seven exogenous variables D, P, E, s^e, τ^e, τ^c, and F to maximize its profit. Then the platform's optimal response strategy is obtained by solving the following Platform Response Model:

[**Platform Response Model**]

$$\begin{aligned} \max_{D,P,E,s^e,\tau^e,\tau^c,F} \quad & z - \overbrace{\varphi \cdot N \cdot s^e \cdot \eta^e}^{\text{subsidy cost}} \\ s.t. \quad & (1a)-(1g),(1i),(1j) \\ & u^e = \frac{(1-\tau^e)\cdot F - (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s)\cdot \frac{\lambda^e \cdot E}{E - \frac{\delta\kappa}{2}\sqrt{\frac{A}{D}}}}{w^p + w^r + w^s + w^c} - \eta^e \cdot (1-s^e) \end{aligned} \tag{2}$$

where u^e is the EV driver's earning after receiving vehicle upgrade subsidy from the platform, and z is the platform profit under different regulatory policies. Note that CC adds two constraints $\tau^e \le \hat{\tau^e}, \tau^c \le \hat{\tau^c}$ to model (2).

5.3. Policy evaluation

Before we dive into the analysis of proposed regulatory policies, it is important to discuss how they will be evaluated. In this study, we examine three aspects, including effectiveness, cost-efficiency, and feasibility. To facilitate our presentation, the unregulated market equilibrium under the platform's profit maximization is referred to as benchmark, and the corresponding variables are denoted as with ' (e.g., ϕ' and φ').

(i) A policy is *feasible*, if it yields non-negative utilities for all participants (i.e., drivers and the platform).

(ii) A policy is *effective* if it reduces GHG emission, or equivalently, the fuel consumption. This study uses the e-VMT rate, i.e., the proportion of clean VMTs completed by EVs, to measure the effectiveness. Thus an effective policy leads to a new market equilibrium with $\phi > \phi'$.

(iii) The *cost-efficiency* of a policy is measured by the change in social welfare for a unit fuel consumption reduction.

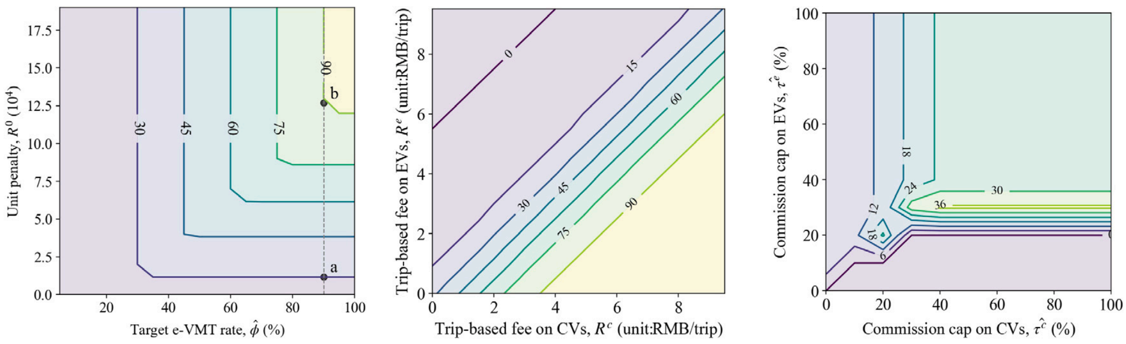
Given a market equilibrium, the fuel consumption is calculated as:

$$FC(\phi) = (1-\phi)\cdot Q \cdot (d^r + w^p \cdot v + \sigma \cdot v \cdot w^s)\cdot \rho \tag{3}$$

where ρ represents the fuel consumption per distance traveled.

Let $V(\phi)$ denote the social welfare under an e-VMT rate ϕ and is calculated as the sum of platform profit, driver surplus, and customer surplus (see Eq. (4)).

$$\begin{aligned} V(\phi) = & \overbrace{(\phi \cdot \tau^e + (1-\phi)\cdot \tau^c)\cdot Q \cdot F}^{\text{platform income}} - \overbrace{D \cdot \eta^d - \phi \cdot N \cdot \eta^e \cdot s^e}^{\text{platform cost}} + \\ & \overbrace{\frac{N}{\theta}\ln(\exp(\theta \cdot u^c) + \exp(\theta \cdot u^e) + \exp(\theta \cdot u^0))}^{\text{driver surplus}} + \overbrace{\int_F^{\infty} Q(x)dx}^{\text{customer surplus}} \end{aligned} \tag{4}$$



(a) (b) (c)

Fig. 8. e-VMT rates under (a) AP, (b) TB and (c) CC.

Then the cost-efficiency of a policy is calculated as $\frac{\Delta V}{\Delta FC} = \frac{V(\phi)-V(\phi')}{FC(\phi)-FC(\phi')}$, where the denominator is the total reduced fuel consumption and numerator is the change in social welfare. When $\Delta V > 0$, the society benefits from ridesourcing electrification. Note that under AP, the platform income reduces to $[(\phi \cdot \tau^e + (1-\phi)\cdot\tau^c)\cdot Q \cdot F - R]$ while the government revenue increases to R. Similarly, under TB, the platform income reduces to $[\phi \cdot Q \cdot (\tau^e \cdot F - R^e) + (1-\phi)\cdot Q \cdot (\tau^c \cdot F - R^c)]$ and the government revenue increases to $[\phi \cdot Q \cdot R^e + (1-\phi)\cdot Q \cdot R^c]$. Thus AP and TB only change the income distribution between the platform and the government, and the social welfare under all proposed policies can be calculated with Eq. (4).

6. Effects of proposed policies

In this section, we examine the effects of proposed policies, i.e., AP (annual permit fees), TB (differential trip-based fees), and CC (differential commission caps). We require EV battery size should be no less than the current market average size (40 kWh) and the charging power should not exceed the upper bound $\bar{P} = 100$ kW. The platform bears charger construction cost, which includes the cost for charger purchase, installation and maintenance. The charger construction cost is calibrated as $\eta^d = \alpha^d \cdot \exp(\beta^d \cdot P) + \gamma^d$, with $\alpha^d = 0.086$, $\beta^d = 0.059$, and $\gamma^d = 3.36$. The fuel consumption per kilometer is $\rho = 9.4L/100$ km. When no regulations are implemented, the benchmark market equilibrium under the platform's profit maximization yields an e-VMT rate of $\phi' = 24.8\%$. The corresponding optimal commission rate is $\tau^{e'} = 40.5\%$ for EVs and $\tau^{c'} = 34.2\%$ for CVs. This suggests that the platform charges higher commissions on EVs (i.e., $\tau^{e'} > \tau^{c'}$) and EVs are still profitable.

6.1. *Effectiveness*

As shown in Figs. 8(a) and 8(b), both AP and TB are effective at achieving different target e-VMT rates. Higher target e-VMT rates in AP combined with a larger unit penalty can lead to higher electrification. For example, when the target e-VMT rate is set as 90% (denoted as a dashed gray line in Fig. 8(a)), a unit penalty of $R_0 = 11{,}120$ can effectively lead to a low e-VMT rate of 30% (denoted as the point a), while the required unit penalty surges to $R_0 = 126{,}000$ for a high e-VMT rate of 90% (denoted as the point b). The platform will stop electrifying its fleet once it reaches the target e-VMT rate. Under TB, charging higher trip-based fees on CVs leads to a higher e-VMT rate. For example, when EVs are fully exempted from operation fees ($R^e = 0$ RMB/trip), a trip-based fee of $R^c = 0.32$ RMB/trip and $R^c = 3.7$ RMB/trip yields an e-VMT rate of 30% and 90%, respectively.

As shown in Fig. 8(c), CC is only effective for e-VMT rates lower than 36%. Particularly, CC can steer the ridesourcing system towards an e-VMT rate between 30% to 36% only when the government sets commission caps on EVs lower than the unregulated optimal ($26\% \leq \hat{\tau^e} \leq 34\%$, while $\tau^{e'} = 41\%$), and commission caps on CVs as $\hat{\tau^c} \geq 32\%$. The reasons are as below. When commission caps on EVs are low ($\hat{\tau^e} < 26\%$), EVs are less profitable and fail to attract the platform to take action. When both commission caps are higher than the effective thresholds ($\hat{\tau^e} > 34\%$ and $\hat{\tau^c} > 32\%$), the regulations lose effects and the platform tends to adopt the unregulated response. When the government only raises caps on EVs and lowers caps on CVs ($\hat{\tau^e} > 34\%$ and $\hat{\tau^c} < 32\%$), the platform can charge higher on EVs and will seek to take action. But the low caps on CVs makes the commission rates favorable to CVs and more drivers sticking to CVs. Note that this study assumes the platform treats CVs and EVs equally during the matching process. Given high caps on EVs and low caps on CVs, if we relax this assumption, the platform will be motivated for electrification and can assign CV drivers fewer trips to steer them towards EVs. This suggests that CC promises to be effective for high electrification if the platform can differentiate EVs in the matching process.

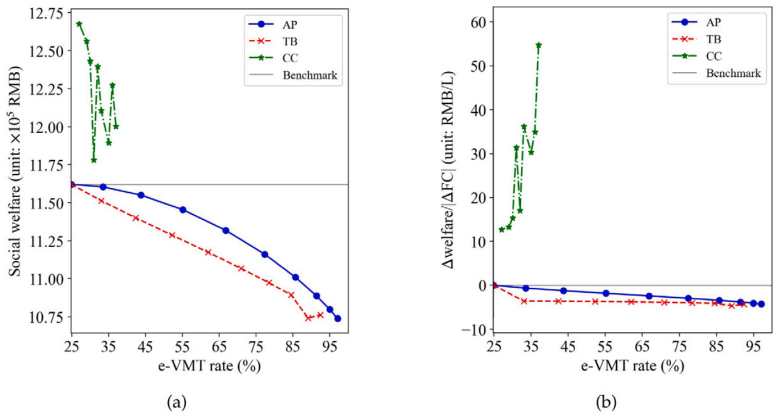


Fig. 9. (a) Social welfare and (b) cost-efficiency of proposed polices under different e-VMT rates. Note: only effective situations are presented, i.e. $\phi > 24.8\%$ (same as below).

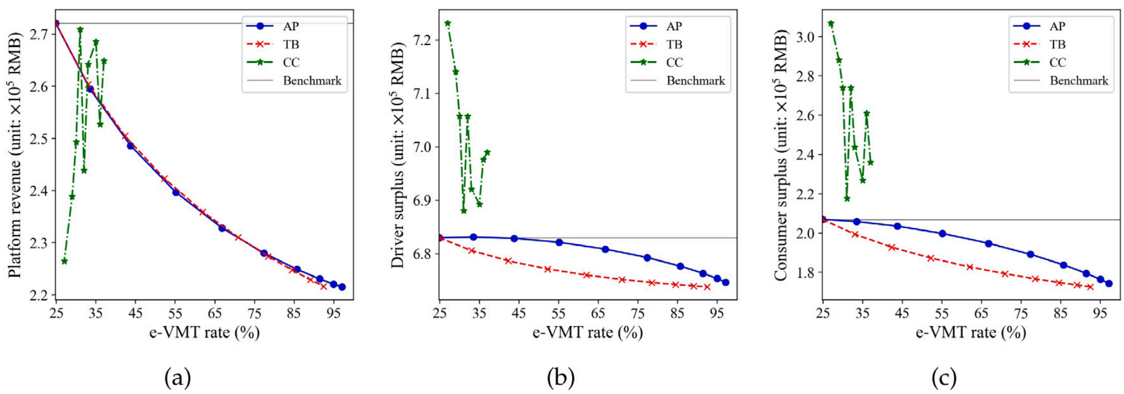


Fig. 10. (a) Platform profit, (b) driver surplus and (c) customer surplus given proposed polices under different e-VMT rates.

6.2. Cost-efficiency

In this section, we examine the cost-efficiency of proposed regulatory policies. For each regulatory policy, the parameter combination yielding the best social welfare is selected when different parameters result in the same e-VMT rate. For example, both trip-based operation fees of $R^e = 0$ RMB/trip and $R^c = 0.32$ RMB/trip, as well as $R^e = 0.5$ RMB/trip and $R^c = 0.82$ RMB/trip yield an e-VMT rate of 30%. We select the former combination as it entails higher driver surplus and higher social welfare.

As shown in Fig. 9(a), the ride-sourcing system benefits from electrification under CC whereas AP and TB lead to worse social welfare. The social welfare reduces as the market becomes more electrified under all proposed policies. As shown in Fig. 9(b), CC is the most cost-efficient for low electrification and becomes more cost-efficient with higher e-VMT rates not greater than 36%, while TB turns out to be the least cost-efficient. Explanations are given as follows.

By definition, social welfare can be decomposed into three parts: platform profit, driver surplus, and customer surplus. As shown in Fig. 10(a), the platform pays for charger construction and vehicle upgrade subsidy, and its profit shrinks under all proposed policies. By contrast, both drivers and customers become worse off under AP and TB; only under CC will drivers and customers benefit from electrification. This is because CC simultaneously benefits drivers and customers in this two-sided market. That is, given commission caps under CC, the platform charges fewer commissions on both types of drivers (see Figs. 11(a) and 11(b)) and driver surplus thus increases. By contrast, CV drivers face much higher commissions and the total fleet size is reduced under AP and TB. Thus CV driver surplus decreases under AP and TB as the market becomes more electrified despite the consistent increase in EV drivers' earning.

In the meantime, under CC, capping the commission rates encourages the platform to lower trip fares to attract more customers (see Fig. 12(a)) and the customers also become better off. In the contrast, the platform gradually raises trip fares under AP and TB as the market becomes more electrified, resulting in decreased customer surplus. Moreover, each trip is charged with additional fees under TB, thus the platform delivers fewer customers to avoid the trip-based fees (see Fig. 12(b)). At the same time, the platform seeks to impose higher commissions on drivers and higher trip fares on customers to increase the per-trip profit, further reducing the driver and customer surplus under TB.

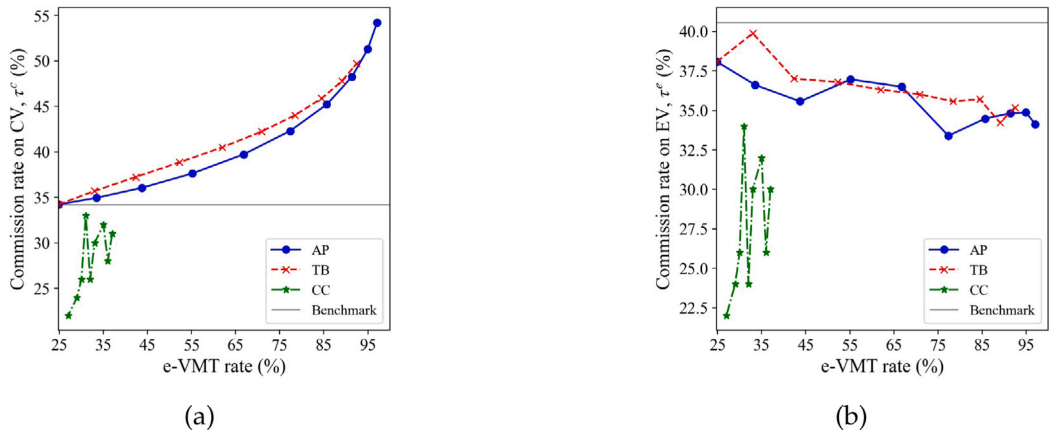


Fig. 11. (a) Optimal commission rates for CVs and (b) EVs given proposed polices under different e-VMT rates.

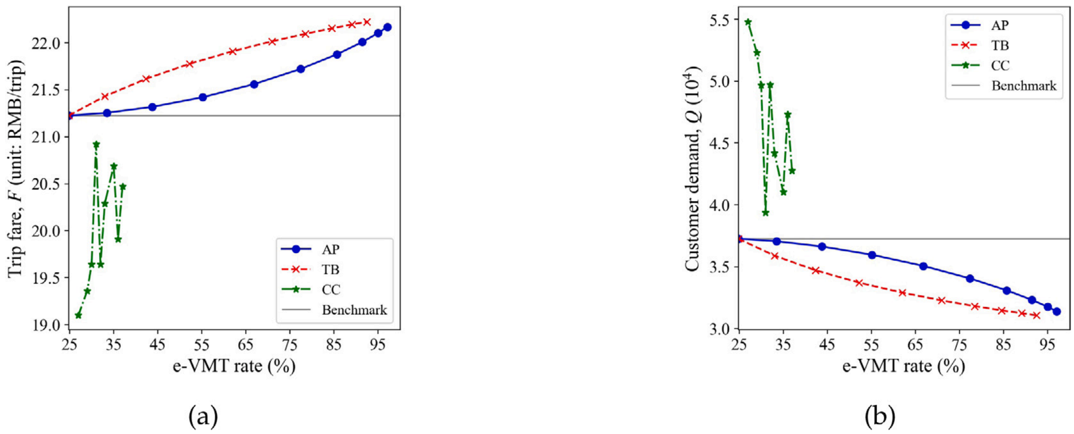


Fig. 12. (a) Optimal trip fares and (b) customer demand given proposed polices under different e-VMT rates.

6.3. Feasibility

We examine the effects of proposed policies on drivers' earnings and the platform profit. Fig. 13 shows the allocation of total trip fares (i.e., $Q \cdot F$) among the platform, government, and drivers under the benchmark and with low (30%) and high (90%) e-VMT rates. As CC fails to achieve a high e-VMT rate, it is excluded in the latter scenario. Given the numerical results in Section 6.1 for achieving various e-VMT rates, we adopt the following parameter settings: (i) Under the low electrified scenarios, we set the target e-VMT rate as $\hat{\phi} = 30\%$ and applies a unit penalty of $R_0 = 11{,}700$. EVs are fully exempted from operation fees ($R^e = 0$ RMB/trip) and a trip-based fee of $R^c = 0.32$ RMB/trip is applied to CVs under TB. The commission cap on EVs is $\hat{\tau^e} = 34.5\%$ and no commission cap is imposed on EVs. (ii) Under the high electrified scenario, we set the target e-VMT rate as $\hat{\phi} = 90\%$ and apply a unit penalty of $R_0 = 126{,}000$. Similarly, EVs are fully exempted from operation fees ($R^e = 0$ RMB/trip) and a trip-based fee of $R^c = 3.7$ RMB/trip is applied under TB.

As shown in Fig. 13, the platform pays for charger construction and vehicle subsidy, and its profit share shrinks as the market becomes more electrified. Specifically, when the e-VMT rate is low, the platform profit maintains the highest share of 34.4% under AP among the three proposed regulatory policies. The government charges a total of 1.0% trip-based fees, and the platform profit shrinks to 34% under TB. Under CC, the platform charges less from EVs with the commission caps, reducing its profit to 33.2%. In the meantime, EV drivers earn more money for one trip and can tolerate longer charging downtime. As a result, the platform invests less on charger construction under CC, reducing its cost to 0.6%. EV drivers enjoy higher profits as 11.1% under CC but have to suffer higher operations costs as 8.6% due to longer charging downtime. This suggests the monopoly platform entails longer charging downtime and uses its fleet less effectively under CC.

As shown in Fig. 13, when TB steers the market from low to high electrification, the government's share increases from 1.0% to 1.6%, whereas the platform's share decreases from 34.0% to 32.1%. This suggests that the platform risks huge profit loss if the government charges excessive fees to steer the platform towards a high e-VMT rate. Therefore, the government should carefully

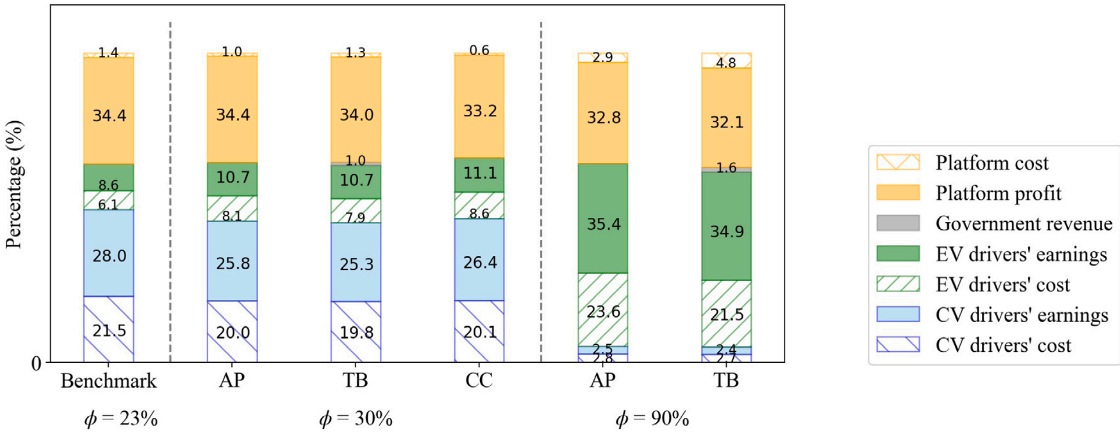


Fig. 13. Allocation of the total trip fare among the platform, government, and two types of drivers.

Table 2
Comparison of proposed regulatory policies.

Policy	Effectiveness	Cost-efficiency	Feasibility
AP	Effective for all target e-VMT rates	Cost-efficient	Possible zero government revenue
TB		Least cost-efficient	Huge platform profit loss under high e-VMT rates
CC	Only effective for low e-VMT rates	Most cost-efficient	Both drivers and customers become better off

design trip-based fees to avoid negative platform profit under TB. Zero government revenue is possible if the government subtly selects the target e-VMT rate and unit penalty under AP.

To sum up, AP and TB are effective for all e-VMT rates whereas AP is more cost-efficient. CC is only effective for a low e-VMT rate, but it turns out to be the most cost-efficient when it is effective. Table 2 summarizes the effectiveness, cost-efficiency, and feasibility of proposed regulatory policies.

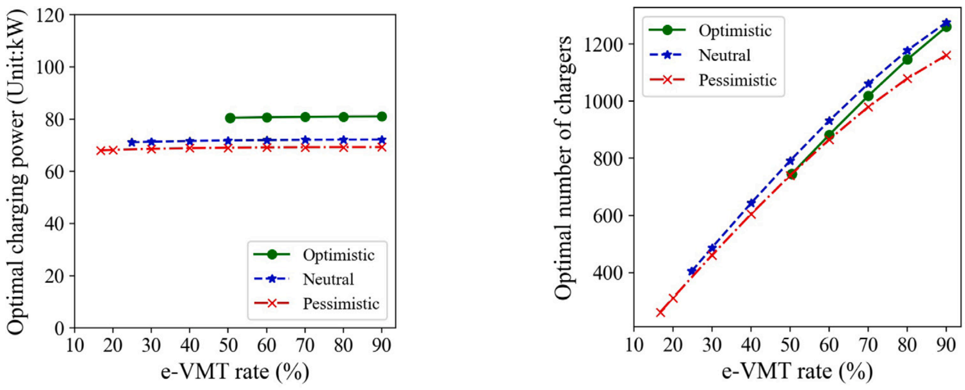
So far, it seems as if no policy performs so well for all measures. Although AP could handle all-target e-VMT rates, it is not the most cost-efficient one. We consider taking advantage of both the cost-efficiency of CC and effectiveness of AP, i.e., combining AP and CC (this combined policy denoted as AP+CC), and exploring whether the performance of the combined policy is better. Without loss of generality, we set the target e-VMT rate as 90% and set sufficient penalties to achieve this target e-VMT rate. Since different combinations of commission caps can achieve the same e-VMT rates. We conduct a grid search and select the combination with the highest welfare as $\hat{\tau^e} = 12.5\%$ and $\hat{\tau^c} = 31.7\%$.

The numerical results show that AP + CC is effective for all-target e-VMT rates and more cost-efficient than AP alone. Similar to the effects of CC, both customers and drivers (especially EV drivers) benefit from the electrification under AP+CC. Under AP, the platform will set $\tau^e = 37.5\%$ and $\tau^c = 48.3\%$ to achieve a 90% e-VMT rate. Capping the commission rates limits the per-trip profit and encourages the platform to lower trip fares from 22.2 RMB/trip to 19.1 RMB/trip to attract more customers, and the customers become better off. Given commission caps under CC, the platform charges fewer commissions on both types of drivers and drivers become better off. Additionally, the platform has huge profit loss under AP+CC and may have huge profit loss if the government uses unreasonable commission caps and annual permit fees to steer the platform towards a high e-VMT rate.

6.4. Sensitivity analysis of the platform

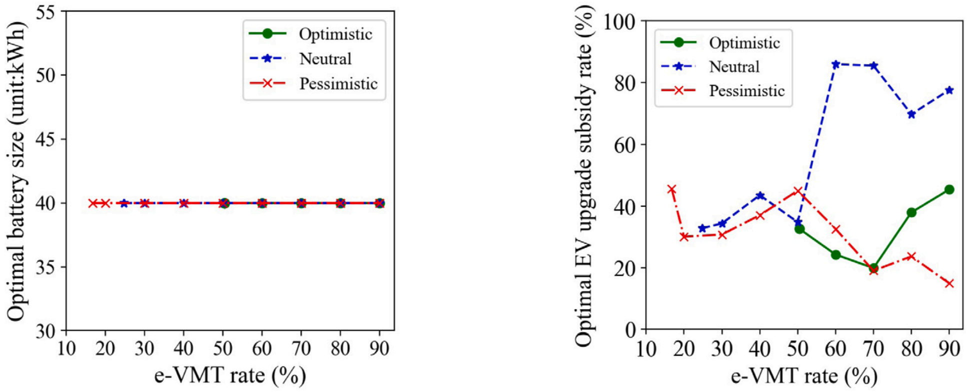
This section extends our discussion to the platform's optimal electrification strategy under different e-VMT rates. Given that AP is effective for all electrification levels and more cost-efficient than TB, we assume it is adopted by the government in this subsection. We set different levels of $\hat{\phi}$ and adopt sufficient large R_0 to steer the system towards electrification. The platform designs its charger construction strategy (D and P), EV adoption strategy (E and s^e), commission support (τ^e and τ^c) and pricing (F). Three different scenarios are considered to demonstrate the potential equilibrium in the long run. The unregulated e-VMT rate varies under different scenarios.

- *Nominal*: current prices for chargers and EVs are used: $\alpha^e = 0.78$, $\beta^e = 0.02$, $\alpha^d = 0.09$, $\beta^d = 0.06$ and $\gamma^d = 3.36$. Consider technique limits, the charging power P should not exceed the upper bound $\bar{P} = 100$ kW. Moreover, EVs have less operation costs than CVs in the long run, i.e., $\lambda^c = 0.75$ RMB/trip and $\lambda^e = 0.65$ RMB/trip.
- *Optimistic*: since EV-related technologies are evolving rapidly, the prices for chargers and EVs drop to 90% of current level: $\alpha^e = 0.70$, $\beta^e = 0.02$, $\alpha^p = 0.08$, $\beta^d = 0.05$ and $\gamma^d = 3.02$. The upper bound of charging power increases to $\bar{P} = 120$ kW. The EV operation cost drops to $\lambda^e = 0.6$ RMB/trip, while the fuel prices increases to $\lambda^c = 0.8$ RMB/trip.



(a) (b)

Fig. 14. Optimal (a) charging power and (b) number of chargers under different scenarios.



(a) (b)

Fig. 15. Optimal (a) battery size and (b) vehicle upgrade subsidy under different scenarios.

- *Pessimistic*: the government stops offering subsidies, so the prices for chargers and EVs increase to 150% of current level: $\alpha^e = 1.17$, $\beta^e = 0.038$, $\alpha^p = 0.135$, $\beta^d = 0.09$ and $\gamma^d = 5.04$. The vehicle operation costs and upper bound of charging power remain unchanged, i.e., $\lambda^c = 0.75$ RMB/trip, $\lambda^e = 0.65$ RMB/trip, and $\bar{P} = 100$ kW.

Fig. 14 shows the optimal charger construction strategy under different scenarios. Under all scenarios, the platform should adopt chargers with high charging power (see Fig. 14(a)) to shorten the recharge time and queuing time. And it should gradually expand the charging network to accommodate the charging needs of the expanding EV fleet and shorten the queuing time at each charger (see Fig. 14(b)). When the charger price reduces under optimistic scenarios, the platform builds fewer chargers with higher charging power.

Fig. 15(a) shows that a small battery size equivalent to the lower bound adopted in this section (i.e., 40 kWh) is preferred to avoid high vehicle upgrade costs. As the market becomes more electrified, more chargers are deployed to further reduce charging downtime, making large batteries unnecessary. Conversely, vehicle upgrade subsidies are necessary for ridesourcing electrification under all scenarios (see Fig. 15(b)). Specifically, under optimistic and nominal scenarios, higher subsidy rates from the platform are required to lower the adoption barrier when a high electrification level is targeted at. Under pessimistic scenarios, however, the high EV upgrade costs discourage the platform from adopting high subsidy rates. Instead, the platform chooses to lower commission rates on EVs (see Fig. 16(a)) to attract drivers. Thus the vehicle subsidy rates are lower under pessimistic scenarios. Note that the amount of subsidy is not necessarily low under the pessimistic scenario.

Fig. 16 describes the optimal commission rate on EVs and CVs under different e-VMT rates. As we can see, the platform should charge higher commissions on EVs under low e-VMT rates in order to gain motivation to further expand its EV fleet; but favorable commissions for EVs (i.e., $\tau^e < \tau^c$) should be adopted at high e-VMT rates. As shown in Fig. 17, the platform raises the trip fare with the e-VMT rate as it pays more for the charger construction and vehicle upgrade subsidies during the electrification process. Under the optimistic scenario, lower trip fares are required as the updated technology lowers the electrification costs.

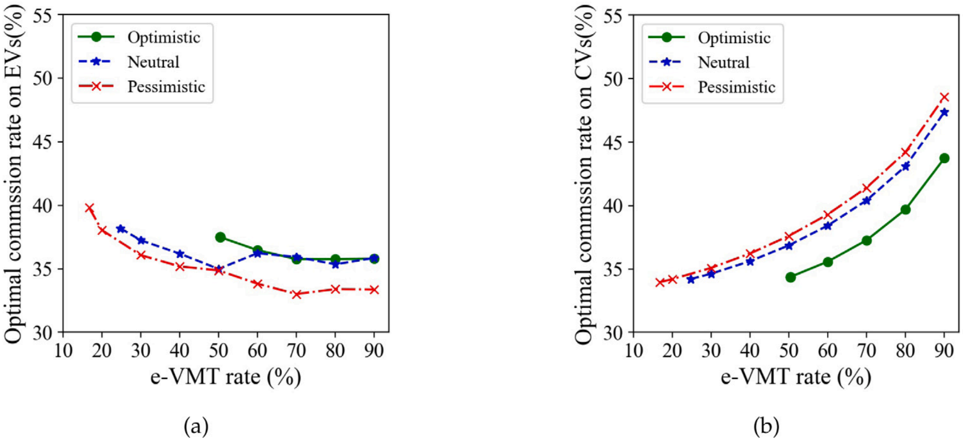


Fig. 16. Optimal commission rates on (a) EVs and (b) CVs under different scenarios.

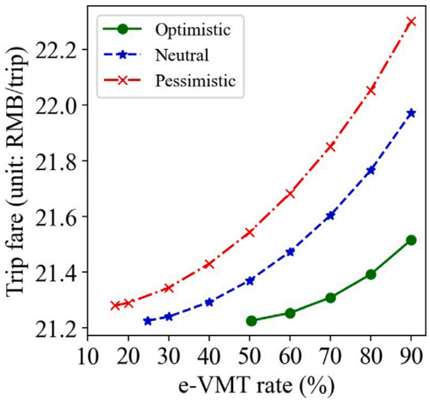


Fig. 17. Optimal trip fare under different scenarios.

7. Model extension

So far, the proposed modeling framework considers a monopoly market with homogeneous drivers. Ridesourcing driver characteristics, however, indubitably vary in reality. For example, part-time EV drivers may choose to recharge their vehicles during off-working hours or with home chargers. This leads to more discussion on how to attract *heterogeneous* ridesourcing drivers to adopt EVs.

Consider a ridesouring system with M class of drivers. Each class $i \in M$ has an equivalent N_i number of drivers, which depends on the length of working hours. For example, if a full-time driver works eight hours a day and $N_f = 1$, then a part-time driver working two hours a day has the equivalent $N_p = 0.25$. Since part-time drivers must work after finishing another job and cannot choose to be full-time drivers, we assume each class has a potential fleet size N_i^0 independent of other classes.

Drivers in different classes differ in vehicle types and charging behavior. Drivers in class i use vehicles with battery size E_i, battery efficiency κ_i, and vehicle upgrade cost η_i^e. When EV drivers in class i reach the least SOC, there is a probability ϵ_i that it fully recharges itself at the public charger and a $1 - \epsilon_i$ probability that it uses the home-charging. Similarly, the arrival rate of charging EVs in class i at the public charger is calculated as:

$$\hat{K}_i = \frac{\kappa_i \cdot (d^r + d^p + \sigma \cdot v \cdot w^s)}{(E_i - r \cdot \kappa_i) \cdot (w^p + w^r + w^s + w_i^c)} \cdot \epsilon_i \cdot \varphi_i \cdot N_i$$

where the electrified fleet rate φ_i denotes e-fleet rate in the class i and ϵ_i denotes the proportion of charging that drivers in class i completes with public charging.

Assume the arrival of charging EVs in class i follows a Poisson process. The total arrival rate at a public charger follows a Poisson process with arrival rate of $\frac{\sum_{i \in M} \hat{K}_i}{D}$. Denote the total arrival rate of all driver classes as $\hat{K} = \sum_{i \in M} \hat{K}_i$. The expected service time of a public charger is $\sum_{i \in M} \frac{\hat{K}_i}{\hat{K}} \cdot \frac{E_i}{P}$, where $\frac{\hat{K}_i}{\hat{K}}$ is the probability that a charger is occupied by the ith class arrival. The charging process at a charger is thus an M/D/1 queuing system with arrival rate $\frac{\sum_{i \in M} \hat{K}_i}{D}$ and service rate $\frac{\hat{K} \cdot P}{\sum_{i \in M} \hat{K}_i \cdot E_i}$. The system is stable when $\frac{\sum_{i\in M}\hat{K}_i\cdot E_i}{D\cdot P}<1$. Therefore charging EVs in class i experience a charging downtime $\hat{w^c}$ at the public charger:

$$\hat{w_i^c}=\frac{r}{v}+\frac{(\sum_{i\in M}\hat{K}_i\cdot E_i)^2}{2\cdot\hat{K}\cdot P\cdot(D\cdot P-\sum_{i\in M}\hat{K}_i\cdot E_i)}+\frac{E_i}{P}$$

Home-charging is a limiting scenario when the charger power $P\to\infty$ and the number of charger $D\to\infty$ and the EV driver experience zero charging downtime if it uses home-charging. The expected charging downtime for EV driver in class i is $\epsilon_i\cdot\hat{w_i^c}+(1-\epsilon_i)\cdot 0=\epsilon_i\cdot\hat{w_i^c}$. The basic model is a limiting scenarios when $M=\{1\}$ and $\epsilon_1=1$.

The drivers choice within each class follows a Logit model and the e-fleet rate of class i is $\varphi_i=\frac{1}{1+e^{\theta(u^c-u_i^e)}}$. Let $N=\sum_{i\in M}N_i$ denote the total fleet size. The total e-fleet rate and e-VMT rates are calculated as weighted average of each class, i.e., $\varphi=\sum_{i\in M}\frac{N_i}{N}\varphi_i$ and $\phi=\sum_{i\in M}\frac{N_i}{N}\phi_i$. At a steady state, the following conservation holds as per Little's law: $\sum_{i\in M}N_i=(w^p+w^r+w^s)\cdot Q+\sum_{i\in M}\hat{w_i^c}\cdot\hat{K}_i$.

To sum up, the Extended Equilibrium Model is given as

[Extended Equilibrium Model]

$$Q=f(F+\gamma^p\cdot w^p+\gamma^r\cdot w^r) \tag{5a}$$

$$\sum_{i\in M}N_i=(w^p+w^r+w^s)\cdot Q+\sum_{i\in M}\hat{w_i^c}\cdot\hat{K}_i \tag{5b}$$

$$w^p=\frac{D^p(w^s\cdot Q)}{v} \tag{5c}$$

$$\hat{K}_i=\frac{\kappa\cdot(d^r+w^p\cdot v+\sigma\cdot v\cdot w^s)}{(E-\frac{\delta\cdot\kappa}{2}\sqrt{\frac{A}{D}})\cdot(w^p+w^r+w^s+\epsilon_i\cdot w_i^c)}\cdot\epsilon_i\cdot\varphi_i\cdot N_i \qquad \forall i\in M \tag{5d}$$

$$\hat{w_i^c}=\frac{r}{v}+\frac{(\sum_{i\in M}\hat{K}_i\cdot E_i)^2}{2\cdot P\cdot(\sum_{i\in M}\hat{K}_i)\cdot(D\cdot P-\sum_{i\in M}\hat{K}_i\cdot E_i)}+\frac{E_i}{P} \qquad \forall i\in M \tag{5e}$$

$$w_i^c=\frac{\epsilon_i\cdot\hat{w_i^c}\cdot\kappa_i\cdot(d^r+w^p\cdot v+\sigma\cdot v\cdot w^s)}{E_i-\frac{\delta\cdot\kappa_i}{2}\sqrt{\frac{A}{D}}} \qquad \forall i\in M \tag{5f}$$

$$u^c=\frac{(1-\tau^c)\cdot F-(d^r+w^p\cdot v+\sigma\cdot v\cdot w^s)\cdot\lambda^c}{w^p+w^r+w^s} \tag{5g}$$

$$u_i^e=\frac{(1-\tau^e)\cdot F-(d^r+w^p\cdot v+\sigma\cdot v\cdot w^s)\cdot\frac{\lambda^e\cdot E_i}{E_i-\frac{\delta\cdot\kappa_i}{2}\sqrt{\frac{A}{D}}}}{w^p+w^r+w^s+w_i^c}-\eta_i^e \qquad \forall i\in M \tag{5h}$$

$$N_i=N_i^0\cdot\left(1-\frac{1}{1+e^{\theta(u^c-u_i^0)}+e^{\theta(u_i^e-u_i^0)}}\right) \qquad \forall i\in M \tag{5i}$$

$$\varphi_i=\frac{1}{1+e^{\theta(u^c-u_i^e)}} \qquad \forall i\in M \tag{5j}$$

To numerically illustrate the effect of driver and vehicle heterogeneity on market equilibrium and policy analysis, we consider a ridesourcing system with full-time (denoted as f) and part-time (denoted as p) drivers, i.e. $M=\{f,p\}$. Full-time drivers fully rely on public chargers and part-time drivers fully rely on home-charging, i.e., $\epsilon_f=1$ and $\epsilon_p=0$. Vehicle types are assumed to be homogeneous with battery size E and energy efficiency κ due to the lack of empirical data. The equilibrium results are qualitatively consistent with the previous results in Section 4. The only difference is part-time drivers fully rely on home-charging and experience no charging delay, i.e., $\hat{w_p^c}=w_p^c=0$. The e-VMT rate of part-time drivers is unaffected by charger construction and there is no gap between e-fleet rate and e-VMT rate, i.e., $\varphi_p=\phi_p$.

Then we examine how will the driver heterogeneity influence the platform's optimal response and proposed regulatory policies. More specifically, the government uses AP to electrify a ridesourcing systems with both full-time and part-time drivers to an e-VMT rate of $\phi=90\%$. We set the target e-VMT rate as $\hat{\phi}=90\%$ and use sufficient penalties to achieve this target e-VMT rate. Numerical analysis shows that the platform takes different strategies to electrify the full-time and part-time drivers. For part-time drivers, there is no need to upgrade home-charging facilities and the platform should set lower commission rates on EVs to attract drivers. Besides lowering commissions on EVs, charger construction is necessary to decrease charging downtime and attract full-time drivers.

As shown in Fig. 18, considering part-time drivers can make the electrification process either easier or harder, depending on part-time drivers' vehicle upgrade cost. As illustrated in Fig. 18(a), when the vehicle upgrade cost for part-time drivers is high (denoted as scenario 'high'), it is more difficult to attract part-time drivers to use EVs than full-time drivers and $\phi_p<\phi_f$. The platform must largely raise the commission rates on CVs as the proportion of part-time drivers increases (see Fig. 18(b)). Meanwhile, more part-time drivers replace the need for public charging with the need for home-charging, requiring a smaller charging network.

Moreover, the basic model assumes one public charging station has one charger. We can relax this assumption and assume the platform constructs D charging stations with S chargers in each station. Then the queuing process at each charging station is a M/D/S queue with S homogeneous servers in parallel. The arrival rate of each charger is $\frac{\hat{K}}{D\cdot S}$ and service rate is $\frac{P}{E}$. As a result, the average queuing time experienced by one arriving EV is $\frac{\hat{K}\cdot E^2}{2P\cdot(D\cdot S\cdot P-\hat{K}\cdot E)}$ and the recharging time is $\frac{E}{P}$. Under this setting, EV drivers

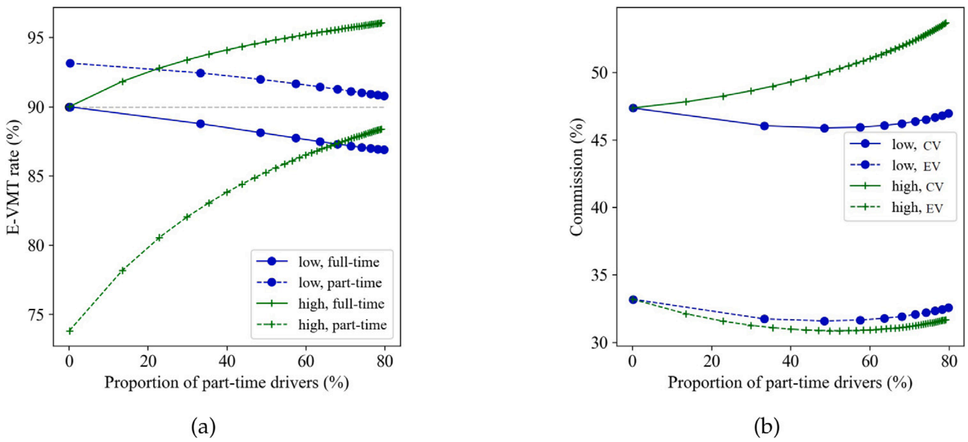


Fig. 18. The effects of proportion of part-time driver on (a) e-VMT rates and (b) optimal commission rates.

prefer many small charging stations over one large charging station because evenly distributing the chargers over the whole space reduces the traveling time.

8. Conclusions

We have explored three potential regulatory policies, i.e., annual permit fees or AP, differential trip-based fees or TB, and differential commission caps or CC, and discussed their effectiveness, cost-efficiency and feasibility considering the platform's response strategy. We have developed an aggregate modeling framework capturing the behavioral difference of EV drivers and the impact of charging downtime on drivers and customers. Our numerical analyses lead to the following insights.

- AP and TB are viable choices if the government targets at high e-VMT rates, say 90%. TB is less cost-efficient as the platform delivers fewer customers to avoid the trip-based fees and surcharges drivers and customers for higher per-trip profits under TB.
- CC is effective for low-level electrification but turns out to be the most cost-efficient, as it simultaneously benefits drivers and customers and allows finer intervention to the market.
- The platform should adopt chargers with high charging power and gradually expand the charging network to accommodate the charging needs of the expanded EV fleet.
- Small batteries are preferred to avoid high upgrade costs for EVs under all proposed policies.
- Favorable commissions for EVs are only needed for high e-VMT rates under AP and TB.

To facilitate the analysis and comparison of various types of regulatory policies, this study made several assumptions regarding EV drivers' charging behaviors, some of which may be deviated from the real-world observation and should be relaxed in the future to consider more elaborate policies. First, chargers are assumed to be identical and uniformly distributed, so each EV driver will choose her nearest charger for charging and every charger thus has the same queue length. In reality, however, there may be different types of chargers with different charging powers and prices located unevenly in the urban area, and EV drivers thus do not necessarily choose their nearest chargers. Furthermore, in this study, EV drivers are assumed to be homogeneous regarding their charging behaviors. For example, every EV driver will head to chargers when the battery can only support the trip to her target charger, and fully recharges the battery at each charging event. Nevertheless, empirical data has shown that different EV drivers may have different preferences regarding, say, their remaining battery SOC before charging and desired SOC after charging. For example, based on a real-world large-scale data set in Shanghai, we found that, on average, the former can be as high as 58%, while the latter can be as low as 78% (Li et al., 2022). To relax the above assumptions, we can apply the causal inference process to specify the critical factors impacting EV drivers' charging behaviors, including when and where to charge, and establish tractable behavioral models to capture such impacts. Integrating the behavioral models, simulation-based optimization platforms can be developed to optimize the design of a variety of sophisticated regulatory policies and examine their performance. A possible alternative approach is to divide the study area into a set of subareas, in each of which the chargers are evenly distributed. Incorporating the established behavioral models into our proposed modeling framework can delineate the operation of EV drivers in each subarea, and the macroscopic fundamental diagram (MFD) framework (Geroliminis and Daganzo, 2008) can then be applied to capture the complex interaction among these subareas. Accordingly, the design of various policies can be optimized and their performance can be examined and compared.

While our model analyzes the policy effect and captures the platform's response strategy under market equilibrium, it only considers a long-run steady state. As the ridesourcing market gradually evolves to a highly electrified level, a few questions arise in the context of time-dependent development. For example, the battery and charging technology update rapidly (Sun et al., 2020), suggesting that the cost function may be time-dependent, and optimal strategy design also changes with time. Moreover, the temporal distribution of ridesourcing drivers' charging needs are imbalanced within one day, and we did not consider these within-day dynamics in the current model. More in-depth analysis of these aspects is needed if the platform targets at operational strategies.

Additionally, this study considers a monopoly market with homogeneous customers. Customers are surely not uniform in reality. Some of them are pool riders, and their trip distances vary. Considering such heterogeneity of customers in matching promises to further reduce emissions in the ridesourcing sector. Related studies will be pursued in our future work. Lastly, in this study, we consider a fixed average operating speed and ignore the effect of traffic congestion. Nevertheless, traffic congestion has been shown to have a significant impact on vehicles' speed, drivers' income, trip fares imposed on passengers, and the platform's revenue (Vignon et al., 2021; Beojone and Geroliminis, 2021; Li et al., 2021). Thus, future research can extend the proposed models by taking into account the congestion impact.

CRediT authorship contribution statement

Zhichen Liu: Methodology, Writing – original draft, Software, Visualization. **Zhibin Chen:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Yafeng Yin:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Zhengtian Xu:** Conceptualization, Methodology.

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