Working Paper

Evaluating second-hand EVs subsidies: Efficiency and Welfare Gains

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Evaluating second-hand EVs subsidies: Efficiency and Welfare Gains

Ariane Bousquet, Juan-Pablo Montero, and Maria-Eugenia Sanin*

Abstract

Decarbonizing transport is crucial to achieving net-zero emissions, with private cars contributing significantly to greenhouse gas emissions. While subsidies for new electric vehicles (EVs) are common, the recent inclusion of second-hand EV subsidies in several countries raises questions about their economic rationale. Contrary to conventional thinking, we show that while subsidies for second-hand EVs are often justified on equity grounds, they also improve efficiency as they influence the equilibrium composition of the vehicle fleet. Using a theoretical model that incorporates both vertical (vintage) and horizontal (fuel type) differentiation, along with empirical evidence from the French car market, we demonstrate that subsidies for new and second-hand EVs function as complements. By employing both types of subsidies and adjusting them over time, policymakers can achieve substantial welfare gains compared to focusing solely on new EVs.

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1 Introduction

Decarbonizing transport is one of the key milestones of succeeding the net-zero objective for mid-century. Globally, 24% of CO_2 emissions from energy consumption come from the transport sector, 18% due to road transport. In France, the impact of the transport accounts for 31% of total CO_2 emissions, and from these emissions, private cars account for 56%, alongside other local externalities.

Numerous countries have implemented incentive policies to promote the renewal of the private car fleet by targeting the purchase of new electric vehicles (EVs).[1] In particular, France has first implemented a feebate policy as from 2008, with a tax on carbon emissive vehicles and a subsidy for low-carbon vehicles. The policy has evolved since then to account for different car characteristics such as weight, and more recently, to include second-hand EVs.

The inclusion of subsidies for used EVs may at first appear counterintuitive from an economic perspective: if we want to substitute polluting cars for EVs shouldnt we care only about the cars that enter the fleet? However, France is not alone in the trend toward incentivizing used EVs. This trend is gaining momentum, primarily motivated by equity considerations. For example, New Zealand introduced the Clean Car Discount Scheme from April 2022 to December 2023, offering registration discounts based on CO_2 emissions for both new and used vehicles.[2] The Netherlands offers a €2,000 subsidy for used EVs since July 2020, which has led to a significant increase in their adoption. More recently, Luxembourg reduced its maximum subsidy for new EVs from €8,000 to €6,000 and introduced a €1,500 subsidy for used EVs over three years old.

While the stated objective of these governments may appear to focus on equity concerns, this paper demonstrates that allocating subsidies between new and used cars is not solely about equity but fundamentally a matter of efficiency. Contrary to common thinking, we show that subsidizing used EVs, rather than exclusively focusing on new EVs, positively impacts the equilibrium composition of the vehicle fleet and yields greater welfare gains than a subsidy for new EVs alone.

Specifically, this paper develops a simple theoretical framework that extends the vertical differentiation model of Barahona, Gallego, and Montero (2020), which considers vehicles differing only by vintages, by adding a horizontal dimension—the distinction between gasoline and electric vehicles. This extension yields several novel findings.

First, we observe that drivers trade off horizontal and vertical attributes, leading to het-

[1] In the United States EV purchases are eligible for federal tax credits up to USD 7,500. Some states, such as California, offer additional incentives, including rebates (for details see U.S. Department of Treasury). China, the largest EV market, provides extensive subsidies and tax exemptions to encourage both production and adoption. In Norway, extensive tax exemptions have provoked that nearly 90% of new car sales are EVs today. In the EU, several countries have implemented purchase incentives, particularly in the biggest car markets like Germany, even if under revision nowadays, the United Kindom (UK), Italy, France and Spain.

[2] Although this program successfully incentivized the registration of low-emission cars, it was ultimately discontinued due to budget constraints (see Ministry of Transport, New Zealand, 2024). Similarly, some German states, such as Baden-Württemberg, have implemented reductions in registration fees for used EVs.

erogeneous vehicle rankings and therefore different substitution patterns. This distinct feature implies that, in this context, subsidies do not replicate Pigouvian taxes—one of the rare instances where this occurs. Second, we demonstrate that subsidies for new and second-hand EVs work as complements rather than substitutes, a critical insight for designing efficient policies. Finally, we show that subsidies on new EVs should decline over time as second-hand vehicles become more important within the vehicle fleet. We add to the previous contributions an empirical estimation of the theoretical model for France, what allows us to simulate alternative subsidies structures as compared to the Pigouvian first best. To the best of our knowledge, this has not been studied before.

In the following section, we discuss the main contributions to the existing literature and address the challenges involved in estimating a vehicle fleet model that incorporates both horizontal and vertical differentiation.

2 Literature review

The Industrial Organization literature focusing on the car market can be broadly divided into two main strands.

The first examines demand in the new car market, leveraging structural models that estimate consumer preferences for a wide range of vehicle characteristics. This line of research, grounded in the seminal work of Berry, Levinsohn, and Pakes (1995) (BLP), has advanced our understanding of substitution patterns, merger impacts, and policy effects. Notably in France, (D'Haultfœuille, Durrmeyer, and Février 2016) and (Givord, Grislain-Letrémy, and Naegele 2018) employ nested logit models that they estimate on separated socio-demographic groups to evaluate French policies like fuel taxes and the 2008 feebate. However, these models typically assume unrestricted substitution across vehicles, as consumers do not agree on the ranking of alternatives. Yet, this may mask the nature of consumer preferences, whether driven by vertical differentiation (quality) or horizontal differentiation (taste). Addressing this gap poses significant estimation challenges. Unlike standard logit models, which rely on a Type I Extreme Value error term for identification, alternative approaches such as the pure characteristics model of Berry and Pakes (2007) remove this assumption to better capture pure taste for product characteristics. Although promising, such models are rarely implemented due to their complexity, with notable applications like (Song 2015; Song 2007) for the CPU market and (Barahona, Gallego, and Montero 2020) for the car market. In this paper, we get inspired by a recent work by Duch-Brown et al. (2023), that build an adapted BLP-type model in which the same product is sold through different distribution channels, and approximate it by a random coefficient nested logit (RCNL) model for the estimation. Using a RCNL model is a way of estimating the heterogeneity in preferences for discrete variables. Another option to RCNL is to use a random coefficient logit model and put individual coefficients on discrete variables, as described by Grigolon and Verboven (2014).

The second strand of the literature investigates equilibrium dynamics in the entire car fleet, analyzing trade-offs between new, used, and scrapped vehicles. Studies like Gavazza, Lizzeri, and Roketskiy (2014) model vertical differentiation to explain transactions among heterogeneous drivers in their willingness to pay for quality, while Bento (2009) link multiple car markets to assess gasoline taxes' effects. More directly related to our work, Barahona, Gallego, and Montero (2020) use a vertical differentiation model and estimate it with Berry and Pakes (2007)'s pure characteristics model to study first- and second-best policies against local pollution, focusing on vehicle age as the key driver of vertical differentiation. While valuable, these frameworks do not explicitaly account for horizontal differentiation, such as the choice between gasoline and electric vehicles, which is necessary for modeling the energy transition.

Our paper bridges the gap between these two strands of literature. We first develop a simple framework that integrates vertical and horizontal differentiation in a durable good market with a two car types that stay in the fleet for two periods. Concretely, we add an horizontal dimension to the two-period vertical model of Barahona, Gallego, and Montero (2020).

The theoretical development of including vertical and horizontal preferences not only presents a more complete representation or reality but also proves to be a crucial contribution since it breaks the equivalence between Pigouvian taxes and subsidies. Our main findings in this regard is that subsidies do not replicate the work of Pigouvian taxes, and that a subsidy on second-hand EVs must be implemented in the transition to net-zero emissions. This seems in contradiction with the well known theoretical result that a Pigouvian tax (or an equivalent subsidy) can implement the first-best on its own. This is because previous literature does not consider the potential trade-offs between horizontal (here, fuel type) and vertical (here, vintages) characteristics. The theoretical model also finds that subsidies to new and used EVs work as complements in the implementation of the optimal policy and that subsidies to new EVs should decrease as the number of used vehicles in the fleet increases.

To quantify the importance of previous results, we then turn to a more complete structural model of demand. To this end we get inspiration from Duch-Brown et al. (2023), and estimate a random coefficient model à la Grigolon and Verboven (2014) with random coefficient on key vertical and horizontal characteristics, using 2019 French data at the district (supra-municipality) level. We then simulate the impact of pollution taxes and subsidies to test for the theoretical insights from the two-period model. Our main findings from the estimation are that vertical preferences and price matter more to lower-income households while the preference for EVs is higher for richer households. The simulation results from implementing pollution taxes and alternative subsidy designs are in line with the theory, as we find that subsidies are not symetric in their impacts to Pigouvian taxes and that a subsidy on the used-EV market brings larger welfare then a new-car subsidy alone. Overall one of the main messages from this work, although still preliminary, is the fact that subsidizing EVs on the used-car market is not only a matter of equity but also proves more efficient.

The paper is organized as follows. Section 2 describes the simple model with horizontal and vertical differentiation. Discussion of empirical strategy and data is in Section 3. Policy counterfactual analysis is in Section 4. Section 5 concludes.

3 A simple model of the car market

We develop a simple model of a market for durable goods where consumers differ in their vertical and horizontal preferences for these goods. Some consumers place higher value on newer goods, while others prioritize cleaner goods over conventional ones. We are interested in the market equilibrium, where taxes and subsidies on second-hand units do have allocative implications, i.e., they cannot be seen as simple transfers from or to consumers.

3.1 Market setting

Consider a market with two types of cars, electric vehicles (EVs) and gasoline (and diesel) cars, each of which lasts for two periods, first as new and then as second-hand. For the purpose of this simple model, think of new cars as cars that are few years old and younger and second-hand as anything older than that. We will discuss the implications on our results of allowing cars to last for an endogenous number of periods.

There are three agents in the market: car producers, car dealers, and drivers. The cost of producing a new car is the same for both types of cars and equal to c. This is also the price at which perfectly competitive producers sell new cars to car dealers.[3] A large number of car dealers buy new cars from car producers and rent them, together with second-hand cars, to drivers.[4] In the second period, dealers can either rent their cars for one more time or scrap them for a value v. If the car is rented, its dealer can scrap it afterward for v, provided it still exists, which happens with probability γ. To save on notation, we normalize the scrappage value v to zero (we will come back to this normalization below).[5]

In addition, there is a unit mass of drivers who vary in their vertical preferences for new *vs.* second-hand cars and their horizontal preferences for EVs *vs.* gasoline cars. These preferences are captured, respectively, by the variables θ and η, which, for simplicity, are assumed to be uniformly distributed over the unit square. Thus, a driver with preferences θ and η who rents a type-i car, either electric ($i = EV$) or gasoline-based ($i = G$), of age a, either new ($a = 0$) or second-hand ($a = 1$), obtains

$$u_a^i(\theta, \eta) = V + \theta s_a - tx^i(\eta) - p_a^i \quad (1)$$

[3] In non-competitive markets, we could change the interpretation of c to represent marginal cost plus a mark up and conclusions from the model would not change.

[4] Note that the renting assumption, which is also in Barahona et al (2020) and Bento et al (2009), is only to facilitate the presentation. The model would be the same without dealers and but with forward-looking drivers purchasing cars from producers and trading them to other drivers.

[5] Considering a positive scrappage value does not change any of our results. It only introduces additional notation and, as we comment below, a slight bias in (optimal) policy interventions. In any case, scrappage values are only a small fraction of the value of a new car, less than 4% in Barahona, Gallego, and Montero (2020). We consider a similar value in the empirical section.

where V is a positive constant, s_a is the car's quality, with $s_0 > s_1$, t is the horizontal differentiation parameter (**Hotelling1929**'s transportation cost) parameter, $x^i(\eta)$ is the "distance" of the consumer to its fuel-type renting choice i, either $x^i(\eta) = \eta$ if $i = G$ or $x^i(\eta) = 1 - \eta$ if $i = EV$, and p_a^i is the car's rental price paid by the consumer, which may differ from the rental price received by car dealers, denoted by $\tilde{p}_a^i$, in the presence of taxes and/or subsidies. The driver's problem is to decide in each period what age and fuel-type to rent so as to maximize (1).

Unlike EVs, gasoline cars emit all sorts of pollutants, some with global effects (e.g., CO_2) while other with local effects, i.e., effects at the city level lasting for a few hours (e.g., fine particulates, CO, HC, NO_x). Since polluting cars are more harmful as they age, even if they are driven less (Barahona, Gallego, and Montero 2020; Jacobsen et al. 2022), we let h_a be the per-period pollution harm of a gasoline car of age a, with $h_1 > h_0$.

3.2 Market equilibrium

We are interested in theoretically modelling two equilibria, depending on the market share of EVs. One is the steady-state equilibrium, when there are both new and second-hand EVs in the market. The other is the transition equilibrium, when there are only new EVs in the market. In our two-period setting, where the transition lasts only one period, the two equilibria can be treated separately.[6]

There are several conditions that must hold in equilibrium for car dealers, with and without policy interventions. The first is that when a dealer brings an extra car to the market, he or she expects to break even, that is,

$$c = \tilde{p}_0^i + \delta \tilde{p}_1^i + \gamma \delta^2 v \tag{2}$$

for $i = EV, G$ and where $\delta < 1$ is the discount factor (we will come back to this break-even condition for when cars may last for more than two periods).

The second condition is that dealers must be indifferent between scrapping a second-hand car and renting it for the last time and scrapping it afterward, provided the car still exits, that is

$$v = \tilde{p}_1^i + \gamma \delta v \tag{3}$$

Whether we are in the transition equilibrium or in the steady-state equilibrium, conditions (2) and (3) imply that in equilibrium dealers face rental prices $\tilde{p}_0^i = c$ and $\tilde{p}_1^i = 0$.[7].

Given the durable-good nature of cars, the number of second-hand vehicles available for rental one period cannot be larger than the number of new cars brought to the market in the previous period. Considering the two-period model, this condition can be summarized simply as:

[6] Adda and Cooper (2000) is another example where adjustments take one period.
[7] Recall we have normalized to zero the scrappage value of a car, i.e., $v = 0$

$$q_1 \leq \gamma q_0 \tag{4}$$

In the absence of any policy intervention, consumers face the same prices as dealers (i.e., $p_a^i = \tilde{p}_a^i$), so their decisions, summarized in Figure 1, are easy to characterize. We first focus on the panel on the left and the indifferent consumer's conditions. To find the vertical cutoffs θ_G and θ_{EV}, we determine the consumers that are indifferent between renting a new and a used car of each energy type, following the seminal work of **Shaked1982** on pure vertical product differentiation. Consumers with high valuation for quality, those with $\theta > \theta_G \equiv (p_0^G - p_1^G)/\Delta s = (p_0^{EV} - p_1^{EV})/\Delta s \equiv \theta_{EV} = c/\Delta s$ (with $\Delta s \equiv s_0 - s_1$), rent new cars ($a = 0$) of either type in each period, while consumers with a lower valuation for quality, $\theta < \theta_G = \theta_{EV}$, rent second-hand cars ($a = 1$). On the other hand, we find the horizontal cutoffs η_0 and η_1 by looking at the consumers indifferent between renting a new (respectively used) gasoline car and a new (respectively used) EV, similarly to the seminal work of **Hotelling1929** on pure horizontal product differentiation. Consumers located closer to the gasoline option, $\eta < \eta_0 \equiv 1/2 + (p_0^{EV} - p_0^G)/2t = 1/2 + (p_1^{EV} - p_1^G)/2t \equiv \eta_1 = 1/2$, rent gasoline cars, while those closer to the EV option, $\eta > \eta_0 = \eta_1$, rent EVs.

We restrict parameter values to ensure certain properties to hold in any market equilibrium (with and without policy interventions), namely, (i) full coverage (the fact that all drivers rent a car in equilibrium), (ii) a positive number of both new and second-hand gasoline cars being rented, and (iii) a positive number of second-hand cars of either type being scrapped, except during the transition, when there are no second-hand EVs. Note that necessary conditions for ensuring properties (i) and (iii) above hold are $\upsilon > t/2$, and $\Delta s > 2c$, respectively. Property (ii) holds automatically, given the symmetry of the no-intervention outcome. This property will become more demanding as the social planner targets dirty cars, whether directly by taxing them or indirectly by subsidizing clean ones.

Consider now the panel on the right of Figure 1, describing the transition equilibrium. The only difference with the panel on the left is the absence of second-hand EVs, which explains the relatively larger share of new EVs (EV_0) and of second-hand gasoline cars (G_1). In reality, given the steady decline in their costs, the number of new EVs coming to the market during the early years of the transition could be certainly smaller than the number when the steady-state is reached. However, we do not want to enter into this possibility here. We want to concentrate on policy design while keeping all else constant (we will come back to this declining-cost possibility in the empirical section).

The absence of second-hand EVs in Figure 1(b) has also created consumers indifferent between a new EV (EV_0) and a second-hand gasoline car (G_1). Their preferences lie over the line $\eta_{EV/G}(\theta) \equiv 1/2 + (p_0^{EV} - p_1^G - \theta\Delta s)/2t = 1/2 + (c - \theta\Delta s)/2t$ that comes from the indifference $u_0^{EV} = u_1^G$.[8] The way this indifference line is drawn assumes that vertical preferences

[8] We could also express this indifference by setting $\theta_{EV/G}(\eta)$

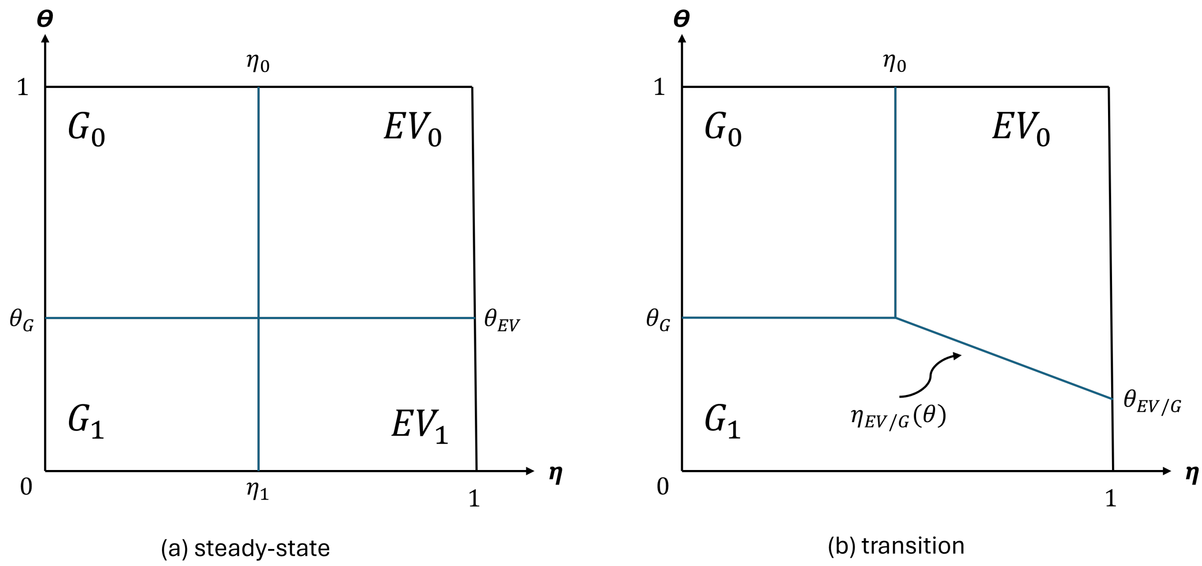

Figure 1: The no-intervention equilibrium

are stronger than horizontal preferences in that $\theta_{EV/G} \equiv (c-t)/\Delta s > 0$.[9]

Given that the car market is perfectly competitive, it is not entirely surprising that the no-intervention equilibrium depicted in Figure 1 is socially optimal in the absence of pollution, i.e., whenever $h_0 = h_1 = 0$.

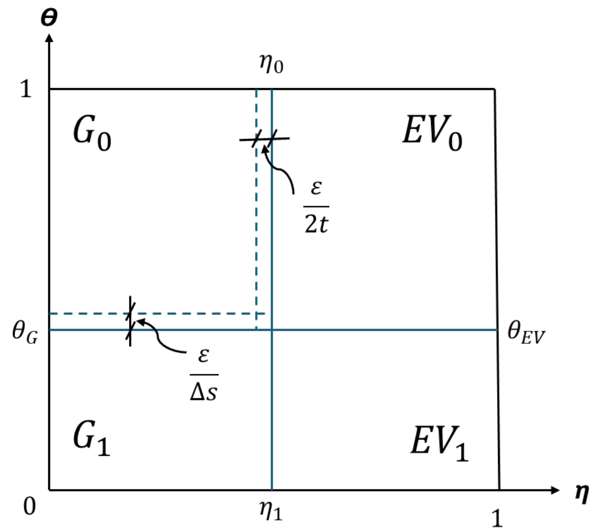

Figure 2: Social optimality of the no-intervention outcome in the absence of pollution

To see the previous statement formally, use Figure 2 to see the impact of introducing an arbitrarily small tax, say of ε, on one of the four rental options, say on new gasoline cars. The consumer rental price of these cars has now increased to $p_0^G = \tilde{p}_0^G + \varepsilon = c + \varepsilon$, while the

[9]Results hold equally under the alternative assumption where horizontal preferences are stronger than vertical preferences. The empirical section will help us determine which assumption is more likely to hold in practice.

remaining rental prices have stayed the same. The increase in the price of new gasoline cars has moved the vertical and horizontal preferences of the indifferent consumers by $\varepsilon/\Delta s$ and $\varepsilon/2t$, respectively.[10]

The moves just described in Figure 2 have welfare implications of different nature, giving rise to marginal gains and losses.

Let $1_a^i(\theta,\eta)$ indicate that the utility-maximizing rental choice for consumer type (θ,η) is a car of age a and fuel-type i. Then, welfare in any given steady-state period is given by

$$W = \sum_i \sum_a \int_\theta \int_\eta \hat{u}_a^i(\theta,\eta) dF(\theta,\eta) - c \sum_i q_0^i - \sum_a h_a q_a^G \tag{5}$$

where $\hat{u}_a^i(\theta,\eta) = u_a^i(\theta,\eta) + p_a^i$ is the consumer's utility before prices, $F(\theta,\eta)$ is the uniform distribution over the unit square, and $q_a^i = \int_\theta \int_\eta 1_a^i dF(\theta,\eta)$ is the number of cars of fuel-type i and age a rented.

Marginal gains, which amount, respectively, to (only first-order effects are relevant)

$$\Delta W^{(+)} = \frac{\varepsilon}{2t}\left(1-\theta_G\right)c + \frac{\varepsilon}{\Delta s}\eta_0 c \tag{6}$$

and

$$\Delta W^{(-)} = \frac{\varepsilon}{2t}\left(1-\theta_G\right)c + \frac{\varepsilon}{\Delta s}\eta_0\theta_G\Delta s + \frac{\varepsilon}{2t}\int_{\theta_G}^{1}(1-2\eta_0)t d\theta \tag{7}$$

where $\theta_G = c/\Delta s$ and $\eta_0 = 1/2$. The two terms in eq. (6) correspond to savings from fewer new gasoline cars entering the market, in response to some individuals switching to new EVs (the first term) and some others switching to second-hand gasoline cars (the second term). These gains are completely offset by the first two terms in (7), as the result of more new EVs in the market (the first term) and of some individuals suffering a vertical (i.e., quality) downgrade (the second term). The last term in (7) captures the horizontal losses suffered by individuals who switch from new gasoline cars (their preferred no-intervention option) to new EVs.[11] Since these individuals are located right at the middle of the horizontal space (at $\eta_0 = 1/2$), their losses vanish.

It is easy to anticipate that any other marginal adjustment in prices will also lead to no welfare changes at the margin, confirming the social optimality of the no-intervention outcome in the absence of pollution. This conclusion also extends to the transition phase shown in Figure 1(b).[12]

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[10] These results are obtained from the updated indifference conditions.

[11] $\int_{\eta_0-\epsilon/2t}^{\eta_0}\int_{\theta_G}^{1}(\hat{u}_0^{EV} - \hat{u}_0^G)d\eta d\theta = \int_{\eta_0-\epsilon/2t}^{\eta_0} 1 d\eta \int_{\theta_G}^{1}(1-2\eta_0)t d\theta$

[12] When the scrappage value of a second-hand car is strictly positive, the planner can improve upon the no-intervention outcome with a small tax on new cars. This responds to a residual positive term, equal to $\varepsilon\eta_0(1-\gamma\delta)v/\Delta s$, as we add eqs. (6) and (7). By reducing (or postponing) their scrapping, this positive term indicates that new cars have become relatively more expensive from a social point of view. In practice, this term is small because both γ and δ are close to 1 (scrapping an old car a year later does not make much difference for its survival and discounted scrappage value). For this reason we neglect all this in the theoretical part of this work.

3.3 Policy interventions

We now turn to the case when gasoline cars pollute, as happens in reality, i.e., when $h_1 > h_0 > 0$. Clearly, in the absence of any policy intervention the market equilibrium described above would result in socially inefficient levels of pollution. We will consider two types of price-based interventions: taxes on dirty cars and subsidies on clean cars.[13] There is no gain in considering quantity instruments. With enough prices, the social planner can arrive at any arbitrary allocation of cars.

As prescribed by Pigou, one way for the social planner to improve upon the no-intervention outcome is to tax drivers of polluting cars an amount equal to the externality their driving impose on the rest of society; here, to place taxes $\tau_0 = h_0$ and $\tau_1 = h_1$ on new and second-hand gasoline cars, respectively.[14] It turns out, not surprisingly, that doing so restores the first-best.

Proposition 1 *Taxing gasoline cars at their Pigouvian levels, $\tau_0 = h_0$ and $\tau_1 = h_1$, restores the social optimum (i.e., first-best).*

Proof. See the Appendix. ■

Figure 3(a) illustrate how placing taxes τ_0 and $\tau_1 > \tau_0$ on gasoline cars affect the steady-state market-equilibrium outcome. Given their higher rental prices, $c + \tau_0$ and τ_1, new and second-hand gasoline cars see their market shares reduced significantly. Note that we require $t > h_1$ for these shares to remain strictly positive under Pigouvian taxation. The figure also assumes that a fraction of second-hand cars, particularly EVs, continue to the scrapped in equilibrium. It is worth noting that, as compared to the previous figure, the segment AB of indifference between new gasoline cars and second-hand EV appears in the presence of emissions. Take, for example, individual A, who is indifferent between G_0, EV_0 and EV_1. To ensure this individual correctly internalizes the external cost of his choice, we need $\sigma_0 = \sigma_1 = h_0$. Individual B, on the other hand, is indifferent between G_0, G_1 and EV_1.[15]

The first part of the proof of Proposition 1 consists precisely in showing that there are no gains of adjusting either tax away from its Pigouvian level by a marginal amount. Proceeding as above (with the only difference that now we must also account for changes in pollution), the marginal gains of doing so would be

$$\Delta W_{\tau_0} = \frac{\varepsilon}{2t\Delta s}(t - \tau_1)(\tau_1 - h_1 - \tau_0 + h_0) + \frac{\varepsilon}{2t\Delta s}(\Delta s - c - \tau_1 + \tau_0)(h_0 - \tau_0) \tag{8}$$

when adjusting τ_0, and

$$\Delta W_{\tau_1} = \frac{\varepsilon}{2t\Delta s}(t - \tau_1)(h_1 - \tau_1 - h_0 + \tau_0) + \frac{\varepsilon}{2t\Delta s}(c - \tau_1 + \tau_0)(h_1 - \tau_1) \tag{9}$$

[13] We rule out lump-sum subsidies. A tax policy can always be replicated with lump-sum subsidies by making them large enough transfers to all individuals so as to cover the largest possible tax.

[14] For a global pollutant like CO2, a gasoline tax can function as a Pigouvian tax. For local pollutants, while there is no equivalent tax, a registry tax based on expected (annual) pollution can work reasonably well, as shown by Barahona et al. (2020). We are considering such taxes here and will also consider them in the empirical application.

[15] We will see that this point is particularly telling to understand how taxes and subsidies work differently.

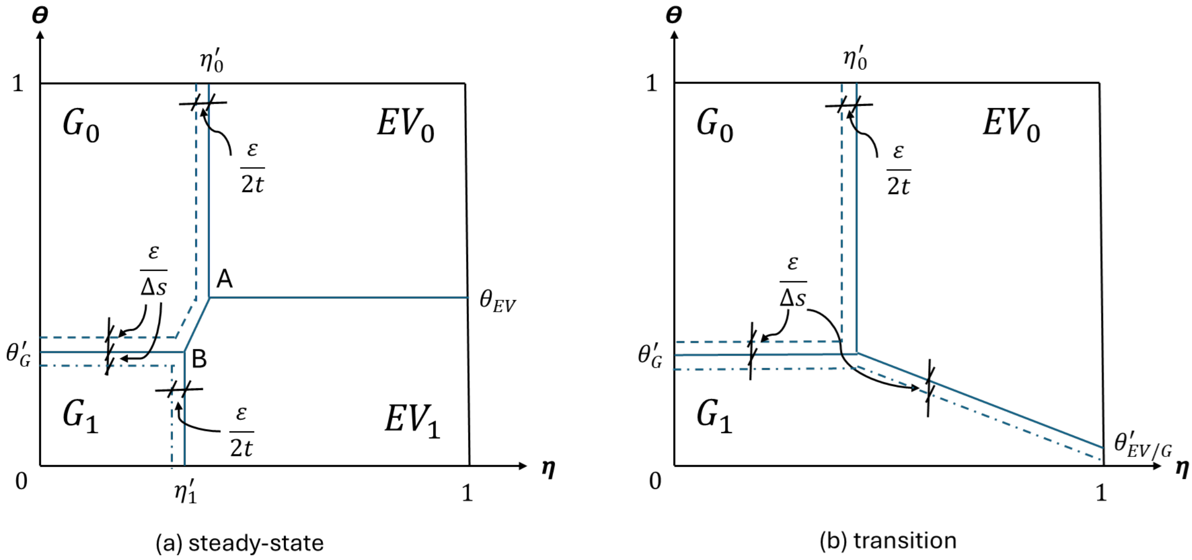

Figure 3: First-best allocation

when adjusting τ_1 (see the Appendix for details). It is immediate that these marginal gains go to zero when $\tau_0 = h_0$ and $\tau_1 = h_1$. These results extend straightforwardly to the transition phase, pictured in Figure 3(b), so they are omitted.

The second part of the proof requires showing that the planner cannot do better with an additional price instrument, say a subsidy on one of the EVs, which is what would be needed to arrive at any arbitrary allocation of cars. The latter already sheds some light on why two subsidies on EVs may not be enough to replicate the work of two taxes.

One goal of this paper is to understand to what extent subsidies on clean technologies can replicate the allocative work of Pigouvian taxes on polluting technologies. In most instances taxing pollution is equivalent—from a welfare perspective—to subsiding pollution reduction.[16] According to the existing literature there are few situations in which they are not. One is when public funds are costly to raise (see, e.g., Bovenberg and Goulder (1996)). Taxing pollution allows the government to reduce distortionary taxation somewhere else in the economy, while giving subsidies to clean technologies (or pollution reduction) asks for more of such distortionary taxation. Another situation emerges in a long-run context with free entry and exit of economic agents (see, e.g., Baumol and Oates (1988), Spulber (1985)). Since any economic gain or loss is dissipated in the long-run, subsidies necessarily lead to more entry than taxes, therefore they must be set below their Pigouvian levels. In other words, subsidies cannot properly handle both short and long-run decisions, i.e., pollution and entry decisions.

None of these considerations apply to our model (and empirical application). Besides abstracting from costly public funds, our economic agents' only decision is which technology to adopt at any given point in time. There is no exit and entry in our setting; all individuals

[16] A good example where the equivalence holds is Weitzman's (1974) prices vs. quantities.

obtain positive surplus at all times. Yet, our market setting is another instance in which the allocative equivalence of taxes and subsidies breaks down.

Proposition 2 *Subsidies on new and second-hand EVs, σ_0 and σ_1, respectively, cannot replicate the work of Pigouvian taxes.*

Proof. See Appendix. ■

To find the optimal subsidies we can proceed as above and ask what would be the marginal gains of adjusting them away from their optimal levels. These gains would be

$$\Delta W_{\sigma_0}(\sigma_0,\sigma_1)=\frac{\varepsilon}{2t\Delta s}(t+\sigma_0)(\sigma_1-\sigma_0)+\frac{\varepsilon}{2t\Delta s}(\Delta s-c-\sigma_1+\sigma_0)(h_0-\sigma_0) \tag{10}$$

from adjusting σ_0, and

$$\Delta W_{\sigma_1}(\sigma_1,\sigma_0)=\frac{\varepsilon}{2t\Delta s}\left(h_0-t-\sigma_0-\sigma_1\right)(\sigma_1-\sigma_0)+\frac{\varepsilon}{2t\Delta s}c(h_1-\sigma_1) \tag{11}$$

from adjusting σ_1. The optimal subsidies solve the system $\Delta W_{\sigma_0}=\Delta W_{\sigma_1}=0$, which clearly fail to implement the first-best, unlike taxes. While $\Delta W_{\sigma_0}=0$ calls, for example, for $\sigma_1=\sigma_0=h_0$, $\Delta W_{\sigma_1}=0$ calls for $\sigma_1=\sigma_0=h_1$. The previous shows that subsidies can only implement the first-best when pollution levels of gasoline cars are equal ($h_0=h_1$). Otherwise, subsidies will be set at a level that is different from (at least one) of the pollution levels, away from the Pigouvian level (i.e. equal to marginal damage). The previous example serves also to establish the following result that we will use later.

Lemma 1 *Let σ_0^* and σ_1^* be the optimal steady-state subsidies, i.e., those that solve the system $\Delta W_{\sigma_0}=\Delta W_{\sigma_1}=0$. Then, $h_0<\sigma_0^*<\sigma_1^*<h_1$.*

Proof. See the Appendix. ■

What is it about our setting that subsidies for pollution reduction fail to replicate the work of taxes on pollution? While taxes make drivers directly face the external costs of their choices, subsidies attempt to do the same but indirectly, by compensating drivers for moving away from their best alternatives or outside options. This would not be a problem if everyone's outside option to a second-hand (resp. new) EV were a second-hand (resp. new) gasoline car.

Our drivers, however, are willing to tradeoff vertical for horizontal attributes, giving rise to more outside options to consider.[17] For some individuals the outside option to a second-hand EV is not a used gasoline car, but a new gasoline car. Thus, for subsidies to replicate taxes, they would need a broader set of prices to account for these different outside options. In other words, subsidies would need to be contingent on individuals' outside options, with all the implementation challenges (including information asymmetries) that this entails. One way to handle this multi-attribute problem is to also subsidize some polluting technologies (in

[17] A similar multi-attribute problem arises in Lindenlaub and Postel-Vinay's (2023) matching model.

addition to clean ones).[18] In our model this can be done either by subsidizing new gasoline cars for $h_1 - h_0$, or by taxing old gasoline cars in an amount equal to $h_1 - h_0$. Either alternative, together with $\sigma_0 = \sigma_1 = h_1$, would implement the first-best.

One might speculate that, if for budget constraints the planner cannot rely on subsidies for second-hand EVs, she would need to be more aggressive with subsidies for new EVs. A key observation for the design of these subsidies, however, points to the exact opposite: in a context with differentiation as we present herein subsidies work as complements, not as substitutes. In other words, from expressions (10) and (11) it is clear that subsidies for both new and second-hand EVs are needed.

Proposition 3 *Subsidies for new and second-hand EVs act as complements: $d\sigma_a^r(\sigma_{a'})/d\sigma_{a'} > 0$, where $\sigma_a^r(\sigma_{a'})$ is the optimal subsidy for an age a EV given some subsidy $\sigma_{a'}$ for an age a' EV, i.e., $\sigma_a^r(\sigma_{a'})$ solves $\Delta W_{\sigma_a}(\sigma_a, \sigma_{a'}) = 0$ with $a' \neq a$ and $a, a' \in \{0, 1\}$.*

Proof. See the Appendix. ∎

A hint of the proof can be provided with help of expression (10). Let $\sigma_0^r(\sigma_1)$ be the value of σ_0 that solves $\Delta W_{\sigma_0}(\sigma_0, \sigma_1) = 0$ for any $\sigma_1 > \sigma_0$. As shown in the Appendix, $\partial \Delta W_{\sigma_0}(\sigma_0, \sigma_1)/\partial \sigma_0 < 0$ and $\partial \Delta W_{\sigma_0}(\sigma_0, \sigma_1)/\partial \sigma_1 > 0$. These two inequalities imply that $d\sigma_0^r(\sigma_1)/d\sigma_1 > 0$. The proof proceeds likewise with (11) to show that $d\sigma_1^r(\sigma_0)/d\sigma_0 > 0$, where $\sigma_1^r(\sigma_0)$ is the solution of $\Delta W_{\sigma_1} = 0$, and then continues with cases where $\sigma_0 > \sigma_1$ in the relevant range.

A case particularly illustrative of the implications of Proposition 3 is when the planner considers allocating the majority of the subsidy budget to new EVs, even if Lemma 1 already showed this is to be non-optimal. Figure 4 depicts the specific case of $\sigma_0 > \sigma_1 = 0$, where $\eta_0'' = 1/2 - \sigma_0/2t$ and $\theta_{EV}'' = (c - \sigma_0)/\Delta s$. Estimating the net gains from marginally increasing σ_0 and letting these gains go to zero yields the first-order condition

$$(\Delta s - c)(h_0 - \sigma_0) = \sigma_0^2 + \sigma_0(t - h_1) \tag{12}$$

with its positive root being the relevant solution (recall that $\Delta s > c$ and $t > h_1$).

The comparative statics of condition (12) are clear: higher values of either h_0, h_1 or Δs call for a higher (optimal) σ_0, further displacing polluting cars and making the (vertical) upgrade to a new EV more attractive. On the other hand, higher values of either c or t call for a lower σ_0, saving on production costs and horizontal losses. More striking in this comparative statics analysis is the fact that if new gasoline cars are relatively clean (as is often the case for local pollution), condition (12) suggests that the subsidy for new EVs should be zero when $h_0 \approx 0$, provided there are no subsidies for second-hand EVs. Allocating subsidies to new EVs in this

[18] This alternative sounds like charging pollution taxes in combination with lump-sum subsidies to all individuals and large enough to cover even the largest possible tax payment. Such way of replicating Pigouvian taxation with subsidies is not only misleading—since behavior is still driven by taxes, not subsidies—but unrealistic. For one, the subsidies involved would need to be substantial; and for another, consumers may perceive these two instruments as acting separately rather than in tandem.

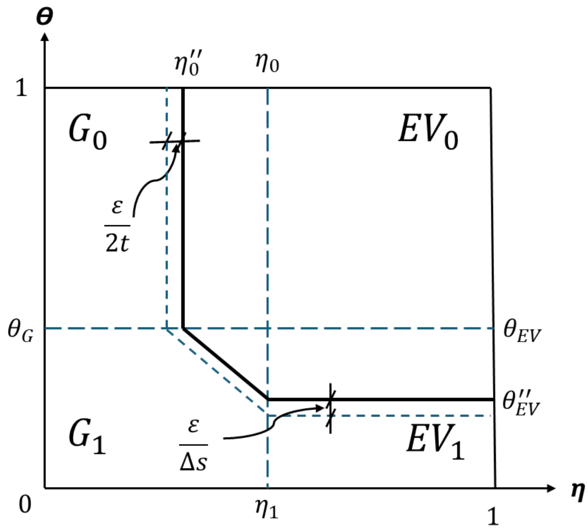

Figure 4: Subsidies on new EVs only

case, even if the subsidy budget permits it, would be not only a waste of fiscal resources but also inefficient.

Why is this? The answer is in Figure 4. A subsidy on new EVs has a relatively minor impact on second-hand gasoline cars. Pushing too hard on this is costly, as it distorts decisions not only regarding second-hand EVs but also new gasoline cars, especially if the latter are relatively clean. The French feebate (*bonus-malus*) in place since 2008 only applies to the purchase of new cars, subsidizing EVs and taxing gasoline cars. In our steady-state equilibrum, the application of such policy would imply that η moves to the left and θ up, increasing the relative attractiveness of G_1 as compared to G_0.[19]. Such a policy succeeds in reducing the number of new gasoline cars entering the market but results in a quality downgrade for drivers while increasing the number of cars polluting h_1.

But there is more, somewhat hidden in our two-period setup. If we let the time at which old cars are scrapped and retired from the market to be endogenous, say, after T years, then increasing subsidies for new EVs has the perverse consequence of extending the life of old gasoline cars. The reason is implicit in condition (2). Car dealers must break even in equilibrium. Since in an endogenous-T setup an increase in the subsidy for new EVs necessarily depresses the rental price of new gasoline cars, this leads to an increase in the rental price of older gasoline cars. As a result, it becomes more attractive for dealers to keep these older and polluting models on the market longer rather than scrapping them.[20]

For the same break-even reason, extending subsidies to second-hand EVs depresses the rental price of second-hand gasoline cars (and increases the rental price of new gasoline cars),

[19]It is worth noting that the indifference between EV_0 and G_1 also changes and could entail a welfare gain or a welfare loss, depending on the relative value of $\epsilon/\delta s$

[20]This break-even condition is also behind many of the results in Barahona et al's (2020) vertical-differentiation model, including the complementarity of prices, whether taxes or subsidies, for different vintages.

accelerating their exit from the market. This further speaks of the strong complementarity of subsidies for new and second-hand EVs. We come back to these price adjustments in the empirical section.

So far we have focused on the steady-state outcome, when there are enough second-hand cars of either type. Issuing subsidies for second-hand cars that don't yet exist in the market is obviously not possible, raising questions about the recommendations outlined above for the transition phase, i.e., when there is a limited or nonexistent presence of second-hand EVs, as in our two-period setting. Unlike in the steady state, the planner should be more aggressive with subsidies for new EVs during the transition phase.

Proposition 4 *Subsidies on new EVs should decline over time with the presence of second-hand EVs in the market: $\sigma_0^{**} > \sigma_0^*$, where σ_0^{**} and $\sigma_0^* \equiv \sigma_0^r(\sigma_1^*)$ are the optimal subsidies for new EVs during the transition phase and in steady state, respectively.*

Proof. See the Appendix ■

Some intuition for the proposition can be conveyed with the aid of Figure 5, where $\theta_{EV}''' = (c - t - \sigma_0)/\Delta s$, from which we arrive at the first-order condition

$$(\Delta s - c)(h_0 - \sigma_0) = \sigma_0^2 + \sigma_0(t - h_1) - th_1 \tag{13}$$

that solves for σ_0^{**} (see the Appendix for details). The gap between σ_0^{**} and σ_0^* can be viewed as the result of two opposing effects: "only-new" and "new-and-used" effects. When the planner decides to rely exclusively on (optimal) subsidies for new EVs (i.e., $\sigma_1 = 0$), it is natural to expect these subsidies to decline over time, as these subsidies become less effective at reaching holders of second-hand gasoline cars (see Figures 4 and 5). This result—that $\sigma_0^{**} > \sigma_0^r(\sigma_1 = 0)$—can be formally seen by comparing first-order conditions (13) and (12). This is the "only-new" effect.

Acting in the opposite direction is the "new-and-used" effect, which stems directly from the complementarity of subsidies for new and used EVs established in Proposition 3. As the used or second-hand EV market expands, the planner finds it optimal to increase the subsidies on used models, which in turn makes it optimal to increase the subsidies on new EVs as well, i.e., $\sigma_0^* > \sigma_0^r(\sigma_1 = 0)$. As stated in the proposition, however, this new-and-used effect is not large enough to fully offset the only-new effect.

In the next sections we take propositions 1 to 3 to the French car market and examine their fiscal and welfare implications. As for proposition 4, we give a numerical example in the Appendix.

4 Estimation

Herein, we estimate horizontal and vertical preferences that we then use to simulate the fleet composition and welfare impacts of various policy instruments. Subsection 4.2 presents our

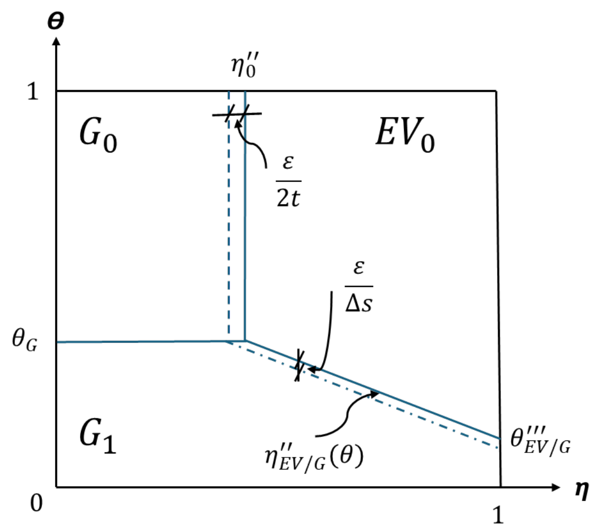

Figure 5: Transition phase

empirical strategy to adapt the simple model of vertical and horizontal differentiation into a structural demand model that retains the essence of the theoretical framework while accommodating the data and addressing estimation challenges. In subsection 4.3, we describe how we build a unique database of the French car fleet that is used for estimating horizontal and vertical preferences and to calibrate other fleet parameters such as the survival rate γ. Global and local pollution parameters are calibrated using various datasources described in subsection 4.4. On the other hand, costs c^k and scrapping values v^k are determined endogeneously in section 5.

4.1 Demand model

We specify a structural demand model à la BLP (Berry, Levinsohn, and Pakes (1995)) with random coeffficients on discrete parameters as discussed in Grigolon and Verboven (2014). The indirect utility of consumer i buying car model j is given by:

$$u_{ij} = \alpha_i p_j + x_j\beta + \xi_j + \sum_{a=0}^{2} \beta_i^a \mathbf{1}_a + \zeta_i \mathbf{1}_{k=EV} + (1-\rho)\epsilon_{ij} \tag{14}$$

with p_j the price, and x_j a vector of observable car characteristics. Herein x_j contains a constant, fuel costs (in €/100km), and a measure of acceleration (power in 10kW divided by weight in 100kg). ξ_j is the unobserved quality of product j. The fourth term captures the preference for car vintages, with $\mathbf{1}_a$ a dummy variable that takes the value one if the car is of vintage a. $\mathbf{1}_{k=EV}$ is a dummy variable that takes the value one if the car is an EV. ϵ_{ij} is the individual-specific taste for product j that is Type 1 extreme-value distributed. ρ is a nesting parameter[21] representing the degree of correlation for products of the same fuel type. It is

[21] $0 \leq \rho < 1$

worth noting that Equation 14 is the empirical version of Equation 1 considering additional vintages and vertical characteristics.

We allow price sensitivity α_i to vary linearly with income, where we define i's income as the median income of the district where consumer i lives. This is the case because we are interested in studying how preferences for vertical (vintage) and horizontal (EV) characteristics change with income. To capture income heterogeneity we put an individual coefficient on both the vintage dummy *new* (a=0) and the fuel-type dummy EV (k=EV). We also specify an outside good, corresponding to not renting a car ($u_{i0} = \epsilon_{i0}$). We can write $u_{ij} = \delta_j + \mu_{ij} + \epsilon_{ij}$ with $= \bar{\alpha} p_j + x_j \beta + \bar{\zeta} \mathbf{1}_{k=EV} + \sum_{a=0}^{2} \beta^a + \xi_j$ and $\mu_{ij} = \alpha inc_i + \zeta inc_i \mathbf{1}_{k=EV} + \beta^0 inc_i \mathbf{1}\{a = 0\}$ with inc$_i$ the median income of the district where consumer i lives.

We consider three alternative specifications: (i) a simple logit model with $\rho = 0$ and $\alpha = \zeta = \beta^0 = 0$, (ii) a nested logit model without heterogeneity $\rho \neq 0$ and $\alpha = \zeta = \beta^0 = 0$, and (iii) $\rho = 0$ which gives a random coefficient logit model with district-specific coefficients on discrete horizontal and vertical variables. As discussed in (Grigolon and Verboven 2014), specification (iii) is a good alternative to using a random coefficient nested logit model and brings similar results in terms of substitution patterns between products. Specification (ii) is also interesting since the nesting parameter can be seen as a proxy of the horizontal cutoff η. Specification (i) is a reference without heterogeneity.

Focusing on specification (iii), we use the properties of the distribution of ϵ_{ij} to derive s_{ij}, i.e. the probability that consumer i rents product j. The equivalent expression for specification (ii) and (iii) can be found in the Appendix.

$$s_{ij} = \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{k=1}^{J} \exp(\delta_k + \mu_{ik})} \tag{15}$$

We get the national fleet shares of product j by summing over all districts:

$$s_j = \sum_i \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{k=1}^{J} \exp(\delta_k + \mu_{ik})} \frac{N_i}{\sum_i N_i} \tag{16}$$

With N_i the population of district i.

4.2 Empirical strategy

For the three specifications detailed in the previous section we estimate the preference for product characteristics using the generalized method of moments. For this, we use exogenous car characteristics and traditional Berry, Levinsohn, and Pakes (1995)'s instruments, i.e. the sum of these characteristics for products of the same and of rival brands. For specification (iii) we add to the previous, micro moment estimations following Nurski and Verboven (2016). The micro-moments will help identify the individual-specific terms of utility parameters. In particular, for the micro moments estimation we use the covariance between product characteristics and consumer income at the district level.

4.3 Car fleet database

To estimate the model described in the previous subsection, we build a unique dataset of the French private car fleet for the year 2019. To do so we combine car registration data at the district level obtained from *AAA data* and used-car prices obtained from the online sales website *Leboncoin.fr*[22]. We then extract fuel prices, socio-economic and demographic data from the National Institute of Statistics and Economic Studies (INSEE). Finally, we fill the few missing values using technical data from *Argus.fr* and the French Energy Transition Agency (ADEME).

The car registration dataset contains all private vehicles in 2019 at the supra-municipality level, hence 38.3 million vehicles. For each car, we observe fuel type and unit consumption (l/100km), CO_2 emissions (g/km), brand, model, first registration date, and new car prices.We match the car registration dataset with used-car prices from the online sales website *Leboncoin.fr*.

Mainland France has 34,968 municipalities, and municipalities that are larger than 5,000 inhabitants are subdivided into districts. Herein, we select the 41,173 districts for which we find available demographic data for the year 2019. Our final dataset contains 27,644,447 observations, hence 72% of the French car fleet.

To match Equation 14, we build two fuel-type groups, EVs and gasoline cars, four car segments, small, medium, large, and SUV, and four vintage groups, new, less than 5 years old, 6-10 years old, and old vehicles (11-20). Without loss of generality, we restrict the main estimation sample to small cars representing 45% of the fleet, limiting the influence of vertical characteristics other than vintage. In Appendix we run the estimation for all different segments in the French car market showing results are robust. We aggregate the remaining products by brand, model, vintage group and fuel type, resulting in 336 product types. Product types are constructed as a fleet-weighted average of the characteristics of products sharing the same brand, model, fuel type, and vintage. We construct a rental-price variable as in (Barahona, Gallego, and Montero 2020), using the no-arbitrage condition from Equation 2 given by $p_{ja} = P_{ja} - \delta P_{j,a+1}$ with P_{ja} the price of product j belonging to vintage group a, δ the discount factor, which we set at 0.9 per year.[23]. To lower computational time, we draw 3.981 representative districts based on district income and density (details on representativity are given in Appendix).[24] In each district, we observe quantities for the 336 products, resulting in 1,337,616 observations.

4.4 Pollution Data

We observe tailpipe CO_2 emission levels (g/km) for each car in the dataset. We denote E_{ka} the total emissions from product of fuel type k and vintage group a in a given year.

[22] We thank Quentin Hoarau for providing the data.

[23] Considering that our vintage groups are {new, 1-5 years old, 6-10, 11-20 years old}, we get $p_{j,old} = P_{j,old} - \delta^{10} P_{j,a>20}$ for the last vintage group. To compute prices of cars over 20 years old $P_{j,a>20}$, we consider that old cars lose about 5% of their value each year.

[24] Income is the median income of the district while density is a variable defined by the National Institute of Statistics and Economic studies that takes a value between 1 and 4. 1: very urban, 2: urban, 3: rural, 4: very low-density area.

Table 1: Summary statistics of Prices, CO2, Fuel Costs, and Income. Nb Obs: 1,337,616

	Prices	**CO2**	**Fuel costs**	**Income**
Mean	10605	118	7.43	21942
Min	1327	0	2.32	11540
25%	4639	108	6.83	19890
50%	10562	122	7.40	21530
75%	14880	132	8.06	23590
Max	39346	169	14.6	52280

$$E_{ka} = q_{ka} e_{ka} x_k \tag{17}$$

with q_{ka} the number of cars and e_{ka} total emission level (g/km) of each fuel-vintage type, which we observe in the fleet dataset, and x_k the average number of kilometers driven by a car of energy k, which we get from French government data (Ministry of Environment, 2023). It is worth noting that $e_{ka} * x_k = h_{ka}$ as noted in the theoretical model. For local pollutants, we combine data from the European (Handbook on the external costs of transport, 2019) and (Ministry of Environment). Herein, we consider that EVs do not emit CO_2 nor any local pollutants. In 2019, an average gasoline car is driven 11,909 kilometers per year. The main focus of this paper is on CO_2 which is a global pollutant so we do not differentiate pollution harm by location and we take the average value for dense areas for local pollutants.

Table 2: Average per car yearly environmental harm, from driving gasoline cars of each vintage 11,909 km per year. CO_2 price is the 2020 French carbon price, hence 54€ per tonne of CO_2. Source: Quinet Report (2019), ADEME, Handbook of the external costs of Transport (2019).

Vintage	CO_2 (€/year)	Local pollution (€/year)
new	83	14
1-5	85	92
6-10	90	111
11-20	100	200

We observe in Table 2 that with a low carbon price (54€ per tonne of CO_2), local pollutant harm is larger than global pollutant harm. This is because we choose to use the cost of local pollutants for dense urban areas for the entire territory and because CO_2 emission of gasoline cars are around 1.5 ton. In future developments of this work, we will differentiate this cost between urban and rural areas. As older cars are driven less, we will also differentiate the number of kilometers driven per vintage.

4.5 Estimation results

We present the estimation results for the three specifications mentioned in Section 4.1 in Table 3. Hansen tests validate all specifications. Additionally, we estimate an alternative version of specification (ii) across 10 income groups and specification (iii) for different car segments. The results for these additional specifications are provided in Appendix 8.4.

In all cases, consumers exhibit a preference for newer and younger cars over older ones. Regarding electric vehicles (EVs), specifications (i) and (iii) indicate an overall consumer aversion to EVs. This aligns with the findings of specification (ii), which shows a high nesting parameter of 0.8, indicating a strong correlation in utility among cars of the same fuel type (EV or gasoline). Across all three specifications, the estimated marginal utilities for price are, on average, negative and statistically significant. Consumers are also responsive to fuel costs, with the exception of specification (ii).

Focusing on specification (iii), we observe that price sensitivity decreases slightly as income increases. Interestingly, wealthier households derive less utility from new cars compared to used cars. Moreover, income has a positive effect on preferences for EVs, suggesting that higher-income households experience less disutility from EVs compared to lower-income households.

Table 3: Estimation Results. Price is in 10k€, fuel costs in €/100km, power/weight in kW/10kg, income in 10k€, EV is a dummy variable taken against the reference category Gasoline, vintage groups are taken against cars older than 10 years old. ρ is the nesting parameter giving the degree of correlation between products of the same fuel types. The sample contains 1,337,616 observations classified in 336 product types across 41,173 districts.

Var	**(i)**	**(ii)**	**(iii)**
constant	-9.17**	-8.93***	-9.23***
	(3.59)	(1.17)	(3.38)
price	-7.64**	-5.63***	-8.69***
	(3.28)	(0.355)	(3.07)
fuel cost	-0.542**	0.116	-0.548***
	(0.230)	(0.097)	(0.103)
power/weight	11.92	11.58***	12.18
	(8.12)	(1.53)	(7.47)
EV (ref: Gasoline)	-3.17***		-5.61**
	(1.10)		(2.59)
new (ref: old)	10.05**	7.20***	12.15***
	(4.12)	(0.565)	(3.01)
1-5 (ref: old)	6.75***	4.04***	6.81***
	(2.23)	(0.441)	(2.09)
6-10 (ref: old)	2.51**	1.53***	2.54**
	(0.842)	(0.383)	(0.795)
ρ		0.795***	
		(0.070)	
income*price			0.408***
			(0.0693)
income*EV			1.02**
			(0.454)
income*new			-0.858*
			(0.404)
Hansen test			
Statistics	2.21	3.34	2.10
p-value	0.331	0.0677	0.717

We acknowledge potential concerns about bias in our results due to the limited number of secondhand electric vehicles available in 2019. The high nesting parameter, and consequently the low substitution between energy types, might partly reflect the constrained supply of green used cars. We address some of these concerns in Appendix 8. Nevertheless, our estimates capture preferences for EVs during the energy transition. With this in mind, and considering that we may underestimate the dynamic evolution of environmental preferences driven by crowding-in effects (D'Haultfœuille, Durrmeyer, and Février (2016)), these estimation results can be viewed as conservative.

4.6 Elasticities

Table 4: Mean own-price elasticities per vehicle type in the three specifications

Fuel type	**Vintage**	**(i)**	**(ii)**	**(iii)**
	New	-12.6	-9.23	-8.18
Gasoline	1-5	-8.07	-5.83	-4.19
	6-10	-4.12	-3.01	-4.19
	old	-2.08	-1.52	-2.12
	new	-15.5	-10.2	-15.5
EV	1-5	-9.59	-5.58	-9.43
	6-10	-5.89	-4.13	-5.86

We present mean own-price elasticities for each vehicle type in Table 4. In average, own-price elasticities are larger for electric vehicles and decrease with vehicle age. They are also relatively larger than what we find in the literature, for e.g. D'Haultfœuille, Durrmeyer, and Février (2016) find a mean own-price elasticity of -4.5 and Nurski and Verboven (2016) find -3.14. One reason could be that these papers focus on car purchase decisions while ours focus is on the car fleet.

Table 5: Mean (intra-category) cross-price elasticities per vehicle type in the three specifications.

Fuel type	**Vintage**	**(i)**	**(ii)**	**(iii)**
	New	0.0049	0.0692	0.0051
Gasoline	1-5	0.0102	0.1440	0.0108
	6-10	0.0023	0.0332	0.0024
	old	0.0006	0.0079	0.0006
	new	0.0010	0.0147	0.0017
EV	1-5	0.0013	0.0179	0.0069
	6-10	0.0001	0.0021	0.0005

Mean cross-price elasticities are presented in Table 5. The intra-category mean cross-price elasticity represent an aggregate measure of how products within the same category influence the demand for other products in the same category. For e.g., a 1% increase in the price of new gasoline leads to an average increase in demand of 0.51% for all new gasoline cars. We find that the logit model brings the smallest cross-price elasticities. The random coefficient model also lead to small cross-price elasticities close to the ones of the simple logit model, with an average of 0.0049. In line with Grigolon and Verboven (2014), we find that the nested logit model (ii) brings the largest average cross-price elasticities.

Table 6: Inter-group cross-price elasticities for specification (iii).

Fuel-type 1	**Vintage 1**	**Fuel-type 2**	**Vintage 2**	**inter-group cross-price elasticity**
Gasoline	new	EV	new	0.00472
EV	new	Gasoline	new	0.00107
Gasoline	new	EV	1-5	0.00438
EV	1-5	Gasoline	new	0.00122
Gasoline	new	EV	6-10	0.00454
EV	6-10	Gasoline	new	0.000176
Gasoline	1-5	EV	new	0.0116
EV	new	Gasoline	1-5	0.00126
Gasoline	1-5	EV	1-5	0.0131
EV	1-5	Gasoline	1-5	0.00173
Gasoline	1-5	EV	6-10	0.0124
EV	6-10	Gasoline	1-5	0.000231
Gasoline	6-10	EV	new	0.00250
EV	new	Gasoline	6-10	0.00118
Gasoline	6-10	EV	1-5	0.00257
EV	1-5	Gasoline	6-10	0.00148
Gasoline	6-10	EV	6-10	0.00254
EV	6-10	Gasoline	6-10	0.000205
Gasoline	old	EV	new	0.000578
EV	new	Gasoline	old	0.00115
Gasoline	old	EV	1-5	0.000571
EV	1-5	Gasoline	old	0.00139
Gasoline	old	EV	6-10	0.000575
EV	6-10	Gasoline	old	0.000195

We present inter-group mean cross-price elasticities in Table 6. This is a measure of how the increase of the price of a vehicle in one fuel-vintage category affects demand in another category. Overall, we find that inter-group cross-price elasticities are below 0.01, which is in line with the literature (Grigolon and Verboven (2014)). Specifically, we find that while the increase in gasoline vehicles prices have an effect on demand for EVs, the decrease in EV prices have a very small effect on gasoline demand. For e.g., a 1% increase in Gasoline vehicles of 1-5 years old leads to a increase in 1-5 EV demand of 1.3% while the 1% increase in 1-5 EV leads to an increase in 1-5 gasoline demand of only 0.1%. This will have important consequences in terms of policy design given that, when sustainability among technologies is low, policy impacts are also low.

5 Policy Simulations

This section simulates alternative policy measures. With this purpose we use the preference estimates from model (iii) in Table 3, to predict demand for each product type, and the equilibrium conditions from the theoretical model in Section 3.

First we account for the break-even condition in Equation 2. Using this condition, we determine the marginal costs and scrapping values and report the values in Table 13 of Appendix 8. [25]

The second condition is the one in Equation 4, that ensures that equilibrium quantities are constrained by the existing stock of cars. From this equation, we calibrate the survival rates γ_{ka} for each energy k and vintage group a and present results in Table 7.

The last condition is the scrapping condition from Equation 3. Concretely, the simulation algorithm finds quantities and prices that allows to meet these equilibrium conditions, given the distribution of horizontal and vertical preferences that we estimated in the previous section. The simulation method is further described in Appendix 8.5.

Table 7: Fleet parameters γ_{ka} for gasoline cars and EVs. Parameters are calibrated using fleet data from 2019. They reflect both the survival rate of each vintage-energy combination as well as the different sizes of each vintage-energy group.

	Gasoline	EV
1-5	2.37	1.52
6-10	0.814	0.16
11-20	0.3654	0.014

We define the reference scenario as the equilibrium resulting from 2019 existing policies. In the first policy counterfactual, we simulate the implementation of a pollution tax on top of existing policies[26] These pollution tax levels are our proxy of a Pigouvian tax, and we will refer to it as the first-best policy (FB).

In the second set of counterfactuals, we simulate the implementation of different EV subsidy designs: first, a subsidy on new cars, equal to the pollution harm of new gasoline vehicles. This allows us to discuss a special case of Proposition 3 where all subsidies are given to new EVs. Second, we put a subsidy on new and used-cars with subsidy amounts meeting the pollution harm of the corresponding gasoline vintage. This way, we are interested in discussing Proposition 2, hence to what extent subsidies on either new EVs or new and used EVs can replicate the effect of Pigouvian taxes. Therefore we compare the welfare outcomes of these two subsidy designs with first-best outcomes.

In the following subsections, we first analyze how environmental policies impact the steady-state fleet. Then, we investigate welfare effects, considering consumer surplus variation, costs and benefits from fleet renewal, and environmental benefits.

[25] Note that, differently from the simplified theoretical model with only two vintages, herein we have all the fleet. For the simulations, we aggregate the 336 product types by fuel type and vintage groups to obtain 8 product types. We observe these aggregated products in all the original 41,173 districts.

[26] Keep in mind that we consider the 2020 steady-state carbon value from Quinet (2019), which is 54€/tCO_2 and a cost of local pollution ranging from 14€ to 200€ depending on the (gasoline) car's vintage. Annual external costs of gasoline cars used in the simulations are reported in Table 2.

5.1 Impact on the fleet size and composition

Herein, we simulate the policy scenarios and put the resulting stock variations in Table 8.

Table 8: Simulation results: impact of a pollution tax and of different subsidy designs on the steady-state car fleet. Results are relative quantity variations between the reference scenario and the policy counterfactuals. In the reference scenario, the outside option size is 0.52

Energy	Vintage	FB	Subsidy new cars	Sub new & used EV
	new	-0.0841	-0.000219	-0.0010
gasoline	1-5	-0.0731	-0.000189	-000887
	6-10	-0.03740	-0.000137	-0.000279
	above 10	-0.01276	- 0.000191	-0.000791
	new	0.0611	0.0762	0.0743
EV	1-5	0.0625	-0.000581	0.137
	6-10	0.0616	-0.000429	0.162
	above 10	0.0607	-0.000353	0.255
Outside good shares		0.55	0.52	0.52

Results are expressed in terms of relative variation, hence the difference between counterfactual and reference quantities divided by the reference quantities. In each scenario, the outside option shares (not renting a car) are also given.

5.1.1 Pigouvian tax

In the presence of a Pigouvian tax (first column), the volume of gasoline cars decreases for all vintages, with relative variations ranging from 1.3% to 8.5%. On the other hand, there is an increase of about 6% in all EV vintages. The size of the outside option also increase by 6%, from 0.52 in the reference situation to 0.55 in the presence of a pollution tax. This means that the decrease in gasoline cars is not fully compensated by an increase in EVs and results in some demotorization.

5.1.2 Alternative subsidy designs

We find that putting a subsidy on new EVs increases by 7.6% their quantity but has almost no effect on other products. Although small, the largest negative effect is on used EVs, which are the closest substitutes. On the other hand, putting a subsidy on both new and used EVs (last column) increases the market shares of all EV vintages, 7.4% for new EVs to 26% for the oldest EV group. The effect on gasoline cars increases sligty compared to the sole subsidy on new cars but the effect is very small compared to the pollution tax. This is related to the small cross-price elasticities presented in Table 5 and the clear dislike for EVs found in Table 3.

Finally, both subsidy designs do not affect the outside option, which is good news, as it means that EV renters are not new consumers that were taking public transportation but rather gasoline car consumers that switch to EVs.

Before any welfare considerations, we can already see that subsidies are not replicating the work of the pollution tax. New subsidies alone have almost no effects on gasoline cars, while a combination of new and used subsidies allow some progress but still has a very small effect on gasoline cars. This is consistent with the estimation results and the asymmetry in inter-group elasticities reported in Table 6.

5.2 Welfare Impacts

Herein, we focus on steady-state welfare. We use a modified version of Equation 3.2 of the two-period model, that incorporates the logit form of consumer surplus and accounts for additional vintages for each fuel type.

In the random coefficient logit model, individual consumer surplus is the expected utility of each consumer's best car choice (Train 2009). The variation of consumer surplus from a counterfactual (indices 1) compared to the reference scenario (indices 0) is:

$$\Delta\mathbf{E}(CS_i)) = \frac{1}{-\alpha_i}\Big(ln\big(\sum_{k=1}^{J_1} \exp\,(\delta_k^1 + \mu_{ik}^1)\big) - ln\big(\sum_{k=1}^{J_0} \exp\,(\delta_k^0 + \mu_{ik}^0)\big)\Big)$$

With CS_i the mean consumer surplus, α_i the mean price sensitivity in district i.

We report total consumer surplus variation, environmental benefits from avoiding local and global pollutions, and fleet renewal benefits for each subsidy counterfactual specification, compared to the first-best scenario in Table 9.[27]

Table 9: Welfare results under different policy counterfactuals. All results are taken against first-best (FB) scenario, and are expressed in 2019B€.

Counterfactual	ΔCS* (2019 B€)	Env. benefits (2019 B€)	Fleet renewal (2019 B€)	ΔW (2019 B€)
EV subsidies				
New	4.59	-0.279	-29.50	-25.5
New+used	4.64	-0.276	-29.2	-25.1

As shown in Table 9, EV subsidies bring large consumer surplus gains compared to the Pigouvian tax. Indeed, in the presence of a pollution tax, consumers either shift from gasoline cars to EVs, suffering large horizontal losses, or to the outside option which utility is normalized to zero. Compared to the first-best policy, subsidies bring negative environmental benefits of about -280 million euros, with slightly better results for the new-and-used EV subsidy design. In both designs, subsidies bring new EVs to the fleet but their impact on the removal of gasoline vehicles from the fleet is very small, leading to large and negative fleet renewal benefits of subsidies compared to the first-best scenario. Overall, the empirical results align with Proposition 2, indicating that subsidies are less effective than Pigouvian taxes in achieving equivalent welfare gains when the subsidy amount matches the marginal environmental damage. Moreover, the finding that outcomes under a new-car subsidy are worse than those under a new-and-used subsidy is consistent with a specific case of Proposition 3 discussed in the theoretical part.

[27] We consider that tax revenues are redistributed to consumers through lump-sum transfers.

6 Concluding remarks

In this paper, we have developed a simple theoretical model of vertical and horizontal differentiation that segments cars by ”EV” and ”gasoline” fuel types as well as by their vintage groups. The theoretical inclusion of vertical and horizontal preferences represents a significant contribution, as it challenges the equivalence between Pigouvian taxes and subsidies of equal amounts. Our main contribution is that implementing subsidies for second-hand EVs is essential during the transition to net-zero emissions, not for equity but for efficiency reasons. This is because subsidies for new and used EVs act as complements in achieving optimal policy outcomes.

To quantify the significance of these finding, we conducted estimations using 2019 fleet data at the district level. We find that, when implementing a pollution tax that accounts for both local and global emissions from gasoline cars, the consumer surplus losses are not fully offset by environmental benefits alone. However, fleet renewal benefits enable substantial and positive welfare gains. Conversely, when subsidies are limited to new EVs, we observe a significant increase in new EV adoption and a reduction in used EVs as their closest substitutes. To expand the EV fleet, introducing an additional subsidy for used EVs emerges as a viable option. However, both subsidy designs brings large welfare losses compared to the first-best outcome as they have very little effects on the removal of gasoline cars from the fleet.

Our empirical analysis has primarily centered on Propositions 1 to 3 of the theoretical model, leaving the empirical testing of Proposition 4 as a focus for future research. Notably, our current estimates reflect a *transition to a net-zero equilibrium* rather than a true steady state. Looking ahead, we aim to conduct dynamic simulations that incorporate preference actualization, further refining the analysis toward a net-zero future

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7 Appendix A

This appendix contains proofs of propositions and lemmas.

7.1 Proof of Proposition 1

Looking at Equation 3.2 we look at the marginal variations provoked by establishing environmental taxes. The proof is divided in two parts.

Part (i). We first show that there are no welfare gains of adjusting either tax away from its Pigouvian level by a marginal amount. With the aid of Figure 3, note that the net benefit of marginal increasing τ_0 by an arbitrarily small amount equal to $\varepsilon \approx 0$ is given by (after neglecting second-order effects)

$$\begin{aligned}\Delta W_{\tau_0} = & \frac{\varepsilon}{2t}\left(1-\theta_{EV}\right)h_0 - \frac{\varepsilon}{2t}\left(1-\theta_{EV}\right)t(1-2\eta_0') \\ & - \frac{\varepsilon}{2t}\int_{\theta_G'}^{\theta_{EV}} \theta\Delta s d\theta - \frac{\varepsilon}{2t}\int_{\theta_G'}^{\theta_{EV}} t(1-2\tilde{\eta}(\theta))d\theta + \frac{\varepsilon}{2t}(\theta_{EV}-\theta_G')(c+h_0) \\ & - \frac{\varepsilon}{\Delta s}\eta_1'\theta_G'\Delta s - \frac{\varepsilon}{\Delta s}\eta_1'(h_1-h_0) + \frac{\varepsilon}{\Delta s}\eta_1' c\end{aligned} \tag{18}$$

where $\tilde{\eta}(\theta) = (t+\theta\Delta s-c-\tau_0)/2t$ connects the horizontal and vertical preferences of individuals indifferent between a new gasoline car and a second-hand EV.

Each line captures gains and losses associated to three different groups of individuals. The first line corresponds to individuals located on the vertical line that intersects the horizontal axis at $\eta_0' = 1/2 - \tau_0/2$ and with vertical preferences that go from $\theta = \theta_{EV} = c/\Delta s$ to $\theta = 1$. By switching from new gasoline cars to new EVs these individuals contribute with pollution gains equal to h_0 each (the first term in the first line). These individuals also suffer horizontal losses by moving further away from their preferred (no-intervention) choice (the second term in the first line). In fact, an individual located at $\eta \leq 1/2$ incurs a disutility of $t\eta$ when buying a new gasoline car and $t(1-\eta)$ when buying a new EV. Hence, switching to the latter entails an extra utility loss of $t(1-2\eta)$. There is an additional effect not reflected in the first line: the extra costs from additional new EVs entering the market are exactly offset by the savings from fewer new gasoline cars being sold.

The second line captures the costs and benefits associated with individuals located along the diagonal, extending from $\eta_1' = 1/2 - \tau_1/2t$ to η_0', and from $\theta_G' = (c-\tau_1+\tau_0)/\Delta s$ to θ_{EV}, who switch from new gasoline cars to second-hand EVs in response to the marginal increase in τ_0. The first two terms of the line are losses from the vertical downgrade (from moving from a new to a second-hand car) and additional horizontal disutility, respectively. These private losses contrast with the social gains—captured in the last term of the line—from fewer new gasoline cars entering the market and reduced pollution. Finally, the third line includes welfare changes associated with individuals with vertical preferences θ_G' and horizontal preferences extending from $\eta = 0$ to $\eta = \eta_1'$. These changes include losses from vertical downgrades and more pollution (first and second terms of the line, respectively), and gains from fewer new gasoline cars entering the market (last term of the line).

Similarly, the net benefit of marginal increasing τ_1 by an arbitrarily small amount equal to $\varepsilon \approx 0$ is given by

$$\begin{aligned}\Delta W_{\tau_1} = \frac{\varepsilon}{\Delta s}\eta_1'\theta_G'\Delta s + \frac{\varepsilon}{\Delta s}\eta_1'(h_1 - h_0) - \frac{\varepsilon}{\Delta s}\eta_1' c \\ + \frac{\varepsilon}{2t}\theta_G' h_1 - \frac{\varepsilon}{2t}\int_0^{\theta_G'} t(1-2\eta_1')d\theta\end{aligned} \tag{19}$$

The first line includes welfare changes associated with individuals with vertical preferences θ_G' and horizontal preferences extending from $\eta = 0$ to $\eta = \eta_1'$ who switch from second-hand to new gasoline cars in response to the marginal increase in τ_1. These changes include vertical upgrades (first term of the line), less pollution (second term), and extra costs from more new gasoline cars (last term). And the second line includes wlefare changes associated with individuals located on the vertical line that intersects the horizontal axis at η_1' and with vertical preferences that go from $\theta = 0$ to $\theta = \theta_G'$. These changes include less pollution (first term of the line) and horizontal disutilities (second term). Collecting terms in expressions (18) and (19) and rearranging yields expressions (8) and (9) in the text. Making $\tau_0 = h_0$ and $\tau_1 = h_1$ in (18) and (19) solves the system $\Delta W_{\tau_0} = \Delta W_{\tau_1} = 0$.

Part (ii). Since any arbitrary allocation of cars in Figure 3 requires three price interventions, we now show that the social planner cannot do better with a third price instrument, such as a tax (which could be negative) on either new or second-hand EVs. Consider the former. The net benefit of adding an arbitrarily small tax $\varepsilon \approx 0$ on new EVs is given by

$$\begin{aligned}\Delta W_{\tau_0^{EV}} &= -\frac{\varepsilon}{2t}(1-\theta_{EV})\,h_0 + \frac{\varepsilon}{2t}(1-\theta_{EV})\,t(1-2\eta_0') \\ &\quad + \frac{\varepsilon}{\Delta s}(1-\eta_0')c - \frac{\varepsilon}{\Delta s}(1-\eta_0')\theta_{EV}\Delta s\end{aligned}$$

where $\eta_0' = 1/2 - \tau_0/2$ (with $\tau_0 = h_0$) and $\theta_{EV} = c/\Delta s$. It is easy to see that $\Delta W_{\tau_0^{EV}} = 0$. The same holds if we consider an arbitrarily small tax on second-hand EVs, confirming that the planner can reach the first-best by relying exclusively on taxes on polluting vehicles.

7.2 Proof of Lemma 1

By contradiction. Suppose that $\sigma_0^* = \sigma_1^*$. If so, $\Delta W_{\sigma_0} = 0$ in (10) leads to $\sigma_0^* = h_0$, but $\Delta W_{\sigma_1} = 0$ in (11) leads to $\sigma_1^* = h_1$; a contradiction since $h_1 > h_0$. Suppose then that $\sigma_0^* > \sigma_1^*$. If so, $\Delta W_{\sigma_0} = 0$ implies that $\sigma_0^* < h_0$ (recall that $\Delta s > c + \sigma_1 - \sigma_0$), but $\Delta W_{\sigma_1} = 0$ implies that $\sigma_1^* > h_1$ (recall that $h_0 < t$); again, a contradiction since $h_1 > h_0$. Therefore, it must hold that $\sigma_0^* < \sigma_1^*$. This and $\Delta W_{\sigma_0} = 0$ imply that $\sigma_0^* > h_0$. On the other hand, $\sigma_0^* < \sigma_1^*$ and $\Delta W_{\sigma_1} = 0$ imply that $\sigma_1^* < h_1$, which concludes the proof.

7.3 Proof of Proposition 2

Following the steps of the proof of Proposition 1 we arrive at expressions (10) and (11) below. By lowering their rental prices, placing subsidies σ_0 and $\sigma_1 > \sigma_0$ on EVs can certainly take us to a car allocation similar to that shown in Figure 6.

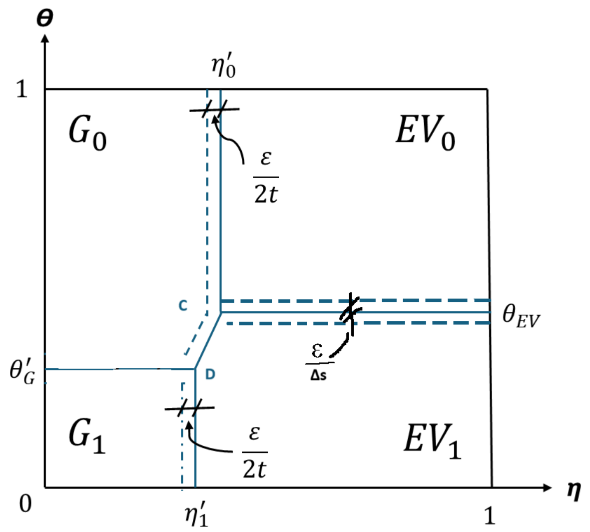

Figure 6: Subdsidies on new and used EVs in steady state

7.4 Proof of Proposition 3

Let $\sigma_0^r(\sigma_1)$ be the value of σ_0 that solves $\Delta W_{\sigma_0}(\sigma_0, \sigma_1) = 0$.

Case (i). For $\sigma_1 > \sigma_0$ (depicted in Figure 6) let us first show that $d\sigma_0^r/d\sigma_1 > 0$, where $\sigma_0^r(\sigma_1)$ is obtained from $\Delta W_{\sigma_0}(\sigma_0, \sigma_1) = 0$ and $\Delta W_{\sigma_0}(\sigma_0, \sigma_1)$ is given by expression (10) in the main text. We know by assumption that $\sigma_1 < t$ (otherwise there would be no used gasoline cars in the market) and that $(c + \sigma_1 - \sigma_0)/\Delta s < 1$ (otherwise there would be no new EVs in the market). Given this and the fact that we are in the case where $\sigma_1 > \sigma_0$, $\Delta W_{\sigma_0}(\sigma_0, \sigma_1) = 0$ implies that $\sigma_0 > h_0$. Using these inequalities, it is possible to establish that ($\varepsilon/2t\Delta s$ has been normalized to 1)

$$\frac{\partial(\Delta W_{\sigma_0})}{\partial \sigma_0} = 2\sigma_1 - 4\sigma_0 + h_0 - t + c - \Delta s < 0$$

which means that $\Delta W_{\sigma_0}(\sigma_0, \sigma_1)$ crosses the σ_0-axis from above. Therefore, to establish that $d\sigma_0^r/d\sigma_1 > 0$ requires to show that

$$\frac{\partial(\Delta W_{\sigma_0})}{\partial \sigma_1} = t - h_0 + 2\sigma_0 > 0$$

which is indeed the case because $t > h_1 > h_0$. Showing that $d\sigma_1^r/d\sigma_0 > 0$ proceeds likewise, so we omit it.

Case (ii). For $\sigma_0 > \sigma_1$ (note that such values would not be optimal as shown in Lemma 1), is depicted in Figure 4. In this case we have that

$$\Delta W_{\sigma_0}(\sigma_0, \sigma_1) = \frac{\varepsilon}{2t\Delta s}(h_1 - t - \sigma_0 - \sigma_1)(\sigma_0 - \sigma_1) + \frac{\varepsilon}{2t\Delta s}(\Delta s - c)(h_0 - \sigma_0)$$

and

$$\Delta W_{\sigma_1}(\sigma_0, \sigma_1) = \frac{\varepsilon}{2t\Delta s}c(h_1 - \sigma_1) + \frac{\varepsilon}{2t\Delta s}(h_0 - t - \sigma_0 - \sigma_1)(\sigma_1 - \sigma_0)$$

Using some of the assumptions, in particular that $t > h_1 > h_0$, $\sigma_0 > \sigma_1$, and $\Delta s > c$, it is immediate that $\partial(\Delta W_{\sigma_0})/\partial\sigma_0 < 0$ and $\partial(\Delta W_{\sigma_0})/\partial\sigma_1 > 0$, which imply that $d\sigma_0^r/d\sigma_1 > 0$. The same assumptions lead to $\partial(\Delta W_{\sigma_1})/\partial\sigma_1 < 0$ and $\partial(\Delta W_{\sigma_1})/\partial\sigma_0 > 0$, which imply that $d\sigma_1^r/d\sigma_0 > 0$.

7.5 Proof of Proposition 4

Let $\sigma_0^{**}(h_0)$ and $\sigma_0^*(h_0)$ be the optimal subsidies for new EVs during the transition and in steady state, respectively, as a function of $h_0 \leq h_1$. Visual inspection of their first-order conditions suggests both functions to be strictly concave.[28] So, the idea of the proof is to show that $\sigma_0^*(h_0)$ crosses $\sigma_0^{**}(h_0)$ from below and only once, at $h_0 = h_1$. Showing that $\sigma_0^{**}(h_0)$ crosses $\sigma_0^*(h_0)$ at $h_0 = h_1$ is immediate from looking at (13) and the system of equations (10) and (11) for $\Delta W_{\sigma_0} = \Delta W_{\sigma_1} = 0$. The unique solution when $h_0 = h_1$ is $\sigma_0^{**} = \sigma_0^* = \sigma_1^* = h_1 = h_0$.

On the other hand, single crossing from below requires (i) $\partial\sigma_0^{**}(h_0 = h_1)/\partial h_0 < \partial\sigma_0^*(h_0 = h_1)/\partial h_0$; and (ii) $\partial^2\sigma_0^{**}(h_0 = h_1)/\partial h_0^2 < \partial^2\sigma_0^*(h_0 = h_1)/\partial h_0^2 < 0$ for all $h_0 \leq h_1$. To show (i), allow h_0 in both (13) and (10) to marginally drop from h_1 to $h_1 - \varepsilon_h$, with ε_h arbitrarily small, and ask what would be the marginal changes in σ_0 for the first-order conditions to continue holding, that is, (13) and $\Delta W_{\sigma_0} = 0$ in (10). Denote these marginal changes by ε'_{σ_0} and ε''_{σ_0}, respectively. It turns out, after simple manipulation, that

$$\varepsilon'_{\sigma_0} = \varepsilon''_{\sigma_0} = \frac{\Delta s - c}{\Delta s - c + t + h_1}\varepsilon_h$$

indicating that both σ_0^{**} and σ_0^* adjust downward by the same amount (recall that $\Delta s > c$). But this is only the direct adjustment. In the case of σ_0^*, there is also an indirect adjustment, as the drop ε_h has also a downward impact on σ_1^*. Given the complementarity of (optimal) subsidies established in Proposition 3, this indirect adjustment shows that σ_0^* must necessarily fall more than σ_0^{**} (to find the actual drop of σ_0^* requires solving the system of first-order conditions for σ_0^* and σ_1^*). Finally, showing (ii) demands a tedious algebraic manipulation and is therefore omitted.

[28] In fact, plugging the parameters values following the proposition yield $\sigma_0^{**}(h_0) = \sqrt{3}\sqrt{59 + 64h_0}/8 - 13/8$ and $\sigma_0^*(h_0) = h_0/2 + 3\sqrt{3 + 4h_0}/8 - 5/8$

7.6 Numerical example for Proposition 4

As a preview, we can generate some numbers with our theory illustrating that some magnitudes can be important. For instance, let $\Delta s = 4$, $c = 1$, $t = 1/2$, $h_1 = 1/4$, and $h_0 = 1/8$. These parameter values ensure that properties (i), (ii) and (iii) hold across all equilibria. Based on these values, the optimal subsidy for new EVs during the transition phase reaches $\sigma_0^{**} = 0.15$, which drops somewhat to $\sigma_0^* = 0.14$ in steady state, provided it is combined with an optimal subsidy for second-hand EVs, set at $\sigma_1^* = 0.20$. However, if the planner neglects this second-hand subsidy, the optimal subsidy for new EVs should be much lower, not higher—27% lower, or $\sigma_0^r(\sigma_1 = 0) = 0.11$.

8 Appendix B

This appendix contains details on the estimation model validity in subsection 8.3, a description of the simulation algorithm in subsection 8.5, and additional empirical results in subsection 8.4.

8.1 French Feebate description

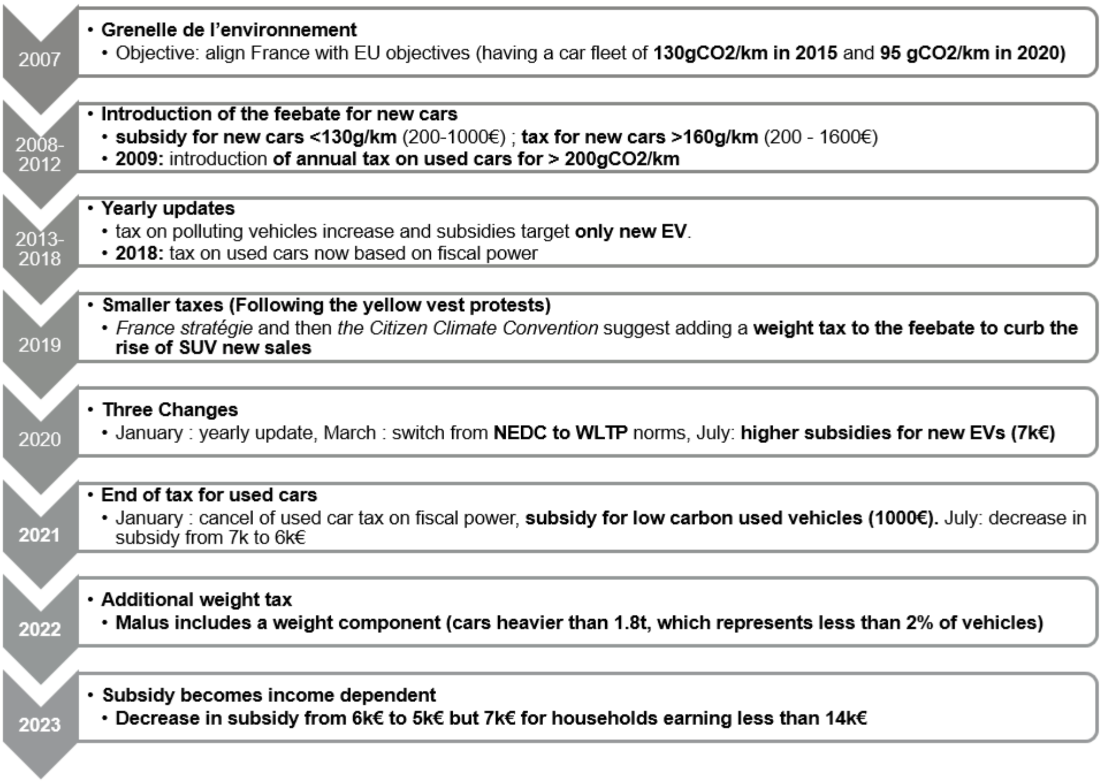

Figure 7: Evolution of EV incentive policies in France

8.2 Demand models

In specification (ii), Equation 14 reduces to

$$u_{ij} = \alpha p_j + \beta x_j + \sum_a \beta^a \mathbf{1}_a + \xi_j + \zeta \mathbf{1}_{k=EV} + (1-\rho)\epsilon_{ij}$$

β^a is the (vertical) preference for vintage a={below 5, 6-10, above 10} compared to vintage *new*, α is the price sensitivity, ξ is the unobserved quality (for e.g. advertising). ζ is the fuel-type-specific shock, ρ gives the degree of correlation within a fuel-type nest. In our setting, ρ can be seen as a proxy for horizontal preferences. The nested model is consistent with random utility maximization for $0 \leq \rho \leq 1$ (McFadden 1978). ϵ_{ij} is the consumer specific *taste for products*. It is type I extreme value distributed. As a result, the probability of choosing product j conditional on fuel-type nest k in a given market is

$$s_{j|k} = \frac{\exp(\frac{\alpha p_j + \beta x_j + \sum_a \beta^a \mathbf{1}_a + \xi_j}{1-\rho})}{\exp(I_k)}$$

With

$$I_k = (1-\rho)\ln\Bigg(\sum_{l \in J_k} \exp(\frac{\alpha p_l + \beta x_l + \sum_a \beta^a \mathbf{1}_a + \xi_l}{1-\rho})\Bigg)$$

The probability of choosing fuel type k is:

$$s_k = \frac{\exp(I_k)}{\exp(I)}$$

With

$$I = \ln\big(1 + \exp(I_{EV}) + \exp(I_G)\big)$$

The probability of choosing product j is then:

$$s_j = s_{j|k} s_k$$

The equation that we take to the data is:

$$\ln(s_j) - \ln(s_0) = \alpha p_j + \beta x_j + \sum_a \beta^a \mathbf{1}_a + \xi_j + \rho \ln(s_{j|k})$$

For specification (i) we simply take the case where $\rho = 0$.

8.3 Validity of the demand models

We use the variables that avoid instrument collinearity, that result in a nesting parameter σ between zero and one, and that pass the Hansen test. The objective of the test is to assess the validity of the additional restrictions imposed by the overidentified model. The null hypothesis H_0 is that the instruments are valid. The alternative hypothesis H_1 is that the additional restrictions due to overidentification, do not hold, indicating model misspecifications. To validate the specified model, the test needs to have a test statistic close to zero and a large p-value. In all specifications presented in Table 3, I fail to reject H_1, which validates the models.

8.4 Additional empirical results

8.4.1 Estimation results - Nested Logit estimation in 10 income groups

The price coefficient is negative and significant at the 1% level. It seems that consumers find utility in CO_2 emissive cars, but note that this variable also reflects the size and fuel economy of the car. Looking at vintage preferences, compared to new cars, people dislike older products and the effect increases as products get older.

We find that price sensitivity is more pronounced in lower-income groups than in higher-income groups. All things equal, lower-income groups exhibit a higher disutility for used cars

Table 10: Regression results for the ten income groups. Stars indicate significance levels. * 10% level, ** 5% level and *** 1% level of significance. Nb. Obs: 336 products in 10 income groups.

Variable	Coef. 1	Coef. 2	Coef. 3	Coef. 4	Coef. 5	Coef. 6	Coef. 7	Coef. 8	Coef. 9	Coef. 10
const	-2.23***	-2.39***	-2.31***	-2.33***	-2.26***	-2.12***	-2.06***	-1.91***	-1.69***	-1.37***
price	-1.31***	-1.29***	-1.29***	-1.30***	-1.28***	-1.26***	-1.25***	-1.22***	-1.17***	-0.99***
power	0.336***	0.333***	0.336***	0.338***	0.338***	0.337***	0.339***	0.338***	0.335***	0.315***
weight	-1.95***	-1.88***	-1.89***	-1.87***	-1.91***	-1.94***	-1.97***	-2.02***	-2.10***	-2.20***
fuel costs	-0.527***	-0.505***	-0.510***	-0.510***	-0.514***	-0.518***	-0.521***	-0.525***	-0.528***	-0.513***
CO2	3.92***	3.74***	3.77***	3.76***	3.79***	3.83***	3.84***	3.87***	3.88***	3.78***
1-5	-0.795***	-0.787***	-0.792***	-0.794***	-0.777***	-0.767***	-0.755**	-0.736**	-0.704**	-0.600**
6-10	-1.49***	-1.45***	-1.46***	-1.46***	-1.43***	-1.41***	-1.40***	-1.36***	-1.30***	-1.09***
old	-1.80***	-1.74***	-1.75***	-1.76***	-1.73***	-1.70***	-1.70***	-1.65***	-1.57***	-1.32***
ρ	0.707***	0.714***	0.717***	0.716***	0.719***	0.725***	0.722***	0.730***	0.739***	0.767***

compared to higher-income groups. The nesting parameter is larger for high-income groups, suggesting greater resistance to switching from gasoline to electric cars, as well as a lower likelihood of returning to a gasoline car after owning an EV. Overall, lower-income households are more sensitive to vertical preferences while higher-income households are more sensitive to horizontal preferences. It also means that it would be costly to incentivize high-income households to switch to electric vehicles. These findings calls for targeted measures aimed at middle- and lower-income households, who are more responsive to price changes and potentially less attached to their current fuel type group. This is in line with the theory as targeting the used-car market is a matter of efficiency and not just of equity.

8.4.2 Estimation results - Random Coef. Logit model in other car segments

We estimate the random coefficient model described in the previous sections on other data samples and present the results in Table 11. Results are consistent with the estimation on the small segment. In particular, heterogeneity parameters are either similar to the main text simulation of non-significant.

8.4.3 Preference for green cars on the new car market

We might worry that our results are biased because of the few number of secondhand green vehicles in 2019. The large nesting parameter, hence the low substitution between energy types might reflect the lack of green used-car supply. As a validity check, we estimate a nested demand model restricting the sample to new vehicles (8 products, 2 energy types, and 4 segments). We use weighted-average list prices as prices in the first specification and the calculated renting price that accounts for reselling on the used-car market. Results are presented in Table 12. Both models are validated by the Hansen test. In specification one, the nesting parameter is larger than in the fleet case and significant at the 10% level while it is smaller but insignificant in the second specification. This suggests that the correlation of utilities between products of the same energy type is even larger when only the new car market is considered. However, this result is to be taken with caution as the two data samples have a different nature. The full

Table 11: Estimation results for the other three car segments: SUVs, large cars and medium cars.

Var	**SUVs**	**Large cars**	**Medium cars**
const	-5.26***	-7.36***	-5.69***
	(0.607)	(1.048)	(0.792)
price	-1.05***	-0.578**	-0.583**
	(0.187)	(0.333)	(0.241)
fc	-0.081*	-0.080	-0.211***
	(0.042)	(0.050)	(0.041)
EV (ref:Gasoline)	-7.60***	-4.56***	-9.30***
	(2.05)	(1.06)	(1.28)
1-5	-1.39**	0.150	0.576
	(0.685)	(1.06)	(0.488)
6-10	-2.82***	-1.00	-0.903
	(0.693)	(1.19)	(0.606)
old	-4.32***	-1.49	-1.70**
	(0.789)	(1.35)	(0.717)
income*price	0.210***	0.00012	-0.023
	(0.041)	(0.065)	(0.046)
income*EV	1.95***	1.02***	2.23***
	(0.491)	(0.256)	(0.311)
income*new	-0.790***	0.030	-0.004
	(0.242)	(0.252)	(0.117)
Hansen test			
Stat	0.696	0.967	0.378
p-value	0.706	0.617	0.828

sample contains the fleet of vehicles in which we assume that consumers rent vehicles each year. On the other hand, the new vehicle sample represents actual sales in 2019 with sales-weighted average list prices that consumers face. With these results, we cannot conclude that the large nesting parameter on energy types is due to the lack of supply of green cars in the fleet.

8.5 Simulations

8.5.1 Simulation Algorithm

In the outer loop, we look for the number of new cars to add to the fleet alongside the vector of product prices so that the break-even, fleet, and scrapping conditions are met. This is similar to what is done in Barahona, Gallego, and Montero (2020) but differs slightly because there are two sets of equilibrium conditions - one for each fuel type - to meet simultaneously instead of one. Each equilibrium condition is a squared difference. Barahona, Gallego, and Montero (2020) minimizes an objective function that is the sum of squares to obtain simultaneously the different equilibrium conditions. Here, we need to minimize two objective functions at the same time. This brings difficulties because of the small number of EVs. As few EVs are in the 2019 fleet, fleet parameters calibrated with 2019 fleet data might not reflect the dynamics of EV sales in the future. The solution so far has been to minimize the squared sum of the two objective functions.

Table 12: Estimation results with the restricted sample of new cars. Prices are sales-weighted listed prices for each aggregated product. In specification 2, prices are rental prices, hence accounting for the used-car market.

Variable	**coef.**	**t-value**	**coef.**	**t-value**
	(1)		**(2)**	
intercept	-13.75**	-5.87	-8.64**	-4.65
price	-3.05*	-3.96	-2.21**	-5.18
fuel costs	0.21	0.44	0.36	0.56
weight	8.73	2.76		
CO2	0.05	2.66	0.04	1.75
σ	0.90*	4.05	0.52	1.41
Hansen test	0.10		0.27	
p-value	0.74		0.87	

In the inner loop, we choose a policy scenario (no additional intervention, Pigouvian taxes, new and used electric car subsidies) that determines an initial price vector. Keeping preferences and other fleet parameters fixed, we calculate predicted quantities in each district using the structure of the random coefficient logit model. Then we sum over the districts to get the total volume for each product and compute the counterfactual market shares. These market shares will then have to meet the equilibrium conditions of the outer loop.

Table 13: Optimal marginal costs and scrapping values in the no intervention equilibrium (in 10,000€)

	gasoline	EV
c	3.46	2.92
v	0.0250	0.0998