Supplementary Appendix A. Choice over several gasoline and electric vehicles

Here we expand the model to allow for a richer consumer choice set. For simplicity we assume there is a single location. There are m_e electric vehicles and m_g gasoline vehicles. Gasoline vehicles are indexed by the subscript i and electric vehicles are indexed by the subscript j. Each vehicle has a different purchase price and price of a mile, and we allow for the possibility of vehicle-specific taxes on miles and purchases. The indirect utility of purchasing the i'th gasoline vehicle is given by

$$V_{gi} = \max_{x,g_i} x + f_i(g_i) \text{ s.t. } x + (p_{gi} + t_{gi})g_i = T - p_{\Psi i}.$$

The indirect utility of purchasing the j'th electric vehicle is given by

$$V_{ej} = \max_{x,e_j} x + h_j(g_j) \text{ s.t. } x + (p_{ej} + t_{ej})e_j = T - (p_{\Omega j} - s_j).$$

The conditional utility, given that a consumer elects gasoline vehicle i, is given by

$$\mathcal{U}_{gi} = V_{gi} + \epsilon_{gi}.$$

The conditional utility, given that a consumer elects the electric vehicle j

$$\mathcal{U}_{ej} = V_{ej} + \epsilon_{ej}$$

The consumer selects the vehicle that obtains the greatest conditional utility. Following the same distributional assumptions as in the main text, the probability of selecting the gasoline vehicle i is

$$\pi_i = \frac{\exp(V_{gi}/\mu)}{\sum_i \exp(V_{gi}/\mu) + \sum_j \exp(V_{ej}/\mu)}.$$

The probability of selecting the electric vehicle j is

$$\tilde{\pi}_j = \frac{\exp(V_{ej}/\mu)}{\sum_i \exp(V_{gi}/\mu) + \sum_j \exp(V_{ej}/\mu)}.$$

And of course $\sum_i \pi_i + \sum_j \tilde{\pi}_j = 1$. The welfare associated with the purchase of a new vehicle is given by

$$\mathcal{W} = \mu \ln \left(\sum_i \exp(V_{gi}/\mu) + \sum_j \exp(V_{ej}/\mu) \right) + R - \left(\sum_i \delta_{gi} \pi_i g_i + \sum_j \delta_{ej} \tilde{\pi}_j e_j \right),$$

where δ_{gi} is the damage per mile from gasoline vehicle i and δ_{ei} is the damage per mile from electric vehicle j. It is useful to define $G_i = \pi_i g_i$ and $E_j = \tilde{\pi}_j e_j$.

Differentiated subsidies on purchase of electric vehicle

Here we consider a policy in which the government selects vehicle-specific tax on the purchase of electric vehicles. Let s_j be the subsidy on the electric vehicle j. Government revenue is $R = -\sum \tilde{\pi}_j s_j$. Now consider a given electric vehicle, say vehicle k. The optimal subsidy on the purchase of this vehicle, s_k, solves the first-order condition

$$\frac{\partial \mathcal{W}}{\partial s_k} = \sum_i \pi_i \frac{\partial V_{gi}}{\partial s_k} + \sum_j \tilde{\pi}_j \frac{\partial V_{ej}}{\partial s_k} + \frac{\partial R}{\partial s_k} - \sum_i \delta_{gi} \frac{\partial G_i}{\partial s_k} - \sum_j \delta_{ej} \frac{\partial E_j}{\partial s_k} = 0.$$

From the Envelope Theorem, we have

$$\frac{\partial V_{gi}}{\partial s_k} = 0$$

and, for $j \neq k$,

$$\frac{\partial V_{ej}}{\partial s} = 0.$$

For $j = k$ we have

$$\frac{\partial V_{ej}}{\partial s_k} = 1.$$

Substituting these expressions into the first-order condition gives

$$\frac{\partial \mathcal{W}}{\partial s_k} = \frac{\partial R}{\partial s_k} + \tilde{\pi}_k - \sum_i \delta_{gi} \frac{\partial G_i}{\partial s_k} - \sum_j \delta_{ej} \frac{\partial E_j}{\partial s_k} = 0.$$

Now

$$\frac{\partial R}{\partial s_k} = -\tilde{\pi}_k - \sum_j \frac{\partial \tilde{\pi}_j}{\partial s_k} s_j.$$

Substituting this into the first-order condition gives

$$\frac{\partial \mathcal{W}}{\partial s_k} = -\sum_j \frac{\partial \tilde{\pi}_j}{\partial s_k} s_j - \sum_i \delta_{gi} \frac{\partial G_i}{\partial s_k} - \sum_j \delta_{ej} \frac{\partial E_j}{\partial s_k} = 0.$$

Because there are no income effects,

$$\frac{\partial G_i}{\partial s_k} = g_i \frac{\partial \pi_i}{\partial s_k}$$

and

$$\frac{\partial E_j}{\partial s_k} = e_j \frac{\partial \tilde{\pi}_j}{\partial s_k}.$$

Substituting these derivatives into the first-order condition gives

$$\frac{\partial \mathcal{W}}{\partial s_k} = -\sum_j \frac{\partial \tilde{\pi}_j}{\partial s_k} s_j - \sum_i \delta_{gi} g_i \frac{\partial \pi_i}{\partial s_k} - \sum_j \delta_{ej} e_j \frac{\partial \tilde{\pi}_j}{\partial s_k} = 0. \tag{A-1}$$

We have one of these equations for each k. So we must solve the system of m_e equations for the m_e unknowns s_j. Since we do not obtain an explicit solution for the optimal taxes on purchase, we cannot derive analytical welfare approximations to the gains from differentiation analogous to Proposition 2. We can, of course, obtain exact welfare measures by numerical methods.

Uniform subsidy on the purchase of an electric vehicle

Now suppose that the government places a uniform subsidy s on the purchase of any electric vehicle. Expected government revenue is given by $R = -\sum_j \tilde{\pi}_j s$. The optimal s can be found as a special case of (A-1). Let $s_k = s$ for every k. Then (A-1) becomes

$$\frac{\partial \mathcal{W}}{\partial s} = -s \sum_j \frac{\partial \tilde{\pi}_j}{\partial s} - \sum_i \delta_{gi} g_i \frac{\partial \pi_i}{\partial s} - \sum_j \delta_{ej} e_j \frac{\partial \tilde{\pi}_j}{\partial s} = 0.$$

Solving for s gives

$$s = -\frac{\sum_i \delta_{gi} g_i \frac{\partial \pi_i}{\partial s} + \sum_j \delta_{ej} e_j \frac{\partial \tilde{\pi}_j}{\partial s}}{\sum_j \frac{\partial \tilde{\pi}_j}{\partial s}}$$

Now since $\sum_i \pi_i + \sum_j \tilde{\pi}_j = 1$ it follows that

$$\sum_i \frac{\partial \pi_i}{\partial s} + \sum_j \frac{\partial \tilde{\pi}_j}{\partial s} = 0.$$

Using this gives

$$s = \frac{\sum_i \delta_{gi} g_i \frac{\partial \pi_i}{\partial s}}{\sum_i \frac{\partial \pi_i}{\partial s}} - \frac{\sum_j \delta_{ej} e_j \frac{\partial \tilde{\pi}_j}{\partial s}}{\sum_j \frac{\partial \tilde{\pi}_j}{\partial s}}.$$

In the special case in which $g_i = g$ and $e_j = e$, we have

$$s = g \frac{\sum_i \delta_{gi} \frac{\partial \pi_i}{\partial s}}{\sum_i \frac{\partial \pi_i}{\partial s}} - e \frac{\sum_j \delta_{ej} \frac{\partial \tilde{\pi}_j}{\partial s}}{\sum_j \frac{\partial \tilde{\pi}_j}{\partial s}}.$$

The subsidy is a function of the weighted sum of marginal damages from each vehicle in the choice set, where the weights are equal to the partial derivative of the choice probabilities with respect to s. This generalizes the result in Proposition 1 in the main text. The informational requirements of the two results are different, however. To evaluate the optimal subsidy in Proposition 1, we need only make an assessment of the damage parameters (the δ's) and the lifetime miles (e and g). To evaluate the optimal subsidy when there is an expanded choice set, we need, in addition, the partial derivatives of the adoption probabilities, which requires a fully calibrated model.

We can also express this result in terms of cross-price elasticities. To see this, consider a special case in which there are two gasoline vehicles (with probability of adoption π_1 and π_2) and a single electric vehicle (with probability of adoption $\tilde{\pi}$.) The equation for the optimal subsidy is

$$s = g \left(\frac{\delta_{g1} \frac{\partial \pi_1}{\partial s} + \delta_{g2} \frac{\partial \pi_2}{\partial s}}{\frac{\partial \pi_1}{\partial s} + \frac{\partial \pi_2}{\partial s}} \right) - e\delta_e.$$

From the definition of π_i it follows that

$$\frac{\partial \pi_1}{\partial s} = -\frac{\pi_1 \tilde{\pi}}{\mu} \text{ and } \frac{\partial \pi_2}{\partial s} = -\frac{\pi_2 \tilde{\pi}}{\mu}.$$

Substituting into the expression for s gives

$$s = g\left(\frac{\delta_{g1}\pi_1 + \delta_{g2}\pi_2}{\pi_1 + \pi_2}\right) - e\delta_e.$$

Now consider the cross-price elasticities for the electric vehicle (i.e., the effect of a change in the price of gasoline vehicle i on the demand for the electric vehicle). For discrete choice goods, price elasticities are defined with respect to the choice probability. So the cross-price elasticity is

$$\varepsilon_i \equiv \frac{\partial\tilde{\pi}}{\partial p_{\Psi i}}\frac{p_{\Psi i}}{\tilde{\pi}} = \frac{\tilde{\pi}\pi_i}{\mu}\frac{p_{\Psi i}}{\tilde{\pi}} = \frac{\pi_i}{\mu}p_{\Psi i}.$$

It follows that

$$s = g\left(\frac{\delta_{g1}\frac{\varepsilon_1}{p_{\Psi 1}} + \delta_{g2}\frac{\varepsilon_2}{p_{\Psi 2}}}{\frac{\varepsilon_1}{p_{\Psi 1}} + \frac{\varepsilon_2}{p_{\Psi 2}}}\right) - e\delta_e.$$

Supplementary Appendix B. Welfare gains from differentiation: taxation of gasoline and electric miles

Here there are taxes on both gasoline and electric miles. We know that location specific Pigovian taxes are first-best, but it is useful to derive this result in our model before turning to other welfare results. For the moment we can drop the location subscript i.

From the Envelope Theorem, we have (under our normalization of the wage rate, the marginal utility of income is equal to one)

$$\frac{\partial V_g}{\partial t_g} = -g,$$

and

$$\frac{\partial V_e}{\partial t_g} = 0.$$

The first-order condition for t_g comes from substituting these expressions into (2) with $\rho = t_g$, setting the resulting expression equal to zero, and simplifying. This gives

$$\left(\frac{\partial R}{\partial t_g} - \pi g\right) - \left(\delta_g\frac{\partial G}{\partial t_g} + \delta_e\frac{\partial E}{\partial t_g}\right) = 0. \tag{A-2}$$

We have taxes on both gasoline and electric miles. Expected revenue is therefore $R = t_g \pi g + t_e(1-\pi)e$. Taking the derivative of revenue with respect to t_g gives

$$\frac{\partial R}{\partial t_g} = G + t_g \frac{\partial G}{\partial t_g} + t_e \frac{\partial E}{\partial t_g}.$$

Using this in the first-order condition gives

$$\left(\left(G + t_g \frac{\partial G}{\partial t_g} + t_e \frac{\partial E}{\partial t_g}\right) - \pi g\right) - \left(\delta_g \frac{\partial G}{\partial t_g} + \delta_e \frac{\partial E}{\partial t_g}\right) = 0.$$

Now, because $G = \pi g$, this simplifies to

$$(t_g - \delta_g)\frac{\partial G}{\partial t_g} + (t_e - \delta_e)\frac{\partial E}{\partial t_g} = 0.$$

Similar calculations with respect to t_e gives

$$(t_g - \delta_g)\frac{\partial G}{\partial t_e} + (t_e - \delta_e)\frac{\partial E}{\partial t_e} = 0.$$

Now, returning the location subscripts, it is clear that the optimal location-specific taxes are the Pigovian taxes $t_{gi}^* = \delta_{gi}$ and $t_{ei}^* = \delta_{ei}$.

Next follow the steps in the proof of Proposition 2, but this time using taxes on miles rather than a subsidy on the purchase of the electric vehicle. Let $\mathcal{W}(T)$ denote the weighted average of per capita welfare across locations as a function of the vector of taxes

$$T = (t_{g1}, t_{g2}, \ldots, t_{gm}, t_{e1}, t_{e2}, \ldots, t_{em}).$$

We have

$$\mathcal{W}(T) = \sum \alpha_i \mathcal{W}_i(t_{gi}, t_{ei}) = \mu \sum \alpha_i \left(\ln(\exp(V_{ei}/\mu) + \exp(V_{gi}/\mu))\right) + R_i - (\delta_{gi} G_i - \delta_{ei} E_i)).$$

First consider the second-best uniform taxes on gasoline and electric miles. Here the central government selects the same taxes t_g and t_e in each location. This implies the values for e_i, g_i, R_i, and π_i will be the same across locations. Under these conditions, the derivatives of $\mathcal{W}(T)$ with respect to t_g and t_e be written as

$$\sum \alpha_i \left((t_g - \delta_{gi}) \frac{\partial G}{\partial t_g} + (t_e - \delta_{ei}) \frac{\partial E}{\partial t_g} \right) = 0.$$

$$\sum \alpha_i \left((t_g - \delta_{gi}) \frac{\partial G}{\partial t_e} + (t_e - \delta_{ei}) \frac{\partial E}{\partial t_e} \right) = 0.$$

The solution to these equations is $\tilde{t}_g = \sum \alpha_i \delta_{gi} \equiv \bar{\delta}_g$ and $\tilde{t}_e = \sum \alpha_i \delta_{ei} \equiv \bar{\delta}_e$. In other words, the second-best uniform tax on gasoline miles is equal to the weighted average of the marginal damages from gasoline emissions across locations.

Next we want to determine a first-order Taylor series approximation to $\mathcal{W}(T)$ at the point $\tilde{T} = (\tilde{t}_g, \tilde{t}_g, \ldots, \tilde{t}_g, \tilde{t}_e, \tilde{t}_e, \ldots, \tilde{t}_e)$. At an arbitrary point, we have

$$\frac{\partial \mathcal{W}}{\partial t_{gi}} = \alpha_i (t_{g_i} - \delta_{gi}) \frac{\partial G_i}{\partial t_{gi}} + \alpha_i (t_{ei} - \delta_{ei}) \frac{\partial E_i}{\partial t_{gi}}$$

and

$$\frac{\partial \mathcal{W}}{\partial t_{ei}} = \alpha_i (t_{g_i} - \delta_{gi}) \frac{\partial G_i}{\partial t_{ei}} + \alpha_i (t_{ei} - \delta_{ei}) \frac{\partial E_i}{\partial t_{ei}}.$$

At $\tilde{T}$, taxes equal in each location, so the gasoline miles and electric miles will be the same each each location. Thus we can drop the subscripts from g, e, G, E and π. From (4) we have

$$\frac{\partial G}{\partial t_g} = g \frac{\pi(1-\pi)}{\mu} \left(\frac{\partial V_g}{\partial t_g} - \frac{\partial V_e}{\partial t_g} \right) + \pi \frac{\partial g}{\partial t_g} = -g^2 \frac{\pi(1-\pi)}{\mu} + \pi \frac{\partial g}{\partial t_g}.$$

$$\frac{\partial E}{\partial t_g} = -e \frac{\pi(1-\pi)}{\mu} \left(\frac{\partial V_g}{\partial t_g} - \frac{\partial V_e}{\partial t_g} \right) + (1-\pi) \frac{\partial e}{\partial t_g} = ge \frac{\pi(1-\pi)}{\mu}.$$

$$\frac{\partial G}{\partial t_e} = g \frac{\pi(1-\pi)}{\mu} \left(\frac{\partial V_g}{\partial t_e} - \frac{\partial V_e}{\partial t_e} \right) + \pi \frac{\partial g}{\partial t_e} = ge \frac{\pi(1-\pi)}{\mu}.$$

$$\frac{\partial E}{\partial t_e} = -e \frac{\pi(1-\pi)}{\mu} \left(\frac{\partial V_g}{\partial t_e} - \frac{\partial V_e}{\partial t_e} \right) + (1-\pi) \frac{\partial e}{\partial t_e} = -e^2 \frac{\pi(1-\pi)}{\mu} + (1-\pi) \frac{\partial e}{\partial t_e}.$$

This gives

$$\left. \frac{\partial \mathcal{W}}{\partial t_{gi}} \right|_{\tilde{T}} = \alpha_i (\bar{\delta}_g - \delta_{gi}) \left(-g^2 \frac{\pi(1-\pi)}{\mu} + \pi \frac{\partial g}{\partial t_g} \right) + \alpha_i (\bar{\delta}_e - \delta_{ei}) \left(ge \frac{\pi(1-\pi)}{\mu} \right)$$

and

$$\frac{\partial \mathcal{W}}{\partial t_{ei}}\bigg|_{\tilde{T}} = \alpha_i(\bar{\delta}_g - \delta_{gi})\left(ge\frac{\pi(1-\pi)}{\mu}\right) + \alpha_i(\bar{\delta}_e - \delta_{ei})\left(-e^2\frac{\pi(1-\pi)}{\mu} + (1-\pi)\frac{\partial e}{\partial t_e}\right)$$

The first-order Taylor series expansion of $\mathcal{W}$ at the point $\tilde{T}$ can be written as

$$\mathcal{W}(T) - \mathcal{W}(\tilde{T}) \approx \sum \frac{\partial \mathcal{W}}{\partial t_{gi}}\bigg|_{\tilde{T}} (t_{gi} - \tilde{t}_g) + \sum \frac{\partial \mathcal{W}}{\partial t_{ei}}\bigg|_{\tilde{T}} (t_{ei} - \tilde{t}_e).$$

Using the expressions above gives

$$\mathcal{W}(T^*) - \mathcal{W}(\tilde{T}) \approx \sum \left(\alpha_i(\bar{\delta}_g - \delta_{gi})\left(-g^2\frac{\pi(1-\pi)}{\mu} + \pi\frac{\partial g}{\partial t_g}\right) + \alpha_i(\bar{\delta}_e - \delta_{ei})\left(ge\frac{\pi(1-\pi)}{\mu}\right)\right)(t^*_{gi} - \tilde{t}_g) +$$

$$\sum \left(\alpha_i(\bar{\delta}_g - \delta_{gi})\left(ge\frac{\pi(1-\pi)}{\mu}\right) + \alpha_i(\bar{\delta}_e - \delta_{ei})\left(-e^2\frac{\pi(1-\pi)}{\mu} + (1-\pi)\frac{\partial e}{\partial t_e}\right)\right)(t^*_{ei} - \tilde{t}_e).$$

Which can be written as

$$\mathcal{W}(T^*) - \mathcal{W}(\tilde{T}) \approx \frac{\pi(1-\pi)}{\mu}\left(\sum \alpha_i \left(g^2(t^*_{gi} - \tilde{t}_g)^2 - 2ge(t^*_{gi} - \tilde{t}_g)(t^*_{ei} - \tilde{t}_e) + e^2(t^*_{ei} - \tilde{t}_e)^2\right)\right) -$$

$$\pi\frac{\partial g}{\partial t_g}\sum \alpha_i(t^*_{gi} - \tilde{t}_g)^2 - (1-\pi)\frac{\partial e}{\partial t_e}\sum \alpha_i(t^*_{ei} - \tilde{t}_e)^2.$$

Substituting in the values $t^*_{gi} = \delta_{gi}$, $t^*_{ei} = \delta_{ei}$, $\tilde{t}_g = \bar{\delta}_g$ and $\tilde{t}_e = \bar{\delta}_e$ gives

$$\mathcal{W}(T^*) - \mathcal{W}(\tilde{T}) \approx \frac{\pi(1-\pi)}{\mu}\left(\sum \alpha_i \left(g^2(\delta_{gi} - \bar{\delta}_g)^2 - 2ge(\delta_{gi} - \bar{\delta}_g)(\delta_{ei} - \bar{\delta}_e) + e^2(\delta_{ei} - \bar{\delta}_e)^2\right)\right) -$$

$$\pi\frac{\partial g}{\partial t_g}\sum \alpha_i(\delta_{gi} - \bar{\delta}_g)^2 - (1-\pi)\frac{\partial e}{\partial t_e}\sum \alpha_i(\delta_{ei} - \bar{\delta}_e)^2,$$

which can be written as

$$\mathcal{W}(T^*) - \mathcal{W}(\tilde{T}) \approx \frac{\pi(1-\pi)}{\mu}\left(\sum \alpha_i \left(g(\delta_{gi} - \bar{\delta}_g) - e(\delta_{ei} - \bar{\delta}_e)\right)^2\right) -$$

$$\pi\frac{\partial g}{\partial t_g}\sum \alpha_i(\delta_{gi} - \bar{\delta}_g)^2 - (1-\pi)\frac{\partial e}{\partial t_e}\sum \alpha_i(\delta_{ei} - \bar{\delta}_e)^2.$$

It is interesting to compare this formula to the corresponding one for purchase subsidies.

Using the fact that $s_i^* = (\delta_{gi}g - \delta_{ei}e)$ and $\tilde{s} = (\bar{\delta}_g g - \bar{\delta}_e e)$ in conjunction with the proof of Proposition 2, we can write the first-order approximation formula for the welfare gain of differentiated purchase subsidies as

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx= \frac{\pi(1-\pi)}{\mu}\left(\sum \alpha_i (e(\delta_{ei} - \bar{\delta}_e) - g(\delta_{gi} - \bar{\delta}_g))^2\right)$$

The first term in the formula for $\mathcal{W}(T^*) - \mathcal{W}(\tilde{T})$ has exactly the same structure as the formula for $\mathcal{W}(S^*) - \mathcal{W}(\tilde{S})$, but the values for π, e, and g will be different across the two formulas. The formula for $\mathcal{W}(T^*) - \mathcal{W}(\tilde{T})$ also has two extra terms that correspond to the price effects of the taxes on the purchase of gasoline and electric miles. Because these price effects are negative, both of the extra terms increase the benefit of differentiated regulation. In the special case in which the population in each location is the same and $e = g$, first term in the formula for $\mathcal{W}(T^*) - \mathcal{W}(\tilde{T})$ is proportional to the variance of the difference between the list of numbers δ_{gi} and δ_{ei}, the second term is proportional to the variance the list of numbers δ_{gi}, and the third term is proportional to the variance of the list of numbers δ_{ei}.

Supplementary Appendix C. Comparison with Mendelsohn (1986)

Applying our approximation methodology to Mendelsohn's model reveals the differences in the welfare gains from differentiation in our model and his. In Mendelsohn's model, the derivative of the objective function with respect to the policy variable is linear in the environmental parameter. And the second derivative does not depend on the environmental parameter. In contrast, in our model, both the first and second derivatives are linear in the environmental variable.

More formally, consider Mendelsohn's model and let Q^* be the optimal differentiated regulation and $\bar{Q}$ be the optimal uniform regulation. The first-order Taylor series approximation to the welfare gain form differentiation is

$$W(Q^*) - W(\bar{Q}) \approx \frac{\partial W}{\partial Q}(Q^* - \bar{Q}).$$

Both $\frac{\partial W}{\partial Q}$ and $(Q^* - \bar{Q})$ are linear in the environmental parameter, so the welfare difference is is quadratic in the environmental parameter. Now consider the second-order Taylor series:

$$W(Q^*) - W(\bar{Q}) \approx \frac{\partial W}{\partial Q}(Q^* - \bar{Q}) + \frac{1}{2}\frac{\partial^2 W}{\partial Q^2}(Q^* - \bar{Q})^2.$$

The first term in this expression is quadratic in the environmental parameter. In the second term, the second derivative does not depend on the environmental parameter, so the second term in quadratic in the environmental parameter as well. So we see for both the first and second order approximations, the welfare difference is quadratic in the environmental parameter. Because Mendelsohn's objective is quadratic, the second order approximation is in fact exact.

In our model, the second-order approximation has a term that is cubic in the environmental variable, which implies that the welfare benefit depends on the skewness of the distribution of this variable. As in Mendelsohn's model, $(S^* - \tilde{S})$ is linear in the environmental parameter. So the difference between models is due to differences in the first and second derivatives. In particular, due to the discrete choice nature of our model, the first and second derivatives are both linear in the environmental parameter (recall from (9) and (10) that both derivatives contain $s_i^* - \tilde{s}$ terms.)

Our welfare approximation was defined relative to the reference point of uniform regulation. Suppose instead we define the reference point to be the second-best differentiated regulation. In this case we are measuring the welfare loss of using uniform regulation rather than differentiated regulation.[46] Modifying (9) to evaluate the derivative at S^* rather than $\tilde{S}$ gives

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{S^*} = \frac{\alpha_i}{\mu}\pi_i(1-\pi_i)(-s_i^* + \delta_{gi}g - \delta_{ei}e) = \frac{\alpha_i}{\mu}\pi_i(1-\pi_i)(-s_i^* + s_i^*) = 0. \tag{A-3}$$

As we would expect, the first derivative of the welfare function is equal to zero at the second-best differentiated regulation. Similar modifications of (10) gives

$$\left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{S^*} = -\frac{1}{\mu}(1-2\pi_i)\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{s_i^*} - \frac{\alpha_i}{\mu}\pi_i(1-\pi_i) = -\frac{\alpha_i}{\mu}\pi_i(1-\pi_i), \tag{A-4}$$

[46]In the main text we measured the welfare gain of using differentiated regulation rather than uniform regulation. Because we are using approximation formulas, these two measures will not be exactly the same.

because the first derivative is zero. Now we want to evaluate $\mathcal{W}(\tilde{S}) - \mathcal{W}(S^*)$. Because the first derivative is zero at S^*, we have

$$\mathcal{W}(\tilde{S}) - \mathcal{W}(S^*) \approx -\frac{1}{2\mu} \sum \pi_i (1 - \pi_i) \alpha_i (s_i^* - \tilde{s})^2.$$

This expression is quadratic in $s^* - \tilde{s}$. But also notice that we can't factor out the π's, because they are defined at the points s_i^*, and hence are not all the same. So there is not a simple interpretation in terms of the distribution of the environmental benefits of an electric vehicle. For this reason, we use the other welfare expression (with the reference point of uniform regulation) in the main text.

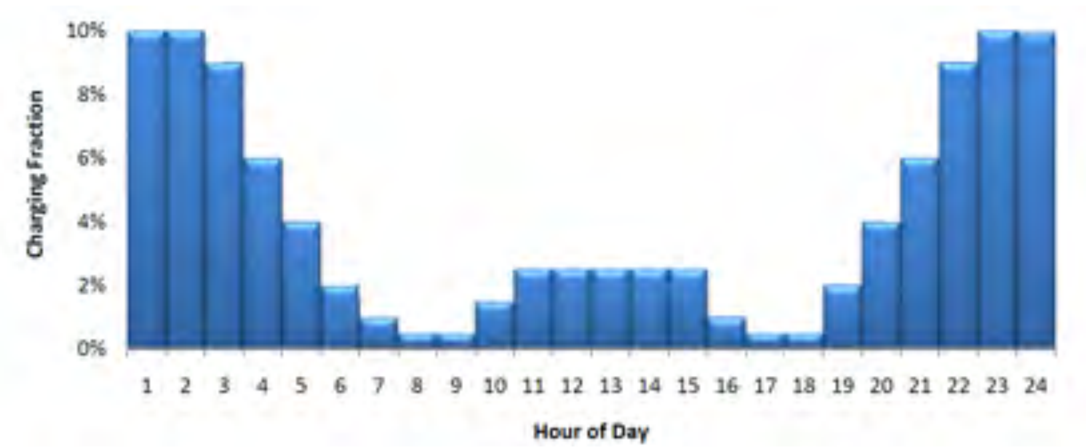
Supplementary Appendix D. Car data and EPRI charging profile

Table A: 2014 Electric vehicles and gasoline equivalent vehicles

Electric Vehicle	kWhrs/Mile	Gasoline Equivalent	MPG	NO_X	VOC	PM2.5	SO_2
Chevy Spark EV	0.283	Chevy Spark	39/31	0.04	0.127	0.017	0.004
Honda Fit EV	0.286	Honda Fit	33/27	0.07	0.147	0.017	0.005
Fiat 500e	0.291	Fiat 500e	40/31	0.07	0.147	0.017	0.004
Nissan Leaf	0.296	Toyota Prius	48/51	0.03	0.112	0.017	0.003
Mitsubishi i-Miev	0.300	Chevy Spark	39/31	0.04	0.127	0.017	0.004
Smart fortwo electric	0.315	Smart fortwo	38/34	0.07	0.147	0.017	0.004
Ford Focus electric	0.321	Ford Focus	36/26	0.03	0.112	0.017	0.005
Tesla Model S (60 kWhr)	0.350	BMW 740i	29/19	0.07	0.147	0.017	0.007
Tesla Model S (85 kwhr)	0.380	BMW 750i	25/17	0.07	0.147	0.017	0.008
Toyota Rav4 EV	0.443	Toyota Rav4	31/24	0.07	0.147	0.017	0.006
BYD e6	0.540	Toyota Rav4	31/24	0.07	0.147	0.017	0.006

Notes: NO_X, VOC, PM2.5, and SO_2 emissions rates for gasoline equivalent cars are in grams per mile.

Supplementary Appendix Figure 1: EPRI charging profile.



Source: "Environmental Assessment of Plug-In Hybrid Electric Vehicles, Volume 1: Nationwide Greenhouse Gas Emissions" Electric Power Research Institute, Inc. 2007. p. 4-10.

Supplementary Appendix E. The effect of temperature on electric vehicle energy use

Let E_{68} be the energy usage (in KWhr/mile) at a baseline temperature of 68°F (obtained from EPA data). In this Appendix, we determine a temperature adjusted energy usage $\tilde{E}$. The range of an electric vehicle R is given by

$$R = \frac{C}{E}$$

where C is the battery capacity of the vehicle (in KWhr). We first determined a function $R(T)$ that describes the range as a function of temperature and then use this function in conjunction with weather data to calculate the temperature adjusted energy usage $\tilde{E}$ for each county.

There are three recent studies of the effect of temperature on electric vehicle range.

1. *Transport Canada.* This engineering study considered three different electric vehicles, three temperatures (68°F, 19.4°F, -4°F), and cabin heat on/off conditions. The original data is available on the internet (https://www.tc.gc.ca/eng/programs/environment-etv-electric-passenger-vehicles-eng-2904.htm)

2. *AAA.* This engineering study considered three different electric vehicles, three temperatures (75°F, 20°F, 95°F). We were unable to obtain the original data, but the results are summarized on the internet (http://newsroom.aaa.com/2014/03/extreme-temperatures-affect-electric-vehicle-driving-range-aaa-says)

3. *Nissan Leaf Crowdsource.* This study summarizes user reported driving ranges at a variety of temperatures for the Nissan leaf. The results are posted on the internet (http://www.fleetcarma.com/nissan-leaf-chevrolet-volt-cold-weather-range-loss-electric-vehicle/)

There is clear evidence in these studies that significant range loss in electric vehicles occurs both at low and high temperatures.[47] We use a Gaussian function to describe this range loss

$$R(T) = R_{68} e^{-\frac{(T-68)^2}{y}}, \tag{A-5}$$

where R_{68} is the range at the baseline temperature of 68°F and y is a parameter to be fitted from the range loss data. The transport Canada study indicates a 20 percent range loss at 19.4°F with the heat off and a 45 percent range loss at 19.4°F with the heat on. We took the average of these figures and assumed a 33 percent range loss. This gives[48]

$$y = \frac{-1(19.4-68)^2}{\ln(0.67)}.$$

Temperature data was obtained from the CDC website.[49] This gave us the average monthly temperature in each county for the years 1979-2011. In a given month j with temperature T_j, the energy usage per mile in that month is given by

$$E_j = \frac{C}{R(T_j)} = E_{68}\frac{R_{68}}{R(T_j)}.$$

Let the total miles driven in month j be denoted by x_j, the temperature adjusted energy usage is given by the formula

$$\tilde{E} = \left(\frac{1}{\sum x_j}\right)\sum_{j=1}^{12} E_j x_j = \left(\frac{1}{\sum x_j}\right)\sum_{j=1}^{12}\left(\frac{E_{68}}{e^{-\frac{(T_j-68)^2}{y}}}\right) x_j.$$

We evaluate this formula assuming the number of miles driven per day is constant over all months.

[47]Yuksel and Michalek, forthcoming (2015) use the Nissan Leaf data in their analysis of the effect of temperature on electric vehicle range.

[48]The assumed range loss is $(R(19.4) - R_{68})/R_{68} = -0.33$ which implies $R(19.4)/R_{68} = 0.67$. Using this in (A-5), we have $0.67 = e^{-\frac{(19.4-68)^2}{y}}$, which we can then solve for y.

[49]http://wonder.cdc.gov/nasa-nldas.html.

Supplementary Appendix F. Methods details

Data sources for emissions of gasoline vehicles

The emissions of SO_2 and CO_2 follow directly from the sulfur or carbon content of the fuels. Since emissions per gallon of gasoline does not vary across vehicles, emissions per mile can be simply calculated by the efficiency of the vehicle.[50] For emissions of NO_X, VOCs and $PM_{2.5}$, we use the Tier 2 standards for NO_X, VOCs (NMOG) and PM. We augment the VOC emissions standard with GREET's estimate of evaporative emissions of VOCs and augment the PM emissions standard with GREET's estimate of $PM_{2.5}$ emissions from tires and brake wear. Electric vehicles are likely to emit far less $PM_{2.5}$ from brake wear because they employ regenerative braking. We had no way of separating emissions into tires and brake wear separately, so we elected to ignore both of these emissions from electric vehicles. This gives a small downward bias to emissions of electric vehicles.

Data sources for the electricity demand regressions

The Environmental Protection Agency (EPA) provides data from its Continuous Emissions Monitoring System (CEMS) on hourly emissions of CO_2, SO_2, and NO_X for almost all fossil-fuel fired power plants. (Fossil fuels are coal, oil, and natural gas. We aggregate data from generating units to the power-plant level. Some older smaller generating units are not monitored by the CEMS data.) CEMS does not monitor emissions of $PM_{2.5}$ but does collect electricity (gross) generation. We match emissions data from the 2011 NEI to annual gross generation reported on the DOE form 923, by plant, to estimate an average annual average emissions rate expressed as tons of $PM_{2.5}$/kWh. Power plant emissions of VOCs are negligible. Based on the NEI for 2008, power plants accounted for about 0.25% of VOC emissions, but 75% of SO_2 emissions and 20% of NO_X emissions. In contrast, the transportation sector accounted for about 40% of VOC emissions.

The hourly electricity load data are from the Federal Energy Regulatory Commission's

[50] The carbon content of gasoline is 0.009 $mTCO_2$ per gallon and of diesel fuel is 0.010 $mTCO_2$ per gallon. For sulfur content we follow the Tier 2 standards of 30 parts per million in gasoline (0.006 grams/gallon) and 11 parts per million diesel fuel (0.002 grams/gallon).

(FERC) Form 714. Weekends are excluded to focus on commuting days. See Graff Zivin et al. (2014) for more details on the CEMS and FERC data.

Details of the AP2 model

AP2 is a standard integrated assessment model in that it links emissions to damages using six modules. The model first uses an air quality module to map the emissions by sources into ambient concentrations pollutants at receptor locations. Next, concentrations are used to estimate exposures using detailed population and yield data for each receptor county in the lower-48 states. Exposures are then converted to physical effects through the application of peer-reviewed dose-response functions. Finally, an economic valuation module maps the ambient concentrations of pollutants into monetary damages. AP2 also employs an algorithm to determine the marginal damages associated with emissions of any given source.

The inputs to the air quality module are the emissions of ammonia (NH_3), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen oxides (NO_X), and volatile organic compounds (VOC)—from all of the sources in the contiguous U.S. that report emissions to the USEPA.[51] The outputs from the air quality module are predicted ambient concentrations of the three pollutants—SO_2, O_3, and $PM_{2.5}$— at each of the 3,110 counties in the contiguous U.S. The relationship between inputs and outputs captures the complex chemical and physical processes that operate on the pollutants in the atmosphere. For example, emissions of ammonia interact with emissions of NO_X, and SO_2 to form concentrations of ammonium nitrate and ammonium sulfate, which are two significant (in terms of mass) constituents of $PM_{2.5}$. And emissions of NO_X and VOCs are linked to the formation of ground-level ozone, O_3. The predicted ambient concentrations from the air quality module give good agreement with the actual monitor readings at receptor locations (Muller, 2011).

The inputs to the economic valuation module are the ambient concentrations of SO_2, O_3,

[51] There are about 10,000 sources in the model. Of these, 656 are individually-modeled large point sources, most of which are electric generating units. For the remaining stationary point sources, AP2 attributed emissions to the population-weighted county centroid of the county in which USEPA reports said source exists. These county-point sources are subdivided according to the effective height of emissions because this parameter has an important influence on the physical dispersion of emitted substances. Ground-level emissions (from vehicles, trucks, households, and small commercial establishments without an individually-monitored smokestack) are attributed to the county of origin (reported by USEPA), and are processed by AP2 in a manner that reflects the low release point of such discharges.

and $PM_{2.5}$ and the outputs are the monetary damages associated with the physical effects of exposure to these concentrations. The majority of the damages are associated with human health effects due to O_3 and $PM_{2.5}$, but AP2 also considers crop and timber losses due to O_3, degradation of buildings and material due to SO_2, and reduced visibility and recreation due to $PM_{2.5}$. For human health, ambient concentrations are mapped into increased mortality risk and then increased mortality risks are mapped into monetary damages.[52] AP2 uses the value of a statistical life (or VSL) approach to monetize an increase in mortality risk (see Viscusi and Aldy, 2003). In this paper we use the USEPA's value of approximately \$600 per 0.0001 change in annual mortality risk.[53] This value of an incremental change in mortality risk yields a VSL of $\$6 \times 10^6 = \$600/0.0001$.

AP2 is used to compute marginal (\$/ton) damages over a large number of individual sources (power plants in the present analysis) and source regions (counties within which vehicles are driven). First, baseline emissions data that specifies reported values for all emissions at all sources is used to compute baseline damages. (For this paper, we use emissions data from USEPA (2014) that contains year 2011 emissions.) Next, one ton of one pollutant, NO_X perhaps, is added to baseline emissions at a particular source, perhaps a power plant in Western Pennsylvania. Then AP2 is re-run to estimate concentrations, exposures, physical effects, and monetary damage at each receptor conditional on the added ton of NO_X. The difference in damage (summed across all receptors) between the baseline case and the add-one-ton case is the marginal damage of emitting NO_X from the power plant in Western Pennsylvania.[54] This routine is repeated for all pollutants and all sources in the model, first for full damages, and then second for native damages (which only looks at receptors in the state or county of interest).

[52] Because baseline mortality rates vary considerably according to age, AP2 uses data from the U.S. Census and the U.S. CDC to disaggregate county-level population estimates into 19 age groups and then calculates baseline mortality rates by county and age group. The increase in mortality risk due to exposure of emissions is determined by the standard concentration-response functions approach (USEPA, 1999; 2010; Fann et al., 2009). In terms of share of total damage, the most important concentration-response functions are those governing adult mortality. In this paper, we use results from Pope et al (2002) to specify the effect of $PM_{2.5}$ exposure on adult mortality rates and we use results from Bell et al (2004) to specify the effect of O_3 exposure on adult mortality rates.

[53] Of course not all lifetime vehicle miles are driven in the same year. But we assume that marginal damages grow at the real interest rate so that there is no need to discount damages from miles over the life of the vehicles.

[54] We can also analyze the marginal damages at each receptor.

Supplementary Appendix G. State electric vehicle incentives

The Department of Energy maintains a database of alternative fuels policies by state.[55] Using this information, we determined four measures of state electric vehicle policy.[56] The first measure is the actual subsidies for the purchase of an electric vehicle. The second measure is equal to the total number electric vehicle of policies (including both incentives and regulations). The third measure is equal to the number of policies that were classified as by the Department of Energy as incentives. The fourth measure is equal to the number of incentives that were deemed by us to be significant (thus excluding, for example, an incentive that would only apply to the first 100 consumers to install electric vehicle charging equipment).

The four measures are shown in Table B for each state along with the full damage subsidy and the native damage subsidy. Each of the four measures is more highly correlated with the native damage subsidy than with the full damage subsidy.

Supplementary Appendix H. Calibration and sensitivity

To analyze welfare issues, we must have a value for μ. We determine this value by calibrating a numerical version of the model. For this calibration, we assume a specific constant elasticity functional form for the utility of consuming electric miles and gasoline miles. For gasoline miles we have

$$f(g) = k_g \frac{g^{1-\gamma_g} - 1}{1 - \gamma_g}$$

and for electric miles we have

$$h(e) = k_e \frac{e^{1-\gamma_e} - 1}{1 - \gamma_e} + H.$$

As in the main text, we compared the Ford Focus with the Ford Focus Electric. The exogenous parameters are shown in Table C. The elasticity of demand for gasoline miles

[55] http://www.afdc.energy.gov/laws/matrix?sort_by=tech

[56] The state electric vehicle policies are changing over time. Our measures were accurate as of January 1, 2015.

Table B: State electric vehicle policies

State	Full Damage Subsidy	Native Damage Subsidy	Actual Subsidy	Significant Incentives	All incentives and regulations	All incentives
Alabama	-1537	47	0	1	4	2
Arizona	1093	272	0	5	14	6
Arkansas	-1536	-33	0	0	2	0
California	3025	1572	2500	2	45	21
Colorado	1123	320	6000	1	11	5
Connecticut	-1719	-126	0	0	7	3
Delaware	-2462	-23	0	0	2	0
District of Columbia	-801	441	0	1	4	3
Florida	-829	296	0	1	8	4
Georgia	-955	601	5000	2	8	8
Idaho	702	49	0	0	1	1
Illinois	-1475	990	4000	2	13	7
Indiana	-2543	241	0	1	9	6
Iowa	-4118	-109	0	0	4	2
Kansas	-920	124	0	0	1	0
Kentucky	-1665	88	0	1	4	1
Louisiana	-1452	7	0	0	4	2
Maine	-2619	-393	0	0	4	1
Maryland	-1945	462	3000	3	12	7
Massachusetts	-1498	220	2500	1	7	4
Michigan	-2720	291	0	1	6	6
Minnesota	-3951	304	0	1	9	2
Mississippi	-1793	-51	0	0	2	1
Missouri	-1367	129	0	0	6	2
Montana	87	-43	0	0	1	1
Nebraska	-3856	-11	0	0	2	1
Nevada	940	150	0	2	9	3
New Hampshire	-2252	-324	0	0	2	0
New Jersey	-1367	724	0	2	3	2
New Mexico	702	80	0	0	6	3
New York	-1122	645	0	0	5	3
North Carolina	-1411	205	0	1	12	5
North Dakota	-4773	-213	0	0	1	0
Ohio	-2437	414	0	0	4	1
Oklahoma	-791	209	0	0	5	2
Oregon	841	148	0	0	12	5
Pennsylvania	-2472	322	0	0	5	3
Rhode Island	-1746	-132	0	0	7	1
South Carolina	-1511	48	0	0	6	5
South Dakota	-3787	-173	0	0	0	0
Tennessee	-1512	61	0	1	3	1
Texas	784	394	2500	1	8	7
Utah	1320	557	650	2	8	4
Vermont	-2858	-430	0	0	6	2
Virginia	-1532	73	0	2	13	5
Washington	1108	319	0	0	20	6
West Virginia	-2930	-87	0	0	4	0
Wisconsin	-3720	67	0	0	6	2
Wyoming	381	-42	0	0	0	0
Correlation with full damage subsidy			0.29	0.35	0.51	0.51
Correlation with native damage subsidy			0.50	0.52	0.68	0.77

($-1/\gamma_g$) comes from Espey (1998). The elasticity of demand for electric miles ($-1/\gamma_e$) is assumed to be equal to the elasticity of demand for gasoline miles.

The endogenous parameters are determined as follows. The values for k_g and k_e are selected such that the consumer would, in the absence of any policy intervention, consume 150,000 lifetime miles for each type of vehicle. This gives $k_g = 2.58 \times 10^9$ and $k_e = 8.93 \times 10^8$. The values for μ and H were determined such that two conditions held. First, in the absence of any policy intervention, the consumer would select the gasoline vehicle with some given probability. Second, consistent with Li et al (2015)'s observation, at the current federal subsidy of $7500, half of electric vehicles sales would be due to the subsidy. See Table D.

The expression for welfare $\mathcal{W}$ in the main text gives the welfare associated with the purchase of a new vehicle. For the calculations in Tables 6a and 6b, we multiply the welfare per new vehicle sale by 15 million (the approximate number of new vehicle sales per year in the U.S.).

Table C: Exogenous Calibration Parameters (2013 Dollars) : Ford Focus and Ford Focus Electric

Param.	Value	Economic Interpretation	Source/Notes
I	438641	Income over 10 year vehicle lifetime	US BLS : $827 week
p_e	0.0389	Price of electric miles ($ per mile)	EIA : 0.1212 $ per kWh * 0.321 kWh/mile
p_g	0.1126	Price of gasoline miles ($ per mile)	CNN : 3.49 $ per gallon / 31 miles/gallon
p_Ω	35170	Price of electric vehicle ($)	Ford Motors
p_G	16810	Price of gasoline vehicle ($)	Ford Motors
γ_g	2	Gives elasticity for gasoline miles of -0.5	Espey 1998
γ_e	2	Gives elasticity for electric miles of -0.5	Assumption
lm_g	150,000	BAU lifetime miles gasoline	Assumption
lm_e	150,000	BAU lifetime miles electric	Assumption
L	50%	% electric sales from $7500 subsidy	Li et al (2015)

A sensitivity analysis of the exogenous calibration parameters is given in Table E. Baseline corresponds to a BAU probability of 0.01 of selecting the electric vehicle (which corresponds to the first columns in Table 6a and 6b). Changes in the price of the vehicles and income have no effect on the results. Changes in the price of miles and the elasticity of demand for miles have no effect on the benefits of differentiated subsidies, but do effect the benefits of differentiated taxes. Changes in the lifetime miles driven and percentage of sales due to the current federal subsidy effect the benefits of both differentiated subsides and differentiated taxes.

Table D: Value of μ and H as a function of the probability, with no policy intervention, of selecting the gasoline vehicle

Probability	H	μ
0.99	1688947865	10664
0.95	1688967313	10037
0.90	1688976546	9249

Table E: Sensitivity of Exogenous Calibration Parameters

Parameter	Welfare Loss Subsidy		Welfare Loss Tax		Gain from Differentiation	
	Federal	State	Federal	State	Subsidy	Tax
Baseline	2023.6	2000.3	162.7	89.5	23.4	73.2
Gasoline Miles Elasticity + 33%	1393.9	1370.5	121.2	62.6	23.4	58.6
Gasoline Miles Elasticity 33%	2640.0	2616.6	201.6	114.3	23.4	87.3
Electric Miles Elasticity + 33%	2002.4	1979.0	162.1	89.5	23.4	72.5
Electric Miles Elasticity 33%	2043.9	2020.5	163.3	89.6	23.4	73.7
Lifetime Miles Electric 16.6%	2036.2	2007.2	167.5	89.6	28.9	77.9
Lifetime Miles Electric - 16.6%	2010.3	1992.1	158.1	89.5	18.2	68.6
Lifetime Miles Gas +16.6%	2351.1	2325.2	188.7	105.2	25.9	83.5
Lifetime Miles Gas -16.6%	1696.5	1675.4	137.2	74.2	21.2	63.1
Purchases due to subsidy +10%	2029.4	1998.6	169.3	90.8	30.8	78.5
Purchases due to subsidy - 10%	2019.0	2001.7	157.4	88.5	17.3	68.9
Price of Electric Vehicle +16.6%	2023.6	2000.3	162.7	89.5	23.4	73.2
Price of Electric Vehicle -16.6%	2023.6	2000.3	162.7	89.5	23.4	73.2
Price of Gas Vehicle + 16.6%	2023.6	2000.3	162.7	89.5	23.4	73.2
Price of Gas Vehicle -16.6%	2023.6	2000.3	162.7	89.5	23.4	73.2
Price of Electric Miles +16.6%	2016.1	1992.7	162.7	89.5	23.4	73.1
Price of Electric Miles -16.6%	2033.6	2010.2	162.7	89.6	23.4	73.1
Price of Gas Miles + 16.6%	1768.1	1744.8	147.8	80.1	23.4	67.7
Price of Gas Miles 16.6%	2367.3	2343.9	181.5	101.5	23.4	80.1
Income + 16%	2023.6	2000.3	162.7	89.5	23.4	73.2
Income -16%	2023.6	2000.3	162.7	89.5	23.4	73.2

Note: $ Million/year

We conducted a final sensitivity analysis with respect to the price of gasoline and electric miles. Up to now, we have assumed (in both the theoretical model and the empirical calculations) that these prices are the same across locations. In this final sensitivity analysis, we drop this assumption and employ state-specific prices for electric miles and region-specific prices for gasoline miles (using data from EIA.gov). In this analysis, the second best uniform federal subsidy is no longer given by the expression in Proposition 2, and in fact does not have a closed form expression. Likewise for the second best uniform federal taxes. So we determine the these quantities numerically. The benefits of differentiated subsidies, state vs. federal, is \$23.2 million (compared to a baseline of \$23.4 million) and the benefits of differentiated taxes is \$68.4 million (compared to a baseline of \$73.2 million).

Supplementary Appendix I. Single tax policies

Suppose that local government i uses both a tax on gasoline miles and a tax on electric miles. As is well known, the government can obtain the first-best outcome by utilizing the Pigovian solution. Here taxes are equal to the marginal damages, so that $t_{gi} = \delta_{gi}$ and $t_{ei} = \delta_{ei}$.

Now suppose for some reason the government can only tax gasoline miles. What is the optimal gasoline tax, accounting for the externalities from both gasoline and electric vehicles? The answer to this question is given in the next Proposition.

Proposition 3. *The optimal tax on gasoline miles alone in location i is given by*

$$t_{gi}^{*} = \left(\delta_{gi} + \delta_{ei}\left(\frac{e_i}{-g_i\left(\frac{p_G}{g_i(p_g+t_g^{*})}\frac{\varepsilon_g}{\varepsilon_G} + 1\right)}\right)\right),$$

where ε_g is the own-price elasticity of gasoline and ε_G is the own-price elasticity of the gasoline vehicle.

The optimal tax on gasoline miles alone is less than the Pigovian tax on gasoline miles. This occurs because the consumers have the option to substitute into the electric vehicle and thereby avoid taxation on the externalities they generate.

Proof of Proposition 3.

Throughout the proof we can drop the subscript i. The first-order condition for t_g is the same as (A-2):

$$\left(\frac{\partial R}{\partial t_g} - \pi g\right) - \left(\delta_g \frac{\partial G}{\partial t_g} + \delta_e \frac{\partial E}{\partial t_g}\right) + \frac{\partial R}{\partial t_g} = 0.$$

In this case there is only a single tax, so expected tax revenue is given by

$$R = t_g \pi g,$$

and hence

$$\frac{\partial R}{\partial t_g} = G + t_g \frac{\partial G}{\partial t_g}.$$

Using this in the first-order condition gives

$$\left(\left(G + t_g \frac{\partial G}{\partial t_g}\right) - \pi g\right) - \left(\delta_g \frac{\partial G}{\partial t_g} + \delta_e \frac{\partial E}{\partial t_g}\right) = 0.$$

Now, because $G = \pi g$, this simplifies to

$$(t_g - \delta_g)\frac{\partial G}{\partial t_g} - (\delta_e)\frac{\partial E}{\partial t_g} = 0.$$

Solving for t_g gives

$$t_g = \left(\delta_g + \delta_e \frac{\frac{\partial E}{\partial t_g}}{\frac{\partial G}{\partial t_g}}\right).$$

Now from (3), (4), and (5), we have

$$\frac{\partial \pi}{\partial t_g} = -\frac{\pi(1-\pi)}{\mu} g,$$

$$\frac{\partial G}{\partial t_g} = -\frac{\pi(1-\pi)}{\mu} g^2 + \pi \frac{\partial g}{\partial t_g}.$$

and

$$\frac{\partial E}{\partial t_g} = \frac{\pi(1-\pi)}{\mu} eg + (1-\pi)\frac{\partial e}{\partial t_g}.$$

Now because there are no income effects, t_g does not effect the choice of e, so this latter equation simplifies to

$$\frac{\partial E}{\partial t_g} = \frac{\pi(1-\pi)}{\mu} eg.$$

Substituting these into the first-order condition for t_g and simplifying gives

$$t_g = \left(\delta_g + \delta_e \left(\frac{e}{\frac{\frac{\partial g}{\partial t_g}\mu}{(1-\pi)g} - g}\right)\right).$$

We can further express this equation in terms of elasticities. The own-price elasticity of gasoline miles is

$$\varepsilon_g = \frac{\partial g}{\partial t_g}\frac{p_g + t_g}{g}.$$

For discrete choice goods, price elasticities are defined with respect to the choice probability. The own-price elasticity of the gasoline vehicle, given a change in the price of the gasoline vehicle, is

$$\varepsilon_\Psi = \frac{\partial \pi}{\partial p_\Psi}\frac{p_\Psi}{\pi} = \frac{\pi(1-\pi)}{\mu}\left(\frac{\partial V_g}{\partial p_\Psi} - \frac{\partial V_e}{\partial p_\Psi}\right)\frac{p_\Psi}{\pi} = \frac{\pi(1-\pi)}{\mu}(-1-0)\frac{p_\Psi}{\pi} = -(1-\pi)p_\Psi/\mu.$$

Substituting the elasticities into the first-order condition for t_g gives

$$t_g = \left(\delta_g + \delta_e \left(\frac{e}{-g\left(\frac{p_\Psi}{g(p_g+t_g)}\frac{\varepsilon_g}{\varepsilon_\Psi} + 1\right)}\right)\right).$$

■

Supplementary Appendix J. CAFE standards

Consider an automobile manufacturer that produces three models a, b, and g with corresponding fuel economies in miles per gallon $f_a < f_b < f_g$. As the notation indicates, vehicle g will play the role of the gasoline vehicle in the main text (and thereby be the substitute for the electric car.) The sales are each model are n_a, n_b and n_g. The CAFE standard requires that fleet fuel economy (defined as the sales-weighted harmonic mean of individual fuel economies) exceeds a given value k. So we have

$$\frac{n_a + n_b + n_g}{\frac{n_a}{f_a} + \frac{n_b}{f_b} + \frac{n_g}{f_g}} \geq k.$$

Suppose initially that the cafe standard is binding, which implies that the market would prefer to swap from a high MPG vehicle purchase to a low MPG vehicle purchase, but cannot do so because of the standard. It is helpful to write the initial condition in terms of gallons per mile rather than miles per gallon:

$$\frac{\frac{n_a}{f_a} + \frac{n_b}{f_b} + \frac{n_g}{f_g}}{n_a + n_b + n_g} = \frac{1}{k}.$$

We want to analyze the impact of selling an electric vehicle on the composition of the fleet, under the assumption that the total amount of vehicles sold stays the same. For CAFE purposes, the electric vehicle is assigned it's MPG equivalent, which is typically much greater than the MPG of the most efficient gasoline vehicle Let this be denoted by f_e where $f_e > f_g$. Since the total amount of vehicles sold stays the same, the sale of an electric vehicle leads to a reduction in sales of another type of vehicle. This clearly raises the fleet fuel economy, the CAFE standard is no longer binding, and so the previously restricted swap from high to low MPG may now be allowed to take place. Assume that the electric vehicle sale replaces a sale of a model g vehicle, and that the desired swap is from b to a. Also assume that the footprint of g and e are the same, and the footprint of b and a are the same. (This keeps the value of k constant.) The swap of a for b can be done if the resulting fleet fuel economy satisfies the standard:

$$\frac{\frac{n_a+1}{f_a} + \frac{n_b-1}{f_b} + \frac{n_g-1}{f_g} + \frac{1}{f_e}}{n_a + n_b + n_g} \leq \frac{1}{k}. \tag{A-6}$$

Using the initial condition this becomes

$$\frac{1}{k} + \frac{\frac{1}{f_a} + \frac{-1}{f_b} + \frac{-1}{f_g} + \frac{1}{f_e}}{n_a + n_b + n_g} \leq \frac{1}{k},$$

and so the condition becomes

$$\frac{1}{f_a} - \frac{1}{f_b} \leq \frac{1}{f_g} - \frac{1}{f_e}. \tag{A-7}$$

The right-hand-side of (A-7) specifies the maximum feasible increase in gallons per mile that may occur in the rest of the fleet due to the sale of an electric vehicle. If the CAFE constraint binds in the resulting fleet (which we would generally expect to be the case), then this maximum will be obtained. And of course this increase in gallons per mile has an associated cost to society from emissions damage.

We see that CAFE regulation induces an additional environmental cost from electric vehicles due to the substitution of a low MPG vehicle for a high MPG vehicle We can sketch a back-of-the-envelope calculation for the magnitude of this CAFE induced environmental cost and its effect on the second-best subsidy on electric vehicles as follows. Assume that vehicle a and vehicle b are in the same Tier 2 "bin". For vehicles in the same bin, the vast majority of environmental damages are due to emissions of CO_2. In addition, without a explicit model of the new vehicle market, we don't know which location the vehicle a will be driven. So we are content to calculate the CAFE induced environmental cost due to CO_2 emissions only. Let δ_a and δ_b be the damage (in \$ per mile) due to CO_2 emissions from vehicle a and b, respectively.[57] It follows that the additional environmental cost is give by $(\delta_a - \delta_b)g$.

Next we integrate CAFE standards with the model in the main part of the paper. We do not try to model both supply and demand for the market for vehicles. Rather we simply assume that the consumer chooses between the electric vehicle and vehicle g, and this choice induces a change in the composition of the rest of the fleet due to CAFE regulation considerations. The basic single-location welfare equation becomes

$$\mathcal{W} = \mu \left(\ln(\exp(V_e/\mu) + \exp(V_g/\mu))\right) + R - (\pi(\delta_b + \delta_g)g + (1-\pi)(\delta_e e + \delta_a g)).$$

We see that if the consumer selects the gasoline vehicle, then the fleet consists of this gasoline vehicle in conjunction with vehicle b. But if the consumer selects the electric vehicle, then the fleet consists of the electric vehicle in conjunction with vehicle a. (We are ignoring the utility benefit generated by the switch from b to a.) Following similar arguments as in the

[57] For example, $\delta_a = \frac{\$0.403}{f_a}$, where the numerator is the CO_2 damages per gallon in our model.

proof of Proposition 1, the optimal subsidy is determined to be

$$s^* = ((\delta_g - (\delta_a - \delta_b))g - \delta_e e).$$

We see that the optimal subsidy is decreased by the amount equal to the CAFE induced environmental cost $(\delta_a - \delta_b)g$. Using our Ford Focus baseline numbers, the CAFE induced environmental cost turns out to be \$1439.[58]

Starting in 2017, CAFE regulation will make things worse, because it will allow the manufacturer to claim credit for two electric vehicle sales for each actual sale of an electric vehicle. Thus (A-6), the condition for the swap from b to a becomes

$$\frac{\frac{n_a+1}{f_a} + \frac{n_b-1}{f_b} + \frac{n_c-1}{f_c} + \frac{2}{f_e}}{n_a + n_b + n_c + 1} \leq \frac{1}{k}.$$

Notice that we are keeping the actual amount of vehicles sold constant, but the CAFE regulation enables the manufacturer to do the calculation as if they had sold one additional electric vehicle. Using the initial condition, this can be written as

$$\frac{\frac{1}{f_a} + \frac{-1}{f_b} + \frac{-1}{f_c} + \frac{2}{f_e}}{n_a + n_b + n_c} \leq \frac{\frac{n_a}{f_a} + \frac{n_b}{f_b} + \frac{n_c}{f_c}}{n_a + n_b + n_c}(n_a + n_b + n_c + 1) - \left(\frac{n_a}{f_a} + \frac{n_b}{f_b} + \frac{n_c}{f_c}\right).$$

Which simples to

$$\frac{1}{f_a} - \frac{1}{f_b} \leq \left(\frac{1}{f_c} - \frac{1}{f_e}\right) + \left(\frac{1}{k} - \frac{1}{f_e}\right). \tag{A-8}$$

Comparing (A-7) with (A-8), we see that the effect of double counting the electric vehicle is to more than double the CAFE induced environmental cost of the electric vehicle, provided the gallons per mile used by vehicle c is smaller than CAFE limit on gallons per mile $1/k$.

[58] The right-hand-side of (A-7) is given by $1/30 - 1/105 = 0.0238$. Assuming this equation holds with equality, we have $(\delta_a - \delta_b) = 0.403 * 0.0238$. Multiplying by a lifetime of 150,000 miles gives \$1439. We should also note that the EPA posted MPG number for a given vehicle is different from the CAFE MPG number for that same vehicles. On average, the EPA number is eighty percent of the CAFE number. We use the EPA number in the calculation of the additional environmental cost because it more accurately reflects real word gasoline consumption.

Supplementary Appendix References

References

[1] Espey, M. (1998), "Gasoline demand revisited: an international meta-analysis of elasticities," *Energy Economics*, 20: 273-295.