Twisting the Toll: Electric Vehicles and Information Provision

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Abstract

The transportation sector generates the largest share of greenhouse gas emissions, which concerns governments and communities worldwide. Electric vehicles (EVs) are believed to be the future. Various incentives have been provided to further broaden their acceptance and accelerate their adoption, including toll-exemption programs for EVs. At the same time, an individual's driving behaviors are largely shaped by navigation applications that provide real-time traffic conditions. In this paper, we aim to understand how information provision affects the optimal structure of the EV-exempt toll. By analyzing a Bayesian routing game, we illustrate the optimality of a non-monotonic tolling strategy as a function of the EV adoption rate. For policymakers, our finding reveals the importance of understanding how the IT-enabled information provision has altered individual drivers' behavior. In addition, the results uncover the general impact of IT, which expands the action space of individuals and the effective regimes of policies.

Keywords: Electric Vehicles, Toll Strategy, Information Design

Introduction

Climate change and global warming have become severe issues that concern governments and communities worldwide. As the largest source, the transportation sector generates approximately 7.3 billion metric tons of carbon dioxide (CO_2) emissions (EPA 2021; Statista 2021). In the United States, in November 2021, Congress passed the Bipartisan Infrastructure Deal (Infrastructure Investment and Jobs Act) – a "once-in-a-generation" investment in nation's infrastructure. The aims of this historic legislation include rebuilding roads and bridges with a focus on climate change mitigation and establishing a national network of electric vehicle (EV) chargers. This latter goal also complements President Joe Biden's executive order signed in August 2021 that called for half of all new vehicles sold in 2030 zero-emissions vehicles. Though EV is seeing an unprecedented surge since the 21st century, various incentives have been provided to further broaden its acceptance and accelerate its adoption. For instance, in Atlanta, EVs are exempt from tolls when using some of the express lanes (ElectrifyAtlanta 2022).

Together with the arising new transportation-related rules and policies are the dramatic changes in individual's driving behaviors and habits. The old days of secret shortcuts are far behind us. The advancement of new information technology enables more sources of information for drivers to make routing decisions. Drivers count on mobile applications like Google Maps and Waze for navigation. With the development of Internet of Things (IoT) technology, smartphones and other digital devices have become ubiquitous. It facilitates the collection of a vast array of data and enables the real-time distribution of data to everyone – it is much easier for drivers to be aware of real-time traffic conditions and quickly adapt to them.

Presumably, granting access to a growing amount of accurate data provides an opportunity for better decision-making. However, the indirect impact of such emerging technology is often neglected. Prior theory underscores the important mediating role of individuals in linking macro-level variables (Coleman 1986; Coleman 1994; Melville 2010). The macro-level factor of the wide-spreading IoT technology shapes individual driver's actions, which will further affect the effectiveness of macro-level policies. If policymakers fail to recognize such links, rules or regulations may turn out to be suboptimal. Thus, in this study, we are interested in analyzing the context where social planners implement environmental-oriented transportation policies, while at the same time, traffic patterns are largely shaped by navigation apps that share real-time traffic information.

In this paper, we focus on the practice of concessional or discount for toll fees for EVs, which has been implemented by various states and provinces, including California, Georgia, Florida, Minnesota, and British Columbia. For example, in California, the Clean Air Vehicle program allows EVs to use HOV lanes and includes a 15% discount on the I-10 and I-110 Metro ExpressLanes (Fowler et al. 2018). In addition, the National Highways Authority of India (NHAI) has been considering a similar option of exempting electric vehicles from toll fees (ET Bureau 2019). Observing such sustainability-oriented programs, we are interested in understanding their interplay with individual's driving patterns, which have been influenced by the live traffic information provided the navigation apps. Specifically, this study asks the research questions: *How does the IT-enabled traffic information provided by the navigation apps affect the effectiveness of the EV-toll exemption policy? How should the city planner better set the EV-exempt toll to control* CO_2 *emissions?*

To answer the above research questions, we develop a Bayesian routing game with two types of vehicles – electric vehicles (EVs) and gasoline vehicles (GVs). All vehicles will receive updates about the traffic condition on the roads from a navigation app. Based on the information they receive (although it may not be fully accurate), vehicles update their belief about the traffic condition and choose their routes strategically. The city planner sets tolls on a road. However, EVs will be exempt from the toll. The objective of the city planner is to control GVs' emissions by mitigating the congestion that they experience. This modeling framework we employ is general enough to incorporate different information-provision scenarios. To be specific, the parameters of the information accuracy can be adjusted to accommodate different levels of the richness of IT-enabled information provision. To one extreme, we can set the accuracy parameters to assume that all vehicles receive completely precise traffic conditions. On the other hand, we can adjust the accuracy parameters to a scenario where vehicles do not have access to any traffic information. The latter case serves as the benchmark model, as we compare the optimal toll structure under other information-provision scenarios to that of the benchmark. This comparison allows us to conduct comparative studies to understand how traffic information provision and accuracy affect the equilibrium vehicle flows and the toll structure.

Analyzing the equilibrium flows of both types of vehicles and deriving the optimal toll yield several key findings. First, we find that providing traffic information to vehicles has a separating effect. Specifically, compared to the benchmark model, providing traffic information splits the equilibrium regimes and expands the action space of vehicles. This finding serves as a basis for investigating the optimal toll. Second, we discover that providing information to vehicles will impose a structural change to the optimal toll. In the benchmark model, we find that the optimal toll has a monotonic nature in the EV adoption rate – the higher the adoption rate, the less powerful tolling as a tool to control GV congestion and emissions, and the lower the optimal toll. Surprisingly, this monotonic structure no longer holds when vehicles have access to traffic condition updates. Specifically, our analysis reveals that a turning point in the EV adoption rate exists, such that the optimal toll jumps dramatically at this point while maintaining a decreasing pattern in regions above and below it. Such an abrupt changing the toll pattern as a function of the EV adoption rate stems from the separating effect when potentially different traffic information is provided to vehicles. As the city planner has to take into account the distinct route decisions of vehicles under disparate traffic conditions, a non-monotonic tolling strategy emerges. Our findings reveal, for policymakers, the importance of understanding how individual drivers' behavior has been shaped by the IT-enabled information provision, when applying the pricing weapon. In general, the results also uncover the impact of IT, which expands the action space of individuals and the effective regimes of policies.

The remainder of this paper is organized as follows: In §2, we present the model. Then, in §3, we analyze the equilibrium outcome of the full model, together with that of the benchmark model in which drivers do not receive traffic condition updates. In §4, we examine the city planner's optimal tolling strategy and discuss the impact of information provision. We conclude the paper with a discussion of future directions in §5.

Related Work

Both academia and industry have joined the extensive discussion about information technology and sustainability. A recent survey by IBM suggests that 42% of the 5,000 CIOs and CTOs polled said sustainability was the area where information technology would have the biggest impact on their organization, which has been leading the effort to switch from power-hungry computer-processing applications to the cloud (Bousquette 2022). Research also has empirically and theoretically analyzed the interplay between green IT practice and organization performance. Seidel et al. (2013) propose information system-enabled organizational change to adjust for better sustainability transformation Khuntia et al. (2018) demonstrate a positive association between green IT investment and a higher profit impact surveying nearly 300 organizations in India. (Plambeck and Wang 2009) construct a stylized model to analyze how different forms of e-waste regulation affect new product introduction. As the relationship between digitization and carbon-based emissions becomes more evident (Gelenbe and Caseau 2015), there is a greater need for research to understand the transformative power of IS in creating an ecologically sustainable society (Watson et al. 2010). Dao et al. (2011) introduce an integrated theoretical model in helping firms coordinate bundles of complex human and non-human resources to achieve sustainability goals. In addition, Melville (2010) constructs a belief-action-outcome (BAO) framework subsuming both macro and micro perspectives. Relevant to the topic we study, Cheng et al. (2020) consolidate a longitudinal data set on road traffic and the deployment of intelligent transportation systems, and illustrate a significant decrease in traffic congestion following the adoption of the systems. Our research builds upon Melville (2010) with a combination of micro and macro levels, and formalizes how IT-enabled information sharing strategy affecting individual behaviors can potentially shape the decisions of sustainability-oriented city planners.

Another relevant literature to our study is the discussion of the interaction between information technology and public policy. Rothwell and Wissema (1986) show dependency on cultural factors and how the public acceptance of new technology is stimulated by public policies in certain areas. Tolbert and Mossberger (2006) propose leveraging information technology and e-government to improve interactions with citizens, leading to better trust in government. However, the diffusion of new technology also raises concerns from several public policy perspectives. For example, new technology may reduce household incomes for low and median-income households Ding et al. (2011). Gordon (2012) concludes that recent changes in productivity are a permanent phenomenon, which suggests the changes in income may also be long-term without suitable policy intervention. Some technological optimists also argue that there will be new progress in technology, the labor just needs to adapt to the new market (Brynjolfsson and McAfee 2011). Our research shed insights on how the policy should be designed with the adoption of new technology.

Lastly, our work is related to the studies focusing on strategies to mitigate traffic congestion. Congestion pricing was studied extensively since it adjusts all aspects of drivers' behaviors, including their route choices, time of day, etc. (Chen et al. 2020; De Palma and Lindsey 2011). However, its effectiveness is ambiguous: Baghestani et al. (2020) suggest positive performance; little support to limit demand for car use in urban areas was also shown (Metz 2018). Many other approaches were studied to reduce traffic congestion, including using a smart parking system (Kazi et al. 2018), a dynamic road incident information delivery strategy (Qi et al. 2018), and more compact metropolitan land-use patterns (Ewing et al. 2018), etc. In terms of using IT to mitigate traffic, existing studies have focused on real-time path planning (Guo et al. 2018), route-and-departure-time assignment (Yu et al. 2020) and intelligent transportation systems (Cheng et al. 2020). Two studies are particularly related to our study while focusing on different objectives. Acemoglu et al. (2018) study how changes in the information sets of users in a traffic network impact the traffic equilibrium in a congestion game, abstracting the effects of additional information received by drivers. Wu et al. (2021) study a routing game in an environment with multiple heterogeneous information systems. We also adopt a Bayesian persuasion framework as in Wu and Amin (2019) and Wu et al. (2021). On top of it, we introduce EVs to the model and aim to understand how tolling can potentially interplay with the information design strategy.

Model

We consider a traffic routing problem on a road network with two parallel roads $R = \{r_1, r_2\}$ which share the common origin and destination. For each road $r \in R$, there is an associated load-dependent cost (latency) function $c_r^\omega(\cdot)$ that may vary across the state of nature $\omega \in \Omega$. For simplicity, we assume $\Omega = \{a, n\}$ following the literature (Wu and Amin 2019). The state a ("accident") corresponds to an accident on r_1; and state n ("nominal") indicates no accident. There are two types of vehicles, electric vehicles (EVs) and gasoline vehicles (GVs). The total traffic demand is denoted by D and the fraction of EVs is denoted by $\lambda \in [0, 1]$. All drivers have a common prior belief on the distribution over states. We assume that an accident happens with probability of p, which is denoted by θ, where $\theta(a) = p$ and $\theta(n) = 1 - p$. The cost functions of roads are defined as

$$c_1^\omega(f_1) = \alpha_1^\omega f_1 + b_1,$$
$$c_2(f_2) = b_2.$$

We assume the cost function of road r_1 is state-dependent, while the cost function of road r_2 will not change by the state. Moreover, we assume that $\alpha_1^a > \alpha_1^n$ and $b_1 < b_2$. To be specific, we assume that Road 1 is "shorter" than Road 2 in that its free-flow travel time is smaller, i.e. $b_1 < b_2$. In addition, the congestion rate α_1^a is larger than α_1^n in the n state ("normal"). That is, if an accident happens, as the traffic flow increases, the travel time increases at a higher rate relative to a normal state. We also assume that $D > \frac{b_2 - b_1}{\alpha_1^n}$ to avoid trivial solutions.

Access to real-time traffic information: an information design framework

Drivers often seek real-time information and routing guidance from navigation applications to better understand the traffic situation. We consider the effect of such information technology and model it using the framework of Bayesian Persuasion (Kamenica and Gentzkow 2011). We assume that such apps keep drivers updated based on traffic situations of whether an accident happens. We call such an app an "information designer", who is able to influence an individual's optimal decision via the information conveyed (Bergemann and Morris 2019). The information designer will provide vehicles with traffic information in the form of a "signal", denoted by s. As shown by Kamenica and Gentzkow (2011), WLOG, we can restrict our attention to a set of signals which has the same domain as the state. That is, $s \in S = \{a, n\}$. The information designer commits to an information-provision mechanism to convey the traffic information. Such a mechanism defines the probability of sending each signal given a state. To be more specific, we use $\pi(s|\omega)$ to denote the probability of sending signal s when the state is ω. Then, $\pi(a|\omega) + \pi(n|\omega) = 1, \ \forall \omega \in \Omega = \{a, n\}$. And the information-provision mechanism can be presented by a family of distributions $\{\pi(\cdot|\omega)\}_{\omega\in\Omega}$. WLOG, we assume that

$$\pi(a|a) \geq \pi(n|a) \text{ and } \pi(n|n) \geq \pi(a|n). \tag{1}$$

These two inequalities assume that, if the true state is a (or n), then the information designer will be more likely to send signal a (or n). We can make this assumption without loss of generality since by switching signals a and n, we can obtain an equivalent information structure.

For vehicles, when receiving signal s, update their belief about the traffic state by the Bayesian rule. Specifically, the posterior of a vehicle is

$$\beta^s(\omega) = \frac{\theta(\omega)\pi(s|\omega)}{\sum_{\omega\in\Omega}\theta(\omega)\pi(s|\omega)} = \frac{\mu(s,\omega)}{P(s)}, \tag{2}$$

where $\mu(s,\omega) \triangleq \theta(\omega)\pi(s|\omega)$ is the joint probability of signal s and state ω, and $P(s) \triangleq \sum_{\omega\in\Omega}\theta(\omega)\pi(s|\omega)$ is the marginal probability with which the information designer sends signal s. The posterior $\beta^s(\omega)$ represents a driver's belief about the probability of the state to be ω when receiving signal s, and $\beta^s(a)+\beta^s(n) = 1, \ \forall s \in S$. By assumption (1), $\beta^a(a) \geq p$ and $\beta^n(n) \geq 1-p$, which means that, after receiving signal a (or n), the driver will believe that the accident is (or not) indeed happening with a probability no less than prior probability p (or $1-p$).

To illustrate the idea of information design, consider an example of the apps sending completely accurate signals:

$$\begin{aligned} &\pi(a|a) = 1, \ \pi(n|a) = 0, \\ &\pi(a|n) = 0, \ \pi(n|n) = 1. \end{aligned} \tag{3}$$

That is, when an accident is (or not) happening, the information designer precisely informs all vehicles about it. Then, by (2), the posteriors $\beta^a(a) = \beta^n(n) = 1$ and $\beta^a(n) = \beta^n(a) = 0$. That is, the driver will believe that there is (or not) an accident if she receives signal a (or n), since the information designer commits to truthfully convey the traffic information. Now, consider another example where the information structure is given by

$$\begin{aligned} &\pi(a|a) = 0.5, \ \pi(n|a) = 0.5, \\ &\pi(a|n) = 0.5, \ \pi(n|n) = 0.5. \end{aligned} \tag{4}$$

In fact, this information structure is completely uninformative. To see this, consider drivers update her belief when receiving either signal based on (2), knowing this information provision strategy. The posterior is, in fact, the same as the prior, $\beta^s(\omega) = \theta(\omega), \ \forall s, \omega$.

The above examples illustrate two extreme cases, fully informative and uninformative, of the information-provision mechanisms. In our analysis, we do not restrict to any special form of mechanisms, but instead, consider a general representation of such a mechanism. The navigation apps may have limited capability to collect accurate real-time traffic information. The accuracy of the traffic information provided can be captured by the informativeness of signals sent by the information designer. And we are also interested in understanding how information mechanism affects public policy.

The equilibrium and the tolling strategy

As discussed in §1, to reduce traffic congestion and GHG emission, the central authority sets a toll to regulate the traffic flow. We assume that, EVs are exempt from such a toll, while GVs are subject to toll τ assessed for passage on r_1. The route selection strategy of vehicles is a function of the received signal and toll. For GVs, we use $q^G = (q_r^G(s,\tau))_{r\in R, s\in S}$ to denote the amount of GVs taking road r when receiving signal s and toll τ. Similarly, for EVs, we use $q^E = (q_r^E(s,\tau))_{r\in R, s\in S}$ to denote the number of EVs taking road r when receiving signal s and toll τ. Define $q = (q^E, q^G)$ as the strategy profile[1]. With these, the flow vector is $f = (f_r(s,\tau))_{r\in R, s\in S}$, where $f_r(s,\tau) = q_r^E(s,\tau) + q_r^G(s,\tau)$.

Given any strategy profile q, the expected cost of road r for EVs is

$$EC_r^E(s,\tau) \triangleq \mathbb{E}[c_r(f)|s] = \sum_{\omega\in\Omega} \beta^s(\omega) c_r^\omega(f_r(s,\tau));$$

and the expected cost for GVs is

$$EC_r^G(s,\tau) \triangleq \mathbb{E}[c_r(f) + \tau \mathbb{1}_{\{r=r_1\}}|s] = \sum_{\omega\in\Omega} \beta^s(\omega) c_r^\omega(f_r(s,\tau)) + \tau \mathbb{1}_{\{r=r_1\}}.$$

With these, we define the equilibrium: The routing strategy profile q^* is an equilibrium, if for any $r, r' \in R$, and any $s \in S$,

$$q_r^{E*}(s,\tau) > 0 \Rightarrow EC_r^E(s,\tau) \le EC_{r'}^E(s,\tau),$$
$$q_r^{G*}(s,\tau) > 0 \Rightarrow EC_r^G(s,\tau) \le EC_{r'}^G(s,\tau).$$

The above conditions require that, there will be EVs (or GVs) traffic on road r only when the expected cost of using r is no higher than the expected cost of using r'.

Lastly, with the equilibrium flow defined, we describe the objective of the city planner when optimizing the toll τ. We assume that the city planner aims to minimize congestion cost for GVs under the equilibrium, taking the information-provision mechanism as given. Thus, its optimization problem can be defined as to minimize

$$ETC \triangleq \sum_{r\in R}\sum_{s\in S}\sum_{\omega\in\Omega} P(s)\beta^s(\omega) c_r^\omega(f_r^*(s,\tau)) q_r^{G*}(s,\tau).$$

We introduce this objective function for the following reasons. As shown by the literature, the CO_2 emissions in grams per kilometer is a U-shape function of the vehicle speed (Barth and Boriboonsomsin 2008). Specifically, in the low-speed zone (speed less than 40 mph), emissions decrease in speed, remain relatively flat in the mid-speed zone (speed between 40 mph and 60 mph), and increase in speed in the high-speed zone (speed greater than 60 mph). Thus, for the environmental-cost-driven central authority, controlling emissions is aligned with mitigating congestion. Since GVs are the main source of CO_2 emissions, we set the objective to be minimizing the congestion cost for GVs.

Variables	Definition
D	The total traffic demand
λ	The fraction of electric vehicles
$r_j, j \in \{1,2\}$	Two parallel roads
$\omega \in \Omega$	Two states, $\omega = a$ for an accident on r_1, $\omega = n$ for no accident
$\theta(\omega)$	The probability of being at state ω
α_1^ω	The cost of road r_1 depends on state ω
$b_j, j \in \{1,2\}$	Fixed costs for road r_1 and r_2
$s \in S = \{a, n\}$	The signal sent by the information designer
$\beta^s(\omega)$	A driver's Bayesian belief of being at state ω when receiving signal s
$q_r^E(s,\tau)$	The number of EVs on road r when receiving sign s and the toll set as τ
$q_r^G(s,\tau)$	The number of GVs on road r when receiving sign s and the toll set as τ

Table 1. Summary of Notation

The Benchmark Model

To understand the impact of information-provision mechanism on the equilibrium and the related public policy, we introduce a benchmark model where drivers do not have access the the real-time traffic information provided by navigation apps. Under such a scenario, the drivers make route selection decision minimizing the expected costs given their prior belief about the traffic condition and the toll. To be more concrete, we use $\bar{q}^G = (\bar{q}_r^G(\tau))_{r\in R}$ and $\bar{q}^E = (\bar{q}_r^E(\tau))_{r\in R}$ to denote the number of GVs and EVs taking road r given toll τ, respectively, and define the flow vector $\bar{f} = (\bar{f}_r(\tau))_{r\in R}$, where $\bar{f}_r(\tau) = \bar{q}_r^E(\tau) + \bar{q}_r^G(\tau)$.

[1]We use superscripts "E" and "G" to denote EV and GV, respectively; subscripts are used to denote the roads.

Similar to the §3.2, given any strategy profile $\bar{q} \triangleq (\bar{q}^G, \bar{q}^E)$, the expected cost of road r for EVs is

$$\overline{EC}_r^E(\tau) \triangleq \mathbb{E}[c_r(\bar{f})] = \sum_{\omega\in\Omega} \theta(\omega) c_r^\omega(\bar{f}_r(\tau));$$

and the expected cost for GVs is

$$\overline{EC}_r^G(\tau) \triangleq \mathbb{E}[c_r(\bar{f}) + \tau \mathbb{1}_{\{r=r_1\}}] = \sum_{\omega\in\Omega} \theta(\omega) c_r^\omega(\bar{f}_r(\tau)) + \tau \mathbb{1}_{\{r=r_1\}}.$$

The routing strategy profile $\bar{q}^*$ is an equilibrium, if for any $r, r' \in R$,

$$\bar{q}_r^{E*}(\tau) > 0 \Rightarrow \overline{EC}_r^E(\tau) \le \overline{EC}_{r'}^E(\tau),$$
$$\bar{q}_r^{G*}(\tau) > 0 \Rightarrow \overline{EC}_r^G(\tau) \le \overline{EC}_{r'}^G(\tau).$$

Next, we define the objective of the city planner to optimize the toll τ when drivers do not have access the traffic information. Similar to the discussion above, we assume that the toll optimization problem can be defined as to minimize

$$\overline{ETC} \triangleq \sum_{r\in R}\sum_{\omega\in\Omega} \theta(\omega) c_r^\omega(\bar{f}_r^*(\tau)) \bar{q}_r^{G*}(\tau). \tag{5}$$

Note: The benchmark model can also be derived from the information design framework presented in §3.1&3.2. To see it, consider the uninformative mechanism shown by (4), which implies that $\beta^a(\omega) = \beta^n(\omega) = \theta(\omega), \ \forall\omega \in \Omega$. Thus, by the definition of equilibrium, $q_r^{G*}(a,\tau) = q_r^{G*}(n,\tau)$ and $q_r^{E*}(a,\tau) = q_r^{E*}(n,\tau), \ \forall r \in R, \tau$. That is, sending either signal will induce the same equilibrium strategy, which is in fact the equilibrium strategy $\bar{q}^* = (\bar{q}^{G*}, \bar{q}^{E*})$ defined above. However, to avoid any confusions, we use a separate set of notations to denote the expected costs and the corresponding strategies under the benchmark model when vehicles do not have access to the real-time traffic information.

Equilibrium

We start with analyzing the equilibrium strategy for the vehicle's routing selection decision. We first solve for the equilibrium under the benchmark model in §4.1 and extend the analysis when drivers could receive traffic information from the navigation apps in §4.2.

Equilibrium analysis for the benchmark model

First, we solve for the equilibrium flow under the benchmark case where there is no traffic information shared by the navigation apps Let $\bar{\alpha}_1 \triangleq p\alpha_1^a + (1-p)\alpha_1^n$, which represents the *prior* expectation of α_1^ω. The following Proposition 1 demonstrates the equilibrium flow on each road depending on the EV adoption rate λ and toll τ. When describing the equilibrium flows in the following proposition and all analyses beyond, WLOG, we focus on the flows of two types of vehicles on road 1

Proposition 1. *There exists a threshold on the EV adoption rate* $\bar{\lambda} \triangleq \frac{b_2-b_1}{\bar{\alpha}_1 D}$ *and a threshold based on the toll* $\tilde{\lambda}(\tau) \triangleq \frac{b_2-b_1-\tau}{\bar{\alpha}_1 D}$ *such that the strategy profile* $\bar{q}^*$ *in the equilibrium satisfies:*

(i) when $\lambda \ge \bar{\lambda}$*, then* $\bar{q}_1^{E*} = \frac{b_2-b_1}{\bar{\alpha}_1}, \bar{q}_1^{G*} = 0$*;*

(ii) when $\lambda < \bar{\lambda}$*, then*

$$\begin{cases} \bar{q}_1^{E*} = \lambda D, \ \bar{q}_1^{G*} = 0, & \textit{if } \lambda \ge \tilde{\lambda}(\tau), \\ \bar{q}_1^{E*} = \lambda D, \ \bar{q}_1^{G*} = \frac{b_2-b_1-\tau}{\bar{\alpha}_1} - \lambda D, & \textit{otherwise.} \end{cases}$$

Since GVs are subject to a toll for passage on road 1, from Proposition 1, it is intuitive to learn that there always exist some EVs taking road 1, and some GVs taking road 2 at the same time. Proposition 1 also reveals that the equilibrium for the benchmark model is divided into three regimes based on the EV adoption rate and the toll, as shown in Figure 1. If the portion of EVs is high, then EVs split into two roads and all the GVs take road 2. When the portion λ decreases, the equilibrium flow also depends on the toll. We define $\tilde{\tau}(\lambda) \triangleq b_2 - b_1 - \bar{\alpha}_1\lambda D$ which is the inverse function of $\tilde{\lambda}(\tau)$, and $\lambda \le \tilde{\lambda}(\tau) \Leftrightarrow \tau \le \tilde{\tau}(\lambda)$. When the toll is set to be above the threshold $\tilde{\tau}(\lambda)$ (or $\lambda \ge \tilde{\lambda}(\tau)$), a separating equilibrium emerges where all EVs take road 1 while all GVs take road 2. However, if the toll is below the threshold $\tilde{\tau}(\lambda)$ (or $\lambda < \tilde{\lambda}(\tau)$), then all EVs remain on road 1, but GVs split on two roads.

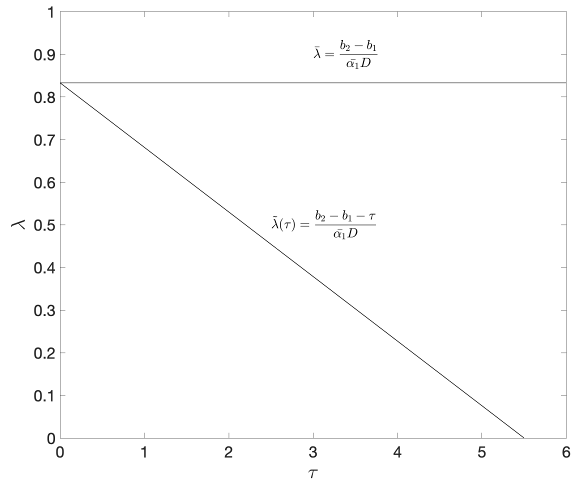


Figure 1. Illustration of Equilibrium Regimes. Parameters:
$\alpha_1^a = 15, \alpha_1^n = 2, b_1 = 12, b_2 = 18, p = 0.4, D = 1.$

Figure 2 shows how equilibrium flow changes under different EV adoption rate. When the toll does not exceed the difference between the non-congested travel cost of two roads (i.e., $\tau \le b_2 - b_1$), then there exists GVs that are willing to take road 1. Such GVs will start deviating to road 2 when the EV adoption rate increases and more EVs are present on road 1. Such deviation lasts until no GV is willing to deviate to road 1. Note that more EVs taking road 1 will also create competition among EVs and increase their congestion costs. EVs split on road 1 and road 2 when existing EVs already make road 1 congested enough. In comparison, when the toll is high enough (i.e., $\tau > b_2 - b_1$), no GV deviates from taking road 2 to road 1 as their expected cost is always lower when taking road 1 due to the high toll. In this case, all EVs will take road 1 until it is congested enough, making them split on road 1 and road 2, similar to the previous scenario.

Next, we assess how the equilibrium flow responds to different tolls. When the EV adoption rate is high ($\lambda > \bar{\lambda}$), setting a toll on road 1 will not affect the strategy profile of either type of vehicle. The reason is that the high volume of EVs will squeeze GVs out of road 1 for any non-zero toll, and all GVs will choose road 2. The strategy of EVs will not be affected by the toll when $\lambda \le \bar{\lambda}$, either. As shown by Figure 3, all EVs remain on road 1 for any toll ($\bar{q}_1^{E*} = \lambda D$). At the same time, the portion of GVs on road 1 will be affected by the toll – intuitively, $\bar{q}_1^{G*}$ decreases in τ.

Equilibrium analysis when drivers have access to traffic information

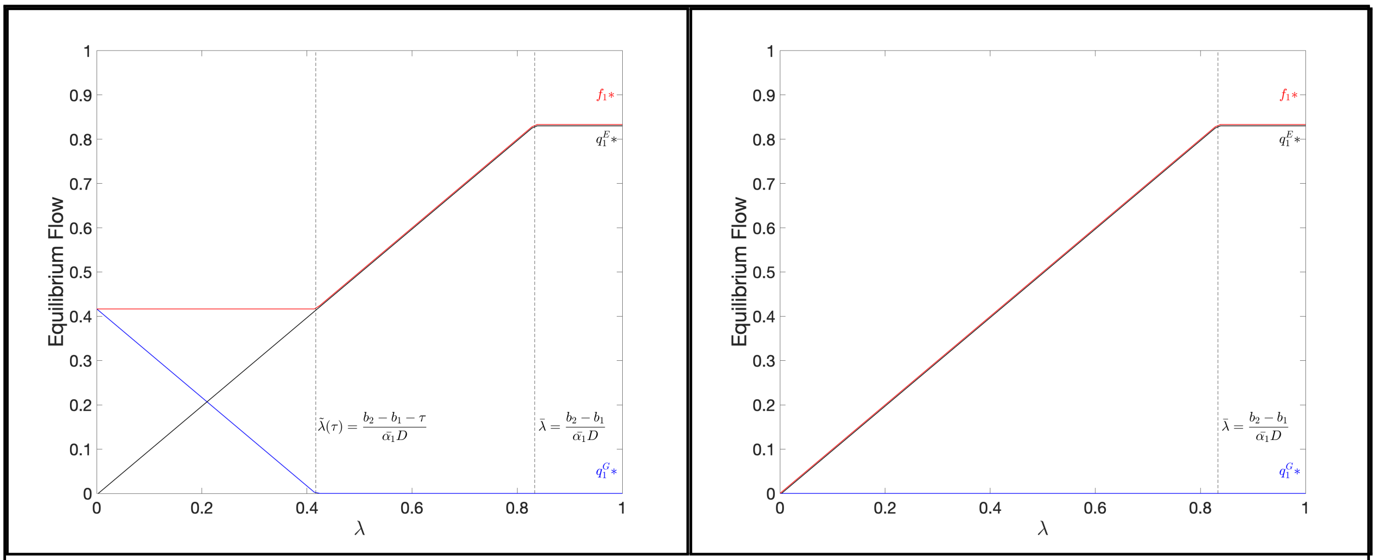
In this section, we characterize the equilibrium strategy when drivers have access to real-time traffic information. Let $\bar{\alpha}_1(\beta^s) \triangleq \beta^s(a)\alpha_1^a + \beta^s(n)\alpha_1^n$, which represents the *posterior* expectation of α_1^ω when receiving signal s. Specifically, $\bar{\alpha}_1(\beta^a) \triangleq \sum_{\omega\in\Omega} \beta^a(\omega)\alpha_1^\omega$, $\bar{\alpha}_1(\beta^n) \triangleq \sum_{\omega\in\Omega} \beta^n(\omega)\alpha_1^\omega$, and $\bar{\alpha}_1(\beta^a), \bar{\alpha}_1(\beta^n) \in [\alpha_1^n, \alpha_1^a]$. Also, by assumption (1), $\bar{\alpha}_1(\beta^a) \ge \bar{\alpha}_1 \ge \bar{\alpha}_1(\beta^n)$.

Proposition 2. *There exists two thresholds on the EV adoption rate,* $\bar{\lambda}^a \triangleq \frac{b_2 - b_1}{\bar{\alpha}(\beta^a)D}$ *and* $\bar{\lambda}^n \triangleq \frac{b_2 - b_1}{\bar{\alpha}(\beta^n)D}$ *with* $\bar{\lambda}^a \le \bar{\lambda}^n$*, together with two thresholds based on the toll,* $\tilde{\lambda}^a(\tau) \triangleq \frac{b_2 - b_1 - \tau}{\bar{\alpha}(\beta^a)D}$ *and* $\tilde{\lambda}^n(\tau) \triangleq \frac{b_2 - b_1 - \tau}{\bar{\alpha}(\beta^n)D}$ *with* $\tilde{\lambda}^a(\tau) \le \tilde{\lambda}^n(\tau)$*, such that the strategy profile* q^* *in the equilibrium satisfies:*

(i) when $\lambda \ge \bar{\lambda}^n$*, then* $q_1^{E*}(s) = \frac{b_2 - b_1}{\bar{\alpha}_1(\beta^s)},\ q_1^{G*}(s) = 0,\ \forall s \in S;$

(ii) when $\bar{\lambda}^a \le \lambda < \bar{\lambda}^n$*, then*

$$\begin{cases} q_1^{E*}(a) = \frac{b_2 - b_1}{\bar{\alpha}_1(\beta^a)},\ q_1^{G*}(a) = 0,\ q_1^{E*}(n) = \lambda D,\ q_1^{G*}(n) = 0, & \text{if } \lambda \ge \tilde{\lambda}^n(\tau), \\ q_1^{E*}(a) = \frac{b_2 - b_1}{\bar{\alpha}_1(\beta^a)},\ q_1^{G*}(a) = 0,\ q_1^{E*}(n) = \lambda D,\ q_1^{G*}(n) = \frac{b_2 - b_1 - \tau_1}{\bar{\alpha}_1(\beta^n)} - \lambda D, & \text{otherwise;} \end{cases}$$



a. When $\tau \leq b_2 - b_1$ **b. When $\tau > b_2 - b_1$**

Figure 2. Illustration of the equilibrium outcome and the impact of EV adoption rate. Parameters: $\alpha_1^a = 15, \alpha_1^n = 2, b_1 = 12, b_2 = 18, p = 0.4, D = 1.$

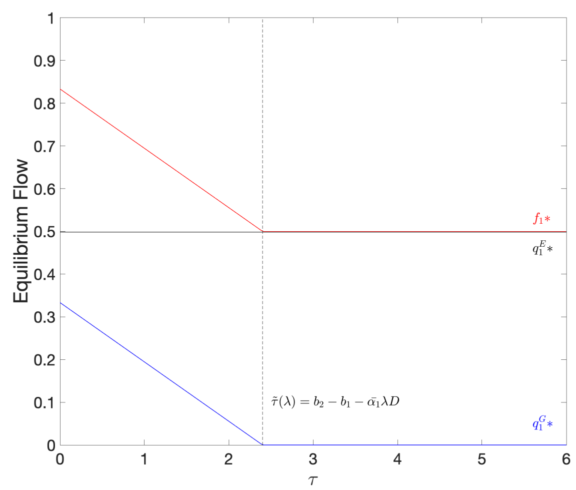


Figure 3. Illustration of the equilibrium outcome and the impact of toll when $\lambda \leq \bar{\lambda}$. Parameters: $\alpha_1^a = 15, \alpha_1^n = 2, b_1 = 12, b_2 = 18, p = 0.4, D = 1.$

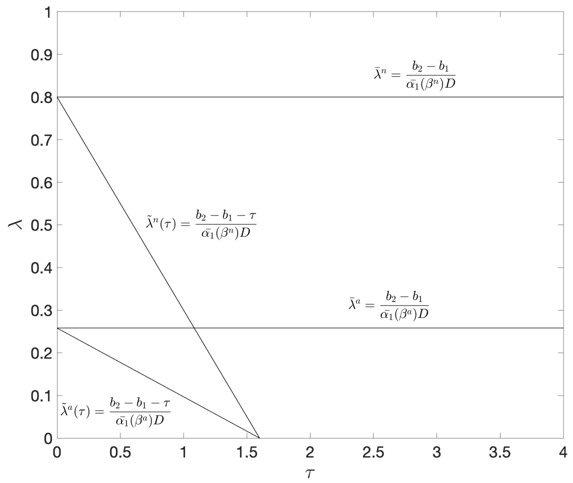


Figure 4. Illustration of equilibrium scenarios when $\tau_1 > 0$. Parameters: $\alpha_1^a = 8, \alpha_1^n = 2, b_1 = 14, b_2 = 18, p = 0.6, D = 2.5, \beta^n(n) = 1, \beta^a(a) = 0.7.$

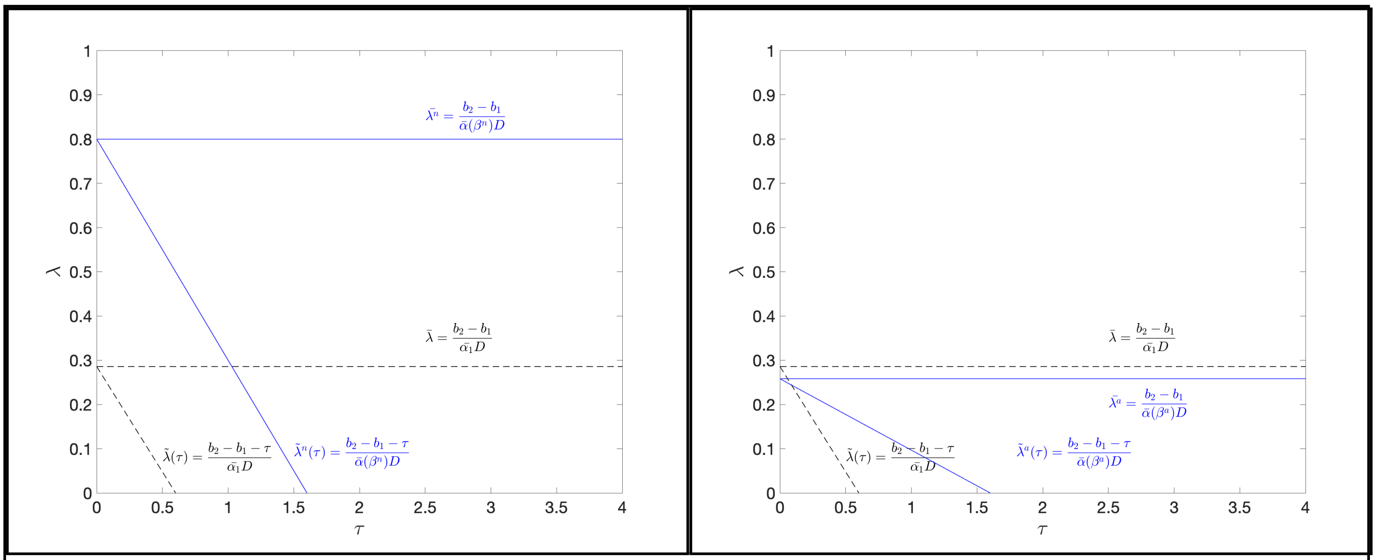
(iii) when $\lambda < \bar{\lambda}^a$, then

$$\begin{cases} q_1^{E*}(s) = \lambda D,\ q_1^{G*}(s) = 0,\ \forall s \in S, & \textit{if}\ \lambda \geq \tilde{\lambda}^n(\tau), \\ q_1^{E*}(a) = \lambda D,\ q_1^{G*}(a) = 0,\ q_1^{E*}(n) = \lambda D,\ q_1^{G*}(n) = \frac{b_2 - b_1 - \tau_1}{\bar{\alpha}_1(\beta^n)} - \lambda D, & \textit{if}\ \lambda \in [\tilde{\lambda}^a(\tau), \tilde{\lambda}^n(\tau)), \\ q_1^{E*}(s) = \lambda D,\ q_1^{G*}(s) = \frac{b_2 - b_1 - \tau_1}{\bar{\alpha}_1(\beta^s)} - \lambda D,\ \forall s \in S, & \textit{otherwise}. \end{cases}$$

Proposition 2 demonstrates the equilibrium outcome under different EV adoption rates, which are further moderated by the toll. We illustrate the above regimes in Figure 4. Compared to the benchmark model, drivers behave differently when receiving disparate information from the app. However, the structure of the equilibrium strategy of vehicles when either signal is received remains similar to that of the benchmark model. To see this, we present the strategy profiles in the equilibrium separately under each type of signal in Figure 5. By comparing to the benchmark model, Figure 5 clearly demonstrates an important *separating effect* of information provision from the app. Firstly, sending traffic information will split the equilibrium regimes defined by $\bar{\lambda}$ and $\tilde{\lambda}$ into signal-dependent regimes, defined by $\bar{\lambda}^s$ and $\tilde{\lambda}^s$ with $s \in S$ being the signal sent. On top of it, comparing to $\bar{\lambda}$ (or $\tilde{\lambda}$), $\bar{\lambda}^a$ (or $\tilde{\lambda}^a$) and $\bar{\lambda}^n$ (or $\tilde{\lambda}^n$) move in opposite directions. In other words, $\bar{\lambda}^a \leq \bar{\lambda} \leq \bar{\lambda}^n$ and $\tilde{\lambda}^a \leq \tilde{\lambda} \leq \tilde{\lambda}^n$. These observations also apply to the equilibrium strategy profiles. The intuition behind these findings is that, drivers of either type of vehicle make a routing decision based on the posterior of the traffic condition, updated by the information they receive from the app. A "no accident" signal will increase the number of vehicles taking road 1, while an "accident" signal does the opposite.

Figure 6 shows how equilibrium flows change with the EV adoption rate. Similar to the benchmark case, all EVs stay on road 1 when the EV adoption rate is low, and spill over to road 2 as the adoption rate reaches the threshold. However, the turning point varies based on the information about the uncertain traffic condition shared by the app. This disparity introduces an intermediate regime of the adoption rate where $\bar{\lambda} \in [\bar{\lambda}^a, \bar{\lambda}^n]$. When λ falls into this region, the traffic information from the app will affect a portion of EVs (equal to $\lambda D - \frac{b_2 - b_1}{\bar{\alpha}_1(\beta^a)}$), switching between road 1 and 2. When the adoption rate further increases and exceeds $\bar{\lambda}^n$, no matter what traffic information is shared, there will always be EVs taking road 2. Besides, the number of EVs switching between two roads based on the traffic information will be $\frac{b_2 - b_1}{\bar{\alpha}_1(\beta^n)} - \frac{b_2 - b_1}{\bar{\alpha}_1(\beta^a)}$. The traffic information also impacts the equilibrium flow of GVs. As the EV adoption rate increases, the equilibrium flow of GVs demonstrates a reversed and opposite pattern compared to that of EVs. No matter what signal is received, the equilibrium flow of GVs decreases linearly with the rise of the adoption rate. When a signal n is received, the initial equilibrium flow of GVs remaining on road 1 is higher compared with the case when a signal of a is received.

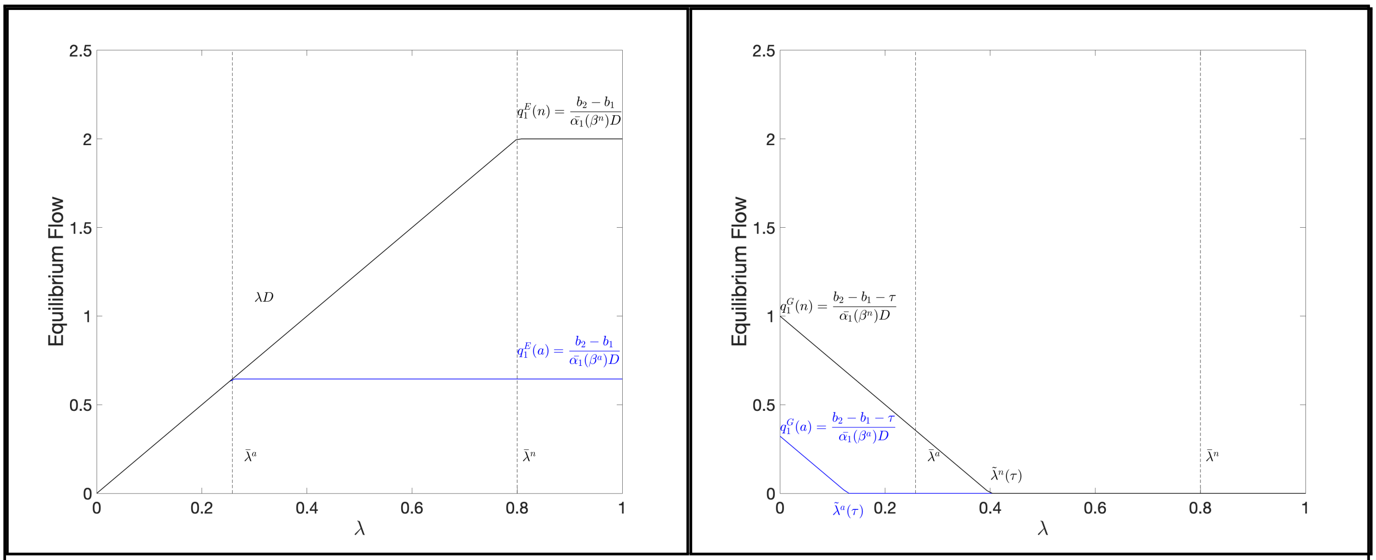
Next, we illustrate the comparative analysis of GVs' equilibrium flows with respect to toll in Figure 7. Here, we focus on the scenario when EVs do not dominate the market (i.e., $\lambda \leq \bar{\lambda}^n$). Similar to the impact of the EV adoption rate, the toll differentiates equilibrium into three regions. When a small toll is set such that $\lambda \leq \tilde{\lambda}^n(\tau)$, the number of EVs



a. Traffic information "no accident" (signal n) is received

b. Traffic information "accident" (signal a) is received

Figure 5. Illustration of equilibrium scenarios when $\tau_1 > 0$. Parameters:
$\alpha_1^a = 8, \alpha_1^n = 2, b_1 = 14, b_2 = 18, p = 0.6, D = 2.5, \beta^n(n) = 1, \beta^a(a) = 0.7.$



a. Equilibrium flows of EVs

b. Equilibrium flows of GVs

Figure 6. Illustration of the equilibrium outcome and the impact of EV adoption rate when $\tau \leq b_2 - b_1$. Parameters:
$\alpha_1^a = 8, \alpha_1^n = 2, b_1 = 14, b_2 = 18, p = 0.6, D = 2.5, \beta^n(n) = 1, \beta^a(a) = 0.7.$

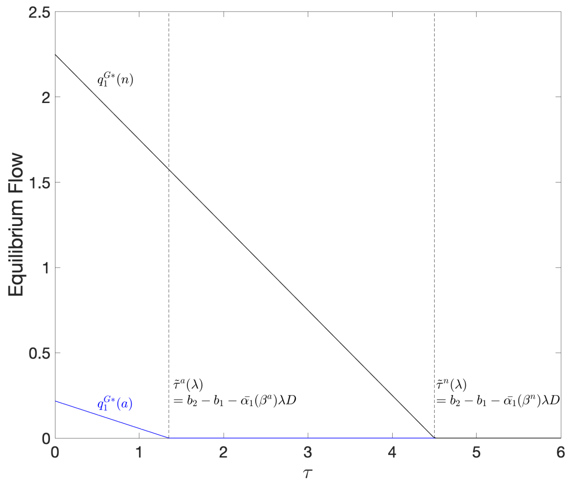


Figure 7. Illustration of the equilibrium outcome and the impact of toll when $\lambda \leq \bar{\lambda}^n$. Parameters: $\alpha_1^a = 8, \alpha_1^n = 2, b_1 = 14, b_2 = 18, p = 0.6, D = 2.5, \beta^n(n) = 1, \beta^a(a) = 0.7.$

switching between two roads based on the traffic information will be $\frac{b_2 - b_1 - \tau}{\bar{\alpha}_1(\beta^n)} - \frac{b_2 - b_1 - \tau}{\bar{\alpha}_1(\beta^a)}$, which decreases in τ. As the toll increases to a greater extent, if a signal a is received, the GVs, considering the higher chance of congestion due to an accident, all take road 2. And the portion of GVs switching between two roads further decreases until no GV joins road 1 when either signal is received. To summarize, when realizing a relatively higher probability of congestion, GVs still take the risk of taking road 1 when the toll is low. Otherwise, it does not worth separating and deviating from road 2.

The Optimal Toll

Thus far, we have analyzed the equilibrium strategies of drivers of both types of vehicles given the toll of accessing road 1 and the EV adoption rate. In this section, we derive the optimal toll that minimizes the expected congestion cost for GVs. As we have stated in §3, this objective demonstrates the sustainable consideration of the city planner to reduce emissions from GVs. We start with the optimal toll for the benchmark model, and then characterize that for the scenario where drivers have access to traffic information.

Optimal toll for the benchmark model

In the benchmark model, the equilibrium results in Proposition 1 indicate that the toll affects the equilibrium vehicle flows when the EV adoption rate is below the threshold $\bar{\lambda}$. We solve for the optimal toll based on the equilibrium flow by minimizing the objective $\overline{ETC}$ defined in (5). We summarize the result for the optimal toll in Proposition 3.

Proposition 3. *Setting a toll is effective when $\lambda < \bar{\lambda}$. Under such a condition, the optimal toll is $\bar{\tau}^* = \frac{1}{2}(b_2 - b_1 - \bar{\alpha}_1 \lambda D)$.*

Recall from the discussion following Proposition 1 that with a small portion of GVs, they will be discouraged by the toll set on road 1 and all take road 2. As a result, setting a toll on road 1 to regulate emissions from GVs will only be effective when $\tau < \tilde{\tau}(\lambda)$. Proposition 3 also shows that the optimal toll linearly decreases in λ, which is illustrated in Figure 8. Note that, for the toll, there always exists an interior optimal solution. That is, $\bar{\tau}^* \in (0, \tilde{\tau}(\lambda))$ as long as $\lambda < \bar{\lambda}$, indicating that the toll can effectively balancing the congestion of GVs on both roads to reduce the emissions.

In addition, $\bar{\tau}^*$ decreases with $\bar{\alpha}_1$, the prior expectation of α_1^ω. When an accident is more likely to happen (i.e., larger p), the higher the prior expectation will be. Recall that the equilibrium flow of GVs decreases with $\bar{\alpha}_1$ as shown in Proposition 4. The city planner can afford to set a lower toll to balance the congestion as more GVs are deviating to road 2 to avoid accidents.

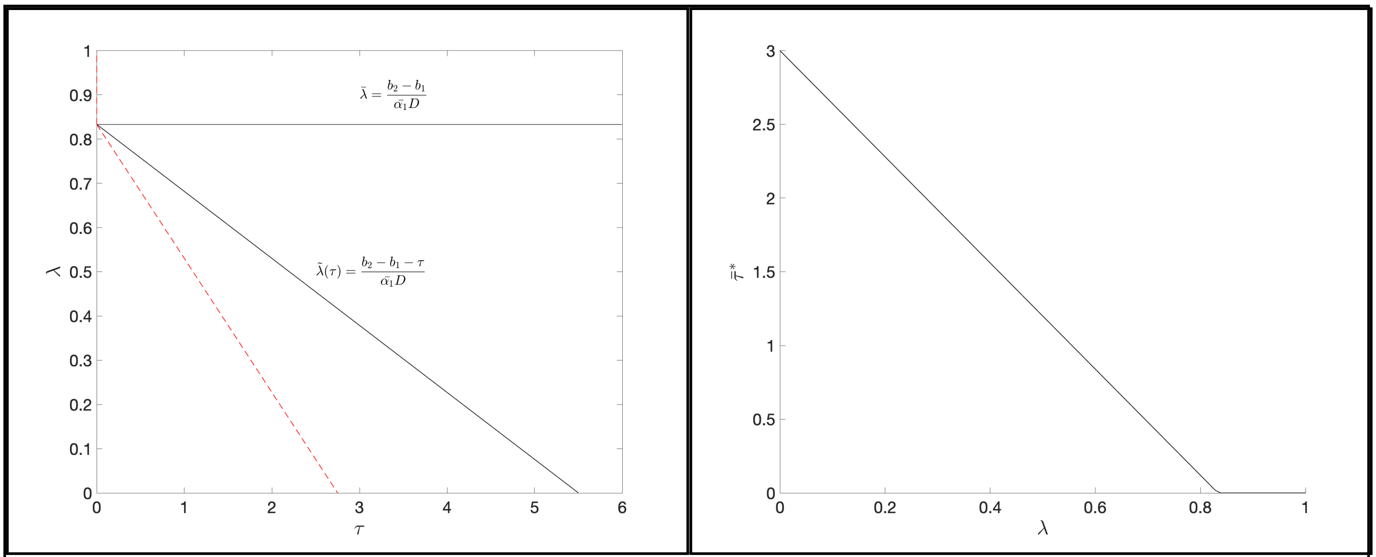


Figure 8. Illustration of the optimal toll for the benchmark model. Parameters: $\alpha_1^a = 15, \alpha_1^n = 2, b_1 = 12, b_2 = 18, p = 0.4, D = 1.$

Optimal toll when drivers have access to traffic information

In §4.2, we have characterized the equilibrium strategy profile, and the resulted traffic flows when vehicles have access to traffic information provided by the app. We have also shown how drivers behave differently when receiving disparate signals. In what follows, we derive the optimal toll in Proposition 4.

Proposition 4. *Setting a toll is effective when $\lambda \leq \bar{\lambda}^n$. Under such a condition, there exists a threshold $\hat{\lambda} \leq \bar{\lambda}^a$ such that the optimal toll satisfies*

(i) when $\hat{\lambda} < \lambda \leq \bar{\lambda}^n$, $\tau^* = \frac{1}{2}\left(b_2 - b_1 - \bar{\alpha}_1(\beta^n)\lambda D\right)$;

(ii) when $\lambda \leq \hat{\lambda}$, $\tau^* = \frac{1}{2}\left(b_2 - b_1 - \frac{\bar{\alpha}_1(\beta^n)\bar{\alpha}_1(\beta^a)}{P(a)\bar{\alpha}_1(\beta^n)+P(n)\bar{\alpha}_1(\beta^a)}\lambda D\right)$.

Similar to Proposition 3, the toll will be effective only if the EV adoption rate is not high, or in other words, there is a significant portion of GVs with some of them taking road 1 in equilibrium. However, note that the regime of λ within which setting a toll will be effective *expands*. When the app shares traffic information, the highest EV adoption rate below which the toll can potentially regulate the traffic congestion stretches to $\bar{\lambda}^n$, which is greater than $\bar{\lambda}$. As discussed in §4.2, providing traffic conditions to drivers expand their action space, leaving more room for the city planner to further regulate congestion using the price tool. In the intermediate adoption rate region $\lambda \in [\bar{\lambda}^a, \bar{\lambda}^n]$, the toll will be able to affect the routing decision of drivers when signal n is sent by the app, indicating a higher probability of "no accident". Thus, the toll optimization problem is similar to that of the benchmark model, except that the city planner has to consider the posterior travel cost factor $\bar{\alpha}_1(\beta^n)$ when the app sends signal n. The structure repeats that in the benchmark model for the region $[0, \bar{\lambda}]$. Similar to the discussion in §5.1 for the benchmark model, the optimal toll for this EV adoption rate region decreases in λ and $\bar{\alpha}_1(\beta^n)$.

What is more interesting is that when the EV adoption rate is below $\bar{\lambda}^a$, a turning point $\hat{\lambda}$ exists such that the optimal toll is no longer monotone in λ. In the low EV adoption region, for a given λ, recall from Proposition 2 that three possible scenarios emerge from different levels of the toll. When the toll is low, it will affect the traffic of GVs when either traffic information is sent; when the toll is moderate, it will only be effective when signal n is sent; otherwise, setting a toll will no longer be effective. These three possible scenarios change the structure of the city planner's objective as a function of the toll. Specifically, optimizing in the low-toll region requires considering the traffic pattern under both signals and the probability of sending either information. We define $\tilde{\tau}^s(\lambda) = b_2 - b_1 - \bar{\alpha}_1(\beta^s)\lambda D$ which is the inverse function of $\tilde{\lambda}^s(\tau)$, and $\tilde{\tau}^a(\lambda) \leq \tilde{\tau}^n(\lambda)$. When $\tau \in (\tilde{\tau}^a(\lambda), \leq \tilde{\tau}^n(\lambda)]$, the problem of optimizing toll is simplified as only the pattern under signal n need to be addressed. However, when $\tau \leq \tilde{\tau}^a(\lambda)$, the city planner has to account for the possibility of drivers receiving both types of traffic information. These potential different information regimes lead to distinct considerations for regions $(\tilde{\tau}^a(\lambda), \leq \tilde{\tau}^n(\lambda)]$ and $[0, \tilde{\tau}^a(\lambda)]$. As a result, the objective function is no longer unimodal – it becomes piece-wise quadratic with a bimodal pattern. Therefore, identifying the optimal toll requires deriving the minima in both low- and medium-toll regions, as well as how they change in λ. In the proof of

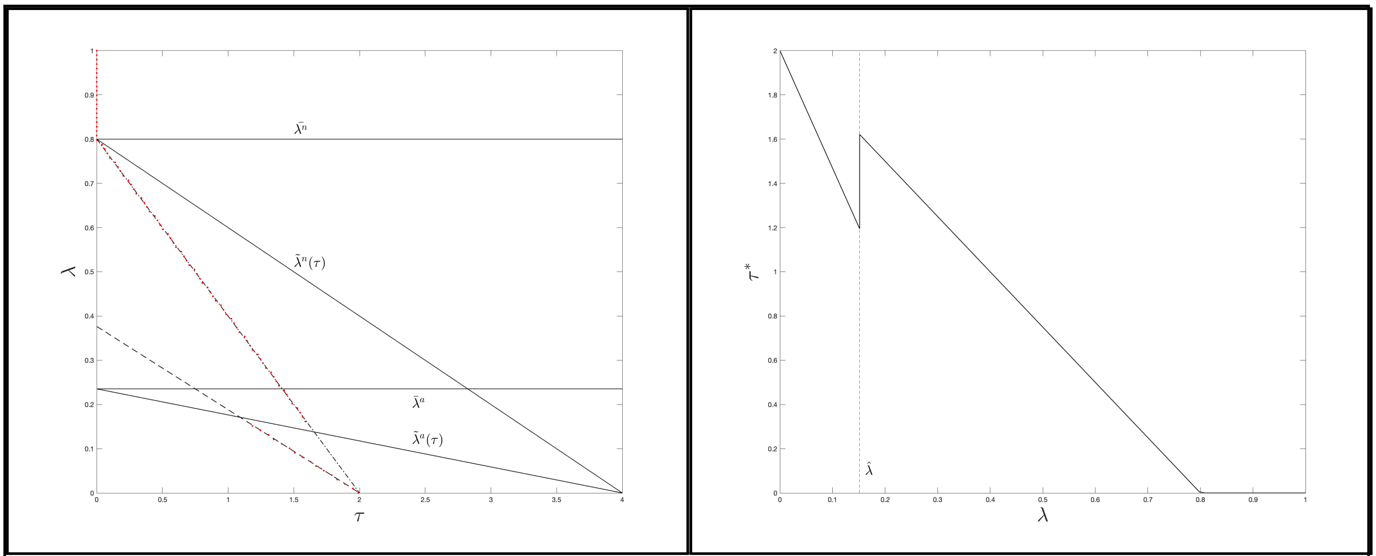


Figure 9. Illustration of the optimal toll. Dash-dotted line: $\tau_1 = \frac{1}{2}\left(b_2 - b_1 - \lambda D\bar{\alpha}_1(\beta^n)\right)$. **Dashed line:** $\tau_1 = \frac{1}{2}\left(b_2 - b_1 - \frac{\bar{\alpha}_1(\beta^n)\bar{\alpha}_1(\beta^a)}{P(a)\bar{\alpha}_1(\beta^n)+P(n)\bar{\alpha}_1(\beta^a)}\lambda D\right)$. **Red dotted line: the optimal toll. Parameters:** $\alpha_1^a = 8, \alpha_1^n = 2, b_1 = 14, b_2 = 18, p = 0.6, D = 2.5, \beta^n(n) = 1, \beta^a(a) = 0.7$.

Proposition 4, we have showed the existence of the turning point $\hat{\lambda}$ based on the quadratic property of the objective functions, resulting that the optimal toll to be piece-wise linear in τ. We also illustrate the optimal toll in Figure 9. In each region, τ^* still preserves the behavior of decreasing in λ. Yet the global monotonicity no longer exists.

In summary, we illustrate how providing traffic information to drivers alters the structure of the optimal toll. This finding stems from the separating effect that drivers make distinct routing decisions when disparate information is provided. The navigation apps expand the action space of vehicles, which further stretches the effective zone of using toll to regulate emissions. However, when designing the toll policy, the city planner has to be mindful of the EV adoption rate and adjust the toll to it accordingly.

Conclusion

Government and public administration have implemented various rules and policies to tackle the climate crisis. Our paper is motivated by the programs that exempt electric vehicles from paying toll to access express lanes. At the same time, all drivers, no matter of electric vehicles or gasoline cars, rely more and more on navigation apps for real-time traffic condition updates. In this work, we build a stylized model to understand how information provision from apps affects vehicle flows in equilibrium, which further has an impact on the optimal toll to control emissions from gasoline vehicles. We find that, not surprisingly, vehicles alter their route selection based on the traffic information received, which expands their action space. As a result, the effective regime of using tolls as a weapon to regulate emissions also expands. On top of it, we find novel results that the optimal toll is no longer monotonic in the EV adoption rate. We identify an abrupt changing pattern in that the toll first drops in the adoption rate and jumps to a higher point before further dropping down.

Our analysis generates insights that have implications for policymakers. As discussed in Coleman's micro-macro model (Coleman 1986; Coleman 1994), micro-level individual behaviors play a pivoting role in connecting macro-level variables. Our findings showcase the importance of realizing such a connection for policymakers when using the price weapon to regulate emissions from the transportation sector. Recognizing the increase in EV adoption and investigating the advancement in traffic-related information technology will help maintain the effectiveness of the tolling scheme.

We conclude our paper by discussing several directions for future research. In the current study, we focus on analyzing how the optimal toll should change with respect to the EV adoption level for a given information provision strategy. Analyzing how information accuracy affects the toll structure may yield interesting insights. Another question we can ask is whether providing the information is always good. If not, is there any optimal information provision strategy that will further decrease the emissions? In addition, welfare analysis will also help us understand the impact of tolling and traffic information provision on drivers of different types of vehicles. Also, it will shed light on the long-run impact of incentivizing EV adoptions.

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Appendix

Proof of Proposition 1.

We start with the equilibrium where there is a positive number of EVs taking road 1 (i.e., $q_1^E(\tau) > 0$). The expected costs for EVs taking road 1 can not exceed the costs for road 2 such that there is no EV having incentives to deviate to the other road. Specifically, we have

$$\begin{aligned} \sum_{\omega\in\Omega}\theta(\omega)c_1^\omega(f_1(s)) &\leq \sum_{\omega\in\Omega}\theta(\omega)c_2(f_2(s)) \\ \Rightarrow \sum_{\omega\in\Omega}\theta(\omega)[\alpha_1^\omega(q_1^E(\tau)+q_1^G(\tau))+b_1] &\leq \sum_{\omega\in\Omega}\theta(\omega)b_2 \\ \Rightarrow \left(\sum_{\omega\in\Omega}\theta(\omega)\alpha_1^\omega\right)(q_1^E(\tau)+q_1^G(\tau)) &\leq b_2-b_1. \end{aligned}$$

Similarly, if there exists a positive number of EVs taking road 2 (i.e., $q_2^E(\tau) > 0$ or $q_1^E(\tau) < \lambda D$), we have

$$\left(\sum_{\omega\in\Omega}\theta(\omega)\alpha_1^\omega\right)(q_1^E(\tau)+q_1^G(\tau)) \geq b_2-b_1.$$

Similar for GVs, if there exists a positive number of EVs taking road 1 (i.e., $q_1^G(\tau) > 0$), we have,

$$\begin{aligned} \sum_{\omega\in\Omega}\theta(\omega)c_1^\omega(f_1(s))+\tau &\leq \sum_{\omega\in\Omega}\theta(\omega)c_2(f_2(s)) \\ \Rightarrow \sum_{\omega\in\Omega}\theta(\omega)[\alpha_1^\omega(q_1^E(\tau)+q_1^G(\tau))+b_1+\tau] &\leq \sum_{\omega\in\Omega}\theta(\omega)b_2 \\ \Rightarrow \left(\sum_{\omega\in\Omega}\theta(\omega)\alpha_1^\omega\right)(q_1^E(\tau)+q_1^G(\tau)) &\leq b_2-b_1-\tau. \end{aligned}$$

While if there exists a positive number of GVs taking road 2 (i.e., $q_2^G(s,\tau) > 0$ or $q_1^G(s,\tau) < (1-\lambda)D$), we have,

$$\left(\sum_{\omega\in\Omega}\theta(\omega)\alpha_1^\omega\right)(q_1^E(\tau)+q_1^G(\tau)) \geq b_2-b_1-\tau.$$

Now we define $\bar{\alpha}_1 = \sum_{\omega\in\Omega}\theta(\omega)\alpha_1^\omega = p\alpha_1^a + (1-p)\alpha_1^n$, $\bar{\lambda} \triangleq \frac{b_2-b_1}{\bar{\alpha}_1 D}$ and a threshold based on the toll $\tilde{\lambda}(\tau) \triangleq \frac{b_2-b_1-\tau}{\bar{\alpha}_1 D}$. Also, define

$$\begin{aligned} Eq_E &= \bar{\alpha}_1(q_1^E(\tau)+q_1^G(\tau)) - (\alpha_2 D + b_2 - b_1), \\ Eq_G &= \bar{\alpha}_1(q_1^E(\tau)+q_1^G(\tau)) - (\alpha_2 D + b_2 - b_1 - \tau). \end{aligned}$$

If $Eq_E \geq 0$, we have $q_1^E(\tau) \geq \frac{b_2-b_1}{\bar{\alpha}_1 D}$. Therefore, when $\bar{q}_1^{E*} = \frac{b_2-b_1}{\bar{\alpha}_1}$, EVs' preferences for two roads will be indifferent. To sustain such a equilibrium, we need to have $\lambda \geq \bar{\lambda}$. Note that $Eq_G > 0$ will be satisfied in this case, which leads to $\bar{q}_1^{G*} = 0$.

If $Eq_E < 0$, all EVs will take road 1, which leads to $\bar{q}_1^{E*} = \lambda D$. If $Eq_G > 0$, $\lambda D \geq \frac{b_2-b_1-\tau}{\bar{\alpha}_1}$ needs to be satisfied such that no GVs will take road 1. If $Eq_G \geq 0$, we have $q_1^G(\tau) \leq \frac{b_2-b_1-\tau}{\bar{\alpha}_1} - \lambda D$. When $\bar{q}_1^{G*} = \frac{b_2-b_1-\tau}{\bar{\alpha}_1} - \lambda D$, GVs' preferences for two roads will be indifferent.

Proof of Proposition 2.

We start with the equilibrium where there is a positive number of EVs taking road 1 (i.e., $q_1^E(s,\tau) > 0$). The expected costs for EVs taking road 1 can not exceed the costs for road 2 such that there is no EV having incentives to deviate to the other road. Specifically, we have

$$\begin{aligned} \sum_{\omega\in\Omega} \beta^s(\omega) c_1^\omega(f_1(s)) &\leq \sum_{\omega\in\Omega} \beta^s(\omega) c_2(f_2(s)) \\ \Rightarrow \sum_{\omega\in\Omega} \beta^s(\omega)[\alpha_1^\omega(q_1^E(s,\tau) + q_1^G(s,\tau)) + b_1] &\leq \sum_{\omega\in\Omega} \beta^s(\omega) b_2 \\ \Rightarrow \left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) &\leq b_2 - b_1. \end{aligned}$$

Similarly, if there exists a positive number of EVs taking road 2 (i.e., $q_2^E(s,\tau) > 0$ or $q_1^E(s,\tau) < \lambda D$), we have

$$\left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) \geq b_2 - b_1.$$

Similar for GVs, if there exists a positive number of EVs taking road 2 (i.e., $q_1^G(s,\tau) > 0$), we have

$$\begin{aligned} \sum_{\omega\in\Omega} \beta^s(\omega) c_1^\omega(f_1(s)) + \tau &\leq \sum_{\omega\in\Omega} \beta^s(\omega) c_2(f_2(s)) \\ \Rightarrow \sum_{\omega\in\Omega} \beta^s(\omega)[\alpha_1^\omega(q_1^E(s,\tau) + q_1^G(s,\tau)) + b_1 + \tau] &\leq \sum_{\omega\in\Omega} \beta^s(\omega) b_2 \\ \Rightarrow \left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) &\leq b_2 - b_1 - \tau. \end{aligned}$$

While if there exists a number of GVs tkaing road 2 (i.e., $q_2^G(s,\tau) > 0$ or $q_1^G(s,\tau) < (1-\lambda)D$), we have,

$$\left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) \geq b_2 - b_1 - \tau.$$

Define $\bar{\alpha}_1(\beta^s) = \sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega$. Then, $\bar{\alpha}_1(\beta^a) > \bar{\alpha}_1(\beta^n)$. Also, define

$$\begin{aligned} Eq_E(s) &= \left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) - (b_2 - b_1), \\ Eq_G(s) &= \left(\sum_{\omega\in\Omega} \beta^s(\omega)\alpha_1^\omega\right)(q_1^E(s,\tau) + q_1^G(s,\tau)) - (b_2 - b_1 - \tau). \end{aligned}$$

Then, if $Eq_E(s) = 0,\ q_1^E(s) \in (0, \lambda D)$; if $Eq_E(s) > 0,\ q_1^E(s) = 0$; otherwise, $q_1^E(s) = \lambda D$. Similarly, if $Eq_G(s) = 0,\ q_1^G(s) \in (0, (1-\lambda)D)$; if $Eq_G(s) > 0,\ q_1^E(s) = 0$; otherwise, $q_1^G(s) = (1-\lambda)D$. Also, note that, $Eq_E(s) < Eq_G(s)$, $Eq_E(a) > Eq_E(n)$ and $Eq_G(a) > Eq_G(n)$.

Case 1: $Eq_E(s) = 0,\ Eq_G(s) > 0,\ \forall s$.

Then, $q_1^E(s) = \frac{b_2-b_1}{\bar{\alpha}_1(\beta^s)}$ and $q_1^G(s) = 0, \forall s$. The condition is $\lambda D \geq \frac{b_2-b_1}{\bar{\alpha}_1(\beta^n)}$.

Case 2: $Eq_E(n) = 0,\ Eq_E(a) < 0$, and $Eq_G(s) > 0,\ \forall s$.

Then, $q_1^E(a) = \frac{b_2-b_1}{\bar{\alpha}_1(\beta^a)},\ q_1^E(a) = \lambda D$ and $q_1^G(s) = 0,\ \forall s$. The condition is $\frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)} \leq \frac{b_2-b_1}{\bar{\alpha}_1(\beta^a)} \leq \lambda D < \frac{b_2-b_1}{\bar{\alpha}_1(\beta^n)}$.

Case 3: $Eq_E(s) < 0$, and $Eq_G(s) > 0,\ \forall s$.

Then, $q_1^E(s) = \lambda D,\ q_1^G(s) = 0,\ \forall s \in s$. The condition is $\frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)} < \lambda D \leq \frac{b_2-b_1}{\bar{\alpha}_1(\beta^a)}$.

Case 4: $Eq_E(n) < 0$, $Eq_E(a) = 0$ and $Eq_G(s) > 0,\ \forall s$.

Then, $q_1^E(a) = \frac{b_2-b_1}{\bar{\alpha}_1(\beta^a)}, q_1^G(a) = 0$ and $q_1^E(n) = \lambda D,\ q_1^G(n) = \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)} - \lambda D$. The condition is, $\frac{b_2-b_1}{\bar{\alpha}_1(\beta^a)} \leq \lambda D < \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)}$.

Case 5: $Eq_E(s) < 0\ \forall s$ and $Eq_G(n) = 0, Eq_G(a) > 0$.

Then, $q_1^E(a) = \lambda D,\ q_1^G(a) = 0$, and $q_1^E(n) = \lambda D,\ q_1^G(n) = \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)} - \lambda D$. The condition is, $\frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^a)} \le \lambda D < \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^n)}$

Case 6: $Eq_E(s) < 0\ \forall s$ and $Eq_G(n) < 0, Eq_G(a) = 0$.

Then, $q_1^E(s) = \lambda D,\ q_1^G(s) = \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^s)} - \lambda D,\ \forall s \in S$. The condition is, $\lambda D < \frac{b_2-b_1-\tau}{\bar{\alpha}_1(\beta^a)}$.

Proof of Proposition 3.

When $\lambda \in [0, \tilde{\lambda}(\tau))$, the objective function can be written as

$$\overline{ETC} = b_2(1-\lambda)D + \lambda D\tau - \frac{\tau\,(b_2 - b_1 - \tau)}{\bar{\alpha}_1}.$$

Take the derivative. w.r.t. τ,

$$\frac{d\overline{ETC}}{d\tau} = \frac{(b_1 - b_2 + \lambda D\bar{\alpha}_1 + 2\tau)}{\bar{\alpha}_1}.$$

ETC is convex in τ. Thus, ETC is minimized at $\bar{\tau}^* = \frac{1}{2}\,(b_2 - b_1 - \lambda D\bar{\alpha}_1)$.

Proof of Proposition 4.

(i) Intermediate EV adoption regime: $\lambda \in [\bar{\lambda}^a, \bar{\lambda}^n)$**.**

When $\lambda \in [\bar{\lambda}^a, \bar{\lambda}^n)$, the objective function can be written as

$$ETC = b_2(1-\lambda)D + P(n)\lambda D\tau - \frac{P(n)\tau\,(b_2 - b_1 - \tau)}{\bar{\alpha}_1(\beta^n)}.$$

Take the derivative. w.r.t. τ,

$$\frac{dETC}{d\tau} = \frac{b_1 - b_2 + \lambda D\bar{\alpha}_1(\beta^n) + 2\tau_1}{\bar{\alpha}_1(\beta^n)}.$$

ETC is convex in τ. Thus, ETC is minimized at $\tau^* = \frac{1}{2}\,(b_2 - b_1 - \lambda D\bar{\alpha}_1(\beta^n))$.

(ii) Low EV adoption regime: $\lambda \in [0, \bar{\lambda}^a)$**.**

When $\lambda \in [0, \tilde{\lambda}^a(\tau))$, the objective function can be written as

$$ETC = b_2(1-\lambda)D + \lambda D\tau - \frac{P(n)\tau\,(b_2 - b_1 - \tau)}{\bar{\alpha}_1(\beta^n)} - \frac{P(a)\tau\,(b_2 - b_1 - \tau)}{\bar{\alpha}_1(\beta^a)}$$

Take the derivative. w.r.t. τ,

$$\frac{dETC}{d\tau} = \lambda D + \frac{(b_1 - b_2 + 2\tau)(P(a)\bar{\alpha}_1(\beta^n) + P(n)\bar{\alpha}_1(\beta^a))}{\bar{\alpha}_1(\beta^n)\bar{\alpha}_1(\beta^a)}.$$

ETC is convex in τ. Then, ETC is minimized at $\tau_1^* = \frac{1}{2}\left(b_2 - b_1 - \lambda D\frac{\bar{\alpha}_1(\beta^n)\bar{\alpha}_1(\beta^a)}{P(a)\bar{\alpha}_1(\beta^n)+P(n)\bar{\alpha}_1(\beta^a)}\right)$. Note that, setting $\tau_1^* = 0$ gives $\lambda D = (b_2 - b_1)(\frac{P(a)}{\bar{\alpha}^1(\beta^a)} + \frac{P(n)}{\bar{\alpha}^1(\beta^n)}) \in [\frac{b_2-b_1}{\bar{\alpha}^1(\beta^a)}, \frac{b_2-b_1}{\bar{\alpha}^1(\beta^n)}]$. Thus, to the problem of minimizing ETC when $\lambda \in [0, \tilde{\lambda}^a(\tau))$, the solution is $\min\{\tau_1^*, b_2 - b_1 - \lambda D\bar{\alpha}^1(\beta^a)\}$. Define λ_1 to be the λ solves $\tau_1^* = b_2 - b_1 - \lambda D\bar{\alpha}^1(\beta^a)$.

When $\lambda \in [\tilde{\lambda}^a(\tau), \tilde{\lambda}^n(\tau))$, the objective function can be written as

$$ETC = b_2(1-\lambda)D + P(n)\lambda D\tau - \frac{P(n)\tau\,(b_2 - b_1 - \tau)}{\bar{\alpha}_1(\beta^n)}.$$

The analysis replicates that of the scenario when $\lambda \in [\bar{\lambda}^a, \bar{\lambda}^n)$, and thus, $\tau_2^* = \frac{1}{2}\,(b_2 - b_1 - \lambda D\bar{\alpha}_1(\beta^n))$. Also, to the problem of minimizing ETC when $\lambda \in [\tilde{\lambda}^a(\tau), \tilde{\lambda}^n(\tau))$, the solution is $\max\{\tau_2^*, b_2 - b_1 - \lambda D\bar{\alpha}^1(\beta^a)\}$. Define λ_2 to be the λ solves $\tau_2^* = b_2 - b_1 - \lambda D\bar{\alpha}^1(\beta^a)$.

Based on the discussion above, when $\lambda \in (\lambda_1, \bar{\lambda}^a]$, the optimal solution τ_2^*; when $\lambda \in (0, \lambda_2]$, the optimal solution τ^*. In what follows, we analyze the scenario when $\lambda \in (\lambda_2, \lambda_1]$. Note that, $ETC|_{\lambda\in[\tilde{\lambda}^a(\tau),\tilde{\lambda}^n(\tau)),\tau=\tau_2^*}$ and $ETC|_{\lambda\in[0,\tilde{\lambda}^a(\tau)),\tau=\tau_1^*}$ are both quadratic functions in λ. Also, note that $ETC|_{\lambda=\lambda_2,\tau=\tau_1^*} \le ETC|_{\lambda=\lambda_2,\tau=\tau_2^*}$ and $ETC|_{\lambda=\lambda_1,\tau=\tau_2^*} \le ETC|_{\lambda=\lambda_1,\tau=\tau_1^*}$. Thus, $ETC|_{\lambda\in[\tilde{\lambda}^a(\tau),\tilde{\lambda}^n(\tau)),\tau=\tau_2^*}$ and $ETC|_{\lambda\in[0,\tilde{\lambda}^a(\tau)),\tau=\tau_1^*}$, as functions of λ, have one and only one point of intersection, which we define as $\hat{\lambda}$. Thus, when $\hat{\lambda} < \lambda \le \bar{\lambda}^n$, $\tau^* = \frac{1}{2}\,(b_2 - b_1 - \bar{\alpha}_1(\beta^n)\lambda D)$; when $\lambda \le \hat{\lambda}$,

$$\tau^* = \frac{1}{2}\left(b_2 - b_1 - \frac{\bar{\alpha}_1(\beta^n)\bar{\alpha}_1(\beta^a)}{P(a)\bar{\alpha}_1(\beta^n) + P(n)\bar{\alpha}_1(\beta^a)}\lambda D\right).$$