Transition to Electric Mobility: An Optimal Price Subsidy Rule

René Aïd and Imen Ben Tahar

Abstract Many public policies declare electric mobility as a key lever for insuring the carbon emission target and attaining the objectives of oil-dependence reduction. However, the cost of an electric vehicle (`ev`) is still way too expensive compared to the conventional fuel-powered vehicle (`fv`) and constitutes a serious barrier against its diffusion. In this note we formulate a tractable model to analyse the dynamics of the adoption of `ev`'s. The dynamic is driven by increasing marginal production returns and consumer's willingness to pay. We define the social benefit of replacing an `fv` by an `ev` as the fuel-economy it allows to realize, and solve for the optimal subsidy rule. We show that in a context of expensive fuel price, a voluntary policy of subsidy can transform the present fuel-powered fleet into an electric one.

1 Introduction

As highlighted in [7, 8], the last decade is marked by new socio-technical developments which have the potential to trigger the emergence of a viable trajectory for electric mobility. These new developments are mainly led by: (i) *Progress in battery technology*: where significant achievements in terms of performance and range have already been realized making `ev` a more viable product. (ii) *Public policies*: the last decade witnessed greater concerns about climate change. Many governments are committed to binding green-house-gas (GHG) emission reduction targets and number of public policies support electric mobility, declaring it as a key lever for insuring the sustainability of the transport sector while attaining the objectives of GHG limitation and oil-dependence reduction. For instance, the European Commission states a set of objectives among which halving the use of

R. Aïd (✉)
EDF R&D, Finance for Energy Market Research Centre, Clamart, France
e-mail: rene.aid@edf.fr

I. Ben Tahar
Université Paris-Dauphine, CEREMADE, France and Finance for Energy Market Research Centre, Clamart, France
e-mail: imen@ceremade.dauphine.fr

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'conventionally-fuelled' cars in urban transport by 2030 and phasing them out in cities by 2050 [9].

Alongside these favorable elements, there are however important obstacles hindering the deployment of evs. A major one is the high cost of the battery. Surveys about *Consumers Willingness to pay for* ev reveal that, in spite of the high premium some consumers are willing to pay, 'battery cost need to drop considerably if ev are to be competitive without subsidy at current gasoline prices' [10]. A critical question is to understand how subsidy policies combine with potential battery-cost reduction via technological learning (*learning-by-doing* and *increasing returns to scale* effects) so that the ev becomes economic.

We formulate a tractable model allowing to quantify the effect of purchase subsidy on the dynamics of ev's adoption. Here, we assimilate the benefit of substituting an fv by an ev to the realized fuel economy over the lifetime of the vehicle. Indeed, while the individual consumer has a short-term view, the public authority has a long-term policy, which gives, from a social perspective, advantage to ev's future fuel economy over present battery expenses. In this note, we stick to a simple deterministic setting where the fv's purchase price and the energy costs for both vehicles are assumed to be constant over time. It constitutes a reference case for a more involved stochastic model which is the object of an upcoming paper.

In Sect. 2 we present the basic hypothesis of our model and introduce the dynamics of the ev adoption. This dynamics is inspired from Brian Arthur [1] seminal paper analyzing competing technologies with increasing returns. It captures the fact that the cost of ev is experiencing a learning curve where the speed at which learning occurs, is spurred by the number of new ev adopters. It implies that the post-subsidy purchase price spread between ev and fv , denoted by $x(t)$, evolves according to

$$\dot{x}(t) = -\alpha\mu x(t)\Phi(x(t) - s(t))$$

where s is the subsidy rule, and Φ is the complementary cumulative distribution function for *the consumers' willingness to pay for* evs. In Sect. 3, we justify the social benefit of subsidizing ev purchases, then we formulate and solve the problem of optimal purchase subsidy rule allowing to maximize the social benefit. We show that the optimal subsidy rule consists in guaranteeing a relatively low net purchase price P^* which is *constant* (up to the interest rate). The value of the subsidy vanishes as the pre-subsidy price of the ev tends to $P^\star$. We show that using this optimal subsidy rule in a context of hugh fuel price, the fuel-powered vehicle fleet can be transform into an electric one in a few decades. Finally, Sect. 4 is dedicated to concluding remarks.

2 Modeling the Dynamics of Electric Vehicle Adoption

Analyzing the potential demand for `ev` is crucial to model or forecast how manufactures strategies and public policy incentives may influence the deployment of electric mobility. Several studies addressed the demand side, in particular consumers willingness to pay for an electric car compared the reference gasoline powered vehicle, see for example [5, 10]. For our model, we retain two important observations which are often reported:

(i) significant preference (willingness to pay) heterogeneity across the population,
(ii) required substantial battery price reduction if `ev`s are to meet target volume.

These facts are illustrated on Fig. 1 with a sample of data extracted from [5] on willingness-to-pay of European consumers. We will use these data for the numerical application in Sect. 3.3.

As for battery technology, there is an on-going intense R&D activity where close collaborations between automakers and manufacturers are observed [8]. As shown in Fig. 2, the industry projects better performances as well as cost reductions to follow through *learning-by-doing* and *increasing returns to scale* effects: production costs for the not yet mature battery technology shall decline as production cumulates.

2.1 Basic Hypothesis and Notations

For the sake of tractability, we make some simplifying assumptions on the market of new personal vehicles:

Potential Market We assume a constant annual rate of new car purchases, denoted by μ. We suppose that consumers have the choice between two types of standard vehicles, either an electric vehicle (`ev`) or a fossil-fuel powered car (`fv`). The hypothesis for standard vehicle we consider are given in Table 1 and correspond to genuine data, except for the gasoline price for which a high price scenario is considered.

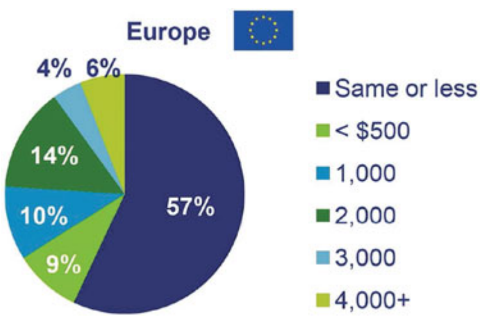

Fig. 1 Willingness-to-pay for `ev` for European consumers according to [5]

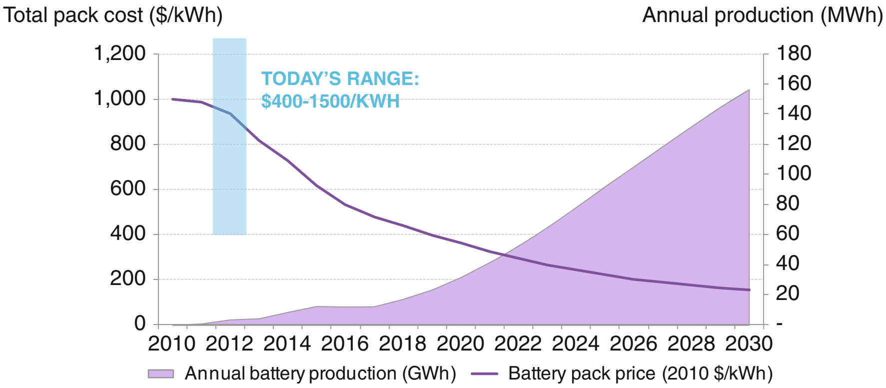

Fig. 2 Battery learning curve: LI-ION battery pack cost and production 2010–2030—*Source*: Bloomberg new energy finance

Purchase Price and the Battery Learning Curve The purchase price of the conventional fv, p, is supposed to be constant over time. Whereas, accounting for potential technological learning, the purchase price of the ev, p_t^e, is supposed to vary (possibly decline) in the future. We denote by x_t the purchase price spread:

$$x_t := p_t^e - p \; . \tag{1}$$

We assume that this spread is essentially explained by the battery cost. Indeed, relevant literature report that the cost of batteries is the critical factor within the investment cost for electric vehicle [4, 6, 11, 12]. As it is explained in the French Green Book on non-emissive vehicles [12, p. 42] fv and ev share most of their costs (body work, passenger space, communication to drive wheels. . .) and the only differences come for the battery. Following [2], we assume that the battery costs, and consequently the spread x_t, decreases at a *learning rate* proportional to the number of new ev adopters.

Energy Cost We denote, respectively, by f and e the annual energy cost of an fv and an ev. They are assumed to be constant over time. Hence, in our model we do not take into account possible future energy cost reduction. We also do not take into account uncertainty regarding oil prices. Indeed, we intend to isolate the effect of battery technological learning.

2.2 Dynamics of Electric Vehicle Adoption

To model the dynamics of ev deployment, we adapt the framework of Brian Arthur [1] who proposed a simple and insightful model of explore the dynamics of allocation between competing technologies with increasing returns.

Sequentially arriving consumers, indexed by i, choose between the competing `ev` and `fv` technologies each agent i is characterized by his willingness-to-pay for the `ev`, denoted by ω^i. Let t_i denote the date at which consumer i makes his purchase decision. The consumer i chooses an `ev` if and only if

$$x_{t_i} \leq \omega^i \ .$$

where x_{t_i} is the purchase price spread defined in (1). The sequence $(\omega^i)_{i\geq 1}$ is assumed to be a sequence of i.i.d. random variables. We denote by Φ the complementary cumulative distribution function of ω^i:

$$\Phi(x) := \mathbb{P}(\omega^i \geq x) \ . \tag{2}$$

As explained in the previous subsection, we aim to capture the fact that the spread x_t decreases because the cost of `ev` is experiencing a learning curve where the speed at which learning occurs, is spurred by the number of new `ev` adopters. For now on, we fix a time step δt, and assume the following dynamics:

$$x_{t+\delta t} = x_t - \alpha \, x_t \, \mathbf{n}_t^{ev} \ . \tag{3}$$

Here, $\mathbf{n}_t^{ev}$ is number of new `ev` adopters between the dates t and $t + \delta t$, and α represents the learning rate.

A Limiting o.d.e. It can be shown that the stochastic system (3) can be approximated by the solution of ordinary differential equation (o.d.e.)

$$\dot{\xi}_t = -\alpha\mu\xi_t\Phi(\xi_t) \, , \quad \xi_0 = x_0 \ , \tag{4}$$

where μ is the annual rate of new vehicle purchases.

Proposition 2.1. *Define the piecewise continuous linear interpolation $\bar{x}$ by*

$$\bar{x}(t_k) = x_{t_k} \text{ and } \bar{x}(t) = x_{t_k} + (x_{t_{k+1}} - x_{t_k})\frac{(t-t_k)}{(t_{k+1}-t_k)}, \ t \in [t_k, t_{k+1}] \, , \ t_k := k\delta t \ .$$

Then, for any $T > 0$

$$\mathrm{e}\left[\sup_{t\in[0,T]} |\bar{x}_t - \xi_t|^2\right] = O(\delta t) \ .$$

Proof. This result follows from a direct application of Lemma 9.2.1 in [3]. □

3 Social Benefit and Optimal Subsidy Rule

3.1 Social Benefit of the Electric Vehicle

In our analysis, we identify the social benefit of the electric mobility with the fuel economy realized by substituting `ev` to `fv`. When estimating the lifecycle cost to energy, a key issue is the discount rate at which future consumption is valued today. The individual consumers has a short-term view, reflected by a relative high discount rate. On the other hand, the public authority has a long-term policy reflected by a relatively low discount rate. Considering our standard vehicles data, Table 1, this difference in the discount rate is sufficient to justify from the social perspective the energy-economy benefits resulting from substituting an `ev` to an `fv` ; a collective benefit which is not perceived at the individual level.

In order to formalize this discussion, we introduce the social cost, P, of a single `fv`

$$P = p + \int_0^\infty e^{-\rho t} f dt \;=\; p + f/\rho \,, \tag{5}$$

and the social cost, P^e_t, of a single `ev`

$$P^e_t = p^e_t + \int_0^\infty e^{-\rho t} e dt \;=\; p^e_t + e/\rho \,, \tag{6}$$

Here, ρ, is the social discount rate supposed to be constant over time. We consider the lifetime of the vehicle to be sufficiently long to make the approximation of an infinite time horizon. There is a social benefit to the `ev` if $P^e_0 \le P$. Consider the cost difference:

$$P - P^e_t = p - p^e_t + (f - e)/\rho \;=\; b - x_t$$

Table 1 Cost and fuel economy for the electric vehicle

	`fv`		`ev`
Energy consumption	5 l/100 km		20 kWh/100 km
Fuel price	1,5 €/l		0,9 €/kWh
Km/year	15.000		15.000
Energy cost/year (€)	1.125		270
Vehicle price (€)	15.000		30.000
Individual discount rate	16 %		16 %
Individual cost	22.000		31.700
Individual benefit of the `ev`(€)		−9.700	
Social discount rate	4 %		4 %
Social cost (€)	43.125		36.750
Social benefit of the `ev`(€)		6.375	

where $b := (f - e)/\rho$ is, from the social perspective, the fuel economy resulting from substituting an ev to an fv.

Table 1 summarizes the various costs for the standard vehicles. Energy consumption, fuel price, km per year and vehicle price are taken from the French Green Book on non-emissive vehicle [12, p. 42] . These data corresponds to a urban use of the vehicle. The electricity price is an off-peak price, considering that the vehicles will charge during the night or on non-peaking hours. The hypothesis for the fuel price is high. It corresponds to a situation where the oil would be around 200 USD per baril. The individual discount rate (16 %) is sensibly higher then the social rate (4 %). It reflects the individual's 'impatience' when arbitrating between immediate costs and future benefits. From the social perspective, substituting an fv by an ev results in a benefit of €6,000: a fuel economy of $b =$ €21,000, minus the initial battery cost $x_0 =$ €15,000.

3.2 Optimal Purchase Subsidy

A purchase subsidy is used as a public policy to stimulate the number of ev adopters. We denote by s_t the value of the purchase subsidy at time t, and by x^s the price spread resulting from applying the subsidy rule $s = \{s_t,\ t \geq 0\}$. Here we shall work directly with the approximating dynamics (4). Then, the rate of new ev adopters, when applying the subsidy rule s, is approximated by

$$\mu\, \Phi(x_t^s - s_t)\ , \tag{7}$$

the resulting price-spread dynamics is given by

$$\dot{x}_t^s = -\alpha\mu\Phi(x_t^s - s_t)\, x_t^s \quad \text{with } x_0^s = x_0\ . \tag{8}$$

Hence, from the social perspective, the subsidy rule $s = \{s_t, t \geq 0\}$ leads to an energy-economy evaluated by

$$\int_0^\infty \mu\Phi(x_t^s - s_t)\left(P - P_t^e\right) dt = \int_0^\infty \mu\Phi(x_t^s - s_t)\left(b - x_t^s\right) dt\ .$$

Here the objective of the public authority is to maximise over a fixed time horizon T the *social surplus* defined as the social energy-economy minus the subvention amount:

$$\max_s \int_0^T \mu\, \Phi(x_t^s - s_t)\left(b - x_t^s - s_t\right) dt. \tag{9}$$

The question of financing this subsidy policy is left aside here.

It turns out that is possible to characterize explicitly the optimal subsidy rule. We shall assume the complementary distribution function Φ satisfies:

$$\Phi \text{ has a bounded support } [\mathbf{x_{min}}, \mathbf{x}_{max}] \tag{10}$$

$$\Phi' > 0 \text{ on }]\mathbf{x}_{min}, \mathbf{x}_{max}] \tag{11}$$

$$h: \; z \mapsto z + \Phi(z)/\Phi'(z) \text{ is non-decreasing on } [\mathbf{x}_{min}, \mathbf{x}_{max}] \tag{12}$$

and consider as a canonical example the truncated Pareto distribution function:

$$\Phi_p(z) := \left(\frac{\mathbf{x}_{max} - z}{\mathbf{x}_{max} - \mathbf{x}_{min}} \right)^p \mathbf{1}_{[\mathbf{x}_{min}, \mathbf{x}_{max}]}(z) \;\; \text{with } p > 0 \,. \tag{13}$$

Proposition 3.1. *Assume (10)–(12) hold. Let $x_0 < b$ be the initial spread value. If $s^\star$ is an optimal subsidy strategy, then $s^\star$ consists in having the consumer pay for the* ev *a post subsidy price which is constant equal to $p + x_t^{s^\star} - s_t^\star = p + z^\star$ where:*

$$\begin{cases} z^\star = \mathbf{x}_{min} & \text{if } 2x_0 e^{-\alpha\mu T} - b \le h(\mathbf{x}_{min}), \\ z^\star = \mathbf{x}_{max} & \text{if } 2x_0 - b \ge h(\mathbf{x}_{max}), \\ \text{and } h(z^\star) = 2x_0 e^{-\alpha\mu\Phi(z^\star)T} - b \text{ otherwise} \,. \end{cases} \tag{14}$$

Proof. Let H be the Hamiltonian function for the control problem (9)–(8):

$$H: \;\; (x, p) \mapsto \sup_{s \ge 0} \mu\Phi(x - s) \{b + x - s - x(2 + \alpha p)\}$$

Assume that $s^\star := \{s_t^\star, \; t \in [0, T]\}$ is an optimal subsidy strategy. Denote by $x^\star := x^{s^\star}$ the associated price spread and let $z^\star := x^\star - s^\star$. Then, by Pontryagin Maximum principle, there exists an absolutely continuous map $p^\star : \; [0, T] \to \mathbb{R}$ such that $(x^\star, p^\star)$ satisfies the Hamiltonian system

$$\begin{cases} \dot{x}^\star(t) = \nabla_p H(x^\star(t), p^\star(t)) = -\alpha x^\star \mu\Phi(z^\star(t)), & x(0) = x_0 \\ \dot{p}^\star(t) = -\nabla_x H(x^\star(t), p^\star(t)) = (2 + \alpha p^\star(t))\mu\Phi(z^\star(t)), & p(T) = 0 \,. \end{cases} \tag{15}$$

and the condition

$$H(x^\star, p^\star) = \mu\Phi(z^\star) \{b + z^\star - x^\star(2 + \alpha p^\star)\} \,. \tag{16}$$

From (15) we get

$$\frac{d}{dt} (x^\star(2 + \alpha p^\star)) = 0 \,.$$

Then, by (16), $z^\star$ is constant on $[0, T]$ with: $z^\star = \text{argmax}\, \Phi(z^\star) \{b + z^\star - x^\star(2 + \alpha p^\star)\}$, and from conditions (10)–(12) we get (14). □

In the case where the willingness to pay follows a truncated Pareto distribution function $\Phi = \Phi_p$, then (14) fully characterizes the subsidy policy:

Proposition 3.2. *Let $\Phi = \Phi_p$, and assume that*

$$\textit{either (i): } p \leq 1 \quad \textit{or (ii): } p > 1 \textit{ and } (\mathbf{x}_{max} - \mathbf{x}_{min}) < \frac{p}{1+p}(\mathbf{x}_{max} + b)$$

Let $x_0 < b$ be the initial spread value. An optimal subsidy strategy $s^\star$ consists in having the consumer pay for the EV *a post subsidy price which is constant equal to $p + z^\star(x_0)$ where $z^\star(x_0)$ is defined by*

$$\text{(i)} \quad z^\star(x_0) = \mathbf{x}_{min} \ \textit{ if } \ 2x_0 e^{-\alpha\mu T} - b \leq h(\mathbf{x}_{min}),$$

$$\text{(ii)} \quad z^\star(x_0) \textit{ is the unique solution in } [\mathbf{x}_{min}, \mathbf{x}_{max}] \textit{ to : }$$

$$h(z) = 2x_0 e^{-\alpha\mu\Phi(z)T} - b \ \textit{ otherwise.}$$

Proof. Let $\Psi : (\tau, x, z) \mapsto h(z) + b - 2xe^{-\alpha\mu\tau\Phi(z)}$, and denote by U the set:

$$U := \{(\tau, x) : \ x < b \ \text{ and } \ \Psi(\tau, x, \mathbf{x}_{min}) < 0\} \ .$$

Notice that for all $(\tau, x) \in U$, $\Psi(\tau, x, \mathbf{x}_{max}) = \mathbf{x}_{max} + b - 2x_0 > 0$. If either (i) or (ii) is satisfied, then a straightforward, but rather lengthy, analysis of the variations of the function $z \to \Psi(\tau, x, z)$ shows that for all $(\tau, x) \in U$ there exists a unique $z^\star(\tau, x) \in]\mathbf{x}_{min}, \mathbf{x}_{max}[$ such that

$$\Psi(\tau, x, z^\star(\tau, x)) = 0 \text{ with } \frac{\partial\Psi}{\partial z}(\tau, x, z^\star(\tau, x)) > 0.$$

Then $(\tau, x) \in U \mapsto z^\star(\tau, x)$ is C^1 on $U \times]\mathbf{x}_{min}, \mathbf{x}_{max}[$ with

$$\frac{\partial z^\star}{\partial \tau}(\tau, x) = -\frac{\partial_\tau \Psi(\tau, x, z^\star(\tau, x))}{\partial_z \Psi(\tau, x, z^\star(\tau, x))} \text{ and } \frac{\partial z^\star}{\partial x}(\tau, x) = -\frac{\partial_x \Psi(\tau, x, z^\star(\tau, x))}{\partial_z \Psi(\tau, x, z^\star(\tau, x))}$$

For $(\tau, x) \notin U$ we set $z^\star(\tau, x) = \mathbf{x}_{min}$.

To verify that $s^\star$ is indeed the optimal strategy rule, we consider the function:

$$\begin{aligned} w(t,x) &= \int_t^T \mu\Phi(z^\star(T-t,x)) \left\{ b + z^\star(T-t,x) - 2xe^{-\alpha\mu\Phi(z^\star(T-t,x))(u-t)} \right\} du \\ &= \mu\Phi(z^\star(T-t,x))(b + z^\star(T-t,x))(T-t) - \frac{2x}{\alpha}(1 - e^{-\alpha\mu\Phi(z^\star(T-t,x))(T-t)}) \end{aligned}$$

A direct calculation shows that w solves the Hamilton-Jacobi-Bellman-Equation associated to our problem:

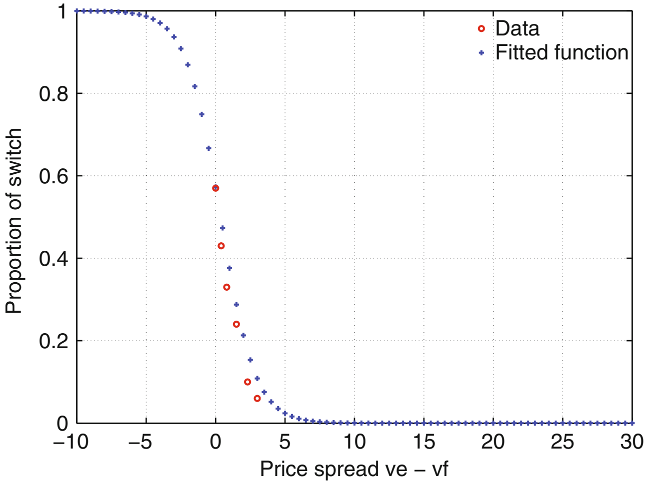

Fig. 3 Complementary cumulative distribution function Φ fitted to the panel data of European consumers from [5]

$$\frac{\partial w}{\partial t_0} + H(x_0, \frac{\partial w}{\partial x_0}) \;=\; 0\;,\;\; w(T, \cdot) = 0\;.$$

and we conclude by standard verification argument that $s^\star$ is optimal. □

3.3 Numerical Experiments

First, we fitted the willing-to-pay function Φ with the data provided by [5] and presented in Sect. 2 on European consumers. Although the sample is very sparse, Fig. 3 shows that the approximation captures the threshold effect around a null value of the spread.

Now we illustrate and compare the evolution of `ev` adoption over a time horizon of 50 years for three policies:

- the zero purchase subsidy case,
- with the optimal subsidy rule solving (9),
- and with a subsidy capped at €7,000 as it is the case for the current French policy.

The evolution of the price spread x and of the number of `ev` annual purchases are reported in Fig. 4. We see that the optimal subsidy rule leads to a relatively rapid decrease in the price spread. The optimal policy itself, illustrated in Fig. 5, decreases at the same rate as the price of the `ev`: it ensures a constant 'post-subsidy' price for the `ev` which, approximatively exceeds the price of the `fv` by €1,000.

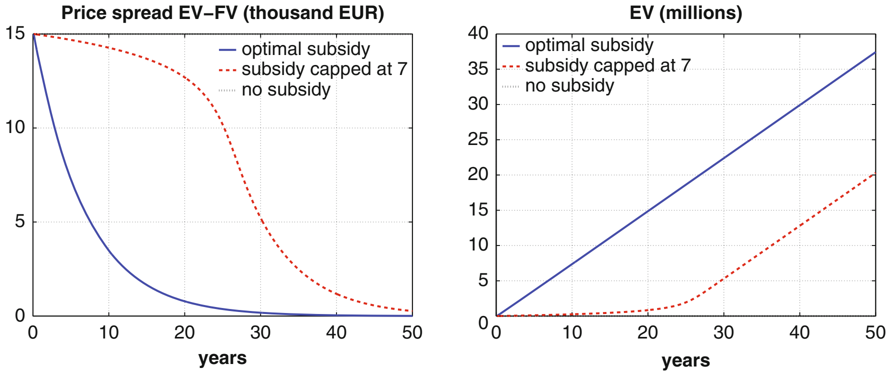

Fig. 4 Evolution of the price spread and of the ev adoption for the three rules

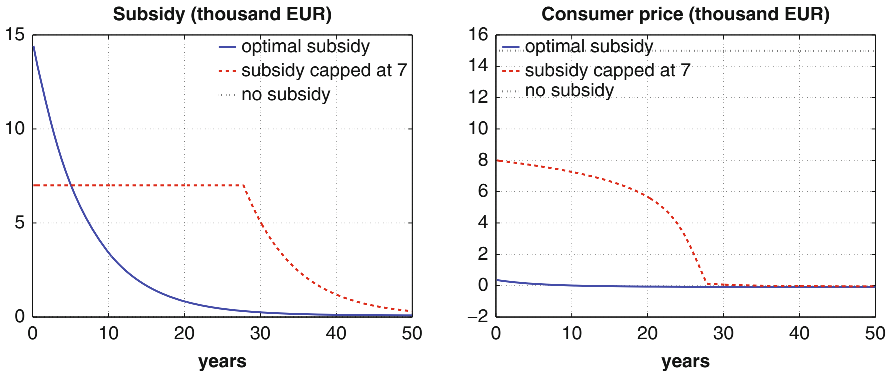

Fig. 5 Optimal subsidy policy and of the ‘post-subsidy’ purchase price

When applying the optimal subsidy policy, the evolution of ev adoption is immediate and corresponds to a constant annual number of 800,000 ev purchases. Indeed, from the social perspective, there is an immediate social benefit to replacing fvs by evs, and it is optimal to ensure a very rapid transition. Notice that the amount of the optimal subsidy at the initial date is significantly larger than the €7,000 of the current French subsidy policy.

Observe, as it is illustrated in Fig. 4, that the effect current subsidy policy of €7,000 is not significantly different from the no-subsidy case during the first 25 years. It appears that this current subsidy amount is not sufficient—with regard to consumers willingness-to-pay—to insure a rapid transition to the electric mobility. This relatively negligible effect during decades may quickly discourage the public decision-maker to persevere in this policy.

The effect of the optimal subsidy policy is illustrated in Fig. 6. It appears that the optimal policy induces at first losses due to substantial subsidies, before insuring large gains from future fuel-economy. In the first 5 years the cumulated amount of

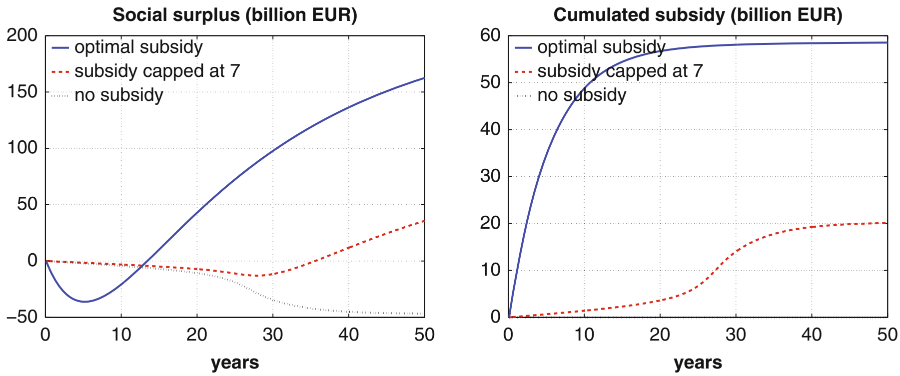

Fig. 6 Evolution of the social surplus and of the cumulated amount of subsidy

subsidies is of € 35 billion, whereas the social surplus is negative. Yet, after 10 years, le social surplus is about € 25 billion for a total amount of subsidy equal to € 50 billion. These short term losses may explain the reluctance of current public policies to put in place the important subsidies needed for massive ev adoption.

4 Conclusion

Motivated by the tractability of the qualitative analysis of the optimal subsidy for ev market, we adopted a quite simple and stylized model for the transition to electric mobility. Hence, the numerical experiments presented here are intended to be illustrative and do not pretend to be accurate. Nevertheless, this model allows to have important insights about the nature of the optimal subsidy rule which may allow a rapid adoption of evs.The optimal subsidy rule derived here, consists in insuring a constant 'post-subsidy' purchase price for the consumer. This result does not depend on the form of the cumulative distribution function of consumers willingness to pay. However, a precise knowledge of the willingness-to-pay distribution is crucial in determining the amount of the subsidy and reveals to be more important that the battery learning rate. The findings of our model allow, also, to question the efficiency of the current subsidy policy, and the modalities with which subsidy amounts are decided.

Perspectives However, in this state of development, this model can not escape certain criticisms. In particular, the fact that the gasoline price is constant and high makes the transition to electric mobility quite natural whereas one main problem is the uncertainty on the oil price. Thanks to the fact that the present model is simple, we have good confidence in our capacity to deal with the introduction of various forms of oil price uncertainty in the same kind of dynamic.

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