Toward Mass Adoption of Electric Vehicles: Impact of the Range and Resale Anxieties

Michael K. Lim
Department of Business Administration, University of Illinois, Urbana-Champaign, IL 61820, mlim@illinois.edu,

Ho-Yin Mak
Department of Industrial Engineering and Logistics Management, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, hymak@ust.hk,

Ying Rong
Antai College of Economics and Management, Shanghai Jiao Tong University, China, yrong@sjtu.edu.cn,

Key to the mass adoption of electric vehicles (EVs) is the establishment of successful business models based on sound understanding of consumer behavior in adopting this new technology. In this paper, we study the impact of two major barriers to mass adoption of EVs: (i) range anxiety, the concern that the driving range of EVs may be insufficient to meet the driving needs, and (ii) resale anxiety, the concern that used values of EVs may deteriorate quickly. Using a stylized model calibrated to a data set based on the San Francisco Bay Area, we show that, while both types of consumer anxieties typically harm the firm's profit, they often improve consumer surplus. In addition, we show that a business model that requires consumers to lease the EV batteries (rather than purchase them) may lead to a greater level of adoption and emission savings when the level of resale anxiety is high. Further, a business model that offers EV range improvement through enhanced charging infrastructure typically yields greater adoption and consumer surplus, but lowers the firm's profit, compared with one that offers enlarged batteries. Overall, we find that the combinations of battery owning/leasing with enhanced charging service, referred to as the (O,E) and (L,E) models in our paper, typically yield the best balance among the objectives of EV adoption, emission savings, profitability, and consumer surplus, when the degree of resale anxiety is low and high, respectively.

Key words: electric vehicles, consumer anxieties, durable goods, secondary market, emission savings
History:

1. Introduction

"No one can tell us when we'll run out of oil, but we will. Everyone will tell you we will."

–John W. Mendel, Executive Vice President, Honda

Diminishing oil reserves and rising environmental concerns have compelled the transportation sector to focus on the development of Electric Vehicles (EVs). The automotive industry is heavily investing on EVs with the hope of achieving substantial reductions in fossil fuel consumption and pollutant gas emissions. Carlos Ghosn, CEO of Nissan and Renault, advocates electrification of automobiles as the way carmakers can contribute to making the world more sustainable (Forbes

2012), and predicts EVs will occupy 10% of all car sales by 2020 (USA Today 2012b). Governments across the world are also investing billions of dollars in the development of EVs and their components. President Obama's administration has pledged $2.4 billion in federal grants for research on EV batteries (USA Today 2010). The European Union collectively has invested €43 billion (including public and private sector investments) on EV-related research (URBACT 2012). China alone is investing $15 billion in its nascent EV industry (New York Times 2010).

The successful mass adoption of EVs, however, depends not only on the technology and the associated infrastructure, but also on consumer behavior in adopting this new technology (Washington Post 2011). In this paper, we study the implications of the two major psychological barriers known as *range anxiety* and *resale anxiety* that appear in the EV adoption process (Bronfer 2011).

Range anxiety, the psychological concern that the driving range of EVs (which is typically constrained to approximately 80 miles due to battery capacity) may be insufficient to meet the needs of drivers, impedes consumers from adopting EVs (National Public Radio 2011, National Geographic 2011, Wall Street Journal 2012). EV advocates often dismiss range anxiety as irrational (Washington Post 2011); after all, the majority U.S. drivers commute less than 40 miles a day (and commuting distances for Europeans are even shorter). Yet, even with the industry's recent proposals on enhanced charging technologies such as quick-charging and battery swapping, this psychological fear on limited driving range still remains a barrier to EV adoption. A recent field test conducted by BMW (Franke et al. 2011) confirms that drivers indeed tend to underestimate the battery capacity of EVs (or, overestimate their driving needs) and feel anxious when they approach the limit of their "comfortable range". Interestingly, the study reveals that this psychological factor of range anxiety tends to diminish significantly over time and with experience. Related studies also show that general attitudes of drivers toward EVs become much pragmatic (i.e., favorable) after having driven them for some time (Bühler et al. 2011, Franke and Krems 2013).

Given the durable nature of EVs, consumers take into account their future values when making adoption decisions. Unfortunately, with the EV industry still in its infancy stage, consumers show low degrees of confidence on the future values (National Research Council 2013), especially due to lack of confidence in the durability of EVs (USA Today 2013b). Such psychological concern on the future values of used EVs, referred to as the resale anxiety, is another major barrier to EV adoption (Garthwaite 2010, Chandler 2011, Bronfer 2011). Interestingly, EV manufacturers show much higher degrees of confidence in the durability and resale values of EVs, as evident from their recently announced guarantee programs on resale values and battery depreciation. For example, Tesla launched a resale value guarantee program that allows consumers to sell their used EVs at prices no lower than comparable gasoline premium cars (USA Today 2013a); Nissan guarantees to replace an EV battery if it deteriorates beyond a certain level within six years of purchase (USA Today 2012a). The launch of these programs not only shows the manufacturers' awareness of resale anxiety, it also signifies their confidence on the EV's durability. As the market matures, resale anxiety will likely diminish as the durability of EVs will be *observed* as well as the true EV resale price. From the field experiment, Bühler et al. (2011) also find that, as the consumers' perception on EV reliability (durability) improves, so will the overall acceptance of EVs.

To capture the impact of consumer anxieties and their tendency to diminish over time, we employ a two-stage modeling framework akin to that proposed by Desai and Purohit (1998), a setting commonly used in the durable goods literature. We characterize the equilibrium behavior among consumers heterogeneous in their valuations of EVs. The first stage represents the introduction phase, in which only new EVs are available. At this stage, consumers have little experience with the product and thus exhibit both types of anxieties. The second stage represents the maturity phase, in which both new and used EVs are available in the market. We assume both anxieties diminish in this stage. Using this model and further calibrating it to a data set based on the San Francisco Bay Area, we evaluate the effectiveness of business practices that are currently deployed or have been proposed in the EV market. In particular, we consider four representative business practices based on the type of *battery ownership* and *battery charging options* as illustrated in Figure 1.

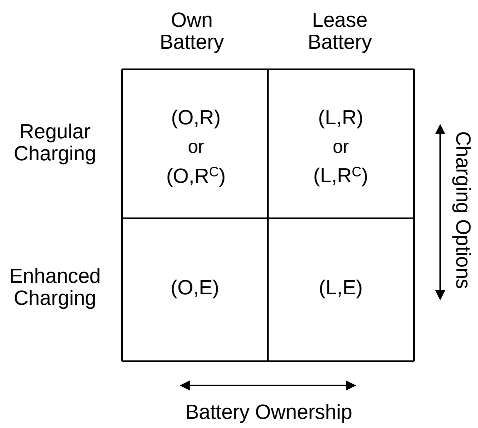


Figure 1 Four EV business practices categorized by battery ownership and charging options

First, the (O,R) model represents the baseline case in which consumers *own* the entire vehicle and charge their battery mostly at home using *regular* overnight charging. This business model has been proposed mostly for urban drivers (e.g., Mitsubishi's plan for its Model i (Los Angeles Times 2012)). The (L,R) model is a decoupled business model in which consumers own the vehicle only and subscribe to a battery *leasing service*. This is one of the business models currently in place in the European market (Masson 2012). The (O,E) model represents the case in which battery *enhanced charging* service is made available through additional support infrastructure. This includes, for example, the quick charging stations that are being introduced in the U.S. by firms such as Chargepoint and NRG eVgo (Wall Street Journal 2012, New York Times 2013). In the (L,E) model, consumers lease the batteries and are offered enhanced battery charging services. The business model proposed by (now bankrupt) Better Place and studied by Avci et al. (2014), which offers enhanced charging in the form of battery swapping coupled with the battery leasing service, is a good example of the (L,E) model (New York Times 2009). Renault is also selling its ZOE EV in Europe with battery leasing and the support of quick charging infrastructure (Renault 2014). In addition to the baseline $(\cdot,\mathrm{R})$ models, we also consider models with extended EV driving range through an *enlarged battery capacity* in §4, referred to as the $(\cdot,\mathrm{R}^{\mathrm{C}})$ models.

This paper has three objectives: (i) to examine the impact of consumer anxieties on the EV adoption process and the choice of range enhancement technology, (ii) to evaluate the effectiveness of prevalent EV business practices, and (iii) to identify EV policy implications that will help achieve EV mass adoption and balanced objectives for the key stakeholders involved in the EV market. The key findings and contributions of the paper are summarized as follows:

- Our work brings the consumer behavioral dimension (i.e., anxieties) in understanding the EV adoption process. Despite the qualitative similarity between the two types of anxieties, we show that their impacts can be quite different. Specifically, range anxiety can either help or hurt adoption depending on what type of (or whether) range enhancement strategy is chosen, i.e., via enhanced charging infrastructure or via enlarged battery capacity; resale anxiety can also help adoption depending on the production cost level. We further show that anxieties do not necessarily harm the consumer surplus, but rather often work in favor of consumers at the firm's expense.
- We show that battery leasing service improves the firm's profit due to greater level of surplus extraction from the secondary market and neutralizes the impact of resale anxiety; and, when not offered with the enhanced charging option, harms adoption and consumer surplus. However, due to the front-heavy adoption behavior induced by battery leasing, the economic value of emission savings may possibly be greater than under the owning model, even when the overall adoption size is smaller. In addition, we explore the trade-offs between the two EV range enhancement strategies (i.e., (O,E) vs. $(\mathrm{O},\mathrm{R}^{\mathrm{C}})$) which lead to very different adoption outcomes. In particular, we find that range enhancement via enhanced charging infrastructure typically yields more socially-desirable adoption outcomes (greater adoption and emission savings) than via enlarged battery capacity.

- Through data calibration based on a realistic parameter setting, we derive relevant insights and policy implications. We show that enhanced charging service is conducive to mass adoption and emission savings, and improves consumer surplus; whereas battery leasing and range enhancement with enlarged batteries increase the firm's profit. Overall, under many instances, we find that the (O,E) model provides the highest social surplus (sum of EV adoption, emission savings, profitability of private sector, and consumer surplus) unless resale anxiety is high. However, when the level of resale anxiety is relatively high, we find that the (L,E) model typically offers more desirable outcome. Therefore, policymakers must take into account these factors in implementing governmental policies to properly incentivize the involved parties (especially the private sector).

2. Related Literature

Our paper contributes to the expanding literature on environmentally sustainable operations management (Kleindorfer et al. 2005). This prominent body of literature covers a wide range of domains including product design (e.g., Plambeck and Wang (2009), Subramanian et al. (2009)), remanufacturing strategies (e.g., Debo et al. (2005, 2006), Oraiopoulos et al. (2012)) and supply chain design (e.g., Benjaafar et al. (2013), Cachon (2014), Jacobs and Subramanian (2012)). More related to our study, there are recent papers in operations management that study the adoption of environmentally sustainable technologies. Using empirical data on LEED standard buildings and dry cleaning stores, respectively, Corbett and Muthulingam (2007) and Bollinger (2011) study the adoption behavior of green practices and technologies. Lobel and Perakis (2013) investigate the adoption and optimal subsidy policies for the solar photovoltaic technology using German solar market data. Bellos et al. (2014) study the economic and environmental impacts of car sharing, one of the emerging transportation business models, in the presence of conventional car sales.

Very few papers, however, discuss the economics and adoption of EVs. Mak et al. (2013) study optimization problems of locating EV infrastructure under demand uncertainty. In contrast, we aim to evaluate performances of business practices toward the goal of mass adoption. In this sense, Avci et al. (2014) study an issue that is closely related to ours, the environmental impact of EV adoption with a battery swapping service. Focusing on the intriguing business model introduced by Better Place (referred to as the (L,E) model in our paper), they show that, although this business model can increase EV adoption, it also induces higher driving volume. Calibrating the model to real data, they find that, surprisingly, the business model would be harmful to the environment possibly in just 10 years. We add on to this literature by studying the impacts of consumer anxieties on the performances of prevalent business practices in the EV market.

As for the modeling framework, our paper is closely related to the literature on durable goods. One important factor to consider in studying durable products, such as EVs, is the interaction between heterogeneous consumers and the secondary market. We adopt a modeling framework proposed by Desai and Purohit (1998) to capture such effects. This framework divides consumers into several segments based on their adoption behaviors, i.e., whether the consumer buys (sells) a new or used car, or remains inactive. Under such setting, the model allows us to capture the competition between the new and used products (indirectly) because the firm chooses to behave optimally, anticipating the effect of the secondary market. Using this (or a similar) modeling framework, Desai and Purohit (1998), Bhaskaran and Gilbert (2005), Tilson et al. (2009), and Agrawal et al. (2012) discuss the interaction between selling and leasing. In particular, Agrawal et al. (2012) discuss the relationship between product leasing and the environmental impact of the product. Although many firms have adopted leasing strategies based on the belief that leasing is “greener” than buying (or selling), they show that leasing durable products may worsen the environmental impact because the manufacturer may prematurely dispose of off-lease products. Interestingly, Agrawal and Bellos (2013) find that the environmental performance of leasing (referred to as “servicizing”) can be improved when the resources can be properly pooled. Oraiopoulos et al. (2012) also employ a similar framework to determine the optimal relicensing strategy for the secondary market when original equipment manufacturers (OEMs) can charge a relicensing fee to remanufacturers. Similar to these papers, we study how battery ownership affects the extent and timing of EV adoption by influencing the competition between new and used EVs through the secondary market.

In contrasting the firm’s EV range enhancement options of deploying enhanced charging infrastructure and offering an enlarged battery capacity, we find that the trade-off the firm faces is similar to that in outsourcing decision. In particular, one of the key economic motivations for a firm to outsource its products or components is to convert fixed costs (such as investment in plants and equipments) into variable costs (unit purchasing cost) (Razzaque and Sheng 1998, Kremic et al. 2006, Enterpreneur.com 2010). In our setting, the firm makes a range enhancement technology choice based on a similar trade-off, to incur a fixed cost for deploying charging stations or to install a battery with enlarged capacity at a variable cost. We show implications on EV adoption based on this trade-off and further discuss the implications for policymakers. We note that Krishnan and Zhu (2006) also capture similar trade-offs in the new product development context, where the fixed cost nature of quality forces the firm to increase the quantity of product sold.

Finally, we note that, anxiety, one of the key features in this paper, is also present in the literature in other disciplines. In psychology, anxiety is considered to be one of the sources of consumers’ biased beliefs, the presence of which often leads to less desirable outcomes (e.g., Svenson (1981), Weinstein (1980), Taylor and Brown (1988)). There is also a recent growing body of literature in microeconomics that studies the firm's optimal pricing and product terms decisions in the presence of biased consumers (e.g., Spiegler (2007), Eliaz and Spiegler (2008)). Examples include health clubs (DellaVigna and Malmendier 2006), insurance (Sandroni and Squintani 2007), and cell phone usage pattern (Grubb 2009). A study that employs a modeling framework similar to ours (but under a principal-agent setting) is de la Rosa (2011), where agents have biased beliefs that may differ from the principal's. Despite acknowledging differences in beliefs, they "agree to disagree" because the agent convinces himself that "I know myself better than anybody else," while the principal discounts the agent's belief since "everyone thinks they're better than average." We model anxieties in a two-stage setting, similar to Grubb (2009): anxieties exist in the first stage and diminish in the second stage as the market learns the true functionality and resale values of EVs.

3. The Model

3.1. Setting and Assumptions

We consider a consumer who can complete $(1-\lambda)$ fraction of his/her trips using an EV, where $\lambda \in [0,1]$, and obtains a utility of $U^E = (1-\lambda)\theta$. The value of λ represents the uncovered fraction of the driver's daily traveling needs using an EV. For example, for the data set used in §5, an EV with an 80-mile range can only complete all (round) trips shorter than 80 miles, which amount to 69% of all trips; i.e., λ is 0.31 for this scenario. When the enhanced charging (E) or enlarged battery ($\mathrm{R^C}$) models are deployed, the proportion of trips that can be completed by EVs will increase and thus λ will decrease compared with under the baseline regular charging (R) model.

The value of θ is a consumer-specific parameter that may reflect the valuation of "greenness" or price differential between electricity and gasoline, among others; that is, instead of purchasing an EV, consumers can purchase gasoline cars. We normalize the utility of this alternative option to 0. We assume that θ follows a uniform distribution scaled to the range of $[0,1]$. Note that the actual automobile market might include consumers with negative θ values (i.e., those who will still prefer gasoline cars over EVs even when they are offered at the same price). We exclude such consumers from the analysis as they do not play any role.

We employ a two-stage model to represent the introductory and maturity phases of EVs, respectively, indexed by $t=1,2$. We consider the effective production cost of an EV including its battery (normalized to the incremental level over a conventional gasoline vehicle) denoted by c_t, adjusted for any governmental purchase rebate (e.g., federal tax credit, state rebate programs) offered to the first-stage EV adopters. We assume the effective production cost does not increase over time, i.e.,

$c_1 \geq c_2$. This implies that the rebate reduction over time does not exceed the cost improvements from production technology advancement. In reality, the EV production cost may heavily depend on the firm's choice of battery capacity (which in turn determines the range) and/or the production scale. We consider implications of the firm's choice of battery capacity in §4.2, and a possible reduction in the production cost due to economies of scale (as in Lobel and Perakis (2013)) in §5.

In the first stage, the firm sets the (effective) selling price p_1 for new EVs. For the leasing models, the firm additionally sets the first-stage battery leasing price at r_1. After the pricing decisions are made and announced, consumers will then make individual adoption decisions accordingly, based on their perceived utility from EVs. In Stage 1, consumers can either buy a new EV (referred to as action N) or remain inactive (I). Thus, the size of EV adoption in the first stage, which we denote by q_1, is determined by the size of the N segment in the first stage. In Stage 2, EVs purchased in the first stage can be traded in the secondary market among consumers. We assume that a used EV deteriorates and loses a fraction (δ) of its utility compared with a new EV. Taking these into account, the firm announces p_2 (and r_2), and consumers make further adoption decisions.

In the presence of range and resale anxieties, consumers base their (first-stage) EV adoption decisions on *perceived* rather than the *actual* utility. In particular, due to range anxiety, consumers underestimate the driving range of EVs (or equivalently, overestimate their daily driving needs). We capture this effect by expressing the perceived utility of owning an EV in the first stage as $(1-\alpha_r\lambda)\theta$, where the range anxiety factor α_r lies in $[1, 1/\lambda]$. This is due to consumers underestimating the EV's driving range, and thus the proportion of travel needs that can be accommodated. In addition to range anxiety, consumers also exhibit resale anxiety. That is, they believe EVs (including their batteries) depreciate faster than they really do, and thus impose greater level of discount on the used EVs. We similarly capture this effect by applying the perceived depreciation factor of $(1-\alpha_s\delta)$ on the utility of a used EV in the second stage, where the resale anxiety factor α_s lies in $[1, 1/\delta]$. When $\alpha_r = \alpha_s = 1$, the model reduces to the case with no anxieties. As the public gains more exposure to EVs through various channels (e.g., word-of-mouth and media coverage) during the first stage, we assume anxieties regarding the functionality and resale value of EVs diminish to zero in the second stage. In §3.3.1, we explore the cases in which the anxieties may not diminish completely and thus the two parties' beliefs on the utility of EVs converge in-between.

Despite the different beliefs of the firm (which is aware of the true utility of owning EVs) and consumers (who believe in the perceived utility), we do not consider asymmetric information. For new technologies, such as EVs, it is possible that the firm may possess better information regarding the quality of the product than consumers do; i.e., information asymmetry may exist. However, we believe the disparity in information is not too high since EVs have been publicly tested and reviewed by many third parties, and they are conveniently available for test driving (Franke et al. 2011, Brauer 2010). Thus, the lack of consumer's confidence in EVs results more from biased belief (due to anxieties) than from lack of information. One consequence of this treatment is that, in contrast to an asymmetric information setting, consumers do not draw inferences on utility values upon observing firm's pricing decisions in the first stage. The utility from owning an EV depends on the true range and durability of the EV, as well as the consumer's own driving and charging habits, which affect how fast the battery deteriorates and loses value. Naturally, consumers acknowledge that their driving and charging habits may be different from what the firm assumes in factory test settings and thus tend to take a conservative stance (i.e., underconfidence). Such consumer bias is similar to conflicting beliefs as studied in de la Rosa (2011), and thus, consumers with anxieties do not adjust their beliefs upward upon observing firm's actions. Although the degrees in consumer anxieties may be heterogeneous, we first consider a uniform level of anxiety; the impact of heterogeneous anxieties will be studied later in §3.3.2.

Akin to the modeling framework in Desai and Purohit (1998), we segment consumers based on the actions taken in the two stages: buy a new EV in each stage (NN), buy a new EV only in the second stage (IN), buy a used EV in the secondary market (IU) and remain inactive in both stages (II). We assume the used EV price, p_u, is determined endogenously as a market clearing price in the secondary market. The volume of new EV sales in the second stage, which is denoted as q_2, is determined by the collective size of the NN and IN segments. We denote the total adoption by $Q = q_1 + q_2$. Figure 2 illustrates the timeline of the events for the model. Note that the number of used EVs traded in the secondary market is equal to the number of new EVs sold in Stage 1 (i.e., the segment size of NN equals IU). We note that segment NH (buying a new EV in Stage 1 and holding on to it in Stage 2) is not considered, as the employed modeling framework of Desai and Purohit (1998) does not allow coexistence of IN and NH segments in the equilibrium. We discuss this in more detail in Appendix B.1. Given that EV is a new technology with a growing market and that more consumers are expected to participate as the industry matures, we consider the IN segment instead of NH in this model. Moreover, in the presence of anxieties, consumers underestimate the utility of EVs in the first stage but the anxieties diminish in the second stage. Thus, the role of late adopters (IN) becomes critical in the EV adoption process, which is also observed in the numerical study based on the San Francisco Bay Area. These collectively reinforce our modeling choice.

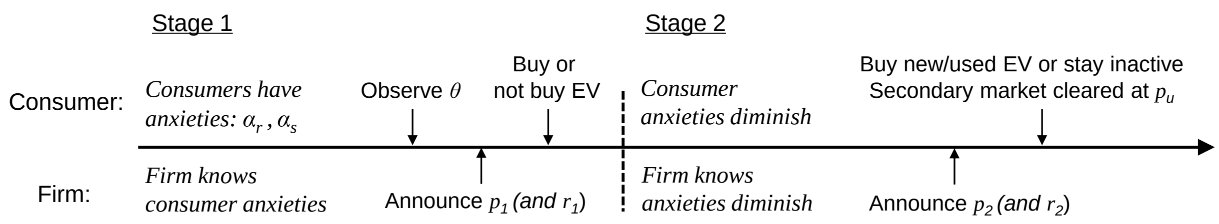


Figure 2 **The timeline of events in the model: two parties have different beliefs in the first stage and anxieties diminish in the second stage**

3.2. Analysis of (O,R) Model

We first consider the (O,R) model, in which the firm sells EVs without offering a battery leasing service. This is a common business model in practice and will serve as a baseline case for our study. Using the consumer's utility under each segment, we can identify thresholds in consumer valuation: consumers choose NN if $\theta \in (\theta_1, 1]$, IN if $\theta \in (\theta_2, \theta_1]$, IU if $\theta \in (\theta_3, \theta_2]$, and II if $\theta \in [0, \theta_3)$. Considering the problem backward, we consider the second stage where the first-stage adoption size q_1 has been observed and the consumer anxieties are resolved. Based on this information, the firm determines q_2 by solving $\pi_2(q_1) = \max_{q_2}(p_2(q_1, q_2) - c_2)q_2$. Hence, the second-stage price $p_2(q_1, q_2)$ is determined in the adoption equilibrium by solving the following equations for $(p_2, p_u, \theta_2, \theta_3)$:

$$\begin{aligned} (1-\lambda)\theta_2 - p_2 &= (1-\lambda)(1-\delta)\theta_2 - p_u, \\ (1-\lambda)(1-\delta)\theta_3 - p_u &= 0, \\ q_2 &= 1 - \theta_2, \\ \theta_2 - \theta_3 &= q_1. \end{aligned} \tag{1}$$

In the first stage, the firm determines q_1 by maximizing the optimal profit over the two stages, $\max_{q_1}(p_1(q_1) - c_1)q_1 + \pi_2(q_1)$. Because the firm knows that consumers exhibit anxieties in the first stage, it obtains $p_1(q_1)$ by solving the following set of equations based on the perceived utility:

$$\begin{aligned} (1-\alpha_r\lambda)\hat{\theta}_2 - \hat{p}_2 &= (1-\alpha_r\lambda)(1-\alpha_s\delta)\hat{\theta}_2 - \hat{p}_u, \\ (1-\alpha_r\lambda)(1-\alpha_s\delta)\hat{\theta}_3 - \hat{p}_u &= 0, \\ \hat{q}_2 &= 1 - \hat{\theta}_2, \\ \hat{\theta}_2 - \hat{\theta}_3 &= q_1. \end{aligned} \tag{2}$$

In the above, "hat" indicates that the associated second-stage variables are inferences based on consumers' perception. For example, $\hat{p}_2$ represents the consumers' perceived EV price in the second stage. In solving the above system of equations, we assume that consumers have rational expectations regarding the firm's Stage 2 decision $\hat{p}_2$ and corresponding $\hat{p}_u$, $\hat{\theta}_2, \hat{\theta}_3$, based on their beliefs. Because the consumers believe that their perceived utility of owning EVs is correct and that the firm will make decisions accordingly in the second stage, they believe the firm will be maximizing the profit of $\hat{p}_2(\hat{q}_2, q_1)\hat{q}_2$, where $\hat{p}_2(\hat{q}_2, q_1)$ is obtained by solving the following system:

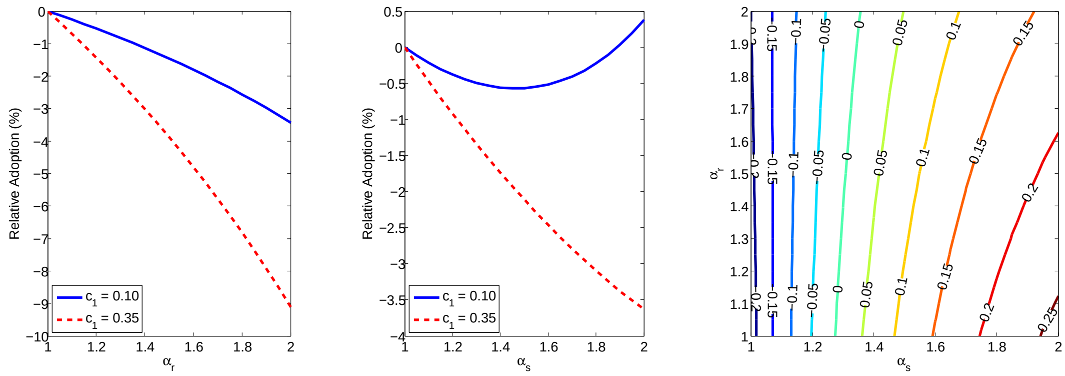
$$\begin{aligned} (1-\alpha_r\lambda)\theta_1 - p_1 + \rho\big((1-\alpha_r\lambda)\theta_1 - \hat{p}_2 + \hat{p}_u\big) &= \rho\big((1-\alpha_r\lambda)\theta_1 - \hat{p}_2\big), \\ q_1 &= 1-\theta_1. \end{aligned} \tag{3}$$

By solving $\max_{\hat{p}_2} \hat{p}_2\hat{q}_2(\hat{p}_2, q_1)$, one can obtain $\hat{p}_2(q_1)$, the firm's optimal price in the second stage as perceived by consumers. Using these, $p_1(q_1)$ can be obtained, which allows us to derive the firm's optimal decision in Stage 1 by maximizing the overall profit, $\max_{q_1}(p_1(q_1) - c_1)q_1 + \pi_2(q_1)$. Using this result, we identify the impact of anxieties on EV adoption.

PROPOSITION 1. *(i) An increase in α_r results in a decrease in $q_1^{(O,R)}(\alpha_r, \alpha_s)$ and $Q^{(O,R)}(\alpha_r, \alpha_s)$, but an increase in $q_2^{(O,R)}(\alpha_r, \alpha_s)$ for any level of α_s.*
(ii) There exists a threshold $\bar{c}(c_2) > 0$ such that, for $c_1 > \bar{c}(c_2)$ ($c_1 \leq \bar{c}(c_2)$), an increase in α_s results in a decrease (increase) in $q_1^{(O,R)}(\alpha_r, \alpha_s)$ and $Q^{(O,R)}(\alpha_r, \alpha_s)$, but an increase (decrease) in $q_2^{(O,R)}(\alpha_r, \alpha_s)$.

Proofs of all the analytical results are provided in Appendix A.1. In the presence of range anxiety, the first-stage adoption decreases due to underestimation of the true value of EVs. This consequently shrinks the secondary market (note, q_1 is identical to the size of NN as well as the IU segment), which in turn reduces the competition between the new and the used EVs in the second stage; consequently, the new EV sales in the second stage increases. All in all, larger range anxiety still harms the total adoption size.

Interestingly, when the effective production cost is relatively low ($c_1 \leq \bar{c}(c_2)$), we observe that the EV adoption size increases with resale anxiety. This trend can be explained as follows. When resale anxiety diminishes in the second stage, the perceived value of used EVs in the hands of NN consumers increase. This poses two counteracting effects to the firm. On the one hand, the firm can partially extract these extra surpluses through higher prices when the NN consumers purchase new EVs in the second stage (extraction effect). On the other hand, due to the higher perceived values of used EVs, they pose stronger competition against the firm's new EV offerings to the IN consumers (competition effect). Whether these effects collectively benefit or harm the firm's profit depends on the relative sizes of the NN and IN segments. With a low first-stage effective prodution cost (e.g., due to a large government purchase rebate), consumers are encouraged to move from IN to NN, making the extraction effect more prominent than the competition effect in determining the firm's profit. Thus, in such a scenario, a higher degree of resale anxiety makes it optimal for the firm to further promote the NN segment in the first stage. Therefore, increasing resale anxiety results in the increase in q_1 and Q, and the decrease in q_2. In contrast, when c_1 is relatively high (e.g., the government rebate is relatively small), more consumers are induced to defer adoption, which makes the competition effect outweigh the extraction effect. Thus, the firm strategically promotes the IN over the NN segment, which results in the decrease in q_1 and Q (increase in q_2) as resale anxiety increases.



(a) Relative adoption in α_r (b) Relative adoption in α_s (c) Characterization of $\bar{c}$

Figure 3 **Impact of anxieties on the total adoption size $Q^{(O,R)}$ and $\bar{c}(c_2)$ for $\lambda = 0.2, \delta = 0.5$, $\rho = 0.7$, and $c_2 = 0.05$**

Figure 3 demonstrates this contrast between the impacts of the two consumer anxieties. To contrast the impacts of range and resale anxieties under different levels of c_1, we demonstrate the relative total adoption sizes in Figures 3(a,b). The relative adoption size is defined as $\left(\frac{Q^{(O,R)}(\alpha_r,\alpha_s)}{Q^{(O,R)}(1,1)} - 1\right) \cdot 100\%$, i.e., the relative change in the adoption size ($Q^{(O,R)}(\alpha_r, 1)$ or $Q^{(O,R)}(1, \alpha_s)$) compared with the no anxiety case ($Q^{(O,R)}(1,1)$), while varying one type of anxiety from 1 to 2 and fixing the other to 1. Although the presence of anxieties typically hurts EV adoption, as shown in Figure 3(b) ($c_2 = 0.05$), we observe that the increasing resale anxiety may help improve adoption size when c_1 is small (e.g., governmental subsidy is large). This trend confirms Proposition 1. In Figure 3(c), we observe that the threshold $\bar{c}(c_2)$ typically decreases in both α_r and α_s for fixed c_2.

Observation 1. *An increase in α_r and α_s decreases $\Pi^{(O,R)}(\alpha_r, \alpha_s)$.*

Not surprisingly, we observe that an increase in consumer anxieties typically harms the firm's profit, as the perceived value of EVs becomes lower.

3.3. Discussions on Anxiety Modeling Assumptions

Next, we extend the model by relaxing two modeling assumptions. We first study the case in which consumer anxieties do not completely diminish in the second stage, i.e., the consumers' utility in the second stage converges to a convex combination of the two parties' beliefs instead of the firm's.

Second, we study the case in which consumers are heterogeneous in the anxiety levels. Although the following analysis is based on the baseline model of (O,R), we note that similar analyses are provided in Appendix A.2 for other business models which will be introduced later in §4.

3.3.1. Incomplete diminution of anxieties. Whereas the consumers and the firm make their respective first-stage decisions anticipating anxieties to persist and completely diminish in the second stage, respectively, one may wonder what would happen if the true utilities in the second stage are realized at some point in between the two parties' beliefs. Specifically, in the second stage, the consumers may still exhibit (some fraction of) anxieties and that the firm has to concede to such reality. To reflect this, we consider that β_i fraction of anxiety (where $1/\alpha_i \leq \beta_i \leq 1$) remains in the second stage for $i \in (r, s)$. Hence, in the second stage, the realized utility from owing a new EV becomes $(1 - \beta_r \alpha_r \lambda)\theta$ and the depreciation factor of a used EV is $(1 - \beta_s \alpha_s \delta)$. When $\beta_r = 1/\alpha_r$ and $\beta_s = 1/\alpha_s$, the model reduces to the original case where anxieties completely diminish. We assume $c_2 \leq 1 - \beta_r \alpha_r \lambda$ to avoid the case in which no one (even for the highest valuation consumers with $\theta = 1$) obtains positive utility from owning EVs in the second stage.

COROLLARY 1. *For given values of β_r and β_s, (i) the directional impacts of anxieties on $q_1^{(O,R)}$ and $Q^{(O,R)}$ are consistent with the complete diminution case; and (ii) the threshold in the first-stage production cost $\bar{c}(c_2)$ remains identical.*

This result shows that the qualitative impact of anxieties on EV adoption identified in Proposition 1 is not affected by the assumption that the anxieties completely diminish in the second stage. This is because β_i only affects the realized utility in the second stage and not how the firm or the consumers perceive(s) the EV in the first stage. Therefore, the first-stage adoption $q_1^{(O,R)}$ is independent of β_i and the threshold in the second-stage production cost also remains the same as in §3.2. Furthermore, in the second stage, incomplete diminution of anxieties yields the same directional effect on utilities as complete diminution, albeit with smaller magnitude.

3.3.2. Heterogeneity in anxieties. We next consider the case in which consumers exhibit different degrees of anxieties. To maintain analytical tractability, we consider two groups of consumers where γ fraction of consumers (where $0 < \gamma \leq 1$) exhibit anxieties and the remaining $(1 - \gamma)$ do not. One possible example where such heterogeneity may arise is when there are both individual and fleet consumers. For the latter, purchase decisions are largely driven by cost considerations and are less susceptible to psychological factors such as anxiety. Furthermore, fleet consumers are often given the opportunity to engage in extended trial periods (e.g., FedEx (2014)), through which they can accurately learn and gain confidence in the real operating characteristics of EVs.

Because consumers have different degrees of anxieties in the first stage, their adoption paths become different. That is, γ fraction of consumers make decision based on anxieties whereas the remaining segment makes decision based on no anxieties. For simplicity, we assume the firm and consumers are aware of this heterogeneity (and the value of γ). In the first stage, both the firm and consumers with no anxieties make their decisions knowing that anxious consumers make their first-stage purchase decisions based on their belief that anxieties will persist in the second stage. Due to the heterogeneity in anxieties, the EV purchasing behaviors in the first stage are different for the two consumer types. Let θ_1^a and θ_1^{na} be the thresholds in the EV valuations between NN and IN segments for the consumers with and without anxieties, respectively. Hence, the first-stage adoption size can be obtained by $q_1 = \gamma(1-\theta_1^a) + (1-\gamma)(1-\theta_1^{na})$. Then, in the second stage, anxieties diminish and all consumers realize their true utility values.

COROLLARY 2. *For given value of $\gamma \in (0,1]$, the directional impacts of anxieties on $q_1^{(O,R)}$ and $Q^{(O,R)}$ are consistent with the homogeneous anxiety case.*

This result shows that heterogeneity in consumer anxieties does not affect the directional impact of anxieties on EV adoption identified in Proposition 1.

4. Impact of Business Models

In this section, we study how the different business models affect the adoption behaviors of EVs. Focusing on the two dimensions of business model selection introduced in Figure 1, we first explore the impact of battery ownership and study if leasing can help mitigate consumer anxieties in §4.1. In §4.2, we explore the impact of charging technology by studying the trade-off between deploying enhanced charging infrastructure and offering EVs with larger battery capacity.

4.1. Impact of Battery Ownership: Leasing vs. Owning

We consider the (L,R) model, in which the firm offers a battery leasing service to consumers. Under this business model, a consumer purchases the EV without the battery and subscribes to a battery leasing service at a cost of r_t during each stage $t=1,2$. All other settings and the solution procedure remain the same as in the (O,R) model. For example, in the second stage, the firm determines q_2 by solving $\pi_2(q_1) = \max_{q_2,r_2}(p_2(q_1,q_2)-c_2)q_2 + r_2(q_1+q_2)$ subject to:

$$\begin{aligned}
\lambda\theta_2 - p_2 - r_2 &= \lambda\delta\theta_2 - p_u - r_2, \\
\delta\lambda\theta_3 - p_u - r_2 &= 0, \\
q_2 &= 1-\theta_2, \\
\theta_2 - \theta_3 &= q_1.
\end{aligned}$$

Contrasting the (L,R) with the (O,R) model, it is straightforward to see that the firm's profit for the (L,R) model is greater than or equal to that of the (O,R) model given the same level of anxieties. This is because the (L,R) model is equivalent to the (O,R) model with the additional constraints $r_1 = r_2 = 0$. The option of charging additional via the leasing service enables the firm to extract more surplus from the secondary market, because buyers of used EVs purchased in the second stage also need to pay the firm for battery leasing. For a direct comparison between the two models, we consider the case without consumer anxieties in the following lemma.

Lemma 1. *Comparing the (O,R) and (L,R) models, we obtain:* $q_1^{(O,R)}(1,1) < q_1^{(L,R)}(1,1)$, $q_2^{(O,R)}(1,1) > q_2^{(L,R)}(1,1)$, $Q^{(O,R)}(1,1) > Q^{(L,R)}(1,1)$, *and* $\Pi^{(O,R)}(1,1) < \Pi^{(L,R)}(1,1)$.

This result suggests that battery leasing can generate inefficiency in EV promotion, as it causes the second-stage and overall adoption sizes to decrease, although a greater level of early adoption is achieved. For durable goods with secondary market, one major characteristic is the competition between new and used products in the second stage, which prohibits the firm from possessing monopoly pricing power despite being the only firm in the market. However, Desai and Purohit (1998) show that, if the product is leased instead of sold, the firm retains monopoly status by directly setting the price of used cars. Similarly, we find that leasing a critical component (battery) yields the same effect. With monopoly pricing power on the battery leasing service, the firm is able to extract the surplus of the secondary market completely (i.e., the NN consumers do not obtain any economic profit by selling the used EVs). As a result, the firm's profit increases and overall adoption drops compared with the battery owning case. The results of Lemma 1 hold also in the presence of anxieties for the $(\cdot, R)$ models under reasonable parameter ranges, but may not always hold as range enhancement business models are employed, as we discuss in Section 5.

After drawing a comparison with the (O,R) model, we next investigate the impact of anxieties on the adoption size and profit under the (L,R) model.

Proposition 2. *(i) An increase in* α_r *results in a decrease in* $q_1^{(L,R)}(\alpha_r, \alpha_s)$ *and* $Q^{(L,R)}(\alpha_r, \alpha_s)$, *but an increase in* $q_2^{(L,R)}(\alpha_r, \alpha_s)$ *for any level of* α_s.
(ii) An increase in α_s *has no impact on* $q_1^{(L,R)}(\alpha_r, \alpha_s)$, $q_2^{(L,R)}(\alpha_r, \alpha_s)$, $Q^{(L,R)}(\alpha_r, \alpha_s)$, *and* $\Pi^{(L,R)}(\alpha_r, \alpha_s)$ *for any level of* α_r.

Observation 2. *An increase in* α_r *results in a decrease in* $\Pi^{(L,R)}(\alpha_r, \alpha_s)$, *for any level of* α_s.
The qualitative impact of range anxiety on EV adoption for the (L,R) model is identical to that on the (O,R) model. Interestingly, that is not the case for resale anxiety as α_s has no impact on adoption behavior as well as on the firm's profit. This implies that the firm can be effectively

immunized from the impact of resale anxiety by employing the battery leasing model. The following proposition shows how the firm takes advantage of the (L,R) models in the presence of range anxiety.

PROPOSITION 3. *An increase in α_r results in an increase in $r_2^{(L,R)}/p_2^{(L,R)}$.*

This indicates that the firm increases the ratio between the battery leasing and the second-stage EV prices with range anxiety. To effectively recoup the loss resulting from increased anxiety, the firm extracts further surplus from all EV buyers (both new and used) in the second stage via r_2.

In addition to EV adoption size, emission savings are another crucial metric that reflects the environmental benefits of EVs. For example, the U.S. Government (2013) uses the social cost of carbon (SCC) to measure environmental impacts of its policies, where the SCC estimates the social cost arising from a one-time, unit (one metric ton) increase in CO_2 emissions in a given year. In our context, EV adoption leads to savings in such social costs by reducing CO_2 emissions from gasoline consumption. Hence, to further explore the impact of business models on the environment, we consider the net present value of the SCC values associated with such CO_2 emissions during the adoption process. Specifically, we define *emission savings* as $E^{(\cdot,R)} = \omega_1 q_1^{(\cdot,R)} + \omega_2 Q^{(\cdot,R)}$, where we capture the GHG emission savings by the aggregate of the weighted EV usage in each stage. The parameters $\omega_1, \omega_2 > 0$ capture the respective weights in the emission savings between the early (i.e., q_1 EVs in the first stage) and late usages (i.e., Q EVs in the second stage). Note that the values of ω_1 and ω_2 can be different due to several reasons. First, the same volume of emissions causes more harm at a later stage (as damages are superadditive). Second, the emission volumes for the two vehicle types may change over time due to changes in fuel economy and sources of electricity.

COROLLARY 3. *For sufficiently large ω_1/ω_2, we have $E^{(L,R)}(1,1) > E^{(O,R)}(1,1)$.*

This shows that leasing model can help reduce the environmental burden, despite the fact that it may induce smaller total adoption, when there are no anxieties. This is due to the larger early adoption induced by the leasing model. In fact, the numerical analysis in §5 based on the San Francisco Bay area reveals that this may happen under a realistic scenario with anxieties.

On the final note, it is noteworthy that some firms provide a full leasing service in which both the vehicle and the battery are leased to consumers. Although we do not explicitly consider this business model, one can show that the battery leasing model yields an equivalent adoption equilibrium to that of the full leasing model, as shown in Appendix B.2. Furthermore, in reality, it is possible that anxiety levels and EV deterioration factors may be different under different business practices. We will discuss this issue in Appendix C.2.

4.2. Impact of Charging Option: Enhanced Charging vs. Enlarged Battery

Now we explore the impact of the other dimension of business model selection regarding battery charging options. To enrich the analysis of charging options, we contrast the two EV range enhancement strategies: offering enhanced charging infrastructure, the (O,E) model, and offering a regular charging model with an enlarged battery capacity, the (O,$\mathrm{R^C}$) model. In essence, this analysis resembles the debate between the EV business models of mainstream manufacturers (such as Nissan Leaf which offers about 80 miles per charge and requires a high density of public quick charging stations) and some of the upscale models (such as Tesla Model S which offers about 300 miles per charge, requiring lower density of quick charging stations).

We capture the enhanced range of EV by $(1-g\lambda)$ where $g \in [0,1]$ is the range enhancement factor. Note that a decrease in g represents greater range enhancement in the EV driving range. In practice, enhanced charging and enlarged battery strategies will incur variable and fixed costs. However, to focus on the key cost trade-off in contrasting the two business models, we assume that the enhanced charging model only incurs *fixed cost* and enlarged batteries only incurs *variable cost*, while considering the remaining cost to be zero. Specifically, for the firm to achieve the range improvement of g, it may either deploy a set of enhanced charging stations with a fixed cost of $F(g)$, or manufacture EVs with enlarged batteries at unit variable costs $\eta(g)c_1$ and $\eta(g)c_2$ in the two stages respectively, where $\eta(g) \geq 1$ is the battery enlargement cost factor. Note that we assume $\eta(g)$ is identical over the two stages for analytical convenience. Naturally, both $F(\cdot)$ and $\eta(\cdot)$ are increasing in the degree of range enhancement (i.e., decreasing in g). For tractability, we assume $\eta(g) = 1 + a(1-g)$ where $a \geq 1$ is a production cost conversion parameter. When there is no range enhancement ($g = 1$), we have $\eta(1) = 1$, thus the production costs reduce to c_1 and c_2. We do not impose any specific functional form for $F(\cdot)$, as we shall see that it does not affect the directionality in the firm's decision. To model the firm's strategic choice between the two options and to avoid complications arising from the potential gaming behaviors between the firm and the consumers, we assume that the range enhancement factor g is applied from the outset of Stage 1. We denote the optimal adoption sizes in Stage 1, Stage 2, the total adoption size, and the optimal profit for given $F(g)$, $\eta(g)$, and g by $q_1^{(\cdot,\cdot)}(F(g),g)$, $q_2^{(\cdot,\cdot)}(F(g),g)$, $Q^{(\cdot,\cdot)}(F(g),g)$, and $\Pi^{(\cdot,\cdot)}(F(g),g)$, respectively.

PROPOSITION 4. *(i) For the enhanced charging model, a decrease in g results in an increase in $q_1^{(O,E)}(F(g),g)$ and $Q^{(O,E)}(F(g),g)$, for any form of $F(g)$.*

(ii) Consider the regular charging model with enlarged battery under $\alpha_r = 1$. A decrease in g results in a decrease in $q_1^{(O,R^C)}(\eta(g),g)$ and $Q^{(O,R^C)}(\eta(g),g)$, if and only if $a \geq \frac{\lambda}{1-\lambda}$.

Proposition 4 suggests that achieving the same range enhancement (same value of g) with different strategies may lead to very different adoption scenarios. Specifically, although the enhanced charging model always results in greater early and total EV adoptions, we find that increasing the battery capacity, when there is no range anxiety, results in decrease in early and total adoptions if the variable cost of producing larger batteries is relatively large (a is large). We numerically confirm that this directional impact remains the same in the presence of anxieties in Figures 4(a) and (b), which illustrate the cases corresponding to Proposition 4(ii) with small and large values of a, respectively. Hence, from the perspective of promoting mass adoption, this suggests that enhanced charging is a more favorable strategy for enhancing range of EVs.

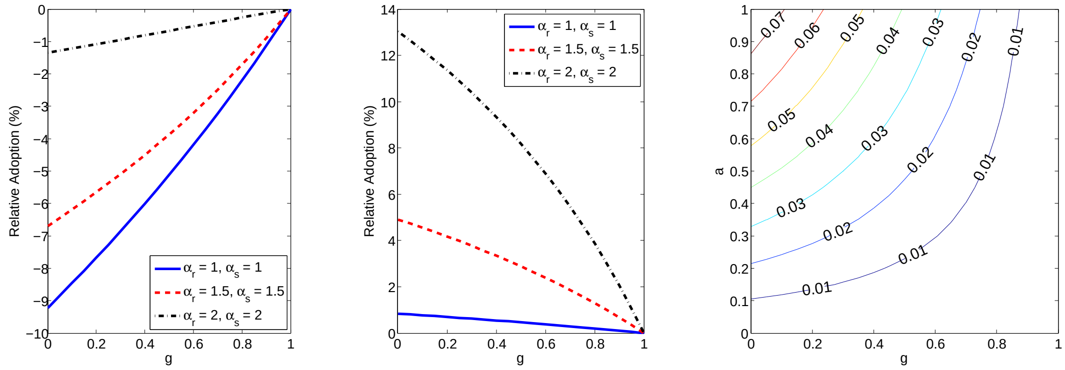
The contrast between the (O,E) and (O,R$^{\mathrm{C}}$) models is due to the fixed cost nature of infrastructure deployment and the variable cost nature of enlarged battery manufacturing. Intuitively, in the case where charging infrastructure is deployed, the investment becomes a sunk cost when the firm makes the pricing decisions. In contrast, when the firm decides to offer enlarged battery without enhanced charging infrastructure, it is converting the fixed cost into a variable cost, and may charge a higher price and sell fewer EVs in the equilibrium. Therefore, from the EV mass adoption perspective, the (O,E) model is favorable over the (O,R$^{\mathrm{C}}$) model. Indeed, this was a major criticism against Tesla's early (O,R$^{\mathrm{C}}$) strategy of selling high-end, long-range EVs (New York Times 2008) before its recent announcement of its plan to produce mass market, shorter-range EVs along with a massive expansion of the Supercharger network (Silicon Valley Business Journal 2014).

Considering the possible difference in the EV adoption behavior, it is also of interest to investigate the incentives in the firm's choice between the two range enhancement strategies.

Proposition 5. *For a given level of g, there exists a critical level in the infrastructure deployment cost $\hat{F}^O(g)$, below which the firm prefers offering the (O,E) model; otherwise, the firm prefers offering the (O,R^C) model. That is, $\Pi^{(O,R^C)}(\eta, g) \leq \Pi^{(O,E)}(F, g)$ holds if and only if $F \leq \hat{F}^O(g)$.*

Proposition 5 suggests that the firm's choice on range enhancement strategy depends on a critical level $\hat{F}^O(g)$ in the fixed infrastructure deployment cost. Hence, without government intervention, the firm may prefer increasing the EV range via the (O,R$^{\mathrm{C}}$) model if the infrastructure deployment is costly. Therefore, taking the perspective of inducing mass adoption, the government may need to reduce the burden of firm's infrastructure cost and thereby promote the (O,E) model. Specifically, this subsidy must be sufficiently large to reduce the effective deployment cost to below the critical level $\hat{F}^O(g)$. Figure 4(c) characterizes the critical level in the infrastructure deployment cost.

Finally, we note that the findings in this subsection do not depend on the type of battery ownership. Specifically, as shown in Appendix A.2, we find that the counterpart results for Propositions 4 and 5 still hold for the leasing models.



(a) Relative adoption for $a = 0.8$ (b) Relative adoption for $a = 0.2$ (c) Characterization of $\hat{F}^O(g)$

Figure 4 **Impact of anxieties on the first-stage adoption for the** $(\mathrm{O}, \mathrm{R}^\mathrm{C})$ **and the critical infrastructure deployment cost for** $\lambda = 0.2, \delta = 0.5, \rho = 0.7, c_1 = 0.3$, **and** $c_2 = 0.05$

5. Data Calibration and Insights

In this section, we take a more comprehensive and realistic perspective in examining the impact of anxieties by calibrating the model to the San Francisco Bay Area, one of the early-mover regions in the U.S. EV market. Through this numerical exercise, we also further contrast different business models, particularly focusing on the perspectives of the three major stakeholders involved in the industry, the firm, the consumers, and the government. Using these results, we finally address relevant policy implications for promoting the EV industry.

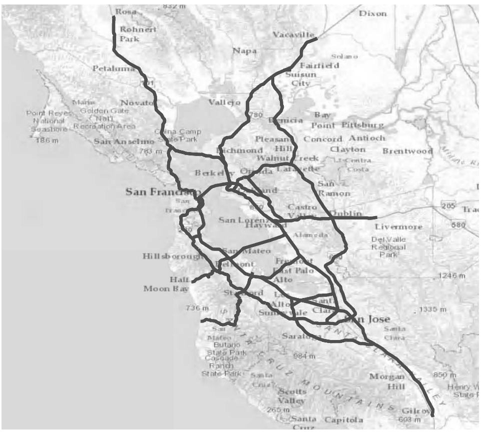
In conducting the numerical study, we consider the following four key performance measures: firm's profit, consumer surplus, adoption size, and emission savings. The *firm's profit* is of a primary interest to the private sector players who invest in the EV business. The *consumer surplus* is defined as the aggregate true utility of all consumers owning EVs, hence is of a primary interest to the consumers. We derive the consumer surplus by integrating the utilities of consumers with respect to the valuation parameter θ over the NN, NH and IU segments (the II segment has zero utility). Thus, for example, the consumer surplus for the (O,R) model is evaluated as follows:

$$CS^{(O,R)} = \int_{\theta_1^{(O,R)}}^{1} \left((1-\lambda)\theta - p_1^{(O,R)} + \rho((1-\lambda)\theta - p_2^{(O,R)} + p_u^{(O,R)})\right) d\theta$$
$$+ \int_{\theta_2^{(O,R)}}^{\theta_1^{(O,R)}} \left(\lambda\theta - p_1^{(O,R)} + \rho(1-\delta)(1-\lambda)\theta\right) d\theta + \int_{\theta_3^{(O,R)}}^{\theta_2^{(O,R)}} \rho((1-\delta)(1-\lambda)\theta - p_u^{(O,R)}) d\theta.$$

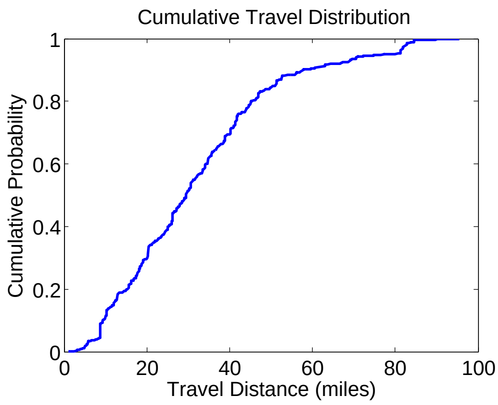
Note that because the anxieties are purely psychological effects, they affect the consumer surplus only by influencing firm's pricing (and infrastructure deployment) decisions and consumers' purchasing decisions, but not the actual usage experiences of EVs. Finally, the *adoption size* and the *emission savings* reflect the government's EV adoption target and the associated environmental benefit, and are therefore relevant performance measures for the public sector. Next, we discuss the construction of the data set we use along with the detailed procedure of our numerical analysis.

5.1. Data Description and Calibration Procedure

Our numerical data set is estimated based on the freeway network in the San Francisco Bay Area, shown in Figure 5(a). Based on the topology of the network and population density of cities in the region, we estimate the travel patterns of drivers (potential consumers of EVs). From this, we derive the cumulative distribution for travel distance shown in Figure 5(b). Other EV related parameters are estimated based on the current auto market figures and industry reports. The details of the data set and parameter estimation process are provided in Appendix C.1.



(a) San Francisco Bay Area network



(b) Estimated travel distribution

Figure 5 **An illustration of the geographical data set used for the numerical study**

5.1.1. The San Francisco Bay Area Freeway Network. We constructed a realistic data set based on the network of major freeways in the San Francisco Bay Area: I80, CA 84, CA 92, US 101, CA 237, I280, I580, I680 and I880. We define 554 segments by considering sections between adjacent exits and ramps connecting two freeways. In defining the travel paths, we consider all 53 cities in the Bay Area. We define the collection of travel paths as the shortest paths connecting the segments nearest to the centers of every pair of cities in the list. We assume that one of every three consecutive segments (i.e., the exit at the end point) is a candidate station location.

5.1.2. Range Enhancement Estimations. In the enlarged battery models, the firm chooses the optimal level of g by evaluating the resulting profit $\Pi^{(\cdot,R^C)}(\eta(g),g)$ for candidate g values corresponding to driving ranges of 80 to 200 miles based on the travel distribution.

In the enhanced charging models, the firm attempts to optimize infrastructure deployment to cover the travel needs of potential consumers. It is straightforward to observe that the firm's profits in the enhanced charging model, excluding the station deployment costs, are increasing in the resulting range (i.e., decreasing in g). That is, for any given number of stations to be deployed, denoted by B, it maximizes the profit by selecting the set of locations that maximize the resulting coverage of travel needs. This is done by solving an extension of the enhanced charging station location model in Mak et al. (2013) with a maximum-covering-type objective. By varying B, the firm can obtain a set of candidate location plans yielding different degrees of range extension (i.e., values of g), from which the firm selects the one that maximizes its profit $\Pi^{(\cdot,E)}(F(g),g)$ taking into account the different fixed costs involved.

To determine optimal enhanced charging station locations, we consider a set of candidate facility locations J on the network. By locating a number of enhanced charging stations, the firm covers a subset of all travel paths exceeding the EV range, denoted by P. Following the estimated travel pattern distribution, let ϕ_p denote the proportion of EV flows along path p. We define binary decision variables $X_j, j \in J$ to indicate whether a station is built at a candidate location j ($X_j = 1$), or not ($X_j = 0$). If a station is located, the firm incurs a fixed cost of f. To cover a path $p \in P$, it is required that at least one station be located along any subpath of p (i.e., sub-segment of p exceeding the driving limit). We denote the set of subpaths by K. Similar to Mak et al. (2013), we also define binary decision variables Z_{jk} to indicate whether EVs traveling along subpath $k \in K$ will visit an enhanced charging station at location $j \in J$. Finally, the binary decision variables Y_{jp} indicate whether the EVs traveling path $p \in P$ will visit a swapping station at location $j \in J$. To facilitate the modeling, we also define binary parameters b_{pk} to indicate whether a subpath $k \in K$ is part of path $p \in P$ ($b_{pk} = 1$) or not ($= 0$). We also define a binary parameter a_{jk} to indicate whether candidate location $j \in J$ is along subpath $k \in K$ ($a_{jk} = 1$) or not ($a_{jk} = 0$). Then, the following facility location model can be formulated to determine the locations that jointly cover the largest amount of flow along paths, given a budget of B stations to be located.

$$
\begin{aligned}
\max_{X,Y,Z\in\{0,1\}} \quad & \sum_{p\in P} \phi_p Y_p \\
\text{subject to:} \quad & X_j \geq a_{jk} Z_{jk} \text{ , for each } j \in J, k \in K \\
& Y_p \leq b_{pk} \sum_{j\in J} Z_{jk} \text{ , for each } p \in P, k \in K \\
& \sum_{j\in J} X_j = B.
\end{aligned}
$$

In the above formulation, the objective is to maximize the total proportion of flows covered. The first constraint requires that a station be located if it is used to cover any subpath. The second constraint indicates that a path can only be covered if all subpaths along it are covered by some stations. The third constraint requires that B stations be built.

After solving the above problem with 508 paths (exceeding the range of EVs), $6,023$ subpaths, and 180 candidate sites, we can determine the optimal enhanced charging station locations and the optimal trip coverage $(1-\lambda g^B)$, which is the proportion of potential trips that can be covered by EVs with the infrastructure. We use this to obtain an estimate of the firm's operating profit, $\Pi^{(\cdot,E)}(F(g^B),g^B)$. Note that our analysis in §3 is performed by scaling the potential market size to 1 and the range of consumer valuations to $[0,1]$. Therefore, the overall operating profit will be $M\bar{\theta}\Pi^{(\cdot,E)}(F(g^B),g^B)$, where M denotes the (pre-scaling) potential market size and $\bar{\theta}$ denotes the maximum valuation in dollars.

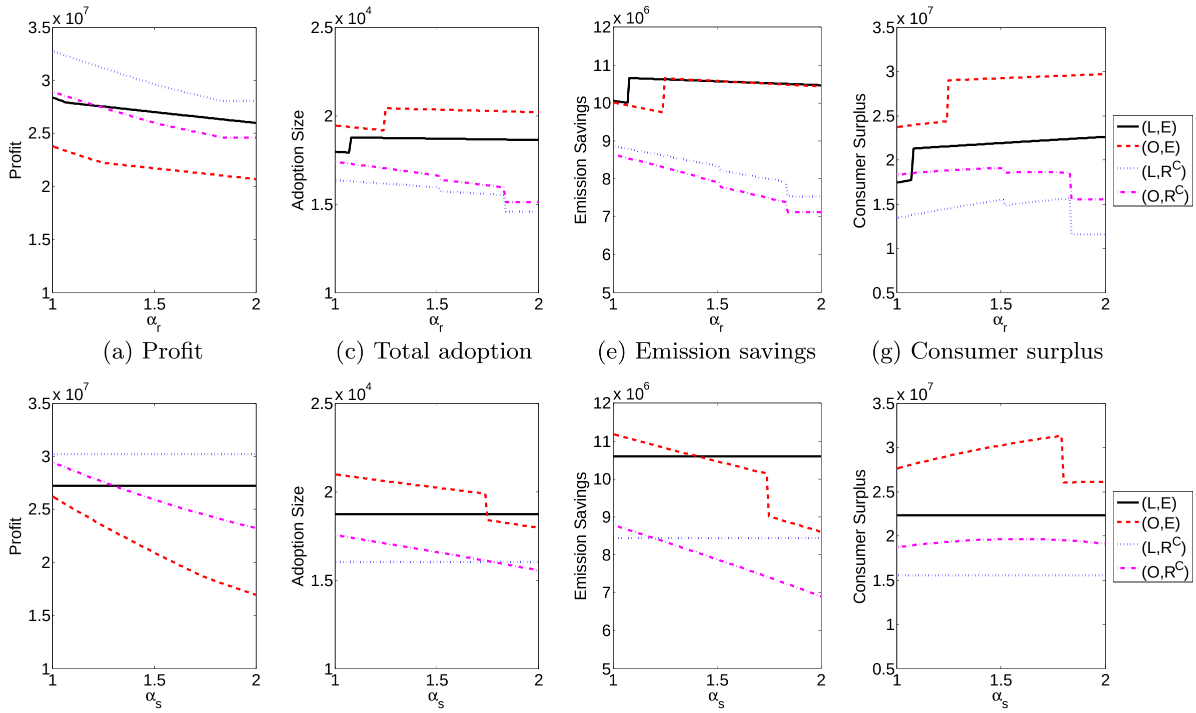
Based on the above procedure, we obtain the profit from deploying each value of B stations within the firm's budget, i.e., $[\underline{B},\bar{B}]$. Then, the profit-maximizing solution can be obtained by evaluating the total profit associated with each location plan: $\max_{B=\underline{B},\underline{B}+1,\ldots,\bar{B}} N\bar{\theta}\Pi^{(\cdot,E)}(F(g^B),g^B)-F(g^B)$, where $F(g^B)=fB$ is the fixed cost of building B stations.

5.1.3. Technology Improvement Estimations. For new technologies such as EVs, production costs are typically high in the early stage due to small production scale. Over time, as production scales up with growing adoption, economies of scale can be reached and unit production costs can potentially be reduced significantly. For example, Tesla projects to achieve a 30% reduction of EV battery production cost by building a large-scale battery plant named the "Gigafactory" with a capacity of 500,000 EV batteries per year (Bloomberg 2014). However, critics question whether such a scale can be realistically reached considering the current (relatively low) EV adoption level; and in the case it cannot, whether the new plant will deliver significant cost improvements (e.g., Barron's (2014)). Indeed, whether adoption sizes grow rapidly enough to support production scale economies is one key factor behind the mass adoption of a new technology.

In light of this, we allow the degree of cost improvement between the two stages to depend on adoption size in the numerical analysis. In particular, we assume that the second-stage production cost c_2 to be a decreasing function of q_1. Similar treatment has been considered by Lobel and Perakis (2013) to capture the evolution of production costs of solar photovoltaic panels. The negative relationship between production cost and (early) adoption size creates a positive feedback in the market evolution, such that early success in promoting adoption produces a positive effect on the long-term development of the market. This type of positive feedback is qualitative similar to product diffusion (see, e.g., Bass (1969)) in the sales of new products, despite the difference in the source of feedback: in the marketing literature, diffusion is typically triggered by word-of-mouth effects. For tractability, we assume $c_2(q_1)=m-nq_1$, where m and n are constants.

5.2. Implications of Anxieties, Business Models, and Policy

Using the network data and estimated parameter values, we now investigate the impact of anxieties and compare the performance of business practices. With the goal of recommending policy design for supporting the EV industry, we focus our attention to the four business models generated by the options of leasing (L,·) versus owning (O,·), and the two range enhancement strategies, enlarged battery capacity (·,R^C) versus enhanced charging infrastructure (·,E). The key performance measures are presented in Figure 6, in which we vary each type of anxiety while fixing the other type at a moderate level of 1.4.



(a) Profit (c) Total adoption (e) Emission savings (g) Consumer surplus

(b) Profit (d) Total adoption (f) Emission savings (h) Consumer surplus

Figure 6 **Performance comparison of the four business models under varying consumer anxieties**

5.2.1. Impact of Anxieties. We first observe that both range and resale anxieties generally harm the firm's profit, except that the (L,R) and (L,R^C) models are immune from resale anxiety, as shown in Proposition 2(ii). To further discuss the impact of anxieties on the other three performance measures, we note that anxieties may change the firm's optimal level of range enhancement (i.e., enhanced charging infrastructure investment or battery capacity) under the (·,E) and (·,R^C) models, corresponding to vertical jumps in performance measures shown in Figures 6(c-h).

We first consider the impact of range anxiety. Intuitively, under the (·,E) models, higher degrees of range anxiety tend to trigger larger investments in enhanced charging stations, because the return on additional investment increases for a fixed infrastructure deployment cost. While the firm increases the investments to overcome range anxiety, it attempts to recover the fixed investment costs by selling larger quantities of EVs. Hence, this increases the adoption sizes, in line with Proposition 4(i), which then may lead to increases in the emission savings and consumer surplus, as the degree of range anxiety increases. Interestingly, we observe an opposite trend for the ($\cdot$,R$^{\mathrm{C}}$) models. Although the firm similarly counters the range anxiety by increasing the EV range (through larger batteries), the adoption size actually decreases due to the variable cost nature of the battery, in line with Proposition 4(ii). Hence, this increases the EV price significantly, and as a result, both emission savings and consumer surplus may also suffer.

As for the resale anxiety, we first note that the impact of resale anxiety on the optimal range enhancement strategies shows a contrast against that of range anxiety. In particular, under the (O,E) model, resale anxiety can cause the firm to reduce investments in enhanced charging infrastructure, leading to smaller adoption sizes (thus, smaller emission savings and consumer surplus). One main reason is that, in the perception of consumers in the first stage, the secondary market will now pose weaker competition against the firm due to resale anxiety. This gives the firm extra (virtual) monopoly power such that its incentive for attracting consumers via infrastructure investments decreases. Moreover, leasing neutralizes the effect of resale anxiety (Proposition 2) that is otherwise detrimental to the firm's profit. Hence, we observe that, resale anxiety may potentially alter the favorability of the business model; specifically, owning models may become less favorable than the leasing models (in terms of adoption size, emission savings, and profit) if the resale anxiety is high enough. This highlights a possible benefit of battery leasing, namely, it maintains the firm's incentives to invest in enhanced charging infrastructure under high levels of resale anxiety.

While the discrete impacts of anxieties (jumps) are attributed by changes in the range enhancement decisions as discussed above, the continuous impacts of anxieties (slope) are driven by different factors. We may draw observations based on the trends of Figures 6 (c-h) for regions of anxieties that do not trigger changes in range enhancement investments. Overall, as long as the degree of range enhancement remains unchanged, adoption sizes and emission savings tend to decrease in anxiety levels under all four models, except for (L,$\cdot$) which are immune from resale anxiety. Note that, under the current estimation, c_1 is projected to be greater than the threshold values $\bar{c}(c_2)$ and thus we observe decreasing local trends of adoption sizes for the (O,$\cdot$) models as resale anxiety increases (in line with Proposition 1(ii)).

Interestingly, we note that anxieties do not necessarily harm consumer surplus, even when the degree of range enhancement remains unchanged, as shown in Figures 6(e,f). This is because the consumer surplus of the market is determined by both the total number of adoptions and the individual surplus levels of adopting consumers. As the degree of anxieties increases, the firm is forced to take price cuts to offset consumers' bias toward EVs. In turn, consumers who purchased EVs in the first stage enjoy their true values (which are greater than the perceived values) at the firm's expense. In the sense that one actually benefits from carrying a negative bias, a similar effect is also observed in the labor market (Sautmann 2013); underconfident workers tend to earn more than overconfident ones because the firms may adjust their offers accordingly based on the workers' estimate of their expected payoffs. However, one main difference between the two results is that our performance measure of consumer surplus is an aggregate over the population of consumers, while Sautmann's result refers to individual agents. In our case, consumer surplus increases as the additional gains of individual surplus more than offset the decrease in adoption size.

Finally, we remark that the above findings have implications on adoption outcomes under different market compositions of fleet and individual consumers. In a fleet-dominant market where consumers have lower anxiety levels, the firm has smaller incentives to invest in range enhancement, possibly leading to lower adoption, emission savings, and consumer surplus, while improving the firms profit compared with in a private-consumer-dominant market. Furthermore, the battery leasing models may become less socially favorable because resale anxiety is less of a concern.

5.2.2. Comparisons of Business Models. Contrasting the (L,·) and (O,·) models pairwise, we observe that the leasing models generate higher profits for the firm than do the owning models as shown in Figures 6(a,b). This is due to the surplus extraction through the battery leasing service, through which the firm immunizes itself from competition against the secondary market and gains monopoly pricing power. As a result of surplus extraction, the battery leasing service can result in less desirable outcomes, typically inducing smaller adoption size and consumer surplus, particularly when anxiety levels are low. However, interestingly, we find that the leasing models yield greater emission savings when consumer anxieties are sufficiently high. This is because leasing models promote early adoptions more heavily than the owning model do, as shown in Lemma 1, and are insensitive to resale anxiety which reduces emission savings for the owning models. This illustrates another potential benefit of the leasing business models.

Contrasting the (·,E) and (·,$\mathrm{R^C}$) models pairwise, we observe that offering range enhancement by enlarged battery capacity typically increases the firm's profit by targeting the high-margin market segment. Among other factors, this may partially explain the current development that Tesla, the EV manufacturer selling long-range EVs at high prices, has enjoyed the best profitability in the EV market. However, as discussed in §4.2, we find that the enhanced charging models result in

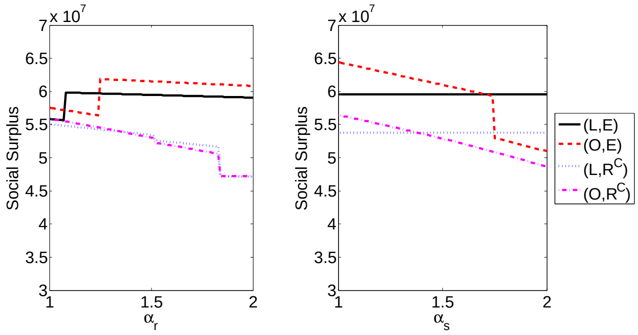


Figure 7 **Social surplus under varying anxieties**

α_r	α_s	(L,E)	(O,E)	(L,R^C)	(O,R^C)
low	low	1.90	$\star$	6.17	4.75
low	med.	$\star$	0.00	4.27	0.00
low	high	$\star$	0.00	4.27	0.00
med.	low	2.14	$\star$	4.76	3.22
med.	med.	6.28	$\star$	8.90	4.68
med.	high	$\star$	0.00	2.62	0.00
high	low	2.21	$\star$	4.08	2.87
high	med.	6.25	$\star$	8.11	4.01
high	high	$\star$	0.00	1.86	0.00

Table 1 **Subsidy to induce socially-favorable model (\$$10^6$)**

greater environmental benefits by attracting more adoption. Furthermore, due to larger adoption and lower selling prices, consumer surplus is also typically larger under the (·,E) models. This is consistent with the claim often made by the industry that the enhanced charging infrastructure is crucial to the success of EV markets (e.g., New York Times (2009), Wall Street Journal (2012)).

5.2.3. Policy Implications. Overall, we find that the interests of the firm, consumers, and the government are not perfectly aligned; that is, although one of the government's objectives is to induce EV mass adoption, the profitability of the private sector (the firm's profit) and consumer surplus are also crucial factors to the sustainable development of this nascent industry. To provide a broader understanding of the impact of anxieties and the favorability of business models from the policymaker's perspective, we consider *social surplus*, illustrated in Figure 7, that is defined as the sum of the firm's profit, emission savings, and the consumer surplus. We only include emission savings (but not the EV adoption size), since the three measures are all evaluated in the monetary units. However, one can easily extend this exercise with a modified social surplus incorporating the EV adoption size.

We find that the existence of range anxiety does not always harm the social surplus. As discussed before, the negative bias of consumers compels the firm to lower prices, leading to improvements in consumer surplus. Furthermore, a high degree of range anxiety can lead to additional enhanced charging investments under the (·,E) models which induces greater emission savings. These factors can outweigh the firm's reduced profits and lead to an overall improvement in social surplus.

Resale anxiety, on the other hand, typically hurts social surplus under the owning models, as the negative impacts on the firm's profit and emission savings dominate. Overall, when resale anxiety is small, (O,E) is typically the most socially-favorable business model, because it avoids the firm's surplus extraction (via leasing) while offering enhanced EV range, yielding larger emission savings and consumer surplus. The observation that (L,E) is less socially-favorable at low resale anxiety levels is consistent with the finding of Avci et al. (2014), albeit for different reasons; they show that the (L,E) model is favorable in the short term but inadvisable in the long term, because of the moral hazard issue that may increase the volume of driving. In our paper, the adverse effect of the leasing models arises from surplus extraction from the secondary market via the battery leasing contract. However, when the level of resale anxiety is high, we find that the (O,E) model suffers from the firm's reduced incentive to invest in enhanced charging infrastructure, and (L,E) becomes more socially-favorable option. This is because leasing eliminates the negative effects of resale anxiety. Therefore, we find that (O,E) tends to be the most socially-favorable option when resale anxiety is low; otherwise (L,E) tends to be more favorable when resale anxiety is high.

Taking the policymaker's perspective, the policy packages developed for supporting the EV industry should appropriately balance the benefits between the public and private sectors as well as the consumers. In particular, while it is socially favorable to encourage the (O,E) or (L,E) model under low and high resale anxiety levels, respectively, we note that these models are typically dominated by the (L,R^C) in terms of the firm's profit as seen in Figures 6(a,b). Therefore, the government must consider offering favorable policies (such as subsidies, loans, and tax breaks) to the private sector to induce the most socially-favorable models. Examples in practice include the agreement by the California Public Utilities Commission (Wall Street Journal 2012) or the government-led deployment of quick-charging stations in Beijing (People's Daily 2010), in both of which firms are provided incentives to employ enhanced charging. In the former example, the investment was funded by a legal settlement originally owed by the firm to the government; in the latter example, the investments are directly funded by the government.

Table 1 shows the required subsidy amounts for inducing the most socially-favorable business model under low (1.1), medium (1.5) and high (1.9) anxiety levels; that is, the required subsidy amount for the firm to switch from each business model to the one that maximizes social surplus, denoted by $\star$ in the table. We observe that the required subsidy amounts are largest when the firm employs the typically most profitable (L,R^C) model, and lowest (often zero) under the typically less profitable (O,E) model. We also note that the required subsidy amounts are below the additional emission savings and consumer surplus generated from the switch to (O,E) or (L,E) (whichever maximizes social surplus). Therefore, surplus re-balancing mechanisms (e.g., taxing consumers to transfer consumer surplus to the firm) can help induce the socially-favorable business models.

5.3. Summary and Discussion

Next, we provide a summary of key insights and discussion on robustness of data calibration.

- Although anxieties generally harm the firm's profit, they typically improve consumer surplus by compelling the firm to mark down prices. Further, range anxiety may lead to increased adoptions under the enhanced charging model due to increased infrastructure investments; and resale anxiety does not affect adoptions under the battery leasing model.
- Enhanced charging service is typically conducive to mass adoption and emission savings, and improves consumer surplus. In contrast, battery leasing service and enlarged batteries typically increase the firm's profit while limiting EV adoption.
- Overall, the (O,E) and (L,E) models generally provide the highest social surplus when the degree of resale anxiety is relatively low to moderate and high, respectively. In light of this, policy-makers should carefully design policy instruments to balance surpluses among stakeholder groups and properly incentivize the private sector to employ the socially-favorable business models.

Finally, we note that our parameters estimations are mainly based on predictions and thus it is important to check the robustness of the results as well as exploring varying business environments. In Appendix C.2, we conduct a robustness test for (i) varying parameter estimations within a range of $\pm 10\%$, (ii) varying levels of anxieties under different business practices, and (iii) varying degrees of production cost improvements. We find that all results continue to hold qualitatively. For example, an increase of the cost reduction parameter n (i.e., the same q_1 causes a more significant cost reduction in the second stage) can expand the range of anxiety levels under which the (O,E) model is socially-favorable, but does not change the overall pattern as shown in Figures 6.

6. Conclusion

With substantial economic and environmental potentials, sustainable growth and successful establishment of the EV industry are critical steps toward greener transportation. While many studies (e.g., Becker et al. 2009, Gartner Study 2011) have primarily focused on the technological and engineering aspects of EV (such as battery technology and service networks for recharging vehicles) in forecasting the future of the industry, we study the economics of the EV adoption process taking into account consumer anxieties and the secondary market.

Given the nascent nature of EV technology, we draw interesting observations on EV adoption behavior that contrast with regular durable goods, due to the presence of consumer anxieties. We also study various business models proposed to address the ownership cost structure (owning or leasing battery) and limited driving range (enhanced charging or enlarged battery) of EVs. Such new aspects, which were not present for conventional cars, pose opportunities to deploy new business models that imply different adoption trajectories. We find that the business models that offer enhanced charging infrastructure and require consumers to own and lease the batteries (i.e., the (O,E) and (L,E) models) provide the most favorable societal outcome incorporating the objectives of mass adoption, profitability of private sector, and consumer surplus, at low and high levels of resale anxiety, respectively. In order to induce adoption of the socially-favorable business model, policymakers should carefully transfer surplus from consumers to the firm through proper policies. Our analyses and findings highlight the value of modeling the consumer behaviors and exploring emerging business models, and complement the classical results in the sustainable durable goods literature. Our paper also contributes by taking into account respective perspectives of various stakeholders as well as policymakers in this emerging green technology industry.

Although we limit the scope of this study to issues related to the consumer anxieties, it is worthwhile to consider other factors that affect the EV adoption process. For example, it would be interesting to study, with the same budget, whether the government should subsidize consumers to promote early EV adoption or the private sector to encourage the early service network establishment, or a combination of both. Another important issue to study is the effect of competition as more automakers participate in the EV market. If one considers competition in our model setting, we expect that it will have relatively greater impact on the leasing model than the owning model, because the leasing model exhibits greater monopoly power to the consumers. However, to conduct a complete analysis, one must consider other relevant factors that may also affect the adoption outcome and desirability of the business model (e.g., is the enhanced charging infrastructure made available to other firms' users?). This can potentially be a fruitful area for future research.

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Online Appendix to
Toward Mass Adoption of Electric Vehicles:
Impacts of the Range and Resale Anxieties

Appendix A. Analyses of the Main Results

Appendix A.1. Proofs of Analytical Results

Proof of Proposition 1.

Following the solution procedure, it is straightforward to obtain the equilibrium outcome:

$$q_1^{(O,R)}(\alpha_r,\alpha_s) = \frac{2-2c_1+(c_2(2-\delta-\alpha_s\delta)+\lambda+\delta(1-\alpha_s-\lambda))\rho-\alpha_r\lambda(2+(1-\alpha_s\delta)\rho)}{4-4\alpha_r\lambda+\rho(1+\lambda-2\alpha_r\lambda+\delta(2-2\lambda-\delta(1-\lambda+2\alpha_s^2(1-\alpha_r\lambda))))},$$
$$q_2^{(O,R)}(\alpha_r,\alpha_s) = \frac{(1-\lambda)(1-(1-\delta)q_1^{(O,R)})-c_2}{2(1-\lambda)}, \quad Q^{(O,R)}(\alpha_r,\alpha_s) = \frac{(1-\lambda)(1+q_1^{(O,R)}(1+\delta))-c_2}{-2(1-\lambda)}.$$

Part (i): By taking the partial derivative, we obtain

$$\frac{\partial q_1^{(O,R)}(\alpha_r,\alpha_s)}{\partial \alpha_r} = \frac{4c_1\lambda(-2-(1-\alpha_s^2\delta^2)\rho)+\lambda\rho(2c_2(2-\delta-\alpha_s\delta)(2+\rho-\alpha_s^2\delta^2\rho)-(1-\delta)(1-\lambda)(2(1+\delta)+(1-\alpha_s\delta)(1+\delta+2\alpha_s\delta)\rho))}{\left(4-4\alpha_r\lambda+\rho(1+\lambda-2\alpha_r\lambda+\delta(2-2\lambda-\delta(1-\lambda+2\alpha_s^2(1-\alpha_r\lambda))))\right)^2}.$$

We note that the denominator is strictly positive. The numerator is linear in c_2, thus we can verify its sign by checking the cases where $c_2=0$ and $c_2=c_1$, which both can be shown to be strictly negative. Therefore, $\frac{\partial q_1^{(O,R)}(\alpha_r,\alpha_s)}{\partial \alpha_r}<0$. The impact of α_r on $q_2^{(O,R)}(\alpha_r,\alpha_s)$ and $Q^{(O,R)}(\alpha_r,\alpha_s)$ directly follow from the relationship with $q_1^{(O,R)}(\alpha_r,\alpha_s)$.

Part (ii): By taking the partial derivative, we obtain

$$\frac{\partial q_1^{(O,R)}(\alpha_r,\alpha_s)}{\partial \alpha_s} = \frac{\delta\rho}{\left(4-4\alpha_r\lambda+(1+\lambda-2\alpha_r\lambda+\delta(2-2\lambda-\delta(1-\lambda+2\alpha_s^2(1-\alpha_r\lambda))))\rho\right)^2}\cdot$$
$$\Big(\big(1+c_2-\alpha_r\lambda\big)\big(4-4\alpha_r\lambda+(1+\lambda-2\alpha_r\lambda+\delta(2-2\lambda-\delta(1-\lambda+2\alpha_s^2(1-\alpha_r\lambda))))\rho\big)$$
$$-4\alpha_s\delta\big(1-\alpha_r\lambda\big)\big(2-2c_1+(c_2(2-\delta-\alpha_s\delta)+\lambda+\delta(1-\alpha_s-\lambda))\rho-\alpha_r\lambda(2+(1-\alpha_s\delta)\rho)\big)\Big).$$

One can see that the sign of above is determined by the numerator which is linear in c_1. Since the coefficient of c_1 is negative, the sign of $\frac{\partial q_1^{(O,R)}(\alpha_r,\alpha_s)}{\partial \alpha_s}$ is negative if and only if

$$c_1 > \bar{c}(c_2) = \frac{1}{8\alpha_s\delta(-1+\alpha_r\lambda)}\cdot$$
$$\Big(c_2(4+(1+\lambda+2\delta(1-4\alpha_s-\lambda)-\delta^2(1-2\alpha_s(2+\alpha_s)-\lambda))\rho-2\alpha_r\lambda(2+(1-\alpha_s\delta(4-(2+\alpha_s)\delta))\rho))$$
$$+(1-\alpha_r\lambda)(4+(1+(2-\delta)(1-\lambda)\delta+\lambda)\rho+2\alpha_s^2\delta^2(1-\alpha_r\lambda)\rho-2\alpha_r\lambda(2+\rho)-4\alpha_s\delta(2+(\delta+\lambda-\delta\lambda)\rho-\alpha_r\lambda(2+\rho)))\Big).$$

The impact of α_s on $q_2^{(O,R)}(\alpha_r,\alpha_s)$ and $Q^{(O,R)}(\alpha_r,\alpha_s)$ directly follows their relationship with $q_1^{(O,R)}(\alpha_r,\alpha_s)$. The proof of $c_1\le\bar{c}(c_2)$ follows similarly. $\square$

Proof of Corollary 1.

The solution procedure with β_r and β_s are identical to that of the case where anxieties completely diminish. Hence, we can similarly obtain the equilibrium outcome:

$$q_1^{(O,R)}(\alpha_r,\alpha_s) = \frac{2-2c_1+(c_2(2-\delta-\alpha_s\delta)+\lambda+\delta(1-\alpha_s-\lambda))\rho-\alpha_r\lambda(2+(1-\alpha_s\delta)\rho)}{4-4\alpha_r\lambda+\rho(1+\lambda-2\alpha_r\lambda+\delta(2-2\lambda-\delta(1-\lambda+2\alpha_s^2(1-\alpha_r\lambda))))},$$
$$Q^{(O,R)}(\alpha_r,\alpha_s) = \frac{(1-\alpha_r\beta_r\lambda)(1+(1+\alpha_s\beta_s\delta)q_1^{(O,R)})-c_2}{2(1-\alpha_r\beta_r\lambda)}.$$

From the above, $q_1^{(O,R)}$ does not depend on β_i; in fact, it is identical to that from the complete diminishing anxiety case. Hence, the directionality of $q_1^{(O,R)}$ follows from the proof of Proposition 1. In addition, (ii) holds immediately from this since $\bar{c}(c_2)$ is a solution of $\frac{\partial q_1}{\partial \alpha_s}=0$. For the impact of range anxiety on the total adoption, we obtain

$$\frac{\partial Q}{\partial \alpha_r} = \frac{(1+\alpha_s\beta_s\delta)(1-\alpha_r\beta_r\lambda)^2\frac{\partial q_1}{\partial \alpha_r}-\beta_r c_2\lambda}{2(1-\alpha_r\beta_r\lambda)^2}.$$

Using the fact that $\frac{\partial q_1}{\partial \alpha_r}<0$, one can see that an increase in α_r results in a decrease in $q_1^{(O,R)}$; that is, $\frac{\partial Q}{\partial \alpha_r}<0$. As for the impact of resale anxiety, one can see from the expression of $Q^{(O,R)}$ that the directionality of $Q^{(O,R)}$ with increase in α_s (i.e., $\frac{\partial Q}{\partial \alpha_s}$) directly follows the directionality of $\frac{\partial q_1}{\partial \alpha_s}$ as the second term in the numerator and denominator do not depend on β_s. Thus, there exists a threshold $\bar{c}(c_2)>0$ such that an increase in α_s results in a decrease in $Q^{(O,R)}$ if and only if $c_1 \geq \bar{c}(c_2)$. $\square$

Proof of Corollary 2.

With heterogeneous customers, the first-stage system equations is given by:

$$\begin{aligned}
(1-\alpha_r\lambda)\theta_1^a-p_1+\rho\big((1-\alpha_r\lambda)\theta_1^a-\hat{p}_2+\hat{p}_u\big) &= \rho\big((1-\alpha_r\lambda)\theta_1^a-\hat{p}_2\big),\\
(1-\lambda)\theta_1^{na}-p_1+\rho\big((1-\lambda)\theta_1^{na}-p_2+p_u\big) &= \rho\big((1-\lambda)\theta_1^{na}-p_2\big),\\
q_1 &= \gamma(1-\theta_1^a)+(1-\gamma)(1-\theta_1^{na}),
\end{aligned} \tag{A.1}$$

where p_2, p_u, $\hat{p}_2$, and $\hat{p}_u$ are obtained similarly from system equations (1) and (2). Through (A.1), the firm obtains $p_1(q_1)$. By solving the profit maximization problem, we obtain

$$q_1^{(O,R)} = \frac{2-2\lambda(1+\alpha_r-\alpha_r\lambda)-2c_1(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)+(2c_2(1-\delta)+(1-\alpha_s)(1+c_2)\delta\gamma)\rho}{(1-\lambda)\big(4+\big(1+\delta(2-3\delta+2(1-\alpha_s^2)\delta\gamma)+(1-\delta)^2\gamma\lambda\big)\rho-\alpha_r\lambda\big(4+(1+\gamma+\delta(2-3\delta-(2-3\delta+2\alpha_s^2\delta)\gamma))\rho\big)\big)}$$
$$-\frac{\lambda(\alpha_r(2c_2(1-\delta)(1-\gamma)+(1-\alpha_s\delta)\gamma(1-\lambda))-\gamma(1-c_2(2-\delta-\alpha_s\delta)-\lambda-\delta(2-\alpha_s-\lambda)))\rho}{(1-\lambda)\big(4+\big(1+\delta(2-3\delta+2(1-\alpha_s^2)\delta\gamma)-(1-\delta)^2\gamma\lambda\big)\rho-\alpha_r\lambda\big(4+(1+\gamma+\delta(2-3\delta-(2-3\delta+2\alpha_s^2\delta)\gamma))\rho\big)\big)}.$$

Note that the remaining adoption expressions ($q_2^{(O,R)}$ and $Q^{(O,R)}$) are identical to the case with homogenous anxiety case. Then, we have

$$\frac{\partial q_1^{(O,R)}}{\partial \alpha_r} =$$

$$\frac{\gamma\lambda}{(4+(1+\delta(2-3\delta+2(1-\alpha_s^2)\delta\gamma)+(1-\delta)^2\gamma\lambda)\rho-\alpha_r\lambda(4+(1+\gamma+\delta(2-3\delta-(2-3\delta+2\alpha_s^2\delta)\gamma))\rho))^2}\cdot$$
$$\Big[4c_1\big(-2-(1-\delta^2)\rho\big)$$
$$+\rho\big(4c_2(2-\delta-\alpha_s\delta)+c_2(1-\delta)(4+\delta(1-\alpha_s-\delta-3\alpha_s\delta))\rho+(1-\delta)(1-\lambda)(2(1+\delta)+(1-\delta)(1+3\delta)\rho)\big)$$
$$+\gamma\big(4(-1+\alpha_s^2)c_1\delta^2\rho+(1-\alpha_s)c_2\delta(1+\delta(2-\delta+2\alpha_s(2-(2+\alpha_s)\delta)))\rho^2+(1-\alpha_s)(1-\delta)\delta(1-3\delta-2\alpha_s\delta)(1-\lambda)\rho^2\big)\Big].$$

It is easy to see that the first term is positive. The remaining terms (the last three lines) are linear in γ. When $\gamma=1$, Proposition 1(i) shows that $\frac{\partial q_1^{(O,R)}}{\partial\alpha_r}$ is negative. Hence, we only need to verify for the case in which $\gamma=0$. Since the remaining terms (the last two lines) are linear in c_1 and c_2, we verify the signs for the extreme points $c_1=c_2=1-\lambda$, $c_1=c_2=0$, and $c_1=0$, $c_2=1-\lambda$. With algebra, it is straightforward to show that these terms are negative under all three cases.

Next, we have

$$\frac{\partial q_1^{(O,R)}}{\partial\alpha_s}=$$
$$\frac{\delta\gamma\rho}{(4+(1+\delta(2-3\delta+2(1-\alpha_s^2)\delta\gamma)+(1-\delta)^2\gamma\lambda)\rho+\alpha_r\lambda(4+(1+\gamma+\delta(2-3\delta-(2-3\delta+2\alpha_s^2\delta)\gamma))\rho))^2}$$
$$+\Big[\frac{8\alpha_s\delta(1-\alpha_r\lambda)(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)}{1-\lambda}c_1$$
$$-\frac{4\alpha_s\delta(1-\alpha_r\lambda)(2-2\lambda(1+\alpha_r-\alpha_r\lambda)+(2c_2(1-\delta)+(1-\alpha_s)(1+c_2)\delta\gamma)\rho)}{1-\lambda}$$
$$+\frac{4\alpha_s\delta\lambda\rho(1-\alpha_r\lambda)(\alpha_r(2c_2(1-\delta)(1-\gamma)+(1-\alpha_s\delta)\gamma(1-\lambda))-\gamma(1-c_2(2-\delta-\alpha_s\delta)-\lambda-\delta(2-\alpha_s-\lambda)))}{1-\lambda}$$
$$+(1+c_2-\alpha_r\lambda)\big(4+(1+\delta(2-3\delta+2(1-\alpha_s^2)\delta\gamma)+(1-\delta)^2\gamma\lambda)\rho-\alpha_r\lambda(4+(1+\gamma+\delta(2-3\delta-(2-3\delta+2\alpha_s^2\delta)\gamma))\rho)\big)\Big].$$

One can see that the sign of the coefficient of c_1 is determined by that of $8\alpha_s\delta(1-\alpha_r\lambda)(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)$. Since $\alpha_r\lambda\leq 1$ and $\alpha_r\geq 1$, this term is positive which leads the same directionality of $\frac{\partial q_1^{(O,R)}}{\partial\alpha_s}$ in Proposition 1.

Finally, using the relationship among $q_1^{(O,R)}$ and $Q^{(O,R)}$, it is straightforward to show the directional impact of anxieties in Corollary 2. □

Proof of Lemma 1.

It is straightforward to see $q_1^{(O,R)}(1,1)=\frac{2(1-c_1-\lambda+c_2(1-\delta)\rho)}{(1-\lambda)(4+(1+2\delta-3\delta^2)\rho)}\leq\frac{2(1-c_1-\lambda+c_2(1-\delta)\rho)}{4(1-\lambda+(1-\delta)\delta(1-\lambda)\rho)}=q_1^{(L,R)}(1,1)$ holds comparing the denominators. Moreover, we have $q_2^{(O,R)}(1,1)=\frac{-c_2+(1-\lambda)(1-(1-\delta)q_1^{(O,R)})}{2(1-\lambda)}\geq\frac{-c_2+(1-\lambda)(1-2(1-\delta)q_1^{(L,R)})}{2(1-\lambda)}=q_2^{(L,R)}(1,1)$ using $q_1^{(O,R)}(1,1)\leq q_1^{(L,R)}(1,1)$. For the total adoption size, we can compare $Q^{(O,R)}(1,1)=\frac{-c_2+(1-\lambda)(1+(1+\delta)q_1^{(O,R)})}{2(1-\lambda)}$ and $Q^{(L,R)}(1,1)=\frac{-c_2+(1-\lambda)(1+2\delta q_1^{(L,R)})}{2(1-\lambda)}$ by checking the sign of $(1+\delta)q_1^{(O,R)}(1,1)-2\delta q_1^{(L,R)}(1,1)=\frac{(1-\delta)(1-c_1-\lambda+c_2(1-\delta)\rho)(2+(1-\delta)\delta\rho)}{(1-\lambda)(1+(1-\delta)\delta\rho)(4+(1-\delta)(1+3\delta)\rho)}$. Since all terms are strictly positive with $0<\delta<1, 0<\rho<1$, and $c_1\leq 1-\lambda$, we conclude that $Q^{(O,R)}(1,1)>Q^{(L,R)}(1,1)$.
□

Proof of Proposition 2.

Following the solution procedure, it is straightforward to obtain the equilibrium outcome:

$$q_1^{(L,R)}(\alpha_r,\alpha_s)=\frac{1-c_1-\alpha_r\lambda+c_2(1-\delta)\rho}{2(1-\alpha_r\lambda+(1-\delta)\delta(1-\lambda)\rho)},\quad q_2^{(L,R)}(\alpha_r,\alpha_s)=\frac{(1-\lambda)(1-2(1-\delta)q_1^{(L,R)}-c_2)}{2(1-\lambda)},$$

$$Q^{(L,R)}(\alpha_r,\alpha_s)=\frac{(1-\lambda)(1+2\delta q_1^{(L,R)}-c_2)}{2(1-\lambda)}.$$

Part (i): By taking the partial derivative, we obtain

$$\frac{\partial q_1^{(L,R)}(\alpha_r,\alpha_s)}{\partial\alpha_r}=-\frac{\lambda(c_1-c_2(1-\delta)\rho+\delta(1-\delta)(1-\lambda)\rho}{2(1-\alpha_r\lambda+(1-\delta)(1-\lambda)\delta\rho)^2}$$

which is negative. The impact of α_r on $q_2^{(L,R)}(\alpha_r,\alpha_s)$ and $Q^{(L,R)}(\alpha_r,\alpha_s)$ directly follows their relationship with $q_1^{(L,R)}(\alpha_r,\alpha_s)$.

Part (ii): Since α_s is not involved in $\partial q_1^{(L,R)}(\alpha_r,\alpha_s)$, it has no impact on $q_1^{(L,R)}(\alpha_r,\alpha_s)$, and $q_2^{(L,R)}(\alpha_r,\alpha_s)$. $\square$

Proof of Proposition 3.

Let $G=\frac{r_2^{(L,R)}}{p_2^{(L,R)}}$. Then, we have $G=-\frac{(1-\delta)(c_2+(1-\lambda)(1-2\delta q_1^{(L,R)}))(1-\alpha_r\lambda+(1-\delta)\delta(1-\lambda)\rho)}{\delta(c_1(1-\delta)(1-\lambda)-(c_2+(2-\delta)(1-\lambda))(1-\alpha_r\lambda)-(1-\delta)(1-\lambda)(c_2+\delta-\delta\lambda)\rho)}$. By taking the partial derivative, we obtain

$$\frac{\partial G}{\partial\alpha_r}=\frac{(1-\delta)^2(1-\lambda)\lambda(c_2+(1-\lambda)(1-2\delta q_1^{(L,R)}))(c_1-(1-\delta)(c_2-\delta(1-\lambda))\rho)}{\delta\big(c_1(1-\delta)(1-\lambda)-(c_2+(2-\delta)(1-\lambda))(1-\alpha_r\lambda)-(1-\delta)(1-\lambda)(c_2+\delta-\delta\lambda)\rho\big)^2}.$$

The denominator is positive. Also, it is straightforward to see that the numerator is positive. $\square$

Proof of Corollary 3.

The proof of this follows immediately from Lemma 1 since $q_1^{(L,R)}(1,1)>q_1^{(O,R)}(1,1)$ and $Q^{(L,R)}(1,1)<Q^{(O,R)}(1,1)$ holds. Therefore, there exists a threshold in ω_2/ω_1 below which $E^{(L,R)}>E^{(O,R)}$ holds. $\square$

Proof of Proposition 4.

Part (i): Since $F(g)$ only appears in the profit function as a separate term, we only need to consider $F(g)=0$. Then we have,

$$\frac{\partial q_1^{(O,E)}(0,g)}{\partial g}=\frac{\lambda}{(4-4\alpha_r g\lambda+(1+g(\lambda-2\alpha_r\lambda)+\delta(2-2g\lambda-\delta(1-g\lambda-2\alpha_s^2(1-\alpha_r g\lambda))))\rho)^2}\cdot$$
$$\big[(1-\alpha_r)(1-\delta)\rho(2+\rho-\alpha_s(1+2\alpha_s)\delta^2\rho+\delta(2+\rho+\alpha_s\rho))-\big(4\alpha_r(2+(1-\alpha_s^2\delta^2)\rho)-2(1-\delta)^2\rho\big)c_1$$
$$+(4\alpha_r(2-\delta-\alpha_s\delta)\rho+(2-\delta-\alpha_s\delta)((1-\delta)^2+2\alpha_r(1-\alpha_s^2\delta^2))\rho^2)c_2\big].$$

We can see that the sign of $\frac{\partial q_1^{(O,E)}(g)}{\partial g}$ is determined by its numerator which is linear in c_2. Since $\alpha_r\geq 1$, $\delta\leq 1$, and $\alpha_s\delta\leq 1$, we have the first line of numerator to be negative. When $c_2=c_1$, the numerator becomes $(1-\alpha_r)(1-\delta)\rho(2+\rho-\alpha_s(1+2\alpha_s)\delta^2\rho+\delta(2+\rho+\alpha_s\rho))+(2-(2-\delta-$

$\alpha_s\delta)\rho)(-4\alpha_r + ((1-\delta)^2 - 2\alpha_r(1-\alpha_s^2\delta^2))\rho)c_1$, which is also can be shown to be negative. Thus, $\frac{\partial q_1^{(O,E)}(0,g)}{\partial g}$ is negative.

In addition, we have $Q^{(O,E)}(0,g) = \frac{1}{2} - \frac{c_2}{2-2g\lambda} + \frac{1+\alpha_s\delta}{2} q_2^{(O,E)}(0,g)$. It is straightforward to see that $Q^{(O,E)}(0,g)$ is decreasing in g.

Part (ii): We have

$$\frac{d}{dg} q_1^{(O,R^C)}(\eta(g), g|\alpha_r = 1) = \frac{(a(1-\lambda)-\lambda)(2c_1 - c_2(2-\delta-\alpha_s\delta)\rho)}{(1-g\lambda)^2(4+(1+\delta(2-\delta-2\alpha_s^2\delta))\rho)}. \tag{A.2}$$

It is clear that the denominator of (A.2) is negative. In addition, $\frac{d}{dg} q_1^{(O,R^C)}(\eta(g), g|\alpha_r = 1)$ is linear in c_2. When $c_2 = 0$, the numerator of (A.2) is $2c_1(a(1-\lambda)-\lambda)$ which is positive when $\lambda \leq \frac{a}{1+a}$. When $c_2 = c_1$, the numerator of (A.2) is $c_1(a(1-\lambda)-\lambda)(2-(2-\delta-\alpha_s\delta)\rho)$ which is positive when $\lambda \leq \frac{a}{1+a}$. Thus, $\frac{d}{dg} q_1^{(O,R^C)}(\eta(g), g|\alpha_r = 1)$ is positive when $\lambda \leq \frac{a}{1+a}$.

In addition, $Q^{(O,R^C)}(\eta(g), g) = \frac{1}{2} - \frac{c_2(1+a-ag)}{2-2g\lambda} + \frac{1+\alpha_s\delta}{2} q_2^{(O,E)}(0,g)$. It is straightforward to see that $Q^{(O,E)}(0,g)$ is increasing in g when $\lambda \leq \frac{a}{1+a}$.

Next, we have

$$\frac{d}{dg} q_2^{(O,R^C)}(\eta(g), g|\alpha_r = 1) = -\frac{(a(1-\lambda)-\lambda)(2c_1(1-\delta) - c_2(4+(1-\alpha_s\delta)(3-\delta+2\alpha_s\delta)\rho))}{2(1-g\lambda)^2(4+(1+\delta(2-\delta-2\alpha_s^2\delta))\rho)}. \tag{A.3}$$

It is clear that the denominator of (A.3) is positive. In addition, $\frac{d}{dg} q_2^{(O,R^C)}(\eta(g), g|\alpha_r = 1)$ is linear in c_2. It is easy to verify that when $c_2 = \frac{2(1-\delta)}{(4+3\rho-\delta\rho-\alpha_s\delta\rho+\alpha_s\delta^2\rho-2\alpha_s^2\delta^2\rho)} c_1$, we have $\frac{d}{dg} q_2^{(O,R^C)}(\eta(g), g|\alpha_r = 1) = 0$. The coefficient in front of c_2 in the numerator of (A.3) is $(a(1-\lambda)-\lambda)(4+(1-\alpha_s\delta)(3-\delta+2\alpha_s\delta)\rho)$ which is positive when $\lambda \leq \frac{a}{1+a}$. Thus, $\frac{d}{dg} q_2^{(O,R^C)}(\eta(g), g|\alpha_r = 1)$ is positive when $\lambda \leq \frac{a}{1+a}$ and $c_2 \leq \frac{2(1-\delta)}{(4+3\rho-\delta\rho-\alpha_s\delta\rho+\alpha_s\delta^2\rho-2\alpha_s^2\delta^2\rho)} c_1$. □

Proof of Proposition 5.

The profit under each business model is

$$\Pi^{(O,E)}(F(g), g) = (p_1^{(O,E)} - c_1)q_1^{(O,E)} + \rho((p_2^{(O,E)} - c_2)q_2^{(O,E)}) - F(g),$$

$$\Pi^{(O,R)}(\eta(g), g) = (p_1^{(O,R^C)} - \eta(g)c_1)q_1^{(O,R^C)} + \rho((p_2^{(O,R^C)} - \eta(g)c_2)q_2^{(O,R^C)}).$$

It is easy to see that $\Pi^{(O,E)}(F(g), g)$ is linear in $F(g)$. When $F(g) = 0$, we have

$$\begin{aligned}
\Pi^{(O,R^C)}(\eta(g), g) &= (p_1^{(O,R^C)} - \eta(g)c_1)q_1^{(O,R^C)} + \rho((p_2^{(O,R^C)} - \eta(g)c_2)q_2^{(O,R^C)}) \\
&\leq (p_1^{(O,R^C)} - c1)q_1^{(O,R^C)} + \rho((p_2^{(O,R^C)} - c2)q_2^{(O,R^C)}) \\
&\leq (p_1^{(O,E)} - c1)q_1^{(O,E)} + \rho((p_2^{(O,E)} - c2)q_2^{(O,E)}) \\
&= \Pi^{(O,E)}(0, g).
\end{aligned}$$

The first inequality holds due to $\eta(g) \geq 1$. The second inequality holds due to the fact that $p_1^{(O,E)}, q_1^{(O,E)}, p_2^{(O,E)}, q_2^{(O,E)}$ is the maximizer of the profit maximization problem. When $F(g) = \infty$, we have $\Pi^{(O,R^C)}(\eta, g) > -\infty = \Pi^{(O,E)}(\infty, g)$. Thus, by the linearity of $\Pi^{(O,E)}(f,g)$ in $F(g)$, we have Proposition 5. $\square$

Proof of Lemma 2.

The critical level $\hat{F}^O(g)$ is given by the fixed infrastructure investment cost under which the firm is indifferent between the (O,R$^{\mathrm{C}}$) and (O,E) models. Therefore, $\hat{F}^O(g) = \Pi^{(O,E)}(0,g) - \Pi^{(O,R^C)}(\eta, g)$ holds, because $\Pi^{(O,E)}(F,g) = \Pi^{(O,E)}(0,g) - F$ holds for any F. Then,

$$\hat{F}^O(g) = \max_{p_1,p_2}[(p_1 - c_1)q_1 + \rho(p_2 - c_2)q_2] - \max_{p_1,p_2}[(p_1 - \eta(g)c_1)q_1 + \rho(p_2 - \eta(g)c_2)q_2],$$

where the maximization operations are subject to equations (1),(2), and (3) imposed as constraints. Hence, we have

$$\begin{aligned}
\hat{F}^O(g) &= (p_1^{(O,E)}(0,g) - c_1)q_1^{(O,E)}(0,g) + \rho(p_2^{(O,E)}(0,g) - c_2)q_2 - \max_{p_1,p_2}[(p_1 - \eta(g)c_1)q_1 + \rho(p_2 - \eta(g)c_2)q_2] \\
&\leq (p_1^{(O,E)}(0,g) - c_1)q_1^{(O,E)}(0,g) + \rho(p_2^{(O,E)}(0,g) - c_2)q_2^{(O,E)}(0,g) \\
&\quad -(p_1^{(O,E)}(0,g) - \eta(g)c_1)q_1^{(O,E)}(0,g) + \rho(p_2^{(O,E)}(0,g) - \eta(g)c_2)q_2^{(O,E)}(0,g) \\
&= \overline{F}^O(g).
\end{aligned}$$

In the above, the inequality holds because $p_1^{(O,E)}(0,g)$ and $p_2^{(O,E)}(0,g)$ define a feasible, but not necessarily optimal, solution to the second maximization problem. Similarly, we have

$$\begin{aligned}
\hat{F}^O(g) &= \max_{p_1,p_2}[(p_1 - c_1)q_1 + \rho(p_2 - c_2)q_2] - [(p_1^{(O,R^C)}(\eta,g) - \eta(g)c_1)q_1^{(O,R^C)}(\eta,g) \\
&\quad +\rho(p_2^{(O,R^C)}(\eta,g) - \eta(g)c_2)q_2^{(O,R^C)}(\eta,g)] \\
&\geq (p_1^{(O,R^C)}(\eta,g) - c_1)q_1^{(O,R^C)}(\eta,g) + \rho(p_2^{(O,R^C)}(\eta,g) - c_2)q_2^{(O,R^C)}(\eta,g) \\
&\quad -(p_1^{(O,R^C)}(\eta,g) - \eta(g)c_1)q_1^{(O,R^C)}(\eta,g) + \rho(p_2^{(O,R^C)}(\eta,g) - \eta(g)c_2)q_2^{(O,R^C)}(\eta,g) \\
&= \underline{F}^O(g).
\end{aligned}$$

Therefore we have Lemma 2. $\square$

Appendix A.2. Additional Analytical and Numerical Results

In this section, we present additional results to provide completeness in our analyses.

Relaxation of Anxiety Modeling Assumptions. We first relax anxiety modeling assumptions (allowing for incomplete diminution of anxieties and heterogeneity in anxieties provided in §3.3 for the owning model) in the battery leasing model.

Corollary A.1. For given values of β_r and β_s, the directional impacts of anxieties on $q_1^{(L,R)}$ and $Q^{(L,R)}$ are consistent with the complete diminution case. Specifically, we have $\frac{\partial q_1^{(L,R)}}{\partial \alpha_r} < 0$, $\frac{\partial q_1^{(L,R)}}{\partial \alpha_s} = 0$, and $\frac{\partial Q^{(L,R)}}{\partial \alpha_r} < 0$, $\frac{\partial Q^{(L,R)}}{\partial \alpha_s} \geq 0$ where the last holds at equality when $\beta_s = 0$.

Proof. The solution procedure with β_r and β_s are identical to that of the case where anxieties completely diminish. Hence, it is straightforward to obtain the equilibrium outcome:

$$q_1^{(L,R)}(\alpha_r, \alpha_s) = \frac{1 - c_1 - \alpha_r\lambda + c_2(1-\delta)\rho}{2(1 - \alpha_r\lambda + (1-\delta)\delta(1-\lambda)\rho)},$$
$$Q^{(L,R)}(\alpha_r, \alpha_s) = \frac{1}{2} + \frac{c_2}{-2 + 2\alpha_r\beta_r\lambda} + \alpha_s\beta_s\delta q_1^{(L,R)}.$$

As in the (O,R) model, $q_1^{(L,R)}$ above is identical to the complete anxiety diminution case and thus its directionality follows from Proposition 2; i.e., $\frac{\partial q_1}{\partial \alpha_r} < 0$ and $\frac{\partial q_1}{\partial \alpha_s} = 0$. For the impact on total adoption, we first obtain

$$\frac{\partial Q}{\partial \alpha_r} = \alpha_s\beta_s\delta\frac{\partial q_1}{\partial \alpha_r} - \frac{c_2}{4(1-\alpha_r\beta_r\lambda)^2},$$

which can be shown negative using $\frac{\partial q_1}{\partial \alpha_r} < 0$. Further, we obtain

$$\frac{\partial Q}{\partial \alpha_s} = \alpha_s\beta_s\delta\frac{\partial q_1}{\partial \alpha_s} + \beta_s\delta q_1,$$

which is nonnegative due to $\frac{\partial q_1}{\partial \alpha_s} = 0$. Note that $\frac{\partial Q}{\partial \alpha_s}$ approaches 0 as β_s approaches 0 (i.e., the case where anxiety completely diminishes). □

Figure A.1 below shows the impact of incompletely diminishing anxieties under the four business models. Comparing with Figure 6, we observe that, with the exception that the impact of α_s does not completely diminish under the leasing models, all other qualitative findings remain the same.

Corollary A.2. For given value of $\gamma \in (0,1]$, the directional impacts of anxieties on $q_1^{(L,R)}$ and $Q^{(L,R)}$ are consistent with the homogeneous anxiety case. Specifically, we have $\frac{\partial q_1^{(L,R)}}{\partial \alpha_r} < 0$, $\frac{\partial q_1^{(L,R)}}{\partial \alpha_s} = 0$, and $\frac{\partial Q^{(L,R)}}{\partial \alpha_r} < 0$, $\frac{\partial Q^{(L,R)}}{\partial \alpha_s} = 0$.

Proof.

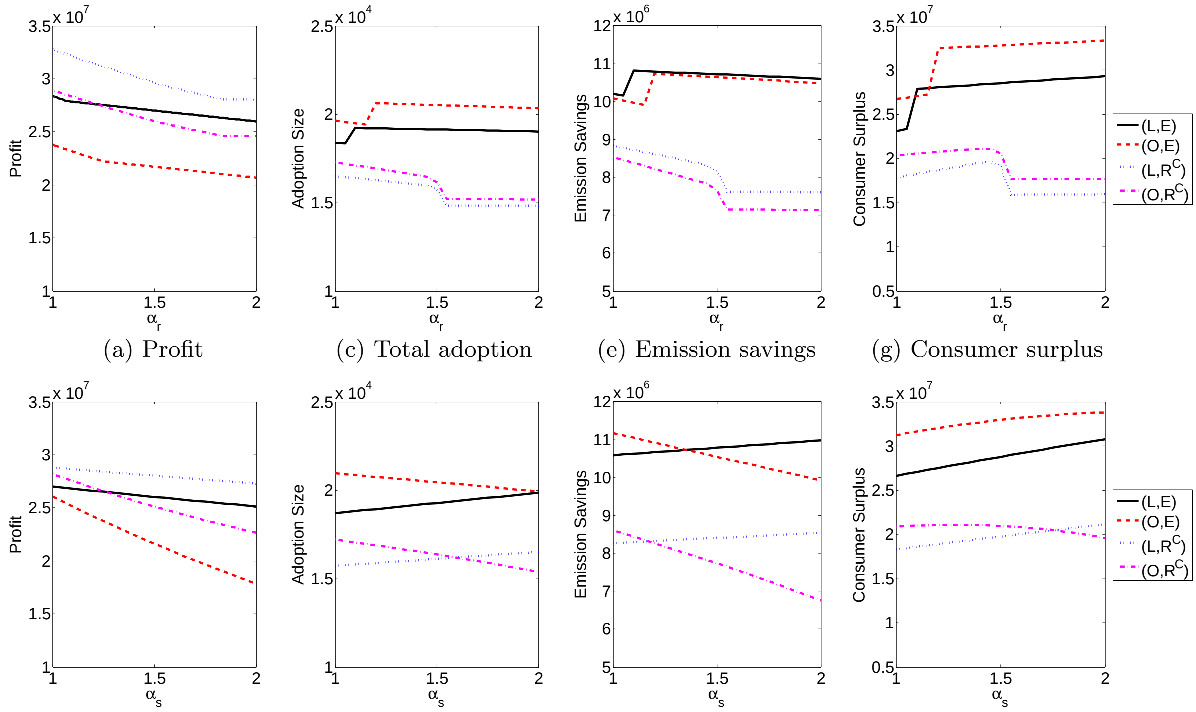
The solution procedure with heterogeneous customers for the leasing model is identical to that of the owning model and we can obtain the equilibrium outcome as

$$q_1^{(L,R)} = \frac{(1-\lambda)(1-\alpha_r\lambda) - c_1(1-(\alpha_r+\gamma-\alpha_r\gamma)\lambda) + c_2(1-\delta)(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)\rho}{2(1-\lambda)(1-\alpha_r\lambda+(1-\delta)\delta(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)\rho)},$$

while the remaining adoption expressions ($q_2^{(L,R)}$ and $Q^{(L,R)}$) are identical to the homogenous anxiety case. Then, we have

$$\frac{\partial q_1}{\partial \alpha_r} = -\frac{\gamma\lambda(c_1 - (1-\delta)(c_2 - \delta(1-\lambda))\rho)}{2(1-\alpha_r\lambda+(1-\delta)\delta(1-\alpha_r(1-\gamma)\lambda-\gamma\lambda)\rho)^2},$$

which both the numerator (from $c_1 > c_2$) and denominator are positive, and thus $\frac{\partial q_1}{\partial \alpha_r} < 0$. Further, we can easily see that $\frac{\partial q_1}{\partial \alpha_s} = 0$ because q_1 does not depend on α_s. For the impact on total adoption, one can easily see that the directionalities of total adoption ($\frac{\partial Q}{\partial \alpha_r}$ and $\frac{\partial Q}{\partial \alpha_s}$) follow immediately from $\frac{\partial q_1}{\partial \alpha_r}$ and $\frac{\partial q_1}{\partial \alpha_s}$ from its expression, $Q^{(L,R)} = \frac{(1-\lambda)(1+2\delta q_1)-c_2}{2(1-\lambda)}$. □



(a) Profit (c) Total adoption (e) Emission savings (g) Consumer surplus

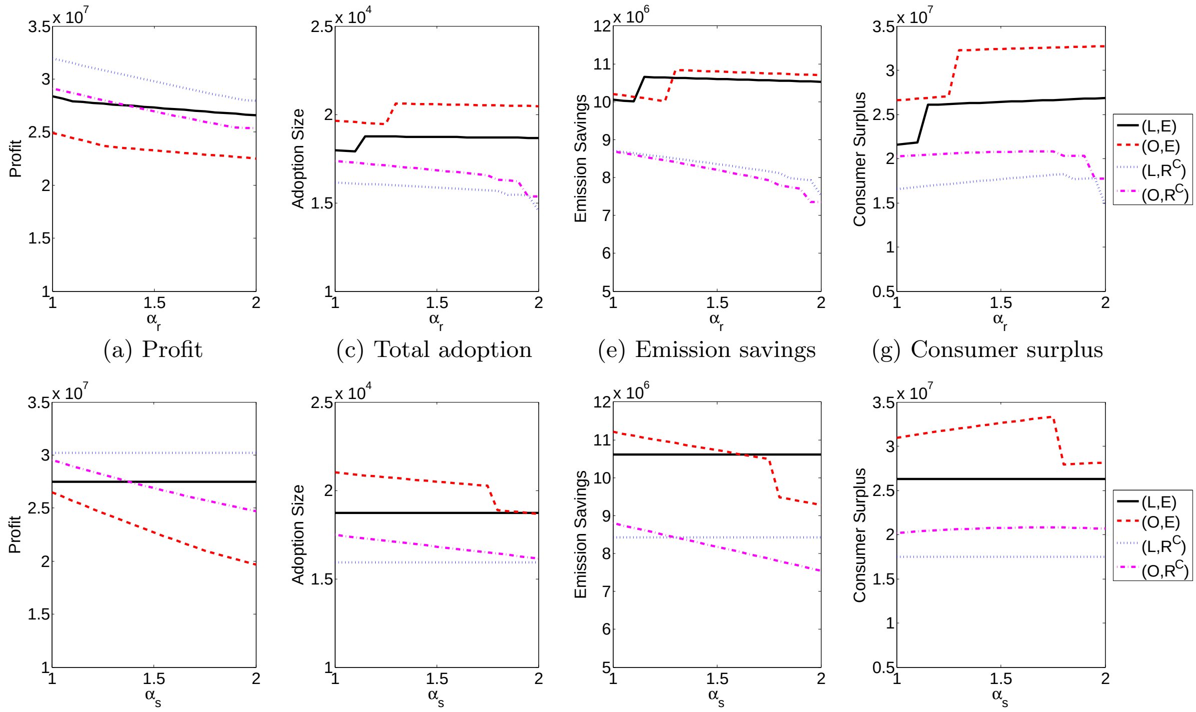
(b) Profit (d) Total adoption (f) Emission savings (h) Consumer surplus

Figure A.1 **Performance comparison of the four business models with incomplete diminution of anxieties when** $\beta = 0.3 + 0.7/\alpha$

Figure A.2 below shows the impact of heterogeneity in anxieties under the four business models. Comparing with Figure 6, we observe that all qualitative findings remain the same.

Impact of Anxieties on Emission Savings. Next, we provide additional numerical illustrations on the impact of anxieties. In Figure A.3, we first present the difference in the emission savings between the (L,R) and (O,R) models under three scenario varying ω_2. Greater value of ω_2 represents larger technological improvement that leads to greater level of CO_2 emission savings. We find that the improvement in the emission saving (i.e., $E^{(L,R)} - E^{(O,R)}$) between the (L,R) and (O,R) models is increasing in both α_r and α_s. In addition, we observe that the emission savings of (L,R) tend to be greater than that of (O,R) when ω_2 is smaller.

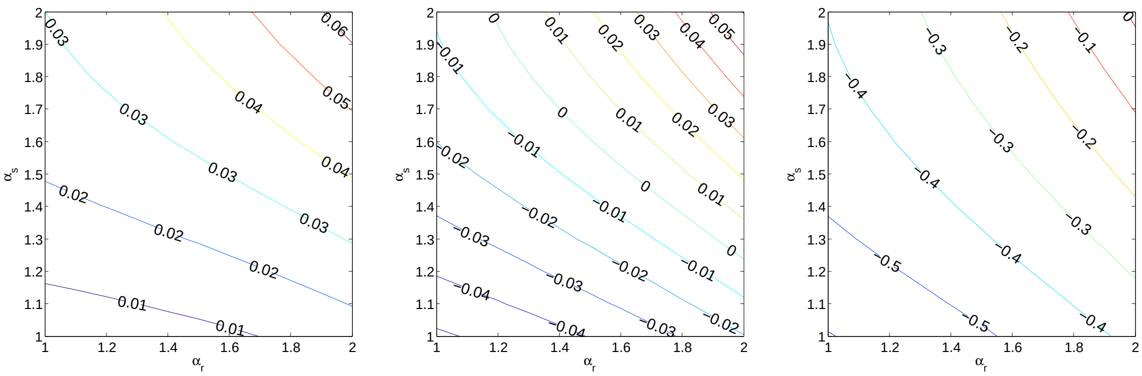
In the numerical studies reported in Section 5, we consider emission savings to be given by $\omega_1 q_1 + \omega_2 Q$. Recall that EVs can cover only $1 - g\lambda$ fraction of travel needs of consumers. In reality, one can expect that the emissions from the uncovered trips will not exceed the emissions of using gasoline vehicle, because in the worst case the consumer can simply rent an gasoline vehicle for long trips; in the best case, the per-trip emission savings associated with these uncovered trips may even exceed those of using EVs, because consumers may switch to even cleaner transportation modes (e.g., public transportation).



(a) Profit (c) Total adoption (e) Emission savings (g) Consumer surplus

(b) Profit (d) Total adoption (f) Emission savings (h) Consumer surplus

Figure A.2 **Performance comparison of the four business models with heterogeneity in anxieties when** $\gamma = 0.7$



(a) $\omega_2 = 0.1$ (b) $\omega_2 = 1$ (c) $\omega_2 = 10$

Figure A.3 **Impact of anxieties on emission savings** $(E^{(L,R)} - E^{(O,R)})$ **for** $\lambda = 0.2, \delta = 0.5, \rho = 0.7, c_1 = 0.3, c_2 = 0.05$, **and** $\omega_1 = 1$

In the next analysis, we provide the counterpart results as reported in Figures 6 and 7 using a more conservative estimate of emission savings (to show robustness of our result), assuming that the uncovered trips are completed with modes that achieve emission savings amounting up to just 50% of those enabled by driving EVs. This corresponds to a reasonably conservative scenario regarding the emissions of the uncovered trips. Note that this new assumption does not affect the firm's profit, adoption sizes, and consumer surplus, and therefore we only report consumer surplus and social surplus in Figure A.4 below. We observe that all qualitative findings remain unchanged.

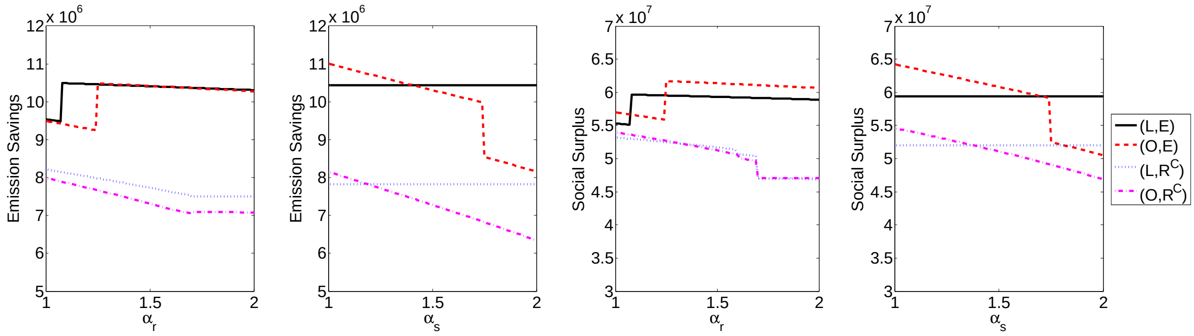


Figure A.4 **Performance comparison of the four business models when uncovered tips only achieve 50% of emission savings**

Comparison of Range Enhancement Strategies under Leasing. In the following corollary, we present the counterpart results of Proposition 4 under the leasing option.

Corollary A.3. (i) For the enhanced charging model with leasing, a decrease in g results in an increase in $q_1^{(L,E)}(F(g),g)$ and $Q^{(L,E)}(F(g),g)$, for any form of $F(g)$.

(ii) Consider a regular charging model with an enlarged battery capacity under $\alpha_r = 1$. A decrease in the range enhancement factor g results in an decrease in $q_1^{(L,R)}(\eta(g),g)$ if and only if $a \geq \frac{\lambda}{1-\lambda}$.

Proof.

Part (i): Similar to Proposition 4, we only need to consider $F(g) = 0$. Then we have,

$$\frac{\partial}{\partial g} q_1^{L,E}(0,g) = \frac{1}{2(1-\alpha_r g\lambda + (1-\delta)\delta(1-g\lambda)\rho)^2} \cdot \Big[(1-\alpha_r)(1-\delta)\delta\rho - c_1(\alpha_r + (1-\delta)\delta\rho) + c_2(\alpha_r(1-\delta)\rho + (1-\delta)^2\delta\rho^2)\Big].$$

It is clear that the first two terms of numerator are negative. Let $c_2 = c_1$. Then, the numerator is

$$(1-\alpha_r)(1-\delta)\delta\rho - c_1(1-(1-\delta)\rho(\alpha_r + (1-\delta)\delta\rho)).$$

Hence, it is also clear that the above term is also negative. In addition, we obtain $Q^{(L,E)}(0,g) = \frac{1}{2} - \frac{c_2}{2-2g\lambda} + \delta q_2^{(O,E)}(0,g)$. Therefore, it follows that $Q^{(O,E)}(0,g)$ is decreasing in g.

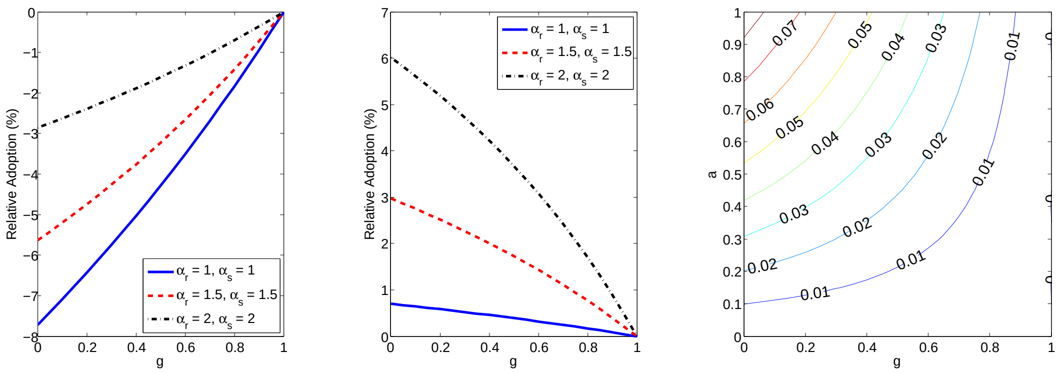
Part (ii): We have

$$\frac{\partial}{\partial g} q_1^{L,R}(\eta(g), g|\alpha_r = 1) = \frac{(a(1-\lambda)-\lambda)(c_1 - c_2(1-\delta)\rho)}{2(1-g\lambda)^2(1+(1-\delta)\delta\rho)}.$$

It is clear to see that $\frac{\partial}{\partial g} q_1^{L,R}(\eta(g), g|\alpha_r = 1)$ is positive only when $\lambda \leq \frac{a}{1+a}$. Since we know that $Q^{(L,R)}(\eta(g), g) = \frac{1}{2} - \frac{c_2}{2-2g\lambda} + \delta q_2^{(O,R)}(\eta(g), g)$, it follows that $Q^{(L,R)}(\eta(g), g)$ is increasing in g only when $\lambda \leq \frac{a}{1+a}$. $\square$

Under the leasing option, we again find that the two range enhancement strategies ((L,E) and (L,R$^{\mathrm{C}}$) models) may lead to very different adoption behaviors. We also note that similar results hold for Proposition 5 under the leasing option. Furthermore, we note that Proposition 2 also holds for both the (L,E) and (L,R$^{\mathrm{C}}$) models for any level of g.

Figure A.5 is a counterpart depiction of Figure 4, under the leasing model. In Figures A.5(a) and (b), we present the impact of anxieties on the first-stage EV adoption for the (L, R$^{\mathrm{C}}$) model. We find that the trend of anxiety impacts are the same under both business models, while its magnitude is smaller for the leasing model. In Figure A.5(c), we characterize the critical infrastructure deployment cost.



(a) Relative adoption for $a = 0.8$ (b) Relative adoption for $a = 0.2$ (c) Characterization of $\hat{F}^O(g)$

Figure A.5 **Impact of anxieties on the first-stage adoption for the** $(\mathrm{L}, \mathrm{R}^{\mathrm{C}})$ **and the critical infrastructure deployment cost for** $\lambda = 0.2, \delta = 0.5, \rho = 0.7, c_1 = 0.3,$ **and** $c_2 = 0.05$

Appendix B. Supplementary Discussions on Results

B.1. Discussion on the Consumer Strategy

Under consumer anxieties, the perceived utility obtained by a consumer with valuation θ under the five possible strategies are given by: $(1-\alpha_r\lambda)\theta - p_1 + \rho((1-\alpha_r\lambda)\theta - p_2 + p_u)$ (NN), $(1-\alpha_r\lambda)\theta - p_1 + \rho((1-\alpha_s\delta)(1-\alpha_r\lambda)\theta)$ (NH), $\rho((1-\alpha_r\lambda)\theta - p_2)$ (IN), $\rho(1-\alpha_s\delta)(1-\alpha_r\lambda)\theta - p_u)$ (IU), and 0 (II), respectively. For a customer with type θ, if NH strategy is better than NN and IU strategies, this implies $p_2 - p_u - \alpha_s\delta(1-\alpha_r\lambda)\theta > 0$ and $-p_1 + p_u\rho + \theta - \alpha_r\lambda\theta > 0$, respectively. If IN strategy is better than NN and IU strategies, then it requires $-p_1 + p_u\rho + \theta - \alpha_r\lambda\theta < 0$

and $p_2 - p_u - \alpha_s \delta(1-\alpha_r \lambda)\theta < 0$, respectively. Note that these conditions cannot hold concurrently. Therefore, either NH or IN, but not both, can be an optimal strategy in equilibrium.

We however note that our findings do not change qualitatively even when NH is considered in equilibrium (instead of IN). For parameter ranges in which NH is active in equilibrium for all 4 business models (when c_2 is large and α_r, α_s values are small), we observe that the numerical results are very similar as discussed in Section 5.

B.2. Discussion on Full Leasing Business Model

Under the battery leasing scenario, the firm's profit in the second stage is strictly increasing in r_2. On the other hand, the used EV price p_u is decreasing in r_2. Therefore, in the optimality, p_u becomes zero. Thus, we can interpret $p_1 + r_1$ as the leasing price of the entire car in the first stage, $p_2 + r_2$ as the leasing price of a new car in the second stage, and r_2 as the leasing price of the used car in the second stage. Based on this interpretation, we find that battery leasing model is equivalent to the full leasing model studied in Desai and Purohit (1998). That is, the firm can exert its monopoly power by setting the prices of both new and used EV in second stage directly under both leasing models. Therefore, our findings regarding consumer anxieties under the battery leasing model hold under the full leasing model.

Despite this modeling equivalence, however, we note that the outcomes under the two cases can be different when competition exists in the market. In particular, battery leasing essentially gives the firm more monopoly power because consumers cannot switch to another firm in the second stage, which is not the case under full leasing.

Appendix C. Data Set and Robustness for Numerical Analysis

C.1. Data Description and Parameter Estimation

The flow proportions ϕ_p are generated using a gravity model such that ϕ_p is proportional to the product of the populations of the origin and destination cities divided by the squared path length. These gravity models are widely used in transportation studies (see, e.g., Ortúzar and Willumsen (2011)) and reflect that more people travel out of and into cities with high populations that are separated by shorter distances. In particular, for a path of length d connecting two cities with populations p_o and p_d, the flow will be proportional to $p_o p_d d^{-\gamma}$ where $\gamma = 0.01$. The flow proportions as computed by the gravity model are scaled such that the sum over all paths in the network, $\sum_{p\in P} \phi_p$, equals 1. This results in the cumulative distribution for travel distance shown in Figure 5(b). The mean of this distribution is approximately 35 miles, which is consistent with the U.S. average daily travel distance of 36 miles according to the 2009 National Household Travel Survey

(U.S. Department of Transportation 2011). Furthermore, we consider enhanced charging to be necessary for paths longer than half of the typical range of EVs, or 40 miles, because such paths need to be covered during round trips. The estimate cost of a range-extension is \$4.5 million per station, which includes the costs of building, financing and operating a battery swapping/quick-charging station (New York Times 2009).

Schiraldi (2011) shows that the average length of holding a car is between 4 and 7 years depending on the car brand. In the present study, we set the length of each stage at 5 years. Assuming a discount rate of 10% per year, the discount factor for the second-stage utilities, ρ, is $1/1.1^5 = 0.62$. Finally, the deterioration rate of the used EVs, δ, is considered to be 0.57, which is approximately the ratio of the value of a 5-year-old Toyota Prius in good condition to that of Toyota Prius Style Two in the Bay Area according to the Kelley Blue Book (Kelley Blue Book 2013).

In the models discussed in §3 and §4, θ represents an individual consumer's willingness to pay for EVs in addition to conventional vehicles, including the lifetime cost savings and the psychological utility of greenness. Although we scale this parameter from the actual range of $[0, \bar{\theta}]$ (in dollars) to the interval [0, 1], we are interested in estimating the pre-scaling maximum value of $\bar{\theta}$. Doing so allows us to translate the model output into dollar units.

The parameter $\bar{\theta}$ is the sum of two values: the net present value of the lifetime fuel cost savings (c_f) and the maximum valuation of greenness among consumers ($\bar{g}$). The figure for cost savings, c_f, is relatively straightforward to obtain. According to Forbes (2012), the lifetime fuel cost estimate over 120,000 miles for EVs (mid-sized, 100-mile range, under the high-electricity price scenario) is \$8,693, whereas that of comparable conventional vehicles (4-cyl, mid-sized) is \$20,455. Because these figures are not discounted, we may apply a 10% discount rate for a lifetime of 10 years to obtain an estimate of c_f to be \$7,583.

The second component, $\bar{g}$, cannot be estimated using current EV prices because the current market for EVs is not yet mature. Instead, we will estimate the equivalent measure, $\bar{\theta}$, for the Toyota Prius, a hybrid car that offers both fuel cost savings and greenness over conventional vehicles and that has a mature market. We denote the maximum willingness to pay for the Prius over a comparable conventional car, the Toyota Corolla, by $\bar{\theta}^p$. The 2012 listed prices of these two cars differ by \$7,299. Therefore, this differential is the valuation of the marginal consumer who buys the Prius over the Corolla, taking into account both the lifetime cost savings and greenness. The next step is to scale this marginal value to the maximum value, assuming that consumer valuations follow a uniform distribution. We can do this by considering the size of the two markets of the Prius versus conventional vehicles. In 2012, the sales volume of the Prius (which makes up the vast majority of mid-size hybrid sales) and the sales of all mid-sized cars were 236,659 and 3,588,099 (Wall Street Journal 2013), respectively. Therefore, consumers with valuations from \$0 to \$7,299 accounted for a fraction of $3,351,440/3,588,099 = 0.934$. This suggests that the highest valuation in the distribution should be \$7,299/0.934=\$7,815. Recall that this value is the sum of the net present value of lifetime fuel cost savings and the greenness measure for the Prius. Based on the MPG of the Prius and Corolla (48 MPG versus 34 MPG, respectively), assuming usage for 120,000 miles over 10 years and a gasoline price equal to \$3, the former amounts to \$1,991. Therefore, the maximum greenness measure for the Prius is \$5,823.

Finally, we estimate the maximum greenness measure for EVs based on the Prius figure. We assume that greenness is inversely proportional to the per-mile carbon emissions of the two types of vehicles. In California, the well-to-wheel carbon emissions of pure EVs are estimated to be 26% lower than those of hybrid vehicles (Scientific American 2010). Therefore, the maximum greenness measure for EVs can be estimated to be $\bar{g} = \$5,823/(1-0.26) = \$7,869$. Combined with the fuel cost savings, the maximum valuation is \$7,869 + \$7,583 = \$15,452. Note that this value refers to the *lifetime* present value of the incremental utility of using an EV. This estimation is consistent with the findings from a survey study of U.S. residents conducted by Hidrue et al. (2011), which shows that the maximal willingness to pay for EVs over conventional cars is \$16,930. Because each stage will be approximately 5 years long in our model, we can estimate $\bar{\theta}$ to be the net present value of the utility from the first five years, which amounts to \$9,534.

To estimate c, we compared Nissan Leaf, a pure EV, and Nissan Versa, its counterpart gasoline vehicle. The price of Leaf was \$28,800 (Washington Post 2013) and that of Versa was \$16,030 (Kelley Blue Book 2013). It is known that Nissan is just breaking even recently on the Leaf model Reuters (2013). We obtained the net sales and cost of sales for Nissan as 9.41 trillion Yen and 7.77 trillion Yen, respectively, based on Nissan Annual Report (2012). Therefore, assuming the gross margins of the Leaf and Versa are equal to zero (breaking even) and the company average, respectively, the current production cost difference between the two vehicles are \$28,800-16,030 × 7.77/9.41 = \$15,564. In addition, the current federal tax credit for alternative fuel vehicle was \$7,500 and the current California EV purchase rebate was \$2,500. Thus, the net cost difference for California is \$15,449 - \$7,500 - \$2,500 = \$5,664. Therefore, the first-stage production cost parameter c_1 is $5,664/9,534 = 0.59$. Recall in §5.1.2 that we assume $c_2 = m - nq_1$. We assume that the baseline cost improvement is 50%, so that $m = 0.59 \times 0.5 = 0.3$. To quantify the value of economies of scale, we refer to Tesla's recent announcement on the Gigafactory that will run at a scale of producing 500,000 EV batteries per year and will lead to 30% cost reduction (Bloomberg

2014). Based on the estimated market share implied by the 500,000 figure, we obtain a value of n around 0.18. Furthermore, we also obtain an estimate for the parameter a which reflects the cost of producing EVs with enlarged batteries. From the travel demand distribution, we find that a range increase of 80 to 100 miles (about 25%) would increase the trip coverage from about 70% to about 85% ($\lambda = 0.3$ and $g\lambda = 0.15$, i.e., $g = 0.5$). Recall that we consider the incremental production cost on top of the gasoline car manufacturing cost, the majority of which is the battery production cost. Therefore, we assume that the battery enlargement cost factor $\eta(g)$ is proportional to range increase (i.e., battery size). Because $\eta(g) = 1 + a(1-g)$, we have $1.25 = 1 + a(0.5)$, leading to the estimate $a = 0.5$.

Finally, we estimate the total number of potential consumers, i.e., the size of the market. Mid-size car sales in the year 2012 were at 3.59 million (Wall Street Journal 2013). Projecting this figure to a period of 10 years and multiplying the resulting figure by the population of the Bay Area as a fraction of the total U.S. population, we obtain approximate mid-size car sales within the Bay Area of 826,719 for the time horizon considered. Based on the industry prediction that the proportion of electrified vehicles (including pure EVs, hybrids and plug-in hybrids) will not exceed 15% within the next decade (TechJournal 2012), we consider 5% of mid-size car sales (i.e., assume pure EVs to be one third of the entire electrified vehicles) would be potential market for the EV. In other words, we consider the potential market size for EVs (M) to be approximately 41,336.

Finally, the weights ω_1 and ω_2 in the expression for emission savings are estimated as follows. Our benchmark EV, the Leaf, consumes 29kWh of electricity per 100 miles driven (U.S. Department of Energy 2014). Within the California grid, one kWh of electricity is associated with 610 pounds (or 2.77×10^{-4} metric tons) of CO_2 emissions (U.S. Environmental Protection Agency 2014). Therefore, the Leaf emits $29 \times 2.77 \times 10^{-4}/100 = 8.024 \times 10^{-4}$ metric tons per mile. The Versa emits 335 grams (335×10^{-6} metric tons) of CO_2 per mile driven. Over 12,000 miles driven per year, the CO_2 emission reduction from driving the Leaf equals $12{,}000 \times (3.35 \times 10^{-4} - 8.024 \times 10^{-5}) = 3.06$ metric tons. From the U.S. government's SCC estimates (U.S. Government 2013), we take the moderate scenario figures of \$37 and \$43 per metric ton of CO_2 emitted in 2015 (Stage 1) and 2020 (Stage 2), respectively. We then take the net present value of the emission savings the first 5 years (for Stage 1 adoptions) and the next 5 years (for Stage 2 adoptions) to obtain $\omega_1 = \$471$ and $\omega_2 = \$340$.

In summary, the estimated parameter values are provided in Table C.1.

ρ	δ	θ before scaling	λ	g	c_1	c_2	M	Cost per station	a	ω_1	ω_2
0.62	0.43	\$9534	0.31	$0.0 \sim 0.64$ (·,E) $0.01 \sim 0.69$ (·,R$^{\mathrm{C}}$)	0.59	$0.3 - 0.18q_1$	41,336	\$4.5 million	0.5	\$471	\$340

Table C.1 Estimation of the Parameters

C.2. Robustness of the Numerical Study

To ensure robustness of our model predictions with respect to our parameter estimations, we performed a robustness test by varying the parameter values estimated in Table 2 within a range of ± 10%. All of the results discussed in §5 hold qualitatively unchanged, and all findings remain valid.

One of the parameters used, the EV deterioration factor, δ, is of particular interest in the robustness test. In the durable goods literature, the deterioration factors are often different for sold and leased products because consumers may have less incentive to maintain leased products in good working condition, whereas the firm, which may be able to perform maintenance at a lower cost, may have more incentive to ensure good working condition. Therefore, the values of δ may be different for the battery leasing and battery owning models. By testing our models with different δ values under the (O,·) and (L,·) models, we confirmed that the overall trends of our findings discussed in Section 5 do not change.

Another key parameter to vary is n, which reflects the effect of economies of scale on production cost reduction. As n increases (i.e., the same q_1 leads to a larger cost reduction), the region of anxiety levels under which (O,E) is more socially-favorable than (L,E) grows. Nonetheless, the overall qualitative pattern of results as discussed in Section 5 remain the same.

We also note that the levels of anxieties may possibly vary under different business practices. In particular, the level of range anxiety may be lower under the battery enlargement models, (O,R$^{\mathrm{C}}$) and (L,R$^{\mathrm{C}}$), as consumers are likely to gain confidence with an enlarged battery that reduces the need for finding charging stations. In addition, the level of resale anxiety may decrease under the battery leasing models, (L,R) and (L,E), because consumers may be less concerned about selling the used EV without the battery. One can verify from Figures 6 and 7 that our results involving the comparisons of business practices continue to hold under these possible discrepancies. In particular, a reduction of range anxiety for the $(\cdot, \mathrm{R}^{\mathrm{C}})$ models effectively causes the corresponding curves in the figures to shift leftward in Figures 6(a,c,e,g) and 7. This reinforces our finding that the $(\cdot, \mathrm{R}^{\mathrm{C}})$ models give rise to higher profit for the firm, and does not change the result that they lead to lower adoption, emission savings, consumer surplus and social surplus for reasonable ranges of anxiety discrepencies. Further, the possible reduction of resale anxiety under the leasing model also does not affect our results, as the battery leasing models neutralizes the effects of resale anxiety at all levels.

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