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

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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 although 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.

Keywords: electric vehicles; consumer anxieties; durable goods; secondary market; emission savings
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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, chief executive officer of Nissan and Renault, advocates electrification of automobiles as the way carmakers can contribute to making the world more sustainable (Ghosn 2012), and predicts EVs will occupy 10% of all car sales by 2020 (Healey 2012). Governments across the world are also investing billions of dollars in the development of EVs and their components. U.S. President Barack Obama's administration has pledged \$2.4 billion in federal grants for research on EV batteries (Carty 2010). The European Union collectively has invested €43 billion (including public and private sector investments) on EV-related research (EVUE 2012). China alone is investing \$15 billion in its nascent EV industry (Barboza 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 (Plumer 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).

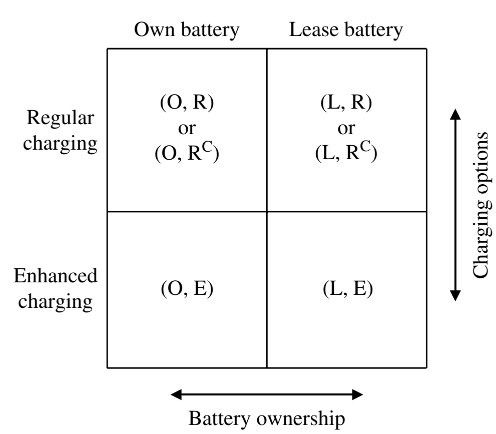
Range anxiety, the psychological concern that the driving range of EVs (which is typically constrained to approximately 80 miles due to battery capacity) may be insufficient to meet the needs of drivers, impedes consumers from adopting EVs (National Public Radio 2011, Garthwaite 2011, *Business Wire* 2012). EV advocates often dismiss range anxiety as irrational (Plumer 2011); after all, the majority of 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 more pragmatic (i.e., favorable) after EVS have been driven 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 in the future values (National Research Council 2013), especially because of lack of confidence in the durability of EVs (Woodyard 2013a). Such psychological concern about 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 (Woodyard 2013b); Nissan guarantees to replace an EV battery if it deteriorates beyond a certain level within six years of purchase (Woodyard 2012). The launch of these programs not only shows the manufacturers' awareness of resale anxiety, it also signifies their confidence in 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.

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 (Undercoffler 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 United States by firms such as Chargepoint and NRG eVgo (*Business Wire* 2012, Wald 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 (Squatriglia 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

Figure 1 **Four EV Business Practices Categorized by Battery Ownership and Charging Options**



$(\cdot, \mathrm{R})$ 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 because of 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, it harms adoption and consumer surplus. However, because of 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) versus $(\mathrm{O}, \mathrm{R}^{\mathrm{C}})$), 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, policy makers 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 Leadership in Energy and Environmental Design (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 (2011) 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 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 (2014) 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, Reiss 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 policy makers. 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 (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 because 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 because of economies of scale (as in Lobel and Perakis 2011) in §5.

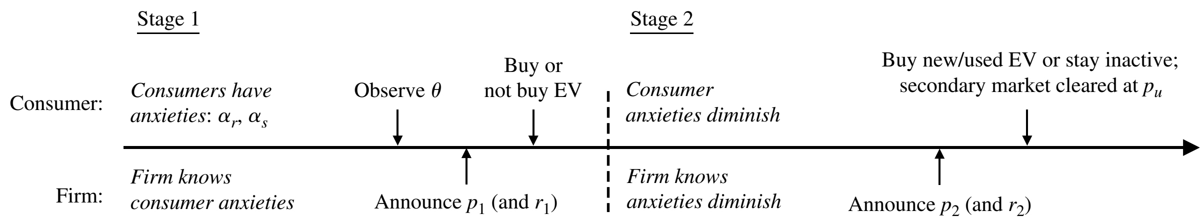
In the first stage, the firm sets the (effective) selling price p_1 for new EVs. For the leasing models, the firm additionally sets the first-stage battery leasing price at r_1. After the pricing decisions are made and announced, consumers will then make individual adoption decisions accordingly, based 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, because of 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 (because of 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); 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, because the employed modeling framework of Desai and Purohit (1998) does not allow coexistence

Figure 2 Timeline of Events in the Model: Two Parties Have Different Beliefs in the First Stage, and Anxieties Diminish in the Second Stage



of *IN* and *NH* segments in the equilibrium. We discuss this in more detail in Online Appendix B.1 (available as supplemental material at http://dx.doi.org/10.1287/msom.2014.0504). 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.

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 set of equations above, the "hat" ($\hat{}$) 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:

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

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 $c_1 > \bar{c}(c_2)$ ($c_1 \le \bar{c}(c_2)$), 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 Online Appendix A.1. In the presence of range anxiety, the first-stage adoption decreases because of 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 ($c_1 \le \bar{c}(c_2)$), 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 increases. 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, because of 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 production 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.

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) and 3(b). The relative adoption size is defined as $(Q^{(O,R)}(\alpha_r, \alpha_s)/Q^{(O,R)}(1,1)-1)\cdot 100\%$, 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. Figure 3(c) characterizes the threshold $\bar{c}(c_2)$ in both α_r and α_s for fixed c_2.

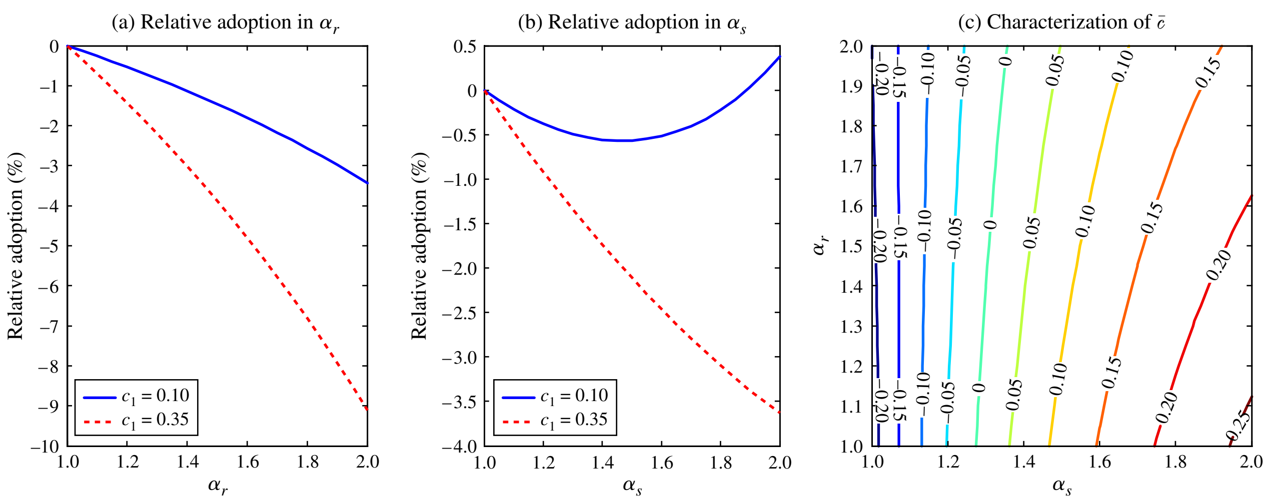
Observation 1. An increase in α_r and α_s decreases $\Pi^{(O,R)}(\alpha_r, \alpha_s)$.

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

Figure 3 **(Color online) 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 $c_2 = 0.05$**



is based on the baseline model of (O, R), we note that similar analyses are provided in Online 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 owning 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 $q_1^{(\mathrm{O,R})}$ and $Q^{(\mathrm{O,R})}$ 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 $q_1^{(\mathrm{O,R})}$ 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 decisions based on anxieties, whereas the remaining segment makes decisions 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. Because of 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 $q_1^{(\mathrm{O,R})}$ and $Q^{(\mathrm{O,R})}$ 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

$$(1-\lambda)\theta_2 - p_2 - r_2 = (1-\lambda)(1-\delta)\theta_2 - p_u - r_2,$$
$$(1-\lambda)(1-\delta)\theta_3 - p_u - r_2 = 0,$$
$$q_2 = 1-\theta_2,$$
$$\theta_2 - \theta_3 = q_1.$$

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, because 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 §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 because α_s has no impact on adoption behavior or 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 for 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 because of 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 caused by 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.

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 Online 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 Online 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 $(\mathrm{O},\mathrm{R}^{\mathrm{C}})$ 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.

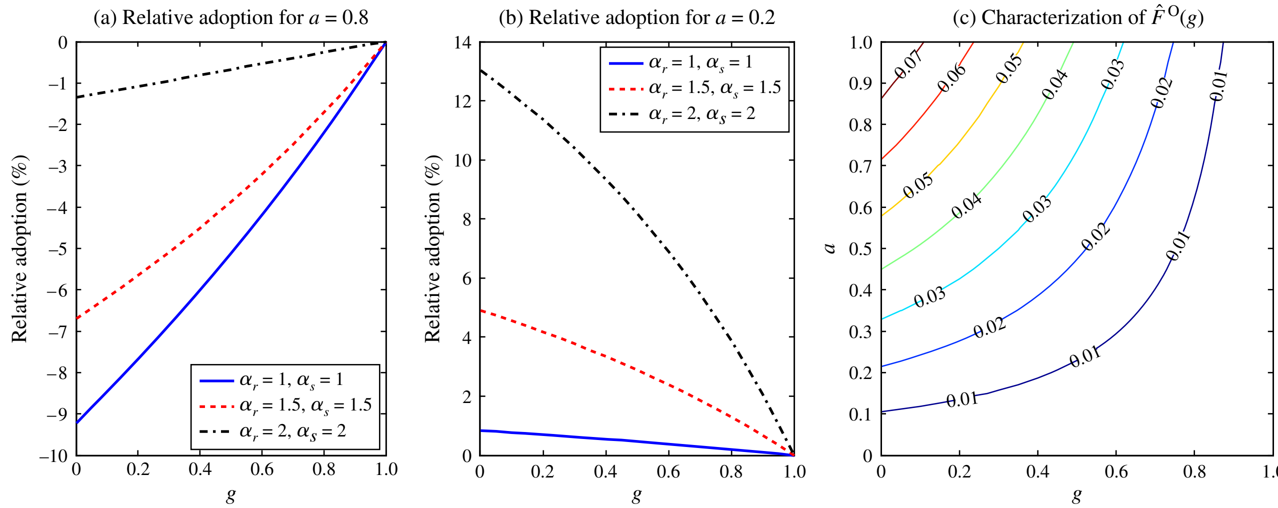
Proposition 4. (i) *For the enhanced charging model, a decrease in g results in an increase in $q_1^{(\mathrm{O},\mathrm{E})}(F(g),g)$ and $Q^{(\mathrm{O},\mathrm{E})}(F(g),g)$, for any form of $F(g)$.*

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

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 4(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 $(\mathrm{O},\mathrm{R}^{\mathrm{C}})$ 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 $(\mathrm{O},\mathrm{R}^{\mathrm{C}})$ model. Indeed, this was a major criticism against Tesla's early $(\mathrm{O},\mathrm{R}^{\mathrm{C}})$ strategy of selling high-end, long-range EVs (Stross 2008) before its recent

Figure 4 **(Color online) Impact of Anxieties on the First-Stage Adoption for the** $(\mathrm{O}, \mathrm{R^C})$ **and the Critical Infrastructure Deployment Cost for** $\lambda = 0.2$, $\delta = 0.5$, $\rho = 0.7$, $c_1 = 0.3$, **and** $c_2 = 0.05$



announcement of its plan to produce mass market, shorter-range EVs along with a massive expansion of the Supercharger network (Van Susteren 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* $\hat{F}^{\mathrm{O}}(g)$, *below which the firm prefers offering the* (O, E) *model; otherwise, the firm prefers offering the* $(\mathrm{O}, \mathrm{R^C})$ *model. That is,* $\Pi^{(\mathrm{O}, \mathrm{R^C})}(\eta, g) \le \Pi^{(\mathrm{O}, \mathrm{E})}(F, g)$ *holds if and only if* $F \le \hat{F}^{\mathrm{O}}(g)$.

Proposition 5 suggests that the firm's choice on range enhancement strategy depends on a critical level $\hat{F}^{\mathrm{O}}(g)$ in the fixed infrastructure deployment cost. Hence, without government intervention, the firm may prefer increasing the EV range via the $(\mathrm{O}, \mathrm{R^C})$ 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 $\hat{F}^{\mathrm{O}}(g)$. 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 Online Appendix A.2, we find that the counterpart results for Propositions 4 and 5 still hold for the leasing models.

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, it 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:

$$
\begin{aligned}
\mathrm{CS}^{(\mathrm{O},\mathrm{R})} = {} & \int_{\theta_1^{(\mathrm{O},\mathrm{R})}}^{1} \Big((1-\lambda)\theta - p_1^{(\mathrm{O},\mathrm{R})} \\
& \qquad + \rho\big((1-\lambda)\theta - p_2^{(\mathrm{O},\mathrm{R})} + p_u^{(\mathrm{O},\mathrm{R})}\big)\Big)\, d\theta \\
& + \int_{\theta_2^{(\mathrm{O},\mathrm{R})}}^{\theta_1^{(\mathrm{O},\mathrm{R})}} \big((1-\lambda)\theta - p_1^{(\mathrm{O},\mathrm{R})} + \rho(1-\delta)(1-\lambda)\theta\big)\, d\theta \\
& + \int_{\theta_3^{(\mathrm{O},\mathrm{R})}}^{\theta_2^{(\mathrm{O},\mathrm{R})}} \rho\big((1-\delta)(1-\lambda)\theta - p_u^{(\mathrm{O},\mathrm{R})}\big)\, d\theta.
\end{aligned}
$$

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 Online Appendix C.1.

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.

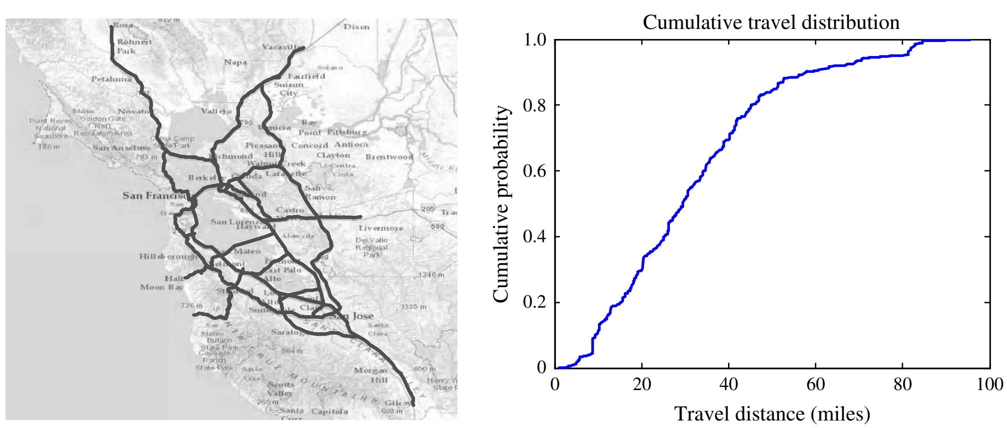
In the enhanced charging models, the firm attempts to optimize infrastructure deployment to cover the travel needs of potential consumers. It is straightforward to observe that the firm's profits in the enhanced charging model, excluding the station deployment costs, are increasing in the resulting range (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., subsegment of p exceeding the driving limit). We denote the set of subpaths

Figure 5 (Color online) An Illustration of the Geographical Data Set Used for the Numerical Study

(a) San Francisco Bay Area network

(b) Estimated travel distribution



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 (prescaling) 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 because of 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 (Ohnsman 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., Alpert 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.

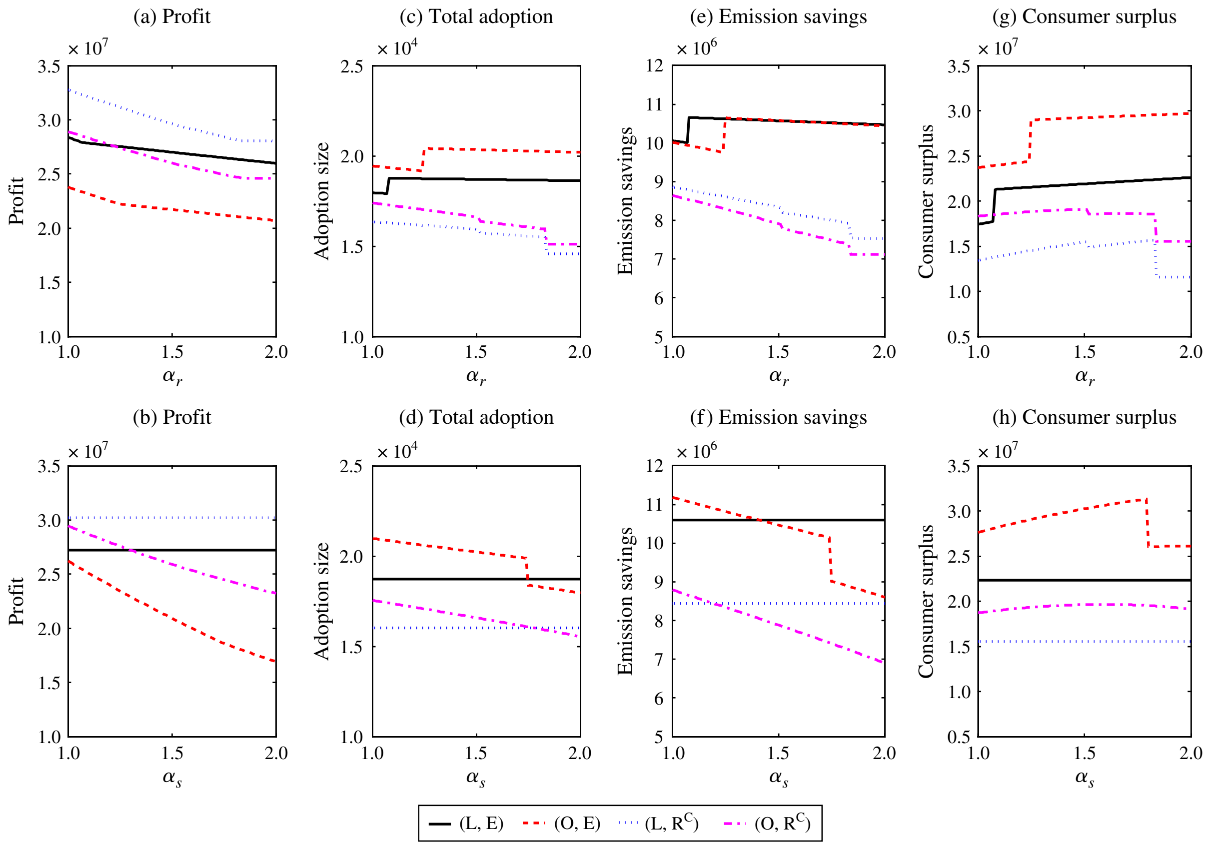
In light of this, we allow the degree of cost improvement between the two stages to depend on adoption size in the numerical analysis. In particular, we assume the second-stage production cost c_2 to be a decreasing function of q_1. Similar treatment has been considered by Lobel and Perakis (2011) to 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 on the four business models generated by the options of leasing (L, $\cdot$) versus owning (O, $\cdot$), and the two range enhancement strategies, enlarged battery capacity ($\cdot$, R^C) versus enhanced charging infrastructure ($\cdot$, 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.

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

Figure 6 (Color online) Performance Comparison of the Four Business Models Under Varying Consumer Anxieties



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 $(\cdot, \mathrm{E})$ and $(\cdot, \mathrm{R^C})$ models, corresponding to vertical jumps in performance measures shown in Figures 6(c)–6(h).

We first consider the impact of range anxiety. Intuitively, under the $(\cdot, \mathrm{E})$ 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 $(\cdot, \mathrm{R^C})$ models. Although the firm similarly counters the range anxiety by increasing the EV range (through larger batteries), the adoption size actually decreases because of 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 because of 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.

Whereas 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)–6(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 $(\mathrm{L}, \cdot)$, which are immune from resale anxiety. Note that under the current estimation, c_1 is projected to be greater than the threshold values $\bar{c}(c_2)$; thus, we observe decreasing local trends of adoption sizes for the $(\mathrm{O}, \cdot)$ 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) and 6(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, whereas 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 firm's profit compared to a private-consumer-dominant market. Furthermore, the battery leasing models may become less socially favorable because resale anxiety is less of a concern.

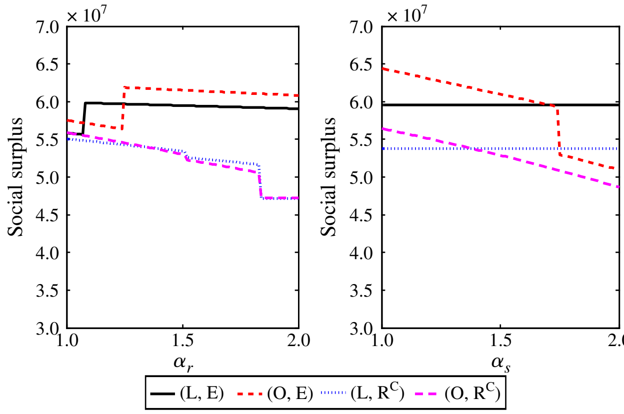
5.2.2. Comparisons of Business Models. Contrasting the $(\mathrm{L}, \cdot)$ and $(\mathrm{O}, \cdot)$ models pairwise, we observe that the leasing models generate higher profits for the firm than do the owning models as shown in Figures 6(a) and 6(b). This is because of the surplus extraction through 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 $(\cdot, \mathrm{E})$ and $(\cdot, \mathrm{R^C})$ 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 greater environmental benefits by attracting more adoption. Furthermore, because of larger adoption and lower selling prices, consumer surplus is also typically larger under the $(\cdot, \mathrm{E})$ 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., Squatriglia 2009, *Business Wire* 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 policy maker'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,

Figure 7 (Color online) Social Surplus Under Varying Anxieties



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 $(\cdot, E)$ 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 policy maker'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, although it is socially favorable to encourage the (O, E) or (L, E) model under

Table 1 Subsidy to Induce Socially Favorable Model ($\$10^6$)

α_r	α_s	(L, E)	(O, E)	(L, R^C)	(O, R^C)
Low	Low	1.90	*	6.17	4.75
Low	Medium	*	0.00	4.27	0.00
Low	High	*	0.00	4.27	0.00
Medium	Low	2.14	*	4.76	3.22
Medium	Medium	6.28	*	8.90	4.68
Medium	High	*	0.00	2.62	0.00
High	Low	2.21	*	4.08	2.87
High	Medium	6.25	*	8.11	4.01
High	High	*	0.00	1.86	0.00

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) and 6(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 (*Business Wire* 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 an asterisk (*) 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 rebalancing 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 because of 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; thus, it is important to check the robustness of the results as well as explore varying business environments. In Online 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 it does not change the overall pattern as shown in Figure 6.

6. Conclusion

With substantial economic and environmental potentials, sustainable growth and successful establishment of the EV industry are critical steps toward greener transportation. Whereas many studies (e.g., Becker and Sidhu 2009, Koslowski 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 because of 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, policy makers 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 they 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 policy makers 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. (For example, is the enhanced charging infrastructure made available to other firms' users?) This can potentially be a fruitful area for future research.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2014.0504.

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CORRECTION

In this article, "Toward Mass Adoption of Electric Vehicles: Impact of the Range and Resale Anxieties," by Michael K. Lim, Ho-Yin Mak, and Ying Rong (first published in Articles in Advance, November 3, 2014, *Manufacturing & Service Operations Management*, DOI: 10.1287/msom.2014.0504), the sentence directly above Observation 1 in Section 3.2 has been corrected; the displayed equation in Section 4.1 has been corrected (i.e., all "λ" have been replaced with "$(1-\lambda)$"; "δ" has been replaced with "$(1-\delta)$"); and the displayed equation in Section 5 has been corrected (i.e., "λ" has been replaced with "$(1-\lambda)$").