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# The Impact of Demand Uncertainty on Consumer Subsidies for Green Technology Adoption

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This paper studies government subsidies for green technology adoption while considering the manufacturing industry's response. Government subsidies offered directly to consumers impact the supplier's production and pricing decisions. Our analysis expands the current understanding of the price-setting newsvendor model, incorporating the external influence from the government, who is now an additional player in the system. We quantify how demand uncertainty impacts the various players (government, industry, and consumers) when designing policies. We further show that, for convex demand functions, an increase in demand uncertainty leads to higher production quantities and lower prices, resulting in lower profits for the supplier. With this in mind, one could expect consumer surplus to increase with uncertainty. In fact, we show that this is not always the case and that the uncertainty impact on consumer surplus depends on the trade-off between lower prices and the possibility of underserving customers with high valuations. We also show that when policy makers such as governments ignore demand uncertainty when designing consumer subsidies, they can significantly miss the desired adoption target level. From a coordination perspective, we demonstrate that the decentralized decisions are also optimal for a central planner managing jointly the supplier and the government. As a result, subsidies provide a coordination mechanism.

**Keywords:** government subsidies; green technology adoption; newsvendor; cost of uncertainty; supply chain coordination

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## 1. Introduction

Recent developments in green technologies have captured the interest of the public and private sectors. For example, electric vehicles (EVs) historically predate gasoline vehicles but have only received significant interest in the last decade (see Eberle and Von Helmot 2010 for an overview). In the height of the economic recession, the U.S. government passed the American Recovery and Reinvestment Act (ARRA) of 2009, which granted a tax credit to consumers who purchased electric vehicles. Besides boosting the U.S. economy, this particular tax incentive was aimed at fostering further research and scale economies in the nascent electric vehicle industry. In December 2010, the all-electric car, Nissan Leaf, and General Motors' plug-in hybrid, Chevy Volt, were both introduced in the U.S. market. After a slow first year, sales started to pick up, and most major car companies are now in

the process of launching their own versions of electric vehicles.

More recently, in 2012 Honda introduced the Fit EV model and observed low customer demand. After offering sizable leasing discounts, Honda quickly sold out in Southern California (Hirsch and Thevenot 2013). It is not uncommon to read about waiting lists for Tesla's new Model S or the Fiat 500e while other EVs are sitting unwanted in dealer parking lots. Both stories of supply shortages or oversupply have been commonly attributed to electric vehicle sales. At the root of both these problems is demand uncertainty. Sallee (2011) studied the supply shortages and customer waiting lists shortly after Toyota launched the hybrid electric Prius in 2002. When launching a new product, it is hard to know how many units customers will request. In addition, finding the correct price point is also not a trivial task, especially with the presence of a government subsidy. In fact, understanding

demand uncertainty should be a first-order consideration for manufacturers and policy makers alike.

For the most part, the subsidy design literature in green technologies has not studied demand uncertainty (see, for example, Benthem et al. 2008, Atasu et al. 2009, Alizamir et al. 2013, and Lobel and Perakis 2013). In practice, demand uncertainty has also often been not considered. As suggested in private communication with several sponsors of the MIT Energy Initiative,<sup>1</sup> policy makers often ignore demand uncertainty when designing consumer subsidies for green technology adoption (Stauffer 2013). The purpose of this paper is to study whether incorporating demand uncertainty in the design of subsidy programs for green technologies is important. In particular, we examine how governments should set subsidies when considering the manufacturing industry's response under demand uncertainty. We show that demand uncertainty plays a significant role in the system's welfare distribution and should not be overlooked.

Consider the following two examples of green technologies: electric vehicles and solar panels. By the end of 2013, more than 10 GW of solar photovoltaic (PV) panels had been installed in the United States, producing an annual amount of electricity roughly equivalent to two Hoover Dams. Although still an expensive generation technology, this large level of installation was only accomplished via the support of local and federal subsidy programs, such as the SunShot Initiative. In 2011, U.S. Secretary of Energy Steven Chu announced that the goal of the SunShot Initiative by 2020 is to reduce the total cost of PV systems by 75%, or an equivalent of \$1 a watt (U.S. Department of Energy 2012), at which point solar technology will be competitive with traditional sources of electricity generation. Even before this federal initiative, many states had been actively promoting solar technology with consumer subsidies in the form of tax rebates or renewable energy credits.

Similarly, federal subsidies were also introduced to stimulate the adoption of electric vehicles through the ARRA. As we previously mentioned, General Motors (GM) and Nissan have recently introduced affordable electric vehicles in the U.S. market. GM's Chevy Volt was awarded the most fuel-efficient compact car with a gasoline engine sold in the United States, as rated by the U.S. Environmental Protection Agency (2012). However, the price tag of the Chevy Volt is still considered high for its category. The cumulative sales of the Chevy Volt in the United States since it was launched in December 2010 until September 2013 amount to 48,218. It is likely that the \$7,500 government subsidy offered to each buyer through

federal tax credit played a significant role in the sales volume. The manufacturer's suggested retail price (MSRP) of GM's Chevy Volt in September 2013 was \$39,145, but the consumer was eligible for \$7,500 tax rebates so that the effective price reduced to \$31,645. The amount of consumer subsidies has remained constant since the launch in December 2010 until the end of 2013. This seems to suggest that, to isolate the impact of demand uncertainty without complicating the model, it is reasonable to consider a single period setting.

In this paper, we address the following questions: How should governments design green subsidies when facing an uncertain consumer market? How does the uncertain demand and subsidy policy decision affect the supplier's price (MSRP) and production quantities? Finally, what is the resulting effect on consumers? In practice, policy makers often ignore demand uncertainty and consider average values when designing consumer subsidies. This ignorance may be caused by the absence (or high cost) of reliable data, among other reasons. We are interested in understanding how the optimal subsidy levels, prices, and production quantities, as well as consumer surplus, are affected when one explicitly considers demand uncertainty relative to the case when demand is approximated by its deterministic average value.

Although the government designs subsidies to stimulate the adoption of new technologies, the manufacturing industry responds to these policies with the goal of maximizing its own profit. In this paper, we model the supplier as a price-setting newsvendor that responds optimally to the government subsidy. More specifically, the supplier adjusts its production and price depending on the level of consumer subsidies offered by the government to the consumer. This study also helps us to expand the price-setting newsvendor model while accounting for the external influence of the government.

In our model, the government is assumed to have a given adoption target for the technology. This is motivated by several examples of policy targets for electric vehicles and solar panels. For instance, in the 2011 State of the Union, U.S. President Barack Obama mentioned the following goal: "With more research and incentives, we can break our dependence on oil with biofuels, and become the first country to have a million electric vehicles on the road by 2015" (U.S. Department of Energy 2011, p. 2). Another example of such an adoption target has been set for solar panels in the California Solar Incentive (CSI) program, which states: "The CSI program has a total budget of \$2.167 billion between 2007 and 2016 and a goal to install approximately 1,940 MW of new solar generation capacity" (CSI 2007). Hence, in our model, we

<sup>1</sup> See <http://mitei.mit.edu/about/external-advisory-board> (accessed January 3, 2014).

optimize the subsidy level to achieve a given adoption target level while minimizing government expenditure. In §3, we discuss alternative models for the government (such as maximizing the total welfare) as well as consider the subsidy program budget, emission reductions, and social welfare.

We then quantify the impact of demand uncertainty on government expenditures, firm profit, and consumer surplus. We further characterize who bears the cost of uncertainty depending on the structure of the demand model. Finally, we study the supply chain coordination (i.e., when the government owns the supplier) and show that subsidies coordinate the overall system. More precisely, we show that the price paid by consumers, as well as the production level, coincides in both the centralized (where the supplier is managed/owned by the government) and the decentralized (where the supplier and government act separately) models.

### 1.1. Contributions

Given the recent growth of green technologies, supported by governmental subsidy programs, this paper explores a timely problem in supply chain management. Understanding how demand uncertainty affects subsidy costs, as well as the economic surplus of suppliers and consumers, is an important part of designing sensible subsidy programs. The main contributions of this paper are as follows.

- *Demand uncertainty does not always benefit consumers: nonlinearity plays a key role.* As uncertainty increases, quantities produced increase, whereas the price and the supplier's profit decrease. In general, demand uncertainty benefits consumers in terms of effective price and quantities. One might hence expect the aggregate consumer surplus to increase with uncertainty. In fact, we show that this is not always true. We observe that the effect of uncertainty on consumer surplus depends on the demand form. For example, for linear demand uncertainty increases the consumer surplus, whereas for isoelastic demand the opposite result holds. Depending on the demand pattern, the possibility of not serving customers with high valuations can outweigh the benefit of reduced prices for the customers served.

- *By ignoring demand uncertainty, the government will undersubsidize and miss the desired adoption target.* Through the case of the newly introduced Chevy Volt by General Motors in the U.S. market, we measure by how much the government misses the adoption target by ignoring demand uncertainty. We show that when the supplier takes into account demand uncertainty information while the government considers only average information on demand, the resulting expected sales can be significantly below the desired target adoption level.

- *The cost of demand uncertainty is shared between the supplier and the government.* We analyze who bears the cost of demand uncertainty between government and supplier, which we show depends on the profit margin of the product. In general, the government expenditure increases with the added inventory risk. For linear demand models, the cost of demand uncertainty shifts from the government to the supplier as the adoption target increases or the production cost decreases.

- *Consumer subsidies are a sufficient mechanism to coordinate the government and the supplier.* We compare the optimal policies to the case where a central planner manages jointly the supplier and the government. We determine that the price paid by the consumers and the production levels coincide for both the decentralized and the centralized models. In other words, consumer subsidies coordinate the supply chain in terms of price and quantities.

## 2. Literature Review

Our setting is related to the newsvendor problem, which has been extensively studied in the literature (see, e.g., Porteus 1990, Winston 1994, Zipkin 2000, and the references therein). An interesting extension that is even more related to this research is the price-setting newsvendor (see Petruzzi and Dada 1999 and Yao et al. 2006). More recently, Kocabiyıkoğlu and Popescu (2011) identified a new measure of demand elasticity, the elasticity of the lost sales rate, to generalize and complement assumptions commonly made in the price-setting newsvendor. Kaya and Özer (2012) provide a good survey of the literature on inventory risk sharing in a supply chain with a newsvendor-like retailer, which is closer to our framework. Nevertheless, our problem involves an additional player (the government) that interacts with the supplier's decisions and complicates the analysis and insights. Most previous works on the stochastic newsvendor problem treat the additive and multiplicative models separately (e.g., in Petruzzi and Dada 1999) or focus exclusively on one case, with often different conclusions regarding the price of demand uncertainty. In our problem, however, we show that our conclusions hold for both demand models.

In the traditional newsvendor setting, the production cost is generally seen as the variable cost of producing an extra unit from raw material to finished good. In capital-intensive industries such as electric vehicles, the per-unit cost of capacity investment in the manufacturing facility is usually much larger than the per-unit variable cost. For this reason, we define the production quantities of the supplier to be a capacity investment decision, similar to Cachon and Lariviere (1999).



Another stream of research related to our paper considers social welfare and government subsidies in the area of vaccines (see, e.g., Arifoğlu et al. 2012, Mamani et al. 2012, Taylor and Xiao 2014). Arifoğlu et al. (2012) study the impact of yield uncertainty, in a model that represents both supply and demand, on the inefficiency in the influenza vaccine supply chain. They show that the equilibrium demand can be greater than the socially optimal demand. Taylor and Xiao (2014) assume a single supplier with stochastic demand and consider how a donor can use sales and purchase subsidies to improve the availability of vaccines.

Among those studying the design of subsidies for green technologies, Carlsson and Johansson-Stenman (2003) examine the social benefits of electric vehicle adoption in Sweden and report a pessimistic outlook for this technology in the context of net social welfare. Avci et al. (2014) show that adoption of electric vehicles has societal and environmental benefits, as long as the electricity grid is sufficiently clean. Benthem et al. (2008) develop a model for optimizing social welfare with solar subsidy policies in California. These two papers assume nonstrategic industry players. While considering the manufacturer's response, Atasu et al. (2009) study the use of a take-back subsidy and product recycling programs. In a similar way to the papers mentioned above, they optimize social welfare of the system, assuming a known environmental impact of the product. Our work focuses on designing optimal policies to achieve a given adoption target level, which can be used to evaluate the welfare distribution in the system. In this paper, we also incorporate the strategic response of the industry into the policy-making decision. Also considering an adoption-level objective, Lobel and Perakis (2013) study the problem of optimizing subsidy policies for solar panels and present an empirical study of the German solar market. The paper shows evidence that the current feed-in-tariff system used in Germany might not be efficiently using the positive network externalities of early adopters. Alizamir et al. (2013) also tackle the feed-in-tariff design problem, comparing strategies for welfare maximization and adoption targets. Finally, Raz and Ovchinnikov (2015) present a price-setting newsvendor model for the case of public interest goods. The authors compare, for the case of linear demand, different government intervention mechanisms and study under what conditions the system is coordinated in terms of welfare, prices, and supply quantities. On the other hand, in this paper we investigate the impact of demand uncertainty on the various players of the system for nonlinear demands and model explicitly the strategic response of the manufacturer to the subsidy policy.

Numerous papers in supply chain management focus on linear demand functions. Examples include Anand et al. (2008) and Erhun et al. (2011) and the references therein. These papers study supply chain contracts where the treatment mainly focuses on linear inverse demand curves. In this paper, we show that the impact of demand uncertainty on the optimal policies differs for some classes of nonlinear demand functions relative to linear models. In particular, we observe that the effect of demand uncertainty depends on whether demand is convex (rather than linear) with respect to the price. In addition, the demand nonlinearity plays a key role on the consumer surplus.

As mentioned before, our paper also contributes to the literature on supply chain coordination (see Cachon 2003 for a review). The typical supply chain setting deals with a supplier and a retailer, who act independently to maximize individual profits. Mechanisms such as rebates (Taylor 2002) or revenue sharing (Cachon and Lariviere 2005) can coordinate the players to optimize the aggregate surplus in the supply chain. Liu and Özer (2010) examine how wholesale price, quantity flexibility, or buybacks can incentivize information sharing when introducing a new product with uncertain demand. Lutze and Özer (2008) study how a supplier should share demand uncertainty risk with the retailer when there is a lead-time contract. In Granot and Yin (2005, 2007, 2008), the authors study different types of contracts in a Stackelberg framework using a price-setting newsvendor model. In particular, Granot and Yin (2008) analyze the effect of price and order postponements in a decentralized newsvendor model with multiplicative demand, wherein the manufacturer possibly offers a buyback rate. In our setting, the government and the supplier are acting independently and could perhaps adversely affect one another. Instead, we show that the subsidy mechanism is sufficient to achieve a coordinated outcome. Chick et al. (2008) and Mamani et al. (2012) have looked at supply chain coordination in government subsidies for vaccines. Nevertheless, as we discussed above, the two supply chains are fairly different.

Without considering demand uncertainty, there is a significant amount of empirical work in the economics literature on the effectiveness of subsidy policies for hybrid and electric vehicles. For example, Diamond (2009) shows that there is a strong relationship between gasoline prices and hybrid adoption. Chandra et al. (2010) show that hybrid car rebates in Canada created a crowding out of other fuel-efficient vehicles in the market. Gallagher and Muehlegger (2011) argue that sales tax waivers are more effective than income tax credits for hybrid cars. The increase in hybrid car sales from 2000 to 2006 is mostly

explained by social preferences and increasing gasoline prices. Aghion et al. (2012) show that the auto industry innovates more in clean technologies when fuel prices are higher. Jenn et al. (2013) determine that incentives are only effective when the amount is sufficiently large. For plug-in electric cars, Sierzechula et al. (2014) argue that financial incentives, charging infrastructure, and local presence of production facilities are strongly correlated with electric vehicle adoption rates across different countries.

Also in economics literature, one can find a vast number of papers that consider welfare implications and regulations for a monopolist (see, e.g., Train 1991). There is also a relevant stream of literature on market equilibrium models for new product introduction (see, e.g., Huang and Sošić 2010). However, most of these papers do not consider demand uncertainty.

The issue of how demand uncertainty creates a mismatch in supply and demand has been mostly researched in the operations management literature; therefore, we mainly focus our literature survey in this area. There are some exceptions in economics, such as Sallee (2011), who essentially argues that consumers captured most of the incentives for the Toyota Prius, while the firm did not appropriate any of that surplus despite a binding production constraint. Sallee (2011) shows that there was a shortage of vehicles manufactured to meet demand when the Prius was launched. This reinforces our motivation for studying a newsvendor model in this context.

Also considering demand uncertainty, Fujimoto and Park (1997) show that an export subsidy (as opposed to a tax) is the equilibrium government strategy for a duopoly where each firm is in a different country and is uncertain about demand in the other country. In a slightly different setting, Boadway and Wildasin (1990) argue that subsidies can be used to protect workers from uncertain industry shocks, when there is limited labor mobility.

Some works on electricity peak-load pricing and capacity investments address the stochastic demand case (see Crew et al. 1995 for a review on that topic). In this context, it is usually assumed that the supplier knows the willingness to pay of customers and can therefore decline the ones with the lowest valuations in the case of a stockout. In our application, however, one cannot impose such an assumption, and the demand model follows a general price-dependent curve while the customers arrive randomly and are served according to a first-come-first-served logic.

The remainder of the paper is structured as follows. In §3, we describe the model. In §4, we consider both additive and multiplicative demand with pricing (price-setter model), analyze special cases, and finally study the effect of demand uncertainty on consumer

surplus. In §5, we study the supply chain coordination, and in §6, we consider a different mechanism where the government subsidizes the manufacturer's cost. Finally, in §7, we present some computational results, and our conclusions are reported in §8. The proofs of the different propositions and theorems are relegated to the appendix.

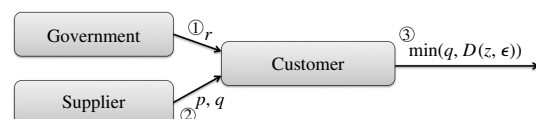
### 3. Model

We model the problem as a two-stage Stackelberg game where the government is the leader and the supplier is the follower (see Figure 1). We assume a single time period model with a unique supplier and consider a full-information setting. The government decides the subsidy level  $r$  per product, and the supplier follows by setting the price  $p$  and production quantities  $q$  to maximize his or her profit. The subsidy  $r$  is offered from the government directly to the end consumer. We consider a general stochastic demand function that depends on the effective price paid by consumers,  $z = p - r$ , and on a random variable  $\epsilon$ , denoted by  $D(z, \epsilon)$ . Once demand is realized, the sales level is determined by the minimum of supply and demand; that is,  $\min(q, D(z, \epsilon))$ . It should be noted that this single period model is particularly suitable for policies with a short time horizon, such as one year. For policies with longer time horizons, a dynamic model with prices, quantities, and subsidies changing over time would perhaps be more realistic. For the purpose of studying the impact of demand uncertainty, it is sufficient to look at a single period without the added complexity of time dynamics.

The selling price  $p$  can be viewed as the MSRP—that is, the price the manufacturer recommends for retail. Additionally, in industries where production lead time is long and incurs large fixed costs, we consider the production quantities to be equivalent to the capacity investment built in the manufacturing facility.

The goal of our model is to study the overall impact of demand uncertainty. To isolate this effect, we consider a single period monopolist model. These modeling assumptions are reasonable approximations for the Chevy Volt, which we use in our numerical analysis. Note that, since the introduction of electric vehicles, the MSRP for the Chevy Volt and the subsidy level have remained fairly stable. Consumer subsidies were posted before the introduction of these products

Figure 1 Order of Events: (1) Subsidies, (2) Price and Quantity, and (3) Sales



and have remained unchanged (\$7,500) since it was launched in December 2010. We assume the supplier is aware of the amount of subsidy offered to consumers before starting production. The supplier modeling choice is motivated by the fact that consumer subsidies for EVs started at a time when very few competitors were present in the market and the product offerings were significantly different. The Chevy Volt is an extended-range midpriced vehicle, the Nissan Leaf is a cheaper, all-electric alternative, and the Tesla Roadster is a luxury sports car. These products are also significantly different from traditional gasoline engine vehicles so that they can be viewed as price-setting firms within their own niche markets.

Given a marginal unit cost,  $c$ , and consumer subsidy level,  $r$ , announced by the government, the supplier faces the following profit maximization problem:

$$\Pi = \max_{q, p} \{p \cdot \mathbb{E}[\min(q, D(z, \epsilon))] - c \cdot q\}. \quad (1)$$

Denote as  $\Pi$  the optimal expected profit of the supplier. Note that the marginal cost  $c$  may incorporate the manufacturing cost (such as material and labor) as well as the cost of building an additional unit of manufacturing capacity. Depending on the application setting, the cost of building capacity can be more significant than the per-unit manufacturing cost. If there is no demand information gained between the building of capacity and the production stage, then capacity is built according to the planned production. Therefore, we can assume both of these costs to be combined in  $c$ . Furthermore, we can extend the model to incorporate a salvage value  $v$  for each unsold unit, such that  $v < c$ , or an underage cost  $u$  as a penalty for unmet demand. These extensions do not qualitatively affect our results. They simply shift the newsvendor production quantile. To keep the exposition simple, we assume that salvage value and underage cost are both zero:  $v = u = 0$ .

We consider the general case for which the supplier decides on both the price (MSRP) and the production quantities (i.e., the supplier is a price setter). An alternative case of interest is the one for which the price is exogenously given (i.e., the supplier is a price taker and decides only production quantity). As mentioned before, we consider the early stages of the EV market as a good application of the monopolist price-setting model. It should be noted that a similar analysis can be done for the simpler price-taker model, which might be more appropriate in a different context.

We assume that the government is introducing consumer subsidies  $r$  in order to stimulate sales to reach a given adoption target. We denote by  $\Gamma$  the target adoption level, which is assumed to be common knowledge. Conditional on achieving this target in expectation, the government wants to minimize

the total cost of the subsidy program. Define  $\text{Exp}$  as the minimal expected subsidy expenditure, which is defined through the following optimization problem:

$$\begin{aligned} \text{Exp} &= \min_r \{r \cdot \mathbb{E}[\min(q, D(z, \epsilon))]\} \\ \text{s.t. } &\mathbb{E}[\min(q, D(z, \epsilon))] \geq \Gamma, \\ &r \geq 0. \end{aligned} \quad (2)$$

In what follows, we discuss the modeling choices for the government in more detail.

### 3.1. Government's Constraints

The adoption-level constraint used in (2) is motivated by real policy-making practice. For example, President Obama stated the adoption target of one million electric vehicles by 2015 (see U.S. Department of Energy 2011). More precisely, the government is interested in designing consumer subsidies so as to achieve the predetermined adoption target. An additional possibility is to incorporate a budget constraint for the government in addition to the adoption target. In various practical settings, the government may consider both requirements (see, for example, CSI 2007). Incorporating a budget constraint in our setting does not actually affect the optimal subsidy solution of the government problem (assuming that the budget does not make the problem infeasible). In addition, one can show that there exists a one-to-one correspondence between the target adoption level and the minimum budget necessary to achieve this target. Hence, we will only solve the problem with a target adoption constraint, but the problem could be reformulated as a budget allocation problem with similar insights.

Given that actual sales are stochastic, the constraint used in our model meets the adoption target in expectation:

$$\mathbb{E}[\min(q, D(z, \epsilon))] \geq \Gamma. \quad (3)$$

Our results can be extended to the case where the government aims to achieve a target adoption level with some desired probability (chance constraint) instead of an expected value constraint. Such a modeling choice will be more suitable when the government is risk averse and is given by

$$\mathbb{P}(\mathbb{E}[\min(q, D(z, \epsilon))] \geq \Gamma) \geq \Delta, \quad (4)$$

where  $\Delta$  represents the level of conservatism of the government. For example, when  $\Delta = 0.99$ , the government is more conservative than when  $\Delta = 0.9$ . We note that the insights we gain are similar for both classes of constraints (3) and (4); therefore, in the remainder of this paper, because of space limitations, we focus on the case of an expected value constraint.

Note that one can consider a constraint on greenhouse gas reduction instead of an adoption target.



If the government has a desired target on emissions reduction, it can be translated to an adoption target in EV sales, for example. In particular, one can compute the decrease in carbon emissions between a gasoline car and an electric vehicle (see, e.g., Arar 2010). In other words, the value of  $\Gamma$  is directly tied to a value of a carbon emissions reduction target. The results in this paper remain valid with a constraint on the expected sales amount. More generally, if we set a target on any increasing function of sales, the results also remain the same.

### 3.2. Government's Objective

Two common objectives for the government are to minimize expenditures or to maximize the welfare in the system. In the former, the government aims to minimize only its own expected expenditures, given by

$$\text{Exp} = r \cdot \mathbb{E}[\min(q, D(z, \epsilon))]. \quad (5)$$

Welfare can be defined as the sum of the expected supplier's profit (denoted by  $\Pi$  and defined in (1)) and the consumer surplus (denoted by  $CS$ ) net the expected government expenditures:

$$W = \Pi + CS - \text{Exp}. \quad (6)$$

The consumer surplus is formally defined in §4.3 and aims to capture the consumer satisfaction. Interestingly, one can show that, under some mild assumptions, both objectives are equivalent and yield the same optimal subsidy policy for the government. The result is summarized in the Proposition 1.

**PROPOSITION 1.** *Assume that the total welfare is a concave and unimodal function of the subsidy  $r$ . Then, there exists a threshold value  $\Gamma^*$  such that for any given value of the target level above this threshold, i.e.,  $\Gamma \geq \Gamma^*$ , both problems are equivalent.*

**PROOF.** Since the welfare function is concave and unimodal, there exists a unique optimal unconstrained maximizer solution. If this unconstrained solution satisfies the adoption-level target, the constrained problem is solved to optimality. However, if the target adoption level  $\Gamma$  is large enough, this solution is not feasible with respect to the adoption constraint. Since the expected sales increase with respect to  $r$ , one can see that the optimal solution of the constrained welfare maximization problem is obtained when the adoption-level constraint is exactly met. Otherwise, by considering a larger subsidy level, one still satisfies the adoption constraint but does not increase the welfare. Consequently, both problems are equivalent and yield the same optimal solution for which the adoption constraint is exactly met.  $\square$

In conclusion, if the value of the target level  $\Gamma$  is sufficiently large, both problems (minimizing expenditures in (5) and maximizing welfare in (6)) are

equivalent. Note that the concavity and unimodality assumptions are satisfied for various demand models including the linear demand function. In particular, for linear demand, the threshold  $\Gamma^*$  can be characterized in closed form and is equal to twice the optimal production with zero subsidy and therefore satisfied in most reasonable settings. Furthermore, for smaller adoption target levels, Cohen et al. (2015b) show that, even for multiple products in a competitive environment, the gaps between both settings (minimizing expenditures versus maximizing welfare) are small (if not zero) so that both problems yield solutions that are close to one another. For the remainder of the paper, we assume the government objective is to minimize expenditures while satisfying an expected adoption target, as in (2). This modeling choice was further motivated by private communications with sponsors of the MIT Energy Initiative.

Besides minimizing the subsidy cost, another objective for the government often is maximizing the positive environmental externalities of the green technology product. Assume there is a positive benefit, denoted by  $p_{\text{CO}_2}$ , for each ton of  $\text{CO}_2$  emission avoided by each unit sold of the green product. By introducing a monetary value to emissions, one can consider a combined government objective of minimizing the subsidy program cost, minus the benefit of emission reduction; i.e.,

$$r \cdot \mathbb{E}[\min(q, D(z, \epsilon))] - p_{\text{CO}_2} \cdot \mathbb{E}[\min(q, D(z, \epsilon))]. \quad (7)$$

As in Proposition 1, we can show that if there is an adoption target larger than a certain threshold  $\bar{\Gamma}$ , then the objectives in (5) and (7) are equivalent and yield the same outcomes. In particular, if  $\Gamma \geq \bar{\Gamma}$ , the optimal subsidy policy will be defined by the tightness of the adoption target constraint. Alternatively, if the subsidy level  $\bar{r}$  required to reach  $\Gamma$  is significantly larger than the price of carbon,  $p_{\text{CO}_2}$ , the optimal subsidy is defined by the target constraint. Given a certain adoption target level  $\Gamma$ , there is a threshold level  $\bar{p}_{\text{CO}_2}$  such that for any price of carbon below this level,  $p_{\text{CO}_2} \leq \bar{p}_{\text{CO}_2}$ , the optimal subsidy policy is defined by the adoption target constraint. We next show that for an EV such as the Chevy Volt, a conservative estimate for the price of carbon emission mitigated for each EV sold is much lower than this threshold level.

As we mentioned above, the positive externalities of EVs correspond to the reductions in  $\text{CO}_2$  emissions throughout their lifetime, converted to U.S. dollars. Following the analysis in Arar (2010), the emission rate per unit of energy is 755 kg of  $\text{CO}_2$  per MWh. By using the calculations in Cohen et al. (2015b), an estimate for an EV gas emission reduction is approximately 50.3 tons of  $\text{CO}_2$ . To convert this number to U.S. dollars, we use the value assigned by the U.S.



Environmental Protection Agency to a ton of CO<sub>2</sub>. The value for 2014 is \$23.3 per ton of CO<sub>2</sub>)<sup>-1</sup> so that the monetary positive externality of an EV is equal to \$1,172. One can see that the positive externality for an EV is smaller than the consumer subsidies (equal to \$7,500), and therefore, it is sufficient to minimize expenditures, as described in (5).

With the formal definitions of the optimization problems faced by the supplier (1) and the government (2), in the next section we analyze the optimal decisions of each party and the impact of demand uncertainty.

## 4. The Model

For products such as electric vehicles, for which there are only a few suppliers in the market, it is reasonable to assume that the selling price (MSRP) of the product is an endogenous decision of the firm. In other words,  $p$  is a decision variable chosen by the supplier in addition to the production quantity  $q$ . In this case, the supplier's optimization problem can be viewed as a price-setting newsvendor problem (see, e.g., Petruzzi and Dada 1999). Note, however, that in our problem the solution also depends on the government subsidy. In particular, both  $q$  and  $p$  are decision variables that should be optimally chosen by the supplier for each value of the subsidy  $r$  set by the government. To keep the analysis simple and to be consistent with the literature, we consider separately the cases of a stochastic demand with additive or multiplicative uncertainty. In each case, we first consider general demand functions and then specialize to linear and isoelastic demand models that are common in the literature. Finally, we compare our results to the case where demand is approximated by a deterministic average value and draw conclusions about the cost of ignoring demand uncertainty.

In practice, companies very often ignore demand uncertainty and consider average values when taking decisions such as price and production quantities. As a result, we are interested in understanding how the optimal subsidy levels, prices, and production quantities are affected when we explicitly consider demand uncertainty relative to the case when demand is just approximated by its deterministic average value. For example, the comparison may be useful in quantifying the value of investing some large efforts in developing better demand forecasts.

We next present the analysis for both additive and multiplicative demand uncertainty.

### 4.1. Additive Noise

Define additive demand uncertainty as follows:

$$D(z, \epsilon) = y(z) + \epsilon. \quad (8)$$

Here,  $y(z) = \mathbb{E}[D(z, \epsilon)]$  is a function of the effective price  $z = p - r$  and represents the nominal deterministic part of demand and  $\epsilon$  is a random variable with cumulative distribution function (CDF)  $F_\epsilon$ .

**ASSUMPTION 1.** We impose the following conditions on demand functions with additive noise:

- Demand depends only on the difference between  $p$  and  $r$ , denoted by  $z$ .
- The deterministic part of the demand function  $y(z)$  is positive, twice differentiable, and a decreasing function of  $z$  and hence invertible.
- When  $p = c$  and  $r = 0$ , the target level cannot be achieved; i.e.,  $y(c) < \Gamma$ .
- The noise  $\epsilon$  is a random variable with zero mean:  $\mathbb{E}[\epsilon] = 0$ .

We consider that the demand function represents the aggregate demand for all the consumers in the market during the entire horizon. As a result, the assumption that the target level cannot be achieved if the product is sold at cost and there are no subsidies translates to the fact that the total number of consumers will not reach the desired adoption target level without government subsidies. Under Assumption 1, we characterize the solution of problems (1) and (2) sequentially. First, we solve the optimal quantity  $q^*(p, r)$  and price  $p^*(r)$  offered by the supplier as a function of the subsidy  $r$ . By substituting the optimal solutions of the supplier problem, we can solve the government problem defined in (2). Note that problem (2) is not necessarily convex, even for very simple instances, because the government needs to account for the supplier's best response  $p^*(r)$  and  $q^*(p, r)$ . Nevertheless, one can still solve this using the tightness of the target adoption constraint. Because of the nonconvexity of the problem, the tightness of the constraint cannot be trivially assumed. We formally prove the constraint is tight at optimality in Theorem 1. Using this result, we obtain the optimal subsidy of the stochastic problem (2), denoted by  $r_{\text{sto}}$ . The resulting optimal decisions of price and quantity are denoted by  $p_{\text{sto}} = p^*(r_{\text{sto}})$  and  $q_{\text{sto}} = q^*(p_{\text{sto}}, r_{\text{sto}})$ . From problems (1) and (2), the optimal profit of the supplier is denoted by  $\Pi_{\text{sto}}$  and government expenditures by  $\text{Exp}_{\text{sto}}$ .

We consider problems (1) and (2), where demand is equal to its expected value; that is,  $\mathbb{E}[D(z, \epsilon)] = y(z)$ . We denote this deterministic case with the subscript "det," with optimal values:  $r_{\text{det}}, p_{\text{det}}, q_{\text{det}}, z_{\text{det}}, \Pi_{\text{det}}, \text{Exp}_{\text{det}}$ . We next compare these metrics in the deterministic versus stochastic case.

**THEOREM 1.** Assume that the following condition is satisfied:

$$2y'(z) + (p - c) \cdot y''(z) + \frac{c^2}{p^3} \cdot \frac{1}{f_\epsilon(F_\epsilon^{-1}((p - c)/p))} < 0. \quad (9)$$

The following holds:

1. The optimal price of problem (1) as a function of  $r$  is the solution of the following nonlinear equation:

$$y(p-r) + \mathbb{E}\left[\min\left(F_{\epsilon}^{-1}\left(\frac{p-c}{p}\right), \epsilon\right)\right] + y'(p-r) \cdot (p-c) = 0. \quad (10)$$

In addition, using the solution from (10), one can compute the optimal production quantity:

$$q^*(p, r) = y(p-r) + F_{\epsilon}^{-1}\left(\frac{p-c}{p}\right). \quad (11)$$

2. The optimal solution of the government problem is obtained when the target adoption level is exactly met.

3. The optimal expressions follow the following relations:

$$z_{\text{sto}} = y^{-1}(\Gamma - K(p_{\text{sto}})) \leq z_{\text{det}} = y^{-1}(\Gamma),$$

$$q_{\text{sto}} = \Gamma + F_{\epsilon}^{-1}\left(\frac{p_{\text{sto}} - c}{p_{\text{sto}}}\right) - K(p_{\text{sto}}) \geq q_{\text{det}} = \Gamma,$$

where  $K(p_{\text{sto}})$  is defined as

$$K(p_{\text{sto}}) = \mathbb{E}\left[\min\left(F_{\epsilon}^{-1}\left(\frac{p_{\text{sto}} - c}{p_{\text{sto}}}\right), \epsilon\right)\right]. \quad (12)$$

If, in addition, the function  $y(z)$  is convex,

$$p_{\text{sto}} = c + \frac{\Gamma}{|y'(z_{\text{sto}})|} \leq p_{\text{det}} = c + \frac{\Gamma}{|y'(z_{\text{det}})|},$$

$$\Pi_{\text{sto}} = \frac{\Gamma^2}{|y'(z_{\text{sto}})|} - c \cdot (q_{\text{sto}} - \Gamma) \leq \Pi_{\text{det}} = \frac{\Gamma^2}{|y'(z_{\text{det}})|}.$$

**REMARK 1.** Note that, for a general function  $y(p-r)$ , one cannot derive a closed-form solution of (10) for  $p^*(r)$ . Consequently, one cannot find a closed-form expression for the optimal price  $p_{\text{sto}}$  for a general additive demand. This is consistent with the fact that there does not exist a closed-form solution for the price-setting newsvendor. However, one can use (10) to characterize the optimal solution and even numerically compute the optimal price by using a binary search method (see more details in the appendix).

Similarly, one cannot generally express  $K(p_{\text{sto}})$  in closed form. Instead,  $K(p_{\text{sto}})$  represents a measure of the magnitude of the noise that depends on the price  $p_{\text{sto}}$  and the noise distribution. The measure  $K(p_{\text{sto}})$  is mainly used to draw insights on the impact of demand uncertainty on the optimal decision variables.

Assumption (9) guarantees the uniqueness of the optimal price as a function of the subsidies, because it implies the strict concavity of the profit function with respect to  $p$ . In case this condition does not hold, problem (1) is still numerically tractable (see Petruzzi and Dada 1999). For the remainder of this paper, we

will assume that condition (9) is satisfied. For the case of linear demand, we discuss relation (15), which is a sufficient condition that is satisfied in many reasonable settings.

Note that the optimal ordering quantity in (11) is expressed as the expected demand plus the optimal newsvendor quantile  $(p-c)/p$  related to the demand uncertainty. The government can ensure that the expected sales achieve the desired target adoption level  $\Gamma$  by controlling the effective price  $z$ . When demand is stochastic, to achieve expected sales of  $\Gamma$ , the government must encourage the supplier to produce a higher quantity than  $\Gamma$  to compensate for the demand scenarios where stockouts occur. The additional production level is captured by  $K(p_{\text{sto}})$ .

The optimal price  $p$  is characterized by the optimality condition written in (10) that depends on the cost and on the price elasticity evaluated at that optimal price  $p$ , denoted by  $E_d(p)$ . This can be rewritten so that the marginal cost equals the marginal revenue; i.e.,  $c = p(1 - 1/E_d(p))$ . Even without knowing a closed-form expression for the optimal price, we can still show that the optimal price decreases in the presence of demand uncertainty and so does the firm profit.

**REMARK 2.** The results of Theorem 1 can be generalized to describe how the optimal variables (i.e.,  $z$ ,  $q$ ,  $p$ , and  $\Pi$ ) change as demand uncertainty increases. Instead of comparing the stochastic case to the deterministic case (i.e., where there is no demand uncertainty), one can instead consider how the optimal variables vary in terms of the magnitude of the noise (for more details, see the proof of Theorem 1 in the appendix). In particular, the quantity that captures the effect of demand uncertainty is  $K(p_{\text{sto}})$ .

Since the noise  $\epsilon$  has zero mean, the quantity  $K(p_{\text{sto}})$  in (12) is always nonpositive. In addition, when there is no noise (i.e.,  $\epsilon = 0$  with probability 1),  $K(p_{\text{sto}}) = 0$  and the deterministic scenario is obtained as a special case. For any intermediate case,  $K(p_{\text{sto}})$  is negative and nonincreasing with respect to the magnitude of the noise. For example, if the noise  $\epsilon$  is uniformly distributed, the inverse CDF can be written as a linear function of the standard deviation  $\sigma$  as follows:

$$F_{\epsilon}^{-1}\left(\frac{p-c}{p}\right) = \sigma\sqrt{3} \cdot \left(2 \cdot \frac{p-c}{p} - 1\right). \quad (13)$$

Therefore,  $K(p_{\text{sto}})$  scales monotonically with the standard deviation for uniform demand uncertainty. In other words, all the comparisons of the optimal variables (effective price, production quantities, etc.) are monotonic functions of the standard deviation of the noise. This result is true for a large class of common distributions that can be parameterized by the standard deviation, such as uniform, normal, and exponential. As a result, one can extend our insights in a

continuous fashion with respect to the magnitude of the noise. For example, the inequality of the effective price is given by  $z_{\text{sto}} = y^{-1}(\Gamma - K(p_{\text{sto}}))$ . This equation is nonincreasing with respect to the magnitude of  $K(p_{\text{sto}})$  and is maximized when there is no noise (deterministic demand) so that  $z_{\text{det}} = z_{\text{sto}} = y^{-1}(\Gamma)$ . In general, as the magnitude of the noise increases, the gaps between the optimal decision variables increase (see plots of optimal decisions as functions of the standard deviation of demand uncertainty in Figure 4). For more general demand distributions, the relationship with the standard deviation is not as simple. The quantile  $F_{\epsilon}^{-1}((p - c)/p)$  may not move monotonically with the standard deviation, for example with nonunimodal distributions.

**REMARK 3.** The solutions of the optimal quantity  $q$  and the effective price  $z$  provide another interesting insight. Theorem 1 states that, when demand is uncertain, the consumers are better off in terms of effective price and production quantities (this is true for any decreasing demand function). Furthermore, the selling price and the profit of the supplier are lower in the presence of uncertainty, assuming that demand is convex. These results imply that the consumers are, in general, better off when demand is uncertain. Nevertheless, as we will show in §4.3, this is not always the case when we use the aggregate consumer surplus as a metric.

By focusing on a few demand functions, we can provide additional insights. We will first consider the linear demand case, which is the most common in the literature. The simplicity of this demand form enables us to derive closed-form solutions and a deeper analysis of the impact of demand uncertainty. Note that the insights can be quite different for nonlinear demand functions. The results presented in Theorem 1 justify the need for considering nonlinear functions as well. For this reason, we later consider the isoelastic demand case and compare it to the linear case.

The impact of demand uncertainty on the subsidy level  $r$  and the overall government expenditure is harder to observe for a general demand form. To explore this further, we focus on the cases of linear and isoelastic demands. For both cases, we show that the subsidy increases with the added inventory risk captured by  $K(p_{\text{sto}})$ .

**4.1.1. Linear Demand.** In what follows, we quantify the effect of demand uncertainty on the subsidy level and the expected government expenditures. We can obtain such results for specific demand models, among them the linear demand model. Define the linear demand function as

$$D(z, \epsilon) = \bar{d} - \alpha \cdot z + \epsilon, \quad (14)$$

where  $\bar{d}$  and  $\alpha$  are given positive parameters that represent the maximal market share and the price elasticity, respectively. Note that, for this model, a sufficient condition for assumption (9) to hold is given by

$$\alpha > \frac{1}{2c \cdot \inf_x f_{\epsilon}(x)}.$$

For example, if the additive noise is uniformly distributed, i.e.,  $\epsilon \sim U[-a_2, a_2]$ ;  $a_2 > 0$  (note that since the noise is uniform with zero mean, it has to be symmetric), we obtain

$$\alpha > \frac{a_2}{c}. \quad (15)$$

One can see that by fixing the cost  $c$ , condition (15) is satisfied if the price elasticity  $\alpha$  is large relative to the standard deviation of the noise. Next, we derive closed-form expressions for the optimal price, production quantities, subsidies, profit, and expenditures for both deterministic and stochastic demand models and compare the two settings.

**THEOREM 2.** *The closed-form expressions and comparisons for the linear demand model in (14) are given by*

$$\begin{aligned} p_{\text{sto}} &= c + \frac{\Gamma}{\alpha} = p_{\text{det}}, \\ q_{\text{sto}} &= \Gamma + F_{\epsilon}^{-1}\left(\frac{p_{\text{sto}} - c}{p_{\text{sto}}}\right) - K(p_{\text{sto}}) \geq q_{\text{det}} = \Gamma, \\ r_{\text{sto}} &= \frac{2\Gamma}{\alpha} + c - \frac{\bar{d}}{\alpha} - \frac{1}{\alpha} \cdot K(p_{\text{sto}}) \geq r_{\text{det}} = \frac{2\Gamma}{\alpha} + c - \frac{\bar{d}}{\alpha}, \\ \Pi_{\text{sto}} &= \frac{\Gamma^2}{\alpha} - c \cdot (q_{\text{sto}} - \Gamma) \leq \Pi_{\text{det}} = \frac{\Gamma^2}{\alpha}, \\ \text{Exp}_{\text{sto}} &= \Gamma \cdot r_{\text{sto}} \geq \text{Exp}_{\text{det}} = \Gamma \cdot r_{\text{det}}. \end{aligned}$$

We note that the results of Theorem 2 can be presented in a more general continuous fashion as explained in Remark 2. Surprisingly, the optimal price is the same for both the deterministic and stochastic models. In other words, the optimal selling price is not affected by demand uncertainty for linear demand. On the other hand, with increased quantities, the expected profit of the supplier is lower under demand uncertainty. At the same time, the optimal subsidy level and expenditures increase with uncertainty. Therefore, both the supplier and government are worse off when demand is uncertain. Corollary 1 and the following discussion provide further intuition of how this cost of demand uncertainty is shared between the supplier and the government.

**COROLLARY 1.** (1) *The difference in quantity,  $q_{\text{sto}} - q_{\text{det}}$ , decreases in  $c$  and increases in  $\Gamma$ .*

(2) *The difference in subsidy,  $r_{\text{sto}} - r_{\text{det}}$ , increases in  $c$  and decreases in  $\Gamma$ .*



(3) Assume that  $\epsilon$  has support  $[a_1, a_2]$ . Then, the optimal subsidy for the stochastic and deterministic demands relates as follows:

$$r_{\text{det}} \leq r_{\text{sto}} \leq r_{\text{det}} + \frac{|a_1|}{\alpha}.$$

Corollary 1 can be better understood in terms of the optimal service level for stochastic demand, denoted by  $\rho = (p_{\text{sto}} - c)/p_{\text{sto}}$ . Note that  $\rho$  is an endogenous decision of the supplier, which is a function of the optimal price  $p_{\text{sto}}$ . For linear demand, the optimal service level can be simplified as  $\rho = \Gamma/(c\alpha + \Gamma)$ . This service level is decreasing in the cost  $c$  but increasing with respect to the target adoption  $\Gamma$ .

On one hand, when the optimal price is significantly higher than the production cost, i.e.,  $p_{\text{sto}} \gg c$ , the high profit margin encourages the supplier to satisfy a larger share of demand by increasing its production. In this case, the supplier has incentives to overproduce and bear more of the inventory risk. The government may then set low subsidies, in fact the same as in the deterministic case, which guarantee that the average demand meets the target. On the other hand, when  $p_{\text{sto}}$  is close to  $c$  (low profit margin), the supplier has no incentives to bear any risk and produces quantities to match the lowest possible demand realization. In this case, the government will bear all the inventory risk by increasing the value of the subsidies.

Note that as production cost  $c$  increases, the required subsidy is larger for both stochastic and deterministic demands, meaning the average subsidy expenditure is higher. At the same time, the service level  $\rho$  decreases, and from Corollary 1, the gap between  $r_{\text{sto}}$  and  $r_{\text{det}}$  increases. The supplier's cost increase amplifies the cost of demand uncertainty for the government.

A similar reasoning can be applied to the target adoption level. As  $\Gamma$  increases, the overall cost of the subsidy program increases, as expected. Interestingly, the service level  $\rho$  also increases. From Corollary 1, the production gap between  $q_{\text{sto}}$  and  $q_{\text{det}}$  widens while the subsidy gap between  $r_{\text{sto}}$  and  $r_{\text{det}}$  shrinks. Effectively, the burden of demand uncertainty is transferred from the government to the supplier as  $\Gamma$  increases. This means that a higher target adoption will induce the product to be more profitable. This will make the supplier take on more of the inventory risk, consequently switching who bears the cost of demand uncertainty.

Part (3) of Corollary 1 shows that the government subsidy decision is bounded by the worst-case demand realization normalized by the price sensitivity. In other words, it provides a guarantee on the gap between the subsidies for stochastic and deterministic demands.

In conclusion, by studying the special case of a linear demand model, we obtain the following additional insights: (i) The optimal price does not depend on demand uncertainty. (ii) The optimal subsidy set by the government increases with demand uncertainty. Consequently, the introduction of demand uncertainty decreases the effective price paid by consumers. In addition, the government will spend more when demand is uncertain. (iii) The cost of demand uncertainty is shared by the government and the supplier and depends on the profit margin (equivalently, service level) of the product. As expected, lower/higher margins mean the supplier takes less/more inventory risk. Therefore, increasing the adoption target or decreasing the manufacturing cost will shift the cost of demand uncertainty from the government to the supplier.

#### 4.2. Multiplicative Noise

In this section, we consider a demand with a multiplicative noise (see, for example, Granot and Yin 2008). The nominal deterministic part is assumed to be a function of the effective price, denoted by  $y(z)$ :

$$D(z, \epsilon) = y(z) \cdot \epsilon. \quad (16)$$

**ASSUMPTION 2.** We impose the following conditions on demand functions with multiplicative noise:

- Demand depends only on the difference between  $p$  and  $r$ , denoted by  $z$ .
- The deterministic part of the demand function  $y(z)$  is positive, twice differentiable, and a decreasing function of  $z$  and hence invertible.
- When  $p = c$  and  $r = 0$ , the target level cannot be achieved; i.e.,  $y(c) < \Gamma$ .
- The noise  $\epsilon$  is a positive and finite random variable with mean equal to 1:  $\mathbb{E}[\epsilon] = 1$ .

One can show that the results of Theorem 1 hold for both additive and multiplicative demand models. The proof for multiplicative noise follows a similar methodology and is not repeated because of space limitations. We next consider the isoelastic demand case to derive additional insights on the optimal subsidy.

Isoelastic demand models are very popular in various application areas. In particular, a large number of references in economics consider such models (see, e.g., Simon and Blume 1994, Pindyck and Rubinfeld 2001) as well as revenue management (see Talluri and Van Ryzin 2006). Isoelastic demand is also sometimes called the log-log model, and its main property is that elasticities are constant for any given combination of price and quantities. In addition, it does not require one to know a finite upper limit on price. For more details, see, for example, Huang et al. (2013). Various papers on oligopoly competition consider isoelastic demand (see, e.g., Puu 1991, Lau and Lau 2003, Beard 2015). Puu (1991) studies the dynamics of two



competing firms in a market in terms of Cournot's duopoly theory. Lau and Lau (2003), consider (among others) an iso-elastic demand in a multiechelon inventory/pricing setting and show that the results might differ depending on the demand shape. Another application that uses isoelastic demands relates to commodity pricing (see, e.g., Deaton and Laroque 1992). Finally, practitioners and researchers have used isoelastic demand models for products in retail such as groceries, fashion (see, e.g., Capps 1989, Pindyck and Rubinfeld 2001, Andreyeva et al. 2010), and gasoline (e.g., Bentzen 1994).

**4.2.1. Isoelastic Demand.** Define the isoelastic demand as

$$y(z) = \bar{d} \cdot z^{-\alpha} \quad (\alpha > 1). \quad (17)$$

The isoelastic model considered in the literature usually assumes that  $\alpha > 1$  in order to satisfy the increasing price elasticity property (see, e.g., Yao et al. 2006). Note that the function  $y(z)$  is convex with respect to  $z$  for any value  $\alpha > 1$ . Therefore, the results from Theorem 1 hold. Using this particular demand structure, we obtain the following additional results on the optimal subsidy.

**PROPOSITION 2.** *For the isoelastic demand model in (17), we have*

$$r_{\text{sto}} \geq r_{\text{det}}.$$

We note that the result of Proposition 2 can be presented in a continuous fashion, as explained in Remark 2. Note also that this allows us to recover the same results as the linear additive demand model regarding the impact of demand uncertainty on the subsidies. These two cases show that the subsidy increases with demand uncertainty.

### 4.3. Consumer Surplus

In this section, we study the effect of demand uncertainty on consumers using consumer surplus as a metric. For that purpose, we compare the aggregate level of consumer surplus under stochastic and deterministic demand models. The consumer surplus is an economic measure of consumer satisfaction calculated by analyzing the difference between what consumers are willing to pay and the market price. For a general deterministic price demand curve, the consumer surplus is denoted by  $CS_{\text{det}}$  and can be computed as the area under the demand curve above the market price (see, e.g., Vives 2001):

$$CS_{\text{det}} = \int_0^{q_{\text{det}}} (D^{-1}(q) - z_{\text{det}}) dq = \int_{z_{\text{det}}}^{z_{\text{max}}} D(z) dz. \quad (18)$$

We note that, in our case, the market price is equal to the effective price paid by consumers  $z = p - r$ . Denote as  $D^{-1}(q)$  the effective price that will generate demand exactly equal to  $q$ . Note that  $z_{\text{det}}$  and  $q_{\text{det}}$  represent the

optimal effective price and production, whereas  $z_{\text{max}}$  corresponds to the value of the effective price that yields zero demand. The consumer surplus represents the surplus induced by consumers that are willing to pay more than the posted price.

When demand is uncertain, however, defining the consumer surplus (denoted by  $CS_{\text{sto}}$ ) is somewhat subtler because of the possibility of a stockout. Several papers on peak-load pricing and capacity investments by a power utility under stochastic demand partially address this modeling issue (see Brown and Johnson 1969, Carlton 1986, Crew et al. 1995). Nevertheless, the models developed in this literature are not applicable to the price-setting newsvendor. More specifically, Brown and Johnson (1969) assume that the utility power facility has access to the willingness to pay of the customers so that it can decline the ones with the lowest valuations. This assumption is not justifiable in our setting where a first-come-first-served logic with random arrivals is more suitable. Raz and Ovchinnikov (2015) study a price-setting newsvendor model for public goods and consider the consumer surplus for linear additive stochastic demand.

For general stochastic demand functions, the consumer surplus  $CS_{\text{sto}}(\epsilon)$  is defined for each realization of demand uncertainty  $\epsilon$ . If there is no supply constraint, considering the effective price and the realized demand, the total amount of potential consumer surplus is defined as

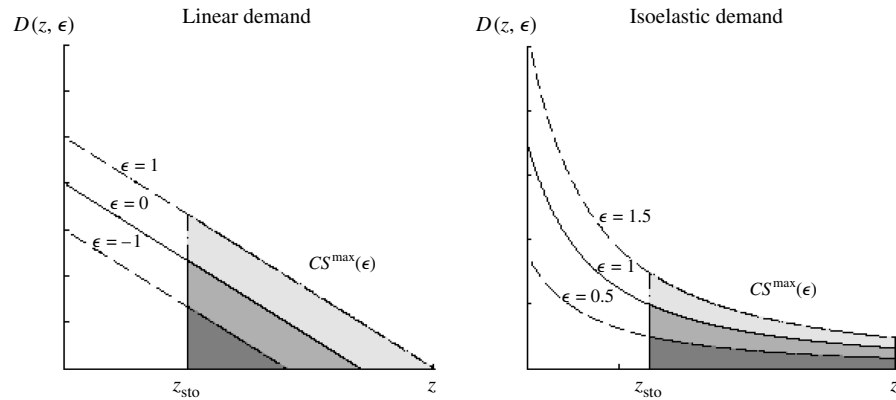
$$CS^{\text{max}}(\epsilon) = \int_{z_{\text{sto}}}^{z_{\text{max}}(\epsilon)} D(z, \epsilon) dz.$$

Figure 2 displays the area under the demand curves (linear and isoelastic) that defines the maximum consumer surplus  $CS^{\text{max}}(\epsilon)$  for a given demand realization  $\epsilon$ . Note that the actual consumer surplus will be a fraction of this maximum surplus, based on the fraction of customers that are actually served. Since customers are assumed to arrive in a first-come-first-served manner, irrespective of their willingness to pay, under certain demand realizations some proportion of these customers will not be served because of stockouts. The proportion of served customers under one of these demand realizations is given by the ratio of actual sales over potential demand:  $\min(D(z_{\text{sto}}, \epsilon), q_{\text{sto}})/D(z_{\text{sto}}, \epsilon)$ . Therefore, the consumer surplus can be defined as the total available surplus times the proportion of that surplus that is actually served:

$$CS_{\text{sto}}(\epsilon) = CS^{\text{max}}(\epsilon) \cdot \frac{\min(D(z_{\text{sto}}, \epsilon), q_{\text{sto}})}{D(z_{\text{sto}}, \epsilon)}. \quad (19)$$

We note that, in this case, the consumer surplus is a random variable that depends on the demand through the noise  $\epsilon$ . Note that we are interested in

Figure 2 Consumer Surplus for Stochastic Demand, Before Demand Rationing



comparing  $CS_{\text{det}}$  to the expected consumer surplus  $\mathbb{E}_{\epsilon}[CS_{\text{sto}}(\epsilon)]$ . For stochastic demand, (19) has a similar interpretation to its deterministic counterpart. Nevertheless, we also incorporate the possibility that a consumer who wants to buy the product does not find it available. As we will show, the effect of demand uncertainty on consumer surplus depends on the structure of the nominal demand function. In particular, we provide the results for the two special cases we have considered in the previous section and show that the effect is opposite. For the linear demand function in (14), we have

$$CS_{\text{det}} = \int_0^{q_{\text{det}}} (D^{-1}(q) - z_{\text{det}}) dq = \frac{q_{\text{det}}^2}{2\alpha} = \frac{\Gamma^2}{2\alpha}. \quad (20)$$

For the isoelastic demand from (17), we obtain

$$\begin{aligned} CS_{\text{det}} &= \int_0^{q_{\text{det}}} (D^{-1}(q) - z_{\text{det}}) dq \\ &= \frac{\bar{d}}{\alpha - 1} \cdot \left(\frac{\bar{d}}{\Gamma}\right)^{(1-\alpha)/\alpha} \quad (\alpha > 1). \end{aligned} \quad (21)$$

One can then show the following results regarding the effect of demand uncertainty on the consumer surplus for these two demand functions.

**PROPOSITION 3.** *For the linear demand model in (14), we have*

$$\mathbb{E}[CS_{\text{sto}}] \geq CS_{\text{det}}. \quad (22)$$

*For the isoelastic demand model in (17) with  $\alpha > 1$ , we have*

$$\mathbb{E}[CS_{\text{sto}}] \leq CS_{\text{det}}. \quad (23)$$

The consumer surplus result in Proposition 3 is perhaps one of the most counterintuitive findings of this paper. Proposition 3 shows that, under linear demand, the expected consumer surplus is larger when considering demand uncertainty, whereas it is lower for the isoelastic model. We already have shown in Theorem 1 that the effective price is lower and that the production quantities are larger when

considering demand uncertainty relative to the deterministic model. In addition, this result was valid for both models (i.e., additive and multiplicative noises for linear and nonlinear demand). As a result, demand uncertainty benefits overall the consumers in terms of effective price and available quantities. With this in mind, one could expect consumer surplus to increase with uncertainty. However, when comparing the consumer surplus using Equation (19) for stochastic demand, we obtain that, for the isoelastic demand, consumers are in aggregate worse off when demand is uncertain. On one hand, demand uncertainty benefits the consumers since it lowers the effective price and increases the quantities. On the other hand, demand uncertainty introduces a stockout probability because some of the consumers may not be able to find the product available. These two factors (effective price and stockout probability) affect the consumer surplus in opposite ways.

For isoelastic demand, the second factor is dominant, and therefore the consumer surplus is lower when demand is uncertain. In particular, the isoelastic demand admits some consumers that are willing to pay a very large price. If these consumers experience a stockout, it will reduce drastically the aggregate consumer surplus. In fact, the gap between the stochastic and deterministic consumer surplus widens when  $K(p_{\text{sto}})$  is smaller. This happens when the profit margin is low, meaning that there is more inventory risk for the supplier. For linear demand, the dominant factor is not the stockout probability, and consequently, the consumer surplus is larger when demand is uncertain. We note that this result is related to the structure of the nominal demand rather than the noise effect. For example, if we were to consider a linear demand with a multiplicative noise, we would have the same result as for the linear demand with additive noise.

Next, we compare and contrast our findings on production quantity, price, and profit as well as consumer surplus against what is already known in the

literature about the classical price-setting newsvendor problem. This way, we can investigate the impact of incorporating the government as an additional player in the system. In the classical price-setting newsvendor, there does not exist a closed-form expression for the optimal price and production even for simple demand forms. However, one can still compare the outcomes between stochastic and deterministic scenarios. We compare the results of Theorems 1 and 2 to the classical price-setting newsvendor (i.e., without the government). The optimal price, quantity, and profit can be found in a similar way to that in this paper. First, one can show that the optimal price follows the same relation as in our paper; i.e.,  $p_{\text{sto}} \leq p_{\text{det}}$ . Note that, in the classical model,  $p$  is equivalent to the effective price paid by consumers, and therefore, similar insights apply (see Theorem 1). However, the relation for the optimal quantity differs. More precisely, the inequality on quantity depends on the critical newsvendor quantile being larger or smaller than 1. For symmetric additive noises, if the profit margin is below 0.5 (this is usually the case for the EV industry), the supplier will not take the overstocking risk, and the optimal quantity decreases with respect to the magnitude of the noise. As a result, the optimal quantity relation will be opposite to the one we obtain in this paper, where the government is an additional player in the supply chain. In addition, the results on optimal profits agree with the case of the paper (again, assuming that the profit margin is below 0.5) so that the expected profits for stochastic demand are lower relative to the case where demand is deterministic, as expected. In conclusion, the effect of demand uncertainty for the classical price-setting newsvendor (assuming that the profit margin is below 0.5) states that quantity, price, and profit are all lower when demand is stochastic. When comparing to Theorem 1, we first observe that the results do not depend on the profit margin. In addition, the optimal quantity follows the opposite relation, whereas the price and profit follow the same one. Therefore, in our setting, the government is bearing some uncertainty risk together with the supplier and incentivizes the supplier to overproduce in order to make sure that the adoption target is achieved as expected. Finally, one can do a similar analysis for the expected consumer surplus. However, the analysis is not straightforward and depends on the demand function, the structure of the noise (additive or multiplicative), and the capacity rationing rule (see Cohen et al. 2015a). Indeed, when the government is present in the supply chain, it can help by increasing the production and, consequently, by inducing larger consumer surplus in expectation. Note that the profit is still lower, because the stochastic scenario remains more risky for the supplier.

## 5. Supply Chain Coordination

In this section, we examine how the results change in the case where the system is centrally managed. In this case, one can imagine that the government and the supplier take coordinated decisions together. The central planner needs to decide the price, the subsidy, and the production quantities simultaneously. This situation may arise when the firm is owned by the government. We study the centrally managed problem as a benchmark to compare to the decentralized case developed in the previous sections. In particular, we are interested in understanding if the decentralization will have an adverse impact on either party and, more importantly, if it will hurt the consumers. We show in this section that this is not the case. In fact, the decentralized problem achieves the same outcome as the centralized problem; hence, government subsidies act as a coordinating mechanism, as far as consumers are concerned. Supply chain coordination has been extensively studied in the literature. In particular, some of the supply chain contracting literature (see, e.g., Cachon 2003) discusses mechanisms that can be used to coordinate operational decisions such as price and production quantities.

Define the central planner's combined optimization problem to maximize the firm's profits minus government expenditures as follows:

$$\begin{aligned} \max_{q, z} \quad & \{z \cdot \mathbb{E}[\min(q, D(z, \epsilon))] - c \cdot q\} \\ \text{s.t.} \quad & \mathbb{E}[\min(q, D(z, \epsilon))] \geq \Gamma. \end{aligned} \quad (24)$$

Note that, in this case, we impose the additional constraint  $p \geq c$  so that the selling price has to be at least larger than the cost. Indeed, for the centralized version, it is not clear that this constraint is automatically satisfied by the optimal solution as it was in the decentralized setting. Our goal is to show how the centralized solutions for  $q$ ,  $p$ , and  $r$  compare to their decentralized counterparts from §4. We consider both deterministic and stochastic demand models and focus on additive uncertainty under Assumption 1.

**THEOREM 3.** *The optimal effective price  $z = p - r$  and production level  $q$  are the same in both the decentralized and centralized models. Therefore, consumer subsidies are a sufficient mechanism to coordinate the government and the supplier.*

Note that for problem (24), one can only solve for the effective price and not  $p$  and  $r$  separately. In particular, there are multiple optimal solutions for the centralized case and the decentralized solution happens to be one them. If the government and the supplier collude into a single entity, this does not affect the consumers in terms of effective price and production quantities. Therefore, the consumers are not

affected by the coordination. This result might be surprising because one could think that the coordination would add additional information and power to the central planner, as well as mitigate some of the competition effects between the supplier and the government. However, in the original decentralized problem, the government acts as a quantity coordinator in the sense that the optimal solutions in both cases are obtained by the tightness of the target adoption constraint.

## 6. Subsidizing the Manufacturer's Cost

In this section, we consider a different incentive mechanism where the government offers subsidies directly to the manufacturer (as opposed to the end consumers). In particular, our goals are (i) to study whether the impact of demand uncertainty and most of our insights are preserved if the government were to use a cost subsidy mechanism and (ii) to compare the outcomes of both mechanisms. Offering subsidies directly to the manufacturer can be implemented by partially sharing the cost of production or in the form of loans or free capital to the supplier. An example of this type of subsidy was the \$249 million federal grant provided to battery maker A123 Systems under the ARRA to increase manufacturing of batteries for electric and hybrid vehicles (Buchholz 2010). This grant was later criticized after the company declared bankruptcy, along with another failed subsidy program to solar panel manufacturer Solyndra (Healy 2012). Knowing that this type of subsidy mechanism is also used in practice, in addition to consumer subsidies, we hope to do a similar analysis to observe the impact of demand uncertainty. Below, we formalize the model for this setting and provide the results. We then summarize our findings as well as compare both settings.

The government still seeks to encourage green technology adoption. Instead of offering rebates to the end consumers, the government provides a subsidy, denoted by  $s \geq 0$ , directly to the manufacturer. Note that this mechanism does not have a direct impact on the demand function, which depends only on the selling price  $p$  and not explicitly on  $s$ . As before, the government leads the game by solving the following optimization problem:

$$\begin{aligned} \min_s \quad & \{s \cdot q(p, s)\} \\ \text{s.t.} \quad & \mathbb{E}[\min(q, D(p, \epsilon))] \geq \Gamma, \\ & s \geq 0. \end{aligned} \quad (25)$$

Note that in this case, the government subsidizes the total produced units instead of the total expected sold units as before.

Given a subsidy level  $s$  announced by the government, the supplier faces the following profit maximization problem. Note that  $c$  denotes the cost of building an additional unit of manufacturing capacity, as before:

$$\Pi = \max_{q, p} \{p \cdot \mathbb{E}[\min(q, D(p, \epsilon))] - (c - s) \cdot q\}. \quad (26)$$

For simplicity, we assume a linear and additive demand, but one can extend the results for nonlinear demand models as well as for multiplicative uncertainty. However, to keep the analysis simple, we present the results for the linear case, given by

$$D(p, \epsilon) = \bar{d} - \alpha \cdot p + \epsilon. \quad (27)$$

First, we study the impact of demand uncertainty on the decision variables for the cost subsidy mechanism (denoted by CSM). Second, we compare the outcomes for both mechanisms and elaborate on the differences. The results on the impact of demand uncertainty are summarized in the following theorem.

**THEOREM 4.** Assume a linear demand as in (27). The comparisons for the cost subsidy mechanism are given by

$$\begin{aligned} p_{\text{sto}} &= \frac{\bar{d} - \Gamma}{\alpha} + \frac{1}{\alpha} \cdot K'_\epsilon \leq p_{\text{det}} = \frac{\bar{d} - \Gamma}{\alpha}, \\ q_{\text{sto}} &= \Gamma + F_\epsilon^{-1}\left(\frac{p_{\text{sto}} - c + s_{\text{sto}}}{p_{\text{sto}}}\right) - K'_\epsilon \geq q_{\text{det}} = \Gamma, \\ s_{\text{sto}} &= \frac{2\Gamma}{\alpha} + c - \frac{\bar{d}}{\alpha} - \frac{1}{\alpha} \cdot K'_\epsilon \geq s_{\text{det}} = \frac{2\Gamma}{\alpha} + c - \frac{\bar{d}}{\alpha}, \\ \Pi_{\text{sto}} &= \frac{\Gamma^2}{\alpha} - (c - s_{\text{sto}}) \cdot (q_{\text{sto}} - \Gamma) \leq \Pi_{\text{det}} = \frac{\Gamma^2}{\alpha}, \\ \text{Exp}_{\text{sto}} &= q_{\text{sto}} \cdot s_{\text{sto}} \geq \text{Exp}_{\text{det}} = \Gamma \cdot s_{\text{det}}, \end{aligned}$$

where  $K'_\epsilon = \mathbb{E}[\min(F_\epsilon^{-1}((p_{\text{sto}} - c + s_{\text{sto}})/p_{\text{sto}}), \epsilon)]$ . Note that  $s_{\text{sto}}$  is not given in a closed-form expression because both sides depend on  $s_{\text{sto}}$ , and one needs to solve a nonlinear fixed point equation. The proof of Theorem 4 is not reported here because of space limitations (it is based on a methodology similar to Theorem 2). One can see that the impact of demand uncertainty on all the decision variables is the same as in the consumer rebates mechanism (see Theorem 2). Next, we compare the outcomes of both mechanisms under deterministic and stochastic demands. The results are summarized below.

- The amount of subsidy (per unit) paid by the government follows the following relation:

$$s_{\text{sto}} \leq r_{\text{sto}}; \quad s_{\text{det}} = r_{\text{det}}.$$

- The price paid by the consumers follows the following relation:

$$p_{\text{sto}}^{\text{CSM}} \geq p_{\text{sto}} - r_{\text{sto}}; \quad p_{\text{det}}^{\text{CSM}} = p_{\text{det}} - r_{\text{det}}.$$



• The production quantities follow the following relation:

$$q_{\text{sto}}^{\text{CSM}} \geq q_{\text{sto}}; \quad q_{\text{det}}^{\text{CSM}} = q_{\text{det}}.$$

• For the profit of the supplier and the government expenditures, one cannot find the relation analytically. Instead, we study and compare the expressions computationally (see the discussion below).

Note that for the cost subsidy mechanism, the price paid by consumers is equal to  $p$  (since there is no subsidy to consumers), whereas for the consumer subsidy mechanism, it is captured by  $p - r$ . We observe that the government can save money on the per-unit subsidy, but that does not mean that the overall expenditures are lower, because more units are potentially subsidized. In addition, the consumers are paying a larger price to compensate for this government savings per unit. As a result, the consumers are worse off in terms of price but better off in terms of available quantities. In addition, when the demand is deterministic, all the outcomes are the same for both mechanisms. However, in a stochastic setting, the type of mechanism plays a key role in the risk sharing between the supplier and the government induced by the demand uncertainty.

We next vary the different model parameters to compare the outcomes for both mechanisms computationally. We obtain the following results. As the variance of the noise increases, the expected government expenditures and the expected profit of the supplier under the subsidy mechanism are higher when compared with the consumer subsidy mechanism. Consequently, although the optimal subsidy (per unit) is lower, the overall subsidy program is actually more costly to the government. Indeed, the government is subsidizing all the produced units instead of the sold ones and therefore is bearing some of the overstock risk from the demand uncertainty. Since the supplier is sharing this overstock risk with the government, the supplier can achieve higher profits on expectation despite the fact that the subsidy is smaller by charging a higher price to the consumers.

## 7. Computational Results

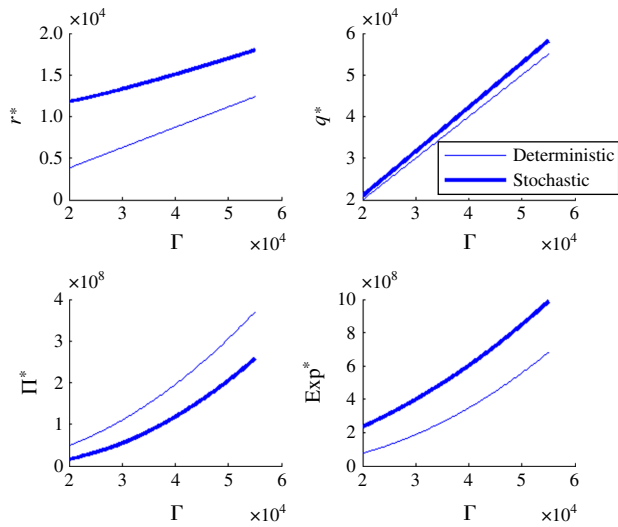
In this section, we present some numerical examples that provide further insights into the results derived in §4. The data used in these experiments are inspired by the sales data of the first two years of General Motors' Chevy Volt (between December 2010 and December 2012). The total aggregate sales was roughly equal to 35,000 (see Cobb 2013) electric vehicles, the listed price (MSRP) was \$40,280, and the government subsidy was set to \$7,500. In addition, we assume a 10% profit margin so that the per-unit cost of building manufacturing capacity is \$36,000. Note that we tested the robustness of all our results and

plots in this section with respect to  $c$  by varying the profit margin from 0.5% to 20% and obtained very similar insights. For simplicity, we present here the results using a linear demand with an additive Gaussian noise. We observe that our results, along with the analysis, are robust with respect to the distribution of demand uncertainty. In fact, we obtain in our computational experiments the same insights for several demand distributions (including nonsymmetric ones). As discussed in §3, the government can either minimize expenditures or maximize the total welfare. In particular, the two objectives are equivalent and give rise to the same optimal subsidy policies for any target level  $\Gamma$  above a certain threshold. In this case, this threshold is equal to 860, and the condition is therefore easily satisfied.

Throughout these experiments, we compute the optimal decisions for both the deterministic and the stochastic demand models by using the optimal expressions derived in §4.1. We first consider a fixed relatively large standard deviation  $\sigma = 42,000$  (note that when demand is close to the sales, this is equivalent to a coefficient of variation of 1.2) and plot the optimal subsidy, production level, supplier's profit, and government expenditures as a function of the target level  $\Gamma$  for both the deterministic and stochastic models. The plots are reported in Figure 3. We have derived in §4.1 a set of inequalities regarding the relations of the optimal variables for deterministic and stochastic demand models. The plots allow us to quantify the magnitude of these differences and study the impact of demand uncertainty on the optimal policies. One can see from Figure 3 that the optimal production levels are not strongly affected by demand uncertainty (even for large values of  $\sigma$ ) when the target level  $\Gamma$  is set close to the expected sales value of 35,000. However, the optimal value of the subsidy is almost multiplied by a factor of 2 when demand uncertainty is taken into account. In other words, when the government and the supplier consider a richer environment that accounts for demand uncertainty, the optimal subsidy nearly doubles.

One can see that the optimal production quantities for deterministic and stochastic cases differ very little, whereas the subsidy and profit show significantly higher discrepancy. By looking at the closed-form expressions for linear demand in Theorem 1, one can see that the difference in optimal quantity is equal to  $F_{\epsilon}^{-1}((p_{\text{sto}} - c)/p_{\text{sto}}) - K(p_{\text{sto}})$ , whereas the difference in optimal subsidy is proportional to  $K(p_{\text{sto}})$ . Note that, in our case, the profit margin is relatively small (order of 0.1), and therefore the quantile value,  $F_{\epsilon}^{-1}((p_{\text{sto}} - c)/p_{\text{sto}})$ , is likely to be negative. In particular, in our example,  $c = 36,000$  and  $\Gamma$  ranges from 20,000 to 55,000. As a result, since we assume a symmetric noise distribution, the quantile is always negative. Consequently, the difference in quantities is

**Figure 3** (Color online) Optimal Values as a Function of the Target Level



clearly smaller than the difference in subsidies. One interesting interpretation relies on the fact that the cost of uncertainty in production quantity is shared between the supplier and the government. Indeed, the government wants to incentivize the supplier to increase production in order to reach the adoption target and therefore is willing to share some of the uncertainty risk so that  $q_{sto}$  is not far from  $q_{det}$ . Finally, the profit discrepancy is larger than the quantity discrepancy because it is equal to the same difference scaled by the cost  $c$  (see Theorem 1). In our example,  $c = 36,000$ , and therefore, we can see a more significant difference.

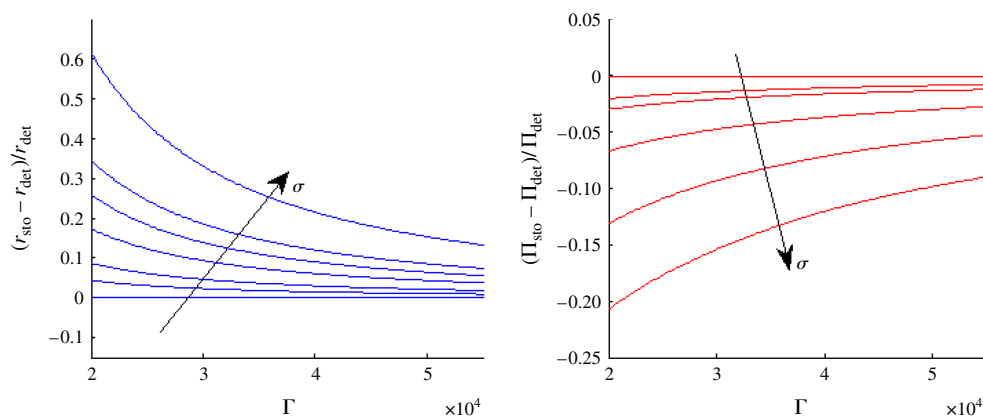
This raises the following interesting question. What happens if the government ignores demand uncertainty and decides to undersubsidize by using the optimal value from the deterministic model? It is clear that in this case, since the real demand is uncertain, the expected sales will not attain the desired expected target adoption. We address this question in

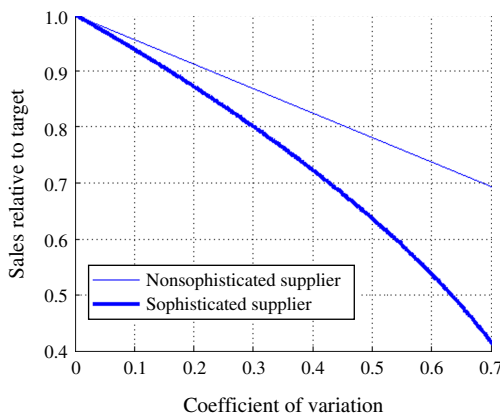
the remainder of this section. We first plot the subsidies and the supplier's profit as a function of the standard deviation of the noise that represents a measure of the demand uncertainty magnitude.

More precisely, we plot in Figure 4 the relative differences in subsidies (i.e.,  $(r_{sto} - r_{det})/r_{det}$ ) as well as the supplier's profit as a function of the target level  $\Gamma$  (or, equivalently, the expected sales) for different standard deviations of the additive noise varying from 35 to 12,500. For  $\Gamma = 35,000$ , this is equivalent to a coefficient of variation varying between 0.001 and 0.357. As expected, one can see from Figure 4 that as the standard deviation of demand increases, the optimal subsidy is larger, whereas the supplier's profit is lower. As a result, demand uncertainty benefits consumers at the expense of hurting both the government and the supplier.

Finally, we analyze by how much the government will miss the actual target level (now  $\Gamma$  is fixed and equal to 35,000) by using the optimal policy assuming that demand is deterministic,  $r_{det}$ , instead of using  $r_{sto}$ . Recall that  $r_{sto} \geq r_{det}$ . In other words, the government assumes a simple average deterministic demand model whereas in reality demand is uncertain. In particular, this allows us to quantify the value of using a more sophisticated model that takes into account demand uncertainty instead of simply ignoring it. Note that this analysis is different from the previous comparisons in this paper, where we compared the optimal decisions as a function of demand uncertainty. Here, we assume that demand is uncertain with some given distribution but the government decides to ignore the uncertainty. To this extent, we consider two possible cases according to the modeling assumption of the supplier. First, we assume that the supplier is nonsophisticated, in the sense that the supplier uses an average demand approximation model as well (i.e., no information on demand distribution is used). In this case, both the supplier and the government assume an average deterministic demand but

**Figure 4** (Color online) Relative Normalized Differences in Subsidies (Left) and Supplier's Profit (Right)



**Figure 5** (Color online) Expected Sales Relative to Target

in reality demand is random. Second, the supplier is more sophisticated. Namely, the supplier optimizes (over both  $p$  and  $q$ ) by using a stochastic demand model together with the distribution information. The results are presented in Figure 5, where we vary the value of the coefficient of variation of the noise from 0 to 0.7. When the government and the supplier are both nonsophisticated, the government can potentially save money (by undersubsidizing) and still get close to the target in expectation when demand uncertainty is not very large. As expected, when the supplier has more information on demand distribution (as is usually the case), the expected sales are farther from the target and the government could miss the target level significantly. If, in addition, demand uncertainty is large (i.e., coefficient of variation larger than 1), the government misses the target in both cases.

One can formalize the previous comparison analytically by quantifying the gap by which the government misses the target by ignoring demand uncertainty. In particular, let us consider the additive demand model given in (8).

**PROPOSITION 4.** Consider that the government ignores demand uncertainty when designing consumer subsidies.

(1) The government misses the adoption target (in expectation) regardless of whether the supplier is sophisticated or not.

(2) The exact gaps are given by the following:

- For a nonsophisticated supplier,

$$\mathbb{E}[\min(q, D(z, \epsilon))] = \Gamma + \mathbb{E}[\min(0, \epsilon)] \leq \Gamma. \quad (28)$$

- For a sophisticated supplier, assuming a linear demand model,

$$\begin{aligned} \mathbb{E}[\min(q, D(z, \epsilon))] \\ = \Gamma + \frac{1}{2} \cdot \mathbb{E}\left[\min\left(F_{\epsilon}^{-1}\left(\frac{p^* - c}{p^*}\right), \epsilon\right)\right] \leq \Gamma. \end{aligned} \quad (29)$$

In addition, the optimal price of the sophisticated supplier,  $p^*$ , is lower than in the deterministic case; i.e.,  $p^* \leq p_{\text{det}}$ .

(3) For low (high) profit margins, the gap is larger (smaller) when the supplier is sophisticated (nonsophisticated).

Note that all the results of Proposition 4 (with the exception of Equation (29)) are valid for a general demand model. Nevertheless, when the supplier is sophisticated, one needs to assume a specific model (in our case, linear) in order to compute the expected sales. As expected, the previous analysis suggests that the target adoption will be missed by a higher margin as demand becomes more uncertain. When comparing the nonsophisticated and sophisticated cases, one can see that in the former the government misses the target by  $\mathbb{E}[\min(0, \epsilon)]$ , whereas in the latter it misses by  $\frac{1}{2} \cdot \mathbb{E}[\min(F_{\epsilon}^{-1}((p^* - c)/p^*), \epsilon)]$ . Consequently, this difference depends not only on the distribution of the noise but also on the profit margin. Since the EV industry has rather low profit margins, the gap may be much larger when the supplier is sophisticated. Indeed, the sophisticated supplier decreases the price (relative to  $p_{\text{det}}$ ). In addition, the supplier, who is not willing to bear significant overstock risk due to the low profit margin, reduces the production quantities. As a result, the expected sales are lower, and therefore the government misses the adoption target level. In conclusion, this analysis suggests that policy makers should take into account demand uncertainty when designing consumer subsidies. Indeed, by ignoring demand uncertainty, one can significantly miss the desired adoption target.

## 8. Conclusions

We propose a model to analyze the interaction between the government and the supplier when designing consumer subsidy policies. Subsidies are often introduced at the early adoption stages of green technologies to help them become economically viable faster. Given the high level of uncertainty in these early stages, we hope to have shed some light on how demand uncertainty affects consumer subsidy policies, as well as price and production quantity decisions from manufacturers and the end consumers.

In practice, policy makers often ignore demand uncertainty and consider only deterministic forecasts of adoption when designing subsidies. We demonstrate that uncertainty will significantly change how these programs should be designed. In particular, we show by how much the government misses the adoption target by ignoring demand volatility. Among some of our main insights, we show that the shape of the demand curve will determine who bears demand uncertainty risk. When demand is uncertain, quantities produced will be higher and the effective price for consumers will be lower. For convex demand

functions, prices will be lower, leading to lower industry profits.

Focusing on the linear demand model, we can derive further insights. For instance, to compensate for uncertain demand, quantities produced and subsidy levels are shifted by a function of the service level, i.e., the profitability of the product. For highly profitable products, the supplier will absorb most of the demand risk. When profit margins are smaller, the government will need to increase the subsidy amount and pay a larger share for the risk.

When evaluating the uncertainty impact on consumers, we must consider the trade-off between lower effective prices and the probability of a stockout (unserved demand). We again show that the shape of the demand curve plays an important role. For linear demand, consumers will ultimately benefit from demand uncertainty. This is not the case, for instance, with an isoelastic demand model, where the possibility of not serving customers with high valuations will outweigh the benefits of decreased prices.

We also compare the optimal policies to the case where a central planner manages jointly the supplier and the government and tries to optimize the entire system simultaneously. We show that the optimal effective price and production level coincide in both the decentralized and centralized models. Consequently, the subsidy mechanism is sufficient to coordinate the government and the supplier, and the collusion does not hurt consumers in terms of price and quantities.

There are interesting directions for future research. Our model focuses on a single period, which is more applicable for policies with short time horizons. In cases where the policy horizon is long, it would be interesting to understand the effect of time dynamics on the actions of both government and supplier. It is not obvious how the frequency of policy adjustment will affect the outcome of the subsidy program, when considering a strategic response of the supplier. Additionally, introducing competition between suppliers could also be an interesting direction to extend the current model.

## Acknowledgments

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## Appendix. Proofs

**PROOF OF THEOREM 1.** We provide proofs for each part of Theorem 1 in turn.

(1) Equations (10) and (11) are obtained by applying the first-order conditions on the objective function of problem (1) with respect to  $q$  and then to  $p$ .

(2) We next prove the second claim about the fact that the optimal solution of the government problem is obtained when the target adoption level is exactly met. Using condition (9), one can compute the optimal value of  $p^*(r)$  by using a binary search algorithm (note that Equation (10) is monotonic in  $p$  for any given value of  $r$ ). In particular, for any given  $r$ , there exists a single value  $p^*(r)$  that satisfies the optimal Equation (10), and since all the involved functions are continuous, we may also conclude that  $p^*(r)$  is a continuous, well-defined function. As a result, the objective function of the government when using the optimal policy of the supplier is also a continuous function of  $r$ . In addition, the target level cannot be attained when  $r = 0$  by Assumption 1. We then conclude that the optimal solution of the government problem is obtained when the inequality target constraint is tight. In addition, one can see that the expected adoption target equation is monotonic in  $r$  so that one can solve it by applying a binary section method.

(3) Finally, let us show the third part. For the deterministic demand model, we have  $q_{\det} = y(z_{\det}) = \Gamma$ . On the other hand, when demand is stochastic, we have  $\mathbb{E}[\min(q_{\text{sto}}, D(z_{\text{sto}}, \epsilon))] = \Gamma$  so that we obtain  $q_{\text{sto}} \geq q_{\det}$ . In addition, the above expression yields  $y(z_{\text{sto}}) = \Gamma - K(p_{\text{sto}}) \geq \Gamma$ . Therefore, we obtain  $y(z_{\text{sto}}) \geq y(z_{\det})$ . Since  $y(z)$  is nonincreasing with respect to  $z = p - r$  (from Assumption 1), we may infer the following relation for the effective price:  $z_{\det} \geq z_{\text{sto}}$ . We next compute the optimal price for the deterministic model  $p_{\det}$  by differentiating the supplier's objective function with respect to  $p$  and equate it with zero (first-order condition):

$$\frac{\partial}{\partial p_{\det}} [q_{\det} \cdot (p_{\det} - c)] = y'(z_{\det}) \cdot (p_{\det} - c) + y(z_{\det}) = 0.$$

One can see that, in both models, we have obtained the same optimal equation for the price:  $y(z) = -y'(z) \cdot (p - c)$ . Namely, the optimal price satisfies  $p = c + \Gamma/|y'(z)|$ . We note that the previous expression is not a closed-form expression because both sides depend on the optimal price  $p$ . This is not an issue because our goal here is to compare the optimal quantities in the two models rather than deriving the closed-form expressions. Assuming that the deterministic part of demand  $y(z)$  is a convex function, we know that  $y'(z)$  is a nondecreasing function and then  $0 > y'(z_{\det}) \geq y'(z_{\text{sto}})$ . We then have the following inequality for the optimal prices:  $p_{\text{sto}} \leq p_{\det}$ . We note that the optimal subsidy in both models does not follow such a clear relation, and it will actually depend on the specific demand function. We next proceed to compare the optimal supplier's profit in both models. For the deterministic demand model, the optimal profit is given by  $\Pi_{\det} = q_{\det} \cdot (p_{\det} - c) = \Gamma^2/|y'(z_{\det})|$ . In the stochastic model, the expression of the optimal profit is given by

$$\begin{aligned} \Pi_{\text{sto}} &= p_{\text{sto}} \cdot \mathbb{E}[\min(q_{\text{sto}}, D(z_{\text{sto}}, \epsilon))] - c \cdot q_{\text{sto}} \\ &= \frac{\Gamma^2}{|y'(z_{\text{sto}})|} - c \cdot (q_{\text{sto}} - \Gamma) \leq \Pi_{\det}. \quad \square \end{aligned}$$



PROOF OF THEOREM 2. For the linear demand model in (14), the optimal solution of the supplier's optimization problem has to satisfy the following first-order condition:

$$\bar{d} + \alpha \cdot (r + c - 2p) + \frac{c}{p} \cdot F_{\epsilon}^{-1}\left(\frac{p-c}{p}\right) + \frac{p-c}{p} \cdot \mathbb{E}\left[\epsilon \mid \epsilon \leq F_{\epsilon}^{-1}\left(\frac{p-c}{p}\right)\right] = 0.$$

Note that it does not seem easy to obtain a closed-form solution for  $p^*(r)$ . In addition, since the previous equation is not monotone, one cannot use a binary search method.

Instead, one can express  $r$  as a function of  $p$ :  $r = 2p - c - \bar{d}/\alpha + (a \cdot c^2)/(\alpha \cdot p^2)$ . We next proceed to solve the government optimization problem by using the tightness of the inequality target adoption constraint:  $\mathbb{E}[\min(q^*(p^*(r), r), D(p^*(r) - r, \epsilon))] = \alpha \cdot (p^*(r) - c) = \Gamma$ . One very interesting conclusion from this analysis is that we have a very simple closed-form expression for the optimal price that is the same for the deterministic case:

$$p_{\text{sto}} = p_{\text{det}} = c + \frac{\Gamma}{\alpha}. \quad (30)$$

We can at this point derive the optimal supplier's profit for both models. In the deterministic case, the profit of the supplier is given by  $\Pi_{\text{det}} = q_{\text{det}} \cdot (p_{\text{det}} - c) = \Gamma^2/\alpha$ . In the stochastic model, the optimal profit is given by

$$\begin{aligned} \Pi_{\text{sto}} &= p_{\text{sto}} \cdot \mathbb{E}[\min(q_{\text{sto}}, D(z_{\text{sto}}, \epsilon))] - c \cdot q_{\text{sto}} \\ &= \frac{\Gamma^2}{\alpha} - c \cdot (q_{\text{sto}} - \Gamma) \leq \Pi_{\text{det}}. \end{aligned}$$

We next derive the optimal production level for both models. In the deterministic case, we obtained that  $q_{\text{det}} = \Gamma$ . For the stochastic case, after substituting all the corresponding expressions, we obtain

$$\begin{aligned} q_{\text{sto}} &= \bar{d} + \alpha \cdot (r_{\text{sto}} - p_{\text{sto}}) + F_{\epsilon}^{-1}\left(\frac{p_{\text{sto}} - c}{p_{\text{sto}}}\right) \\ &= \Gamma + F_{\epsilon}^{-1}\left(\frac{p_{\text{sto}} - c}{p_{\text{sto}}}\right) - K(p_{\text{sto}}) \geq q_{\text{det}}. \end{aligned}$$

We finally compare the effect of demand uncertainty on the optimal subsidy. One can show that after some appropriate manipulations the optimal subsidy for the deterministic linear demand model is given by  $r_{\text{det}} = 2\Gamma/\alpha - \bar{d}/\alpha + c$ . For the stochastic demand model, we have the following optimal equation:  $\alpha \cdot (2p_{\text{sto}} - r_{\text{sto}} - c) - \bar{d} = K(p_{\text{sto}})$ . Hence, one can find the expression for the optimal subsidies as a function of the optimal price  $p_{\text{sto}}$ :  $r_{\text{sto}} = 2p_{\text{sto}} - c - \bar{d}/\alpha - (1/\alpha) \cdot K(p_{\text{sto}})$ . By replacing  $p_{\text{sto}} = c + \Gamma/\alpha$  from (30), we obtain  $r_{\text{sto}} = 2\Gamma/\alpha + c - \bar{d}/\alpha - (1/\alpha) \cdot K(p_{\text{sto}}) = r_{\text{det}} - (1/\alpha) \cdot K(p_{\text{sto}}) \geq r_{\text{det}}$ .  $\square$

PROOF OF COROLLARY 1. We provide proofs for each part of the corollary in turn.

(1) We provide the proof of part (1) by using the facts  $d\rho/dc \leq 0$  and  $d\rho/(c\Gamma) \geq 0$ . We then show that the production gap widens as the service level  $\rho$  increases. Note that  $q_{\text{sto}} - q_{\text{det}} = F_{\epsilon}^{-1}(\rho) - K(p_{\text{sto}}) = \mathbb{E}[\max(F_{\epsilon}^{-1}(\rho) - \epsilon, 0)]$ . Taking the derivative with respect to the cost  $c$ , we obtain

$$\frac{d(q_{\text{sto}} - q_{\text{det}})}{dc} = \frac{d(F_{\epsilon}^{-1}(\rho))}{d\rho} \cdot \frac{d\rho}{dc} \cdot \rho = \frac{1}{f(F_{\epsilon}^{-1}(\rho))} \cdot \frac{d\rho}{dc} \cdot \rho \leq 0.$$

Similarly, for the target level  $\Gamma$ ,

$$\frac{d(q_{\text{sto}} - q_{\text{det}})}{d\Gamma} = \frac{d(F_{\epsilon}^{-1}(\rho))}{d\rho} \cdot \frac{d\rho}{d\Gamma} \cdot \rho = \frac{1}{f(F_{\epsilon}^{-1}(\rho))} \cdot \frac{d\rho}{d\Gamma} \cdot \rho \geq 0.$$

(2) To prove part (2), we show that the subsidy gap decreases with respect to  $\rho$ . Note that  $r_{\text{sto}} - r_{\text{det}} = -K(p_{\text{sto}})/\alpha = -\mathbb{E}[\min(F_{\epsilon}^{-1}(\rho), \epsilon)]/\alpha$ . Taking the derivative with respect to the cost  $c$ , we obtain

$$\begin{aligned} \frac{d(r_{\text{sto}} - r_{\text{det}})}{dc} &= -\frac{1}{\alpha} \left[ \frac{d(F_{\epsilon}^{-1}(\rho))}{d\rho} \cdot \frac{d\rho}{dc} \cdot (1 - \rho) \right] \\ &= -\frac{1}{\alpha} \cdot \frac{1}{f(F_{\epsilon}^{-1}(\rho))} \cdot \frac{d\rho}{dc} \cdot (1 - \rho) \geq 0. \end{aligned}$$

Similarly, for the target level  $\Gamma$ ,

$$\begin{aligned} \frac{d(r_{\text{sto}} - r_{\text{det}})}{d\Gamma} &= -\frac{1}{\alpha} \left[ \frac{d(F_{\epsilon}^{-1}(\rho))}{d\rho} \cdot \frac{d\rho}{d\Gamma} \cdot (1 - \rho) \right] \\ &= -\frac{1}{\alpha} \cdot \frac{1}{f(F_{\epsilon}^{-1}(\rho))} \cdot \frac{d\rho}{d\Gamma} \cdot (1 - \rho) \leq 0. \end{aligned}$$

(3) We next present the proof of part (3). We assume that  $\epsilon$  is an additive random variable with support  $[a_1, a_2]$ , not necessarily with a symmetric probability density function. For the linear demand model from (14), we have

$$r_{\text{sto}} = r_{\text{det}} - \frac{1}{\alpha} \cdot K(p_{\text{sto}}). \quad (31)$$

First, let us prove the first inequality by showing that the term on the right in Equation (31) is nonpositive for a general parameter  $y$ . We have  $\mathbb{E}[\min(y, \epsilon)] = y \cdot \mathbb{P}(y \leq \epsilon) + \mathbb{E}[\epsilon \mid \epsilon < y] \cdot \mathbb{P}(\epsilon < y)$ . Now, let us divide the analysis into two different cases according to the sign of  $y$ . If  $y \leq 0$ , we obtain  $\mathbb{E}[\min(y, \epsilon)] = y \cdot \mathbb{P}(y \leq \epsilon) + \mathbb{P}(\epsilon < y) \cdot \mathbb{E}[\epsilon \mid \epsilon < y] \leq 0$ . In the previous equation, both terms are nonpositive. For the case where  $y > 0$ , we have  $\mathbb{E}[\min(y, \epsilon)] < \mathbb{E}[\epsilon] = 0$ . Therefore,  $\mathbb{E}[\min(F_{\epsilon}^{-1}((p-c)/p), \epsilon)] \leq 0$ , showing the first inequality,  $r_{\text{det}} \leq r_{\text{sto}}$ . We now show the second inequality. We know from the optimality that  $p \geq c$ . Let us evaluate the expression of  $r_{\text{sto}}$  in (31) for different values of  $p$ . If  $p = c$ , we obtain  $F_{\epsilon}^{-1}((p-c)/p) = F_{\epsilon}^{-1}(0) = a_1 < 0$ . Then, we have  $r_{\text{sto}} = r_{\text{det}} - (1/\alpha) \cdot \mathbb{E}[\min(a_1, \epsilon)] = r_{\text{det}} - a_1/\alpha > r_{\text{det}}$ . If  $p \gg c$ , we obtain  $F_{\epsilon}^{-1}((p-c)/p) \rightarrow F_{\epsilon}^{-1}(1) = a_2 > 0$ . Therefore, we obtain  $r_{\text{sto}} \rightarrow r_{\text{det}} - 1/\alpha \cdot \mathbb{E}[\min(a_2, \epsilon)] = r_{\text{det}} - (1/\alpha) \cdot \mathbb{E}[\epsilon] = r_{\text{det}}$ . Since  $r_{\text{sto}}$  is continuous and nonincreasing in  $p$  for any  $p \geq c$ , the second inequality holds.  $\square$

PROOF OF PROPOSITION 2. By applying a similar methodology to that in the proof of Theorem 1, one can derive the following expressions (the steps are not reported for conciseness):

$$\begin{aligned} q_{\text{det}} &= \Gamma, \quad q_{\text{sto}} > \Gamma, \\ p_{\text{det}} &= c + \frac{1}{\alpha} \cdot \left(\frac{\bar{d}}{\Gamma}\right)^{1/\alpha}, \\ p_{\text{sto}} &= \frac{F_{\epsilon}^{-1}((p_{\text{sto}} - c)/p_{\text{sto}})}{K(p_{\text{sto}})} c + \frac{1}{\alpha} \cdot \left(\frac{\bar{d}}{\Gamma} \cdot K(p_{\text{sto}})\right)^{1/\alpha}, \\ r_{\text{det}} &= c + \left(\frac{\bar{d}}{\Gamma}\right)^{1/\alpha} \cdot \left(\frac{1}{\alpha} - 1\right), \\ r_{\text{sto}} &= \frac{F_{\epsilon}^{-1}((p_{\text{sto}} - c)/p_{\text{sto}})}{K(p_{\text{sto}})} c + \left(\frac{\bar{d}}{\Gamma} \cdot K(p_{\text{sto}})\right)^{1/\alpha} \cdot \left(\frac{1}{\alpha} - 1\right). \end{aligned}$$

Here,  $K(p_{\text{sto}}) = \mathbb{E}[\min(F_{\epsilon}^{-1}((p_{\text{sto}} - c)/p_{\text{sto}}), \epsilon)]$ , so that the above expressions for  $p_{\text{sto}}$  and  $r_{\text{sto}}$  are not in closed form. Indeed, in this case, one cannot analytically derive a closed-form expression. However, we are still able to compare the optimal subsidy between the deterministic and stochastic settings. Since  $\mathbb{E}[\epsilon] = 1$  and  $\epsilon \geq 0$ , we have  $0 \leq K(p_{\text{sto}}) \leq 1$ . Consequently, one can see that, since  $\alpha > 1$ ,  $r_{\text{sto}} \geq r_{\text{det}}$ .  $\square$

**PROOF OF PROPOSITION 3.** For the linear additive demand model presented in (14), one can compute the consumer surplus for given values of  $p$ ,  $r$ , and  $q$ :

$$\begin{aligned} \text{CS}_{\text{sto}}(\epsilon) &= \begin{cases} \frac{D(z, \epsilon)^2}{2\alpha} & \text{if } D(z, \epsilon) \leq q, \\ \frac{D(z, \epsilon) \cdot q}{2\alpha} & \text{if } D(z, \epsilon) > q, \end{cases} \\ &= \frac{D(z, \epsilon)}{2\alpha} \cdot [\min(D(z, \epsilon), q)]. \end{aligned}$$

Therefore, we have  $\text{CS}_{\text{sto}}(\epsilon) \geq [\min(D(z, \epsilon), q)]^2/(2\alpha)$ . By applying the expectation operator, we obtain

$$\begin{aligned} \mathbb{E}[\text{CS}_{\text{sto}}(\epsilon)] &\geq \frac{\mathbb{E}[\{\min(D(z, \epsilon), q)\}^2]}{2\alpha} \geq \frac{\{\mathbb{E}[\min(D(z, \epsilon), q)]\}^2}{2\alpha} \\ &= \frac{\Gamma^2}{2\alpha} = \text{CS}_{\text{det}}, \end{aligned}$$

where the second inequality follows by Jensen's inequality (or the fact that the variance of any random variable is always nonnegative). The last equality follows from the previous result that the target inequality constraint is tight at optimality.

We next compute the consumer surplus defined in (19) for the isoelastic demand from (17). In particular, we observe that  $z_{\text{max}}(\epsilon) = \infty$  for any value of  $\epsilon$  (if we assume that  $\epsilon$  is strictly positive and finite). In addition, we have  $z_{\text{sto}} = p_{\text{sto}} - r_{\text{sto}} = [(\bar{d}/\Gamma) \cdot K(p_{\text{sto}})]^{1/\alpha}$ . Note that  $K(p_{\text{sto}})$  is a deterministic constant and does not depend on the realization of the noise  $\epsilon$ . Therefore, when computing  $\text{CS}_{\text{sto}}(\epsilon)$  for a given  $\epsilon$ , since demand is multiplicative with respect to the noise, one can see that  $\epsilon$  cancels out and that simplifies the calculation. We obtain

$$\begin{aligned} \text{CS}_{\text{sto}}(\epsilon) &= \frac{1}{\alpha - 1} \left[ \frac{\bar{d}}{\Gamma} \cdot K(p_{\text{sto}}) \right]^{(1-\alpha)/\alpha} \\ &\quad \cdot \left[ \frac{\bar{d}}{\Gamma} K(p_{\text{sto}}) \right] \min(D(z_{\text{sto}}, \epsilon), q_{\text{sto}}). \end{aligned}$$

Then, by taking the expectation operator, we obtain

$$\begin{aligned} \mathbb{E}[\text{CS}_{\text{sto}}(\epsilon)] &= \frac{\bar{d}}{\alpha - 1} \cdot \left( \frac{\bar{d}}{\Gamma} \right)^{(1-\alpha)/\alpha} \cdot K(p_{\text{sto}})^{1/\alpha} \\ &= \text{CS}_{\text{det}} \cdot [K(p_{\text{sto}})]^{1/\alpha}. \end{aligned}$$

Here, we have used the fact that the inequality adoption constraint is tight at optimality; that is,  $\mathbb{E}[\min(D(z_{\text{sto}}, \epsilon), q_{\text{sto}})] = \Gamma$ . In addition, this is the only term that depends on the noise  $\epsilon$ . Since we have  $0 \leq K(p_{\text{sto}}) \leq 1$ , one can conclude that, for any  $\alpha > 1$ ,  $\mathbb{E}[\text{CS}_{\text{sto}}(\epsilon)] \leq \text{CS}_{\text{det}}$ .  $\square$

**PROOF OF THEOREM 3.** We present first the proof for the deterministic demand model and then the one for stochastic demand. Let us first consider the unconstrained optimization problem faced by the central planner. If demand

is deterministic, the objective function is given by  $J(p, r) = q(p, r) \cdot (p - r - c)$ . We assume that demand is a function of the effective price (denoted by  $z$ ); that is,  $q(p, r) = y(p - r) = y(z)$ . Next, we compute the unconstrained optimal solution denoted by  $z^*$  by imposing the first-order condition:  $dJ(z)/dz = 0 \Rightarrow z^* = c - y(z^*)/y'(z^*)$ . Although, we did not derive a closed-form expression for  $z^*$ , we know that it should satisfy the above fixed point equation. We now show that any unconstrained optimal solution is infeasible for the constrained original problem since it violates the target inequality constraint:

$$q(p^*, r^*) = y(z^*) = y\left(c - \frac{y(z^*)}{y'(z^*)}\right) \leq y(c) < \Gamma.$$

We used the facts that demand is positive, differentiable, and a decreasing function of the effective price (see Assumption 1). In addition, since we assumed that the target level cannot be achieved without subsidies, we have shown that the unconstrained optimal solution is not feasible. Therefore, we conclude that the target inequality constraint has to be tight at optimality:  $q(p_{\text{det}}, r_{\text{det}}) = \Gamma$ . In other words, the optimal effective price and production level are the same as in the decentralized model.

We now proceed to present the proof for the case where demand is stochastic. Let us consider the constrained optimization problem faced by the central planner. We denote as  $J$  the objective function (multiplied by  $-1$ ) and denote as  $\lambda_i$ ;  $i = 1, 2, 3$  the corresponding Karush-Kuhn-Tucker (KKT) multipliers of the three constraints. The KKT optimality conditions are then given by

$$\begin{aligned} \frac{\partial J}{\partial q} - \lambda_2 \cdot \mathbb{P}(q \leq D) &= 0, & \frac{\partial J}{\partial p} - \lambda_1 - A \cdot \lambda_2 &= 0, \\ \frac{\partial J}{\partial r} - \lambda_3 - B \cdot \lambda_2 &= 0. \end{aligned} \quad (32)$$

Here,  $A$  and  $B$  are given by

$$A = \frac{\partial}{\partial p} \mathbb{E}[\min(q, D(z, \epsilon))] = y'(z) \cdot F_{D(z, \epsilon)}(q),$$

$$B = \frac{\partial}{\partial r} \mathbb{E}[\min(q, D(z, \epsilon))] = -y'(z) \cdot F_{D(z, \epsilon)}(q) = -A.$$

If, in addition, the noise is additive, we have  $F_{D(z, \epsilon)}(q) = F_{\epsilon}(q - y(z))$ . We also have

$$\begin{aligned} \frac{\partial J}{\partial q} &= c - z \cdot [1 - F_{D(z, \epsilon)}(q)], \\ \frac{\partial J}{\partial p} &= -\mathbb{E}[\min(q, D(z, \epsilon))] - z \cdot A = -\frac{\partial J}{\partial r}. \end{aligned}$$

We note that the last two equations are symmetric and hence equivalent. Equivalently, the central planner decides only on the effective price  $z = p - r$  and not  $p$  and  $r$  separately. We next assume that  $\lambda_1 = \lambda_3 = 0$ . This corresponds (from the complementary slackness conditions) with the assumption that both corresponding constraints are not tight. Indeed, clearly the optimal subsidies may be assumed to be strictly positive since we assumed that, when  $r = 0$ , the adoption constraint cannot be satisfied. We further assume that the supplier wants to achieve positive profits, so that the optimal price is strictly larger than the cost. Therefore,

the KKT conditions (both stationarity and complementary slackness) can be written as follows:

$$c - (z + \lambda_2) \cdot [1 - F_\epsilon(q - y(z))] = 0, \quad (33)$$

$$-(z - \lambda_2) \cdot y'(z) \cdot F_\epsilon(q - y(z)) = \mathbb{E}[\min(q, D(z, \epsilon))], \quad (34)$$

$$\lambda_2 \cdot (\Gamma - \mathbb{E}[\min(q, D(z, \epsilon))]) = 0. \quad (35)$$

We now have two possible cases depending on the value of  $\lambda_2$ . Let us first investigate the case where  $\lambda_2 = 0$ . From Equation (33), we have  $F_\epsilon(q - y(z)) = (z - c)/z$ . By using Equation (34), we obtain  $z = c - (\mathbb{E}[\min(q, D(z, \epsilon))])/y'(z)$ . Now, we have

$$\begin{aligned} & \mathbb{E}[\min(q, D(z, \epsilon))] \\ &= y\left(c - \frac{\mathbb{E}[\min(q, D(z, \epsilon))]}{y'(z)}\right) + \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{p-c}{p}\right), \epsilon\right)\right]. \end{aligned}$$

Since we assume that the function  $y(z)$  is a decreasing function of the effective price  $z$  and that both  $q$  and  $D(z, \epsilon)$  are nonnegative, we obtain  $\mathbb{E}[\min(q, D(z, \epsilon))] < y(c) + \mathbb{E}[\min(F_\epsilon^{-1}((p-c)/p), \epsilon)] \leq y(c)$ . In the last step, we used the fact that  $\mathbb{E}[\min(F_\epsilon^{-1}((p-c)/p), \epsilon)] \leq 0$ . Therefore, we conclude that  $\mathbb{E}[\min(q, D(z, \epsilon))] < \Gamma$ . In other words, the solution is not feasible since it violates the target inequality constraint. Hence, we must have  $\lambda_2 > 0$ , and the inequality constraint is tight at optimality:  $\mathbb{E}[\min(q, D(z, \epsilon))] = \Gamma$ . Now, by using Equation (33), we obtain  $F_\epsilon(q - y(z)) = (z + \lambda_2 - c)/(z + \lambda_2)$ . We then substitute the above expression in Equation (34):  $z = c - \lambda_2 - \Gamma/y'(z)$ . Now, we have  $\Gamma = y(z) + \mathbb{E}[\min(F_\epsilon^{-1}((z + \lambda_2 - c)/(z + \lambda_2)), \epsilon)]$ . By expressing the previous equation in terms of the effective price, we obtain  $\Gamma = y(z) + \mathbb{E}[\min(F_\epsilon^{-1}(-(\Gamma/y'(z))/(c - (\Gamma/y'(z)))), \epsilon)]$ . Therefore, one can solve the previous equation and find the optimal effective price  $z$ . We note that this is exactly the same equation as in the decentralized case, so that the effective prices are the same. The optimal production levels are given by  $q = y(z) + F_\epsilon^{-1}((-\Gamma/y'(z))/(c - (\Gamma/y'(z))))$ . Similarly, the equations are the same in both the decentralized and centralized models so that the optimal production levels are identical. Finally, we just need to show that  $\lambda_2 > 0$  in order to complete the proof. We have

$$\begin{aligned} \Gamma &= y\left(c - \lambda_2 - \frac{\Gamma}{y'(z)}\right) + \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{-\Gamma/y'(z)}{c - \Gamma/y'(z)}\right), \epsilon\right)\right] \\ &\leq y\left(c - \lambda_2 - \frac{\Gamma}{y'(z)}\right) < y(c - \lambda_2). \end{aligned}$$

If we assume by contradiction that  $\lambda_2 < 0$ , we obtain  $\Gamma < y(c - \lambda_2) < y(c)$ . This is a contradiction so that  $\lambda_2 > 0$ , and the proof is complete.  $\square$

**PROOF OF PROPOSITION 4.** We first consider the scenario where the supplier is nonsophisticated. In this case, the optimal decision variables are still  $r_{\det}$ ,  $q_{\det}$ , and  $p_{\det}$ . However, in reality, demand is uncertain, and therefore the expected sales are given by

$$\begin{aligned} \mathbb{E}[\min(q_{\det}, D(z_{\det}, \epsilon))] &= \mathbb{E}[\min(q_{\det}, y(z_{\det}) + \epsilon)] \\ &= \Gamma + \mathbb{E}[\min(0, \epsilon)] \leq \Gamma. \end{aligned} \quad (36)$$

Here, we have used the fact that  $q_{\det} = y(z_{\det}) = \Gamma$ .

Next, we assume that the supplier is sophisticated. Note that, in this case, the optimal subsidies set by the government are still equal to  $r_{\det}$ . In other words, the government does not have any distributional information on demand uncertainty and believes that neither does the supplier. In particular, the subsidies are set such that  $y(p_{\det} - r_{\det}) = \Gamma$ . However, the supplier, who is sophisticated, uses distributional information on demand uncertainty to decide the optimal price and production. In a similar way to that in Equations (10) and (11) from Theorem 1, the optimal price when  $r = r_{\det}$  can be obtained as the solution of the following nonlinear equation:

$$\begin{aligned} & y(p - r_{\det}) + \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{p-c}{p}\right), \epsilon\right)\right] \\ &+ y'(p - r_{\det}) \cdot (p - c) = 0. \end{aligned} \quad (37)$$

In addition, one can compute the optimal production level as follows:

$$q^*(p, r_{\det}) = y(p - r_{\det}) + F_\epsilon^{-1}\left(\frac{p-c}{p}\right).$$

For the linear demand model, Equation (37) becomes  $\bar{d} - \alpha \cdot (2p - r_{\det} - c) + \mathbb{E}[\min(F_\epsilon^{-1}((p-c)/p), \epsilon)] = 0$ . Equivalently, the optimal price denoted by  $p^*$  follows the following relation:

$$p^* = c + \frac{\Gamma}{\alpha} + \frac{1}{2\alpha} \cdot \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{p^*-c}{p^*}\right), \epsilon\right)\right].$$

Note that the optimal price when demand is deterministic is equal to  $p_{\det} = c + \Gamma/\alpha$ , and therefore  $p^* \leq p_{\det}$ . As a result, the expected demand is given by

$$\begin{aligned} y(p^* - r_{\det}) &= \bar{d} - \alpha \cdot (p^* - r_{\det}) \\ &= \Gamma - \frac{1}{2} \cdot \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{p^*-c}{p^*}\right), \epsilon\right)\right] \geq \Gamma. \end{aligned}$$

We next proceed to compute the expected sales:

$$\begin{aligned} & \mathbb{E}[\min(q^*, D(p^* - r_{\det}, \epsilon))] \\ &= \mathbb{E}\left[\min\left(y(p^* - r_{\det}) + F_\epsilon^{-1}\left(\frac{p^*-c}{p^*}\right), y(p^* - r_{\det}) + \epsilon\right)\right] \\ &= \Gamma + \frac{1}{2} \cdot \mathbb{E}\left[\min\left(F_\epsilon^{-1}\left(\frac{p^*-c}{p^*}\right), \epsilon\right)\right] \leq \Gamma. \quad \square \end{aligned}$$

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